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The role of "other information" in analysts' forecasts in understanding stock return volatility

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Abstract This study identifies "other information" in analysts' forecasts as a legitimate proxy for future cash flows and examines its incremental role in explaining stock return volatility. We suggest that "other information" contains information about fundamentals beyond that reflected in current financial statements and reflects firms' fundamentals on a more timely basis than dividends or earnings. Using standardized regressions, we find volatility increases when current "other information" is more uncertain and increases more in response to unfavorable news compared to favorable news. Variance decomposition analysis shows that the variance contribution of "other information" dominates that of expected-return news. The incremental role of "other information" is at least half of the effect of earnings in explaining future volatility. The results are more pronounced for firms with poor information environments. Overall, our results highlight the importance of including "other information" as an additional cash-flow proxy in future studies of stock prices and volatility.

Keywords Other information · Analysts' forecasts · Stock return volatility · Variance decomposition

JEL Classification M41 · G14 · D84

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1 Introduction

Stock return volatility plays an essential role in understanding asset pricing, risk management, portfolio construction, derivative valuation, and the cost of capital.[1] In theory, stock return volatility is a function of variation in cash flow news, expected return news, or both. Empirical research has endeavored to use fundamental variables such as dividends and accounting earnings to explain changes in volatility.[2] However, both dividends and earnings have obvious limitations as cash flow proxies. Dividends tend to be smoothed and do not necessarily reflect future cash flows.[3] On the other hand, accounting earnings reflect transaction-based revenue recognition and the accompanying matching of expenses, so they are unlikely to be a timely source of information about changes in fundamentals (Lev 1989). To the extent that accounting earnings are conservative (Watts 2003), there is also the difficulty of explicitly allowing for the differential timeliness with which earnings reflect good versus bad economic news. In fact, studies have argued that return volatility is too high to be justified by fundamental variables.[4]

We propose and empirically validate "other information" in analysts' forecasts as a novel proxy for future cash flows. "Other information" refers to information contained in analysts' earnings forecasts about a firm's fundamentals beyond that reflected in current financial statements. After controlling for earnings, we confirm the incremental role of other information and find that it has significant and incremental explanatory power for future stock return volatility.

We use analysts' consensus forecasts of next-year's earnings to construct other information, consistent with our application of Ohlson's (1995) linear information dynamics.[5] It is well documented that analysts' earnings forecasts capture forward-looking information about fundamentals from sources other than financial statements (see Cheng 2005a; Kothari 2001). However, we do not assume that the resulting other information variable represents all public and private information. Rather, we simply assume that earnings forecasts incorporate timely and unique information that is not readily available from financial statements. We also

[1] Reasons why firm-level volatility is important include the following: the relation between perceived riskiness and cost of capital (Froot et al. 1992), the fact that high volatility can make stock-price-based compensation less effective and more costly (Baiman and Verrecchia 1995), the evidence that investment strategies based on volatility can earn significant abnormal returns (e.g., Ang et al. 2006), and, finally, the fact that arbitrageurs trading to exploit the mispricing of an individual stock face risks related to volatility in the sense that larger pricing error may be associated with higher volatility (Shleifer and Vishny 1997).

[2] See, for example, Campbell (1991); Campbell and Vuolteenaho (2004); Irvine and Pontiff (2009); Sadka (2007); Vuolteenaho (2002), and Wei and Zhang (2006).

[3] See Lintner (1956); Chen and Zhao (2009) and Chen et al. (2013).

[4] Campbell (1991) and Campbell and Vuolteenaho (2004) find that dividend news explains only 15–20 % of the variation in market returns. In addition, several studies argue that volatility is likely to reflect market irrationality, trading on the part of retail (noise) traders, or both (Shiller 1981; Black 1986; Brandt et al. 2010; Foucault et al. 2011).

[5] See Ohlson (2001) and Hand (2001). Ohlson (2001) suggests that "analysts' consensus forecasts of next-year earnings would seem to be a reasonable measure of expected earnings." Dechow et al. (1999) use analysts' earnings forecasts to measure the other information variables and report evidence that supports the economic modeling of residual income as an autoregressive process.

recognize that earnings forecasts may not incorporate all available information from financial statements, as prior studies suggest that analysts fail to fully account for the information contained in accounting earnings or earnings components.[6] Accordingly, we view other information as an additional cash-flow proxy and consider the relative importance of accounting earnings and other information in influencing stock return volatility as an empirical question.

The theoretical link between other information and stock return volatility can be understood through an extension of the accounting version of the Campbell-Shiller model (Campbell and Shiller 1988a; Vuolteenaho 2002; Wei and Zhang 2006).[7] We incorporate Ohlson's linear information dynamics into the model and assume that the linear information dynamics error terms follow a conditional heteroskedastic process. We find that the conditional variance of other information is part of the conditional variance of stock returns. We therefore derive two testable predictions between other information and stock return volatility.[8]

Our first hypothesis is rather intuitive. Given the assumption of market efficiency, if current other information is more uncertain, thereby increasing uncertainty about firms' future cash flows, then future stock returns are expected to be more volatile. Our second hypothesis predicts that volatility increases more in response to unfavorable other information news than to favorable news. Other information news (i.e., the signed level of other information) can be thought of as an aggregate indicator of value-relevant events that have yet to have an impact on the financial statements. Previous studies provide consistent evidence that stock return volatility increases after the release of firm-specific news (Clayton et al. 2005) and also that volatility increases more in response to unfavorable news (Engle and Ng 1993; Rogers et al. 2009). This result can be understood in the context of either rational regime-switching models (Veronesi 1999) or behavioral finance theories (Barberis et al. 1998; Daniel et al. 1998).

We employ two widely used approaches to examine the incremental role of other information: standardized regression analysis and variance decomposition analysis. We recognize the advantages and limitations of both approaches and believe that the implementation of both methods provides robust conclusions and informative comparisons to the existing literature.[9] We measure other information in two ways.

[6] See Ramnath et al. (2008) for a review. Typically, the literature indicates that financial analysts do not fully adjust forecasts for earnings reversals, the earnings surprise in prior earnings announcements, and past abnormal accruals.

[7] More generally, the theoretical link between other information and stock return volatility can be derived from discounted cash flow models and is not limited to the Campbell-Shiller (1988a) loglinear version. However, without loss of generality, the accounting version of the Campbell-Shiller (1988a) model enables us to derive a straightforward, closed form solution that is empirically testable. A related approach is used by Wei and Zhang (2006) and Irvine and Pontiff (2009), although with a different purpose.

[8] Callen (2009) follows Ohlson (1995) and assumes that the error terms of Ohlson's linear information dynamics are mean-zero independent error terms with inter-temporally homoskedastic variance and suggests a link between the *unconditional* variance of stock returns and the *unconditional* variance of other information. However, this link is difficult to test empirically, because the unconditional variance of other information is assumed to be constant over time.

[9] Detailed discussion can be found in Sect. 2.4.

The first approach follows Bryan and Tiras (2007), who measure other information as the residual from regressing 1-year-ahead analysts' forecasts of future earnings on current publicly available financial information (Ohlson and Shroff 1992; Manry et al. 2003). The second approach follows Dechow et al. (1999) and measures other information as analysts' consensus forecasts minus earnings forecasts predicted from past financial accounting information.

A summary of our findings is as follows. Using standardized regressions, we find an economically significant relationship between other information and future volatility. Volatility increases when current other information is more uncertain and increases more in response to unfavorable other information news. A one standard deviation change in unfavorable other information news results in a more than 14 % change in future volatility, significantly higher than the effect of favorable news (3 %), while a one standard deviation increase in the uncertainty of other information is associated with a 17 % increase in future volatility. The results are robust to controlling for other volatility covariates and the existing cash-flow proxy (ROE and ROE volatility), technology bubbles, loss reporting, corporate governance attributes, financial reporting quality, and the inclusion of lagged stock return volatility.[10] We find the effect of other information on volatility is slightly lower than that for earnings.

The results using a variance decomposition approach also confirm that other information is a legitimate cash-flow proxy and plays an incremental role in determining stock return volatility. Other information news explains around 70 % of the total unexpected return variance, around eight times as large as the variance of expected-return news (9 %). The variance of negative other information news is significantly higher than the variance of positive news. When comparing the relative importance of other information and earnings, we find that both dominate expected-return news and that the incremental variance of other information news is about half of the variance of earnings news in explaining stock return variations. As variance contribution is a function of persistence and variability, the lower variance contribution of other information relative to accounting earnings is due to the fact that other information is less persistent and has lower variability.

In addition, we find the relationship between other information and volatility holds for both systematic and idiosyncratic volatility.[11] This result suggests that other information has substantial undiversified variation and contains both firm-specific and market-level information. This is consistent with recent studies examining the predictive content of aggregate earnings (Ball et al. 2009), earnings announcements (Cready and Gurun 2010), accrual and cash flow components of earnings (Hirshleifer et al. 2009), and earnings dispersion (Jorgensen et al. 2012).

[10] See Chan et al. (2001) and Schwert (2002) for technology bubbles, Givoly and Hayn (2000) for loss reporting, Ferreira and Laux (2007) for corporate governance effects, and Rajgopal and Venkatachalam (2011) for financial reporting quality. Our results are also robust to several different measures of stock return volatility, different sample periods, different industry categories, and different econometric estimations such as Fama–MacBeth (1973) regressions and fixed effect regressions. See Sect. 4.3 for additional discussion.

[11] Total volatility is decomposed into systematic and idiosyncratic components by using the CAPM and the Fama–French three factor model (Fama and French 1993, 1996), respectively.

Finally, we document that the relationship between other information and future volatility is more pronounced for firms with a relatively poor information environment. We use earnings quality, forecast dispersion, and forecast bias as proxies for differences in firms' information environments. Our results imply that financial analysts place greater weight on other information, and lower weight on reported accounting information, when following firms with a poor information environment. This is also consistent with Bryan and Tiras (2007), who suggest that Ohlson's (1995) valuation model better describes market pricing in poor information environments.

Our study makes several contributions. First, we are among the first to propose and validate other information as a novel and legitimate proxy for future cash flows. We show that the incremental role of other information is at least half of the role of accounting earnings in explaining both market-wide and firm-specific volatility. Although Chen et al. (2013) use analysts' forecast revisions for cash flow estimation, our approach differs from Chen et al.'s (2013) in important ways. Because we use earnings forecasts rather than forecast revisions to compute cash-flow news, our approach can be directly applied to the variance decomposition framework and compared with prior studies. Chen et al. however, require a different definition of news that is not directly comparable to the results obtained from other methods. Further, our approach is relatively easy to implement. In contrast, Chen et al. require computation of the implied cost of capital from analysts' forecasts and then define cash-flow news as the price change calculated from a pricing function by assuming constant implied cost of capital. Our approach may also generate more reliable cash-flow news estimates, as their approach likely amplifies the measurement error in cash-flow proxies attributable to the intermediate step of implied cost of capital estimation.

Second, by introducing other information, we extend the variance decomposition methodology of Campbell (1991), Vuolteenaho (2002), and Callen and Segal (2004) to evaluate and compare the variance contribution of accounting earnings and other information. We also contribute to broader capital market research by addressing the question of what drives stock return volatility cross-sectionally. While a limited amount of evidence relates volatility with financial disclosure (Bushee and Noe 2000), firm age (Pástor and Veronesi 2003), accounting earnings (Wei and Zhang 2006), governance mechanisms (Ferreira and Laux 2007), and financial reporting quality (Rajgopal and Venkatachalam 2011), we identify other information as an additional fundamental determinant of volatility. Taken together, our results highlight the importance of other information and suggest that future studies that attempt to explain stock prices or volatility should consider other information as a cash-flow proxy.

Our paper also adds to the literature on accounting-based valuation models. Our results indicate that unfavorable other information is more important in explaining volatility and that the relationship between other information and volatility is more apparent for firms with a poor information environment. While several studies find that Ohlson's model is of limited empirical validity (Bar-Yosef et al. 1996; Myers 1999), our evidence on volatility indicates that Ohlson's valuation model is more descriptive for firms with unfavorable other information and poor information environments.

Finally, our results have important implications for corporate disclosure policy. The disclosure of other information is often discretionary and released strategically. Our evidence of a positive relationship between the uncertainty of other information and future volatility suggests that improved disclosure of other information helps to reduce uncertainty about firms’ fundamentals and thus firm-specific risk.[12] However, more frequent disclosure of value relevant information may not be advantageous for firms with poor information environments, as both good and bad other information is associated with increased volatility. Evidence of an asymmetric effect of other information news on future volatility also supports the view that managers have incentives to delay disclosure of bad news relative to good news (Kothari et al. 2009), as the release of bad news tends to increase a firm’s expected risk much more than the release of good news.

The rest of the paper is organized as follows. Section 2 develops our model incorporating other information and hypotheses. Section 3 discusses sample construction, the measurement of other information variables, and descriptive statistics. Sections 4 and 5 present the results of standardized regressions and the variance decomposition approach respectively. Section 6 examines how firms’ information environment affects the relationship between other information and volatility. Section 7 concludes.

2 Motivation

2.1 The model

At the fundamental level, stock prices are the sum of expected future payoffs adjusted by the appropriate discount rate. Campbell and Shiller (1988a, b) use a loglinear approximation to represent the relationship between prices, dividends, and returns. Using a variance decomposition approach, Campbell (1991), Campbell and Ammer (1993), and Campbell and Vuolteenaho (2004) find that expected-return news dominates dividend news in driving equity returns at the market level. However, although the literature often focuses on dividends as a proxy for future cash flows, dividends are subject to the discretion of managers and do not necessarily reflect changes in fundamentals.

To mitigate this problem, Vuolteenaho (2002) extends the Campbell-Shiller model using the accounting clean surplus relationship (Ohlson 1995), replacing dividends with accounting earnings. The result is a new link between unexpected stock returns and changes in future discount rates and expected future ROEs as follows:

$$r_{it} - E_{t-1} r_{it} = \Delta E_t \sum_{j=0}^{\infty} \rho^j \left(ROE_{i,t+j} - f_{t+j} \right) - \Delta E_t \sum_{j=0}^{\infty} \rho^j r_{i,t+j} + \kappa_{it} \quad (1)$$

where r_{it} is the return on stock i in period $(t-1, t)$; $\mathrm{ROE}_{i,t+j}$ is the return on equity in period $(t+j-1, t+j)$; f_{t+j} is the risk-free rate for period $(t+j-1, t+j)$; ρ is a constant slightly less than one; and κ_{it} is an approximation error. In Eq. (1), E_{t-1} is the expectation conditional on the information available at $t-1$, and $\Delta E_t = E_t - E_{t-1}$ is the change in expectation from $t-1$ to t.

[12] For example, an increase in the frequency and precision of disclosure might increase the number of observations drawn from the firm’s underlying earnings series and thus lower investors’ uncertainty about the parameters of the distribution of future earnings.

The variance of unexpected stock returns can be decomposed into three components as follows,

$$Var(r_{it} - E_{t-1}r_{it}) = Var\left(N_{r.i,t}\right) + Var\left(N_{cf,i,t}\right) - 2\text{cov}\left(N_{r.i,t}, N_{cf,i,t}\right) \tag{2}$$

where $N_{cf,i,t}$ (cash-flow news) represents $\Delta \mathrm{E_t}\sum\limits_{j=0}^{\infty}\rho^{\mathrm{j}}\left(\mathrm{ROE_{i,t+j}} - f_{t+j}\right)$, and $N_{r,i,t}$ (expected-return new) represents $\Delta \mathrm{E_t}\sum\limits_{j=0}^{\infty}\rho^{\mathrm{j}}r_{\mathrm{i,t+j}} + \kappa_t$. Vuolteenaho (2002) finds the cash-flow news is dominant in the right hand side of Eq. (2) at the firm level, and the variance of cash-flow news is more than twice that of expected-return news.

Following Wei and Zhang (2006), we take a first approximation of the unexpected-return variance and focus our attention on the conditional variance of the cash flow news. The relationship can be derived from Eq. (2) as:

$$\mathrm{Var}_{t-1}(\mathrm{r_{it}}) = Var_{t-1}\left[\Delta \mathrm{E_t}\sum_{\mathrm{j=0}}^{\infty}\rho^{\mathrm{j}}\mathrm{ROE_{i,t+j}}\right] + \xi_{i,t-1} \tag{3}$$

where $\xi_{i,t-1}$ encompasses the conditional variances of the expected-return news and the conditional covariance between the cash flow news and expected-return news.

The key fundamental variable in our study is other information. Other information is expected to be a timelier source of information about changes in fundamentals, compared to either dividends or accounting earnings, the latter having been argued to be a backward-looking measure (Ball and Shivakumar 2008). Following Vuolteenaho (2002), we use an equivalent to Ohlson's ROE-based linear information dynamics based on abnormal earnings. The economic intuition behind Ohlson's linear information dynamics is that competition will erode above-normal returns, while firms experiencing below-normal rates of return will either recover or eventually exit. Providing that the normal level of ROE is equal to r, a typical firm's ROE satisfies the following autoregressive process with conditional heteroskedastic error terms:

$$ROE_t - r = w(ROE_{t-1} - r) + v_{t-1} + u_t \tag{4a}$$

$$Var_{t-1}(u_t) = g(u_{t-1}^2, u_{t-2}^2, \ldots, u_{t-k}^2, u_{t-1}) \tag{4b}$$

$$v_t = \phi v_{t-1} + \varepsilon_t \tag{4c}$$

$$Var_{t-1}(\varepsilon_t) = f(\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \ldots, \varepsilon_{t-k}^2, \varepsilon_{t-1}) \tag{4d}$$

where v_t is other information, namely information about future earnings not in current earnings; w and φ are fixed persistence parameters that are nonnegative and less than one; and u_t and ε_t are error terms independent of each other and are assumed to follow a conditional heteroskedastic process (Wei and Zhang 2006).[13]

[13] We follow Callen (2009) and assume that u_t and ε_t are independent of each other to simplify the exposition. Relaxing this independence assumption would result in an additional covariance term in Eqs. (6) and (7). However, the focus of our study is on the (incremental) role of other information in explaining future volatility. Furthermore, the assumption that the error terms follow a conditional heteroskedastic process ensures that the predicted link between the conditional variance of stock returns and the conditional variance of other information is empirically testable. In other words, based on this assumption, the predicted link suggests that the conditional variance of stock returns is a function of time-varying other information.

After some simple algebra, we have

$$ROE_t = c + wROE_{t-1} + v_{t-1} + u_t \tag{5a}$$

$$Var_{t-1}(u_t) = g(u^2_{t-1}, u^2_{t-2}, \ldots, u^2_{t-k}, u_{t-1}) \tag{5b}$$

$$v_t = \phi v_{t-1} + \varepsilon_t \tag{5c}$$

$$Var_{t-1}(\varepsilon_t) = f(\varepsilon^2_{t-1}, \varepsilon^2_{t-2}, \ldots, \varepsilon^2_{t-k}, \varepsilon_{t-1}) \tag{5d}$$

where c (= $r(1 - w)$) is the intercept.[14]

If ROEs follow process (5), it is easy to derive the following (see “Appendix 1” for details):

$$\mathrm{Var}_{t-1}(\Delta \mathrm{E}_t \sum_{j=0}^{\infty} \rho^j \mathrm{ROE}_{t+j}) = \frac{1}{(1-\rho w)^2} \mathrm{Var}_{t-1}(u_t) + \frac{\rho^2}{(1-\rho\phi)^2 (1-\rho w)^2} \mathrm{Var}_{t-1}(\varepsilon_t) \tag{6}$$

and thus

$$\mathrm{Var}_{t-1}(r_t) = \frac{1}{(1-\rho w)^2} g\left(u^2_{t-1}, u^2_{t-2}, \ldots, u^2_{t-k}, u_{t-1}\right) + \frac{\rho^2}{(1-\rho\phi)^2 (1-\rho w)^2} f\left(\varepsilon^2_{t-1}, \varepsilon^2_{t-2}, \ldots, \varepsilon^2_{t-k}, \varepsilon_{t-1}\right) + \xi_{t-1} \tag{7}$$

The above model suggests that the conditional variance of other information contained in analysts’ forecasts ($\mathrm{Var}_{t-1}(\varepsilon_t)$) is part of the conditional variance of stock returns. In the empirical analysis below, we adopt a nonparametric approach in constructing proxies for the conditional variance of other information without modeling the stochastic process for other information. In particular, following Wei and Zhang (2006), we use two variables available at time $t - 1$, realized volatility of other information (ε^2_{t-1}) and realized other information itself (ε_{t-1}), as inputs to the nonparametric estimators. The use of these two nonparametric estimators to construct the conditional variance of other information is also supported by prior studies. For example, Adut et al. (2009) provide evidence that the variance of analysts’ earnings forecasts is smaller when the expected or actual news about earnings is relatively better.

2.2 Variance decomposition method

The relationship between other information and stock return volatility can also be described in a variance decomposition framework. As discussed above, the unexpected stock return is determined by cash flow news and expected-return new as:

$$r_{it} - E_{t-1} r_{it} = N_{cf,i,t} - N_{r,i,t} \tag{8}$$

[14] The ROE-based information dynamic can also be directly derived from Ohlson’s (1995) linear information dynamics using the assumption that the growth rate of book value is constant over time. Easton (1998) and Callen (2009) also utilize similar information dynamics.

Accordingly, the variance of unexpected stock returns can be decomposed into the variance of cash-flow news, the variance of expected-return news and the covariance as in Eq. (2). If we use other information, v, as the key proxy for future cash flow, we will replace N_{cf} in Eq. (2) by other information news, N_v:

$$\mathrm{Var}(r_{it} - E_{t-1}r_{it}) = Var\left(N_{r.i,t}\right) + \mathrm{Var}\left(N_{\mathrm{v,i,t}}\right) - 2\mathrm{cov}\left(N_{r.i,t}, N_{\mathrm{v,i,t}}\right) \tag{9}$$

As both accounting earnings and other information can be considered as future cash-flow proxies, it is unclear which of these contributes more to changes in stock return volatility. To examine the relative importance of earnings news and other information news, we follow the spirit of Ohlson's linear information dynamics and assume that the inclusion of other information provides a better measure of future cash flows. In such respect, the unexpected stock return is now determined by three components: accounting earnings news (N_{roe}), other information news (N_v), and expected-return news (N_r) as below:

$$r_{it} - E_{t-1}r_{it} = N_{roe,i,t} + N_{\mathrm{v},i,t} - N_{r,i,t} \tag{10}$$

Taking the variances of both sides of Eq. (10) yields:

$$\begin{aligned} \mathrm{Var}(r_{it} - E_{t-1}r_{it}) = Var\left(N_{roe.i,t}\right) + \mathrm{Var}\left(N_{\mathrm{v,i,t}}\right) + \mathrm{Var}\left(N_{\mathrm{r,i,t}}\right) \\ -2\mathrm{cov}\left(N_{r.i,t}, N_{\mathrm{roe,i,t}}\right) - 2\mathrm{cov}\left(N_{r.i,t}, N_{\mathrm{v,i,t}}\right) + 2\mathrm{cov}\left(N_{roe.i,t}, N_{\mathrm{v,i,t}}\right) \end{aligned} \tag{11}$$

Equations (9) and (11) are used to motivate our variance decomposition analysis. Equation (9) assesses the relative importance of other information news and expected-return news in explaining stock returns. Equation (11) further assesses the relative importance of other information news, accounting earnings news, and expected-return news. The greater the variance of any factor on the right side, the more power that factor has in explaining unexpected stock returns. The relative variance contribution is therefore defined as the contribution of each factor to the variance of stock returns.

To implement the return variance decomposition, we follow Vuolteenaho (2002) to estimate the one-period expected return, cash flow news, and discount rate news series using a loglinear vector autoregressive (VAR) model as below:

$$\mathrm{Z}_t = \mathbf{A}\mathrm{Z}_{t-1} + \eta_t \tag{12}$$

where Z_t is a vector of (mean-adjusted) log stock returns, log other information variables, log accounting earnings, and log book-to-market ratio at time t. $\mathbf{A}$ is the VAR coefficient matrix. The error terms, η_t, are vectors of shocks and assumed to have a variance–covariance matrix $\boldsymbol{\Omega}$ and be independent of everything known at $t - 1$.

With the VAR model expressed in this form, the three unexpected stock return components, accounting earnings news (N_{ROE}), other information news (N_v), and expected-return news (N_r), can be calculated as:

$$N_{r,t} = e1'\rho\mathbf{A}(\mathbf{I} - \rho\mathbf{A})^{-1}\eta_t = \lambda_1\eta_t$$

$$N_{v,t} = e2'(\mathbf{I} - \rho\mathbf{A})^{-1}\eta_t = \lambda_2\eta_t$$

$$N_{roe,t} = (e1' - e2')(\mathbf{I} - \rho\mathbf{A})^{-1}\eta_t = \lambda_3\eta_t$$

where $'$ denotes the transpose operator, ek$'$ = [0,…, 1,…, 0] is a vector with one as the kth element and zero otherwise.

The variance and covariance of the variance decomposition as expressed in Eq. (11) can be computed as:

$$\begin{aligned}\text{var}(N_{r,t}) &= \lambda_1' \mathbf{\Omega} \lambda_1 \\ \text{var}(N_{v,t}) &= \lambda_2' \mathbf{\Omega} \lambda_2 \\ \text{var}(N_{roe,t}) &= \lambda_3' \mathbf{\Omega} \lambda_3 \\ \text{cov}(N_{r,t}, N_{v,t}) &= \lambda_1' \mathbf{\Omega} \lambda_2 \\ \text{cov}(N_{r,t}, N_{roe,t}) &= \lambda_1' \mathbf{\Omega} \lambda_3 \\ \text{cov}\left(N_{v,t}, N_{roe,t}\right) &= \lambda_2' \mathbf{\Omega} \lambda_3\end{aligned}$$

2.3 Hypothesis development

Equation (7) suggests a positive relationship between realized volatility of other information (ε_{t-1}^2) and future stock return volatility. The intuition is as follows. Given the assumption that stock prices fully reflect the implications of current earnings for future earnings, increased uncertainty in current other information is expected to reflect increased uncertainty about future cash flows, and so on average future stock returns will be more volatile.[15] Hence the uncertainty of other information reflected in analysts’ forecasts will be associated with fluctuations in future stock returns. Therefore our first hypothesis is stated as follows:

H1 The future volatility of a firm’s stock returns increases if current other information is more uncertain.

The relationship between realized other information (ε_{t-1}) and future stock return volatility is also of particular interest, as realized other information can be thought of as the aggregate news of all value-relevant events that have yet to have an impact on the financial statements. Volatility can be linked to the quantity and quality of information pertaining to firm’s fundamentals. According to this view, the most important process affecting volatility is the news arrival process (Andersen 1996). Numerous studies have examined price reactions to news releases, typically concluding that firm-specific news increases stock return volatility after the release of information (Clayton et al. 2005). Since volatility tends to be clustered (Schwert 1989), the effect of news releases tends to continue for some time. This implies that stock return volatility is smallest when there is no news (i.e., the level of other information is equal to zero).[16]

[15] A large part of the accounting literature suggests that the market is naive in recognizing the time-series properties of earnings, resulting in significant post-earnings-announcement abnormal returns (Kothari 2001). However, recent studies refine our understanding of the drift. For example, Brown and Han (2000) suggest the market is not entirely naive but rather underestimates the parameters of the true process.

[16] Damodaran (1985) suggests that investors react to news in different ways depending on how they think the information affects the future payoff of their assets and how big a surprise the information was for them. Given that the level of other information is an aggregate indicator of all other information news, the relation between other information news and volatility is ambiguous.

On the other hand, extensive research has found that stock return volatility increases more in response to bad news than in response to good news (i.e., volatility asymmetry). The ARCH-related literature provides a rich set of studies on this issue (Engle and Ng 1993). Beyond research using a time-series setting, previous cross-sectional studies, such as Rogers et al. (2009), also find that the effect of management earnings forecasts on short-term volatility is mainly attributable to forecasts that convey bad news.

Two strands of literature attempt to provide a theoretical framework to better explain the asymmetrical response of stock return volatility to news. The first, based on research in behavioral psychology, suggests that investors inappropriately extrapolate past performance. Therefore bad news has a particularly telling impact after a long period of good news because it has the effect of correcting overoptimistic projections (Barberis et al. 1998; Daniel et al. 1998).[17] The second strand of literature relates to regime-switching rational equilibrium models. Veronesi (1999) suggests that the asymmetric response occurs because news affects not only expected cash flows but also the risk associated with the probability of a regime shift.[18]

Overall, we expect that the response of future stock return volatility to unfavorable other information news to be stronger than for favorable news. Our second hypothesis is stated as follows:

H2 Future stock return volatility increases more in response to unfavorable other information than for favorable other information.

We also separately consider whether other information contained in analysts' forecasts (mainly) drives cross-sectional differences in systematic or idiosyncratic volatility. It would not be surprising for hypotheses one and two to hold for idiosyncratic volatility, because the finance literature shows that idiosyncratic volatility accounts for most of total stock return volatility (Campbell et al. 2001; Wei and Zhang 2006). While our theoretical model does not offer any guidance on systematic volatility or discount rate news, we expect similar results for systematic volatility. Ball et al. (2009) find that accounting earnings have substantial systematic components and undiversified variation and that systematic earnings risk is correlated with market-wide return risk. The above notion has been supported by follow-up research on market reaction to earnings announcements (Cready and Gurun 2010), accrual and cash flow components of accounting earnings (Hirshleifer

[17] For example, to reconcile the empirical findings of overreaction and under reaction, Daniel et al. (1998) use psychological concepts of overconfidence and self-attribution to construct a model of investor sentiment in the sense that "stock prices overreact to private information signals and underreact to public signals" (p. 1,841). Barberis et al. (1998) model investors as typically (but not always) believing that earnings are more stable than they really are. In such a situation, bad news following a series of good news events generates a large negative response because it is a surprise, whereas good news generates little response because it is anticipated.

[18] Veronesi (1999) suggests that, in good times, bad news decreases future expected cash flow and increases investors' uncertainty about a regime shift in the underlying cash flow process. Risk-averse investors thus require a higher discount rate for bearing the increasing risk of a regime shift, and this reinforces the effect of the bad news in good times. However, as there is no similar reinforcement in the case of good news, volatility increases more in response to bad news.

et al. 2009), and earnings dispersion (Jorgensen et al. 2012). Similar to accounting earnings as a proxy for future cash flow, other information would be expected to be associated with systematic volatility if it has significant undiversified variation and contains both firm-specific and market-level information. Our third hypothesis is therefore stated as follows:

H3 Both future systematic volatility and idiosyncratic volatility of a firm’s stock returns will increase if current other information is more uncertain or more unfavorable.

2.4 Standardized regression versus variance decomposition approach

We use two distinct empirical approaches to examine the incremental role of other information in determining stock return volatility: standardized regression analysis and variance decomposition analysis. Each method has advantages and limitations. However, employing both enables us to draw relatively robust conclusions and provide informative comparisons with prior literature.

First, we use regression analysis consistent with many prior volatility studies.[19] The use of regression analysis is consistent with the theoretical predictions and hypotheses derived from Eq. (7). It also enables us to control for a large set of volatility covariates to mitigate spurious correlations. However statistical inferences and interpretation based on the magnitude of regression coefficients are difficult, because the magnitude of an ordinary regression coefficient depends on the scale of both the dependent variable and the independent variables. To identify and interpret the economic significance of other information variables in determining volatility, we use standardized regressions (Bennett et al. 2003; Ferreira and Matos 2008). In particular, we standardize both the independent and dependent variables, such that all variables have the same mean (zero) and standard deviation (one), so that all estimated coefficients based on standardized regressions are presented in comparable units. The interpretation of such standardized regression coefficients is the expected standard deviation change in the dependent variable given a one standard deviation change in the independent variable.

We also adopt a variance decomposition approach in line with volatility studies such as Campbell and Shiller (1988a, b), Vuolteenaho (2002), and Callen and Segal (2004). The variance decomposition analysis provides a variance-based approach to measure value relevance of other information. It offers an intuitive representation of the (relative) importance of other information, accounting earnings, and expected-return news. Moreover, it explicitly controls for changes in expected returns over time. This is important for assessing the value relevance of other information, because small changes in expected discount rates can have a large impact on stock returns, especially when expected returns are persistent (Campbell et al. 1997).

However, variance decomposition requires a system of VAR equations, which cannot include a large set of volatility covariates simultaneously due to estimation complexity. More importantly, several studies have identified empirical limitations

[19] See, for example, Pástor and Veronesi (2003), Wei and Zhang (2006), Ferreira and Laux (2007), Irvine and Pontiff (2009), Brandt et al. (2010) and Rajgopal and Venkatchalam (2011).

associated with this approach (Ball et al. 2009, Chen and Zhao 2009). For example, the expected-return news in the variance decomposition approach cannot be accurately measured due to low predictive power, and the cash flow news, when treated as the residual, inherits the large misspecification error of the expected-return news. A missing state variable in the variance decomposition approach is likely to alter the empirical conclusion. In contrast, such model misspecification is much less damaging for regression analysis. Even if a factor is missing in a regression model, we can still draw statistical inferences about the specified factors despite increased noise, if the omitted variable is not highly correlated with the specified factors.

3 Data, variable measurement and descriptive statistics

3.1 Sample

The empirical analysis employs annual accounting data, daily stock return data, and analysts' forecasts data from the merged Compustat XPF, I/B/E/S, and CRSP database for the period of 1981–2011. Following prior literature, for a firm-year to be included in the sample, it must satisfy the following requirements: (1) non-missing and positive book value of equity at time $t-1$ and $t-2$, where t denotes time in years; (2) non-missing one lag of net income; and (3) a valid figure for market value of equity available for $t-1$ and $t-2$. In addition, we exclude firms with $t-1$ market equity less than \$10 million and a book-to-market ratio more than 100 or less than 0.01 to screen out possible data errors and mismatches.[20] To mitigate the undue influence of outliers, we winsorize the top and bottom one percentile of key variables used in the regression analysis.[21] Consensus analyst forecast data are extracted from the I/B/E/S unadjusted summary file. To ensure that forecasts are current and released after the firm has filed its annual report with the SEC and hence that earnings, book values, and other accounting information are publicly available, 1-year ahead earnings forecasts are extracted as of the fifth month after the fiscal year-end.[22] We require that there be at least three earnings forecasts available. The interaction of CRSP, Compustat, and I/B/E/S databases produces a final sample of 42,700 firm-year observations after applying all the above requirements. "Appendix 2" summarizes the measurement of all variables.

Consistent with Vuolteenaho (2002), the annual stock returns (RETURN) are compounded from CRSP monthly returns, recorded from the beginning of the sixth month after the fiscal year-end.[23] We require a valid stock return during the last

[20] The results remain similar if we do not impose any requirement for market equity.

[21] Our results remain quantitatively similar if we trim the top and bottom percentiles of key variables or keep them in the analysis.

[22] The Compustat data reveal that more than 95 % firms release their annual reports within 3 months after the financial year. Our results are similar if we use earnings forecasts from I/B/E/S in the fourth month after the fiscal year.

[23] The results are quantitatively similar if we calculate returns from the fourth or fifth month after the fiscal year-end.

month of the fiscal year to ensure that the return predictability is not spuriously induced by stale prices. If the firm was delisted we use the delisted return when available in CRSP. If the delisting return is missing, we investigate the reason. If the delisting is performance based, we assume a −30 % delisting return. Otherwise, we assume a zero delisting return.

Stock return volatility is computed as the sample variance of daily stock returns (in percentage) over the same recording period as stock returns.[24] The systematic and idiosyncratic volatilities are computed as follows. First, a factor model is used to decompose the daily stock returns into systematic and idiosyncratic return components. The factor model used is either the CAPM or the Fama–French three-factor model. Daily individual stock returns are applied to the models to obtain the daily systematic and idiosyncratic return components.

In analyzing the relationship between the uncertainty of other information and stock return volatility, we use several control variables that have been previously identified, including return on equity (ROE), the variance of return on equity (VROE), firm size (SIZE), firm age since listing (AGE), financial leverage (LEV), book-to-market ratio (BM), contemporaneous stock return (RETURN), analyst forecast bias (BIAS), and forecast dispersion (DISP).

ROE is measured as net income (NI) divided by lagged book value of equity (CEQ). When the value of ROE is less than −100 %, it is treated as a missing value because the log transformations for the VAR model are not possible for any variable less than 0. VROE is the sample variance of yearly ROE observations over the past 5 years for a minimum of three observations. Age is measured as the logarithm of the number of months from the firm’s IPO date. If IPO dates are unavailable, we use the first tracking date of the firm appearing in the CRSP. SIZE is the logarithm of the firm’s market value of equity, where market value of equity is defined as common shares outstanding (CSHO) multiplied by the stock price (PRCC_F). LEV is equal to the sum of total long-term debt (DLTT) and debt in current liabilities (DLC), divided by total assets (AT). Book-to-market ratio (BM) is book value of equity (CEQ) divided by the market value of equity. In line with prior literature, firms with lower ROE and higher VROE are expected to experience higher stock return fluctuations (Pástor and Veronesi 2003; Wei and Zhang 2006). We expect that younger and smaller firms will experience higher stock return volatility and a negative relationship between BM and volatility because firms with greater growth opportunities are more likely to experience greater fluctuation in stock returns (Bushee and Noe 2000; Ferreira and Laux 2007).

We also control for attributes of analysts’ forecasts to ensure that any link between the uncertainty of other information and stock return volatility is not driven by specific properties of analysts’ forecasts, such as forecast dispersion and forecast bias. Studies by Ajinkya and Gift (1985) and Daley et al. (1988) find that the ex ante variability of stock returns around earnings announcements is positively related to analysts’ forecast dispersion. Ackert and Athanassakos (1997) further show that analysts’ forecast dispersion is positively associated with analyst optimism. We measure forecast bias (BIAS) as the absolute difference between the 1-year-ahead

[24] Inferences are unchanged when the definition of volatility adopted by French et al. (1987) is used.

consensus mean analyst forecast of year $t + 1$ earnings per share reported in the fifth month after the fiscal year-end and the actual earnings per share reported in I/B/E/S, divided by stock price at the fiscal year-end. Forecast dispersion (DISP) is defined as the standard deviation of 1-year-ahead consensus analyst forecasts of year $t + 1$ earnings per share, standardized by the absolute value of consensus forecasted earnings per share.[25]

3.2 Measurement of other information

Our other information variable is measured using two distinct approaches. We use V1 (V2) to represent the other information variable estimated from the first (second) approach outlined below. As discussed in Sect. 2, we use realized volatility of other information as a nonparametric estimator of the conditional variance of other information, denoted as VV1 (VV2). VV1 (VV2) is defined as the sample variance of the yearly V1 (V2) observations over the past 5 years (with a minimum of three observations).

Following earlier studies, our first measure of other information is the residual from regressing 1-year-ahead analysts' forecasts on current publicly available financial information (Bryan and Tiras 2007; Ohlson and Shroff 1992; Manry et al. 2003).[26] We estimate the following cross-sectional regression to identify other information contained in analysts' forecasts that is not contained in current earnings or book value:

$$\mathrm{FROE}_{i,t} = c_0 + c_1 \mathrm{BVPS}_{i,t} + c_2 \mathrm{ROE}_{i,t} + v_{i,t} \tag{13}$$

where, for each firm i, $\mathrm{FROE}_{i,t}$ is the 1-year-ahead consensus mean analyst forecast of earnings per share at year t divided by book value of equity per share at year t; $\mathrm{BVPS}_{i,t}$ is net book value of equity per share at year t; and v_t is a residual that proxies for other information.[27] As the actual EPS reported in I/B/E/S is more consistent with the analysts' EPS forecasts, we also estimate an alternative version of Eq. (13) where $\mathrm{ROE}_{i,t}$ is replaced by $\mathrm{AROE}_{i,t}$ (namely I/B/E/S ROE, measured by the actual earnings per share of year $t + 1$ reported in I/B/E/S, divided by book value of equity per share at year t). Equation (13) is estimated separately for each fiscal year, with each regression using all available observations from that year.[28]

Panel A of Table 1 reports results for the cross-sectional estimation of Eq. (13) for the pooled sample from 1981 through 2010. The explanatory power of the regression using ROE (AROE) is 34.8 % (45.0 %). The intercepts of both regressions are positive and significant, consistent with a systematic positive difference between the 1-year-ahead forecasts and past actual earnings (i.e., optimistic forecasts).

[25] The deflator is commonly used to reduce heteroskedasticity. We also standardize by the firm's stock price at the end of year. The main results are qualitatively similar.

[26] Our results remain similar if we follow Manry et al. (2003) and exclude BVPS as a regressor in Eq. (9).

[27] The results are similar if we use the consensus median forecasts rather than the mean forecast of earnings per share.

[28] We also estimate a separate regression for each fiscal year, with each regression using all available observations in the sample from previous years, going back as far as 1981. The main results hold.

Table 1 Estimation of other information variables

	FROE	FROE
Panel A[a]		
Intercept	0.114***	0.079***
	(28.04)	(15.72)
ROE	0.409***	
	(32.46)	
AROE		0.605***
		(30.71)
BVPS	−0.001***	−0.001***
	(−7.29)	(−6.68)
Adj. R^2	34.8 %	45.0 %

	Coefficient	t value
Panel B[b]		
C	0.027***	(27.30)
ROE_{t-1}	0.591***	(39.47)
ROE_{t-1} *Market share	0.243***	(7.65)
ROE_{t-1} *Total asset	0.005***	(2.85)
ROE_{t-1} *R & D intensity	0.103***	(3.16)
ROE_{t-1} *Advertising intensity	0.718***	(12.28)
ROE_{t-1} *Capital intensity	0.102**	(2.31)
ROE_{t-1} *Magnitude of ROE	−0.114***	(−15.42)
ROE_{t-1} *Magnitude of special items	−0.324***	(−10.90)
ROE_{t-1} *Magnitude of total accruals	−0.024*	(−1.81)
Adj. R^2	28.9 %	

[a] The approach in Panel A follows Bryan and Tiras (2007), which parallels those in Ohlson and Shroff (1992) and Manry et al. (2003) to estimate other information contained in analysts' forecasts that is not contained in earnings or net book value. We run the following cross-sectional regression: $\text{FROE}_{i,t} = c_0 + c_1\text{BVPS}_{i,t} + c_2\text{ROE}_{i,t} + v_{i,t}$, where, for each firm i, $\text{FROE}_{i,t}$ is the 1-year-ahead consensus analyst forecast of earnings per share at year t divided by book value of equity per share at year t; $\text{BVPS}_{i,t}$ is net book value of equity per share at year t; and v_t is residual which proxies for other information. A separate regression is estimated for each fiscal year, with each regression using all available observations for that year. Only the results for the pooled sample are reported. Figures in parentheses are t-statistics. *** (**, *) indicates significant at the 1 % (5 %, 10 %) level for two-tailed test

[b] The approach in Panel B follows Dechow et al. (1999) and Fama and French (2002) to estimate the persistence of ROE as a function of known economic determinants, including market share (the ratio of firm's sales to total industry sales), firm size (the natural logarithm of total assets), R&D intensity (R&D expenditures over sales), advertising intensity (advertising expenditure over sales), capital intensity (the ratio of depreciation, depletion and amortization to sales), the magnitude of earnings (the absolute value of ROE), the magnitude of special items (the absolute value of the ratio of special items to lagged book value), and the magnitude of total accruals (the absolute value of the ratio of total accruals to lagged total assets). The process of ROE is as follows: $\text{ROE}_{i,t+1} = c + b_0\text{ROE}_{i,t} + \sum_{i=1}^{n} b_i(\text{F}_{i,t}\text{ROE}_{i,t}) + u_{i,t+1}$, where $\text{F}_{i,t}$ is the i'th determinant of ROE persistence; $i = 1, 2, \ldots, n$, n is the number of variables used in the cross-sectional estimation. A separate regression of equation is estimated for each fiscal year, with each regression using all available observations for that year. Following Dechow et al. (1999), only the results for the pooled sample are tabulated. Figures in parentheses are t-statistics. *** (**, *) indicates significant at the 1 % (5, 10 %) level for two-tailed test

Our second approach reflects Ohlson's (2001) suggestion that the other information variable, v_t, can be interpreted as the difference between the conditional expectation of earnings for period $t+1$ based on all available information and the expectation of earnings based only on current period earnings.[29] We follow Dechow et al. (1999) and Ohlson (2001) and use consensus analyst earnings forecasts to measure the year t conditional expectation of year $t+1$ earnings. The expectation of earnings based only on current period earnings is estimated from the AR(1) process of ROE. Thus the other information variable can be interpreted as $v_t = \mathrm{FROE}_t - (c + w\mathrm{ROE}_t)$. Here FROE_t is the 1-year-ahead consensus analyst forecast of earnings per share at year $t+1$, divided by book value of equity per share at year t. Both c and w are parameters of the ROE process.

We follow Fama and French (2000) and Cheng (2005b) and use conditional cross-sectional estimation of w to capture cross-sectional variation in the earnings persistence as a function of its economic determinants. Economic determinants employed include market share (the ratio of firm's sales to total industry sales), firm size (the natural logarithm of total assets), R&D intensity (R&D expenditures over sales), advertising intensity (advertising expenditure over sales), capital intensity (the ratio of depreciation, depletion, and amortization to sales), the magnitude of earnings (the absolute value of ROE), the magnitude of special items (the absolute value of the ratio of special items to lagged book value), and the magnitude of total accruals (the absolute value of the ratio of total accruals to lagged total assets). The measurement of the determinants of ROE persistence is summarized in Panel D of "Appendix 2".

The conditional value of ROE persistence (w) used in calculating the other information variable is estimated as follows. We first estimate earnings autoregressive regressions in which each of the eight determinants of ROE persistence are included as interactive effects:

$$\mathrm{ROE}_{i,t+1} = c + b_0\mathrm{ROE}_{i,t} + \sum_{k=1}^{n} b_k(\mathrm{F}_{k,t}\mathrm{ROE}_{i,t}) + u_{i,t+1} \tag{14}$$

where $\mathrm{F}_{k,t}$ is the k'th persistence determinant, $k = 1, 2, \ldots, n$; n is the number of variables used in the estimation with a maximum of eight. Equation (14) is estimated separately for each fiscal year, with each regression using all available observations from that year.[30] The conditional estimated value of ROE persistence for each firm-year is then computed using the parameter estimates from this regression:

$$\hat{w}_{i,t} = \hat{b}_{0,t} + \sum_{k=1}^{8} \hat{b}_{k,t}\mathrm{F}_{k,t} \tag{15}$$

[29] Ohlson (1995) defines his other information variable, v_t, as the difference between the conditional expectation of abnormal earnings for period $t+1$ based on all available information and the expectation of abnormal earnings based only on current period abnormal earnings.

[30] Following Dechow et al. (1999), we also estimate a separate regression for each fiscal year, with each regression using all available observations from previous years, going back as far as 1950. The results are similar to those reported in the text.

If one of the variables required to calculate *w* is missing, then the respective term is set equal to 0.[31]

The results reported in Panel B of Table 1 are the time-series average of the cross-sectional estimates for the annual regressions. All of the eight determinants are found be statistically significant and consistent with their hypothesized signs. Consistent with Dechow et al. (1999) and Cheng (2005b), the coefficients associated with ROE magnitude, special items, and total accruals are all significantly negative, indicating that earnings persistence is lower when earnings contain more transitory accounting items. Market share, firm size, and proxies for firm-level barriers to entry (R&D and advertising intensity) all have positive coefficients.

3.3 Descriptive statistics

Table 2 reports descriptive statistics for the variables used in the analysis. The average firm has a market capitalization of $758 million, a book-to-market ratio of about 0.62, a tracking period in Compustat of 17.5 years, and financial leverage of 22 % of total assets. For brevity, in the following we concentrate on the other information variables estimated from ROE, but all results continue to hold when using estimates from AROE. Results indicate that average (median) annual total volatility is 12.33 % (6.14 %). Outliers and non-normality result in a substantial difference between the mean and median, as evidenced by skewness and kurtosis values of 6.00 and 53.21 respectively. Patterns of positive skewness and significant leptokurtosis are also found in other measures of stock return volatility, the volatility of other information, and ROE volatility. Therefore, following Durnev et al. (2004), we apply a logarithmic transformation. The values of skewness and kurtosis of the natural logarithm of total volatility are equal to 0.34 and 3.12 respectively, indicating the natural logarithm of these variables is more symmetric and normal. Decomposition of total volatility shows that the total variation of stock returns mainly reflects idiosyncratic volatility, which is about 82 % of total volatility.

The mean of V1 is 0 by construction, compared to that of V2 (0.058). Recall that the other information variable is assumed to have a mean of zero and a normal distribution. This suggests that the second measure of other information (V2) may incorporate the influence of forecast bias.[32] The standard deviations of V1 and V2 are 0.123 and 0.118 respectively, both of which are lower than the standard deviation of ROE (0.274). The mean of VV1 is 0.009, slightly lower than that of VV2 (0.010).

4 Results using standardized regression

4.1 Other information and total volatility

We begin with a set of standardized regressions of total volatility on other information variables as well as the control variables discussed above:

[31] A sample restricted to observations without missing values for each persistence determinant yields qualitatively similar results.

[32] We thus control for forecast bias in our regression analysis presented in Sect. 4.

Table 2 Descriptive statistics

	Mean	Median	SD	Skew	Kurt
Total volatility (TVOL)	12.332	6.140	21.326	5.995	53.211
Idiosyncratic volatility from FF model (IVOLF)	10.090	4.561	19.523	6.620	62.938
Systematic volatility from FF model (SVOLF)	2.242	0.907	4.309	7.024	103.784
V1	0.000	−0.010	0.123	0.827	8.640
V2	0.058	0.036	0.118	1.465	8.668
VV1	0.009	0.002	0.016	3.038	13.136
VV2	0.010	0.003	0.017	2.875	11.914
ROE	0.113	0.129	0.274	2.105	25.168
VROE	0.072	0.007	0.243	5.619	37.466
AROE	0.131	0.133	0.217	0.710	12.514
FROE	0.158	0.149	0.200	1.361	13.513
Return	0.131	0.079	0.515	1.533	8.390
Log (Size)	6.631	6.535	1.678	0.252	2.695
Age (months)	210.010	146.000	200.985	1.620	5.411
Lev	0.220	0.196	0.184	0.775	3.250
BM	0.620	0.513	0.479	2.672	14.529
BIAS	0.026	0.004	0.137	7.259	66.557
DISP	0.169	0.056	0.405	5.473	36.658

This table presents summary statistics for volatility, other information variables, and other control variables. Variable definitions can be found in "Appendix 2"

$$\begin{aligned}\mathrm{Log}(\mathrm{VOL}_{i,t}) = {} & \beta_0 + \beta_1 V^{+}_{i,t-1} + \beta_2 V^{-}_{i,t-1} + \beta_3 \mathrm{Log}(\mathrm{VV}_{i,t-1}) + \beta_4 \mathrm{ROE}_{i,t-1} \\ & + \beta_5 \mathrm{Log}(\mathrm{VROE}_{i,t-1}) + \beta_6 \mathrm{R}_{i,t} + \beta_7 \mathrm{Size}_{i,t-1} + \beta_8 \mathrm{Age}_{i,t-1} \\ & + \beta_9 \mathrm{Lev}_{i,t-1} + \beta_{10} \mathrm{Log}(\mathrm{BM}_{i,t-1}) + \beta_{11} \mathrm{BIAS}_{i,t-1} \\ & + \beta_{12} \mathrm{DISP}_{i,t-1} + \varepsilon_{i,t} \end{aligned} \quad (16)$$

where $\mathrm{VOL}_{i,t}$ is the volatility measure of stock i in year t, as defined in (8). $\mathrm{V}_{i,t-1}$ is the measure of other information in year $t-1$. V^{+} represents favorable other information news, equal to V if V is positive and 0 otherwise. V^{-} represents unfavorable other information news, equal to V if V is negative and 0 otherwise. LOG ($\mathrm{VV}_{i,t-1}$), the volatility of other information, is defined as the natural logarithm of the sample variance of V within the past 5 years. All independent variables, with the exception of the contemporaneous return variable $\mathrm{R}_{i,t}$, are lagged by one period to allow the market sufficient time to incorporate financial statement information.

Table 3 presents estimated coefficients of the above regression, where total stock return volatility is the dependent variable. The t-statistics in parentheses are calculated using standard errors corrected for both clustering by firm and by year (Petersen 2009). The results support **H1**, indicating that future stock return volatility is significantly positively associated with the variability of current-period other information. The coefficients on VV are significant and positive in all specifications.

For restricted estimates (Column (1) and (3)), the estimated coefficients are 0.213 ($t = 9.69$) for V1 and 0.171 ($t = 8.23$) for V2, indicating that a one standard deviation increase in the log of other information variance results in a more than 17 % increase in the log of stock return volatility. When combined with all control variables (Column (2) and (4)), the magnitude of the slope coefficient of VV decreases to 0.122 ($t = 6.96$) and 0.092 ($t = 5.10$) but remains significant.

We then compare the effect of favorable versus unfavorable other information. There is a consistent negative association between volatility and V^-. In column (1) and (3), for example, the regression coefficient is -0.204 for V1 ($t = -15.42$) and -0.139 for V2 ($t = -9.09$), suggesting a one standard deviation change in V^- results in more than 14 % change in future stock return volatility. However, the relationship between volatility and V^+ is noticeably weaker. Although the estimated coefficient is statistically significant for V2 but not for V1 (0.006 for V1 with a t value of 0.48 and 0.032 for V2 with a t value of 2.21), its magnitude in both cases implies far lower economic significance. In fact, a one standard deviation increase in V^+ results in less than a 3 % increase in volatility. We use a Wald test with a null that β_1 equals $-\beta_2$ and find that the magnitude of the V^- coefficient is significantly higher than that of the V^+ coefficient. The above results do not alter substantially when all control variables are included. Thus the above results support **H2**, namely that stock return volatility tends to increase more in response to bad other information news than to good news.

Controlling for firm characteristics such as ROE and VROE does not change our conclusions, although the coefficients and robust t-statistics are attenuated (see columns (2) and (4)). The results confirm that other information variables provide incremental explanatory power of explaining future stock return volatility. In column (2), the regression coefficient on V^- is -0.105, comparable to that for ROE (-0.127). The estimated coefficient on VV is 0.122, slightly lower than that for VROE (0.144). Most control variables have significant coefficients. ROE impacts negatively on future volatility, while VROE has a positive association. Small, young, and growth firms tend to be more volatile, as indicated by the significant and consistent signs of SIZE, AGE, and BM. The coefficients on BIAS and DISP are also consistent as hypothesized and statistically significant

We also examine the robustness of our results to the Fama–MacBeth (1973) estimation and report the estimated coefficients in Panel B of Table 3.[33] Comparing the results of Fama–MacBeth regressions to those in Panel A, the magnitude of the coefficients on other information variables declines slightly to -0.180 (V^-) and 0.207 (VV) but still with significant t-statistics of -15.29 and 12.48 respectively (see column (5)). We also divide our sample period into three 10-year sub-periods, namely 1981–1990, 1991–2000, and 2001–2010 and estimate separately for the three subsamples. The results for different time periods are essentially the same and so are not reported in detail.[34]

[33] The t-statistics reported in parentheses are adjusted for autocorrelation and conditional heteroskedasticity (Newey and West 1987). The results of Fama–MacBeth regressions for other tables (untabulated) are similar to the results based on two-way clustering estimation.

[34] We also employ a fixed effect regression to address possible concerns about unobserved individual heterogeneity, where every firm and every year in the sample is assigned a dummy variable. The results (untabulated) are qualitatively similar to those reported above.

Table 3 Standardized regressions of total stock return volatility on other information variables and other variables

	Panel A: two-way clustering				Panel B: Fama–MacBeth regression			
	V1		V2		V1		V2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	−0.088	0.063	−0.088	0.068	−0.113	−0.025	−0.110	−0.020
	(−0.82)	(0.68)	(−0.81)	(0.73)	(−0.86)	(−0.22)	(−0.82)	(−0.17)
V^{+}	0.006	0.019	0.032**	0.012	−0.006	0.001	0.030***	0.003
	(0.48)	(1.24)	(2.21)	(0.75)	(−0.56)	(0.15)	(3.61)	(0.26)
V^{-}	−0.204***	−0.105***	−0.139***	−0.090***	−0.180***	−0.086***	−0.127***	−0.079***
	(−15.42)	(−7.97)	(−9.09)	(−7.11)	(−15.29)	(−9.44)	(−8.46)	(−9.09)
LogVV	0.213***	0.122***	0.171***	0.092***	0.207***	0.107***	0.169***	0.088***
	(9.69)	(6.96)	(8.23)	(5.10)	(12.48)	(10.74)	(9.13)	(6.24)
ROE		−0.127***		−0.128***		−0.121***		−0.120***
		(−7.22)		(−7.20)		(−6.81)		(−6.27)
Log (VROE)		0.144***		0.154***		0.147***		0.154***
		(10.17)		(10.30)		(12.33)		(14.87)
Return		−0.194**		−0.194**		−0.117***		−0.118***
		(−2.21)		(−2.20)		(−3.94)		(−3.94)
Size		−0.215***		−0.223***		−0.271***		−0.275***
		(−5.29)		(−5.56)		(−9.29)		(−9.43)
Age		−0.220***		−0.223***		−0.172***		−0.173***
		(−7.18)		(−7.20)		(−5.16)		(−5.19)
Lev		−0.052***		−0.054***		−0.062***		−0.065***
		(−4.34)		(−4.57)		(−4.56)		(−4.71)
BM		−0.048		−0.047		−0.058*		−0.055*
		(−1.28)		(−1.28)		(−2.07)		(−1.97)

Table 3 continued

	Panel A: two-way clustering				Panel B: Fama–MacBeth regression			
	V1		V2		V1		V2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BIAS		0.124***		0.129***		0.095***		0.098***
		(6.61)		(6.76)		(3.46)		(3.54)
DISP		0.047***		0.053***		0.059***		0.064***
		(5.06)		(5.78)		(7.79)		(8.27)
N	42,699	40,837	42,699	40,837	42,699	40,837	42,699	40,837
Adj. R^2 (%)	10.0	35.5	8.1	34.8	12.2	51.4	8.9	50.9
Wald test	278.57	115.60	135.90	65.37	156.73	60.48	93.84	37.07
p value	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)

This table displays results from regressing stock return volatility on other information variables and other variables at the firm level

$$\mathrm{Log}(\mathrm{VOL}_{i,t}) = \beta_0 + \beta_1 V^{+}_{i,t-1} + \beta_2 V^{-}_{i,t-1} + \beta_3 \mathrm{Log}(\mathrm{VV}_{i,t-1}) + \beta_4 \mathrm{ROE}_{i,t-1} + \beta_5 \mathrm{Log}(\mathrm{VROE}_{i,t-1}) + \beta_6 \mathrm{R}_{i,t} + \beta_7 \mathrm{Size}_{i,t-1} + \beta_8 \mathrm{Age}_{i,t-1} + \beta_9 \mathrm{Lev}_{i,t-1} + \beta_{10} \mathrm{Log}(\mathrm{BM}_{i,t-1}) + \beta_{11} \mathrm{BIAS}_{i,t-1} + \beta_{12} \mathrm{DISP}_{i,t-1} + \varepsilon_{i,t}$$

VOL is a proxy for total volatility, idiosyncratic volatility, or systematic volatility respectively. Other information variable V is calculated by paralleling the approaches in either Bryan and Tiras (2007) or Dechow et al. (1999) (denoted as V1 and V2 respectively). V^{+} equals to V if V is positive and 0 otherwise. V^{-} equals to V if V is negative and 0 otherwise. The volatility of other information, VV, is the sample variance of V within the past 5 years for a minimum of three observations. Control variables include ROE (return on equity), VROE (the sample variance of ROE), RETURN (the contemporaneous annual buy-and-hold returns), SIZE (the natural logarithm of the firm's market value of equity), AGE (the logarithm of the number of months from the firm's IPO date to the current year), LEV (financial leverage), BM (the ratio of the book value of equity to the market value of equity), BIAS (analyst forecast bias), and DISP (analyst forecast dispersion). For Fama–MacBeth regression, the coefficients are time-series averages of cross-sectional estimates. Figures in parentheses are *t*-statistics. All *t*-statistics in Panel A are calculated using standard errors corrected for both clustering by firm and clustering by year. *** (**, *) indicates significant at the 1 % (5, 10 %) level for two-tailed test. The null hypothesis for the Wald test is $\beta_1 = -\beta_2$, and figures in parentheses are the probabilities of accepting the null hypothesis

4.2 Systematic volatility versus idiosyncratic volatility

Our third hypothesis reflects the expectation that fundamental variables can cause both systematic and idiosyncratic variation in stock returns. Although it is widely held that most fundamental variables cause idiosyncratic volatility at the firm level, the relative importance of other information on systematic versus idiosyncratic volatility is ultimately an empirical issue. Table 4 presents the estimated coefficients for idiosyncratic volatility (Panel A) and systematic volatility (Panel B), where the Fama–French three-factor model is used for volatility decomposition.[35]

The results support **H3**, namely that a typical firm's other information variable is associated with differences in both the systematic and idiosyncratic components of volatility. The coefficients on VV are significantly positive in all specifications of either systematic or idiosyncratic volatility. For instance, when combined with all control variables, the magnitudes of the VV1 (VV2) coefficient are 0.098 (0.075) for systematic volatility and 0.127 (0.098) for idiosyncratic volatility, both with significant *t*-statistics. As idiosyncratic volatility accounts for over 80 % of total volatility, it is not surprising that the main results are repeated for idiosyncratic volatility. However, the adjusted R^2 for systematic volatility (5.2 % for V1 and 4.6 % for V2) is much smaller than for idiosyncratic volatility (10.1 % for V1 and 8.0 % for V2). The higher explanatory power of other information for idiosyncratic volatility is consistent with Campbell (1991) and Campbell and Ammer (1993) that expected-return news dominates cash-flow news in driving aggregate stock returns and Vuolteenaho (2002) that cash-flow news is the main factor that drives stock returns at the firm level. We also disentangle the relationship between favorable and unfavorable other information with future systematic and idiosyncratic volatility. All coefficients on V^- are significantly negative, while most coefficients on V^+ are positive but insignificant. As a result, for both systematic and idiosyncratic volatility, the response to "bad news" is significantly stronger than for "good news."

4.3 Additional tests using standardized regression

In this section, we confirm the relationship between stock return volatility and other information variables through a battery of robustness checks. Space constraints limit the following discussion to focusing on total volatility only, but the results for idiosyncratic and systematic volatility are similar and are available upon request.

4.3.1 Controlling for analyst forecast bias

The underlying assumption in our model is that analysts' earnings forecasts reflect the market expectations about a firm's future cash flows in a timely fashion. However, there is ample evidence that analyst forecasts tend to be overly optimistic. Although forecast bias is included as a control, forecast biases may contaminate our other information measures, which in turn would affect our empirical conclusion.

[35] Results for systematic and idiosyncratic volatility estimated from the CAPM are qualitatively similar and are available upon request.

Table 4 Standardized regression of idiosyncratic and systematic stock return volatility on other information variables and other variables

	Panel A: idiosyncratic volatility				Panel B: systematic volatility			
	V1		V2		V1		V2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	−0.135	0.048	−0.136	0.053	0.095	0.086	0.096	0.091
	(−1.44)	(0.57)	(−1.43)	(0.63)	(0.64)	(0.67)	(0.64)	(0.71)
V^+	0.009	0.012	0.044***	0.010	0.007	0.018	0.008	0.013
	(0.96)	(0.97)	(3.83)	(0.75)	(0.37)	(1.11)	(0.37)	(0.69)
V−	−0.207***	−0.096***	−0.137***	−0.087***	−0.113***	−0.114***	−0.094***	−0.097***
	(−18.16)	(−9.40)	(−11.06)	(−7.93)	(−6.04)	(−5.59)	(−4.73)	(−5.51)
LogVV	0.209***	0.127***	0.163***	0.098***	0.189***	0.098***	0.173***	0.075***
	(12.34)	(8.96)	(10.12)	(6.86)	(5.83)	(3.77)	(5.61)	(2.92)
ROE		−0.118***		−0.118***		−0.123***		−0.125***
		(−7.80)		(−7.64)		(−5.79)		(−5.85)
Log (VROE)		0.132***		0.140***		0.123***		0.129***
		(11.02)		(11.26)		(4.42)		(4.58)
Return		−0.163**		−0.163**		−0.128		−0.128
		(−2.45)		(−2.44)		(−1.16)		(−1.16)
Size		−0.334***		−0.341***		0.249***		0.240***
		(−10.64)		(−10.95)		(4.38)		(4.30)
Age		−0.217***		−0.220***		−0.170***		−0.173***
		(−10.04)		(−10.09)		(−4.34)		(−4.37)
Lev		−0.030***		−0.033***		−0.089***		−0.091***
		(−2.85)		(−3.12)		(−4.86)		(−5.02)
BM		−0.090**		−0.088**		0.032		0.038
		(−2.57)		(−2.55)		(0.78)		(0.95)

Table 4 continued

	Panel A: idiosyncratic volatility				Panel B: systematic volatility			
	V1		V2		V1		V2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BIAS		0.133***		0.137***		0.044		0.047
		(9.35)		(9.51)		(1.40)		(1.48)
DISP		0.031***		0.036***		0.065***		0.071***
		(3.31)		(3.84)		(3.29)		(3.65)
N	42,700	40,838	42,700	40,838	42,700	40,838	42,700	40,838
Adj. R^2 (%)	10.1	42.3	8.0	41.7	5.2	13.9	4.6	13.4
Wald test	323.58	135.80	75.90	35.64	16.26	20.34	15.45	17.02
p value	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)

This table displays results from regressing stock return volatility on other information variables and other variables at the firm level

$$\mathrm{Log}(\mathrm{VOL}_{i,t}) = \beta_0 + \beta_1 V^+_{i,t-1} + \beta_2 V^-_{i,t-1} + \beta_3 \mathrm{Log}(\mathrm{VV}_{i,t-1}) + \beta_4 \mathrm{ROE}_{i,t-1} + \beta_5 \mathrm{Log}(\mathrm{VROE}_{i,t-1}) + \beta_6 \mathrm{R}_{i,t} + \beta_7 \mathrm{Size}_{i,t-1} + \beta_8 \mathrm{Age}_{i,t-1} + \beta_9 \mathrm{Lev}_{i,t-1} + \beta_{10} \mathrm{Log}(\mathrm{BM}_{i,t-1}) + \beta_{11} \mathrm{BIAS}_{i,t-1} + \beta_{12} \mathrm{DISP}_{i,t-1} + \varepsilon_{i,t}$$

VOL is a proxy for total volatility, idiosyncratic volatility, or systematic volatility respectively. Other information variable V is calculated by paralleling the approaches in either Bryan and Tiras (2007) or Dechow et al. (1999) (denoted as V1 and V2 respectively). V^+ equals to V if V is positive and 0 otherwise. V^- equals to V if V is negative and 0 otherwise. The volatility of other information, VV, is the sample variance of V within the past 5 years for a minimum of three observations. Control variables include ROE (return on equity), VROE (the sample variance of ROE), RETURN (the contemporaneous annual buy-and-hold returns), SIZE (the natural logarithm of the firm's market value of equity), AGE (the logarithm of the number of months from the firm's IPO date to the current year), LEV (financial leverage), BM (the ratio of the book value of equity to the market value of equity), BIAS (analyst forecast bias), and DISP (analyst forecast dispersion). All *t*-statistics (in parentheses) are calculated using standard errors corrected for both clustering by firm and clustering by year. *** (**, *) indicates significant at the 1 % (5, 10 %) level for two-tailed test. The null hypothesis for the Wald test is $\beta_1 = -\beta_2$, and figures in parentheses are the probabilities of accepting the null hypothesis

To mitigate such concern, we conduct the regression analysis for two subsamples, which include firm-years with high and low forecast biases in a particular year. We also construct three alternative measures of other information. In particular, rather than using the mean forecasts, we use the highest (most optimistic) forecasts, the lowest (most pessimistic) forecasts, and the median forecasts to measure other information. As such, even if there is a bias when analysts' forecasts are used, the bias might not be as strong if the lowest or the highest forecasts are used. Panel A and Panel B of Table 5 report the results for firm-years with high and low forecast biases, respectively, and Panel C and Panel D display the results for alternative other information measures based on the highest and lowest forecasts, respectively. We find that the coefficient on V^- and VV are consistently significant with similar magnitudes as those reported above. We therefore conclude that analyst forecast biases are unlikely to be the main driver of our results.

4.3.2 High technology and loss firm effects

The link between other information and volatility may be attributable to high technology firms, given the increasing number of high technology firms in recent years (Chan et al. 2001, Schwert 2002). We re-estimate our results after separating high-technology firms.[36] Results reported in Panel E and Panel F of Table 5 still support our hypotheses. The magnitude of the V^-, ROE, and VROE coefficients for high-technology firms (for V1, coefficients = −0.060, −0.075, and 0.107, respectively) is lower than those for nontechnology firms (coefficients = −0.115, −0.122, and 0.131, respectively), indicating a less important role for fundamental variables in explaining future volatility of technology firms.

The relationship between other information and volatility may also be at least partially attributable to the effect of losses, as Hayn (1995) shows that the market reaction to a loss differs from the response to a profit, and Givoly and Hayn (2000) show that the number of loss firms has increased since the 1990s. We classify firms into loss and profit firms based on net income (NI). The results shown in Panel G and Panel H of Table 5 generally confirm our previous findings, and we find that the role of other information is more important in explaining volatility for profit firms.[37] This might be due to the fact that loss firms are often expected to have “bad news,” so that the expected level of other information news for losses is negative rather than zero, resulting in a smaller unexpected component of “bad news.”

4.3.3 Listing markets and industry effects

We separately examine results for NASDAQ-traded stocks from those traded on the NYSE/AMEX. Schwert (2002) demonstrates that the NASDAQ portfolio became

[36] Following Francis and Schipper (1999), firms in 14 three-digit SIC codes (283, 357, 360-368, 481, 737, and 873) are identified as technology-intensive industries.

[37] For profit firms, the effect of V^- becomes stronger than VV, ROE, and VROE (e.g., using V1, the comparison is −0.142 compared to 0.111, −0.135, and 0.129, respectively). However, the impact of V^- becomes much weaker in the case of losses (e.g., −0.061 for losses compared to −0.142 for profit firms).

Table 5 Standardized regression of stock return volatility on other information variables and other variables, controlling for analyst forecast bias, high technology firms and loss firms

Variables	Panel A: high forecast bias		Panel B: low forecast bias		Panel C: highest earnings forecast		Panel D: lowest earnings forecast	
	V1 (1)	V2 (2)	V1 (3)	V2 (4)	V1 (5)	V2 (6)	V1 (7)	V2 (8)
V^{+}	0.019	−0.010	0.007	0.020	0.024	0.020	0.012	0.011
	(0.80)	(−0.47)	(0.56)	(1.28)	(1.42)	(1.02)	(0.95)	(0.85)
V^{-}	−0.112***	−0.084***	−0.087***	−0.076***	−0.084***	−0.075***	−0.117***	−0.105***
	(−7.46)	(−5.85)	(−4.78)	(−4.88)	(−6.66)	(−6.38)	(−8.10)	(−7.56)
LogVV	0.131***	0.107***	0.106***	0.093***	0.126***	0.091***	0.120***	0.094***
	(6.35)	(5.06)	(6.08)	(4.25)	(6.90)	(4.97)	(6.96)	(5.35)
ROE	−0.129***	−0.132***	−0.126***	−0.128***	−0.127***	−0.126***	−0.125***	−0.127***
	(−5.83)	(−5.74)	(−7.60)	(−7.58)	(−7.28)	(−6.94)	(−6.99)	(−7.22)
Log (VROE)	0.137***	0.147***	0.120***	0.130***	0.151***	0.156***	0.138***	0.148***
	(8.85)	(9.02)	(7.83)	(8.48)	(10.14)	(9.93)	(9.83)	(10.12)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19,563	19,563	21,273	21,273	40,888	40,888	40,762	40,762
Adj. R^2 (%)	35.4	34.5	33.3	33.0	35.2	34.6	35.6	35.0
Wald test	165.62	142.24	102.35	108.56	98.45	89.76	104.53	112.34
p value	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Variables	**Panel E: high technology firms**		**Panel F: non-technology firms**		**Panel G: loss firms**		**Panel H: profit firms**	
	V1 (9)	V2 (10)	V1 (11)	V2 (12)	V1 (13)	V2 (14)	V1 (15)	V2 (16)
V^{+}	−0.012	−0.009	0.034**	0.025	−0.073***	−0.112***	0.043***	0.042**
	(−0.51)	(−0.38)	(2.22)	(1.46)	(−2.94)	(−4.15)	(3.00)	(2.43)

Table 5 continued

Variables	Panel E: high technology firms		Panel F: non-technology firms		Panel G: loss firms		Panel H: profit firms	
	V1 (9)	V2 (10)	V1 (11)	V2 (12)	V1 (13)	V2 (14)	V1 (15)	V2 (16)
V−	−0.060***	−0.058***	−0.115***	−0.100***	−0.061***	−0.052***	−0.142***	−0.113***
	(−7.37)	(−4.23)	(−5.22)	(−4.79)	(−5.84)	(−2.80)	(−5.99)	(−5.83)
LogVV	0.127***	0.111***	0.120***	0.095***	0.123***	0.109***	0.111***	0.078***
	(5.03)	(4.86)	(6.92)	(4.56)	(4.64)	(3.79)	(6.32)	(4.42)
ROE	−0.075***	−0.080***	−0.122***	−0.116***	−0.136***	−0.178***	−0.135***	−0.123***
	(−2.76)	(−2.76)	(−7.01)	(−6.87)	(−4.13)	(−4.80)	(−5.16)	(−5.29)
Log (VROE)	0.107***	0.110***	0.131***	0.141***	0.103***	0.113***	0.129***	0.139***
	(4.42)	(4.40)	(8.03)	(7.91)	(4.39)	(4.46)	(8.72)	(9.52)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8,214	8,214	32,623	32,623	6,530	6,530	34,307	34,307
Adj. R^2 (%)	38.4	37.8	33.3	32.6	32.1	31.6	29.6	28.9
Wald test	98.64	86.49	112.36	109.46	36.76	85.46	104.34	96.58
p value	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)

This table displays results from regressing stock return volatility on other information variables and other variables at the firm level

$$\mathrm{Log}(\mathrm{VOL}_{i,t}) = \beta_0 + \beta_1 V^{+}_{i,t-1} + \beta_2 V^{-}_{i,t-1} + \beta_3 \mathrm{Log}(\mathrm{VV}_{i,t-1}) + \beta_4 \mathrm{ROE}_{i,t-1} + \beta_5 \mathrm{Log}(\mathrm{VROE}_{i,t-1}) + \beta_6 \mathrm{R}_{i,t} + \beta_7 \mathrm{Size}_{i,t-1} + \beta_8 \mathrm{Age}_{i,t-1} + \beta_9 \mathrm{Lev}_{i,t-1} + \beta_{10} \mathrm{Log}(\mathrm{BM}_{i,t-1}) + \beta_{11} \mathrm{BIAS}_{i,t-1} + \beta_{12} \mathrm{DISP}_{i,t-1} + \varepsilon_{i,t}$$

VOL is a proxy for total volatility, idiosyncratic volatility, or systematic volatility respectively. Other information variable V is calculated by paralleling the approaches in either Bryan and Tiras (2007) or Dechow et al. (1999) (denoted as V1 and V2 respectively). V^+ equals to V if V is positive and 0 otherwise. V^- equals to V if V is negative and 0 otherwise. The volatility of other information, VV, is the sample variance of V within the past 5 years for a minimum of three observations. Control variables include ROE (return on equity), VROE (the sample variance of ROE), RETURN (the contemporaneous annual buy-and-hold returns), SIZE (the natural logarithm of the firm's market value of equity), AGE (the logarithm of the number of months from the firm's IPO date to the current year), LEV (financial leverage), BM (the ratio of the book value of equity to the market value of equity), BIAS (analyst forecast bias), and DISP (analyst forecast dispersion). All *t*-statistics (in parentheses) are calculated using standard errors corrected for both clustering by firm and clustering by year. *** (**, *) indicates significant at the 1 % (5, 10 %) level for two-tailed test. The null hypothesis for the Wald test is $\beta_1 = -\beta_2$, and figures in parentheses are the probabilities of accepting the null hypothesis unusually volatile relative to the S&P portfolio over 1995–2001.[38] Of our full sample, 38 % of all firm-years are from NASDAQ, while the rest come from NYSE/AMEX. We repeat all of the analysis for each subsample and find the results remain similar.

Roll (1992) finds that industry factors can explain substantial variation in stock returns. The importance of industry factors in equity returns is also evident in the so-called momentum effect (Moskowitz and Grinblatt 1999). Firms in different industries might also display different stock price volatility for other reasons.[39] To control for possible industry effects, the sample is divided into subsamples using the Fama and French five-industry classification.[40] We find the results are robust across different industries.

4.3.4 *Controlling for corporate governance, earnings quality, and lagged volatility*

Ferreira and Laux (2007) report a strong negative relationship between corporate governance policy and idiosyncratic volatility. We therefore include an index of a firm's antitakeover provisions, namely the Investor Responsibility Research Center (IRRC) governance index as an additional control.[41] Our sample size reduces to 7,436 because the governance index is only available for 3,787 firms over 1990–2004, but the empirical results are qualitatively similar. Consistent with Ferreira and Laux (2007), the index of antitakeover provisions is found to be negatively and significantly associated with future stock return volatility (−0.028 for V1 and −0.031 for V2).

Rajgopal and Venkatachalam (2011) document a negative relationship between earnings quality and volatility. The rationale in Rajgopal and Venkatachalam (2011) is that when earnings quality is low, financial analysts place less weight on earnings information from financial statements and instead place greater weight on private (possibly idiosyncratic) information. Consistent with Rajgopal and Venkatachalam (2011), we find the earnings quality metric is positively associated with future volatility (0.046 for V1 and 0.038 for V2), with significant *t*-statistics of 8.47 (V1) and 8.15 (V2), respectively. After accounting for earnings quality, we still find a robust relationship between other information and future volatility.[42]

[38] It is also well documented that different markets provide different degrees of liquidity (Christie and Schultz 1994) and cost of executing trades (Huang and Stoll 1996), both of which may differentially influence our volatility analyses.

[39] For instance, firms that operate in finance-related industries (e.g., banks, insurance, life assurance, and investment companies) and utility industries (e.g., water, electricity and gas distribution companies) are highly regulated and have to comply with stringent legal requirements pertaining to their financing.

[40] The five-industry classification approach of Fama and French is available on Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

[41] We thank Andrew Metrick for providing the IRRC governance index.

[42] Earnings quality is measured based on the McNichols (2002)'s modification of the Dechow-Dichev (2002) model. We also use two additional measures of earnings quality based on the modified Jones approach as in Rajgopal and Venkatachalam (2011) and the original Dechow and Dichev (2002) model. All the results are qualitatively similar.

Our prior regression analyses do not include the prior level of stock return volatility (or its components) as a control variable, consistent with most cross-sectional volatility studies (Bushee and Noe 2000; Pástor and Veronesi 2003; Ferreira and Laux 2007; Rajgopal and Venkatachalam 2011). This is because our focus is on explaining the level of volatility rather than the change in volatility (see Bushee and Noe (2000) for more discussion). Furthermore, even though the persistent nature of stock return volatility could cause the residuals from a regression of the level of volatility to be serially correlated, such residual autocorrelation can be corrected by using the Petersen (2009) adjusted standard errors, as we report above. However, we do examine the sensitivity of our results to the inclusion of lagged volatility and find our main results continue to hold.[43] Take V1 as an example. When all control variables including lagged volatility are included, the regression coefficients for V^{+}, V^{-}, and VV are 0.025 ($t = -1.74$), -0.038 ($t = -3.23$), and 0.035 ($t = 2.84$) respectively, reconfirming our previous results.

5 Results using variance decomposition

5.1 Main results

Consistent with prior literature (e.g., Vuolteenaho 2002; Callen and Segal 2004), we estimate the VAR coefficient matrix by trading off efficiency for robustness and simplicity. The VAR is estimated using weighted least squares separately for each Fama–French (1997) industry, with one prediction regression per state variable. Each annual cross-section is weighted equally by deflating the data for each firm-year by the number of firms in the affiliated industry. This approach yields the VAR parameters at the industry level, but the news variable can be computed at the firm-year level. We calculate robust standard errors of the variance components using the Shao-Rao (1993) jackknife method.

We first explore the relative importance between other information news and expected-return news. Panel A and Panel B of Table 6 report parameter estimates of the VAR model for V1 and V2 respectively. The results suggest that expected returns are high when past 1-year returns are low and when other information and the book-to-market ratio are high. Expected other information is high when past other information and the book-to-market ratio are high. Not surprisingly, the expected future book-to-market ratio is mostly affected by the past book-to-market ratio.

The variance decomposition implied by the VAR is shown in Panel C of Table 6. We find that other information news dominates expected-return news in driving firm-level stock returns. The variance of other information news is 13.5 % for V1 and 13.2 % for V2, around eight times as large as the variance of expected-return news (1.7 % for V1 and 1.6 % for V2). We also compare the variance of positive and negative other information news and find that the variance of negative other

[43] We acknowledge the suggestion of an anonymous reviewer in conducting this analysis.

Table 6 Variance decomposition of mean-adjusted returns on other information variables

Variables	$return_{t-1}$	v_{t-1}	bm_{t-1}
Panel A: estimated parameters from the VAR model for V1			
$return_t$	−0.032*	0.342***	0.285***
	(0.120)	(0.367)	(0.194)
v_t	0.004	0.251***	−0.071***
	(0.032)	(0.162)	(0.056)
bm_t	−0.071***	−0.103***	0.710***
	(0.050)	(0.115)	(0.091)

Variables	$return_{t-1}$	$v1_{t-1}$	bm_{t-1}
Panel B: estimated parameters from the VAR model for V2			
$return_t$	−0.029*	0.311***	0.256***
	(0.119)	(0.363)	(0.192)
v_t	−0.008*	0.167***	−0.038***
	(0.031)	(0.136)	(0.054)
bm_t	−0.071***	−0.111***	0.717***
	(0.049)	(0.107)	(0.092)

Variables	var (N_r)	var (N_v)	cov (N_r, N_v)	VR	var $(N_v)^+$	var $(N_v)^-$	DIFF
Panel C							
V1	0.017***	0.135***	−0.017***	0.185***	0.065***	0.070***	−0.005*
	(0.011)	(0.062)	(0.014)	(0.097)	(0.038)	(0.066)	(0.067)
V2	0.016***	0.132***	−0.019***	0.186***	0.064***	0.068***	−0.004*
	(0.011)	(0.061)	(0.014)	(0.097)	(0.038)	(0.063)	(0.065)

Table 6 continued

Variables	VR	V (N_r)/VR	V (N_v)/VR	cov (N_r, N_v)/VR
Panel D				
V1	0.185	0.090	0.731	−0.089
V2	0.186	0.085	0.711	−0.102

Variables	var (N_r)	var (N_v)	cov (N_r, N_v)	VR	V (N_r)/VR	V (N_v)/VR	cov (N_r, N_v)/VR
Panel E							
ROE	0.020***	0.205***	0.006***	0.214***	0.095	0.958	0.027
	(0.137)	(0.551)	(0.194)	(0.482)			

Panel A and Panel B display the coefficient estimates for the log-linear vector autoregressive (VAR) model for V1 and V2 respectively. The model variables include the mean-adjusted log excess returns (*return*), the mean-adjusted log other information variables (v), and the mean-adjusted log book-to-market ratio (bm). The standard errors are presented in parentheses. *** (**, *) indicates significant at the 1 % (5, 10 %) level for two-tailed test

Panel C shows the variance decomposition for the VAR model. var($N_{r,t}$) is the variance of expected-return news. var($N_{v,t}$) is the variance of other information news. cov($N_{r,t}$, $N_{v,t}$) is the covariance between expected-return news and other information news. VR is total variance of mean-adjusted excess return, equal to var($N_{r,t}$) + -var($N_{v,t}$)−2cov($N_{r,t}$, $N_{v,t}$). var(N_v)$^+$ is the variance of other information news when other information news is positive. var(N_v)$^-$ is the variance of other information news when other information news is negative. DIFF is the difference between the variance of positive other information news and the variance of negative other information news, var(N_v)$^+$−var(N_v)$^-$. The standard errors (in parentheses) of the variances are computed using the Shao-Rao (1993) jackknife method. *** (**, *) indicates significant at the 1 % (5, 10 %) level for two-tailed test

Panel D displays the relative size of each variance/covariance component to the total variance

Panel E shows the variance decomposition for the VAR model and the relative size of each variance/covariance component to the total variance. var($N_{r,t}$) is the variance of expected-return news. var($N_{ROE,t}$) is the variance of mean-adjusted earnings (ROE) news. cov($N_{r,t}$, $N_{ROE,t}$) is the covariance between expected-return news and earnings news. VR is total variance of mean-adjusted excess return, equal to var($N_{r,t}$) + var($N_{ROE,t}$) − 2cov($N_{r,t}$, $N_{ROE,t}$). The standard errors (in parentheses) of the variances are computed using the Shao-Rao (1993) jackknife method. *** (**, *) indicates significant at the 1 % (5, 10 %) level for two-tailed test information news is significantly higher than the variance of positive news (7.0 % vs. 6.5 % for V1 and 6.8 % vs. 6.4 % for V2). Panel D of Table 6 shows that other information news explains around 70 % of the total variance of the unexpected change in returns, whereas expected-return news explains only about 9 %. The remainder is explained by the joint negative covariance between other information news and expected-return news. Overall, the results indicate that other information is a legitimate surrogate for future cash flow and other information news is far more fundamental than expected-return news in driving firm-level returns.

We also follow Vuolteenaho (2002)'s decomposition and examine the relative importance between accounting earnings news and expected-return news. Panel E reports the variance decomposition implied by the VAR. The variance of earnings news is 20.5 %, significantly higher than the variance of expected-return news (2.0 %).

Given the importance of both other information news and earnings news, we next examine the relative impact of other information news and earnings news on changes in current stock returns. Parameter estimates of the VAR are presented in Table 7 for V1 (Panel A) and for V2 (Panel B). The return equation shows that returns are positively associated with lagged other information, earnings, and book-to-market ratio. Both other information and earnings are persistent, but the persistence of earnings (0.389 for V1 and 0.422 for V2) is higher than that of other information (0.269 for V1 and 0.179 for V2). Accounting earnings are significantly and positively associated with past returns, while the relationship between other information and past returns is relatively weak and insignificant.

The results of the variance decomposition are presented in Panel C of Table 7. The variance of earnings news is around twice the variance of other information, and the difference between the two is significant. For example, for V1, the variance of other information news and earnings news is 6.1 % and 12.2 % respectively. However, both earnings and other information variances are significantly larger than the variance of expected-return news (1.8 % for V1). The three covariance terms are relatively small in magnitude for both specifications. Similar to the above findings, we confirm that the variance of negative other information news is significantly higher than the variance of positive news (3.3 % vs. 2.8 % for V1 and 2.6 % vs. 2.4 % for V2). Panel D provides an intuitive representation of these results. The table shows that, for V1 (V2), other information explains 33.2 % (27.2 %) of the total variance of the unexpected returns, whereas accounting earnings explains 66.3 % (69 %). By comparison, expected-return news explains less than 10 % of the total variance.

Overall, the results of variance decomposition confirm the incremental role of other information in determining stock return volatility. We find that both other information and accounting earnings news dominate expected-return news and the variance of other information news is around half of the variance of earnings news in driving stock returns. The relative importance between other information and earnings can be understood by Eq. (7), which shows that the variance contribution is a function of both persistence and variability. As shown in Table 7, accounting earnings are found to be more persistent than other information. The persistence of V1 (V2) is 0.269 (0.179), significantly lower than earnings persistence of 0.389

Table 7 Variance decomposition of mean-adjusted returns on other information variables and accounting earnings

Variables	$return_{t-1}$	v_{t-1}	roe_{t-1}	bm_{t-1}
Panel A: estimated parameters from the VAR model for V1				
$return_t$	−0.042**	0.399***	0.159***	0.347***
	(0.114)	(0.346)	(0.205)	(0.183)
v_t	0.000	0.269***	0.084***	−0.039***
	(0.031)	(0.148)	(0.057)	(0.058)
roe_t	0.082***	0.615***	0.389***	−0.109***
	(0.061)	(0.217)	(0.113)	(0.107)
bm_t	−0.072***	−0.090***	0.017*	0.715***
	(0.050)	(0.124)	(0.061)	(0.087)

Variables	$return_{t-1}$	v_{t-1}	roe_{t-1}	bm_{t-1}
Panel B: estimated parameters from the VAR model for V2				
return_t	−0.042**	0.407***	0.182***	0.325***
	(0.112)	(0.381)	(0.240)	(0.177)
v_t	−0.010***	0.179***	0.038***	−0.022***
	(0.030)	(0.155)	(0.058)	(0.056)
roe_t	0.085**	0.600***	0.422***	−0.139***
	(0.063)	(0.241)	(0.137)	(0.120)
bm_t	−0.072***	−0.091***	0.012	0.720***
	(0.049)	(0.143)	(0.077)	(0.088)

	var (N_r)	var (N_v)	var (N_{roe})	DIFF1	cov (N_r, N_v)	cov (N_r, N_{roe})	cov (N_v, N_{roe})	VR	var $(N_v)^+$	var $(N_v)^-$	DIFF2
V1	0.018***	0.061***	0.122***	−0.061***	0.008***	−0.007***	−0.007***	0.184***	0.028***	0.033***	−0.005*
	(0.013)	(0.016)	(0.055)	(0.043)	(0.006)	(0.010)	(0.005)	(0.101)	(0.007)	(0.015)	(0.017)

Table 7 continued

	var (N_r)	var (N_v)	var (N_{roe})	DIFF1	cov (N_r, N_v)	cov (N_r, N_{roe})	cov (N_v, N_{roe})	VR	var $(N_v)^+$	var $(N_v)^-$	DIFF2
V2	0.017***	0.050***	0.127***	−0.077***	0.005***	−0.006***	−0.006***	0.184***	0.024***	0.026***	−0.002*
	(0.012)	(0.006)	(0.063)	(0.058)	(0.003)	(0.011)	(0.004)	(0.101)	(0.003)	(0.005)	(0.006)

	VR	V (N_r)/VR	V (N_v)/VR	V (N_{roe})/VR	cov (N_r, N_v)/VR	cov (N_r, N_{roe})/VR	cov (N_v, N_{roe})/VR
Panel D							
V1	0.184	0.098	0.332	0.663	0.045	−0.036	−0.038
V2	0.184	0.092	0.272	0.690	0.027	−0.032	−0.033

	var (N_r)	var (N_v)	var (N_{roe})	DIFF1	cov (N_r, N_v)	cov (N_r, N_{roe})	cov (N_v, N_{roe})	VR
Panel E1: total asset as the denominator								
V1	0.019***	0.064***	0.123***	−0.059***	0.007***	−0.010***	−0.014***	0.184***
	(0.013)	(0.017)	(0.050)	(0.037)	(0.006)	(0.009)	(0.005)	(0.101)
V2	0.019***	0.049***	0.130***	−0.081***	0.005***	−0.006***	−0.008***	0.184***
	(0.012)	(0.006)	(0.063)	(0.058)	(0.003)	(0.011)	(0.004)	(0.101)
Panel E2: other information variable based on highest earnings forecasts								
V1	0.018***	0.060***	0.124***	−0.068***	0.005***	−0.006***	−0.010***	0.184***
	(0.013)	(0.015)	(0.056)	(0.044)	(0.006)	(0.010)	(0.005)	(0.101)
V2	0.017***	0.048***	0.131***	−0.083***	0.004**	−0.006***	−0.008***	0.184***
	(0.012)	(0.005)	(0.066)	(0.061)	(0.003)	(0.011)	(0.004)	(0.101)
Panel E3: other information variable based on lowest earnings forecasts								
V1	0.020***	0.057***	0.122***	−0.065***	0.009***	−0.008***	−0.007***	0.183***
	(0.013)	(0.017)	(0.054)	(0.042)	(0.006)	(0.009)	(0.006)	(0.101)

Table 7 continued

	var (N_r)	var (N_v)	var (N_{roe})	DIFF1	cov (N_r, N_v)	cov (N_r, N_{roe})	cov (N_v, N_{roe})	VR
V2	0.018***	0.047***	0.128***	−0.081***	0.004***	−0.005***	−0.006***	0.183***
	(0.012)	(0.007)	(0.061)	(0.055)	(0.003)	(0.011)	(0.004)	(0.101)

Panel A and Panel B display the coefficient estimates for the log-linear vector autoregressive (VAR) model for V1 and V2 respectively. The model variables include the mean-adjusted log excess returns (*return*), the mean-adjusted log other information variables (v), the mean-adjusted log accounting earnings (*roe*), and the mean-adjusted log book-to-market ratio (*bm*). The standard errors are presented in parentheses. *** (**, *) indicates significant at the 1 % (5, 10 %) level for two-tailed test

Panel C shows the variance decomposition for the VAR model. var($N_{r,t}$) is the variance of expected-return news. var($N_{v,t}$) is the variance of other information news. var($N_{roe,t}$) is the variance of expected-return news. cov($N_{r,t}$, $N_{v,t}$) and cov($N_{r,t}$, $N_{roe,t}$) are the covariance of expected-return news with other information news and earnings news respectively. cov($N_{v,t}$, $N_{roe,t}$) is the covariance between other information news and earnings news. DIFF1 is the difference between the variance of other information news and the variance of earnings news, var($N_{v,t}$)−var($N_{roe,t}$). VR is total variance of mean-adjusted excess return, equal to var($N_{r,t}$) + var($N_{v,t}$) + var($N_{roe,t}$)−2cov($N_{r,t}$, $N_{v,t}$)−2cov($N_{r,t}$, $N_{roe,t}$) + 2cov($N_{v,t}$, $N_{roe,t}$). var$(N_v)^+$ is the variance of other information news when other information news is positive. var$(N_v)^-$ is the variance of other information news when other information news is negative. DIFF1 is the difference between the variance of positive other information news and the variance of negative other information news, var$(N_v)^+$−var$(N_v)^-$. The standard errors (in parentheses) of the variances are computed using the Shao-Rao (1993) jackknife method. *** (**, *) indicates significant at the 1 % (5, 10 %) level for two-tailed test

Panel D displays the relative size of each variance/covariance component to the total variance

Panel E shows the variance decomposition for the VAR model for alternative other information variables, including other information variables when using total assets as the denominator (Panel E1), when using highest earnings forecasts rather the mean forecasts (Panel E2), and when using lowest earnings forecasts rather the mean forecasts (Panel E3). The standard errors (in parentheses) of the variances are computed using the Shao-Rao (1993) jackknife method. *** (**, *) indicates significant at the 1 % (5, 10 %) level for two-tailed test

(0.422). In addition, summary statistics in Table 1 shows that the standard deviation of earnings (0.274) is also higher than that of other information (0.123 for V1 and 0.118 for V2). The combination of lower persistence and variability therefore results in the fact that other information contributes less than accounting earnings to the variance of unexpected stock returns.

5.2 Additional variance decomposition tests

We also examine whether our results are robust to alternative measures of other information, alternative estimation procedure, or specifications of the models and potential omitted correlated variables. Our previous analysis uses lagged book value of equity as the denominator for measuring other information. However, there may be outliers created by very low book values, even after we have winsorized the variables at the top and bottom percentile and excluded firms with low market value of equity (less than $10 million) and extreme book-to-market ratios (higher than 100 or lower than 0.01). We therefore retest variance decomposition by using total assets as the denominator to measure alternative measures of other information and earnings. The results presented in Panel E1 of Table 7 are found to be qualitatively similar.

As discussed in Sect. 4.3, our other information measures also may be affected by forecast biases, as it is well documented that analyst forecasts tend to be overoptimistic. We report the results of variance decomposition (in Panel E2 and E3 of Table 7) for two alternative measures of other information by using the highest (most optimistic) forecasts and the lowest (most pessimistic) forecasts rather than the mean forecasts. The results are qualitatively similar.

Finally, we follow Vuolteenaho (2002) to estimate the VAR system over the entire sample. In such respect, the VAR is estimated using weighted least squares on the panel data, with one pooled prediction regression per state variable. Each annual cross-section is weighted equally by deflating the data for each firm-year by the number of firms in the cross-section of that year. We also estimate a richer VAR model with two lags of each of the state variables. The results (not tabulated) are quantitatively similar. To minimize the possibility that alternative explanations drive the reported results in Tables 6 and 7, we consider the impact of firm size, technology firms, and loss firms. In particular, we implement these robustness checks by forming two subsamples based on the magnitude of the control variable. Without exception, the results obtained (not tabulated) are similar to those reported above.

6 Information environment and the relationship between other information news and stock return volatility

In this section, we examine how a firm's information environment influences the extent to which uncertainty about other information news impacts firm-specific risk. Bryan and Tiras (2007) suggest that in poor information environments (e.g., poor earnings quality or high forecast dispersion) financial analysts are unlikely to rely on poor-quality earnings when predicting future earnings performance. In fact, financial analysts tend to weight "other" value-relevant information more heavily relative to the weighting on earnings and book value in formulating their forecasts. Given that financial analysts are likely to place greater weight on other information under such circumstances, we would expect the effect of other information news on future stock return volatility to be stronger when firms have a poor information environment.

As our focus is to identify how the effect of other information news and future volatility varies across information quality, we retest Eq. (16) by including a dummy (0,1) indicator variable, H, that represents firms with poor information environment. In particular, when the value of the information environment variable for a firm-year is ranked in the upper or lower half of the distribution in the corresponding year, we classify this observation as having either a "good" or "poor" information environment respectively.[44] Following prior studies (Bryan and Tiras 2007; Ferreira and Laux 2007; Rajgopal and Venkatachalam 2011), we use three proxies for information environment: earnings quality, forecast dispersion, and forecast bias, each as defined above. We include the interaction term of H and other information news to examine the effect of other information news across good and poor information environments. The regression model is as follows:

$$\begin{aligned}\mathrm{Log}(\mathrm{VOL}_{i,t}) = {} & \beta_0 + \beta_1 V^{+}_{i,t-1} + \beta_2 V^{+}_{i,t-1} * H_{i,t-1} + \beta_3 V^{-}_{i,t-1} + \beta_4 V^{-}_{i,t-1} * H_{i,t-1} \\ & + \beta_5 \mathrm{Log}(\mathrm{VV}_{i,t-1}) + \beta_6 \mathrm{ROE}_{i,t-1} + \beta_7 \mathrm{Log}(\mathrm{VROE}_{i,t-1}) + \beta_8 \mathrm{R}_{i,t} \\ & + \beta_9 \mathrm{Size}_{i,t-1} + \beta_{10} \mathrm{Age}_{i,t-1} + \beta_{11} \mathrm{Lev}_{i,t-1} + \beta_{12} \mathrm{Log}(\mathrm{BM}_{i,t-1}) \\ & + \beta_{13} \mathrm{BIAS}_{i,t-1} + \beta_{14} \mathrm{DISP}_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{17}$$

The results in Table 8 suggest that the relationship between other information news and future return volatility varies across good and bad information environments. Take the results in column (1) as an example. For firms classified as having a good information environment, unfavorable other information news tends to increase future volatility (coefficient = −0.084), but the regression coefficient for V^{+} is insignificant (coefficient = −0.003; $t = -0.17$). This is consistent with Kothari et al. (2009), who find that unfavorable disclosures are accompanied by a significant contemporaneous increase in the firm's risk. For firms classified as having a poor information environment, both favorable and unfavorable other information is found to increase future volatility. The coefficient associated with $V^{+}H$ in column (1) is positive (0.034) and significant ($t = 2.79$), while the comparable coefficient for V–H is −0.023 ($t = -2.18$). This suggests that, when confronted with a poor information environment, analysts tend to focus less on accounting fundamentals and rely more on other information. This also supports the argument in Bryan and Tiras (2007) that Ohlson's (1995) valuation model better describes market pricing in poor information environments than in good information environments.

[44] Our results are robust to an alternative ranking based on the entire sample distribution rather than year by year.

Table 8 Standardized regression of stock return volatility on other information variables, controlling for information environment

	Panel A: earnings quality		Forecast dispersion		Forecast bias	
	V1 (1)	V2 (2)	V1 (3)	V2 (4)	V1 (5)	V2 (6)
Intercept	0.108	0.113	0.063	0.068	0.063	0.068
	(1.19)	(1.25)	(0.68)	(0.73)	(0.68)	(0.73)
V^+	−0.003	−0.006	0.004	−0.010	0.010	0.011
	(−0.17)	(−0.31)	(0.31)	(−0.68)	(1.23)	(1.15)
$V^+ * H$	0.034***	0.044***	0.024***	0.039***	0.016*	0.017*
	(2.79)	(3.58)	(2.86)	(4.78)	(1.71)	(1.69)
V^-	−0.084***	−0.083***	−0.065***	−0.082***	−0.075***	−0.080***
	(−5.13)	(−5.22)	(−2.59)	(−3.41)	(−6.96)	(−5.97)
$V^- * H$	−0.023**	−0.023**	−0.049**	−0.021**	−0.047***	−0.015*
	(−2.18)	(−2.01)	(−2.45)	(−1.98)	(−3.52)	(−1.94)
LogVV	0.139***	0.113***	0.121***	0.092***	0.119***	0.091***
	(8.54)	(6.72)	(6.87)	(5.11)	(6.75)	(5.07)
ROE	−0.095***	−0.093***	−0.119***	−0.120***	−0.125***	−0.128***
	(−5.15)	(−5.02)	(−6.51)	(−6.62)	(−6.88)	(−6.99)
Log(VROE)	0.118***	0.122***	0.140***	0.149***	0.146***	0.154***
	(7.43)	(7.43)	(9.58)	(9.77)	(10.25)	(10.34)
Control	Yes	Yes	Yes	Yes	Yes	Yes
N	27,150	27,150	40,837	40,837	40,837	40,837
Adj. R^2 (%)	38.2	37.6	35.6	34.9	35.6	34.8
Wald test	67.18	80.74	63.23	68.41	76.19	77.56
p value	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)

This table presents results from regressing stock return volatility on other information variables and other variables at the firm level

$$\begin{aligned}\mathrm{Log}(\mathrm{VOL}_{i,t}) = \beta_0 + \beta_1 V^+_{i,t-1} + \beta_2 V^+_{i,t-1} * H_{i,t-1} + \beta_3 V^-_{i,t-1} + \beta_4 V^-_{i,t-1} * H_{i,t-1} + \beta_5 \mathrm{Log}(\mathrm{VV}_{i,t-1}) + \beta_6 \mathrm{ROE}_{i,t-1} \\ + \beta_7 \mathrm{Log}(\mathrm{VROE}_{i,t-1}) + \beta_8 \mathrm{R}_{i,t} + \beta_9 \mathrm{Size}_{i,t-1} + \beta_{10} \mathrm{Age}_{i,t-1} + \beta_{11} \mathrm{Lev}_{i,t-1} \\ + \beta_{12} \mathrm{Log}(\mathrm{BM}_{i,t-1}) + \beta_{13} \mathrm{BIAS}_{i,t-1} + \beta_{14} \mathrm{DISP}_{i,t-1} + \varepsilon_{i,t}\end{aligned}$$

VOL is a proxy for total volatility, idiosyncratic volatility, or systematic volatility respectively. other information variable V is calculated by paralleling the approaches in either Bryan and Tiras (2007) or Dechow et al. (1999) (denoted as V1 and V2 respectively). V^+ equals to V if V is positive and 0 otherwise. V^- equals to V if V is negative and 0 otherwise. H is a dummy indicator variable representing firms with poor information environments (proxied by earnings quality, forecast dispersion, or forecast bias) when equal to 1. When the value of the information environment variable (earnings quality, forecast dispersion, or forecast bias) for a firm-year is ranked in the upper or lower half of the distribution in the corresponding year, we classify this observation as a "good" or "poor" information environment, respectively. The volatility of other information, VV, is the sample variance of V within the past 5 years for a minimum of three observations. Control variables include ROE (return on equity), VROE (the sample variance of ROE), RETURN (the contemporaneous annual buy-and-hold returns), SIZE (the natural logarithm of the firm's market value of equity), AGE (the logarithm of the number of months from the firm's IPO date to the current year), LEV (financial leverage), BM (the ratio of the book value of equity to the market value of equity), BIAS (analyst forecast bias), and DISP (analyst forecast dispersion). All *t*-statistics (in parentheses) are calculated using standard errors corrected for both clustering by firm and clustering by year. *** (**, *) indicates significant at the 1 % (5, 10 %) level for two-tailed test. The null hypothesis for the Wald test is $\beta_1 = -\beta_2$, and figures in parentheses are the probabilities of accepting the null hypothesis

7 Conclusion

In this study, we propose other information in analysts' forecasts as an additional proxy for future cash flows and evaluate its validity in explaining stock return volatility. In the spirit of Ohlson (1995, 2001), other information is considered as the information about fundamentals beyond that reflected in current financial statements and is measured by using earnings forecasts made by financial analysts. Our empirical tests based on standardized regressions and variance decomposition indicates that future volatility increases if current other information is more uncertain or unfavorable. While the variance decomposition approach suggests that other information is marginally less important than accounting earnings in explaining future volatility, this is due to the lower persistence and lower variability of other information. Nevertheless, the standardized regressions that we also estimate highlight the economic and statistical significance of other information in influencing future return volatility. We also find that the above pattern holds with respect to both systematic and idiosyncratic volatility and the relationship between other information and future return volatility is stronger for firms with poor information environments.

Our results support the view that other information reflected in analysts' forecasts is an incremental indicator of fundamentals and demonstrate the potential importance of including this proxy in stock price and volatility studies. For managers concerned with the firm-specific risk component of stock volatility, our results suggest that attention to the richness of the information environment for the stock may be warranted. Managers may not necessarily be able to manage market volatility, let alone idiosyncratic volatility, but they can take an active role in ensuring the richness of their firm's information environment, thereby reducing the extent to which information about the firm's fundamentals is uncertain.

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Appendix 1: Detailed derivation of hypotheses

Recall that the ROE-based information dynamic is that ROEs satisfy the following autoregressive process:

$$ROE_t = c + wROE_{t-1} + v_{t-1} + u_t \tag{18a}$$

$$Var_{t-1}(u_t) = g(u_{t-1}^2, u_{t-2}^2, \ldots, u_{t-k}^2, u_{t-1}) \tag{18b}$$

$$v_t = \phi v_{t-1} + \varepsilon_t \tag{18c}$$

$$Var_{t-1}(\varepsilon_t) = f(\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \ldots, \varepsilon_{t-k}^2, \varepsilon_{t-1}) \tag{18d}$$

where v_t is other information, namely information about future earnings not in current financial information; w and φ are fixed persistence parameters that are nonnegative and less than one; c is the intercept; u_t and ε_t are the mean zero disturbance terms.

First, calculating the conditional expectation of ROE_{t+j} at time t:

$$\begin{aligned}
\mathrm{E}_t\left(\mathrm{ROE}_{t+j}\right) &= \mathrm{E}_t(c + w\mathrm{ROE}_{t+j-1} + v_{t+j-1} + \mathrm{u}_{t+j}) \\
&= c + w\mathrm{E}_t\left(\mathrm{ROE}_{t+j-1}\right) + \mathrm{E}_t\left(v_{t+j-1}\right) \\
&= c + w\mathrm{E}_t\left(c + w\mathrm{ROE}_{t+j-2} + v_{t+j-2} + \mathrm{u}_{t+j-1}\right) + \phi^{\mathrm{j}-1} v_t \\
&= c\left(1 + w + w^2 + \ldots + w^{\mathrm{j}-1}\right) + w^{\mathrm{j}}\mathrm{E}_t(\mathrm{ROE}_t) \\
&+ \left(\phi^{\mathrm{j}-1} + w\phi^{\mathrm{j}-2} + \ldots + w^{\mathrm{j}-1}\right) v_t \\
&= c(1 - w^{\mathrm{j}})/(1 - w) + w^{\mathrm{j}}\mathrm{ROE}_t + \sum_{\mathrm{i}=1}^{\mathrm{j}} w^{\mathrm{i}-1}\phi^{\mathrm{j}-\mathrm{i}} v_t
\end{aligned} \tag{19}$$

Similarly, we have:

$$\mathrm{E}_{\mathrm{t}-1}(\mathrm{ROE}_{\mathrm{t+j}}) = \mathrm{c}(1 - w^{\mathrm{j}+1})/(1 - w) + w^{\mathrm{j}+1}\mathrm{ROE}_{\mathrm{t}-1} + \sum_{\mathrm{i}=0}^{\mathrm{j}} w^{\mathrm{i}}\phi^{\mathrm{j}-\mathrm{i}} v_{\mathrm{t}-1} \tag{20}$$

Given (19) and (20), the change of expectation of ROE_{t+j} can be written as:

$$\begin{aligned}
\Delta\mathrm{E}_{\mathrm{t}}(\mathrm{ROE}_{\mathrm{t+j}}) &= \mathrm{E}_{\mathrm{t}}(\mathrm{ROE}_{\mathrm{t+j}}) - \mathrm{E}_{\mathrm{t}-1}(\mathrm{ROE}_{\mathrm{t+j}}) \\
&= w^{\mathrm{j}}(v_{\mathrm{t}-1} + u_{\mathrm{t}}) + \sum_{\mathrm{i}=1}^{\mathrm{j}} w^{\mathrm{j}-\mathrm{i}}\mathrm{r}^{\mathrm{i}-1}(v_{\mathrm{t}} - \phi \mathrm{v}_{\mathrm{t}-1}) - w^{\mathrm{j}} v_{\mathrm{t}-1}
\end{aligned}$$

After some algebra, we obtain:

$$\Delta\mathrm{E}_{\mathrm{t}}(\mathrm{ROE}_{\mathrm{t+j}}) = w^{\mathrm{j}} u_{\mathrm{t}} + \frac{w^j - \phi^j}{w - \phi}\varepsilon_t \tag{21}$$

Summing up the discounted change in the change of expectation of ROE_{t+j}, we have:

$$\Delta\mathrm{E}_{\mathrm{t}}\sum_{\mathrm{j}=0}^{\infty}\rho^{\mathrm{j}}\mathrm{ROE}_{\mathrm{t+j}} = \frac{1}{1 - \rho\mathrm{w}}\mathrm{u}_{\mathrm{t}} + \frac{\rho}{(1 - \rho\mathrm{w})(1 - \rho\phi)}\varepsilon_t \tag{22}$$

Therefore, we have the representation of Eq. (6):

$$\begin{aligned}
\mathrm{Var}_{\mathrm{t}-1}(\Delta\mathrm{E}_{\mathrm{t}}\sum_{\mathrm{j}=0}^{\infty}\rho^{\mathrm{j}}\mathrm{ROE}_{\mathrm{t+j}}) &= \frac{1}{(1 - \rho w)^2}\mathrm{Var}_{\mathrm{t}-1}(u_{\mathrm{t}}) \\
&+ \frac{\rho^2}{(1 - \rho w)^2(1 - \rho\phi)^2}\mathrm{Var}_{\mathrm{t}-1}(\varepsilon_{\mathrm{t}})
\end{aligned}$$

Appendix 2

See Table 9

Table 9 Variable measurement

Variable	Measurement (Compustat items)
Panel A: stock return volatility*	
Total volatility (TVOL)	The sample variance of daily stock returns (in percentage) over the year
Idiosyncratic volatility from Fama–French model (IVOLF)	The sum of squared residuals from the Fama–French three-factor model divided by the number of trading days within the year
Systematic volatility from Fama–French model (SVOLF)	Total volatility minus idiosyncratic volatility from Fama–French model
	*All volatility measures are in percentage and calculated from the fifth month after the fiscal year-end, with the assumption that financial statement numbers is publicly available within four months after the fiscal year-end.
Panel B: firm-specific control variables	
ROE	Net income (NI)/lagged book value of equity (CEQ)
ROE volatility (VROE)	The sample variance of yearly ROEs observations over the past 5 years for a minimum of three observations
Firm stock return (RETURN)	Annual buy-and-hold returns, calculated from the sixth month after the fiscal year-end
AGE	The logarithm of the number of months from the firm's IPO date. If IPO dates are unavailable, we use the first tracking date of the firm appearing in the CRSP
SIZE	The logarithm of the firm's market value of equity at the end of fiscal year, market value of equity is defined as common shares outstanding (CSHO) times price—fiscal year—close (PRCC_F)
Leverage (LEV)	(Total long-term debt (DLTT) + debt in current liabilities (DLC))/ Total assets (AT)
Book-to-market ratio (BM)	Book value of equity (CEQ)/market value of equity
Forecast bias (BIAS)	The absolute difference between the 1-year-ahead consensus analyst forecast of year t + 1 earnings per share reported in the fifth month after the fiscal year-end, and the actual earnings per share reported in I/B/E/S, divided by stock price at the fiscal year-end
Forecast dispersion (DISP)	The standard deviation of one-year-ahead consensus analyst forecasts of year t + 1 earnings per share, measured in the fifth month after the fiscal year-end, standardized by the absolute value of consensus analyst forecasts of year t + 1 earnings per share
Panel C: variables used in calculating other information	
Book value of equity per share (BVPS)	Book value of equity (CEQ)/the multiplier of common shares outstanding (CSHO) and adjusted factor (cumulative) by ex-date (AJEX)
I/B/E/S ROE (AROE)	The actual earnings per share reported in I/B/E/S over BVPS
Forecast ROE (FROE)	The one-year-ahead consensus analyst forecast of year t + 1 earnings per share reported in the fifth month after the fiscal year-end divided by lagged book value of equity per share. The consensus analysts' forecast is taken from the Summary History data set of I/B/E/S. This variable is calculated on the basis of all outstanding forecasts as of (ordinary) the third Thursday of each month. The results are qualitatively similar if using the consensus analysts forecast in the fifth month after the fiscal year-end.
ROE persistence (w)	The persistence of ROE as a function of known determinants, including market share, firm size, R&D intensity, advertising intensity, capital intensity, the magnitude of ROE, the magnitude of special items, and the magnitude of total accruals

Table 9 continued

Variable	Measurement (Compustat items)
Other information variable ONE (V1)	The residual from regressing one-year-ahead analyst forecast of future earnings (FROE) on current publicly available financial information including book value of equity per share (BVPS) and ROE (Bryan and Tiras 2007)
Other information variable TWO (V2)	One-year-ahead analyst forecast of future earnings (FROE) minus the expectation of earnings based only on current period earnings estimated from the AR(1) process of ROE (Dechow et al. 1999 and Ohlson 2001)
Volatility of other information variable ONE (VV1)	The sample variance of yearly V1 observations over the past five years for a minimum of three observations
Volatility of other information variable TWO (VV2)	The sample variance of yearly V2 observations over the past five years for a minimum of three observations
Panel D: determinants of ROE persistence	
Market share (Marketshare)	Sales (sale)/total sales over the industry
Firm size (TA)	The natural logarithm of total assets (AT)
R&D intensity (RD)	R&D expenditures (XRD)/sales
Advertising intensity (AD)	Advertising expenditures (XAD)/sales
Capital intensity (CapIn)	Depreciation, depletion, and amortization expenses (DP)/sales
Magnitude of ROE (ABSROE)	ǀ ROE ǀ
Magnitude of special items (ABSSPI)	ǀ Special items (SPI) ǀ/lagged book value of equity
Magnitude of total accruals (ABSTACC)	ǀ Income before extraordinary items (IBC)—operating cash flow (OANCF) ǀ/lagged book value of equity

If operating cash flow (OANCF) is missing or unavailable (prior to 1987), total accruals are estimated as: change in current assets (ACT)—change in current liabilities (LCT)—change in cash and cash equivalents (CHE) + change in debt in current liabilities (DLC)—depreciation, depletion, and amortization expenses (DP). Debt in current liabilities is set to be zero if it is reported as missing in the Compustat

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