Volatility Risk Decomposition and the Covariation Risk Premium

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Abstract

How does the covariation risk (the risk of *simultaneous* unfavorable shocks to cash flows and discount rate) impact hedging demands of long-term investors and expected stock returns? To address this question, we develop an intertemporal asset pricing model with the time-varying covariance matrix of cash-flow news and discount rate news, in which covariation risk carries separate risk premium. Our model helps account for approximately 71% of the return variation across size, book-to-market and momentum sorted portfolios for the modern U.S. sample period. Collectively, our findings suggest that covariation risk is both economically and statistically important for understanding equity risk premia.

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I. Introduction

Understanding risk factors that explain variation in the cross-section of expected stock returns is a fundamental issue in the asset pricing literature. Intertemporal asset pricing theory, starting with the seminal study ofMerton (1973), predicts that long-term investors care not only about a stock's covariance with the market portfolio (i.e., market beta of a stock) as in Sharpe (1964) and Lintner (1965), but also about stock's covariance with fluctuations in expected returns and variances of their investments. Building on Merton's (1973) Intertemporal Capital Asset Pricing model (ICAPM), Campbell and Vuolteenaho (2004) show that the market beta of an asset decomposes into a cash-flow component and a discount-rate component, and that both components carry distinct risk premia. A recent and growing literature also emphasizes the role of variance fluctuations in determining risk premia and hedging demands of investors. Campbell et al. (2014) extend Campbell and Vuolteenaho (2004) model to allow for stochastic volatility and find evidence that asset sensitivity to the news about aggregate market volatility (i.e.,, volatility risk) is also an important determinant of expected returns. In related study, Bansal et al. (2014) use a consumption-based model to show that long-run consumption volatility risk carries a sizable risk premium.

The results in Campbell et al. (2014) and Bansal et al. (2014) suggest that investors require higher risk premium for holding stocks with higher exposure to volatility risk. In this paper, we posit that investors are concerned not only about the magnitude of exposure to volatility risk (as in Campbell et al. (2014) and Bansal et al. (2014)), but also about the *source* of volatility risk. Specifically, we develop an intertemporal asset pricing model, in which the news about aggregate market volatility — and by inference, volatility risk —decomposes into three news components: cash-flow variation, discount-rate variation, and the covariation between the cash-flow and discount-rate news. In our model, long-term investors are willing to pay a premium to hedge an increase in variation as well as to hedge a decrease in covariation. Our model predicts that these three components of aggregate volatility risk carry different risk premia. Therefore, recognizing these distinct sources of volatility risk is important for better understanding asset pricing dynamics.

In our model, the variation effect arises due to a multi-period precautionary savings motive, which suggests that investors are willing to pay a premium for assets that hedge an increase in stand-alone variations of cash-flow news and of discount-rate news. The covariation effect works in the opposite direction to the variation effect: investors are willing to pay a premium to hedge the risk of being hurt *simultaneously* by unfavorable cash-flow news and unfavorable discount-rate news—a scenario that becomes more likely when covariation becomes more negative. An intuitive way to summarize this "double whammy" effect is to say that cash flow and discount rate news are unconditionally positively correlated (e.g., Campbell and Vuolteenaho (2004), Lettau and Ludwigson (2005), Golez (2014)), and therefore naturally hedge each other in normal times. However, when this covariation decreases, marginal utility increases. That is, marginal utility is higher in times when unfavorable news about decreasing future cash-flows is less likely to be offset by favorable news about decreasing discount-rates, and in times when unfavorable news about increasing discount-rates is less likely to be offset by favorable news about increasing future cash-flows. Therefore, marginal utility is higher in times when covariation is low and this "double whammy" event is more likely. Consequently, long-term investors are averse to decreases in covariation and are willing to pay a premium for assets that hedge this risk. This intuition is formalized in our model, which posits that covariation risk carries a positive risk premium.

Our analytical framework implies a non-linear ICAPM which includes the following factors: (i) cash-flow news, (ii) discount-rate news, (iii) cash-flow variation news, (iv) discount-rate variation news, and (v) covariation news. The non-linearity in our model arises from a second-order approximation of the pricing kernel, which helps better approximate states in which the pricing kernel realization is substantially away from its mean. In these states, a first-order approximation is likely to induce a significantly larger approximation error than a second-order approximation. See e.g. Chen, Cosimano, and Himonas (2013).

To operationalize our model, we use a two-step estimation approach. In the first step, we estimate cash-flow and discount-rate news using the Vector Autoregression (VAR) approach (Campbell and Vuolteenaho (2004)). In the second step, we estimate the three volatility news components under the assumption that cash-flow news and discount rate news follow a multivariate GARCH (MGARCH) process. Utilizing MGARCH framework in the context of our research question has two important advantages. First, while being sufficiently general it helps us parsimoniously estimate our model. Second, it restricts the covariance matrix of cash flow news and discount rate news to be positive definite, and thus prevents the volatility estimates from taking negative values, which may lead to econometric issues that are not easily resolved.[3]

We evaluate the performance of our model using cross-section of returns across size, book-to-market, and past stock performance (momentum) sorted portfolios on the U.S. market.[4] We find that small cap stocks have higher exposure to covariation risk compared to large cap stocks. Further, we find that stocks with good past performance ("past winners") have higher exposure to

[3] For instance, Campbell et al.(2014) show that, if realized volatility is used as an additional variable in a linear VAR model, then future volatility predicted by the VAR can potentially take negative values.

[4] Asset pricing models are often evaluated on their ability to explain the size and value effect (e.g., Campbell and Vuolteenaho (2004), Hahn and Lee (2006)). Jegadeesh and Titman (1993) is the seminal reference for the momentum effect.

covariation risk compared to stocks with poor past performance (“past losers”). The model explains about 71% of the return variation across size, book-to-market, and momentum sorted portfolios over the period of 1963-2010 and is not rejected at conventional significant levels. Furthermore, we find that the explanatory power of our model is predominantly attributed to covariation risk, which carries a positive and statistically significant risk premium. To gauge the robustness of our findings, we also estimate the model using the implied cost of equity approach (Gebhardt, Lee, and Swaminathan(2001), Claus and Thomas(2001), Chen, Chen, and Wei (2011)) for a panel of individual stocks. Our key results continue to hold.

Our study makes several contributions to the existing literature. First, at a broader level, our study contributes to the asset pricing literature by identifying covariation risk as an important determinant of the cross-section of risk premia in the equity market. Specifically, our findings suggest that stocks with higher covariation risk have higher expected returns. These results are consistent with the notion that long-term investors are averse to decreases in covariation, and therefore are willing to pay a premium for assets that hedge this risk.

Second, our findings contribute to a growing stream of research documenting the important role of aggregate market volatility risk in shaping the expected return-risk relation (Bansal et al. 2014, Campbell et al. 2014). We show that news about aggregate market volatility — and by inference, aggregate market volatility risk — can be decomposed into the cash-flow variation, discount-rate variation and covariation news components. Furthermore, our results suggest that the aggregate volatility risk premium is predominantly driven by the covariation risk.In this context, our model can also be viewed as a natural extension of the Campbell and Vuolteenaho (2004) return decomposition model where not only the unconditional correlation between cash-flows and discount rates is important for return decomposition, but also the time-variation in this correlation. Our results suggest that that both the magnitude of exposure to volatility risk and the source of volatility risk should be taken into consideration when modeling the relation between expected returns and volatility risk.

Third, our study provides a potential explanation to the momentum phenomenon; namely, the documented tendency of stocks that experienced high (low) returns in the past to continue outperforming (underperforming) the market (Jegadeesh and Titman (1993)). Specifically, we document that stocks with high past returns ("past winners"), on average, have higher exposure to covariation risk relative to stocks with low past returns ("past losers"). These results suggest that past loser stocks outperform past winner stocks in times of decreasing covariation between the cash-flow and discount-rate news; that is, times when the marginal utility of precautionary savings is high according to our model. As such, our study contributes to the ongoing debate regarding the source of momentum strategy returns by offering a risk-based explanation for the momentum phenomenon.[5]

The rest of the paper is organized as follows. In Section II we set the theoretical framework. We derive our stochastic discount factor in Section III. Section IV describes our estimation procedure. The empirical results are presented and discussed in Section V. Section VI concludes.

II. Theoretical Framework

We commence with a simple example that illustrates the baseline intuition behind our volatility risk decomposition. Consider an economy with a risk averse representative agent whose

[5] We refer to the debate regarding behavioral versus rational explanations of momentum phenomenon. On one hand, several studies suggest that momentum in stock returns is unlikely to be explained by risk and, instead, should be treated as the anomaly driven by behavioral explanations (Fama, 1998; Barberis and Thaler, 2003; and Jegadeesh and Titman, 2005). On the other hand, some studies attempt to rationalize momentum phenomenon by offering risk-related explanations for the observed continuation in stock returns (Bansal, Dittmar, and Lundblad, 2005; Sagi and Seasholes, 2007; Liu and Zhang, 2008).

next-period wealth, the value of the market portfolio (w_{t+1}), is the present value of a perpetuity of dividends (d_{t+2}), starting from period 2 and discounted using discount-rate r_{t+1}, where small case denote logs. Equating log wealth to the log of the present value of dividends, we obtain $w_{t+1} = d_{t+2} - r_{t+1}$. In this special case, the conditional variance of investor wealth is decomposed as $\text{var}_t\left(w_{t+1}\right) = \text{var}_t\left(d_{t+2}\right) + \text{var}_t\left(r_{t+1}\right) - 2\,\text{cov}_t\left(d_{t+2}, r_{t+1}\right)$.

In this basic example, a positive shock to either $\text{var}_t(d_{t+2})$ or $\text{var}_t(r_{t+1})$ increases the volatility of wealth. Consequently, a risk-averse investor will be willing to pay a premium to hold assets that hedge against an increase in the variances of future dividends and discount-rates; that is, assets that perform well at times when either the variance of future dividends or the variance of discount-rate goes up. In contrast, a positive shock to $\text{cov}_t(d_{t+2}, r_{t+1})$ decreases the volatility of wealth. Therefore, a risk-averse investor will be willing to pay premium to hold assets that hedge against a decrease in covariance between future dividends and discount-rates; that is, assets that perform well at times when the covariance between future dividends and discount-rate goes down. In other words, decreasing covariance is a risk that this representative agent will want to hedge against.

We formalize this intuition in our asset pricing model. We begin by outlining several results from prior research that will be helpful for derivation of our model. Similar to prior studies, our starting point is a no arbitrage condition which implies the standard Euler equation:

$$\text{E}_t\left[M_{t+1}R_{i,t+1}\right] = 1, \tag{1}$$

where M_t denotes the stochastic discount factor (SDF) and R_i the return on any traded asset in the economy (see Harrison and Kreps (1979)). The expression for the SDF depends on the preferences of the representative agent and the intertemporal budget constraint[6]. Following prior research (e.g., Campbell and Vuolteenaho (2004), Campbell et al. (204)), we assume a representative agent with Epstein-Zin recursive preferences (Epstein and Zin (1989,1991)). This assumption has the desirable property that the notion of risk aversion is separated from that of the intertemporal elasticity of substitution (IES). In our economy, when risk aversion and IES are not equal and are both larger than 1, agents have a stronger precautionary savings motive than when they are equal or when they are less than 1. That is, they demand larger risk premia for holding assets exposed to the risk of a long-run rise in economic uncertainty (volatility risks). In contrast, when the IES is close to 1, volatility risks do not contribute substantially to their marginal utility (see Campbell and Vuolteenaho (2004)). Since we are interested in understanding the asset pricing implications of various components of volatility risk, we assume Epstein-Zin recursive preferences and allow for IES to be substantially greater than 1.

Epstein andZin (1989, 1991) show that these preferences and a budget constraint imply the following stochastic discount factor M_{t+1} for a representative agent:

$$M_{t+1} = \left\{ \delta \left(\frac{C_{t+1}}{C_t} \right)^{-1/\psi} \right\}^{\theta} R_{t+1}^{-(1-\theta)} \qquad (2)$$

In Equation (2), R_{t+1} is the return on the aggregate wealth W_t, where W_t is defined as the market value of the consumption stream $\{C_t\}$ (including current consumption) owned by the representative agent. The preference parameters are the discount factor δ, risk aversion γ, and the elasticity of intertemporal substitution (IES) ψ. θ is a function of these parameters and is defined as

[6] The investment for the next period is constrained to be the wealth minus the amount consumed in each period. The allocation of consumption over time is chosen so as to maximize the lifetime utility of the agent.

$(1-\gamma)\Big/\left(1-\frac{1}{\psi}\right)$.

A. An approximate stochastic discount factor with second order shocks

Our approach is to derive an expression for SDF in terms of the two news components of the unexpected market returns: cash-flow news $\left(N_{c,t+1}\right)$ and discount-rate news $\left(N_{d,t+1}\right)$. Towards this end, we fist obtain an approximation for the pricing kernel outlined in Equation (2) using a second-order Taylor expansion. For analytical tractability, we first express Equation (2) in terms of logs and then approximate the equation using a second-order Taylor expansion around the conditional expectations of r_{t+1} and Δc_{t+1}, where lower case letters denotes natural logs. This yields an approximation of the SDF around $\rho = \exp\left(\mathrm{E}\left[m_{t+1}\right]\right)$. For convenience, we define $\omega_{r,t+1} = r_{t+1} - E_t r_{t+1}$ and $\omega_{c,t+1} = \Delta c_{t+1} - E_t \Delta c_{t+1}$. The second-order Taylor expansion of Equation (2) gives Equation (3a). For analytical tractability, we re-arrange expression in Equation 3(a) which gives Equation 3(b).

$$M_{t+1} - E_t M_{t+1} \cong E_t M_{t+1} \left\{ -\frac{\theta}{\psi}\omega_{c,t+1} - (1-\theta)\omega_{r,t+1} + \frac{1}{2}\left[\left(\frac{\theta}{\psi}\omega_{c,t+1} + (1-\theta)\omega_{r,t+1} \right)^2 - h_{m,t} \right] \right\}, \quad (3a)$$

$$\omega_{m,t+1} = \frac{M_{t+1}}{E_t M_{t+1}} - 1 = -\frac{\theta}{\psi}\omega_{c,t+1} - (1-\theta)\omega_{r,t+1} + \frac{1}{2}\omega_{v,t+1}. \quad (3b)$$

Equation (3b) expresses the percentage deviation in the SDF from its expected value in terms of shocks to log consumption growth $\left(\omega_c\right)$, shocks to log market return $\left(\omega_r\right)$, and the variance of the first-order approximation of shocks to the SDF: $\omega_{v,t+1} = \left[\left(\frac{\theta}{\psi}\omega_{c,t+1} + (1-\theta)\omega_{r,t+1} \right)^2 - h_{m,t} \right]$, where $h_{m,t} = \mathrm{E}_t\left[\left(\frac{\theta}{\psi}\omega_{c,t+1} + (1-\theta)\omega_{r,t+1} \right)^2 \right]$ or equivalently $h_{m,t} = \mathrm{var}_t\left[\frac{\theta}{\psi}\omega_{c,t+1} + (1-\theta)\omega_{r,t+1} \right]$.

B. Expressing $\omega_{c,t+1}$ *in terms of cash-flow and discount-rate news*

Our next step is to express $\omega_{m,t+1}$ in Equation (3) in terms of the cash-flow and discount-rate news components, $N_{c,t+1}$ and $N_{d,t+1}$, which requires expressing $\omega_{c,t+1}$ and $\omega_{v,t+1}$ in terms of $N_{c,t+1}$ and $N_{d,t+1}$. We commence by deriving an expression for $\omega_{c,t+1}$ in terms of $N_{c,t+1}$ and $N_{d,t+1}$ components. To do so, we first obtain approximate expressions for expected log consumption growth, $\mathrm{E}_t\left[\Delta c_{t+1}\right]$, and expected log return on market portfolio, $E_t r_{t+1}$ by imposing the restriction that Equation (1) holds for any asset *i*, including the aggregate wealth portfolio. Applying Equations (1) and (3b) to the market portfolio and estimating the Euler equation by applying a second-order Taylor expansion around the means of r_{t+1} and Δc_{t+1} gives Equation (4):

$$\mathrm{E}_t \Delta c_{t+1} = \psi \log \delta + \psi \mathrm{E}_t r_{t+1} + \frac{1}{2}\frac{\theta}{\psi}\mathrm{var}_t\left[\Delta c_{t+1} - \psi r_{t+1}\right]. \quad (4)$$

Equation (4) relates deviations of expected consumption growth from its long-term mean to deviations of returns from their long-term means and a precautionary savings term. The sensitivity of consumption deviations to expected return deviations is measured by the IES coefficient (ψ). Consistent with related models such as Campbell et al. (2003), the precautionary savings term measures the influence of an increase in the variance of future consumption growth relative to portfolio returns, $\mathrm{var}_t\left[\Delta c_{t+1} - \psi r_{t+1}\right]$. According to (4), when $\theta < 0$ (our assumed case), an increase in $\mathrm{var}_t\left[\Delta c_{t+1} - \psi r_{t+1}\right]$ decreases expected consumption growth. Using (4) and a standard log-linearization of the budget constraint yields an expression for unexpected consumption growth, which can be used to replace unexpected log consumption growth in the SDF with news components:

$$\omega_{c,t+1} = c_{t+1} - \mathrm{E}_t\left[c_{t+1}\right] = \left(\mathrm{E}_{t+1} - \mathrm{E}_t\right)\sum_{j=0}^{\infty}\rho^j r_{t+1+j} - \left(\mathrm{E}_{t+1} - \mathrm{E}_t\right)\sum_{j=1}^{\infty}\rho^j \Delta c_{t+1+j}$$
$$= N_{c,t+1} - \psi N_{d,t+1} + \frac{1}{2}\frac{\psi}{\theta} N_{v,t+1} \qquad (5)$$

where $N_{d,t+1}$ denotes discount-rate news, and $N_{c,t+1}$, denotes cash-flow news. The last term, $N_{v,t+1}$, denotes news about "future risk", following Campbell et al. (2014). It captures revisions in expectations for the variance of future log returns plus the log stochastic discount factor. The expressions for these news terms are:

$$N_{c,t+1} = \left(E_{t+1} - E_t\right)\sum_{s=0}^{\infty}\rho^s \Delta c_{j,t+1+s}, \quad N_{d,t+1} = \left(E_{t+1} - E_t\right)\sum_{s=1}^{\infty}\rho^s r_{j,t+1+s},$$
$$N_{v,t+1} = \left(\mathrm{E}_{t+1} - \mathrm{E}_t\right)\sum_{j=1}^{\infty}\rho^j\left[\left(\frac{\theta}{\psi}\omega_{c,t+1+j} - \theta\,\omega_{r,t+1+j}\right)^2\right]. \qquad (6)$$

Under the assumption of conditional log-normality, these expressions are equivalent to the expressions in Campbell et al. (2014). However, Equations (5) and (6) are more general and are valid even when the conditional log-normality assumption is violated. Plugging expression for $\omega_{c,t+1}$ from Equation (5) into Equation (3.b) yields Equation (7).

$$\omega_{m,t+1} = -\gamma N_{c,t+1} + N_{d,t+1} + \frac{1}{2} N_{v,t+1} + \frac{1}{2}\omega_{v,t+1}, \qquad (7)$$

Equation (7) generalizes the expressions derived by Campbell et al. (2014) and Bansal et al. (2014) in that the shocks to the squared log SDF are also priced. The difference arises because these studies assume conditional log-normality and therefore ignore second order SDF volatility shocks, which are potentially important in the data. For example, studies such as Harvey and Siddique (2000), show the importance of covariance with the square of the market returns help explain risk premia. Equation (7) allows for these second-order effects in an ICAPM return-decomposition framework. In the next section, we develop a testable model of expected returns based on the SDF in Equation (7).

III. A non-linear ICAPM with volatility risk decomposition

A. Expressing $N_{v,t+1}$ and $\omega_{v,t+1}$ in terms of cash-flow and discount rate news

Recall that our goal is to derive an expression for the pricing kernel in terms of the two components of the unexpected market return—cash-flow news ($N_{c,t+1}$) and discount-rate news ($N_{d,t+1}$). However, the expression for the pricing kernel in Equation (7) depends not only on these two components, but also on the news to future risk ($N_{v,t+1}$) and the news to the volatility of log SDF ($\omega_{v,t+1}$). Therefore, the remaining task is to derive expressions for $N_{v,t+1}$ and $\omega_{v,t+1}$ in terms of $N_{c,t+1}$ and $N_{d,t+1}$.

To derive an expression for news to future risk in terms of $N_{c,t+1}$ and $N_{d,t+1}$, we need to make an assumption regarding the process that governs the time-dynamics of the covariance matrix of $N_{c,t+1}$ and $N_{d,t+1}$. We assume that conditional covariance matrix, $\mathbf{H}_t$, follows an MGARCH process:[8]

$$\mathbf{H}_{t+s} = \mathbf{C}'\mathbf{C} + \mathbf{A}'\mathbf{N}_{t+s-1}\mathbf{N}'_{t+s-1}\mathbf{A} + \mathbf{G}'\mathbf{H}_{t+s\text{-}1}\mathbf{G}\,, \tag{8}$$

where $\mathbf{H}_t$ is the 2×2 conditional covariance matrix of $N_{c,t+1}$ and $N_{d,t+1}$, $\mathbf{N}_t$ denotes a 2×1 vector of the news terms, and $\mathbf{C}$, $\mathbf{A}$ and $\mathbf{G}$ are 2×2 matrices of constants. We assume that

[8] This assumption is sufficiently general as it encompasses a variety of positive definite representations of the covariance matrix (Engle and Kroner, 1995).

the process is covariance stationary. This assumption enables us to estimate our intertemporal model with variation and covariation risks, without estimating shocks to long-term volatility directly. The expression for conditional volatility of cash flow news implied by the MGARCH process defined in Equation (8) is:

$$h_{cc,t+1} = c_{11} + a_{cc}^2 N_{c,t}^2 + 2a_{cc}a_{dc}N_{c,t}N_{d,t} + a_{dc}^2 N_{d,t}^2 + g_{cc}^2 h_{cc,t} + 2g_{cc}g_{dc}h_{cd,t} + g_{dc}^2 h_{dd,t}, \tag{9}$$

where a_{xy} denotes an element of $\mathbf{A}$, the ARCH persistence matrix, and g_{xy} denotes an element of $\mathbf{G}$, the GARCH persistence matrix. With this MGARCH process assumption in hand, we solve for a second-order approximation for $N_{v,t+1}$:

$$\begin{aligned} N_{v,t+1} &\approx \left(\mathrm{E}_{t+1} - \mathrm{E}_t\right)\sum_{j=1}^{\infty}\rho^j\left(1-\gamma\right)^2 N_{c,t+1+j}^2 \approx \left(\mathrm{E}_{t+1} - \mathrm{E}_t\right)\sum_{j=1}^{\infty}\rho^j\left(1-\gamma\right)^2 h_{cc,t+1+j} \\ &\approx \left(1-\gamma\right)^2 \chi\left\{a_{cc}^2 N_{cc,t+1} + a_{dc}^2 N_{dd,t+1} + 2a_{dc}a_{cc}N_{cd,t+1}\right\}. \end{aligned} \tag{10}$$

In Equation (10), $N_{cc,t+1}$, $N_{dd,t+1}$, and $N_{cd,t+1}$ are news to second-order terms of $N_{c,t+1}$ and $N_{d,t+1}$, given by $N_{c,t+1}^2 - h_{cc,t+1}$, $N_{d,t+1}^2 - h_{dd,t+1}$, and $N_{c,t+1}N_{d,t+1} - h_{cd,t+1}$, respectively, and χ is a scale parameter that captures the link between news to long-term aggregate variance and the variance of next period's cash flow news $\left(h_{cc,t+1}\right)$.[9]

To derive an expression for $\omega_{v,t+1}$ in terms of $N_{c,t+1}$ and $N_{d,t+1}$ we commence by eliminating the third order and higher order terms of $N_{c,t+1}$ and $N_{d,t+1}$ from its expression. In Equation (3b),

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[9] In our calibration exercise discussed in Section IV, we set $\chi = \rho \big/ \left(1 - \rho\left(a_{cc}^2 + g_{cc}^2\right)\right)$ to reflect long-term impact of a one period shock to $h_{cc,t+1}$.

we keep only the first and second order terms of $N_{c,t+1}$ and $N_{d,t+1}$ in the expression for $\omega_v = \left[\left(\frac{\theta}{\psi} \omega_{c,t+1} + (1-\theta)\,\omega_{r,t+1} \right)^2 - h_{m,t} \right]$. Note that, according to Equation (10), $N_{v,t+1}$ is a second-order function of $N_{c,t+1}$ and $N_{d,t+1}$. Therefore, the third order and higher order terms of $N_{v,t+1}$ do not contribute to the *second-order* approximation of $\omega_{v,t+1}$. This further implies that the expression for $\omega_{v,t+1}$ in terms of first and second order terms of $N_{c,t+1}$ and $N_{d,t+1}$ (and ignoring higher order terms) is given by:

$$\omega_{v,t+1} \approx \left(\mathrm{E}_{t+1} - \mathrm{E}_t\right)\left(-\gamma N_{c,t+1} + N_{d,t+1}\right)^2 = \gamma^2 N_{cc,t+1} + N_{dd,t+1} - 2\gamma N_{cd,t+1}. \tag{11}$$

B. Intertemporal asset pricing with variation and covariation risks

Having expressed the news to future risk ($N_{v,t+1}$) and the news to the log of SDF ($\omega_{v,t+1}$) in terms of the cash-flow and discount-rate news components, we plug the resulting expressions from Equations (10) and (11) in Equation (7) to obtain the expression for our SDF:

$$\omega_{m,t+1} = -\gamma N_{c,t+1} + N_{d,t+1} - \lambda_{cc} N_{cc,t+1} - \lambda_{dd} N_{dd,t+1} - \lambda_{cd} N_{cd,t+1}, \tag{12}$$

The expressions for $\lambda_{cc}, \lambda_{dd}$ and λ_{cd} are given in Equation(13).

$$\lambda_{cc} = -\frac{\gamma^2 + (\gamma-1)^2 \chi a_{cc}^2}{2}, \tag{13a}$$

$$\lambda_{dd} = -\frac{1 + (\gamma-1)^2 \chi a_{dc}^2}{2}, \tag{13b}$$

$$\lambda_{cd} = \gamma + (\gamma-1)^2 \chi(-a_{dc} a_{cc}), \tag{13c}$$

From the expressions in Equations (13a) and (13b), we note that $\lambda_{cc}, \lambda_{dd} < 0$. Also Equation (13c) implies that $\lambda_{cd} > 0$ when $a_{dc}a_{cc} \leq 0$. If investors demand a risk premium for holding assets that decline when covariation declines, then we should find that either $a_{dc}a_{cc} \leq 0$, or that $\gamma > (\gamma - 1)^2 \chi(-a_{dc}a_{cc})$. The condition $a_{dc}a_{cc} \leq 0$ implies that a decrease in cash flows along with an increase in discount rates increases cash flow volatility ($N_{c,t}N_{d,t} < 0 \Rightarrow \uparrow h_{cc,t+1}$). Consistent with our conjecture of a positive covariation risk premium $\left(\lambda_{cd} > 0\right)$, we find that $a_{dc}a_{cc} < 0$ for our estimated MGARCH parameters (discussed in further detail in Section IV).

Substituting Equation (12) into Equation (1) yields an approximate pricing expression for expected excess return on any traded asset:

$$\begin{aligned} &E_t R_{i,t+1} - R_{f,t} \approx \gamma \operatorname{cov}_t\left[r_{i,t+1}, N_{c,t+1}\right] + \operatorname{cov}_t\left[r_{i,t+1}, -N_{d,t+1}\right] \\ &+\lambda_{cc} \operatorname{cov}_t\left[r_{i,t+1}, N_{cc,t+1}\right] + \lambda_{dd} \operatorname{cov}_t\left[r_{i,t+1}, N_{dd,t+1}\right] + \lambda_{cd} \operatorname{cov}_t\left[r_{i,t+1}, N_{cd,t+1}\right]. \end{aligned} \tag{14}$$

The expressions in Equation (13)along with the restriction that $a_{dc}a_{cc} \leq 0$ provide an important insight. An increase in variation risk is associated with *increase* in marginal utility. This reflects the willingness of investors to pay a premium for assets that hedge against an increase in variance of future cash flows or discount-rate news, as reflected in $\lambda_{cc}, \lambda_{dd} < 0$. In contrast, an increase in covariation risk between future cash flows news and discount rate news is associated with an *decrease* in marginal utility. This reflects an intertemporal investor's preference for states when discount rate news has high positive covariance with cash flow news so that shocks to cash flows and discount rates are likely to offset each other. Consistent with this, investors will require higher risk premium for assets which yield low returns in states when covariance between the cash-flow and discount-rate news is low, as reflected in $\lambda_{cd} > 0$.

C. Relation to other asset pricing models

Among other asset pricing models, our SDF and asset pricing relation are most closely related to Campbell et al. (2014). However, a fundamental difference between our model and the model derived by Campbell et al. (2014) is that in our model the shocks to the second-order terms of cash-flow and discount rate news are also priced. This difference arises for two reasons. First, Campbell et al. (2014)assume conditional log-normality and therefore ignore the extra second order terms due to shocks to the square of the SDF. When this assumption is relaxed, shocks to the second-order terms of the log SDF influence risk premia and hedging demands of long-term investors. Second, Campbell et al. (2014) do not allow for decomposition of volatility risk, which can significantly affect interpretation of the determinants of expected returns. In particular, Equation (13) shows that as γ increases, the second order components carry substantial and distinct risk premia. Therefore, collapsing the components of volatility risk into a single volatility risk measure may significantly distort inferences regarding the risk-return relation. Further, an important empirical advantage of Equations (12) and (14) is that they model the intertemporal effect of stochastic volatility on the expected asset returns without direct reference to news about future volatility. That is, this model can be estimated using a linear VAR that does not include volatility as an additional state variable. This representation helps avoid econometric issues related to estimated negative conditional volatilities, if volatility is included as an additional state variable in a VAR.[11]

While not the main focus of our study, it is interesting to note that Equations (12) and (14) are also related to the three-moment CAPM model of Kraus and Litzenberger (1976) and its

[11] On one hand, when constraints that the predicted values of future realized volatility must be positive are not imposed on the VAR, Campbell et al. (2014) find that the VAR predictions of realized volatility can be negative. On the other hand, the statistical properties of binding non-negative constraints on volatility predictions in a VAR framework are not well-understood.

conditional version derived by Harvey and Siddique (2000). In these models, coskewness of a risky asset with the market return is priced. That is, the pricing kernel in these models is a function of the square of the market return, and the expected return on a risky asset is positively related with the covariance of an asset return with the square of market return. Harvey and Siddique (2000) suggest that this pricing kernel is consistent with several different models of preferences and return distributions, and can be derived using a second-order Taylor expansion under the assumption of nonincreasing absolute risk aversion.

There are two key differences between our model and the model in Harvey and Siddique (2000). First, we consider a long-term investor with Epstein-Zin preferences (1989), which lead to different prices of risk for cash flow and discount rate news. Second, our approach effectively decomposes variation in market return into the variation in cash-flow news, discount-rate news and the covariation components. Thus, our model can be viewed as an intertemporal generalization of the models of Kraus and Litzenberger (1976) and Harvey and Siddique (2000). In the special case, when $\gamma = 1$ as in Harvey and Siddique (2000), we arrive at an expression for the conditional pricing kernel that can be expressed only in terms of the market portfolio's returns.

IV. Estimation of the news components.

As shown in Equation (12), shocks to the pricing kernel in our model depend on cash-flow news ($N_{c,t+1}$), discount-rate news ($N_{d,t+1}$) and shocks to the second-order terms of these two news components ($N_{cc,t+1}, N_{dd,t+1},$ and $N_{cd,t+1}$). We use a two-step process to estimate these terms. In the first step, we estimate the time-series of N_c and N_d news components. In the second step, we fit an MGARCH model to the time-series of N_c and N_d to estimate shocks to the second-order terms of these two news components. Below we provide a detailed description of each of the two steps.

A. Estimation of cash-flow and discount-rate news

We estimate the cash-flow and discount-rate news following Campbell and Vuolteenaho (2004). Specifically, we assume that the dynamics of the relevant state variables are well captured by a first-order vector autoregressive (VAR) process

$$\mathbf{x}_{t+1} = \bar{\mathbf{x}} + \Gamma\left(\mathbf{x}_t - \bar{\mathbf{x}}\right) + \mathbf{u}_{t+1}. \tag{15}$$

Here $\mathbf{x}_t$ is a n × 1 vector of state variables with the log market excess returns as the first element, $\bar{x}$ is a n × 1 vector of constants, Γ is the n × n matrix of VAR coefficients, and $\mathbf{u}_{t+1}$ is a n × 1 vector of shocks to the state variables with conditional mean of zero. The cash flow news ($N_{c,t+1}$) and discount rate news ($N_{d,t+1}$) components of the unexpected market return can be expressed in terms of $\boldsymbol{\lambda} = \rho\boldsymbol{\Gamma}(\mathbf{I} - \rho\boldsymbol{\Gamma})^{-1}$, a matrix that maps instantaneous state variable shocks to the news components of unexpected excess returns. Specifically, $N_{d,t+1} = \mathbf{e}_1'\boldsymbol{\lambda}\mathbf{u}_{t+1}$ and $N_{c,t+1} = \left(\mathbf{e}_1' + \mathbf{e}_1'\boldsymbol{\lambda}\right)\mathbf{u}_{t+1}$. where $\mathbf{e}_1'$ is a vector with one as the first element and zero as the remaining elements.

Consistent with Campbell and Vuolteenaho (2004) we estimate Equation (15) using a 4 × 1 vector of state variables that has the excess market return as the first element and three other variables that help to predict excess market returns: term-spread, small-value spread and the log of P/E ratio.[12] Excess market return is estimated as the difference between the log-returns on CRSP value-weighted index and 3-month Treasury bill. Term spread is estimated as the

[12] In our baseline tests, we use the same state variables as used by Campbell and Vuolteenaho (2004) to facilitate comparison between the…..Chen and Zhao claim that the results of the Campbell and Vuolteenaho (2004) methodology are sensitive to the decision to forecast expected returns explicitly and treat news to cash flows as a residual. They further suggest forecasting cash flows directly. Campbell, Polk, and Vuolteenaho (2010) address this critique and show that a VAR that forecasts expected returns is equivalent to one that forecasts expected dividend growth with the same state variables. However, news term estimates are sensitive to the inclusion of other state variables. In the robustness tests (discussed in further depth below), we modify our estimation approach to include additional state variables identified by prior literature as potential predictors of market returns.

difference between the 10-year and short-term government bond yields. Small value spread is estimated as the log of the ratio of book-to-market ratios of small value and growth stocks. P/E ratio is the ratio of market price to the lagged 10-year moving average of aggregate earnings.[13] Following Campbell and Vuolteenaho (2004) we set ρ equal to 0.95 in annual terms. The estimates of the VAR parameters and the residuals from VAR model are then used to estimate cash flow and discount rate news components. This approach has been widely used in a variety of empirical applications (e.g., Bernanke and Kuttner, 2005; Hecht and Vuolteenaho, 2006; Campbell, Polk, and Vuolteenaho, 2010; and Koubouros, Malliaropulos, and Panopoulou, 2010). Following Campbell and Vuolteenaho (2004), we estimate VAR system with data starting from December 1928 up to December 2010 (i.e., the end of our sample period).

The coefficients of the VAR and the summary statistics for the cash flow and discount rate news for our sample period (i.e., 1963-2010) are reported in Panels A and B of Table I, respectively. The mean N_c is -0.06% and the mean N_d , is -0.05%.[14] The standard deviation of the cash- flow news is 2.32%, much smaller than the standard deviation of the discount rate news of 4.36%, consistent with the results reported by Campbell and Vuolteenaho (2004).

B. Estimation of the shocks to second-order terms of cash-flow and discount-rate news

To estimate the shocks to the second-order terms of cash-flow and discount-rate news, we need to estimate conditional expectations of $N^2_{c,t+1}$, $N^2_{d,t+1}$ and $N_{c,t+1} \times N_{d,t+1}$; that is, the conditional variance of $N_{c,t+1}$ (denoted as $h_{cc,t+1}$), conditional variance of $N_{d,t+1}$ (denoted as

[13] For further details a reader is referred to the Campbell and Vuolteenaho (2004) Data Appendix, available at http://www.aeaweb.org/aer/contents/appendices/dec04_app_campbell.pdf

[5] Since the cash-flow and discount-rate news are linear combinations of VAR residuals, they both have zero means for the sample used to estimate VAR (i.e., December 1928 to December 2010). The means for these news terms in the modern sample (i.e., July 1963-December 2010) is slightly different from zero.

$h_{dd,t+1}$) and the conditional covariance of $N_{c,t+1}$ with $N_{d,t+1}$ (denoted as $h_{cd,t+1}$). Recall that in deriving our asset pricing equations, we assume that the conditional covariance matrix of $N_{c,t+1}$ and $N_{d,t+1}$ follows an MGARCH process. Therefore, we fit the MGARCH model outlined in Equation (8) to the time-series of N_c and N_d, anduse the estimates of the MGARCH model to calculate conditional variances and covariance series of the cash-flow and discount rate news. Next, we estimate the shocks to the quadratics by subtracting the corresponding elements of the conditional covariance matrix predicted by the MGARCH model from the quadratics of cash-flow and discount-rate news. That is, the shock to $N_{c,t+1}^2$ (or to $N_{d,t+1}^2$) is calculated as $N_{c,t+1}^2 - h_{cc,t+1}$ (or as $N_{d,t+1}^2 - h_{dd,t+1}$) and the shock to the $N_{c,t+1} \times N_{d,t+1}$ term is calculated as $N_{c,t+1} \times N_{d,t+1} - h_{cd,t+1}$.

In Panel C of Table I we report the estimated MGARCH coefficients. The ARCH and GARCH coefficients are statistically significant. The sign of the unconditional covariance of shocks to cash flows and discount rates is positive ($E[N_c, N_d] \geq 0$).[15]

C. Time-series of the news components

Figure 1 plots the time series of cash flow news and discount rate news. Figure 2 plots the shocks to second-order terms of cash-flow and discount rate news and their conditional variance and covariance as predicted by our fitted MGARCH model. Campbell and Vuolteenaho (2004) characterize recessions in which stock market declines are attributed to declining cash flows as "profitability" recessions, and those in which stock market declines are attributed to increasing discount rates as "valuation" recessions. We extend this line of logic to our model and

[15] The average of $N_c N_d$ in our sample period and the MGARCH estimate of unconditional covariance of N_c and N_d are positive. Campbell and Vuolteenaho (2004) and Lettau, and Ludvigson (2005) find similar evidence of positive unconditional covariance between cash flow news and discount rate news. Evidence that does not rely on VAR estimates and return decomposition, can be found in Golez (2014)..

characterize recessions in which covariance between cash flows and discount rates is notably negative as "covariation recessions".

[Insert Figure 1 about here]

Major shocks to each of the series plotted in figure 1 seem to coincide with NBER recessions. Recessions in our sample seem to coincide with increases in discount rate variation. The level of cash flow variation also increases in these recessions, but the magnitude of increase is lower. Interestingly, conditional covariance between cash flow news and discount rate news declines most in only two of the recessions in our sample: the 1970s recession and the recent Global Financial Crisis.

[Insert Figure 2 about here]

Our model predicts that these two covariation recessions represent an environment of high economic uncertainty, and high marginal utility for Epstein-Zin investors. Therefore, for our model to be consistent with the data in this stylized setting, the risk premium of stocks that most underperform in covariation recessions should be higher than those that do not, all else equal. We examine this and other predictions of our model in the next section.

V. Empirical results

To evaluate performance of our model we conduct three types of analyses. In the first analysis, we calibrate the parameters of our model using the time-series of aggregate market returns. In the second analysis, we examine the performance of our model using cross-section of portfolio returns sorted based on size, book-to-market, past performance (momentum), and industry characteristics. In the third analysis, we supplement our cross-sectional analysis by estimating our model for a panel of individual stocks using an implied cost of equity capital approach.

A. Calibration of model parameters using the aggregate equity returns

To gain some preliminary understanding of the importance of volatility risk decomposition, we commence our analysis with a simple calibration exercise using aggregate aggregate equity portfolio returns. Specifically, we evaluate the magnitudes of the risk premia attributable to the variation and covariation risk components of volatility risk for different values of the representative investor's risk aversion (γ). Consistent with Equations (13) and (14), the relative contribution of the components of volatility risk will be driven by the price of these risks and the covariance of these risks with the aggregate equity portfolio returns. Panel A of Table II reports the covariances of the aggregate equity portfolio with news to various components of our pricing kernel. We also report scaled covariances (β) of the market portfolio, namely the cash-flow beta (β_c), discount-rate beta (β_d), cash-flow variation beta (β_{cc}), discount-rate variation beta (β_{dd}), and the covariation beta (β_{cd}).Positive values of betas with a certain type of risk indicate that the aggregate equity portfolio is exposed to that risk, and negative values imply that it hedges that risk. Panel B of Table II reports assumed model parameters used to calculate the prices of risk as per Equation (14). The persistence parameter χ is set equal to 9, which is estimated from the long-run impact of a one-period revision in variance for a univariate GARCH process$\left(\chi = \rho \big/ \left(1 - \rho\left(a_{cc}^2 + g_{cc}^2\right)\right)\right)$. The ARCH and GARCH parameters are obtained from the estimated MGARCH coefficients $\left(g_{cc}, a_{cc}, a_{dc}\right)$ reported in panel C of Table I.

In Panel C of Table II, we report the model implied market risk premium and its decomposition into different components, assuming values of the risk aversion coefficient (γ) between one and ten. We proceed as follows. For each value of γ, we first calculate the price of risk (λ) for each of the components of the pricing kernel (as per Equation (12)) using the assumed model parameters reported in Panel B of Table II. We then calculate the contribution of each of these components to the market risk premium by multiplying the price of risk (λ) with the exposure of the market portfolio (β) to obtain the contribution of that particular risk factor to the risk premium of the market portfolio $(\beta_m\lambda)$. We report annualized figures by multiplying this monthly expected return figure by 12. We find that the market portfolio is exposed to both variation risk and covariation risk. Recall that the price of risk of the variation components is negative. This implies that these risks are expected to contribute to the higher returns demanded by investors to hold equities. Though the price of discount rate variation risk is the lowest in our model (at our calibrated parameters), the relatively large exposure of the equity portfolio to discount rate variation risk makes this risk the largest contributor to the risk premium. Overall, this evidence suggests that the our decomposition of aggregate variance into the three components does capture independent risks exposures of equities and that this decomposition is likely to enhance our understanding of the cross-section of expected returns, especially if equity portfolios have significantly different exposures to one or more of these components of aggregate volatility.

B. Estimating Risk Premia Using Portfolios of Stocks

In our second analysis, we estimate and test our model using a cross-section of portfolio returns sorted based on firm size, book-to-market ratio, and past stock performance ("momentum") attributes. Prior research shows that these characteristics have predictive power for the cross-section of stock returns.Specifically, our basic test assets are the Fama-French 25 size/book-to-market sorted portfolios and 25 Fama-French size/momentum sorted portfolios. Size/book-to-market sorted portfolios have been used as the test assets in previous studies (see among others Hodrick and Zhang, 2001; Campbell and Vuolteenaho, 2004; Hahn and Lee, 2006). We also include size/momentum sorted portfolios since momentum factor poses a particular challenge for the asset pricing models (Fama 1998; Jegadeesh and Titman, 2005). For each of these portfolios we estimate its monthly excess return as the difference between the gross monthly return and the yield on the 1-month Treasury bill. All data were obtained from the Kenneth French data library and the Center for Research in Security Prices (CRSP). The sample period for the Fama-MacBeth regressions is from July 1963 to December 2010. All returns are measured on monthly basis.[16]

B.1 Preliminary analysis

We commence by examining whether the average returns on long-short portfolios based on these characteristics, SMB (small minus big stocks), HML (value minus growth stocks), and MOM (winners minus losers) are consistent with a key prediction of our model: that assets that have low returns during times of decreasing covariation have higher risk premia. To provide some intuitive insights to the formal tests that follow, we first examine the prediction that the cross-sectional premia in average returns of SMB, HML, and MOM should be reversed in recessions when covariation is the most negative (recessions that we term "covariation recessions"). That is, the long leg of the portfolios (e.g. small stocks) should perform worse than the short leg of the

[16] The descriptive statistics for the test asset portfolios in our sample (untabulated for brevity) are consistent with prior research (e.g., Jegadeesh and Titman (1993), Hodrick and Zhang (2001), Hahn and Lee (2006)). Specifically, small cap stocks have higher average returns compared to large cap stocks, and stock with high book-to-market ratio ("value stocks") have higher average returns compared to stocks with low book-to-market ratio ("growth stocks"). Also, stocks with stocks with good past performance have higher average returns compared to the stocks with poor past performance, and the effect is more pronounced for the small cap stocks.

portfolio (e.g. large stocks) in "covariation recessions".

We calculate unconditional average and abnormal returns, as well as those conditional on three types of recessions: NBER recessions (NBERD), "covariation recessions" (COVD), and other NBER recessions (ONBERD). If the covariation recessions are different from other recessions then, according to our model, we expect stocks that underperform in these recessions to have higher risk premia. This is because our model predicts that investors have higher marginal utility in recessions with low conditional covariance than in other recessions. Recall that in the previous section we identified covariation recessions as the early 1970s NBER recession and the 2008 NBER recession—the two recessions in which covariation of cash flow news and discount rate news was visibly negative in Figure 2. Other NBER recessions indicate all NBER recessions excluding these two covariation recessions.

We present the results of this preliminary analysis in Table III. The table reports the average and abnormal returns (controlling for exposure to the market portfolio, $\alpha_{i|D} = avg[r_{i,t} - \beta_i r_{m,t}]$) of SMB, HML, and MOM. We also report results where the market beta exposure $\beta_{i|D}$ of a portfolio *i* is allowed to vary conditional on a type of recession (NBERD, COVD, or ONBERD). If our model can explain the average returns on SMB, HML, and MOM, we expect to see a negative sign for average returns and abnormal returns if covariation recessions are indeed associated with times of higher marginal utility.

In Table III, we find that the abnormal returns for SMB and MOM, conditional on COVD, are negative and economically significant.[17] That is, we find that small cap stocks

[17] According to the reported Newey-West *t*-tests, the negative returns on SMB during covariation recessions and the positive returns on MOM in recessions other than covariation recessions are also statistically significant. However, due to concerns of subsample selection based on ex-post conditional covariance, we are cautious as interpreting these abnormal returns as statistically significant. The purpose of our analysis is simply to examine whether a prediction of our model, that covariation recessions are times of high marginal utility of investors, is broadly consistent with the behaviour of return dynamics of these portfolios and their unconditional risk premia.

underperform large cap stocks in covariation recessions and winners underperform losers in these covariation recessions after controlling for the market return and changes in the market beta during recessions. Further, we find that this is not the case when we condition on ONBERD, other NBER recessions in which cash flow and discount rate covariance does not decline as much. These preliminary findings are consistent with our model and provide evidence in favor of the prediction that covariation recessions are more important than regular recessions in explaining the high average returns on these portfolios.

B.2 Risk Exposures of Test Portfolios

The results reported in the previous section provide some preliminary evidence that covariation risk (and, more generally, decomposition of volatility risk) may account for some cross-sectional variation in average stock returns sorted by size and momentum. In this section, we conduct a more formal test of this conjecture by examining the risk exposures (β) of the size/book-to-market and size/momentum sorted portfolios. The results are presented in Table IV, where Panel A reports the estimates of betas for the size/book-to-market sorted portfolios, and Panel B reports the estimates of betas for the size/momentum sorted portfolios. The estimates of Panel A are organized in a square matrix with small cap (large cap) stocks at the top (bottom) and high book-to-market (low book-to-market) stocks at the left (right). In Panel B, the estimates for the small cap (large cap) stocks are reported at the top (bottom) and the estimates for the stocks with the poor (good) past performance are reported at the left (right). The corresponding standard errors are reported in square brackets. For each quintile (size, book-to-market, past performance) we report the differences between the estimated betas for the extreme portfolios, with the corresponding *p*-values reported in parentheses.

First consider the estimates of risk exposures for the size/book-to-market sorted portfolios. The estimates of both cash-flow and discount-rate betas are largely consistent with the results reported by Campbell and Vuolteenaho (2004) for the 1963-2001 sample period. Specifically, cash-flow betas are significantly larger for the value stocks compared to the growth stocks. Also, the discount-rate betas are significantly larger for the small cap stocks compared to the large cap stocks.[18] The estimates of cash-flow variation betas are negative and significant and so are the estimates of the discount-rate variation betas, suggesting that, on average, stocks exhibit a significant exposure to both cash flow and discount rate variation risks. We also find some limited evidence of cash flow variation betas being larger for the value stocks compared to growth stocks. The estimates of covariation risk betas are positive and statistically significant, suggesting that, on average, stocks exhibit significant exposure to covariation risk. Further, the covariation risk betas are significantly larger for the small cap stocks compared to the large cap stocks.

Now consider estimates of risk exposures for the size/momentum sorted portfolios. The estimates of the cash flow betas appear to be slightly lower for the stocks with high past returns compared to the stocks with poor past performance. The difference, however, is not significant for most of the categories.. The discount rate betas, on the other hand, display a distinct U-shape, being largest for the stocks with poor and high past performance. This observation suggests that portfolios comprised of the stocks with poor or high past performance (that is, stocks that experienced in the past large absolute returns) are potentially picking stocks with high sensitivity to the changes in discount-rate. Importantly, the estimates of covariation risk betas are positive and monotonously increasing when moving from the stock with poor past

[18] These results are also consistent with previous studies (Gertler and Gilchrist, 1994; Christiano, Eichenbaum and Evans, 1996; Perez-Quiros and Timmermann, 2000) who find small firms to be more sensitive to fluctuations in interest rates.

performance to the stocks with high past performance, and the difference is also statistically significant. These results suggest that portfolios comprised of the stocks with high past performance have higher exposure to the covariation risk relative to the market. Also, similar to the results reported in Panel A we find the estimates of covariation risk betas to be significantly larger for the small cap stocks relative to the large cap stocks.

B.3 Estimation of Risk Premia

Having estimated risk exposures for the test assets, our next step is to estimate the model risk premia. Following prior research (Campbell and Vuolteenaho 2004; Campbell et al. 2014) we estimate our model using the following cross-sectional regression:

$$\bar{R}_i^e = g_0 + \sum_{k=1}^{K} g_k \hat{\beta}_{i,k} + \varepsilon_i \,, \tag{16}$$

where $\bar{R}_i^e$ is average excess portfolio return, $\hat{\beta}_{i,k}$ is the estimated risk exposure with respect to *k*-th risk factor, g_0 is the zero-beta rate, and g_k is the *k*-th factor risk premium. To incorporate estimation uncertainty due to using estimated betas, we produce standard errors with a bootstrap from 5000 simulated realizations, following Campbell and Vuolteenaho (2004). We consider the following five models: (1) CAPM (Sharpe (1964) and Lintner (1965)), (2) 2-beta ICAPM (Campbell and Vuolteenaho 2004)), (3) CAPM with coskewness (Kraus and Litzenberger (1976); Harvey and Siddique (2000)), (4) our non-linear ICAPM, and (5) 4-factor Fama-French-Carhart model (Carhart 1997)). To assess model performance, for each model we also estimate its pricing error as shown in Equation (17):

$$\vartheta = \left(\sum_{i=1}^{N} (\bar{R}_i^e - \sum_{k=1}^{K} g_k \hat{\beta}_{i,k})^2\right)^{0.5} \tag{17}$$

To evaluate statistical significance of the pricing error, we use a bootstrap method (Campbell and Vuolteenaho (2004), Campbell et al. (2014)). Specifically, for each model we adjust test asset return to be consistent with the model (that is, generate test asset return series under the null that the model prices test assets correctly). Next, we simulate the distribution of the pricing error under the null using bootstrap with 5000 simulated realizations and report *p*-value for the pricing error as a proportion of simulated pricing errors from the bootstrap that exceed the realized pricing error of a given model.

For the 2-beta ICAPM of Campbell and Vuolteenaho (2004) and the proposed non-linear ICAPM we also report the risk aversion parameter (γ) implied by the estimated risk premia of the model. Specifically, for the 2-beta ICAPM the implied risk aversion parameter is estimated as the ratio of the cash-flow news premium to the discount-rate news premium. For the non-linear ICAPM, the situation is not as straightforward as in the 2-beta ICAPM case since the model has four risk premia parameters that depend on risk aversion, as shown in Equations (13) and (14). To obtain implied risk aversion for the non-linear ICAPM we search for the value of γ that minimizes the weighted absolute distance between the estimated risk premia and their theoretical values as per equations (13) and (14), amongst the set of possible parameter values. The weights are estimated as the inverse of the standard errors of the risk premia estimates which allows us to take into account estimation uncertainty inherent in model estimates.

We commence our analysis with the sample of 50 test assets which include 25 Fama-French portfolios sorted based on size/BM and 25 portfolios sorted based on size/momentum. The results are reported in Panel A of Table V. The first tested model is the CAPM of Sharpe (1964) and Lintner (1965) with a single explanatory variable–CAPM beta. Consistent with the results reported by prior studies (Jegadeesh and Titman, 1993; Campbell and Vuolteenaho, 2004; Hahn and Lee, 2006) traditional CAPM fails to explain the size, book-to-market and momentum premia. The estimated price of risk is not significant and the adjusted R^2 is 0.05. The model is strongly rejected based on the data (pricing error=0.091, *p*-value<0.01).

Next, we examine the performance of the two-beta ICAPM of Campbell and Vuolteenaho (2004). Similar to CAPM, the poor performance of the two-beta ICAPM is evident. The estimated risk premia for both cash-flow and discount rate betas are not significant and the adjusted R^2 is 0.06 and the implied risk aversion coefficient is 4.33. The pricing error of the model is 0.121 and is statistically significant (*p*-value<0.01), suggesting that the model is rejected based on the data. Given the results reported in Campbell and Vuolteenaho (2004) which show that the two-beta ICAPM does a good job in pricing size/book-to-market sorted portfolios, our findings suggest that the poor performance of the two-beta model in our sample is driven by the inability of the model to explain momentum effect. This notion is further supported by the results reported in Table V, which show that past "winners" and past "losers" have similar cash-flow and discount rate betas.

The next model is CAPM with coskewness (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000). The risk premium for the coskewness beta is negative and significant, consistent with the notion that investors are willing to accept lower rate of return on assets that hedge against coskewness risk. The model yields adjusted R^2 of 0.46. The negative and significant risk premium for the coskewness beta as well as the good explanatory power of the model are consistent with the findings in Harvey and Siddique (2000) who show that some of the size, book-to-market and momentum related effects could be attributed to the differences in the exposure to coskewness risk. However, the model is still rejected based on the data (pricing error=0.071, *p*-value<0.02). Further, the risk premium for the market beta is negative and significant, in stark contrast to the theoretical predictions of the model. The latter finding further highlights the importance of decomposing market beta into its cash-flow and discount rate components.

Next we test the proposed non-linear ICAPM. The estimated risk premium for the cash-flow beta is positive and statistically significant, and so is the estimated risk premium for covariation risk. The estimates of the cash flow and the discount rate variation risk premia are both statistically insignificant, and so is the risk premia for the discount rate beta The model yields adjusted R^2 of 71% and is not rejected at conventional significance level (pricing error=0.020, *p*-value=0.67). The risk aversion parameter implied by the non-linear ICAPM is 2.39. Overall, the results suggest that the proposed non-linear ICAPM does a good job in explaining size, book-to-market and momentum effects in equity returns. The latter result is particularly important given the ongoing debate regarding the source of momentum phenomenon. Our findings provide a risk-based explanation to momentum effect and are consistent with the results reported in Table V, which show that past "winners" have a higher exposure to covariation risk (i.e., have higher covariation betas) compared to past "losers".

Insofar, we compared the proposed non-linear ICAPM to other theoretically motivated models. As a supplemental analysis we compare the performance of the non-linear ICAPM with the influential empirical four-factor model of Carhart (1997). The adjusted R^2 of the Carhart four-factor model is 79% and the pricing error is 0.025 (*p*-value=0.17) We consider the adjusted R^2 of 71% and the pricing error of 0.02 of the non-linear ICAPM model as comparable and a confirmation of the theoretical insight of our model that the decomposition of volatility risk is important in understanding the cross-section of expected returns.

B.4 Sensitivity Tests

We conduct several sensitivity tests. First, we examine the sensitivity of our results with respect to the choice of conditioning variables in the Campbell and Vuolteenaho (2004) model. Chen and Zhao (2009) note that low predictive power of state variables used in Campbell and Vuolteenaho (2004) may induce substantial measurement errors in the estimates of both N_c and N_d time-series. To address this concern, we repeat our analyses with the N_c and N_d time-series estimated using Campbell and Vuolteenaho (2004) framework augmented with additional conditioning variables, suggested in prior literature.[19] The results (untabulated) remain qualitatively similar to those reported in the paper.

Second, it is possible that the insignificant results for the cash flow and discount rate variation risk premia are driven by the multicollinearity between the components of the volatility risk betas. To address this concern, we estimate three restricted versions of the non-linear ICAPM, where in each version we restrict two of the three risk premia components of the volatility risk to be zero. The results (untabulated) suggest that, among the three components of volatility risk, the explanatory power of the non-linear ICAPM is almost solely driven by the covariation risk component, and thus further confirm the robustness of our results.

Third, given that N_c and N_d time-series are estimated using the whole sample as in Campbell and Vuolteenaho (2004), a hindsight bias is a potential concern. To address this issue, we repeat our analysis with N_c and N_d components estimated using a rolling window approach. The results (untabulated) remain qualitatively similar to those reported in the paper.[20]

To further validate our findings, we conduct two additional analyses. In the first test, we exclude momentum-sorted portfolios from the baseline sample and use 25 size/book-to-market sorted portfolios as the test assets.[21] The results for the 25 size/book-to-market sorted portfolios

[19] Specifically, in addition to the four state variables suggested by Campbell and Vuolteenaho (2004) we include the following variables: default spread (difference between Moody's BAA and AAA-rated corporate yields), 12-month trailing price-to-dividend ratio, and share of equity issues (Campbell and Amer, 1993; Baker and Wurgler, 2000; Petkova, 2006; Chen and Zhao, 2009).
[20] All untabulated results are available from the authors upon request.
[21] As discussed in Lewellen, Nagel, and Shanken (2010), due to distinct factor structure of size/book-to-market sorted portfolios it is not uncommon for an asset pricing model to exhibit significant explanatory power for the cross section of stocks sorted based on these characteristics. Recognizing this important critique, we repeat our analysis using these portfolios solely to facilitate comparison to prior studies (Campbell et al. 2004; Hahn and Lee, 2006).

are reported in Panel B of Table V. The non-linear ICAPM continues to exhibit successful performance (adjusted R^2=0.73, pricing error=0.012, *p*-value=0.74). The estimated risk premium for the covariation risk remains positive and significant and the estimated risk premia for both cash flow and discount rate variation risks remain statistically insignificant. The implied risk aversion coefficient of the model is 2.03. The performance of the non-linear ICAPM continues to be comparable to the performance of the Carhart (1997) four-factor model, both in terms of the adjusted R^2 and the pricing error. The CAPM continues to exhibit poor performance as evident from the adjusted R^2 is 0.04 and the pricing error of 0.061 (*p*-value<0.01). The two-beta ICAPM exhibits a substantial improvement compared to the results reported in Panel A of Table V. Specifically, the adjusted R^2 of the two-beta ICAPM is 0.29 and the model yields positive and statistically significant risk premium for the cash flow beta. The model cannot be rejected at conventional significance level (pricing error=0.029, *p*-value=0.28). The implied risk aversion parameter of the 2-beta ICAPM model is 17.42. These results are generally consistent with findings reported by Campbell and Vuolteenaho (2004) for the 1963-2001 sample period. The results for CAPM with coskewness are similar to those reported in Panel A of Table V. Specifically, the risk premia for market and coskewness betas are both negative and significant, and the model is rejected based on the data (pricing error=0.070, *p*-value=0.01).

In the second test, we extend our baseline sample of test assets to include 30 industry portfolios. Both CAPM and two-beta ICAPM exhibit poor performance as evident from low adjusted R^2 coefficients (largest adjusted R^2 = 0.002) and statistically significant pricing errors (smallest pricing error = 0.079, *p*-value<0.01). In terms of explanatory power, CAPM with coskewness exhibits a better performance compared to these two models (adjusted R^2 = 0.27) but is rejected based on its pricing error. In contrast, non-linear CAPM still explains about 45%

of the variation in the cross-section of the test assets. The estimated risk premium for the covariation risk remains positive and significant and the estimated risk premia for both cash flow and discount rate variation risks remain statistically insignificant. However, the pricing error of non-linear ICAPM is significant at 1% significant level. The results for the Carhart (1997) model are qualitatively similar to those reported for the non-linear ICAPM. Collectively, the results reported in Table V suggest that the proposed non-linear ICAPM is able to explain cross-sectional variation in the average returns across size, book-to-market and momentum sorted portfolios, yet cannot account for the industry effects in stock returns.

C. Estimation of Risk Premia Using Implied Cost of Equity Approach

In previous sections, we examine the prices of risk of the volatility components using realized portfolio returns. While being widely adopted in the prior literature, this method also has several limitations. First, a test of the asset pricing theory requires a measure of ex ante (i.e., expected) rate of return. However, realized returns could be a poor proxy for expected returns (Elton, 1999) with cost-of-capital estimates derived from the average realized returns being "unavoidably imprecise" (Fama and French, 1997). Second, using portfolios sorted based on previously documented pricing anomalies (e.g., size, book-to-market, or momentum) may, potentially, lead to data-snooping bias (Lewellen, 1999; Lewellen et al., 2010). Hence, in this section we supplement our analysis by estimating our model for a panel of individual stocks using the implied cost of equity capital approach.

In terms of research design, we estimate the expected rate of return on equity as a discount-rate that is implied by market prices and analysts' earnings forecasts using four different models introduced by Claus and Thomas (2001), Ohlson and Juettner-Nauroth (2005), Gebhardt et al., (2001), and Easton (2004).[22] Specifically, for each firm-year observation and for each of these four models we estimate the implied expected return on equity that equates current share price of firm *i* in year *t* to the discounted stream of projected future cash flows. Since there is little consensus on which model performs the best, we perform an additional test following Hail and Leuz (2006, 2009) and Chen, Chen and Wei (2011) in using the median of the estimates from the four models as an additional measure of the cost of equity. This leaves us with the total of five estimates of the cost of equity for each firm-year observation. Next, for each model specification we compute the implied risk premium, $IRP_{i,t}$, as the difference between the corresponding implied expected return for firm *i* and year *t* and the 10-year US Treasury bond yield. The details of estimation procedure are outlined in Appendix A.

To estimate prices of risk we run the following regression model:

$$rp_{i,t} = g_0 + g_1\hat{\beta}_{c,i,t} + g_2\hat{\beta}_{d,i,t} + g_3\hat{\beta}_{cc,i,t} + g_4\hat{\beta}_{dd,i,t} + g_5\hat{\beta}_{cd,i,t} + \sum_{j=5}^{N} b_j k_{i,t} + I_{i,t} + \varepsilon_{i,t}\,. \quad (18)$$

For each firm-year observation we compute the estimates of cash flow beta, discount rate beta, and betas of the three volatility risk components using previous 60 months of stock returns (with at least 24 monthly returns). Following prior studies (Gebhardt et al., 2001; Chen et al., 2011) we include firm size, book-to-market ratio, leverage, price momentum, volatility of operating cash flows, number of analysts following the firm, and share turnover as control variables ($k_{i,t}$). We also include growth in the 1-and 2-year analyst earnings forecasts to control for potential effects of analysts' biases on the estimated cost of equity. Also, to control for an industry-related risk component reported in prior studies (e.g., Gebhardt et al., 2001) we estimate Equation (18) with

[22] Our sample starts in 1986 due to data availability in IBES.

industry fixed effects ($I_{i,t}$) based on the 2-digit SIC code. The data used to compute all variables are obtained from IBES, Compustat, and CRSP databases. Consistent with Gebhardt et al. (2001) we estimate Equation (18) cross-sectionally by year following Fama-MacBeth approach. For each slope estimate we report its time-series mean with the corresponding Newey-West *t*-statistics in squared brackets.

The results are reported in Panel A of Table VI. The coefficient for the covariation risk beta is positive and significant for four out of five model specifications. The only exception is Claus and Thomas (2001) model, where the coefficient for covariation risk premium is positive but insignificant.[23] The results suggest that, after controlling for other factors suggested by prior literature, investors consider stock with high covariation betas as being more risky, thereby requiring higher return for holding these stocks. The estimates of cash flow and discount rate variation risk premia are insignificant in all model specifications.

To facilitate economic interpretation of our results, we re-estimate Equation (18) using standardized risk exposure measures. Specifically, we rank each explanatory variable for each year, and then partition the resulting ranks into deciles labeled from 1 (lowest decile) to 10 (highest decile), following Hirshleifer, Lim and Teoh (2009). Next, we re-estimate Equation (9) using decile ranked explanatory variables instead of their raw values.

The results are reported in Panel B of Table VII. The findings further confirm positive and significant risk premium for the covariation risk. The estimates of both cash flow and discount rate variation risk premia remain statistically insignificant. Further, the results suggest that the magnitude of covariation risk premium is also economically meaningful. Specifically, all else equal, moving from the first to tenth decile of covariation risk increases expected return by

[23] Notably, the overall explanatory power of the Claus and Thomas (2001) model is low relative to other models.

$\frac{1}{4}\left(\frac{0.003}{0.01}+\frac{0.005}{0.063}+\frac{0.005}{0.055}+\frac{0.004}{0.024}\right)=16\%$ of the market risk premium.

In sum, we find strong supporting evidence that covariation risk carries a positive and economically meaningful risk premium. Overall, the findings are consistent with the results for realized portfolio returns, and thus confirm the robustness of our results.

VI Conclusion

We develop an intertemporal asset pricing model, in which the news about aggregate market volatility — and by inference, volatility risk —decomposes into three news components: cash-flow variation, discount-rate variation, and the covariation between the cash-flow and discount-rate news. In our model, long-term investors are willing to pay a premium to hedge an increase in variation as well as to hedge a decrease in covariation. We evaluate our model using a cross-section of portfolio returns sorted based on size, book-to-market and past stock performance (momentum). We find that stocks with good past performance, on average, have higher exposure to covariation risk compared to stocks with poor past performance. Further, we find that small cap stocks, on average, have higher exposure to covariation risk compared to large cap stocks. Our model helps account for approximately 71% of the return variation across size, book-to-market and momentum sorted portfolios for the modern US sample period and is not rejected at conventional significance level. Further tests suggest that explanatory power of the model is primarily attributed to covariation risk, which carries a positive and economically significant premium. We conduct a variety of supplemental tests which provide additional support for the notion that covariation risk is an important determinant of risk premia on equity market

Overall, the empirical evidence we present highlights the importance of decomposing aggregate volatility risk into the variation and covariation risk components. In particular, we show that the covariation risk component of aggregate volatility is important in helping explain the cross section of expected returns. We find that during times of decreasing covariation (which increases marginal utility in our model), equities tend to realize low returns. Also, in these times, small stocks tend to underperform large socks and winners tend to underperform losers. These risk exposures account for a sizable amount of the risk premia in equity markets.

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Appendix A

Estimation of Implied Cost of Equity

We estimate the implied cost of equity using four models introduced in prior literature: 1) Gebhardt, Lee, and Swaminathan (2001, hereafter GLS); 2) Claus and Thomas (2001, hereafter CT); 3) Ohlson and Juenttner-Nauroth (2005, hereafter OJ); and 4) the modified PEG model of Easton (2004, hereafter MPEG). In implementing these four models we follow (with some minor modifications) Chen, Chen and Wei (2011).[25] To facilitate our discussion, we first introduce the notations used in the following analysis.

P_t^*	Implied market price of firm's common stock at time *t*. We use price at the end of the month +4 following the fiscal year-end to compute P_t^*
B_t	Book value per share of common equity available from the most recent financial statement at time *t*
$FEPS_{t+i}$	Median forecasted earnings per share from IBES or derived earnings forecast for the next *i*-th year at time *t*
$FROE_{t+i}$	Forecasted return on equity for the next *i*-th year at time *t*
R_j	Implied cost of equity for *j*=GLS, CT, OJ, MPEG
$POUT$	Projected dividends payout ratio, estimated as the ratio of annual indicated dividends from IBES to $FEPS_{t+1}$. When $FEPS_{t+1}$ is negative we assume a return of assets of 6% to compute earnings.

1. Gebhardt, Lee and Swaminathan (2001)

$$P_t^* = B_t + \sum_{t=1}^{T-1} \frac{[FROE_{t+i} - R_{GLS}] \times B_{t+i-1}}{(1+R_{GLS})^i} + \frac{[FROE_{t+T} - R_{GLS}] \times B_{t+T-1}}{(1+R_{GLS})^{T-1} R_{GLS}} \quad \text{(A.1)}$$

We use analysts' consensus forecasts from IBES to proxy for the market expectations of firm's earnings for the next three years available at time *t*. Next, we assume that future return on equity declines to the industry-specific median return on equity starting from the fourth year to the *T*-th year. Following Gebhardt et al. (2001) we assume that *T*=12. We classify all firms into 48 industries following Fama and French (1997). The return on equity (ROE) is computed as income for common shareholders (Compustat data item #237) scaled by the lagged total book value of assets (Compustat data item #60). To estimate the future book value of equity we assume a clean surplus assumption,

[25] The data used to construct the estimates of the implied cost of equity was obtained from IBES and Compustat for the period of 1986-2010.

i.e., $B_{t+1} = B_t + FEPS_{t+1} - FDPS_{t+1}$. We calculate the future dividend, $FDPS_{t+1}$, by multiplying $FEPS_{t+1}$ by the corresponding payout ratio, POUT. We next use a numerical approximation to solve for R_{GLS} that equates both sides of B.1. Following Chen, Chen and Wei (2012) we adjust stock price at month +4 for the partial year discounting, that is, $P_t^* = \frac{P_t}{(1+R_{GLS})^{4/12}}$. We apply similar adjustment to other cost of equity models.

2. Claus and Thomas (2001)

$$P_t^* = B_t + \sum_{t=1}^{5} \frac{[FROE_{t+i} - R_{CT}] \times B_{t+i-1}}{(1+R_{CT})^i} + \frac{[FROE_{t+5} - R_{CT}] \times B_{t+4} \times (1+g)}{(1+R_{CT})^5 (R_{CT} - g)} \qquad \text{(A.2)}$$

We use analysts' consensus forecasts from IBES to proxy for the market expectations of firm's earnings for the next five years available at time *t*. Earnings forecasts for the future fourth and fifth years are computed using earnings forecasts for the third years and the IBES forecasts for the long-term growth rate. If the long-term growth rate is missing we replace it with an implied growth rate from $FEPS_{t+2}$ and $FEPS_{t+3}$. The long-term abnormal earnings growth rate, g, is computed as the contemporaneous yield on ten-year Treasury bond minus 3 percent. In cases when the difference is negative we replace it by the expected inflation rate from the University of Michigan survey. Similar to GLS model we assume a clean surplus assumption to calculate future book value. We next use a numerical approximation to solve for R_{CT} that that equates both sides of A.2.

3. Ohlson and Juettner - Nauroth (2005)

$$P_t^* = \frac{FEPS_{t+1}}{R_{OJ}} + \frac{FEPS_{t+1} \times (g_{st} - R_{OJ} \times (1 - POUT))}{R_{OJ}(R_{OJ} - g_{lt})} \qquad \text{(A.3)}$$

In this model g_{st} is the average of the short-term earnings growth implied in $FEPS_{t+1}$ and $FEPS_{t+2}$ and the analysts' forecasted long-term earnings growth rate. This model requires both $FEPS_{t+1}$ and $FEPS_{t+1}$ to be positive. We calculate g_{lt} as the contemporaneous yield on the ten-year Treasury bond minus 3 percent. In cases when the difference is negative we replace it by the expected inflation rate from the University of Michigan survey. We use a numerical approximation to solve for R_{OJ} that equates both sides of A.3.

4. The Modified PEG ratio by Easton (2004)

$$P_t^* = \frac{FEPS_{t+1}}{R_{MPEG}} + \frac{FEPS_{t+1} \times (g_{st} - R_{MPEG} \times (1 - POUT))}{R_{MPEG}^2} \quad \text{(A.4)}$$

This models requires that $FEPS_{t+2}$>=$FEPS_{t+1}$>=0. We use a numerical approximation to solve for R_{MPEG} that equates both sides of A.4.

Table I

Descriptive Statistics-Market Returns, Cash flow and Discount rate News

Notes: Panel A of the table shows the OLS parameter estimates for a first-order VAR model including a constant, the log excess market return (r^e_{mkt}), term yield spread (TY), price-earnings ratio (PE), and small-stock value spread (VS). Each set of four rows corresponds to a different dependent variable. The first four columns report coefficients on the four explanatory variables, and the remaining columns show R^2 and *F* statistics. In Panel B of this table we report selected descriptive statistics for the unexpected market returns and the estimates of the cash flow and discount rate news for the sample period of July 1963-December 2010. The cash flow (N_c) and discount rate news ($-N_d$) were estimated following Campbell and Vuolteenaho (2004). The conditional covariance of cash flow (N_c) and discount rate news (N_d) is assumed to follow an MGARCH process. The estimated coefficients of this process are presented in Panel C. Monthly means and standard deviations are reported in percentage points. In Panel C, we report the BEKK MGARCH parameters of the volatility process of N_c and N_d: the matrix **A** contains the ARCH coefficients; the matrix **G**, the GARCH coefficients; and the matrix **C**, the intercept parameters. The first element represents cash flows and the second discount rates.

Panel A: VAR Parameter Estimates (1929-2010)

	$r^e_{mkt,t-1}$	TY_{t-1}	PE_{t-1}	VS_{t-1}	R^2	F
r^e_{mkt}	0.109	0.004	-0.016	-0.011	0.03	6.7
TY	-0.011	0.938	-0.003	0.053	0.89	1.9E+03
PE	0.518	0.001	0.992	-0.003	0.99	2.5E+04
VS	-0.013	-0.001	-0.001	0.991	0.98	1.4E+04

Panel B: Summary Statistics

	1929-2010					*1963-2010*				
	Mean	St.dev.	25%	Median	75%	Mean	St.dev.	25%	Median	75%
N_c	0.00	2.65	-1.17	0.18	1.40	-0.06	2.32	-1.13	0.11	1.22
$-N_d$	0.00	4.75	-2.57	0.33	2.74	0.05	4.36	-2.42	0.18	2.69
$N_c^2 \times 10^2$	0.07	0.20	0.00	0.02	0.06	0.05	0.1	0.00	0.01	0.06
$N_d^2 \times 10^2$	0.23	0.54	0.02	0.07	0.20	0.18	0.37	0.02	0.07	0.19
$N_c \times (-N_d) \times 10^2$	0.00	0.22	-0.03	0.00	0.03	-0.02	0.2	-0.03	-0.002	0.02

Panel C: Volatility Process Coefficients

	C$\times 10^4$		**A**		**G**	
N_c	0.00	3.46	-0.16	-0.64	-0.93	-0.03
N_d	3.46	13.36	0.19	0.17	0.70	-0.37

Table II

Asset Pricing Implications of ICAPM with Covariation Risk

In this table we report the estimates of the sensitivities of the equity market portfolio, for the sample period July 1963-December 2010. In Panel A, we report covariance of the market portfolio with news to various components of our pricing kernel. We also report scaled covariance or beta ($\beta_{m,N}$) of the equity market portfolio to various news components, where cash flow beta is estimated as $cov(r_i, N_c)/var(r_m)$; discount rate beta (β_d) as, $cov(r_i, -N_d)/var(r_m)$; cash flow variance beta (β_{cc}) as $cov(r_i, N_{cc})/var(r_m)$; discount rate variance beta (β_{dd}), as $cov(r_i, N_{dd})/var(r_m)$; covariation beta ($\beta_{cd}$) as, $cov(r_i, N_{cd})/var(r_m)$. r_m is the unexpected excess market return. The news terms were estimated following Campbell and Vuolteenaho (2004). News to variances were estimated using an MGARCH model. In Panel B, we report assumed model parameters based on Table I estimates. Lower case letters a represent elements of the ARCH matrix **A** tabulated in Table I. In Panel C, we report risk premium coefficients λ for different values of the risk aversion coefficient γ. We also report the corresponding model implied decomposition of the market risk premium. We report annualized figures by multiplying this monthly expected return figure by 12.

Panel A: Market Risk Exposures

	r_m	N_c	$-N_d$	$N_{cc} \times 10^2$	$N_{dd} \times 10^2$	$N_{cd} \times 10^2$
$\text{cov}(r_m, N) \times 10^4$	20.91	3.53	16.92	-10	-46	9
$\beta_{m,N}$	1	0.17	0.81	-0.50	-2.19	0.44

Panel B: Model Parameters

χ	a_{cc}^2	$2a_{cc}a_{dc}$	a_{dc}^2
9	0.03	-0.06	0.04

Panel C: Market Risk Premium Decomposition

	Total ($\text{E}[R_m - R_f]$)	N_c	$-N_d$	N_{cc}	N_{dd}	N_{cd}
λ		1.00	1.00	-0.50	-0.50	1.00
$\text{cov} \times \lambda \times 12$	2.50%	0.42%	2.03%	0.01%	0.03%	0.01%
λ		3	1	-5.04	-1.22	4.08
$\text{cov} \times \lambda \times 12$	3.48%	1.27%	2.03%	0.06%	0.07%	0.04%
λ		5	1	-14.66	-3.38	9.32
$\text{cov} \times \lambda \times 12$	4.62%	2.12%	2.03%	0.18%	0.19%	0.10%
λ		10	1	-60.94	-15.08	31.87
$\text{cov} \times \lambda \times 12$	8.21%	4.23%	2.03%	0.76%	0.83%	0.35%

Table III

Are covariation recessions (ex-post) different?

In this table we report average excess returns of the small minus big (SMB), value minus growth (HML), and winners minus lowers (MOM) portfolios and their abnormal returns with respect to the market return. We also report the average differences in average excess returns and abnormal returns in a given recession sub-sample (D=1) with the rest of the sample. The sub-samples considered are NBER recessions (NBER), the two recessions in which covariation of cash flow news and discount rate news was visibly negative (COV, the early 1970s NBER recession and the 2008 NBER recession), and other NBER recessions (ONBER). Abnormal returns are calculated by subtracting beta coefficients estimated from the entire sample ($\alpha_{u|D}$) and after allowing for different betas in NBER recessions ($\alpha_{c|D}$). Newey-West *t*-statistics with two lags errors are reported in brackets. The sample period is July 1963-December 2010.

	D=1 for	SMB	HML	MOM
$\bar{r}_{i\|D} = avg\left(r_{i,t} \mid D=1\right) - avg\left(r_{i,t} \mid D=0\right)$	Full Sample	0.95	1.27	0.72
		(5.06)	(5.62)	(3.87)
	NBER	-0.17	0.17	0.45
		(-0.22)	(0.19)	(0.6)
	COVD	-1.4	-0.92	-0.37
		(-1.04)	(-0.55)	(-0.24)
	ONBER	0.65	0.89	1.00
		(0.82)	(0.99)	(1.53)
$\alpha_{u\|D} = avg\left(r_{i,t} - \beta_i r_{m,t} \mid D=1\right) - avg\left(r_{i,t} - \beta_i r_{m,t} \mid D=0\right)$	Full Sample	0.18	0.31	0.83
		(2.01)	(3.87)	(4.54)
	NBER	-0.11	0.23	0.44
		(-0.44)	(0.97)	(0.63)
	COVD	-0.75	-0.11	-0.47
		(-1.63)	(-0.22)	(-0.32)
	ONBER	0.31	0.46	1.05
		(1.28)	(2.16)	(1.71)
$\alpha_{c\|D} = avg\left(r_{i,t} - \beta_i r_{m,t} - \beta_{i\|D} r_{m,t} \times D_{NBER} \mid D=1\right) - avg\left(r_{i,t} - \beta_i r_{m,t} - \beta_{i\|D} r_{m,t} \times D_{NBER} \mid D=0\right)$	Full Sample	0.22	0.35	0.64
		(2.47)	(4.43)	(3.64)
	NBER	-0.11	0.24	0.41
		(-0.43)	(1.02)	(0.64)
	COVD	-0.68	-0.04	-0.81
		(-1.65)	(-0.08)	(-0.67)
	ONBER	0.28	0.43	1.22
		(1.09)	(1.65)	(1.92)

Table IV: Risk Exposures of Test Portfolios

In this table we report the estimates of the sensitivities of the portfolios sorted based on market capitalization (size), book-to-market (BM), and past returns (momentum), for the sample period July 1963-December 2010. Cash flow beta (β_c) are estimated as $cov(r_i, N_c)/var(r_m)$; discount rate beta (β_d), $cov(r_i, -N_d)/var(r_m)$; cash flow volatility beta (β_{cc}) as $cov(r_i, N_{cc})/var(r_m)$; discount rate volatility beta (β_{dd}), as $cov(r_i, N_{dd})/var(r_m)$; covariation beta ($\beta_{cd}$), $cov(r_i, N_{cd})/var(r_m)$. r_i is the return on portfolio, r_m is the unexpected excess market return. "Growth" denotes stocks with largest size/book-to-market, "value"-stocks with lowest size/book-to-market, "small"-stocks with lowest market capitalization, "large"-stocks with largest market capitalization, "Losers"-stocks with lowest returns from month t-12 to t-2, "Winners"-stocks with highest returns in that period,. For each portfolio we report the estimated cash flow beta and the corresponding GMM standard error (in squared brackets) adjusted for heteroskedasticity and serial correlation. "Diff." columns report differences between the estimates of the extreme portfolios and the *p*-values of the corresponding *J*-statistics (in round brackets).

Panel A: Risk Exposures of the Size/Book-to-Market Sorted Portfolios

	Growth		2		3		4		Value		Diff.	
β_c												
Small	0.12	[0.05]	0.14	[0.05]	0.16	[0.04]	0.17	[0.04]	0.2	[0.03]	0.08	(0.01)
2	0.13	[0.04]	0.16	[0.03]	0.17	[0.03]	0.19	[0.03]	0.22	[0.04]	0.09	(0.00)
3	0.13	[0.04]	0.18	[0.03]	0.19	[0.03]	0.2	[0.03]	0.22	[0.03]	0.09	(0.00)
4	0.14	[0.03]	0.19	[0.03]	0.2	[0.02]	0.21	[0.02]	0.24	[0.03]	0.1	(0.00)
Large	0.14	[0.02]	0.18	[0.02]	0.18	[0.03]	0.21	[0.03]	0.21	[0.03]	0.07	(0.00)
Diff.	0.02	(0.69)	0.04	(0.43)	0.02	(0.68)	0.04	(0.36)	0.01	(0.79)		
β_d												
Small	1.25	[0.08]	1.03	[0.06]	0.88	[0.05]	0.8	[0.04]	0.82	[0.04]	-0.43	(0.00)
2	1.22	[0.06]	0.96	[0.04]	0.84	[0.04]	0.78	[0.04]	0.84	[0.04]	-0.38	(0.00)
3	1.16	[0.06]	0.89	[0.03]	0.77	[0.04]	0.71	[0.04]	0.76	[0.05]	-0.4	(0.00)
4	1.05	[0.05]	0.86	[0.03]	0.79	[0.04]	0.72	[0.04]	0.76	[0.05]	-0.29	(0.00)
Large	0.83	[0.04]	0.74	[0.03]	0.68	[0.03]	0.6	[0.04]	0.64	[0.05]	-0.19	(0.00)
Diff.	-0.42	(0.00)	-0.29	(0.00)	-0.20	(0.00)	-0.20	(0.01)	-0.18	(0.01)		
β_{cc}												
Small	-0.69	[0.31]	-0.59	[0.28]	-0.59	[0.23]	-0.55	[0.24]	-0.66	[0.22]	0.04	(0.90)
2	-0.68	[0.25]	-0.62	[0.22]	-0.59	[0.19]	-0.62	[0.19]	-0.70	[0.22]	-0.02	(0.90)
3	-0.64	[0.23]	-0.64	[0.19]	-0.55	[0.17]	-0.56	[0.16]	-0.58	[0.17]	0.06	(0.69)
4	-0.48	[0.20]	-0.59	[0.19]	-0.59	[0.17]	-0.53	[0.14]	-0.75	[0.18]	-0.26	(0.08)
Large	-0.36	[0.16]	-0.50	[0.15]	-0.54	[0.16]	-0.54	[0.13]	-0.65	[0.16]	-0.29	(0.05)
Diff.	0.33	(0.11)	0.09	(0.71)	0.05	(0.80)	0.01	(0.94)	0.01	(0.95)		
β_{dd}												
Small	-2.71	[1.43]	-2.26	[1.26]	-2.09	[1.07]	-1.87	[1.02]	-2.64	[1.15]	0.07	(0.92)
2	-2.55	[1.25]	-2.52	[1.11]	-2.41	[0.99]	-2.34	[1.06]	-2.42	[1.05]	0.13	(0.75)
3	-2.35	[1.21]	-2.40	[0.99]	-2.38	[0.88]	-2.21	[0.91]	-2.41	[1.01]	-0.06	(0.89)
4	-2.07	[1.06]	-2.45	[1.06]	-2.56	[1.13]	-2.05	[0.94]	-2.45	[0.95]	-0.38	(0.45)
Large	-1.59	[0.80]	-1.94	[0.74]	-1.88	[0.75]	-1.68	[0.81]	-2.29	[0.87]	-0.70	(0.11)
Diff.	1.12	(0.16)	0.32	(0.71)	0.21	(0.75)	0.19	(0.79)	0.35	(0.55)		
β_{cd}												
Small	1.00	[0.62]	1.01	[0.54]	0.89	[0.45]	0.89	[0.46]	0.72	[0.43]	-0.28	(0.42)
2	0.82	[0.51]	0.74	[0.46]	0.61	[0.40]	0.53	[0.38]	0.68	[0.42]	-0.14	(0.51)
3	0.69	[0.47]	0.56	[0.40]	0.43	[0.35]	0.33	[0.34]	0.53	[0.39]	-0.16	(0.51)
4	0.55	[0.41]	0.49	[0.42]	0.37	[0.38]	0.27	[0.29]	0.24	[0.37]	-0.31	(0.22)
Large	0.35	[0.34]	0.29	[0.36]	0.21	[0.36]	0.11	[0.28]	0.09	[0.36]	-0.26	(0.28)
Diff.	-0.65	(0.08)	-0.72	(0.11)	-0.68	(0.04)	-0.78	(0.04)	-0.63	(0.05)		

Panel B: Risk Exposures of the Size/ Momentum Sorted Portfolios

	Losers		2		3		4		Winners		Diff.	
β_c												
Small	0.21	[0.04]	0.18	[0.03]	0.17	[0.03]	0.17	[0.03]	0.16	[0.04]	-0.1	(0.15)
2	0.21	[0.05]	0.18	[0.03]	0.18	[0.03]	0.18	[0.03]	0.16	[0.04]	-0.1	(0.21)
3	0.22	[0.04]	0.19	[0.03]	0.18	[0.02]	0.18	[0.03]	0.16	[0.04]	-0.1	(0.16)
4	0.23	[0.04]	0.22	[0.03]	0.19	[0.02]	0.19	[0.02]	0.17	[0.03]	-0.1	(0.15)
Large	0.25	[0.04]	0.18	[0.03]	0.17	[0.02]	0.17	[0.02]	0.17	[0.03]	-0.1	(0.02)
Diff.	0.04	(0.17)	0	(1.00)	0	(1.00)	0	(0.93)	0.01	(0.65)		
β_d												
Small	1.08	[0.07]	0.83	[0.05]	0.77	[0.04]	0.79	[0.04]	1	[0.06]	-0.1	(0.43)
2	1.18	[0.08]	0.88	[0.05]	0.8	[0.04]	0.83	[0.04]	1.09	[0.07]	-0.1	(0.39)
3	1.08	[0.08]	0.85	[0.04]	0.79	[0.04]	0.79	[0.03]	1.03	[0.05]	-0.1	(0.59)
4	1.04	[0.09]	0.84	[0.05]	0.77	[0.04]	0.78	[0.03]	0.96	[0.05]	-0.1	(0.47)
Large	0.94	[0.07]	0.73	[0.05]	0.71	[0.03]	0.7	[0.03]	0.86	[0.05]	-0.1	(0.41)
Diff.	-0.1	(0.02)	-0.1	(0.08)	-0.1	(0.13)	-0.1	(0.04)	-0.10	(0.01)		
β_{cc}												
Small	-0.92	[0.20]	-0.73	[0.19]	-0.69	[0.18]	-0.64	[0.19]	-0.62	[0.25]	0.30	(0.09)
2	-0.91	[0.24]	-0.72	[0.20]	-0.65	[0.19]	-0.63	[0.21]	-0.46	[0.31]	0.45	(0.06)
3	-0.89	[0.21]	-0.65	[0.18]	-0.60	[0.18]	-0.64	[0.20]	-0.52	[0.26]	0.37	(0.11)
4	-0.84	[0.21]	-0.69	[0.19]	-0.59	[0.17]	-0.56	[0.18]	-0.50	[0.22]	0.34	(0.16)
Large	-0.70	[0.19]	-0.53	[0.15]	-0.49	[0.15]	-0.38	[0.14]	-0.41	[0.18]	0.29	(0.13)
Diff.	0.22	(0.12)	0.30	(0.15)	0.20	(0.02)	0.26	(0.01)	0.21	(0.11)		
β_{dd}												
Small	-3.19	[1.23]	-2.71	[1.08]	-2.57	[0.99]	-2.54	[0.98]	-2.55	[1.20]	0.64	(0.28)
2	-3.05	[1.27]	-2.62	[1.12]	-2.42	[1.02]	-2.38	[0.96]	-2.26	[1.37]	0.79	(0.25)
3	-2.39	[1.03]	-2.47	[1.05]	-2.39	[1.02]	-2.42	[0.96]	-2.28	[1.20]	0.11	(0.85)
4	-2.41	[1.11]	-2.47	[1.04]	-2.32	[0.97]	-2.34	[0.95]	-2.29	[1.16]	0.12	(0.87)
Large	-2.29	[1.12]	-1.86	[0.86]	-1.77	[0.71]	-1.62	[0.71]	-1.69	[0.84]	0.60	(0.44)
Diff.	0.90	(0.06)	0.85	(0.09)	0.80	(0.05)	0.92	(0.02)	0.86	(0.06)		
β_{cd}												
Small	0.54	[0.43]	0.56	[0.39]	0.59	[0.40]	0.71	[0.42]	0.99	[0.51]	0.45	(0.06)
2	0.48	[0.43]	0.50	[0.39]	0.54	[0.42]	0.67	[0.43]	1.05	[0.57]	0.57	(0.01)
3	0.25	[0.36]	0.34	[0.36]	0.48	[0.36]	0.56	[0.43]	0.85	[0.49]	0.60	(0.05)
4	0.09	[0.30]	0.23	[0.39]	0.35	[0.37]	0.35	[0.39]	0.72	[0.44]	0.63	(0.06)
Large	0.07	[0.3]	0.02	[0.27]	0.35	[0.33]	0.33	[0.33]	0.51	[0.39]	0.44	(0.11)
Diff.	-0.47	(0.06)	-0.54	(0.01)	-0.24	(0.06)	-0.38	(0.01)	-0.48	(0.01)		

Table V
Asset Pricing Tests using Fama-MacBeth Regressions

In this table we report the estimated regression coefficients and the associated t-statistics from the Fama-MacBeth (1973) two-step regression approach for the sample period July 1963-December 2010. The dependent variable, $\bar{R}^e$, is the cross-section of the average monthly excess returns over the 1-month T Bill on the test assets. Test assets in Panel A are Fama-French 25 size/book-to-market sorted portfolios. Test assets in Panel B are Fama-French 25 size/book-to-market sorted portfolios, 25 size/momentum sorted portfolios, and 12 industry sorted portfolios. Each column reports estimated risk premia and t-statistics for the corresponding asset pricing model. All t-statistics are adjusted for the first-step estimation uncertainty using bootstrap methodology following Campbell and Vuolteenaho (2004).

Panel A: Size/BM and Size/Momentum Sorted Portfolios

Model	CAPM	ICAPM-2 beta	CAPM with coskewness	Non-linear ICAPM	Carhart four-factor
Const	0.012	0.016	0.011	0.002	0.003
[t-stat]	[2.93]	[2.29]	[2.39]	[0.33]	[1.12]
MKT premium	-0.005		-0.017		0.001
[t-stat]	[-1.25]		[-2.88]		[0.30]
MKT^2 premium			-0.349		
[t-stat]			[-2.25]		
N_c premium		-0.026		0.054	
[t-stat]		[-0.93]		[2.16]	
N_d premium		-0.006		-0.009	
[t-stat]		[-1.39]		[-1.18]	
N_{cc} premium				0.012	
[t-stat]				[1.29]	
N_{dd} premium				-0.002	
[t-stat]				[-0.80]	
N_{cd} premium				0.011	
[t-stat]				[2.00]	
SMB premium					0.002
[t-stat]					[1.83]
HML premium					0.004
[t-stat]					[3.23]
MOM premium					0.008
[t-stat]					[4.27]
Adj. R^2	0.05	0.06	0.46	0.71	0.79
Implied γ	N/A	4.33	1	2.39	N/A
Pricing error (ϑ)	0.091	0.121	0.079	0.020	0.025
p-value (ϑ)	0.000	0.000	0.017	0.671	0.172

Table V (continued)

Panel B: Size/BM Sorted Portfolios

Model	CAPM	ICAPM-2-beta	CAPM with coskewness	Non-linear ICAPM	Fama-French-Carhart
Const	0.016	-0.005	0.014	-0.002	0.005
[t-stat]	[3.48]	[-0.70]	[2.54]	[-0.18]	[1.04]
MKT premium	-0.009		-0.021		0.001
[t-stat]	[-1.77]		[-2.56]		[0.18]
MKT^2 premium			-0.373		
[t-stat]			[-2.27]		
N_c premium		0.054		0.064	
[t-stat]		[2.08]		[2.21]	
N_d premium		0.003		-0.006	
[t-stat]		[0.53]		[-0.93]	
N_{cc} premium				0.009	
[t-stat]				[1.06]	
N_{dd} premium				-0.001	
[t-stat]				[-0.53]	
N_{cd} premium				0.009	
[t-stat]				[1.98]	
SMB premium					0.002
[t-stat]					[1.54]
HML premium					0.005
[t-stat]					[3.87]
MOM premium					0.025
[t-stat]					[1.78]
Adj. R^2	0.04	0.29	0.55	0.73	0.73
Implied γ	N/A	17.42	1	2.03	N/A
Pricing error (ϑ)	0.061	0.029	0.070	0.012	0.025
p-value (ϑ)	0.004	0.286	0.011	0.744	0.337

Table V (continued)

Panel C: Size/BM, Size/Momentum and Industry Sorted Portfolios

Model	CAPM	ICAPM-2 beta	CAPM with coskewness	Non-linear ICAPM	Fama-French-Carhart
Const	0.008	0.009	0.008	0.008	0.006
[t-stat]	[2.86]	[2.90]	[2.49]	[2.58]	[2.40]
MKT premium	-0.002		-0.011		-0.001
[t-stat]	[-0.67]		[-2.29]		[-0.32]
MKT^2 premium			-0.256		
[t-stat]			[-2.55]		
N_c premium		-0.009		0.009	
[t-stat]		[-0.64]		[0.60]	
N_d premium		-0.002		-0.008	
[t-stat]		[-0.54]		[-1.56]	
N_{cc} premium				0.002	
[t-stat]				[0.33]	
N_{dd} premium				-0.001	
[t-stat]				[-0.66]	
N_{cd} premium				0.009	
[t-stat]				[2.90]	
SMB premium					0.002
[t-stat]					[1.54]
HML premium					0.003
[t-stat]					[2.31]
MOM premium					0.008
[t-stat]					[2.58]
Adj. R^2	0.002	-0.001	0.27	0.45	0.65
Implied γ	N/A	4.50	1	2.03	N/A
Pricing error (ϑ)	0.079	0.086	0.077	0.075	0.053
p-value (ϑ)	0.000	0.000	0.005	0.005	0.016

Table VI

Asset Pricing Tests Using the Implied Cost of Equity

In this table we report the estimated regression coefficients from the Fama-MacBeth (1973) two-step regression approach for the implied cost of equity on the cash flow beta (β_{NCF}), discount rate beta (β_{NDR}), cash flow volatility beta (β_{NC^2}), discount rate volatility beta (β_{ND^2}), and covariation beta (β_{NC*ND}) for the sample of US firms over the period of 1986-2010. The dependent variable, $IRP_{i,t}$, is the implied risk premium computed as the difference between the implied cost of equity for firm *i* in year *t* and the yield on 10-year US Treasury bond. We compute the implied cost of equity using five different specifications: Claus and Thomas (CT,2001), Ohlson and Juetber-Nauroth (OJ,1995), modified PEG model of Easton (MPEG, 2004), Gebhardt, Lee and Swaminathan (2001), and the median of estimates obtained from the four models. Constant, control variables and industry fixed effects are included in all regressions. The control variables are firm size, firm book-to-market ratio, leverage, price momentum, volatility of operating cash flows, number of analysts following the firm, share turnover and growth in the 1-and 2-year analyst earnings forecasts. Industry fixed effects are based on the first 2 digits of SIC code. Corresponding *t*-statistics adjusted for serial correlation are reported in squared brackets.

Panel A: Raw variables

Model	Median	GLS	OJ	MPEG	CT
N_c premium	0.016	0.008	0.017	0.017	0.009
[t-stat]	[2.56]	[3.09]	[3.02]	[2.98]	[2.29]
$N_d$premium	0.005	0.0003	0.006	0.006	0.008
[t-stat]	[6.19]	[0.43]	[6.48]	[6.45]	[3.84]
N_{cc} premium	0.026	-0.024	0.044	0.018	-0.24
[t-stat]	[0.38]	[-1.07]	[0.55]	[0.24]	[-1.41]
N_{dd} premium	-0.041	-0.002	-0.051	-0.045	-0.009
[t-stat]	[-1.08]	[-0.13]	[-1.41]	[-1.14]	[-0.16]
N_{cd} premium	0.186	0.095	0.187	0.201	0.079
[t-stat]	[3.47]	[3.58]	[3.18]	[3.26]	[0.71]
Implied market premium	0.046	0.010	0.063	0.055	0.024
Controls	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Average Adj. R^2	0.184	0.414	0.219	0.215	0.096

Panel B: Decile ranked variables

Model	Median	GLS	OJ	MPEG	CT
N_c premium	0.004	0.002	0.003	0.004	0.004
[t-stat]	[3.99]	[3.84]	[3.64]	[4.18]	[3.82]
$N_d$premium	0.004	0.002	0.002	0.003	0.004
[t-stat]	[3.88]	[3.58]	[1.32]	[3.01]	[1.78]
N_{cc} premium	-0.001	-0.001	0.001	-0.000	-0.008
[t-stat]	[-0.29]	[-1.69]	[0.22]	[-0.12]	[-1.49]
N_{dd} premium	-0.001	-0.001	-0.001	-0.001	0.003
[t-stat]	[-0.31]	[-0.39]	[-0.46]	[-0.38]	[0.50]
N_{cd} premium	0.005	0.003	0.005	0.005	0.004
[t-stat]	[3.82]	[3.45]	[3.65]	[4.18]	[1.11]
Implied market premium	0.046	0.010	0.063	0.055	0.024
Controls	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Average Adj. R^2	0.236	0.512	0.311	0.292	0.118

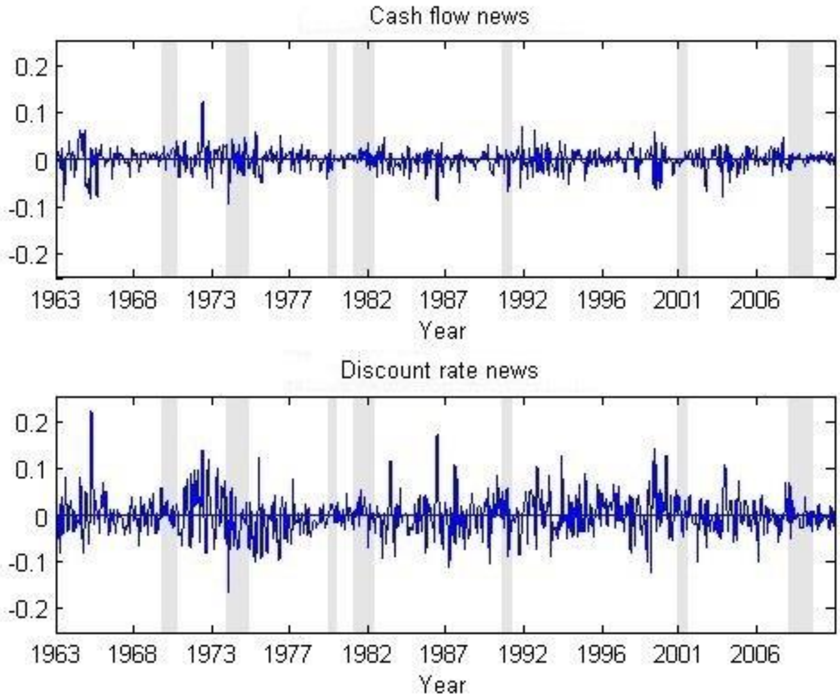

Figure 1: This figure plots the cash-flow news and the negative of discount-rate news series. The sample period is from July 1963 to December 2010. The shaded areas represent NBER recessions.

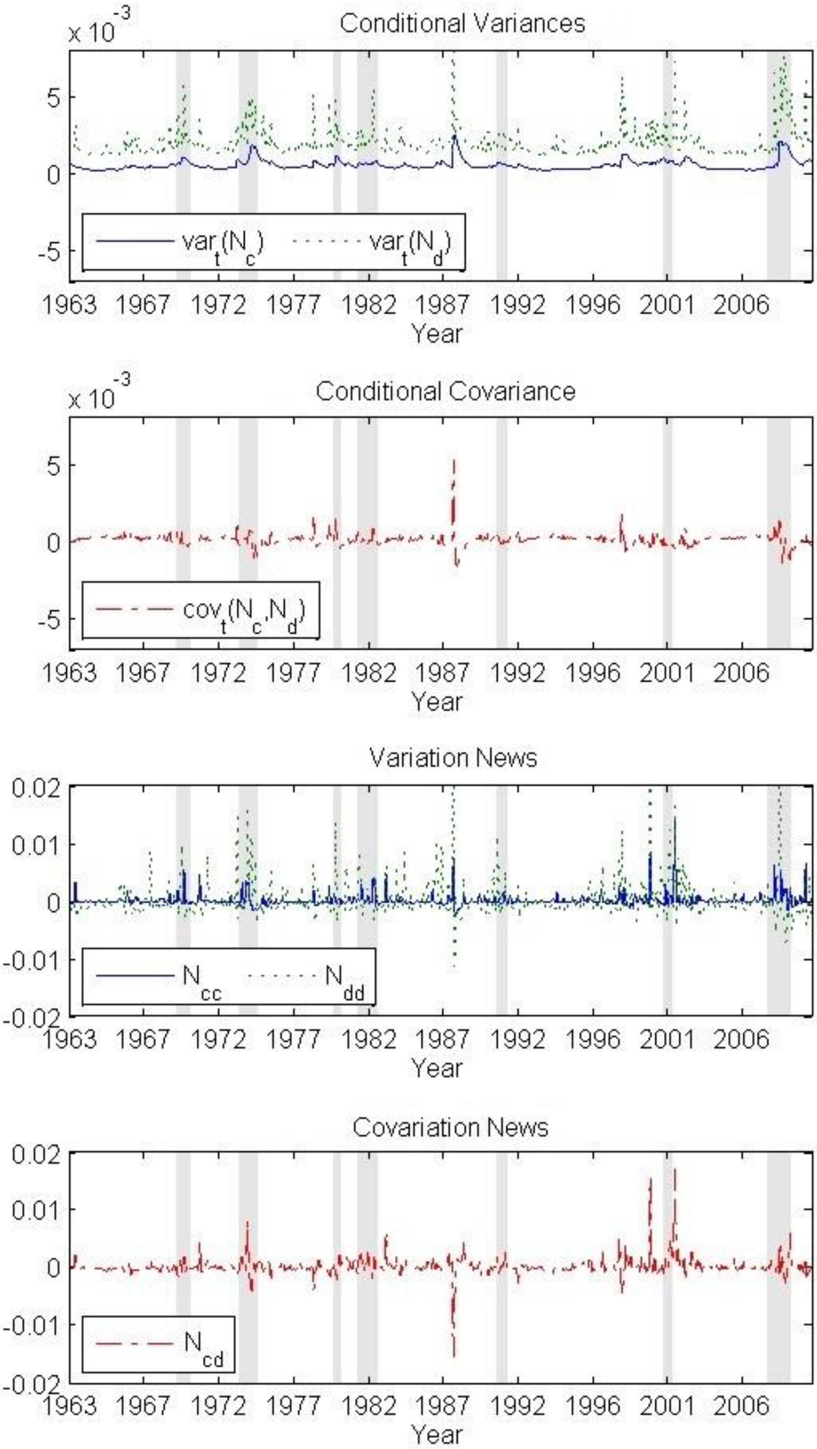

Figure 2: The top two figures show the time series of MGARCH conditional variances and covariance of news to cash flows and discount rates. The bottom two figures show the surprises to these series in every period. The sample period is from July 1963 to December 2010. The shaded areas represent NBER recessions.