What Drives the Idiosyncratic Volatility Puzzle?

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Abstract

I reexamine the idiosyncratic volatility puzzle of Ang et al. (2006) in the cross-section of stock returns at the quarterly horizon and investigate the relative importance of cash flow news and discount rate news in driving this anomaly based on the news decomposition method of Vuolteenaho (2002) with quarterly data. The result from idiosyncratic volatility-sorted quintile portfolios shows that the zero investment portfolio constructed with two extreme portfolios earns about 1.3 percent (1.2 percent) alpha returns per quarter on average after controlling the market factor (Fama–French factors). In addition, I create two decile portfolios sorted on discount rate news volatilities and cash flow news counterparts. While the average return of the arbitrage portfolio from discount rate news volatilities is insignificant, the counterpart from cash flow news volatilities records about 1.5 percent (1.2 percent) alpha returns per quarter on average after considering the market factor (Fama–French factors). These findings indicate that the idiosyncratic volatility anomaly is mainly driven by cash flow news volatilities rather than discount rate news counterparts.

Keywords: Idiosyncratic volatility puzzle, news decomposition, cash flow and discount rate news, panel VAR, EGARCH

JEL classification: G12, G14

The idiosyncratic volatility puzzle in the cross-section has been investigated over the past decade. Not only our intuition but also economic theories predict zero or positive association between returns and volatilities. Most evidences are exactly the opposite—returns and volatilities clearly exhibit a negative relationship. According to a substantial body of empirical finance literature, this counterintuitive anomaly is not only consistent after controlling other factors, but also robust to a variety of research designs (e.g. Ang et al. (2006, 2009), Jiang, Xu and Yao (2009), Chen et al. (2012), Fink, Fink and He (2012), Guo, Kassa and Ferguson (2014)). In particular, it has attracted a lot of interest from researchers because it is hard to reconcile these evidences with traditional asset pricing paradigms.

To fit this puzzle, previous papers have emphasized the importance of behavioral motives including investor sentiment, conditional heteroskedasticity, return reversal, and skewness preference (e.g. Fu (2009), Huang et al. (2010), Bali, Cakici and Whitelaw (2011), Stambaugh, Yu and Yuan (2015)). However, none of papers has paid attention to the role of cash flow and discount rate news, which is a structural determinant of both returns and volatilities. Studies concerning news decomposition methods likewise have paid no attention to the idiosyncratic volatility anomaly notwithstanding its importance. They have highlighted the role of systematic risks instead to explain the cross-section of returns (e.g. Campbell and Vuolteenaho (2004), Campbell, Polk and Vuolteenaho (2010), Campbell, Giglio and Polk (2013), Yeh et al. (2015)).

Many studies have employed news decomposition methods to decompose stock returns at an aggregate level since Campbell and Shiller (1988), but one of the most important papers is Vuolteenaho (2002), which decomposes stock returns at an individual level rather than at an aggregate level using an accounting identity framework and a panel VAR model. Unlike other papers that emphasizes the role of discount rate news in determining stock returns at a macroeconomic level, this paper concludes that stock returns at a firm level are mostly determined by cash flow news. As these two news components fundamentally determine both stock returns and volatilities, one can figure out the structural forces that drive the aforementioned idiosyncratic volatility puzzle by scrutinizing the news components.

In this paper, I reexamine the existence of the idiosyncratic volatility anomaly at the quarterly horizon and investigate the relative importance of cash flow and discount rate news in driving this anomaly. I estimate a panel VAR model with quarterly CRSP and Compustat data obtained from WRDS. Both discount rate and cash flow news volatilities are computed using an EGARCH model following Fu (2009). Two decile portfolios sorted on respective volatilities are created. While the average return of the arbitrage portfolio constructed with discount rate news volatilities is insignificant, the average return of the arbitrage portfolio constructed with cash flow news volatilities is positive and significant after controlling the market factor (α=1.52%/quarter, t-statistic=2.24) or Fama–French factors (α=1.21%/quarter, t-statistic=1.81). This result indicates that cash flow news volatilities rather than discount rate news volatilities mainly drive the idiosyncratic volatility anomaly. These findings are consistent with the result of Vuolteenaho (2002).

TEXT

Subsequent sections are organized in the following manner. Section I recalls the literature related to the idiosyncratic volatility anomaly and the news decomposition methodology. Section II describes economic models employed. Section III illustrates the data analyzed. Section IV demonstrates major findings. Section V concludes this paper.

1 Literature Review

According to many theories, the relation between idiosyncratic risks and subsequent returns should be insignificant or at least positive (Merton (1987), Malkiel and Xu (2006)). Early findings report the insignificant or positive relation between them at the aggregate level (Longstaff (1989), Lehman (1990), Goyal and Santa-Clara (2003)). However, recent evidences from cross-sections show the opposite relation between them at the individual level. In the first subsection, I introduce several papers investigating the idiosyncratic volatility anomaly. In the second subsection, I introduce another group of papers employing news decomposition methods.

1.1 Cross-section of return and volatility

Fama and MacBeth (1973) use idiosyncratic volatilities as well as market betas in their return regression models and exhibit that the coefficients for idiosyncratic volatilities are insignificant in almost every specification. However, their research concentrates on market betas rather than idiosyncratic volatilities hence constructs market beta-sorted portfolios to mitigate measurement errors in market beta estimates. As a result, their coefficients for idiosyncratic volatilities are biased and inconsistent due to measurement errors in idiosyncratic volatility estimates.

In contrast, Ang et al. (2006) concentrate on idiosyncratic volatilities instead of market betas and show the negative relation between idiosyncratic volatilities and subsequent returns. They use daily excess returns and Fama–French model to compute monthly idiosyncratic volatilities and investigate the performance of idiosyncratic volatility-sorted portfolios. The authors confirm that the arbitrage portfolio outperforms even after considering both risks and characteristics. In addition, the outperformance survives in different $L/M/N$ strategies and over various subsamples. This phenomenon is globally observed in the financial markets of G7 countries as well (Ang et al. (2009)).

Since monthly idiosyncratic volatilities are positively autocorrelated, Fu (2009) introduces EGARCH model instead and uses monthly returns rather than daily returns. He demonstrates the positive relation between expected idiosyncratic volatilities and subsequent returns This positive relation is consistent with the theoretical prediction that suggests the positive risk premium for an idiosyncratic volatility under the underdiversification, which is more realistic according to empirical findings (Campbell et al. (2001)). However, other literatures provide the opposite relation between out-of-sample EGARCH volatilities and following returns as well (Fink, Fink and He (2012), Guo, Kassa and Ferguson (2014)).

In order to explain this counterintuitive relation between volatilities and returns, previous researches have adopted skewness preference (Barberis and Huang (2008), Boyer, Mitton and Vorkink (2010), Bali, Cakici and Whitelaw (2011)), liquidity cost (Han and Lesmond (2009)), return reversal (Huang et al. (2010)), January effect (Huang et al. (2011)), arbitrage asymmetry and investor sentiment (Stambaugh, Yu and Yuan (2015)), etc. Hou and Loh (2016) assess the explanatory power of these candidates and confirm that more than half of this anomaly remain unexplained.

1.2 News decomposition of return and volatility

Inherently, stock returns are driven by both cash flow news and discount rate news. This is intuitive since the price is the expected value of discounted payoff (i.e. p=E[mx]). Campbell and Shiller (1988) firstly propose the way to decompose these two components by applying both log-linearized dividend-price ratio model and VAR model. They relate returns to dividend-price ratios as well as dividend growths and use annual time-series at the aggregate level. Though the authors confirm the relative importance of cash flow news and discount rate news in their findings, they focus not on returns but on dividend-price ratios.

Other early studies also investigate both cash flow news and discount rate news at the aggregate level (Campbell (1991), Campbell and Ammer (1993)). These researches report that stock returns are largely determined not by cash flow news but by discount rate news at the aggregate level. On the other hand, Vuolteenaho (2002) suggest another way to decompose by adopting log-linearized book-to-market ratio model and VAR model. The author relates returns to book-to-market ratio and return on equity and use annual panel at the individual level. Unlike the evidence from the aggregate level, the firm-level result indicates that stock returns are mainly driven by cash flow news rather than discount rate news. Subsequent papers applying different methods provide consistent results as well (Callen and Segal (2004), Chen, Da and Zhao (2013)).

Since both aggregate level returns and firm-level returns can be disaggregated, the interaction among the components has also been examined. Campbell and Vuolteenaho (2004) decompose the aggregate level data into cash flow news and discount rate news. For individual returns, they use the two components to estimate cash flow betas (i.e. “bad” betas) and discount rate betas (i.e. “good” betas) separately. The authors show that value stocks tend to have high cash flow betas and growth stocks tend to have high discount rate betas. Overall, this justifies the failure of CAPM after 1963 because cash flow betas are compensated more than discount rate betas. Campbell, Giglio and Polk (2013) adopt the similar framework and compare the downturn of the early 2000s, which is largely driven by discount rate news, and that of the late 2000s, which is mainly driven by cash flow news.

Campbell, Polk and Vuolteenaho (2010) further decompose the firm-level data into cash flow news and discount rate news. They use two aggregate level components CFm, DRm and two firm-level components CFi, DRi to estimate four different betas (i.e. CFi-CFm betas, DRi-CFm betas, CFi-DRm betas, DRi-DRm betas). The authors demonstrate that, while value stocks tend to have high CFi-CFm betas, growth stocks tend to have high CFi-DRm betas. In contrast, they show that two firm-level discount rate betas of value stocks and growth stocks are not significantly different from each other.

Other details of news decomposition methods have also been studied by previous literatures. Chen and Zhao (2009) point out several vulnerabilities of these VAR-based decomposition methods and explore some methodological remedies. Engsted, Pedersen and Tanggaard (2012) suggest another technical way to circumvent these issues. Cenedese and Mallucci (2016) decompose aggregate level international stock returns and report that the international returns are largely driven by cash flow news rather than discount rate news.

2 Economic Model

2.1 Idiosyncratic volatility

Firstly, I estimate idiosyncratic volatilities by using Fama–French model to check whether the idiosyncratic volatility puzzle is consistent or not.

$$r_{itd} - r_{ftd} = \alpha_{it} + \beta_{it}(r_{mtd} - r_{ftd}) + s_{it}SMB_{td} + h_{it}HML_{td} + \varepsilon_{itd}$$

The subscripts i, t and d stand for firm, quarter (or month) and day respectively. Overall, I follow the details of Fama and French (1993) and Ang et al. (2006). Each quarter (month), I estimate this regression model by using daily data and compute $\sqrt{\widehat{\mathrm{Var}}[\varepsilon_{itd}]}$ quarter by quarter (month by month) recursively. I exclude idiosyncratic volatilities that are computed with less than 31 (11) daily observations.

Secondly, I sort stocks based on these volatility estimates at the end of quarter (month) t and construct value-weighted quintile portfolios for the quarter (month) t+1, i.e. 3/3 (1/1) strategy of Jegadeesh and Titman (1993). Portfolios are rebalanced each quarter (month). In addition, I construct zero investment portfolio by buying the first (i.e. the least volatile) portfolio and selling the fifth (i.e. the most volatile) one.

Thirdly, I measure the performance of those portfolios based on their historical returns.

$$r_{pt} - r_{ft} = \alpha_p + \beta_p(r_{mt} - r_{ft}) + s_pSMB_t + h_pHML_t + \varepsilon_{pt}$$

For the portfolio p, I compute (i) sample statistics, (ii) CAPM statistics and (iii) Fama–French model statistics by using its time-series.

2.2 News decomposition

To decompose firm-level stock returns, I adopt the framework of Vuolteenaho (2002). Unlike the method of Campbell and Shiller (1988), this framework incorporates book-to-market ratio, return on equity and clean-surplus relation to disaggregate firm-level returns.

$$\begin{aligned}
\theta_t &\approx \sum_{j=0}^{\infty} \rho^j r_{t+1+j} - \sum_{j=0}^{\infty} \rho^j (e_{t+1+j} - f_{t+j}) \\
\Rightarrow r_t - \mathrm{E}_{t-1}[r_t] &= \Delta \mathrm{E}_t \left[\sum_{j=0}^{\infty} \rho^j (e_{t+j} - f_{t+j}) \right] + \kappa_t - \Delta \mathrm{E}_t \left[\sum_{j=1}^{\infty} \rho^j r_{t+j} \right] \\
&= N_{cf,t} - N_{r,t}
\end{aligned}$$

For simplicity, I omit firm subscripts. The function $\mathrm{E}_t[\,\cdot\,]$ represents the expected value subject to the information set available at time t, i.e. $\mathrm{E}[\,\cdot\,|\Omega_t]$. The function $\Delta\mathrm{E}_t[\,\cdot\,]$ denotes the change of expectation at time t, i.e. $\mathrm{E}_t[\,\cdot\,]-\mathrm{E}_{t-1}[\,\cdot\,]$. The variables θ, r, e and f stand for log book-to-market ratio, log excess return, log return on equity and log interest rate, respectively. The coefficient ρ and the term κ stand for discount factor and approximation, respectively. Therefore, the returns are decomposed into two components, i.e. cash flow news N_{cf} and discount rate news N_r. In addition, this return decomposition implies the following variance decomposition simultaneously.

$$\mathrm{Var}\big[r_t - \mathrm{E}_{t-1}[r_t]\big] = \mathrm{Var}\big[N_{cf,t}\big] + \mathrm{Var}\big[N_{r,t}\big] - 2\mathrm{Cov}\big[N_{cf,t}, N_{r,t}\big]$$

In practice, one is able to decompose the returns by assuming VAR process for state variables. In particular, I assume the first-order VAR process rather than others.

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

The first element of the state vector $\mathbf{z}$ is r, i.e. $\mathbf{z} = (r \quad \cdots)^\top$. This linear process implies the recursive structure hence the change of expectation can be obtained as well.

$$\Delta\mathrm{E}_t\big[\mathbf{z}_{t+j}\big] = \mathbf{\Gamma}^j\mathbf{u}_t$$

Both discount rate news and cash flow news can be obtained by combining the change of expectation with the news decomposition above.

$$\begin{aligned} N_{r,t} &= \Delta\mathrm{E}_t\left[\sum_{j=1}^{\infty}\rho^j r_{t+j}\right] = \Delta\mathrm{E}_t\left[\sum_{j=1}^{\infty}\rho^j \mathbf{e1}^\top\mathbf{\Gamma}^j\mathbf{u}_t\right] = \mathbf{e1}^\top(\mathbf{I}-\rho\mathbf{\Gamma})^{-1}\rho\mathbf{\Gamma}\mathbf{u}_t = \boldsymbol{\lambda}^\top\mathbf{u}_t \\ N_{cf,t} &= r_t - \mathrm{E}_{t-1}[r_t] + N_{r,t} = \mathbf{e1}^\top\mathbf{u}_t + \boldsymbol{\lambda}^\top\mathbf{u}_t = (\mathbf{e1}+\boldsymbol{\lambda})^\top\mathbf{u}_t \end{aligned}$$

The vector $\mathbf{e1}$ contains 1 only for the first element and 0 for the others, i.e. $\mathbf{e1} = (1 \quad \mathbf{0}^\top)^\top$. By defining $\mathbf{\Sigma}$ as the variance of $\mathbf{u}_t$, i.e. $\mathbf{\Sigma} = \mathrm{E}[\mathbf{u}_t\mathbf{u}_t^\top]$, one can rewrite the variance decomposition above.

$$\begin{aligned} \mathrm{Var}\big[N_{r,t}\big] &= \boldsymbol{\lambda}^\top\mathbf{\Sigma}\boldsymbol{\lambda} \\ \mathrm{Var}\big[N_{cf,t}\big] &= (\mathbf{e1}+\boldsymbol{\lambda})^\top\mathbf{\Sigma}(\mathbf{e1}+\boldsymbol{\lambda}) \\ \mathrm{Cov}\big[N_{r,t}, N_{cf,t}\big] &= \boldsymbol{\lambda}^\top\mathbf{\Sigma}(\mathbf{e1}+\boldsymbol{\lambda}) \end{aligned}$$

The coefficient matrix $\mathbf{\Gamma}$ and the variance matrix $\mathbf{\Sigma}$ are estimated using panel data. In order to consider the time effect in the state vector $\mathbf{z}$, I demean the observations cross-section by cross-section and estimate both $\mathbf{\Gamma}$ and $\mathbf{\Sigma}$ using WLS with the weight $1/N_t$ following Fama and MacBeth (1973). N_t stands for the number of firms at time t. In addition, I adopt a time-clustered standard error for both $\mathbf{\Gamma}$ and $\mathbf{\Sigma}$ because it is robust to the time effect (Petersen (2009)). Following Vuolteenaho (2002) and Callen and Segal (2010), I employ 0.967 ($0.967^{1/4}$) as the annual (quarterly) discount factor ρ.

2.3 EGARCH

Ang et al. (2006) exploit daily data to compute idiosyncratic volatilities. Since the news decomposition proposed by Vuolteenaho (2002) requires accounting data, neither daily nor monthly news data are available. In addition, the aforementioned variance decomposition is static so cannot alter traditional idiosyncratic volatilities. Instead, I apply EGARCH model to estimate news volatilities since many papers studying idiosyncratic volatilities adopt this model (Fu (2009), Fink, Fink and He (2012)). These papers use monthly data to calculate EGARCH idiosyncratic volatilities.

$$\begin{aligned} N_{it} - r_{ft} &= \alpha_i + \beta_i(r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it} \\ \sigma_{it}^2 &= \exp\left(a_i + \sum_{l=1}^{p} b_{il} \ln \sigma_{it-l}^2 + \sum_{k=1}^{q} c_{ik}\left[\theta_i\left(\frac{\varepsilon_{it-k}}{\sigma_{it-k}}\right) + \gamma_i\left(\left|\frac{\varepsilon_{it-k}}{\sigma_{it-k}}\right| - \sqrt{\frac{2}{\pi}}\right)\right]\right) \end{aligned}$$

Since volatilities are correlated serially, EGARCH model better reflects the time-varying property. In order to avoid the look-ahead bias mentioned by Guo, Kassa and Ferguson (2014), I compute out-of-sample EGARCH idiosyncratic volatilities recursively. Following above researches, I combine EGARCH model together with Fama–French model. However, unlike these researches, I only consider the case p=q=1, i.e. EGARCH(1,1), because quarterly data provide less available observations than monthly data. Both maximum likelihood and Normal distribution are employed to estimate this model. The log likelihood function is maximized using TR (trust region) method in SAS. I set 32,767 ($2^{15}-1$) as the maximum number of iterations.

3 Data Description

3.1 Raw data

I obtain all CRSP and Compustat data from WRDS. Firstly, I employ CRSP daily stock file to calculate monthly (quarterly) idiosyncratic volatilities and CRSP monthly stock file to construct monthly (quarterly) quintile portfolios sorted on past idiosyncratic volatilities. CRSP daily stock file is from December 31, 1925 to December 31, 2015 and CRSP monthly stock file is from December 1925 to December 2015, respectively. Secondly, I use both Compustat fundamentals annual and Compustat fundamentals quarterly to attain the relevant accounting information such as book-to-market ratio and return on equity. Compustat fundamentals annual is from January 1950 to November 2016 and Compustat fundamentals quarterly is from January 1961 to November 2016, respectively. Thirdly, I merge CRSP and Compustat data by using the linking table of CRSP/Compustat merged. Fourthly, I exploit daily and monthly Fama–French factors to apply CAPM and Fama–French model, which enable to (i) compute an idiosyncratic volatility and (ii) measure the excess performance of a portfolio after considering risk factors.

3.2 Volatility and news

Firstly, I estimate both monthly and quarterly idiosyncratic volatilities with daily data. In detail, I regress firm-level excess returns (r_i—r_f) on Fama–French factors (r_m—r_f, SMB, HML) recursively and adopt the sample standard deviation of residuals ($\sqrt{\widehat{\mathrm{Var}}[\varepsilon_i]}$). I exclude monthly volatilities estimated with less than 11 observations and quarterly volatilities estimated with less than 31 observations. CRSP stocks are sorted on one-month-lagged or one-quarter-lagged volatilities, but excluded if the volatilities are unavailable. Value-weighted quintile portfolios are constructed and rebalanced each month or each quarter.

Secondly, I estimate both annual and quarterly VAR model with annual and quarterly data, respectively. For annual data, I only include the observations at time t with (i) a book equity available at t—1, t—2, t—3, (ii) a net income available at t—1, t—2, (iii) a long-term debt available at t—1, t—2, (iv) a December fiscal-year end month, (v) a market equity more than \$10M and (vi) a log book-to-market ratio bigger than 1/100 but smaller than 100. In order to compare the results conveniently, I follow these requirements imposed by Vuolteenaho (2002) in the annual case. In contrast, I impose only two restrictions in the quarterly case, i.e. an observation must have (i) a log excess return (r), a log book-to-market ratio (θ) and a log excess return on equity (e) available at t—1 and (ii) a December fiscal-year end month. Since idiosyncratic volatilities only require CRSP data, their availabilities are more sufficient than the availabilities of news components that require both CRSP and Compustat data. By relaxing the requirements instead, more returns are able to be decomposed into news components.

Thirdly, I estimate the idiosyncratic volatilities of both discount rate news and cash flow news with the data above using EGARCH model. In detail, I obtain out-of-sample EGARCH volatilities firm by firm with all historical data available at that time, but only include the volatilities computed with more than or equal to 12 quarterly observations (3 years). Since the estimation involves numerical procedures, one cannot be fully apart from the threat of outliers. Following Fu (2009), I winsorize the smallest and biggest 2.5% of news volatilities quarter by quarter. Panel A and Panel B of Figure 1 display the distributions of discount rate and cash flow news idiosyncratic volatilities, respectively.

4 Main Result

4.1 Idiosyncratic volatility

TABLE I HERE

Table I shows the month by month (1/0/1) performance of quintile portfolios sorted on lagged idiosyncratic volatilities. The first column is the portfolio with lowest volatility and vice versa. In addition, the sixth column is the zero cost portfolio formed by selling the most volatile and buying the least volatile. The first three rows contain sample means, corresponding t-statistics and standard deviations of quintile portfolios, respectively. While the average return of the least volatile quintile is positive (0.67%/month) and significant (t-statistic=4.71), that of the most volatile quintile is marginal (0.15%/month) and insignificant (t-statistic=0.53). The average return of the arbitrage portfolio is positive (0.53%/month) and significant (t-statistic=2.65). Though this return is smaller than what is reported by Ang et al. (2006) (1.06%/month), its significance is close enough (Newey–West t-statistic=3.10). Though unreported, the result from matching subsample is consistent (0.94%/month, Newey–West t-statistic=2.89).

The second four rows and last eight rows include the results from CAPM and Fama–French model, respectively. While the CAPM α of quintile 1 is positive (0.13%/month) and significant (t-statistic=3.97), that of quintile 5 is negative (-0.74%/month) and significant (t-statistic=4.69). The CAPM α of the $1-5$ portfolio is positive (0.87%/month) and significant (t-statistic=4.84). Since the CAPM β of this portfolio is negative (-0.53), the abnormal performance cannot be justified by the market risk. Furthermore, this pattern is obvious with Fama–French model as well. The Fama–French model α of the arbitrage portfolio is positive (0.97%/month) and significant (t-statistic=6.90). Risk loadings are also negative (β=−0.31, s=−1.19) or insignificant ($t(h)$-statistic=0.59) so cannot justify the abnormal return. In a nutshell, this confirms the consistency of the results and implies the existence of the idiosyncratic volatility anomaly.

TABLE II HERE

Table II shows the performance of quintile portfolios quarter by quarter (3/0/3) instead. The format of this table is identical to that of Table I. Unlike the case of Table I, the average return of the 1−5 portfolio is negative (−0.81%/quarter). However, this average return is insignificant (t-statistic=−0.78). In contrast, the results from both models indicate that the abnormal return is positive (α_{CAPM}=1.27%/quarter, α_{FF}=1.17%/quarter) and more significant ($t(\alpha_{\text{CAPM}})$-statistic=1.45, $t(\alpha_{\text{FF}})$-statistic=1.61) after controlling other factors. Though unreported, this abnormal performance is even more significant with the subsample after 1963 (Ang et al. (2006)). With the average return 1.90 percent, both CAPM α and FF α are positive (α_{CAPM}=4.19%/quarter, α_{FF}=4.09%/quarter) and significant ($t(\alpha_{\text{CAPM}})$-statistic=3.51, $t(\alpha_{\text{FF}})$-statistic=4.01). The signs of risk loadings are consistent with those in Table I and the magnitudes are bigger than them. In particular, the CAPM β of the quarterly 1−5 portfolio is −0.99 (−1.44 with the post-1963 subsample), which is about twice bigger than that of the monthly counterpart (−0.54). Likewise, the coefficients of Fama–French model from quarterly data (β=−0.54, s=−1.74, h=0.23) are bigger than those from monthly data (β=−0.31, s=−1.19, h=0.02). In short, this implies that the idiosyncratic volatility anomaly is consistent in quarterly data as well.

4.2 News decomposition

TABLE III HERE

Table III displays the descriptive statistics computed from annual data. In order to compare the results conveniently, I record both all sample statistics and subsample counterparts. In detail, all sample is from 1954 to 2015 with 58,554 firm-years and subsample is from 1954 to 1996 with 33,302 firm-years. As aforementioned, observations are demeaned cross-section by cross-section to address time fixed effects. Panel A and Panel B exhibit the descriptive statistics obtained from all sample raw data and all sample demeaned data, respectively. Panel C and Panel D present the descriptive statistics calculated from subsample raw data and subsample demeaned data, respectively. All statistics are calculated from pooled data. For three variables r (log excess return), θ (log book-to-market ratio) and e (log excess return on equity), I estimate sample mean, standard deviation, maximum, minimum and three quartiles. While the demeaning reduces the variations in r and θ significantly (0.48 vs. 0.44, 0.94 vs. 0.91), the reduced portion of the variation in e is marginal (0.41 vs. 0.41).

TABLE IV HERE

Table IV contains the estimates of annual VAR models. In depth, I analyze both all sample (1954–2015) and subsample (1954–1996). Panel A and Panel B report the results obtained from all sample. Panel C and Panel D present the results attained from subsample. The first 3×3 square of Panel A displays the VAR(1) coefficient matrix. Firstly, three coefficients in the first row suggest the positive and significant relation between log return (r_{it}) and three state variables lagged one year (r_{it-1}, θ_{it-1}, e_{it-1}). Secondly, the (2,2) and (3,3) coefficients imply the positive autocorrelation of log book-to-market ratio and log return on equity. The second 3×3 square of Panel A demonstrates the variance matrix. Log return shocks are negatively correlated to log book-to-market ratio shocks, but positively correlated to log return on equity. Panel B shows the result of static news variance decomposition. The ratio of discount rate news variance to cash flow news variance is about 11.35% (0.0157/0.1383). This result indicates that firm-level returns are mainly driven not by discount rate news but by cash flow news. The format of Panel C and Panel D is identical to that of Panel A and Panel B. By and large, the sign and significance of the estimates are comparable. Only the (1,3) and (3,2) coefficients have different results (0.0660 vs. −0.0104, 0.0133 vs. −0.0049). The ratio between discount rate news variance and cash flow news variance is about 9.91% (0.0077/0.0777). In summary, these findings are consistent with those of Vuolteenaho (2002) and Callen and Segal (2004).

TABLE V HERE

Table V exhibits the descriptive statistics computed from quarterly data instead. The format of this table is identical to that of Table III. The sample is from March 1972 to December 2015 (176 quarters) with 235,704 firm-quarters. To address time fixed effects, observations are demeaned cross-section by cross-section. Panel A displays the descriptive statistics calculated from raw data and Panel B demonstrates the descriptive statistics obtained from demeaned data, respectively. All statistics are calculated from pooled data. I estimate sample mean, standard deviation, maximum, minimum and three quartiles for three variables r, θ and e. Similar to the case of Table III, the demeaning reduces the variations in r and θ (0.29 vs. 0.26, 0.98 vs. 0.93), but does not reduce the variation in e (0.18 vs. 0.18).

TABLE VI HERE

Table VI contains the estimates of quarterly VAR model. Panel A exhibits the estimates of both coefficient matrix and variance matrix and Panel B displays the result of static news variance decomposition. In general, the differences are marginal compared to Table IV. In the quarterly VAR model, the (1,1) and (1,2) coefficients are smaller than the counterparts in the annual VAR model (0.0543 vs. 0.0288, 0.0519 vs. 0.0084). In contrast, the (1,3) coefficient is bigger than the counterpart in the annual VAR model (0.0660 vs. 0.0975). This is natural since this VAR model requires quarterly returns instead of annual returns. By and large, both momentum and book-to-market effects are stronger in the long run. On the other hand, the profitability effect is clearer in the short run. Panel B shows the result of static news variance decomposition. The ratio of discount rate news variance to cash flow news variance is about 7.60% (0.0040/0.0526), which is smaller than the ratio computed using annual data (11.35%). Again, this result emphasizes the role of cash flow news in determining quarterly returns. Overall, TEXT

4.3 News volatility

TABLE VII HERE

Table VII shows the performance of quarterly decile portfolios sorted on EGARCH idiosyncratic volatilities of discount rate news. The format of this table is identical to that of Table II. The average return of the 1−10 portfolio is negative (−0.04%/quarter) but insignificant (t-statistic=−0.06). Likewise, both CAPM and Fama–French alphas of this portfolio are positive (α_{CAPM}=0.58%/quarter, α_{FF}=0.09%/quarter) but insignificant ($t(\alpha_{\text{CAPM}})$-statistic=0.88, $t(\alpha_{\text{FF}})$-statistic=0.14). Like the case of Table II, both CAPM and Fama–French betas are negative (β_{CAPM}=−0.32, β_{FF}=−0.26) and significant ($t(\beta_{\text{CAPM}})$-statistic=−4.20, $t(\beta_{\text{FF}})$-statistic=−3.03). Unlike the case of Table II, however, the HML coefficient instead the SMB coefficient is positive (0.36) and significant (t-statistic=3.27). In short, this indicates the difference between the portfolios sorted on traditional idiosyncratic volatilities and the portfolios sorted on discount rate news idiosyncratic volatilities.

TEXT

TABLE VIII HERE

Table VIII shows the performance of quarterly decile portfolios sorted on EGARCH idiosyncratic volatilities of cash flow news. The format of this table is identical to that of Table II. The average return of the zero investment portfolio is positive (0.76%/quarter) but insignificant (t-statistic=1.08). However, both CAPM and Fama–French alphas of this portfolio are positive (α_{CAPM}=1.52%/quarter, α_{FF}=1.21%/quarter) and significant ($t(\alpha_{\text{CAPM}})$-statistic=2.24, $t(\alpha_{\text{FF}})$-statistic=1.81). Like the case of Table II, both CAPM and Fama–French betas are negative (β_{CAPM}=−0.39, β_{FF}=−0.23) and significant ($t(\beta_{\text{CAPM}})$-statistic=−4.95, $t(\beta_{\text{FF}})$-statistic=−2.69). The sign and significance of Fama–French coefficients are identical as well. The SMB coefficient is negative (−0.46, t-statistic=−3.18) and the HML coefficient is positive (0.30, t-statistic=2.74). Unlike the case of Table VII, the portfolios sorted on cash flow news idiosyncratic volatilities are comparable with those sorted on discount rate news idiosyncratic volatilities.

TEXT

5 Conclusion

TEXT

Throughout this paper, I revisit the volatility anomaly of Ang et al. (2006) using quarterly data and compare the relative importance of discount rate and cash flow news volatilities in driving the idiosyncratic volatility puzzle based on the accounting-based approach proposed by Vuolteenaho (2002).

Firstly, I estimate monthly and quarterly idiosyncratic volatilities using daily data and construct quintile portfolios sorted on these volatilities. The arbitrage portfolio here collects 1.3 percent (1.2 percent) alpha returns per quarter on average after considering the market factor (Fama–French factors). The result shows that the anomaly is consistent in both monthly and quarterly data.

Secondly, I estimate annual and quarterly VAR models to decompose firm-level stock returns into discount rate and cash flow news. Overall, the estimates from annual data and those from quarterly data are consistent with each other. Returns are mainly driven by cash flow news rather than discount rate news. In summary, these results are consistent with previous findings as well.

Thirdly, I compute quarterly idiosyncratic discount rate and cash flow news volatilities using quarterly news data obtained above and EGARCH model following Fu (2009). I create two decile portfolios sorted on discount rate and cash flow news volatilities. The average return of the 1−10 portfolio from discount rate volatilities is insignificant, but the matching portfolio from cash flow volatilities acquires about 1.5 percent (1.2 percent) alpha returns per quarter on average after controlling the market factor (Fama–French factors).

All things considered, the results imply that cash flow news volatilities rather than discount rate news volatilities mainly drive the idiosyncratic volatility puzzle in the cross-section of stock returns.

TEXT

Reference

Ang, Andrew, Robert J. Hodrick, Yuhang Xing and Xiaoyan Zhang (2006), The cross-section of volatility and expected returns, *Journal of Finance* 61 (1), 259–299

Ang, Andrew, Robert J. Hodrick, Yuhang Xing and Xiaoyan Zhang (2009), High idiosyncratic volatility and low returns: international and further U.S. evidence, *Journal of Financial Economics* 91 (1), 1–23

Bali, Turan G., Nusret Cakici and Robert F. Whitelaw (2011), Maxing out: stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99 (2), 427–446

Barberis, Nicholas and Ming Huang (2008), Stocks as lotteries: the implications of probability weighting for security prices, *American Economic Review* 98 (5), 2066–2100

Boyer, Brian, Todd Mitton and Keith Vorkink (2010), Expected idiosyncratic skewness, *Review of Financial Studies* 23 (1), 169–202

Callen, Jeffrey L. and Dan Segal (2004), Do accruals drive firm-level stock returns? A variance decomposition analysis, *Journal of Accounting Research* 42 (3), 527–560

Callen, Jeffery L. and Dan Segal (2010), A variance decomposition primer for accounting research, *Journal of Accounting, Auditing and Finance* 25 (1), 121–142

Campbell, John Y. (1991), A variance decomposition for stock returns, *Economic Journal* 101 (405), 157–179

Campbell, John Y. and John Ammer (1993), What moves the stock and bond markets? A variance decomposition for long-term asset returns, *Journal of Finance* 48 (1), 3–37

Campbell, John Y., Stefano Giglio and Christopher Polk (2013), Hard times, *Review of*

Asset Pricing Studies 3 (1), 95–132

Campbell, John Y., Martin Lettau, Burton G. Malkiel and Yexiao Xu (2001), Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, *Journal of Finance* 56 (1), 1–44

Campbell, John Y., Christopher Polk and Tuomo Vuolteenaho (2010), Growth or glamour? Fundamentals and systematic risk in stock returns, *Review of Financial Studies* 23 (1), 305–344

Campbell, John Y. and Robert J. Shiller (1988), The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1 (3), 195–228

Chen, Long, Zhi Da and Xinlei Zhao (2013), What drives stock price movements? *Review of Financial Studies* 26 (4), 847–876

Chen, Linda H., George J. Jiang, Danielle Xu and Tong Yao (2012), Dissecting the idiosyncratic volatility anomaly, Working Paper, Washington State University

Chen, Long and Xinlei Zhao (2009), Return decomposition, *Review of Financial Studies* 22 (12), 5213–5249

Engsted, Tom, Thomas Q. Pedersen and Carsten Tanggaard (2012), Pitfalls in VAR based return decompositions: a clarification, *Journal of Banking and Finance* 36 (5), 1255–1265

Fama, Eugene F. and Kenneth R. French (1992), The cross-section of expected stock returns, *Journal of Finance* 47 (2), 427–465

Fama, Eugene F. and Kenneth R. French (1993), Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33 (1), 3–56

Fama, Eugene F. and James D. MacBeth (1973), Risk, return, and equilibrium: empirical tests, *Journal of Political Economy* 81 (3), 607–636

Fink, Jason D., Kristin E. Fink and Hui He (2012), Expected idiosyncratic volatility measures and expected returns, *Financial Management* 41 (3), 519–553

Fu, Fangjian (2009), Idiosyncratic risk and the cross-section of expected stock returns, *Journal of Financial Economics* 91 (1), 24–37

Guo, Hui, Haimanot Kassa and Michael F. Ferguson (2014), On the relation between EGARCH idiosyncratic volatility and expected returns, *Journal of Financial and Quantitative Analysis* 49 (1), 271–296

Han, Yufeng and David Lesmond (2011), Liquidity biases and the pricing of cross-sectional idiosyncratic volatility, *Review of Financial Studies* 24 (5), 1590–1629

Hou, Kewei and Roger K. Loh (2016), Have we solved the idiosyncratic volatility puzzle? *Journal of Financial Economics* 121 (1), 167–194

Huang, Wei, Qianqiu Liu, S. Ghon Rhee and Liang Zhang (2010), Return reversals, idiosyncratic risk, and expected returns, *Review of Financial Studies* 23 (1), 147–168

Huang, Wei, Qianqiu Liu, S. Ghon Rhee and Liang Zhang (2011), Another look at idiosyncratic volatility and expected returns, *Journal of Investment Management* 9 (4), 26–51

Jegadeesh, Narasimhan and Sheridan Titman (1993), Returns to buying winners and selling losers: implications for stock market efficiency, *Journal of Finance* 48 (1), 65–91

Jiang, George J., Danielle Xu and Tong Yao (2009), The information content of idiosyncratic volatility, *Journal of Financial and Quantitative Analysis* 44 (1), 1–28

Lehman, Bruce N. (1990), Residual risk revisited, *Journal of Econometrics* 45 (1), 71–97

Longstaff, Francis A. (1989), Temporal aggregation and the continuous time capital asset pricing model, *Journal of Finance* 44 (4), 871–887

Malkiel, Burton G. and Yexiao Xu (2006), Idiosyncratic risk and security returns, Working Paper, University of Texas at Dallas

Merton, Robert C. (1987), A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42 (3), 483–510

Peterson, Mitchell A. (2009), Estimating standard errors in finance panel data sets: comparing approaches, *Review of Financial Studies* 22 (1), 436–480

Stambaugh, Robert F., Jianfeng Yu and Yu Yuan (2015), Arbitrate asymmetry and the idiosyncratic volatility puzzle, *Journal of Finance* 70 (5), 1903–1948

Vuolteenaho, Tuomo (2002), What drives firm-level stock returns? *Journal of Finance* 57 (3), 233–264

Yeh, Chung-Ying, Junming Hsu, Kai-Li Wang and Che-Hui Lin (2015), Explaining the default risk anomaly by the two-beta model, *Journal of Empirical Finance* 30, 16–33

Table I. Monthly idiosyncratic volatility-sorted portfolio

This table reports the performance of monthly idiosyncratic volatility-sorted quintile portfolios. I construct these quintile portfolios by using lagged monthly idiosyncratic volatilities. The volatilities are estimated from daily returns and Fama–French model, i.e.

$$r_i - r_f = \alpha_i + \beta_i(r_m - r_f) + s_i SMB + h_i HML + \varepsilon_i$$

For notational convenience, I omit time subscripts. I estimate $\sqrt{\mathrm{Var}[\varepsilon_i]}$ for all firms month by month and construct quintile portfolios recursively (1/0/1). Idiosyncratic volatilities computed with less than 11 daily observations are excluded. The sample is from December 31, 1925 to December 31, 2015. 5 portfolios are from August 1926 to December 2015 (1,073 months). The first row displays quintiles column by column. The last column is the zero investment portfolio (i.e. constructed by buying the first and selling the fifth). The second partition include sample means and standard deviations. The third and fourth partitions contain both CAPM and Fama–French model estimates, respectively. Corresponding t-statistics are reported by using round brackets.

Quintile	1	2	3	4	5	1−5
Mean	0.0067	0.0071	0.0076	0.0052	0.0015	0.0053
	(4.7129)	(3.8419)	(3.4983)	(2.1295)	(0.5280)	(2.6515)
St. dev.	0.0466	0.0606	0.0715	0.0804	0.0900	0.0648
CAPM α	0.0013	0.0000	−0.0006	−0.0036	−0.0074	0.0087
	(3.9674)	(0.0032)	(−1.1564)	(−3.6459)	(−4.6909)	(4.8436)
CAPM β	0.8430	1.1020	1.2830	1.3670	1.3720	−0.5294
	(143.2530)	(159.6910)	(125.0570)	(75.2020)	(47.1820)	(−16.0576)
FF α	0.0013	−0.0004	−0.0013	−0.0043	−0.0084	0.0097
	(4.5894)	(−1.2072)	(−2.7654)	(−5.8466)	(−6.6785)	(6.9000)
FF β	0.8660	1.0810	1.2070	1.2290	1.1730	−0.3074
	(159.4050)	(158.7280)	(131.4350)	(84.1420)	(47.0550)	(−11.0391)
FF s	−0.1687	−0.0092	0.2923	0.7003	1.0214	−1.1902
	(−18.9814)	(−0.8220)	(19.4516)	(29.2910)	(25.0326)	(−26.1115)
FF h	0.0550	0.1466	0.1306	0.0309	0.0308	0.0243
	(6.8963)	(14.6702)	(9.6842)	(1.4401)	(0.8399)	(0.5932)

Table II. Quarterly idiosyncratic volatility-sorted portfolio

This table reports the performance of quarterly idiosyncratic volatility-sorted quintile portfolios. I construct these quintile portfolios by using lagged quarterly idiosyncratic volatilities. The volatilities are estimated from daily returns and Fama–French model, i.e.

$$r_i - r_f = \alpha_i + \beta_i(r_m - r_f) + s_i SMB + h_i HML + \varepsilon_i$$

For notational convenience, I omit time subscripts. I estimate $\sqrt{\mathrm{Var}[\varepsilon_i]}$ for all firms quarter by quarter and construct quintile portfolios recursively (3/0/3). Idiosyncratic volatilities computed with less than 31 daily observations are excluded. The sample is from December 31, 1925 to December 31, 2015. 5 portfolios are from September 1926 to December 2015 (358 quarters). The first row displays quintiles column by column. The last column is the zero investment portfolio (i.e. constructed by buying the first and selling the fifth). The second partition include sample means and standard deviations. The third and fourth partitions contain both CAPM and Fama–French model estimates, respectively. Corresponding t-statistics are reported by using round brackets.

Quintile	1	2	3	4	5	1−5
Mean	0.0204	0.0227	0.0273	0.0248	0.0285	−0.0081
	(4.1454)	(3.0555)	(2.9126)	(2.3107)	(2.1512)	(−0.7767)
St. dev.	0.0933	0.1406	0.1773	0.2029	0.2507	0.1965
CAPM α	0.0034	−0.0030	−0.0047	−0.0105	−0.0093	0.0127
	(3.2583)	(−1.9531)	(−1.8782)	(−2.6013)	(−1.1681)	(1.4525)
CAPM β	0.8170	1.2314	1.5314	1.6875	1.8102	−0.9933
	(89.8724)	(90.0240)	(69.3692)	(47.5046)	(25.7498)	(−12.9130)
FF α	0.0029	−0.0049	−0.0062	−0.0110	−0.0087	0.0117
	(3.1553)	(−3.8043)	(−3.0571)	(−3.5278)	(−1.3149)	(1.6066)
FF β	0.8478	1.1589	1.3680	1.4232	1.3849	−0.5372
	(86.6026)	(86.1318)	(63.7162)	(43.4302)	(19.8181)	(−7.0312)
FF s	−0.1495	0.0970	0.4530	0.9106	1.5917	−1.7412
	(−8.6259)	(4.0700)	(11.9160)	(15.6914)	(12.8622)	(−12.8691)
FF h	0.0617	0.2203	0.1609	0.0053	−0.1721	0.2337
	(4.6777)	(12.1592)	(5.5649)	(0.1199)	(−1.8281)	(2.2713)

Table III. Annual sample descriptive statistic

This table displays the descriptive statistics obtained from annual data. I report both all sample and subsample statistics for convenient comparison. All sample is from 1954 to 2015 (58,554 firm-years) and subsample is from 1954 to 1996 (33,302 firm-years). The variables are demeaned each year to address time fixed effects, i.e.

$$X_{it}^{\text{demeaned}} = X_{it}^{\text{raw}} - \sum_{j=1}^{N_t} X_{jt} \Big/ N_t$$

The subscripts i and t stand for firm and year, respectively. The variables r, θ and e are log excess return, log book-to-market ratio and log excess return on equity, respectively. Panel A–D contain the descriptive statistics of raw data from all sample, those of demeaned data from all sample, those of raw data from subsample and those of demeaned data from subsample, respectively. To be included in the data, an observation must have (i) a book equity available at t–1, t–2, t–3, (ii) a net income available at t–1, t–2, (iii) a long-term debt available at t–1, t–2, (iv) a December fiscal-year end month, (v) a market equity more than \$10M and (vi) a log book-to-market ratio bigger than 1/100 but smaller than 100.

Variable	Mean	St. dev.	Minimum	1Q	Median	3Q	Maximum
			Panel A. All sample raw data				
r_{it}^{raw}	−0.0076	0.4831	−3.9068	−0.2297	0.0284	0.2568	3.3388
θ_{it}^{raw}	−0.3640	0.9402	−4.6024	−0.8689	−0.3232	0.1679	4.5943
e_{it}^{raw}	−0.0490	0.4132	−2.3026	−0.0426	0.0328	0.0907	4.3625
			Panel B. All sample demeaned data				
r_{it}^{demeaned}	0	0.4435	−3.8314	−0.2047	0.0181	0.2362	3.1295
$\theta_{it}^{\text{demeaned}}$	0	0.9061	−4.5725	−0.4605	0.0457	0.4633	5.1649
e_{it}^{demeaned}	0	0.4078	−2.3617	−0.0260	0.0582	0.1549	4.3760
			Panel C. Subsample raw data				
r_{it}^{raw}	0.0349	0.4071	−3.2730	−0.1755	0.0409	0.2524	3.3388
θ_{it}^{raw}	−0.2778	0.8149	−4.5156	−0.7087	−0.1926	0.2383	4.5803
e_{it}^{raw}	−0.0032	0.2940	−2.3026	−0.0180	0.0364	0.0843	4.3625
			Panel D. Subsample demeaned data				
r_{it}^{demeaned}	0	0.3646	−3.1734	−0.1904	0.0024	0.1926	3.1295
$\theta_{it}^{\text{demeaned}}$	0	0.7684	−4.1723	−0.3815	0.0804	0.4546	5.0759
e_{it}^{demeaned}	0	0.2907	−2.3617	−0.0292	0.0266	0.0923	4.3760

Table IV. Annual VAR model estimate

Panel A and Panel C of this table report the estimates of annual firm-level VAR model, i.e.

$$\mathbf{z}_{it} = \mathbf{\Gamma}\mathbf{z}_{it-1} + \mathbf{u}_{it}, \qquad \mathbf{\Sigma} = \mathrm{E}[\mathbf{u}_{it}\mathbf{u}_{it}^\top]$$

Subscripts i and t stand for firm and year, respectively. Above $\mathbf{z}_{it}$ is the vector of three state variables r_{it}, θ_{it} and e_{it}, which are log excess return, log book-to-market ratio and log excess return on equity. To address time fixed effects, all state variables are demeaned year by year. I report both all sample and subsample estimates in Panel A and Panel C. All sample is from 1954 to 2015 (58,554 firm-years) and subsample is from 1954 to 1996 (33,302 firm-years). I estimate both $\mathbf{\Gamma}$ and $\mathbf{\Sigma}$ by using WLS with the weight $1/N_t$. The first and second 3×3 squares include the estimates of $\mathbf{\Gamma}$ and $\mathbf{\Sigma}$, respectively. Corresponding t-statistics are computed with time-clustered standard errors (Peterson (2009)) and reported by using round brackets.

Panel B and Panel D of this table state the variance decomposition, i.e.

$$\mathrm{Var}[N_r] = \boldsymbol{\lambda}^\top\mathbf{\Sigma}\boldsymbol{\lambda}, \qquad \mathrm{Var}[N_{cf}] = (\mathbf{e1}+\boldsymbol{\lambda})^\top\mathbf{\Sigma}(\mathbf{e1}+\boldsymbol{\lambda}), \qquad \mathrm{Cov}[N_r, N_{cf}] = \boldsymbol{\lambda}^\top\mathbf{\Sigma}(\mathbf{e1}+\boldsymbol{\lambda})$$

Note that $\mathbf{e1} = (1 \quad \mathbf{0}^\top)^\top$ and $\boldsymbol{\lambda} = \rho\mathbf{\Gamma}^\top((\mathbf{I}-\rho\mathbf{\Gamma})^{-1})^\top\mathbf{e1}$. N_r and N_{cf} stand for discount rate news and cash flow news. I omit time subscripts for notational convenience. The first row contains the estimates of $\mathrm{Var}[N_r]$, $\mathrm{Var}[N_{cf}]$, $-2\times\mathrm{Cov}[N_r,N_{cf}]$ and $\mathrm{Corr}[N_r,N_{cf}]$. The ratio of each component to the total variance is reported in the second row with a square bracket.

Panel A. All sample VAR model

	$\mathbf{\Gamma}$				$\mathbf{\Sigma}$		
	r_{it-1}	θ_{it-1}	e_{it-1}		r_{it}	θ_{it}	e_{it}
r_{it}	0.0543	0.0519	0.0660	r_{it}	0.1516	−0.1242	0.0225
	(3.1081)	(6.2696)	(2.9213)		(11.5505)	(–11.5470)	(8.2013)
θ_{it}	0.1412	0.8278	0.0633	θ_{it}	−0.1242	0.2043	0.0147
	(7.3666)	(59.7793)	(2.4752)		(–11.5470)	(11.2931)	(4.9005)
e_{it}	0.1178	0.0133	0.4993	e_{it}	0.0225	0.0147	0.0775
	(7.1741)	(2.3366)	(19.5019)		(8.2013)	(4.9005)	(8.4908)

Panel B. All sample variance decomposition

$\mathrm{Var}[N_r]$	$\mathrm{Var}[N_{cf}]$	$-2\times\mathrm{Cov}[N_r,N_{cf}]$	$\mathrm{Corr}[N_r,N_{cf}]$
0.0157	0.1383	−0.0024	0.0259
[0.1035]	[0.9124]	[−0.0159]	

Panel C. Subsample VAR model

	$\mathbf{\Gamma}$				$\mathbf{\Sigma}$		
	r_{it-1}	θ_{it-1}	e_{it-1}		r_{it}	θ_{it}	e_{it}
r_{it}	0.0434	0.0567	−0.0104	r_{it}	0.1007	−0.0844	0.0121
	(2.5414)	(5.4237)	(–0.4520)		(10.6608)	(–10.3151)	(6.9688)
θ_{it}	0.1147	0.8150	0.0921	θ_{it}	−0.0844	0.1373	0.0073
	(5.1928)	(35.4021)	(2.6917)		(–10.3151)	(8.6025)	(2.6708)
e_{it}	0.0868	−0.0049	0.3846	e_{it}	0.0121	0.0073	0.0388
	(4.1457)	(–0.6027)	(7.5094)		(6.9688)	(2.6708)	(5.8756)

Panel D. Subsample variance decomposition

$\mathrm{Var}[N_r]$	$\mathrm{Var}[N_{cf}]$	$-2\times\mathrm{Cov}[N_r,N_{cf}]$	$\mathrm{Corr}[N_r,N_{cf}]$
0.0077	0.0777	0.0153	−0.3117
[0.0769]	[0.7713]	[0.1518]	

Table V. Quarterly sample descriptive statistic

This table displays the descriptive statistics obtained from quarterly data. The sample is from March 1972 to December 2015 (176 quarters, 235,704 firm-quarters). The variables are demeaned each quarter to address time fixed effects, i.e.

$$X_{it}^{\text{demeaned}} = X_{it}^{\text{raw}} - \sum_{j=1}^{N_t} X_{jt} \Big/ N_t$$

The subscripts i and t stand for firm and quarter, respectively. The variables r, θ and e are log excess return, log book-to-market ratio and log excess return on equity, respectively. Panel A, B contain the descriptive statistics of raw data and those of demeaned data, respectively. In order for an observation to be included in the data, here I impose two requirements, i.e. an observation must have (i) r, θ and e available at t–1 and (ii) a December fiscal-year end month.

Variable	Mean	St. dev.	Minimum	1Q	Median	3Q	Maximum
Panel A. Raw data							
r_{it}^{raw}	−0.0196	0.2938	−4.6771	−0.1353	0.0021	0.1242	2.5846
θ_{it}^{raw}	−0.3422	0.9777	−8.4217	−0.8697	−0.3024	0.2052	9.8809
e_{it}^{raw}	−0.0228	0.1842	−2.3026	−0.0146	0.0075	0.0233	4.9245
Panel B. Demeaned data							
r_{it}^{demeaned}	0	0.2649	−4.3816	−0.1113	0.0082	0.1280	2.5366
$\theta_{it}^{\text{demeaned}}$	0	0.9259	−8.3662	−0.4717	0.0431	0.4796	10.5509
e_{it}^{demeaned}	0	0.1826	−2.3052	−0.0046	0.0223	0.0511	4.9665

Table VI. Quarterly VAR model estimate

Panel A of this table reports the estimates of annual firm-level VAR model, i.e.

$$\mathbf{z}_{it} = \mathbf{\Gamma}\mathbf{z}_{it-1} + \mathbf{u}_{it}, \qquad \mathbf{\Sigma} = \mathrm{E}[\mathbf{u}_{it}\mathbf{u}_{it}^{\top}]$$

Subscripts i and t stand for firm and quarter, respectively. Above $\mathbf{z}_{it}$ is the vector of three state variables r_{it}, θ_{it} and e_{it}, which are log excess return, log book-to-market ratio and log excess return on equity, respectively, i.e. $\mathbf{z}_{it} = [r_{it} \quad \theta_{it} \quad e_{it}]^{\top}$. To address time fixed effects, all state variables are demeaned quarter by quarter. The sample is from March 1972 to December 2015 (176 quarters, 235,704 firm-quarters). I estimate both $\mathbf{\Gamma}$ and $\mathbf{\Sigma}$ by using WLS with the weight $1/N_t$. The first 3×3 square includes the estimate of $\mathbf{\Gamma}$. The second 3×3 square contains the estimate of $\mathbf{\Sigma}$. Corresponding t-statistics are computed with time-clustered standard errors (Peterson (2009)) and reported by using round brackets. Panel B of this table states the variance decomposition, i.e.

$$\begin{aligned} \mathrm{Var}[N_r] &= \boldsymbol{\lambda}^{\top}\mathbf{\Sigma}\boldsymbol{\lambda} \\ \mathrm{Var}[N_{cf}] &= (\mathbf{e1}+\boldsymbol{\lambda})^{\top}\mathbf{\Sigma}(\mathbf{e1}+\boldsymbol{\lambda}) \\ \mathrm{Cov}[N_r, N_{cf}] &= \boldsymbol{\lambda}^{\top}\mathbf{\Sigma}(\mathbf{e1}+\boldsymbol{\lambda}) \end{aligned}$$

Note that $\mathbf{e1} = (1 \quad \mathbf{0}^{\top})^{\top}$ and $\boldsymbol{\lambda} = \rho\mathbf{\Gamma}^{\top}((\mathbf{I}-\rho\mathbf{\Gamma})^{-1})^{\top}\mathbf{e1}$. For notational convenience, I omit time subscripts. N_r and N_{cf} stand for discount rate news and cash flow news, respectively. The first row contains the estimates of Var$[N_r]$, Var$[N_{cf}]$, $-2\times$Cov$[N_r,N_{cf}]$ and Corr$[N_r,N_{cf}]$. The ratio of each component to the total variance is reported in the second row with a square bracket.

Panel A. VAR model

	$\mathbf{\Gamma}$				$\mathbf{\Sigma}$		
	r_{it-1}	θ_{it-1}	e_{it-1}		r_{it}	θ_{it}	e_{it}
r_{it}	0.0288	0.0084	0.0975	r_{it}	0.0605	−0.0557	0.0046
	(1.8182)	(2.8660)	(6.6187)		(17.6341)	(−17.1722)	(9.0500)
θ_{it}	0.0421	0.9525	0.0426	θ_{it}	−0.0557	0.1003	0.0089
	(2.4363)	(245.0869)	(1.8873)		(−17.1722)	(19.8868)	(11.0361)
e_{it}	0.0648	0.0057	0.4597	e_{it}	0.0046	0.0089	0.0233
	(10.2844)	(3.4727)	(21.6617)		(9.0500)	(11.0361)	(15.5855)

Panel B. Variance decomposition

Var$[N_r]$	Var$[N_{cf}]$	$-2\times$Cov$[N_r,N_{cf}]$	Corr$[N_r,N_{cf}]$
0.0040	0.0526	0.0039	−0.1331
[0.0657]	[0.8706]	[0.0637]	

Table VII. Quarterly discount rate news volatility-sorted portfolio

This table reports the performance of quarterly discount rate news (N_r) volatility-sorted decile portfolios. I construct these decile portfolios by using lagged quarterly discount rate news volatilities. Following Fu (2009), these volatilities are estimated from quarterly discount rate news data, Fama–French model and EGARCH model, i.e.

$$N_{rit} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it}$$

$$\sigma_{it}^2 = \exp\left(a_i + \sum_{l=1}^{p} b_{il} \ln \sigma_{it-l}^2 + \sum_{k=1}^{q} c_{ik}\left[\theta_i\left(\frac{\varepsilon_{it-k}}{\sigma_{it-k}}\right) + \gamma_i\left(\left|\frac{\varepsilon_{it-k}}{\sigma_{it-k}}\right| - \sqrt{\frac{2}{\pi}}\right)\right]\right)$$

In order to avoid the look-ahead bias mentioned by Guo, Kassa and Ferguson (2014), I estimate out-of-sample EGARCH idiosyncratic volatilities recursively. Idiosyncratic volatilities computed with less than 12 quarterly observations are excluded. 10 portfolios are from December 1974 to December 2015 (165 quarters). The first row displays deciles column by column. The last column is the zero investment portfolio (i.e. constructed by buying the first and selling the tenth). The second partition include sample means and standard deviations. The third and fourth partitions contain both CAPM and Fama–French model estimates, respectively. Corresponding t-statistics are reported by using round brackets.

Decile	1	2	3	4	5	6	7	8	9	10	1−10
Mean	0.0213	0.0229	0.0220	0.0222	0.0245	0.0166	0.0245	0.0115	0.0233	0.0217	−0.0004
	(2.9876)	(3.3858)	(3.1723)	(3.2408)	(3.3829)	(2.1033)	(3.0763)	(1.2655)	(2.6248)	(2.2628)	(−0.0572)
St. dev.	0.0906	0.0865	0.0886	0.0871	0.0924	0.1016	0.1013	0.1164	0.1133	0.1218	0.0855
CAPM α	0.0040	0.0060	0.0041	0.0052	0.0059	−0.0043	0.0047	−0.0123	0.0007	−0.0018	0.0058
	(0.9742)	(1.5841)	(1.0101)	(1.3921)	(1.5631)	(−0.9454)	(1.0934)	(−2.3993)	(0.1459)	(−0.3424)	(0.8841)
CAPM β	0.9008	0.8687	0.8605	0.8873	0.9533	0.9959	1.0285	1.1491	1.1626	1.2230	−0.3223
	(18.8992)	(19.4372)	(18.4553)	(20.4961)	(21.4052)	(18.9358)	(20.2686)	(19.4492)	(20.9381)	(19.5381)	(−4.1973)
FF α	0.0012	0.0043	0.0016	0.0038	0.0034	−0.0080	0.0031	−0.0135	0.0003	0.0002	0.0009
	(0.2883)	(1.1003)	(0.4000)	(0.9991)	(0.8760)	(−1.7753)	(0.7044)	(−2.6179)	(0.0669)	(0.0432)	(0.1433)
FF β	0.9504	0.9211	0.9235	0.8880	0.9778	1.0347	1.0075	1.0742	1.1125	1.2058	−0.2555
	(18.1093)	(18.5468)	(17.8189)	(18.2290)	(19.8866)	(17.9530)	(17.7547)	(16.2990)	(17.8864)	(17.1152)	(−3.0288)
FF s	−0.0391	−0.1026	−0.1118	0.0711	0.0499	0.0461	0.1690	0.3272	0.2142	−0.0462	0.0071
	(−0.4428)	(−1.2295)	(−1.2903)	(0.8683)	(0.6039)	(0.4854)	(1.7716)	(2.9697)	(2.0496)	(−0.3902)	(0.0504)
FF h	0.2133	0.1510	0.2019	0.0893	0.1873	0.2777	0.0930	0.0327	−0.0057	−0.1458	0.3591
	(3.1255)	(2.3379)	(2.9875)	(1.4090)	(2.9284)	(3.7102)	(1.2605)	(0.3807)	(−0.0700)	(−1.5910)	(3.2740)

Table VIII. Quarterly cash flow news volatility-sorted portfolio

This table reports the performance of cash flow rate news (N_{cf}) volatility-sorted decile portfolios. I construct these decile portfolios by using lagged quarterly cash flow news volatilities. Following Fu (2009), these volatilities are estimated from quarterly cash flow news data, Fama–French model and EGARCH model, i.e.

$$N_{cfit} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it}$$

$$\sigma_{it}^2 = \exp\left(a_i + \sum_{l=1}^{p} b_{il} \ln \sigma_{it-l}^2 + \sum_{k=1}^{q} c_{ik}\left[\theta_i\left(\frac{\varepsilon_{it-k}}{\sigma_{it-k}}\right) + \gamma_i\left(\left|\frac{\varepsilon_{it-k}}{\sigma_{it-k}}\right| - \sqrt{\frac{2}{\pi}}\right)\right]\right)$$

In order to avoid the look-ahead bias mentioned by Guo, Kassa and Ferguson (2014), I estimate out-of-sample EGARCH idiosyncratic volatilities recursively. Idiosyncratic volatilities computed with less than 12 quarterly observations are excluded. 10 portfolios are from December 1974 to December 2015 (165 quarters). The first row displays deciles column by column. The last column is the zero investment portfolio (i.e. constructed by buying the first and selling the tenth). The second partition include sample means and standard deviations. The third and fourth partitions contain both CAPM and Fama–French model estimates, respectively. Corresponding t-statistics are reported by using round brackets.

Decile	1	2	3	4	5	6	7	8	9	10	1–10
Mean	0.0215	0.0245	0.0186	0.0210	0.0235	0.0210	0.0249	0.0181	0.0299	0.0139	0.0076
	(2.8606)	(3.4521)	(2.6668)	(3.1173)	(3.1258)	(2.7191)	(3.3580)	(1.9856)	(2.8415)	(1.3073)	(1.0807)
St. dev.	0.0956	0.0905	0.0891	0.0856	0.0960	0.0990	0.0942	0.1169	0.1342	0.1349	0.0899
CAPM α	0.0032	0.0077	0.0001	0.0034	0.0040	−0.0001	0.0056	−0.0053	0.0078	−0.0119	0.0152
	(0.7520)	(1.7340)	(0.0308)	(1.0936)	(1.0517)	(−0.0209)	(1.6110)	(−0.9676)	(1.0134)	(−1.9682)	(2.2378)
CAPM β	0.9507	0.8646	0.8884	0.9143	1.0021	0.9997	1.0041	1.1274	1.1357	1.3427	−0.3920
	(18.9083)	(16.7097)	(20.1506)	(25.0356)	(22.4598)	(20.9885)	(24.8295)	(18.0526)	(12.6414)	(18.9538)	(−4.9501)
FF α	0.0015	0.0038	−0.0037	0.0008	0.0018	−0.0020	0.0060	−0.0045	0.0083	−0.0106	0.0121
	(0.3421)	(0.8705)	(−1.0210)	(0.2417)	(0.4554)	(−0.4829)	(1.6988)	(−0.8106)	(1.0591)	(−1.7935)	(1.8135)
FF β	0.9554	0.9479	0.9765	0.9352	1.0035	1.0116	0.9753	1.0548	1.0630	1.1848	−0.2293
	(16.9066)	(17.1053)	(20.9427)	(23.5492)	(20.2934)	(18.8455)	(21.3704)	(14.9396)	(10.5075)	(15.6762)	(−2.6870)
FF s	0.0753	−0.1042	−0.1376	0.0646	0.1207	0.0563	0.0853	0.2265	0.2504	0.5312	−0.4559
	(0.7927)	(−1.1197)	(−1.7650)	(0.9676)	(1.4524)	(0.6365)	(1.1123)	(1.9188)	(1.4730)	(4.1819)	(−3.1784)
FF h	0.1156	0.3100	0.3082	0.1871	0.1507	0.1419	−0.0487	−0.0955	−0.0805	−0.1888	0.3044
	(1.5727)	(4.3018)	(5.0707)	(3.6217)	(2.3437)	(2.0360)	(−0.8201)	(−1.0375)	(−0.6122)	(−1.9207)	(2.7423)

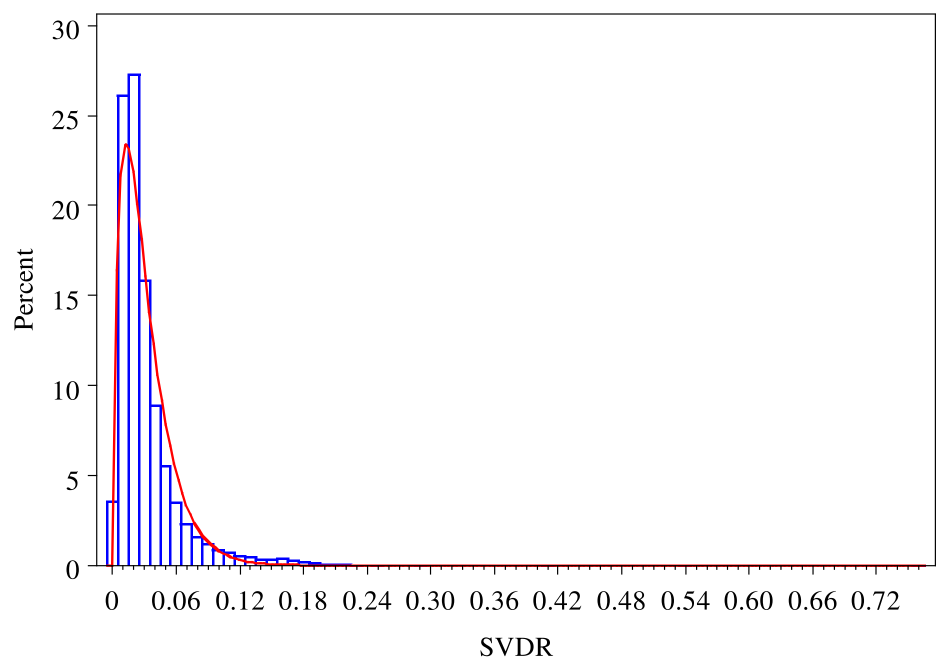
Figure 1. Distributions of discount rate and cash flow news volatilities

This figure displays the distribution of discount rate news volatilities ($\sigma_{it}[N_{r,it}]$) and that of cash flow news volatilities ($\sigma_{it}[N_{cf,it}]$). I first estimate the news data using a panel VAR model with accounting variables following Vuolteenaho (2002) and second estimate the volatilities using an EGARCH model with Fama–French factors following Fu (2009). For each distribution, I estimate a shape parameter k and a scale parameter θ of a gamma distribution using the following probability density function.

$$f_X(x) = \frac{1}{\Gamma(x)\theta^k} x^{k-1} e^{-\frac{x}{\theta}} 1_{\mathbb{R}_+}(x)$$

The mean and variance of the distribution are defined as $k\theta$ and $k\theta^2$, respectively. Idiosyncratic volatilities computed with less than 12 quarterly observations are excluded. The smallest and biggest 2.5% of respective news volatilities are winsorized quarter by quarter to remedy potential measurement errors from intense numerical processes. The sample is from December 1974 to December 2015 (165 quarters, 152,099 firm-quarters).

Panel A. Discount rate news volatilities ($\hat{k} = 1.7096,\ \hat{\theta} = 0.0181$)



Panel B. Cash flow news volatilities ($\hat{k} = 1.9618,\ \hat{\theta} = 0.0735$)