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Unusual News Flow and the Cross-Section of Stock Returns

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Abstract

We document that stocks that experience sudden increases in idiosyncratic volatility underperform otherwise similar stocks in the future, and we propose that this phenomenon can be explained by the Miller (1977) conjecture. We show that volatility shocks can be traced to the unusual firm-level news flow, which temporarily increases the level of investor disagreement about the firm value. At the same time, volatility shocks pose a barrier to short selling, preventing pessimistic investors from expressing their views. In the presence of divergent opinions and short selling constraints, prices end up initially reflecting optimistic views but adjust down in the future as investors' opinions converge.

JEL classification: G10, G12, G14

Keywords: Unusual News Flow, Volatility Shocks, Short Sale Constraints, Market Efficiency

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1. Introduction

In this paper, we investigate the effects of sudden increases in stocks' idiosyncratic volatilities on stock returns. In a somewhat surprising result, we find that positive shocks to idiosyncratic volatility predict future underperformance. Though the negative relation between volatility shocks and future returns goes counter to the expectation that investors, some of whom are undiversified, might want to be rewarded for taking on idiosyncratic risk, we offer an explanation for this result that finds ample support in the data. The explanation proceeds in three steps. First, we show that large volatility increases can be traced to unusual news events at the firm level. Specifically, we document that stocks' idiosyncratic volatility levels significantly increase as a result of the unusual news flow, identified using the Thompson-Reuters news dataset. Second, we document that such unusual news flow temporarily increases the level of investor disagreement about the firm value by showing that volatility shocks coincide with temporary increases in analyst forecast dispersion. Third, high levels of idiosyncratic volatility prevent pessimistic investors from opening short positions for fear of margin calls. Regarding that, we show that short selling demand falls as a result of idiosyncratic volatility shocks. With these three regularities, the Miller (1977) hypothesis offers an explanation for the negative relation between idiosyncratic volatility shocks and future returns. Given the high costs of short selling, pessimistic investors sit on the sidelines, while optimistic investors bid up stock prices to reflect their own valuations. Subsequently, as investors learn more about the value consequences of the news, the levels of both investor disagreement and return volatility decrease. The initially optimistic investors, on average, revise their valuations down, and prices decline. The graphical illustration of this explanation is provided in Figure 1 in the Online Appendix.

That there must be a strong link between idiosyncratic volatility and news has been frequently suggested in the volatility literature. However, it is difficult to observe news, especially because some announced news may be anticipated. Hence, in this literature, news is customarily defined as a residual price movement within the context of a predictive model. Furthermore, having observed that firm-level volatility, though fairly constant, sometimes exhibits periods of high volatility, several studies advocate that news arrival patterns should be classified in accordance with the volatility dynamics into (a) the normal news flow and (b) unusual news events (or the unusual news flow)[1] that is characterized by volatility shocks and subsequent periods of high volatility (e.g., Andersen (1996) and Maheu and McCurdy (2004)).

[1]We will use the terms "unusual news (events)" and "unusual news flow" interchangeably since unusual news events (e.g., corporate lawsuits, product recalls, etc.) tend to generate additional news coverage, making the two highly correlated.

We estimate idiosyncratic volatility shocks as a deviation from the volatility level predicted by the EGARCH model of Nelson (1991) (or, alternatively, as a deviation from the trailing average volatility level). We then document a robust negative relation between idiosyncratic volatility shocks and next month's stock returns. We show that this relation is present in different subsamples and survives controlling for various stock characteristics, as well as for the loadings on the innovations-in-the-aggregate-volatility factor used by Ang, Hodrick, Xing, and Zhang (2006).

Next, we show that idiosyncratic volatility shocks can indeed be traced to the unusual news flow. We calculate the unusual news flow using the Thompson-Reuters News Analytics dataset (TRNA), which is an extensive dataset of firm-specific news, spanning a long time series. Of course, the TRNA dataset cannot be a complete collection of the value-relevant news. Some important news goes unreported, especially for smaller firms, because of journalists' resource constraints and readers' attention constraints. Some relevant news may be first revealed by the firm's customers, suppliers, competitors, business partners, and otherwise similar firms (e.g., Cohen and Frazzini (2008) and Scherbina and Schlusche (2016)). Some news may be disseminated by Internet message-board postings ahead of the official reports. These alternative news channels may deliver important news ahead of the stories reprinted in the TRNA dataset and thereby weaken the effect of the unusual news flow, computed from the dataset, on idiosyncratic volatility. That we find a significantly positive relation between the two nonetheless illustrates that news arrival is an important driver of idiosyncratic volatility shocks.[2]

Volatility shocks tend to coincide with higher levels of disagreement. While the literature on firm disclosure traditionally assumes that public news announcements reduce the level of informational asymmetry and, hence, disagreement in the market (e.g., Healy and Palepu (2001)), Harris and Raviv (1993) show that when agents use different valuation models and interpret new information differently, information arrivals will lead to increased disagreement levels. Unusual firm-level news is very likely to increase rather than to decrease levels of investor disagreement. Indeed, we show that volatility shocks are associated with temporary increases in analyst earnings forecast dispersion.

High idiosyncratic volatility increases short selling risks. The reason is that, whenever a short position in a security is held, upward price movements generate margin calls. An arbitrageur who does not have access

[2]The link between unusual news events and positive volatility shocks is further corroborated by Clayton, Hartzell, and Rosenberg (2005), who find that CEO departures, especially the forced ones that in the authors' view create "higher uncertainty over the firm's strategic direction and management's ability to run the firm" (page 2), lead to significant increases in stock volatility.

to additional capital to meet a margin call may be forced to scale back or even close down the short position prematurely and incur a loss (e.g., DeLong, Shleifer, Summers, and Waldmann (1990), Shleifer and Summers (1990), Shleifer and Vishny (1997), Xiong (2001), and Gromb and Vayanos (2002)).[3] An arbitrageur could potentially reduce the level of idiosyncratic volatility by forming a portfolio of the stocks that have experienced volatility shocks. However, this portfolio would still contain significant idiosyncratic risk. In our sample, the average volatility of the value-weighted portfolio of stocks in the highest volatility-shock decile is, on average, 2.32% per month higher than that for the market portfolio. Most of this volatility is idiosyncratic and cannot be hedged away. Having obtained monthly data on short sale demands for individual stocks from Markit, we show that stocks that experienced shocks to their idiosyncratic volatility see a significant reduction in their short selling demand. Therefore, volatility shocks create a barrier to short selling.

Our results, thus, fit perfectly into the theoretical literature relating investor disagreement and short sale constraints with future returns. The theoretical models of Miller (1977), Harrison and Kreps (1978), Morris (1996), Chen, Hong, and Stein (2001), Scheinkman and Xiong (2003), and Hong, Scheinkman, and Xiong (2006) show that when agents disagree about the fundamental value of a firm and the short-sale constraint binds, stock prices reflect optimistic views. When additional information comes out over time and investor disagreement subsides, the prices converge down to reflect the average investor opinion. To sum up our results, we show that significant news events tend to increase the level of disagreement among investors and also increase stocks' idiosyncratic volatilities, making it costly for pessimistic investors to sell them short. Reflecting the views of the more optimistic investors, stock prices thus overreact to good news and underrect to bad news. In the future, as market participants converge to a consensus view, the initially optimistic investors, on average, revise their views down, and prices decrease.

Our results add to the growing empirical literature that documents the link between investor disagreement, concurrent asset overvaluation, and future underperformance, the theoretical basis of which was discussed earlier. Using various proxies for investor disagreement and for the severity of the short-sale constraint, Chen, Hong, and Stein (2001), Diether, Malloy, and Scherbina (2002), and Boehme, Danielsen, and Sorescu (2006) find that high levels of disagreement predict low stock returns for the next few months. Scherbina (2008) and Berkman, Henk, Jain, Koch, and Tice (2009) show that high investor disagreement also lowers returns around earnings announcements. Houge, Loughran, Suchanek, and Yan (2001) show that high lev-

[3]Mitchell, Pulvino, and Stafford (2002) estimate that for merger arbitrage, the cost of margin calls caused by the volatile path to convergence is roughly 50% of the potential profit. Pontiff (2006) offers a literature review on idiosyncratic volatility as a cost to arbitrage.

els of disagreement help explain the short-run IPO overvaluation and the long-run underperformance, and Loughran and Marietta-Westberg (2005) document the negative relation between disagreement and future stock returns for both IPOs and SEOs. Cao, Leng, Liu, and Megginson (2016) present similar evidence for Chinese IPOs. Hwang, Lou, and Yin (2016) argue that offsetting investor disagreement, which cancels itself out when stocks are combined into portfolios, can explain such long-standing puzzles as the diversification discount and the closed-end fund discount. Finally, in the context of corporate takeovers, Chatterjee, John, and Yan (2012) show that the takeover premium paid by a bidder increases with the level of disagreement about the target's value.

Our findings that volatility shocks predict future underperformance are related to a series of recent papers that document a negative relation between volatility *levels* and future returns in the cross-section of stocks. Ang, Hodrick, Xing, and Zhang (2006) measure idiosyncratic volatility as the standard deviation of the residuals from the three-factor Fama and French (1993) model and show a strong negative link between idiosyncratic volatility and expected stock returns for the U.S. stock market.[4] Boehme, Danielsen, Kumar, and Sorescu (2009) show that this result is present only for the stocks that are likely to be short-sale constrained. Fu (2009) documents a significantly positive relation between conditional idiosyncratic variance and the cross-section of expected returns. Spiegel and Wang (2005) estimate idiosyncratic volatility from monthly rather than daily returns and examine the interaction between idiosyncratic risk and liquidity; they find that stock returns increase with the level of idiosyncratic risk and decrease with the stock's liquidity but that idiosyncratic risk often subsumes the explanatory power of liquidity.

In contrast to these papers, we base our analysis on *shocks* to idiosyncratic volatility rather than on volatility *levels*. Idiosyncratic volatility is highly persistent and exhibits significant cross-sectional differences across stocks and industries.[5] Therefore, volatility shocks rather than levels are the appropriate diagnostics for identifying unusual news events. Our results are robust to the inclusion of other commonly used return predictors, such as short-term return reversals (Jegadeesh (1990)), size and book-to-market (Fama and

[4] Fu (2009) and Huang, Liu, Rhee, and Zhang (2010) point out that the results are related to monthly return reversals and Bali and Cakici (2008) note that the results are sensitive to the portfolio construction methodology and to the data frequency at which volatility is estimated. Chen and Petkova (2012) introduce a new factor based on innovations in average stock variance and argue that positive loadings of high-volatility stocks on this factor, which has a negative price of risk, explain their subsequent underperformance.

[5] For example, stocks in the regulated utility sector exhibit the lowest average (median) monthly idiosyncratic volatility, 5.90% (4.76%), while stocks in the high-tech sector, the highest, 17.34% (13.74%). For this reason, volatility-level sorts inadvertently make industry bets, such that the high volatility-level portfolio loads heavily on high-tech stocks and underweights utilities, while the low volatility-level portfolio exhibits the opposite pattern. Due to these inherent industry bets, volatility-level-sorted portfolios are substantially less correlated with each other than volatility-shock-sorted portfolios, since the latter sort does not load unevenly on different industries. As a result, a long-short position in the extreme volatility-shock-sorted portfolios amounts to a better hedge.

French (1992) and Fama and French (1993)), momentum (Jegadeesh and Titman (1993)), liquidity (Amihud (2002)), skewness (Harvey and Siddique (2000)), demand for lottery-like payoffs (Bali, Cakici, and Whitelaw (2011)), various proxies for differences of opinion (e.g., Diether, Malloy, and Scherbina (2002) and Boehme, Danielsen, and Sorescu (2006)), abnormal trading volume (Gervais, Kaniel, and Mingelgrin (2001)), idiosyncratic volatility, exposure to aggregate volatility factors (e.g., Ang, Hodrick, Xing, and Zhang (2006)), as well as alternative methods of computing volatility shocks.

The rest of the paper is organized as follows. Section 2 describes the methodology for measuring volatility shocks and documents the robust negative relation between volatility shocks and future returns. Section 2 shows that volatility shocks lead to a reduction in the short selling demand. Section 3 documents that volatility shocks are associated with temporary increases in investor disagreement. Section 4 links volatility shocks to the unusual firm-level news flow and shows that news-induced volatility shocks predict future stock underperformance. Section 5 concludes the paper.

2. Idiosyncratic Volatility Shocks and Future Returns

In this section, we describe the methodology for measuring idiosyncratic volatility shocks and show that idiosyncratic volatility shocks are robust negative predictors of future returns.

2.1. Computing idiosyncratic volatility shocks relative to EGARCH forecasts

For the predictive model of idiosyncratic volatility, we choose the Exponential GARCH (EGARCH) specification of Nelson (1991), which includes lagged values of both volatility levels and return innovations. This specification has several advantages over two other commonly used models, ARCH and GARCH. First, since volatility is modeled as a log-process, estimated parameter values need not be restricted to ensure that the volatility forecast is non-negative and that the volatility process is stationary. Second, the specification lets volatility respond asymmetrically to high and low return shocks, thus allowing the estimates to reflect the empirical regularity that volatility tends to increase more in response to bad rather than good news. Various studies have confirmed that EGARCH is indeed superior to ARCH and GARCH in predicting future volatility (e.g., Pagan and Schwert (1990) and Nelson (1991)).

Following Fu (2009), the conditional idiosyncratic volatilities of individual stocks are estimated using the three-factor Fama and French (1993) model for the conditional mean of excess returns and the EGARCH(p,q) model of Nelson (1991) for the conditional variance.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + \eta_i \mathrm{SMB}_t + \delta_i \mathrm{HML}_t + u_{i,t}, \tag{1}$$

$$\ln \sigma_{i,t}^2 = \omega_i + \sum_{j=1}^{q} \lambda_{i,j} \ln \sigma_{i,t-j}^2 + \sum_{j=1}^{p} \left(\theta_{i,j} z_{i,t-j} + \gamma_{i,j} \left[\mid z_{i,t-j} \mid - E \mid z_{i,t-j} \mid \right] \right), \tag{2}$$

where $E(u_{i,t}^2 \mid \Omega_{t-1}) = \sigma_{i,t}^2$ is the conditional idiosyncratic variance of stock i in month t, estimated using the information available at time $t-1$, denoted by Ω_{t-1}. Furthermore, $z_{i,t} = u_{i,t}/\sigma_{i,t}$ has a standard normal distribution, i.e., $z_{i,t} \sim N(0,1)$, and $E \mid z_{i,t} \mid = \sqrt{2/\pi}$. The parameters in equations (1) and (2) are estimated simultaneously by maximizing the following conditional log-likelihood function:

$$L(\Theta) = -\frac{1}{2} \sum_{t=1}^{n} \left[\ln(2\pi) + \ln \sigma_{i,t}^2 + \frac{u_{i,t}^2}{\sigma_{i,t}^2} \right], \tag{3}$$

where n denotes the number of monthly stock return observations used in the estimation and Θ denotes a vector of parameters in the conditional mean $(\alpha_i, \beta_i, \eta_i, \delta_i)$ and the conditional variance $(\omega_i, \lambda_i, \theta_i, \gamma_i)$.

We estimate EGARCH out-of-sample, and, similarly to Fu (2009), we consider nine models of EGARCH, letting the lag lengths q and p vary between 1 and 3. We estimate the model given in equations (1)-(2) separately for each stock i in month t using all observations available through month $t-1$. We further require that the stock has at least 30 monthly return observations prior to month t. Among the nine models being considered, we choose the one with the lowest Akaike Information Criterion.

Having chosen the best model, we compute the volatility forecast for stock i for month t using only information available up to month $t-1$: $\mathrm{E}_{t-1}[IVOL_{i,t}]$. The shock to expected volatility is computed as the difference between the realized and the expected volatility:

$$IVOL_{i,t}^{\text{shock}} = IVOL_{i,t} - \mathrm{E}_{t-1}[IVOL_{i,t}]. \tag{4}$$

Thus, all of our volatility predictions made for the purpose of calculating volatility shocks are made out-of-sample.

The correlation between the predicted and realized values of *IVOL* is significantly positive and equal to 0.334 in our sample. Much like the realized volatility, the predicted volatility tends to be higher for small stocks and growth stocks, for stocks with high levels of analyst disagreement, high turnover, and low liquidity, and for younger firms. Table A1 in the Online Appendix reports the descriptive statistics on the idiosyncratic volatility shock and the expected idiosyncratic volatility level. The summary statistics indicate that, as expected, the idiosyncratic volatility shock is highly right-skewed.

It is important to stress that the volatility shocks that we study are large and, therefore, robust to the choice of the volatility measurement and volatility prediction model. In particular, we have also experimented in computing expected volatility levels using a number of alternative methodologies. In the first methodology, we estimate the average monthly idiosyncratic volatility as in Ang, Hodrick, Xing, and Zhang (2006) and then estimate the expected volatility level using a rolling regression on the trailing monthly average and industry dummies, with either the one-, two-, or three-year trailing estimation window. In the second methodology, we estimate the average monthly idiosyncratic volatility using five-minute return intervals and then predicting the next-month's volatility analogously. These alternative volatility and volatility-shock estimation methods are described in more detail in Section A2 in the Online Appendix. All estimation methods generate a very similar negative relation between volatility shocks and next-month's returns.

2.2. Volatility shocks and future returns

In the remainder of the section, we establish a robust negative relation that exists between the current month's volatility shocks and the following month's returns.

2.2.1. Volatility-shock-sorted portfolios

In order to establish the negative predictive ability of volatility shocks on future returns, every month we sort stocks into decile portfolios based on $IVOL^{\text{shock}}$. We then calculate next-month's equal- and value-weighted portfolio returns and the return differentials between the highest- and lowest-volatility-shock deciles as well as the corresponding four-factor alphas. The results are reported in Panel A of Table 1. The first two columns of the table present portfolios returns and their four-factor alphas for equal- and value-weighted portfolios, and the last column presents the average value of the idiosyncratic volatility shock.

Stocks in the lowest-volatility-shock decile (decile 1) have experienced a lower-than-expected idiosyncratic volatility realization in the current month—the average idiosyncratic volatility shock equals -9.39%. The stocks in the highest volatility-shock decile (decile 10) have experienced a positive volatility shock, which is equal to 14.09% on average. The decile-1 stocks have earned an average equal-weighted return of 1.67% and the average value-weighted return of 1.24% in the following month. The decile-10 stocks have earned a much lower next month's return, 0.64% on the equal-weighted portfolio, and 0.27% on the value-weighted portfolio, and the four-factor alphas of both equal- value-weighted portfolios are significantly negative. The monthly return differential between the high- and low-volatility-shock portfolios is -1.03% (t-statistic$= -9.60$) for the equal-weighted and -0.97% (t-statistic$= -4.50$) for the value-weighted portfolios, and their corresponding four-factor alphas are -0.93% (t-statistic$=-7.99$) and -0.98% (t-statistic$=-4.56$), respectively. Because equal-weighted portfolios are dominated by small stocks, the four-factor alphas of portfolios 1 through 8 are positive because of the size effect present in our sample. For the value-weighted portfolio, significant negative return differential is driven primarily by the negative alpha of the high-volatility-shock portfolio. The last row presents the alpha of the return differential with respect to a five-factor model; besides market, size, book-to-market, and momentum factors, it includes a fifth factor based on the return differential between stocks in the highest and lowest idiosyncratic volatility deciles.[6] The reason for including the fifth factor (just like the momentum factor) is to check whether the ability of the past shock to idiosyncratic volatility to predict returns can be subsumed by the tendency of these stocks to co-move with the volatility-level-based return factor. The five factors (including the volatility-level-based factor) explain some of the underperformance, but the unexplained intercept of the return differential is still significantly negative. (The factor loadings of the return differentials are reported in Table A3 in the Online Appendix; they show that the return differentials load positively on the aggregate idiosyncratic volatility factor).

What is remarkable about volatility-shock-sorted portfolios is that they can be well hedged with the long-short positions, making portfolio return differentials highly statistically significant. (Section A6 in the Online Appendix shows that the predictive ability of the idiosyncratic volatility shock works within industries.) As mentioned briefly in the introduction, the reason lies in the lack of industry bets contained in these portfolios since they have very similar weights across all industries. In contrast, momentum portfolios contain industry bets, loading unequally on industries with high/low past returns (Grinblatt and Moskowitz (1999)). Volatility-level-sorted portfolios, likewise, load differently on safe/risky industries. For example, the low volatility-level portfolio overweights utilities and underweights high-tech stocks, while the high-

[6] Ang, Hodrick, Xing, and Zhang (2006) show that idiosyncratic volatility is a negative significant predictor of future stock returns. *IVOL* factor is calculated as the return differential between the high and low *IVOL*-based decile portfolios. For the equal- (value-) weighted $IVOL^{\text{shock}}$ return differentials, the *IVOL* factor is constructed using equal- (value-) weighted returns.

volatility-level portfolio does the opposite.[7] Furthermore, the initially high level of idiosyncratic volatility of portfolio 10 declines by over 80% in the following month due to the highly transitory nature of volatility shocks.

The average stock characteristics for the stocks in each volatility-shock-sorted portfolio are reported in Table A2 and briefly discussed in Section A4 in the Online Appendix. While portfolios tend to display some differences in the average stock characteristics, we will show later in this section that the negative predictive ability of volatility shocks survives after controlling for the various stock characteristics that might be correlated with volatility shocks.

In addition to reporting the four-factor alphas, we also calculate characteristic-adjusted returns, as specified in Daniel and Titman (1997). The results are reported in Table A4 in the Online Appendix. This table also shows that the size-, book-to-market- and momentum-adjusted returns decline with $IVOL^{\text{shock}}$ and that the characteristic-adjusted-return differential between the high- and low-$IVOL^{\text{shock}}$ portfolios is also highly statistically significant and equal to -0.83% with the t-statistic$= -8.73$.

Panel B of Table 1, presents portfolio returns over two subsamples that roughly cut our time series at a midpoint, 1964-1988 and 1989-2012. The table shows that the portfolio return differentials are highly significant in both subsamples. In fact, the return differentials are somewhat more negative in the second subsample since since the cross-sectional spread in volatility-shock portfolios is considerably larger in the later than in the earlier sample period (24.50% vs. 17.23%).

In sum, the portfolio results show volatility shocks to be significant negative predictors of the next-month's return.

2.2.2. Robustness

In this subsection, we perform a variety of robustness tests to show that the portfolio results are robust to various screens imposed on the sample and to bivariate sorts on volatility shocks and a number of control variables that have been shown to predict stock returns.

[7] The correlation between the extreme value-weighted volatility-*shock* decile portfolios is 0.819, and it is only 0.464 for the extreme volatility-*level* decile portfolios and 0.524 for the extreme momentum decile portfolios for the same sample period. When returns are equal-weighted, the correlations between extreme decile portfolios are 0.938 for volatility-*shock* sorts, 0.582 for volatility-*level* sorts, and 0.672 for momentum sorts. For this reason, taking long-short positions in extreme portfolios based on momentum or volatility level strategies achieve less than perfect hedges.

Screening the sample for size, price and illiquidity. We begin by screening our sample on size, stock price, and illiquidity. It has been shown in prior research that small and illiquid stocks tend to be less efficiently priced because of the low levels of institutional ownership and the high trading costs involved in arbitrage (for example, Bali and Cakici (2008) show that after screening on size, price, and liquidity, no significant relation is observed between idiosyncratic volatility *levels* and future returns.) Hence, we reduce our sample by removing small, low-priced, and illiquid stocks. The results are reported in Panel C of Table 1.

In the left-most subtable of Panel C, we exclude from our sample the stocks that fall in the smallest NYSE-based size decile. In the next subtable, we exclude stocks priced at less than \$5 per share (as in Jegadeesh and Titman (2001)). In the subtable next to that, we perform a similar screening process based on stocks' illiquidity: In each month, we sort all NYSE stocks by their Amihud (2002) illiquidity measure and then exclude all stocks in our sample that would fall into the smallest NYSE-based liquidity decile. Finally, in the right-most table, we screen the sample jointly on size, price and illiquidity. We then recalculate the following month's returns of the volatility-shock-based portfolios using thus-reduced stock samples. The table reports equal- and value-weighted $IVOL^{\text{shock}}$-sorted portfolio returns, the return differentials between the high- and low-$IVOL^{\text{shock}}$ portfolios, as well as their four-factor alphas.

The table shows that the significantly negative relation between volatility shocks and future returns is preserved in all subsamples. As expected, the relation is the weakest in the most restricted subsample that screens jointly on all three variables, but even in this subsample the return differentials between the high and low volatility-shock decile portfolios are highly significant. The equal-weighted return differential is -0.72%, with a t-statistic of -7.58 (and its four-factor alpha is -0.72%, with a t-statistic of -7.24), and the value-weighted return differential is -0.54%, with a t-statistic of -3.06 (and its four-factor alpha to -0.53%, with a t-statistic of -2.77). Thus, these results show that our findings are not driven by small, low-priced, and illiquid stocks.

Screening the sample on momentum and reversals. Since positive returns are unbounded and negative returns are bounded from below by -100%, it is not surprising that the stocks in the high-volatility-shock portfolio tend to have higher contemporaneous returns than other stocks (see Table A2 in the Online Appendix). This raises a question of whether the subsequent underperformance of the high-volatility-shock portfolio can be explained by return reversals. The table also shows that the stocks in the high-volatility-shock portfolio tend to have lower momentum returns than the stocks in the low volatility-shock portfolio. Hence, the next-month's return differential may be explained by the price momentum phenomenon (Jegadeesh and Titman (1993)). In order to dismiss these alternative explanations, in addition to the other tests performed later, we begin by eliminating short-term and long-term winners and losers from our sample to check whether the predictive ability of the volatility shock exists in thus-screened samples. The results are presented in Panel C of Table 1.

In order to screen for reversals, in every month, we eliminate from the sample the stocks that fall in the top and bottom deciles of returns in that month. As indicated by the two left-hand-side columns in the table, we find that, despite eliminating a total of 20% of the stock sample, the return differentials between the highest and lowest $IVOL^{\text{shock}}$ decile portfolios remain highly statistically significant.

We use a similar approach when screening on momentum returns. We eliminate from the sample momentum winners and losers (stocks in top and bottom deciles) based on the 12-month return from month $t-11$ to month $t-1$ (we are forecasting the month-$t+1$ return). Again, despite reducing the sample by 20%, we find that the predictive power of $IVOL^{\text{shock}}$ remains highly significant (see the two right-hand-side columns of the table). Overall, these results indicate that our main findings are not driven by momentum or reversal phenomena.

Bivariate sorts. The fact that the decile-10 stocks exhibit some differences in the average stock characteristics that are known to forecast returns, compared to the rest of the sample, suggests that we need to perform a careful analysis to check whether or not the predictive ability of $IVOL^{\text{shock}}$ is not subsumed by these variables. By performing bivariate sorts on these stock characteristics that can forecast returns and $IVOL^{\text{shock}}$ (as well as running Fama and MacBeth (1973) cross-sectional regressions with these controls, as described in the next subsection), we show that the predictive ability of $IVOL^{\text{shock}}$ is robust to these controls. The results of bivariate sorts are presented in Table A5 and described in Section A5 in the Online Appendix. The results show that the predictive ability of $IVOL^{\text{shock}}$ is significant in all bivariate portfolio sorts.

2.2.3. Cross-sectional return regressions

While offering an advantage of being non-parametric, portfolio-level analysis does not easily allow us to account for the possible simultaneous effect of the control variables. To check whether the forecasting power of volatility shocks remains statistically significant after concurrently controlling for the competing predictors of returns, we run a cross-sectional monthly predictive regression of the form:

$$R_{i,t} = \lambda_{0,t} + \lambda_{i,t} IVOL^{\text{shock}}_{i,t-1} + \lambda_{2,t} X_{i,t-1} + \varepsilon_{i,t}, \tag{5}$$

where $R_{i,t}$ is the realized return for stock i in month t, $IVOL^{\text{shock}}_{i,t-1}$ is the idiosyncratic volatility shock, and $X_{i,t-1}$ is a vector of control variables for stock i in the preceding month $t-1$. We use the Fama and MacBeth (1973) regression methodology, to account for the possible cross-correlation in returns.

The cross-sectional monthly regressions, presented in Panel D of Table 1, show that the predictive ability of the volatility-shock variable is not subsumed by any of the other commonly used return predictors that are based either on stock characteristics (size, CAPM beta, book-to-market, asset value-to-market ratio, and the illiquidity measure), on the statistical properties of past returns (idiosyncratic volatility—expected and realized), idiosyncratic skewness, momentum return, reversal return, and the highest daily return earned in the prior month), on various proxies for investor disagreement (dispersion in analysts' forecasts, turnover, the inverse of the firm's age, and income volatility), abnormally high and low trading volume dummies, and the stock loadings on the innovations to the aggregate volatility factor. To control for possible commonalities in returns and volatility shocks within industries, all regressions also include 10 industry dummies (as in Fama and French (1997)).[8] All explanatory variables, as well as the 10 industries, are described in Section A3 in the Online Appendix.

In all nine regression specifications, the average regression coefficient of $IVOL^{shock}$ is negative and highly significant, ranging between -0.037 and -0.075. This range of the coefficients implies that an increase in idiosyncratic volatility of 14.09% (corresponding to the average across the stocks in the highest volatility-shock decile) will reduce the return in the next month by between 0.52% and 1.06%, which is in line with our portfolio results.

The average slopes on the control variables are in line with those documented in prior literature. Analyst forecast dispersion, size, volatility factor beta, the low-volume dummy, short-term reversal, and the maximum daily return over the prior month are significantly negative predictors, while momentum, book-to-market, the high-volume dummy, and idiosyncratic skewness are significantly positive predictors of the next month's returns over our sample period (the positive coefficient on idiosyncratic skewness is consistent

[8] The results are very similar without industry dummies.

with Bali, Cakici, and Whitelaw (2011)). Idiosyncratic volatility shocks subsume the predictive power of the idiosyncratic volatility level, even turning the coefficient on the idiosyncratic volatility level positive in specification (7).[9] Overall, the results in this section confirm that volatility shock is a robustly significant negative predictor of the return in the subsequent month.

3. Volatility shocks and the short selling demand

Pontiff (2006) calls idiosyncratic risk "the single largest cost faced by arbitrageurs" (page 1). Consider the following example that illustrates how a potential profit of a short position can be reduced due to a further price divergence from the fundamentals. Suppose that a brokerage house requires that the short seller maintains a margin of 30% (which is a common requirement across brokerages—the lowest margin allowed by the regulators is currently 25%). Suppose further that the short seller believes that the current stock price of \$10 per share is too high and will decline to \$9 per share. Therefore, when the short seller sells short 100 shares of the stock, she needs to deposit \$300 in the margin account. Given that she expects to earn \$100 (\$100 shares $\times$ (\$10$-$\$9)), the expected return on investment is equal to $\frac{\$100}{\$300} = 33.33\%$.

Now suppose that instead of steadily decreasing to \$9 per share, the price initially increases by 10%, to \$11/share (the 10% price increase is entirely likely and is, in fact, below the average idiosyncratic volatility shock experienced by the stocks in our top volatility-shock decile, as reported in Table 1). The equity value of the position drops to \$200 (= \$300 (margin) + 100 shares $\times$ \$10 (the initial short-sale proceeds) $-$ 100 shares $\times$ \$11 (the current liability)). The new margin is equal to $\frac{\$200}{100\text{ shares}\times\$11} = 18.18\%$. To comply with the margin requirement, the short seller or her broker needs to reduce the leverage by purchasing and returning 39.40 shares at the current price of \$11/share. This would bring the margin back to 30%. Barring any further price increases until the share price finally converges to \$9, the profit that the short seller will walk away with is \$21.20 (= 100 shares $\times$ \$10/share (the initial short-sale proceeds) $-$ 39.40 shares $\times$ \$11/share (the cost of repurchasing shares to comply with the margin requirement) $-$ (100 shares $-$ 39.40 shares) $\times$ \$9/share (the final liability)). And the actual return on the strategy will decline to only 7.07%, which is about one-fifth of the originally anticipated return. If the initial price increase is instead equal to 12%, the short seller will end up losing 0.7% on the position. And if the initial price increase is equal to 30%, both the

[9]The positive (or insignificant) relation between idiosyncratic volatility and future stock returns is also observed in different contexts, when controlling for a preference for expected skewness, lottery-like payoffs, or death/jackpot returns (see, e.g., Boyer, Mitton, and Vorkink (2010), Bali, Cakici, and Whitelaw (2011), and Conrad, Kapadia, and Xing (2014)).

initial margin and the short-sale proceeds will be used to prematurely repurchase shares and the short seller will end up losing 100% of the initial margin investment.[10]

In light of these concerns, it is, therefore, unlikely that short sellers would want to expose themselves to a much higher risk of margin calls immediately after a news announcement. Moreover, some models predict that arbitrageurs may rationally choose to wait until a mispricing gets larger before establishing their positions. (Consider, for example, the models of Abreu and Brunnermeier (2002) and DeLong, Shleifer, Summers, and Waldmann (1990), in which arbitrageurs initially trade with, rather than against, the mispricing, amplifying it and increasing their expected profits.) Short sellers may elect to open short positions only after the initially high idiosyncratic volatility has sufficiently declined, helping accelerate the convergence of prices to the fundamentals. Consistently, Engelberg, Reed, and Ringgenberg (2012) show that short sellers typically establish their positions not on the day that the news is announced but with a delay.[11]

We investigate the empirical relation between volatility shocks and the short selling demand. For this purpose, we have obtained the data on short selling demand from Markit (the dataset is described in Section A1 in the Online Appendix). Markit collects data on the number of shares available for lending to short sellers and the number of shares borrowed by short sellers. It also computes $Utilization$ as the ratio of the number of shares borrowed to the total number of shares available for lending. The Markit data are available from June 2002 to December 2012. In the earlier part of the sample, the variables are reported at the end of each month, and over time, Markit switches to the weekly and then the daily reporting frequency. For consistency purposes and to maximize the length of the time series, we keep only the month-end observations. The dataset that results from the merger of our original dataset with the Markit dataset contains 59.58% of the firm-month observations of our original dataset over that time period. The descriptive statistics for the variables of interest calculated for our resulting sample, utilization and shares borrowed by short sellers, are reported in Panel A of Table 2.

[10] More generally, assuming that the price initially increases by x percent before decreasing down to the fundamentals by d percent and the margin requirement is m percent, assuming that $x \leq m$, the loss in the expected return due to the margin call is equal to $\frac{x(1+m)(x+d)}{m^2(1+x)}$. Of course, a short seller may want to protect herself from margin calls by increasing the margin account, but that would not entirely solve the problem and would reduce the initially-expected return on the position.

[11] Following this line of reasoning, one might expect arbitrageurs to shy away from stocks that have a tendency to have positive return outliers. The ensuing margin calls force short sellers to buy back the shorted stock at the especially unfavorable prices, substantially reducing their anticipated profits. Therefore, margin calls may serve as a natural mechanism for limited arbitrage, which helps explain the future underperformance of stocks with positive return skewness and positive return outliers (documented in prior literature).

In order to check whether the short selling demand is negatively related to the idiosyncratic volatility shock, we do the following. Every month, we sort stocks into quintiles based on their idiosyncratic volatility computed in that month. Then we compute the average level of utilization and short selling demand as reported by Markit at the end of each month for each volatility-shock quintile. If high idiosyncratic volatility poses a barrier to short selling, short seller will reduce their share demands in anticipation of the continuation of the volatile period.[12] The results, reported in Panel B of Table 2, show that the short selling demand (captured either by utilization or by the number of shares borrowed by short sellers) indeed smoothly decreases with the idiosyncratic volatility shock. The differences in these two measures of the short selling demand between the high- and low-volatility-shock quintiles are significantly negative and economically meaningful. The average utilization is 4.22% lower and the number of shares borrowed by short sellers is 1.49 million lower for the highest than for the lowest volatility-shock quintile.

To make sure that the observed negative relation between volatility shocks and the short selling demand is not driven by past stock returns instead, we also perform a double sort on the last month's return and then, within each return quintile, on the idiosyncratic volatility shock. The results, reported in Panel C of Table 2, show that the short selling demand decreases with the idiosyncratic volatility shock within each prior-month's return quintile.

Of course, the short selling demand may also be also influenced by other stock-specific variables that may be correlated with the idiosyncratic volatility shock. To address this concern, we also run a pooled regression, with the standard errors double clustered by firm and date, that explains the month-end level of the short selling demand, captured by utilization or the number of shares borrowed by short sellers, with the idiosyncratic volatility shock and a number of control variables that could influence the short selling demand. We find that the significant negative predictive ability of idiosyncratic volatility shocks remains across all regression specifications. (The regression results are reported in Table A7 and discussed in Section A7 in the Online Appendix.)

4. The Temporary Increase in Investor Disagreement

In the next section, we will show that idiosyncratic volatility shocks are associated with the unusual firm-level news flow. This unusual news flow may pose investors a challenge when assessing its impact on the

[12] Also, some of short sellers' positions may have been wiped out, and their investment capital reduced by the volatility shock.

firm value and cause a temporary increase in investor disagreement. We turn to analyst forecasts to check whether volatility shocks are correlated with temporary increases in the level of analyst disagreement, which we use as a proxy for investor disagreement about the firm value.

Sell-side analysts forecast a number of accounting values for the firms that they follow. Virtually all analysts forecast the fiscal year's earnings; the following fiscal year's earnings forecasts are also very common; the long-term earnings growth forecasts are less common; while other forecasts (e.g., EBIT, EBITDA, dividend per share, and so on) are substantially less prevalent. In order to maximize the number of observations, we perform our analysis for the most frequently forecasted variable, the current fiscal year's earnings per share.[13] Another advantage of using the current fiscal year's earnings forecasts over, say, long-term growth forecasts, is that analysts are evaluated based on the accuracy of their earnings forecasts and consequently put more effort in forecasting earnings than in forecasting the long-term earnings growth rates, the accuracy of which is more difficult to evaluate.

We use the Unadjusted Detail I/B/E/S files that report individual analysts' forecasts unadjusted for stock splits and provide the forecasts' issuance dates and the dates on which previously issued forecasts are confirmed by I/B/E/S as still accurate. It is common for analysts who stop following a firm to not drop coverage immediately but instead to keep their stale forecasts in I/B/E/S. In order to eliminate the problem of stale estimates, for our analysis of changes in analyst disagreement we use only what we consider to be "active" forecasts. We define a forecast to be active for three months after the issuance date, as long as no new forecast is issued during that time.[14] Since some analysts issue earnings forecasts on the primary and some on the diluted basis, we convert all forecasts to the primary basis using the I/B/E/S conversion factor.[15] As in Diether, Malloy, and Scherbina (2002), analyst disagreement is defined as the standard deviation in the outstanding earnings forecasts for the closest fiscal year end divided by the absolute value of the mean earnings forecast.

[13]The change in disagreement measure constructed from analysts' forecasts is non-missing for 39.31% of firm-months and covers 57.46% of firms in the sample when based on current year's earnings forecasts; it covers 31.58% of firm-months and 51.08% of firms when based on the next-fiscal-year's earnings forecasts; and it is non-missing for 24.19% of firm-months and 40.96% of firms when constructed from long-term earnings growth forecasts.

[14]While I/B/E/S attempts to monitor the timeliness of the forecasts by periodically asking analysts to confirm their outstanding forecasts and removing stale forecasts from the dataset, they are not always consistent in doing so. However, our estimates are very similar when all outstanding forecasts are used.

[15]Diluted earnings per share forecasts scale the total forecasted earnings not by the number of shares currently outstanding but by number of shares that would be outstanding if all exercisable warrants, options, etc., were converted into shares by the earnings announcement date.

When the mean earnings forecast is zero, the observation is dropped.[16] And, as in that paper, we start the sample in January 1983 since the I/B/E/S Detail dataset has sparse cross-sectional coverage before that.

To check whether analyst disagreement increases in the month that a stock experiences a high idiosyncratic volatility shock, we test wether the difference between the current forecast dispersion and the lagged forecast dispersion is higher for the stocks with the currently high volatility shock values than for the stocks with the currently low volatility shock values. It is important to look at the cross-sectional differences because, as the fiscal year progresses, analysts receive new information about annual earnings through quarterly earnings announcements, management earnings forecasts, and other information releases; for this reason, the earnings forecast dispersion naturally decreases over the fiscal year. We look at the change in the disagreement, computed as the change in the dispersion in the active earnings forecasts at the end of the current month and the dispersion two months prior. (We skip one month in between because analysts revise their annual earnings forecasts relatively infrequently, with many analysts revising their annual forecasts only once a quarter.[17]) After each fiscal year's earnings are announced, the closest fiscal year end moves to the year after. In calculating the change in the forecast dispersion, we make sure to compare the dispersion of the earnings forecasted for the same fiscal year end. For example, firms with the December fiscal year end typically announce their earnings in January. Therefore, after January of year t, the next closest year fiscal end becomes December of $t+1$. When calculating the change in dispersion, say in January of 2001, we make sure to subtract the dispersion in the earnings forecasts for the fiscal year 2001 that were outstanding in November of 2000. Panel A of Table 3 describes the statistics on the change in analyst disagreement and shows that it tends to decline over the fiscal year.

Each month, we sort stocks into quintiles based on the value of $IVOL^{\text{shock}}$ that month.[18] We then check the change in the analyst disagreement between that month and two months prior. Moreover, to show that the increase in the disagreement in the high-IVOL-shock month is only temporary, we also check the change in the disagreement between the current month and two months after. The results are reported in Panel B of Table 3.

[16]We also get rid of extreme observations that could be caused by data errors or by scaling problems. Specifically, we delete earnings forecasts with the absolute value of the forecasted earnings to price ratio greater than 0.75 and observations with the scaled change in dispersion greater than 10.

[17]It has been hypothesized that analysts revise their earnings forecasts and stock recommendations only infrequently for incentive reasons (see, e.g., Bernhardt, Xiao, and Wan (2016)).

[18]Quintile rather than decile sorts are performed to increase the number of observations per $IVOL^{\text{shock}}$ group since the number of observations drop by about 60% when the original dataset is merged with the dataset on changes in analyst disagreement.

The table shows that, while dispersion, on average, decreases for the stocks in the $IVOL^{\text{shock}}$ quintiles 1 through 4, it slightly (but insignificantly) increases for the stocks in the quintile 5 during the *before* period. However, since the forecast dispersion typically decreases, the difference in the change in dispersion between the high- and low-$IVOL^{\text{shock}}$ quintiles is significantly positive. This confirms our conjecture that idiosyncratic volatility shocks increase the level of investor disagreement. In the *after* period, the forecast dispersion decreases significantly faster for the stocks in the highest $IVOL^{\text{shock}}$ quintile, making the difference between the extreme quintiles negative and statistically significant. The magnitudes show that in the subsequent two months, the high-volatility stocks experience a decrease in the level of investor disagreement, relative to the low-volatility-shock stocks, that is roughly equal to the initial increase in the disagreement.[19]

To further illustrate that it is volatility shocks that are accompanied by increases in investor disagreement that result in low future returns, we perform an additional test as follows. So far, we have shown that volatility shocks are, on average, associated with increases in investor disagreement. But this may not be true for all stocks, as some volatility shocks may result, for example, from trade order imbalances. Therefore, for each month, we sort the stocks in the high-volatility-shock quintile into further quintiles based on the prior change in analyst disagreement. We find that it is the stocks that fall in the highest-increase-in-disagreement quintile that earn low future returns: they underperform the stocks in the lowest-increase-in-disagreement quintile by 0.71% per month, on average (with the t-statistic$= -2.38$). Furthermore, these stocks also experience a significantly larger subsequent decrease in analyst disagreement than all other stocks, indicating that low returns coincide with the convergence of opinions.[20]

To sum up, in this section, we have shown that investor disagreement increases in the month in which we observe the high idiosyncratic volatility shock, but only temporarily; and that it is the stocks that experience volatility shocks that are combined with an increase in investor disagreement that earn low future returns.

[19] Since it takes a few months for the initial increase in the investor disagreement to disappear, it is not surprising that the month-t volatility shocks negatively predict future returns not only in the month $t+1$, documented in detail earlier in the paper, but also in months $t+2$ through $t+6$ when returns are equal-weighted and in month $t+2$ when returns are value-weighed (these results are available upon request).

[20] We thank the anonymous referee for the suggestion to look at the relation between the change in analyst disagreement and future returns.

5. Idiosyncratic Volatility Shocks, the Unusual News Flow, and Stock Returns

In this section, we explore the link between volatility shocks and the unusual news flow and then proceed to investigating the effect of news-driven volatility shocks on stock returns.

5.1. The effect of the unusual news flow on volatility shock

In this subsection, we provide evidence that the unusual news flow is associated with idiosyncratic volatility shocks. For this purpose, we rely on the Thomson-Reuters News Analytics dataset (TRNA). This is a dataset of machine readable news that covers news about publicly traded firms and is aimed at professional stock traders and institutional investors. The dataset contains all information that Thomson-Reuters considers to be value-relevant and, therefore, useful for traders and investors. The news is reported in a timely matter, as Reuters competes for clients with firms such as Bloomberg and Dow Jones. The dataset includes news items from 41 news media outlets and covers the period from April 1996 to December 2012. Each news item is assigned a sentiment score (positive, neutral, or negative) based on a proprietary linguistic algorithm that counts the relative number of positive and negative words in the text of the news story, as these words pertain to the firm being discussed.[21] Each news item also contains a relevance score, assigned by Reuters; the sentiment score determines how relevant a news story is to each firm mentioned if several firms are co-mentioned in a story. If a firm is mentioned only briefly, in the context of another firm's news, it is assigned a low relevance score. In our analysis, we consider only news stories with the highest relevance score of one. (The TRNA dataset is described in more detail in the Data section in the Online Appendix).

The breadth of the firms covered by the TRNA dataset increases over time. In 1996, the TRNA dataset covers 53.75% of the stocks in our sample; in 2005, the coverage increases to 80.02% of the stocks in our sample, and in 2012, the end of our sample period, the TRNA dataset covers 98.70% of the stocks in our sample. The statistics on the monthly news counts are reported in Panel A of Table 4. The table shows that larger firms tend to receive more news coverage; this is expected since the demand for information is greater for large firms as they have more investors and higher institutional ownership. The news coverage is also highly skewed; some firm-months are getting very intensive coverage, as evidenced by the means being much higher than the medians. It can also be seen that negative news is somewhat less prevalent than neutral and positive news. For our sample of news stories with the relevance score of 1, the percentage of negative news

[21] This methodology for determining news sentiment is used in Tetlock (2007).

is 23.65%, the percentage of neutral news is 38.70%, and the percentage of positive news is 38.65%. Firms in the small-firm tercile are more likely to receive negative coverage than firms in the upper two terciles: the fraction of negative news is 26.20% for small firms vs. 23.51% and 23.36% for the midsize and large firms, respectively. Positive news stories are slightly more prevalent for the large firm tercile (37.71% for the large tercile vs. 36.79% and 36.00% for the small and midsize terciles, respectively).

We define an unusual news flow on a monthly basis as a dummy variable equal to one if the number of news stories written about a firm in the current month exceeds the average monthly number for the firm over the trailing four months and zero otherwise. Similarly, we define a positive unusual news flow to be a dummy variable equal to one if the number of positive news stories in the current month exceeds the average monthly number of positive stories over the trailing four months. The negative and neutral unusual news dummies are defined in the same fashion. The average dummy value is about one-third in our sample, implying that about one third of firm-month observations experiences an unusual news flow. However, because the TRNA news coverage gets more comprehensive over time, the true number of firm-months with the unusual news flow is probably somewhat smaller. To address this concern, we have also tried defining months with the unusual news flow to be the months in which the number of news is 25% higher than the average monthly number of news written about the firm over the trailing four-month period. This definition of the abnormal news flow produces very similar results, and in the paper we report only the results based on the simpler original definition.

In order to show that the unusual news flow causes subsequent idiosyncratic volatility shocks, we run a predictive regression of the form:

$$IVOL^{shock}_{i,t+1} = \kappa_{0,t} + \kappa_{1,t}\text{Unusual News Flow Dummy}_{i,t} + \kappa_{2,t}X_{i,t} + \varepsilon_{i,t+1}, \tag{6}$$

where $X_{i,t}$ is the vector of controls potentially related to future volatility that include lagged volatility shocks, lagged volatility levels, and lagged abnormal returns.

The regression results are reported in Panel B of Table 4. The results show that idiosyncratic volatility shocks are significantly positively related to the unusual news flow in the prior month. When a firm experiences an unusual news flow, its next-month's idiosyncratic volatility increases by over 2% relative to its expected level (this magnitude is economically significant as it constitutes about 20% of the median idiosyncratic volatility level, as reported in Table A1 in the Online Appendix).

Next, we look at the effect of unusual positive, neutral, and negative news flow on the next month's volatility shocks. High-news-flow months typically contain more than one additional news story relative to the months with the usual level of news flow. Some of these stories may be positive in tone, some negative, and some neutral. Hence, a month with a non-zero unsigned unusual news flow dummy will have between one and three non-zero signed news flow dummies. A month with a zero unsigned news flow dummy may have some non-zero signed news flow dummies as long as the tone of news coverage has changed when compared to the trailing period. The results for the signed news flow dummies are presented in the last column of Table 5. The unusual negative news flow has the largest impact on the subsequent volatility shock, followed by the neutral and then by the positive news flow. All signed news flow dummies significantly contribute to the subsequent month's volatility shock.

To further prove the causal effect of the unusual news on the volatility shock, we show that the unusual news flow that is moved further back in time has an increasingly smaller effect on the subsequent month's volatility shock. Our news flow dummies are set to one when the news count in a given month exceeds the average news count over the trailing window, and since we know the date of each news story, we can time the start of the unusual news flow within a month. We hypothesize that the earlier in the month it appeared, the smaller would be the effect on the next-month's volatility shock, since investors will have had more time to process the unusual news. Specifically, if the first news story that exceeded the average rolling count had been reported four weeks before the month-end, we set the dummy for unusual news flow at the 4-week lag equal to one, if it was reported three weeks before the month-end, we set the dummy for unusual news flow at the 3-week lag equal to one, and so on. Thus, when the unusual news flow dummy is equal to one in a given month, only one of the weekly dummies will take on the value of one. We define the signed (positive, neutral, and negative) news dummies at various weekly lags analogously. Then we re-run the regressions in Panel B with these news dummies that are timed within the prior month. The results, reported in Panel C of the table, show that the coefficients on the news dummies tend to decrease with the number of weekly lags. This result indicates that the predictive power of the unusual news flow on subsequent volatility is lower the further back in time the unusual news flow had occurred.

5.2. News-induced volatility shocks and the subsequent stock returns

Here we show that the unusual-news-flow-driven idiosyncratic volatility shocks result in low future returns. Since the TRNA news dataset only covers the April 1996–December 2012 period, and the first four months are used for calculating the unusual news flow, the sample period of this analysis is July 1996–December 2012. Moreover, the cross-section of stocks is limited to the stocks covered in the TRNA dataset in each year.

Our conjecture is that unusual news events generate investor disagreement and result in high volatility, which poses a barrier to short selling. Therefore, the reaction to any news event will be driven by the relatively more optimistic investors. Optimistic investors will overreact to positive news and underreact to negative news, resulting in prices that are too high relative to the fundamentals. As a result, the prices will converge down to their fundamental values over time, as either more information becomes available and investors' opinions converge or the short-selling risks go down as the stock's idiosyncratic volatility reverts to its normal level.

We repeat the cross-sectional monthly return regression presented in Panel D of Table 1, but now we also include the unusual news flow dummies and the unusual news flow dummies interacted with volatility shocks. The results are reported in Table 5. The table shows that during the more recent time period of this sample, $IVOL^{\text{shock}}$ is still a negative predictor of the next month's returns (specifications (1) and (2)). It also shows that, on its own, the unsigned unusual news flow dummy is not a significant predictor of next month's returns (specifications (3) and (4)). However, the interaction between the unusual news dummy and $IVOL^{\text{shock}}$ is a significantly negative predictor of the next month's returns (specifications (7) and (8)). To assess the economic magnitude, we compare these to the regression specifications (5) and (6). The coefficient on $IVOL^{\text{shock}}$ drops by roughly half in the absolute value. The coefficient of -0.0170 or -0.0158 on the interaction term implies that a two-standard-deviation increase in the idiosyncratic volatility shock (the first column of Table A1 in the Online Appendix) that is accompanied by the unusual news flow leads to about a 30 basis point decrease in the next month's return.

Specifications (6) and (7) of the Table investigate the effect of the signed unusual news flow dummies. They show that positive (negative) news flow dummies predict the next month's returns with the positive (negative) sign, consistent with the slow reaction to news. However, the interaction terms with $IVOL^{\text{shock}}$ predict the next month's returns negatively.

Of course, we cannot claim that our TRNA news dataset is a comprehensive dataset of all news. The news coverage in the TRNA dataset is constrained by the finite resources of Reuters' journalists and by the limited attention of the dataset subscribers. Therefore, some news that underlie volatility shocks may never appear in the TRNA dataset; hence, the predictive ability of the volatility shock on its own is never completely eliminated. Despite these concerns, we are still able to confirm our conjecture that the unusual news flows (be they positive or negative news) that are accompanied by volatility shocks predict low future returns.

6. Conclusion

In this paper, we document that stocks that experience high volatility shocks earn low future returns. We provide evidence that this return pattern is explained by the Miller (1977) conjecture. Using the TRNA news dataset, we show that volatility shocks are associated with the unusual firm-level news flow. This unusual news flow causes temporary increases in investor disagreement about the value of the firm: analyst earnings forecast dispersion rises in the months with high volatility shocks and then decreases over the next few months. At the same time, high idiosyncratic volatility acts as a barrier to short selling, as margin calls resulting from price increases would require a short seller to put in additional capital or to reduce the short position at a loss. Indeed, using the Markit dataset on short selling demands, we find that the number of shares borrowed by short sellers drops after a stock experiences an idiosyncratic volatility shock. When investors disagree and short selling is costly, prices end up reflecting the views of the optimistic investors.[22] In the future, as investors start to come to an agreement about the value implications of the news, prices converge downward to an average opinion, thus explaining the negative relation between volatility shocks and subsequent returns.

An interesting follow-up question is whether it is possible to predict the instances of the unusual news flow with increases in option-implied volatilities, which would capture the expectations of a higher price uncertainty in response to rumors and news leaks. In preliminary results, we find that increased implied volatilities in both in- and out-of-the-money options indeed forecast a higher incidence of upcoming unscheduled corporate news announcements.

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[22] Our findings may be related to the findings of Barber and Odean (2008), who show that spikes in the trading volume, extreme returns, or being mentioned on the Dow Jones News Service attract the attention of individual investors and increase their buying demand.

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Table 1
Volatility shocks and future returns

This table documents the predictive relation between previous month's idiosyncratic volatility shock computed relative to the EGARCH-predicted volatility level and future stock returns. Panel A presents returns on decile portfolios formed based on shocks to a stocks' idiosyncratic volatility. Decile portfolios are formed every month by sorting stocks based on $IVOL^{\text{shock}}$. The table reports the equal-weighted (EWRET) and the value-weighted (VWRET) average monthly returns (denoted by *Ret*), the corresponding four-factor alphas (denoted by α), and the Newey and West (1987) adjusted *t*-statistics of the alphas (denoted by *t*, in parentheses). The last six rows present the raw return differential between deciles 1 and 10, their alpha with respect to the four-factor model, their alpha with respect to the five-factor model that in addition to the other four factors also includes the $IVOL$ factor, computed as the return differential between the high- and low-$IVOL$ portfolios, as described in Ang, Hodrick, Xing, and Zhang (2006), and the corresponding Newey and West (1987) adjusted *t*-statistics reported in parentheses. Panel B presents portfolio sort results for two subsamples, 1964-1988 and 1989-2012. Panel C presents volatility-shock-sorted portfolio returns for screened data subsamples. These screens involve the following: (i) the size screen excludes stocks in the smallest NYSE size decile, (ii) the price screen excludes stocks priced below \$5/share, and (iii) the liquidity screen excludes stocks in the lowest NYSE liquidity decile. The screens on last-month's return and momentum (defined as the cumulative return over the past 12 months, ending 2 months previously) removes stocks in the top and bottom deciles based on these variables. Entries report equal-weighted (EWRET) and value-weighted (VWRET) average monthly returns, and the return differentials between the high- and low- IVOL^{Shock} decile portfolios and their the four-factor alphas. Panel D presents results of the Fama and MacBeth (1973) cross-sectional regressions, in which monthly stock returns are regressed on volatility shocks and a set of other predictive variables; the table reports the average regression coefficients and the corresponding Newey and West (1987) adjusted *t*-statistics (in parentheses). The predictive variables are computed as of the end of the prior month (and E[IVOL] is computed one month before that); all regressions include 10 industry dummies; the explanatory variables and the 10 industries are described in Section A3 of the Online Appendix. Returns are expressed in percent. The sample period is from October 1964–December 2012 in specification (1); January 1950–December 2012 in specifications (2)–(5); and January 1986–December 2012 in specifications (6)–(7).

Panel A: Equal- and value-weighted portfolios formed on idiosyncratic volatility shocks

$IVOL^{Shock}$ Decile	EWRET	VWRET	Average $IVOL^{Shock}$
1 (Low)	*Ret* =1.67	1.24	-9.39%
	α =0.53	0.20	
	t =(3.45)	(1.32)	
2	1.52	1.03	-4.80%
	0.43	0.15	
	(4.95)	(1.19)	
3	1.39	1.02	-3.23%
	0.31	0.11	
	(5.31)	(1.51)	
4	1.31	1.02	-2.19%
	0.25	0.16	
	(5.02)	(2.51)	
5	1.29	0.96	-1.32%
	0.24	0.14	
	(4.41)	(2.45)	
6	1.27	0.81	-0.48%
	0.22	-0.07	
	(5.06)	(-1.23)	
7	1.27	0.94	0.46%
	0.20	0.12	
	(3.40)	(1.99)	
8	1.21	0.83	1.77%
	0.14	-0.04	
	(2.01)	(-0.63)	
9	1.05	0.76	4.17%
	-0.01	-0.13	
	(-0.11)	(-1.46)	
10 (High)	0.64	0.27	14.09%
	-0.40	-0.78	
	(-2.16)	(-4.42)	
High-Low	-1.03	-0.97	
	(-9.60)	(-4.50)	
4-factor alpha	-0.93	-0.98	
	(-7.99)	(-4.56)	
5-factor alpha	-0.84	-0.80	
	(-7.98)	(-3.46)	

Panel B: Subsamples

1964 -1988

Decile	EWRET	VWRET	IVOL_shock
1 (Low)	1.65	1.15	-6.92%
2	1.58	0.92	-3.78%
3	1.47	0.89	-2.59%
4	1.40	0.90	-1.74%
5	1.41	0.93	-1.02%
6	1.38	0.83	-0.30%
7	1.39	1.00	0.52%
8	1.29	0.96	1.61%
9	1.15	0.95	3.48%
10 (High)	0.58	0.49	10.31%
High-Low	-1.07	-0.66	
	(-8.66)	(-3.84)	
4-factor	-0.84	-0.61	
alpha	(-5.84)	(-2.83)	

1989-2012

Decile	EWRET	VWRET	IVOL_shock
1 (Low)	1.57	1.21	-9.00%
2	1.75	1.19	-5.86%
3	1.51	0.85	-4.66%
4	1.69	0.96	-3.90%
5	1.53	0.97	-3.33%
6	1.23	1.11	2.72%
7	1.12	0.82	3.67%
8	1.03	0.65	5.08%
9	0.81	0.78	7.55%
10 (High)	0.14	-0.31	15.50%
High-Low	-1.44	-1.53	
	(-7.69)	(-4.86)	
4-factor	-0.93	-1.50	
alpha	(-4.22)	(-4.33)	

Panel C: Restricting the data sample

Screening for size, price and illiquidity

$IVOL^{shock}$ Decile	Screen for size EWRET	Screen for size VWRET	Screen for price EWRET	Screen for price VWRET	Screen for illiquidity EWRET	Screen for illiquidity VWRET	Screen for size, price & illiquidity EWRET	Screen for size, price & illiquidity VWRET
1 (Low)	1.32	1.12	1.43	1.11	1.47	1.15	1.33	1.08
2	1.28	0.97	1.37	1.00	1.36	0.99	1.26	0.96
3	1.24	1.04	1.26	1.02	1.24	1.00	1.23	1.00
4	1.21	0.99	1.27	1.02	1.27	1.00	1.20	0.98
5	1.19	1.03	1.24	0.98	1.18	1.03	1.17	1.03
6	1.17	0.80	1.21	0.84	1.21	0.78	1.17	0.78
7	1.14	0.88	1.16	0.87	1.13	0.89	1.10	0.88
8	1.16	0.85	1.17	0.84	1.20	0.87	1.12	0.87
9	1.02	0.84	1.02	0.82	1.05	0.85	1.06	0.84
10 (High)	0.55	0.53	0.48	0.44	0.52	0.50	0.61	0.54
High-Low	-0.77	-0.59	-0.95	-0.68	-0.95	-0.65	-0.72	-0.54
	(-7.64)	(-3.35)	(-12.03)	(-3.73)	(-8.37)	(-3.52)	(-7.58)	(-3.06)
4-factor	-0.74	-0.55	-0.96	-0.66	-0.90	-0.60	-0.72	-0.53
alpha	(-7.12)	(-2.87)	(-11.75)	(-3.47)	(-7.31)	(-2.97)	(-7.24)	(-2.77)

Screening for past returns

Decile	Screen for prior month's winners and losers EWRET	Screen for prior month's winners and losers VWRET	Screen for momentum winners and losers EWRET	Screen for momentum winners and losers VWRET
1 (Low)	1.51	1.24	1.56	1.04
2	1.42	1.05	1.46	0.90
3	1.32	1.05	1.30	0.94
4	1.25	1.00	1.30	1.02
5	1.24	0.98	1.23	0.91
6	1.25	0.89	1.24	0.78
7	1.23	0.81	1.23	0.87
8	1.22	0.90	1.26	0.86
9	1.09	0.88	1.12	0.80
10 (High)	0.48	0.63	0.86	0.43
High-Low	-1.03	-0.61	-0.70	-0.61
	(-10.72)	(-3.17)	(-7.24)	(-3.13)
4-factor	-0.97	-0.55	-0.71	-0.63
alpha	(-9.89)	(-3.21)	(-6.91)	(-2.98)

Panel D: Monthly cross-sectional return regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$IVOL^{shock}$	-0.054	-0.059	-0.056	-0.056	-0.037	-0.065	-0.075
	(-10.54)	(-11.98)	(-10.79)	(-10.74)	(-2.28)	(-2.70)	(-2.58)
E[IVOL]				-0.033		-0.015	
				(-1.80)		(-0.70)	
IVOL					-0.018		0.133
					(-1.16)		(2.82)
Beta		0.036	0.010	0.059	0.041	0.136	0.134
		(0.36)	(0.11)	(0.76)	(0.51)	(1.18)	(1.12)
Size		-0.139	-0.152	-0.178	-0.157	-0.103	-0.095
		(-3.39)	(-3.86)	(-7.03)	(-5.49)	(-2.69)	(-2.60)
BM		0.288	0.282	0.259	0.272	0.134	0.135
		(5.65)	(5.65)	(5.41)	(5.61)	(2.30)	(2.33)
Mom			0.005	0.005	0.005	0.003	0.003
			(3.74)	(3.64)	(3.61)	(1.69)	(1.69)
Rev						-0.044	-0.044
						(-8.53)	(-8.60)
Illiq						0.019	0.019
						(0.68)	(0.68)
ISkew						0.100	0.096
						(3.22)	(2.93)
Disp						-0.062	-0.064
						(-2.62)	(-2.63)
Turn						0.069	0.068
						(1.77)	(1.74)
Age						-0.031	-0.036
						(-0.90)	(-1.05)
IncVol						-2.154	-2.103
						(-1.24)	(-1.16)
β^{VXO}						-10.081	-10.308
						(-2.09)	(-2.12)
GKM_H						0.447	0.453
						(5.23)	(5.27)
GKM_L						-0.422	-0.424
						(-6.81)	(-6.77)
AM						-0.066	-0.060
						(-0.85)	(-0.78)
Max						-0.062	-0.074
						(-2.36)	(-2.54)

Table 2
Volatility shocks and short selling demand

This table reports the relation between idiosyncratic volatility shocks and the end-of-month short selling demand, measured by Utilization (the percentage of lendable shares on loan to short sellers) and Share Borrowed (the number of shares borrowed by short sellers). Panel A reports the sample statistics for Utilization and Shares Borrowed. Panel B sorts stocks by $IVOL^{shock}$ and calculates the average values of the end-of-month short selling demand variables across the $IVOL^{shock}$ quintiles, as well as the differences between the high- and low-$IVOL^{shock}$ quintiles. Panel C sorts stocks into month-t return quintiles and then, within each return quintile, into $IVOL^{shock}$ quintiles, and the average values of the short selling demand variables are calculated for each of the resulting 25 groups, as well as the differences between each high- and low-$IVOL^{shock}$ groups within each return quintile. The Newey and West (1987) adjusted t-statistics are reported in parentheses. The sample period is June 2002–December 2012.

Panel A: Descriptive statistics

	Mean	Median	25th percentile	75th percentile
Utilization	16.10%	7.83%	1.02%	23.10%
Shares borrowed (mil)	3.428	1.297	0.025	4.526

Panel B: Idiosyncratic volatility shock and measures of short selling demand

$IVOL^{shock}$ Quintile	Utilization	Shares Borrowed (mil)
1 (Low)	18.41%	4.73
2	16.11%	4.47
3	14.93%	4.04
3	14.89%	3.82
5 (High)	14.18%	3.24
High-Low	-4.22%	-1.49
	(-19.87)	(-20.64)

Panel C: Past return, idiosyncratic volatility and measures of shorting demand

Short selling demand measure: Utilization

$IVOL^{shock}$ Quintile	Return Quintile 1 (Low)	2	3	4	5 (High)
1 (Low)	19.53%	17.54%	16.97%	17.68%	19.47%
2	17.66%	15.34%	14.99%	15.64%	17.13%
3	16.65%	14.19%	13.75%	14.53%	16.35%
4	16.28%	14.25%	13.85%	14.40%	16.18%
5 (High)	14.48%	13.37%	13.18%	13.95%	15.58%
High-Low	-5.05%	-4.17%	-3.79%	-3.72%	-3.89%
	(-2.97)	(-12.56)	(-11.30)	(-13.48)	(-10.04)

Short selling demand measure: Shares Borrowed (mil)

$IVOL^{shock}$ Quntile	Return Quintile 1 (Low)	2	3	4	5 (High)
1 (Low)	4.82	4.61	4.51	4.77	4.86
2	4.78	4.27	4.20	4.42	4.72
3	4.40	3.83	3.72	3.99	4.45
4	4.16	3.60	3.57	3.75	4.17
5 (High)	3.17	3.01	3.07	3.38	3.55
High-Low	-1.65	-1.60	-1.44	-1.39	-1.31
	(-14.96)	(-14.00)	(-13.54)	(-13.76)	(-1.66)

Table 3
Change in analyst disagreement around volatility shocks

This table reports changes in analyst earnings forecast dispersion around volatility shocks. Panel B reports the sample statistics on the 2-month changes in earnings forecast dispersion. For the results reported in Panel B, each month stocks are sorted into quintiles based on $IVOL^{\text{shock}}$ realized in that month. Earnings forecast dispersion is calculated as the standard deviation of analysts' current fiscal year's earnings forecasts scaled by the absolute value of the mean earnings forecast (observations with the mean earnings forecast equal to zero are discarded). Changes in the forecast dispersion are calculated for each stock and then averaged across the stocks in each IVOL^{Shock} quintile. The change *before* the current month is calculated as the difference in the forecast dispersion between the outstanding forecasts in the current month and the outstanding forecasts 2 months previously; the change *after* the current month is calculated as the difference in dispersion between the forecasts outstanding 2 months after and the forecasts outstanding in the current month. The last row represents the differential between the high- and low-$IVOL^{\text{shock}}$ quintiles. The corresponding Newey and West (1987) adjusted *t*-statistics are in parentheses. The sample period is March 1983–December 2012.

Panel A: Descriptive statistics for the change in analyst disagreement

Mean	Median	25th percentile	75th percentile
-0.007	-0.002	-0.033	0.021

Panel B: The change in the disagreement before and after the volatility shock

IVOL^{Shock} Quintile	Before	After
1 (Low)	-0.009	-0.003
	(-3.95)	(-0.89)
2	-0.006	0.001
	(-3.52)	(0.34)
3	-0.005	-0.005
	(-2.49)	(-2.77)
4	-0.007	-0.008
	(-3.01)	-(2.99)
5 (High)	0.003	-0.012
	(0.49)	(-2.32)
High-Low	0.012	-0.009
	(2.25)	(-2.00)

Table 4
Predictive relation between unusual news and volatility shocks

Panel A presents sample statistics of the average number of monthly news stories by firm size. Panel B reports the results of Fama and MacBeth (1973) monthly regressions of volatility shocks on the lagged unusual news flow dummies and control variables: $IVOL_{it}^{shock} = b_0 + b_1 \times \mathbb{1}\{unusual\ news\ flow\}_{i,t-1} + b_2 \times Controls_{i,t-1} + \varepsilon_{it}$. The unusual news flow dummy equals one if the number of news items written about firm i in month t exceeds the monthly average over the trailing 4-month window and zero otherwise. Unusual news flow dummies exclusively for positive (negative or neutral) news are calculated analogously by checking whether the count of positive (negative or neutral) news count in the current month for stock i exceeds the average monthly count of positive (negative or neutral) news over the trailing 4-month window. News stories for each firm i are the TRNA news stories with the relevance score of 1. Panel C presents the results of the same regression but times the first story in the unusual news flow based on whether it appeared at a 1-, 2-, 3-, or 4-week lag prior to the current month. Newey and West (1987) adjusted t-statistics are reported in parentheses. The sample period is July 1996–December 2012.

Panel A: Descriptive statistics for monthly news counts

Size	All news		Negative news		Neutral news		Positive news	
tercile	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Small	4.65	2	1.22	0	1.72	0	1.71	0
Midsized	8.98	4	2.11	0	3.64	1	3.23	1
Large	23.49	13	5.49	2	9.14	5	8.86	5
Entire sample	11.98	4	2.83	0	4.51	1	4.64	2

Panel B: Unusual news flow is calculated over the entire month

$\mathbb{1}\{unusual\ news\ flow\}$	2.1635	2.3991	
	(22.57)	(29.49)	
$\mathbb{1}\{unusual\ negative\ news\ flow\}$			1.4967
			(14.53)
$\mathbb{1}\{unusual\ neutral\ news\ flow\}$			0.9447
			(5.30)
$\mathbb{1}\{unusual\ positive\ news\ flow\}$			0.8192
			(7.84)
$\text{Lag}\left(IVOL^{shock}\right)$		0.2662	0.2665
		(13.74)	(13.55)
Rev		0.1026	0.1040
		(11.89)	(12.01)
BM		0.3098	0.3034
		(5.97)	(5.82)
Size		-0.4487	-0.5029
		(-8.28)	(-9.15)
ΔIlliq		-0.0025	-0.0029
		(-0.17)	(-0.20)

Panel C: Unusual news flows at various weekly lags

$\mathbb{1}\{$*unusual news flow at **1-week lag***$\}$	0.9189	1.1458	
	(8.09)	(12.97)	
$\mathbb{1}\{$*unusual news flow at **2-week lag***$\}$	0.9112	1.1641	
	(11.89)	(17.57)	
$\mathbb{1}\{$*unusual news flow at **3-week lag***$\}$	0.7016	0.8546	
	(5.85)	(6.25)	
$\mathbb{1}\{$*unusual news flow at **4-week lag***$\}$	0.3669	0.7401	
	(4.84)	(10.22)	
1-week lag			
$\mathbb{1}\{$*unusual negative news flow*$\}$			0.8878
			(10.78)
$\mathbb{1}\{$*unusual neutral news flow*$\}$			0.5897
			(8.92)
$\mathbb{1}\{$*unusual positive news flow*$\}$			0.3498
			(4.89)
2-week lag			
$\mathbb{1}\{$*unusual negative news flow*$\}$			1.0257
			(14.95)
$\mathbb{1}\{$*unusual neutral news flow*$\}$			0.6445
			(10.27)
$\mathbb{1}\{$*unusual positive news flow*$\}$			0.2415
			(4.55)
3-week lag			
$\mathbb{1}\{$*unusual negative news flow*$\}$			1.0404
			(5.66)
$\mathbb{1}\{$*unusual neutral news flow*$\}$			0.3859
			(1.95)
$\mathbb{1}\{$*unusual positive news flow*$\}$			0.0214
			(0.22)
4-week lag			
$\mathbb{1}\{$*unusual negative news flow*$\}$			0.7120
			(7.44)
$\mathbb{1}\{$*unusual neutral news flow*$\}$			0.5684
			(5.30)
$\mathbb{1}\{$*unusual positive news flow*$\}$			-0.1317
			(-0.67)
Controls	No	Yes	Yes

Table 5
News, volatility shocks, and future returns

The table reports the results of Fama and MacBeth (1973) monthly regressions of the next month's returns on the lagged unusual news flow dummies, volatility shocks, volatility shocks interacted with the unusual news flows dummies, and control variables. The unusual news flow dummy equals one if the number of news written about firm i in month t exceeds the monthly average over the trailing 4-month window and zero otherwise. Unusual news flow dummies exclusively for positive (negative or neutral) news are calculated analogously by checking whether the count of positive (neutral, negative) news count in month t for stock i exceeds the average monthly count of positive (neutral, negative) news over the trailing window 4-month window. News stories for each firm i are obtained from the TRNA dataset, and only news stories with the relevance score of 1 are considered. The set of controls is the same as in Panel D of Table 1, including industry dummies. Newey and West (1987) adjusted t-statistics are reported in parentheses. The sample period is July 1996–December 2012.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$IVOL^{shock}$	-0.0144	-0.0130			-0.0143	-0.0131	-0.0073	-0.0065	-0.0077	-0.0075
	(-2.74)	(-3.05)			(-2.75)	(-3.07)	(-1.94)	(-2.14)	(-2.20)	(-2.28)
$\mathbb{1}\{unusual\ news\ flow\}$			0.0634	-0.0101	0.0132	-0.0158	0.0276	-0.0389		
			(0.86)	(-0.20)	(0.72)	(-0.32)	(0.37)	(-0.81)		
$\mathbb{1}\{unusual\ negative\ news\ flow\}$									-0.1685	-0.2449
									(-2.52)	(-4.36)
$\mathbb{1}\{unusual\ neutral\ news\ flow\}$									0.1274	0.0678
									(1.72)	(1.15)
$\mathbb{1}\{unusual\ positive\ news\ flow\}$									0.1248	0.1546
									(2.24)	(3.05)
$\mathbb{1}\{unusual\ news\ flow\} \times IVOL^{shock}$							-0.0170	-0.0158		
							(-2.60)	(-2.74)		
$\mathbb{1}\{unusual\ negative\ news\ flow\} \times IVOL^{shock}$									-0.0150	-0.0154
									(-1.96)	(-2.00)
$\mathbb{1}\{unusual\ neutral\ news\ flow\} \times IVOL^{shock}$									-0.0066	-0.0085
									(-0.90)	(-1.42)
$\mathbb{1}\{unusual\ positive\ news\ flow\} \times IVOL^{shock}$									-0.0151	-0.0112
									(-2.30)	(-1.85)
Controls	N	Y	N	Y	N	Y	N	Y	N	Y

Online Appendix

Unusual News Flow and the Cross-Section of Stock Returns

A1. Datasets

Return data at daily and monthly frequencies are obtained from the CRSP daily and monthly files and include all NYSE-, Amex-, and Nasdaq-traded financial and non-financial common stocks. Since the daily return dataset offers a large enough cross-section of stocks starting in July 1963, this is when we start our estimation period, as do related papers. We adjust stock returns for delisting in order to avoid survivorship bias (Shumway (1997)).[23]

Accounting variables are obtained from the Merged CRSP/Computstat dataset and are available starting in 1963 (and quarterly earnings announcement dates are available starting later, in 1971). The Fama and French three factors, as well as momentum factor, are obtained from Kenneth French's Online Data Library and start in July 1963. Analysts' earnings forecasts (individual and summary estimates) come from the I/B/E/S dataset and include a reasonably large cross-section of stocks starting in 1983.

The news data are obtained from the Thomson-Reuters News Analytics dataset (TRNA). TRNA is a machine-readable news feed from Thomson Reuters that includes news items from 41 news media outlets and covers the period from April 1996 to December 2012. We use the portion of the TRNA dataset that covers firms-specific news for US-listed public firms. Each firm-specific news story is tagged with a Reuters firm identifier, which we map to its permno. The TRNA dataset provides news stories' headlines, as well as the take date and time. For all take dates that fall on holidays or weekends, we assume that the story date is the next trading day. For all take times after 15:30:00, we assume the story date to be the following trading day. TRNA provides news sentiment scores for each news story, indicating whether the story is positive, negative, or neutral for the firm. (Thompson-Reuters computes sentiment scores based on the relative prevalence of positive and negative words among the words pertaining to the firm in the news story.)

[23] Specifically, when a stock is delisted, we use the delisting return from CRSP, if available. Otherwise, we assume the delisting return is -100%, unless the reason for delisting is coded as 500 (reason unavailable), 520 (went to OTC), 551-573, 580 (various reasons), 574 (bankruptcy), or 584 (does not meet exchange financial guidelines). For these observations, we assume that the delisting return is -30%.

The data on short selling demand are obtained from Markit (formerly, Data Explorers). Markit collects information on total loanable stock inventory, the amount on loan to short sellers, and loan fees (which are calculated as the average of all applicable loan fees weighted by loan value). The dataset covers the period July 2002–December 2012.

Markit claims to capture stock loan trading information on over 85% of the OTC securities lending market; it is worthwhile to note that its universe of reporting participants (custodians and short sellers, from whom Markit gathers the information on the number of shares available for lending, the number of shares borrowed, and lending fees on borrowed shares) is unstable and tends to grow over time. As a result, short interest, which is defined as the number of shares sold short scaled by the number of shares outstanding, would mechanically increase over time if calculated using Markit's data on loaned shares. To avoid this concern, we use utilization as a measure of short-selling activity. Utilization is calculated by Markit as the percentage of the stock inventory available for lending to short sellers that is currently on loan. This measure of short-selling activity is not mechanically determined by the fluctuations in the number of participating short sellers and lenders.

The tables and figures presented throughout the paper mostly cover the July 1964–December 2012 sample period (the first 12 months of the sample are used to estimate the EGARCH volatility), and the sample periods are appropriately shortened when variables based on quarterly earnings announcements, analyst forecasts, TRNA news dataset, or the Markit short sale demand dataset are used.

A2. Alternative estimations of expected idiosyncratic volatility levels

We alternatively measure shocks to idiosyncratic volatility relative to the expected volatility level computed from the trailing average monthly idiosyncratic volatility level, which is estimated as in Ang, Hodrick, Xing, and Zhang (2006). Following Ang, Hodrick, Xing, and Zhang (2006), we compute monthly idiosyncratic volatility of a stock as the standard deviation of the daily regression residuals of its returns on the three-factor Fama and French (1993) model within the month. We begin by estimating the model:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + \eta_i \mathrm{SMB}_d + \delta_i \mathrm{HML}_d + \varepsilon_{i,d}, \tag{7}$$

where $R_{i,d}$ is the daily return on stock i on day d, $R_{f,d}$ is the risk-free return (proxied by the return on a one-month T-bill), $R_{m,d}$ is the daily return on the market portfolio (proxied by the return on the CRSP value-weighted index), SMB_d and HML_d are the daily returns on the size and book-to-market factors, and $\varepsilon_{i,d}$ is the error term. Next, we compute the standard deviation of residuals, $\varepsilon_{i,d}$, for each stock i and for each month t in our sample and convert it into a monthly measure by multiplying it by the number of trading days in the month: $IVOL_{i,t} = \sqrt{var(\varepsilon_{i,d}) \times \text{no. of trading days}}$. We require that a firm has at least 15 daily return observations.

Once we have computed the monthly time series of a stock's idiosyncratic volatility, $IVOL_{i,t}$, we can try to predict future volatility and calculate shocks relative to the predictive model. Since idiosyncratic volatility is highly autocorrelated and also has a significant industry component, our predictive model includes the long-run average volatility and the industry dummy:

$$IVOL_{i,t} = \phi_{0,t} + \phi_{1,t}\overline{IVOL}_{i,t-1} + \sum_{j=1}^{10} \psi_{j,t} D_{i,j} + \nu_{i,t}, \tag{8}$$

where $\overline{IVOL}_{i,t-1}$ is the average stock's idiosyncratic volatility, estimated as a moving average of past idiosyncratic volatility realizations, and $D_{i,j}$ is the industry-classification dummy (we use 10 broad industry classifications, as described in Kenneth French's Online Data Library). $\overline{IVOL}_{i,t-1}$, is estimated over the past two years from month $t-27$ to month $t-4$ (we end the estimation window three months before the month $t-1$ in order to avoid contaminating the estimate with possible recent volatility increases).

The firm-level cross-sectional regressions are estimated on a rolling basis for each month t, such that only explanatory variables that are available in month $t-1$ are used. The mean regression coefficient ϕ_1 is equal to 0.98, and the median to 0.94 (and the average regression R^2 is 78.70% and the median is 78.53%). We are interested in the unexpected shocks to idiosyncratic volatility, defined as: $IVOL^{\text{shock}}_{i,t} \equiv \nu_{i,t}$.

So far, we have discussed measuring $IVOL$ with daily returns, as in Ang, Hodrick, Xing, and Zhang (2006). However, Andersen and Bollerslev (1998) show that the realized volatility measures based on intraday returns provide a dramatic reduction in noise and a radical improvement in temporal stability relative to the realized volatility measures based on daily returns. The importance of intraday returns for measuring realized volatility is further demonstrated by Andersen, Bollerslev, Diebold, and Ebens (2001), Barndorff-Nielsen and Shephard (2001), Andreou and Ghysels (2002), and many follow-up studies. We therefore also estimate volatility levels with five-minute return intervals. As is standard in this literature, we use the total volatility measures (*TVOL*) rather than trying to estimate purely the idiosyncratic component. At high frequencies, the explanatory power of the market for individual stock returns is very small, and the total and idiosyncratic volatilities are very similar: The average cross-sectional correlation between the two for stocks in the CRSP sample is about 0.9.

Our results are robust to both the total and idiosyncratic high-frequency volatility measures, and, in order to be consistent with the literature in this field, the results computed using high-frequency returns are based on the *TVOL* measure. Shocks to *TVOL* are computed in the same fashion as shocks in *IVOL* described earlier.

The predictive relation for the volatility shocks based on either of those volatility prediction methodologies and future returns is very similar to the one described in the main text of the paper.

A3. Variable definition and estimations

This appendix offers a detailed description of the variables used in our predictive regressions and bivariate portfolio sorts. Unless specified otherwise, all variables are calculated at the end of the portfolio formation month. All variables that are computed from daily returns are available starting from October 1964, and all variables that are computed using Compustat are available starting from January 1950. The variables computed from I/B/E/S dataset are available form January 1983. The variables obtained from the Markit dataset are available starting from June 2002.

Book-to-market ratio *(B/M)*. Following Fama and French (1992, 1993, and 2000), we compute the book-to-market equity ratio at the end of June of each year as the book value of stockholders' equity, plus deferred taxes and investment tax credit (if available), minus the book value of preferred stock, scaled by the market value of equity. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock for the last fiscal-year end. The market value of equity is price times shares outstanding at the end of December of the previous fiscal year. We use the natural logarithm of the book-to-market ratio.

Ratio of books assets to the market value of equity *(AM)* is defined as the natural log of the ratio of book value of assets to market value of equity.

Size *(Size)*. A stock's size is defined as the natural logarithm of the product of the price per share and the number of shares outstanding, expressed in millions of dollars.

Beta *(Beta)*. Following Fama and French (1992), the market beta of individual stocks is estimated by running a time-series regression based on the monthly return observations over the prior 60 months if available (or a minimum of 24 months):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^1 (R_{m,t} - R_{f,t}) + \beta_i^2 (R_{m,t-1} - R_{f,t-1}) + \varepsilon_{i,t}, \tag{9}$$

where the market beta of stock i is the sum of the slope coefficients on the current and lagged excess market returns; i.e., $Beta = \hat{\beta}_i^1 + \hat{\beta}_i^2$.

Idiosyncratic volatility *(IVOL)*. Following Ang, Hodrick, Xing, and Zhang (2006), we compute monthly idiosyncratic volatility of a stock as the standard deviation of the daily regression residuals of its returns on the three-factor Fama and French (1993) model within the month:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + \eta_i \mathrm{SMB}_d + \delta_i \mathrm{HML}_d + \varepsilon_{i,d}, \tag{10}$$

where $R_{i,d}$ is the daily return on stock i on day d, $R_{f,d}$ is the risk-free return (proxied by the return on a one-month T-bill), $R_{m,d}$ is the daily return on the market portfolio (proxied by the return on the CRSP value-weighted index), SMB_d and HML_d are the daily returns on the size and book-to-market factors, and $\varepsilon_{i,d}$ is the error term. Next, we compute the standard deviation of residuals, $\varepsilon_{i,d}$, for each stock i and for each month t in our sample and convert it into a monthly measure by multiplying it by the number of trading days in the month: $IVOL_{i,t} = \sqrt{var(\varepsilon_{i,d}) \times \text{no. of trading days}}$. We require that a firm have at least 15 daily return observations.

Expected idiosyncratic volatility *(E[IVOL])* is estimated for each month t using the month-$t-1$ variables with the EGARCH model, as described in the text.

Amihud's illiquidity measure *(Illiq)*. Following Amihud (2002), we measure illiquidity for each stock in month t as the average daily ratio of the absolute stock return to the dollar trading volume within the day:

$$Illiq_{i,t} = \mathrm{Avg}\left[\frac{|R_{i,d}|}{Volume_{i,d}}\right]_t. \tag{11}$$

Aggregate volatility beta *(β^{VXO})*. Following Ang, Hodrick, Xing, and Zhang (2006), we estimate monthly observations for each stock of implied market volatility beta from the bivariate time-series regressions of excess stock returns on the excess market returns and the changes in implied volatility using daily data in a month:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i^{MKT}\left(R_{m,d} - R_{f,d}\right) + \beta_i^{VXO}\Delta VAR_d^{VXO} + \varepsilon_{i,d}, \tag{12}$$

where $R_{i,d}$, $R_{m,d}$ and $R_{f,d}$ are the returns on stock i, market, and the risk-free rate on day d and ΔVAR_d^{VXO} is the change in the S&P 100 index option-implied variance (VXO) on day d; it is available starting in January 1986.

Idiosyncratic skewness Following Harvey and Siddique (2000), we define the idiosyncratic skewness of stock i as the skewness of its daily residuals, $\varepsilon_{i,d}$, in month t, from the following regression:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i\left(R_{m,d} - R_{f,d}\right) + \gamma_i\left(R_{m,d} - R_{f,d}\right)^2 + \varepsilon_{i,d}. \tag{13}$$

Momentum return *(Mom)*. Following Jegadeesh and Titman (1993), momentum is defined as the cumulative return of a stock over a period of 11 months ending 2 months prior.

Last month's return *(Rev)*. Following Jegadeesh (1990), short-term reversal variable is defined as the stock return over the previous month.

Maximum monthly return *(Max)* is the highest daily return observation in each month.

Analyst earnings forecast dispersion *(Disp)* is the standard deviation of annual earnings-per-share forecasts scaled by the absolute value of the average outstanding forecast.

Inverse of firm's age *(Age^{-1})* is the natural logarithm of the inverse of the number of months the stock has been listed in the CRSP database.

Turnover *(Turn)* is defined as daily turnover, scaled by the number of shares outstanding, averaged over the month.

Volatility of the operating income *(IncVol)* is measured as the standard deviation of the seasonally differenced quarterly operating income before depreciation (Computstat Quarterly data #22) divided by average total assets (Compustat Quarterly data #44) over the prior 20 quarters. We require a minimum of eight quarters of operating income data to measure income volatility.

Abnormal trading volume dummy *(GKM_H (GKM_L))*. Following Gervais, Kaniel, and Mingelgrin (2001), we define these abnormal trading volume dummies in the following way. If the dollar trading volume on the one-day formation period is among the highest (lowest) 10% of the daily dollar trading volume over the prior 49 trading days, the stock is classified as a high- (low-) volume stock. The high-volume dummy variable (GKM_H) is set to 1 if a stock belongs to the high-volume group and zero otherwise; the low-volume dummy variable (GKM_L) is set to 1 if a stock resides in the low-volume portfolio and zero otherwise.

Industry dummies We use the 10-industry definitions from Kenneth French's website, assigning firms to one of the following industries: Consumer NonDurables; Consumer Durables; Manufacturing; Energy; HiTec; Telecom; Shops; Health; Utilities; Other. Industry dummies are set to one if a firm belongs to a given industry and zero otherwise.

Utilization *(Utilization)* is defined as the number of shares borrowed by short sellers divided by the number of shares available for lending. The variable is computed by Markit. It is computed at month-end.

Shares Borrowed *(Shares Borrowed)* is the number of shares borrowed by short sellers at the end of each month, as reported by Markit (in millions).

A4. Stock characteristics of volatility-shock-sorted portfolios

Table 1 reports the average stock characteristics of the volatility-shock-sorted decile portfolios, computed in the portfolio formation month (month 0). The average portfolio characteristics are calculated by averaging them first within each portfolio and then over time. (The definitions of all variables of interest are provided in Section A3 of the Online Appendix.)

As can be seen from the table, both extreme-volatility-shock portfolios consist of relatively smaller, less liquid stocks that also tend to have higher book-to-market ratios and market betas and lower share prices than stocks in the middle portfolios. During the portfolio formation month, stocks in the high-volatility-shock portfolio tend to earn higher average returns, *Rev*, which are, not surprisingly, also more positively skewed, than other stocks, and both the average month-0 returns and the average skew increase smoothly with the portfolio volatility-shock decile rank, whereas the average momentum returns, *Mom*, exhibit the opposite pattern. The positive relation between volatility shocks and contemporaneous returns was previously documented by Duffee (1995). This relation is not surprising given our central hypothesis. Reflecting the opinions of the more optimistic investors, stock prices will overreact to good news and underreact to bad news. Thus, the *average* effect of news on returns, averaged over all news, good or bad, will be positive. The table also shows that stocks in the highest volatility-shock decile tend to be higher on the proxies of investor disagreement—analyst forecast dispersion and turnover. They also tend to be less liquid and have higher loadings on the VXO factor, constructed from the change in the S&P 100 index option-implied volatility.

A5. Bivariate sorts

Table A5 presents the results of bivariate sorts on volatility shocks and various variables of interest. We begin by investigating the effect of market capitalization in order to check whether the return predictability also exists for relatively large firms. In each month, we sort stocks into size quintiles and then, within each size quintile, into volatility-shock quintiles. Panel A of the table presents average returns for the resulting 25 portfolios and the high-minus-low return differentials within each size quintile for the following month. Returns shown in the left-side table of the panel are equal-weighted, those right-side table are value-weighted. Both tables show that the average return differential tends to become less negative as size increases, and this tendency is more pronounced for value-weighted returns. This is not surprising because equal-weighting assigns larger weights to smaller stocks within each size quintile and, according to our hypothesis, the underperformance should be more pronounced for the smaller, more obscure stocks, for which unusual news will result in higher investor disagreement. However, the return differentials and their four-factor alphas remain significantly negative for all size quintiles.[24]

The difference in the average stock characteristics between the high-volatility-shock portfolio and the rest of the sample, described in the previous section, raises concerns that the predictive power of $IVOL^{\text{shock}}$ on future returns may be explained by these stock characteristics instead. To show that the predictive ability of $IVOL^{\text{shock}}$ is robust to these control variables, we perform bivariate portfolio sorts on $IVOL^{\text{shock}}$ and

[24]When unconditional sorts are used, the effect of the return differentials diminishing with size is more muted. These results are available upon request.

these variables of interest. In each month, stocks are sorted independently into deciles based on the stock characteristic of interest and the value of $IVOL^{\text{shock}}$, so that decile 1 (decile 10) contains stocks with the lowest (highest) $IVOL^{\text{shock}}$. We then group together the stocks in the same volatility-shock deciles and report the average decile returns and the high-minus-low $IVOL^{\text{shock}}$-decile return differentials for the following month. This sorting procedure creates a set of volatility-shock portfolios with nearly identical levels of the control variable. If the return differential is entirely explained by the control variable, no significant return differences will be observed across $IVOL^{\text{shock}}$ deciles. The summary version of the bivariate sorts on stock characteristics and volatility shocks is presented in Panel B of the table. The top table of the panel reports equal-weighted returns; the bottom table reports value-weighed returns.

The control variables used in this sort include EGARCH-forecasted volatility, CAPM beta, book-to-market, momentum, last-month's return, illiquidity, and idiosyncratic skewness; commonly used proxies for divergence of opinion in order to check whether $IVOL^{\text{shock}}$ contains any additional predictive power (these proxies are: analyst disagreement about future earnings (*Disp*), stock turnover (*Turn*), the inverse of the firm's age (Age^{-1}), and the volatility of the operating income (*IncVol*)); the beta with respect to the aggregate volatility factor (β^{VXO}); the book assets to market value ratio (*AM*); the highest daily return over the prior month (*Max*); and the high and low abnormal trading volume dummies (*GKM_H* and *GKM_L*). These variables are described in detail in Section A3 in the Online Appendix. As noted in the variable descriptions, some control variables are not available for the entire time series of our sample. For these control variables, the sample periods in the bivariate sorts are, therefore, reduced accordingly.

The observed significant return differentials across the $IVOL^{\text{shock}}$ dimension indicate that controlling for other known predictors of returns, as well as for the commonly used proxies for differences of opinion, does not eliminate the predictive ability of idiosyncratic volatility shocks.

A6. Within-industry portfolio sorts

In order to illustrate that the predictive ability of the idiosyncratic volatility shock works within industries, we sort individual stocks into deciles based on $IVOL^{\text{shock}}$ within the 10 Fama-French industries. The results of these sorts are reported in Table A6 in the Online Appendix. The table shows that the return differentials are negative and economically large in all industries, and statistically significant in most industries (in 7 out of 10 industries for both equal- and value-weighted portfolios). It is not surprising to find that the statistical significance falls relative to the full sample—the cross-section of stocks available within each industry is much smaller.

The right-most columns of each Panel, labeled "Combined," show the portfolio returns of the volatility-shock-sorted portfolios combined across the 10 industries to create the resulting portfolios with near-identical industry loadings. The return differentials are highly statistically significant for both equal- and value-weighted portfolio. The resulting monthly return differentials are: -0.91% (t-statistic$= -7.89$) for the equal-weighed portfolio (its four-factor alpha equal -0.68% with the t-statistic$= -6.26$); -0.91% (t-statistic$= -5.54$) for the value-weighted portfolio (its four-factor alpha equal -0.85% with the t-statistic$= -5.28$).

That results presented in this section show that the predictive ability of $IVOL^{\text{shock}}$ works at the level of individual stocks rather than industries.

A7. Determinants of the short selling demand

Table A7 of the Online Appendix presents the results of regressing the short sale demand on volatility shocks and a number of control variables. As in the main text, we employ two proxies for the short sale demand: utilization and the number of shares borrowed, as reported by Markit at the month-end. The control variables are measured over the month. We report regression results with and without industry dummies; all regression specifications include year dummies. The regressions are run on the pooled data, and the standard errors are clustered by firm and month.

Utilization, which is the ratio of shares borrowed to the shares available for lending, can decline either because the number of shares borrowed declines or the number of shares available for lending increases.[25] For this reason, Shares Borrowed is perhaps a better, less noisy, proxy for the short sale demand.

Both tables show that the short sale demand negatively depends on the idiosyncratic volatility shock, and this holds true across all regression specification. Moreover, the table shows that the short sale demand is greater for the lower book-to-market stocks (as the low book-to-market ratio may indicate an overvaluation), as well as stocks with the high Max return, which has probably resulted in a temporary increase in investor attention and, hence, overvaluation.

[25] See, e.g., Cohen, Diether, and Malloy (2007) for the importance of differentiating between the change in supply and the change in demand for loanable shares.

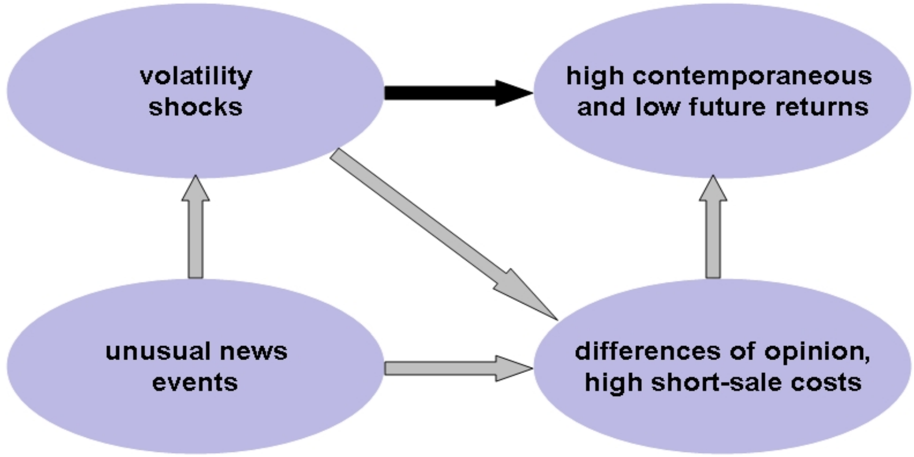

Figure 1. Graphical illustration of the hypothesis. The figure illustrates the logic of our explanation for how volatility shocks are related to concurrent and future returns.

Table A1
Descriptive statistics for volatility measures

The table reports various statistics for stocks' monthly idiosyncratic volatility shocks relative to the EGARCH-predicted volatility level (IVOL^{Shock}), EGARCH-predicted volatility levels (E[IVOL]), and idiosyncratic volatility levels estimated as in Ang, Hodrick, Xing, and Zhang (2006) (IVOL). The sample period is October 1964–December 2012.

	Cross-sectional statistics on time-series averages	Time-series statistics on cross-sectional averages
	IVOL^{Shock}	
Mean	1.79%	1.29%
Median	1.14%	1.09%
25th percentile	-1.03%	-0.91%
75th percentile	4.77%	3.19%
Standard deviation	8.46%	2.91%
	E[IVOL]	
Mean	11.50%	10.47%
Median	10.92%	10.71%
25th percentile	7.36%	9.62%
75th percentile	15.17%	11.53%
Standard deviation	5.51%	1.80%
	IVOL	
Mean	17.15%	12.68%
Median	13.61%	11.52%
25th percentile	9.09%	9.70%
75th percentile	21.14%	15.34%
Standard deviation	17.48%	3.69%
Number of observations	19,292	569

Table A2
Average stock characteristics

The table reports average portfolio characteristics for the stocks in each $IVOL^{\text{shock}}$-sorted portfolios presented in Panel A of Table 1. The variable definitions are presented in Section A3 of the Online Appendix. Size is in millions of $. The sample period is October 1964–December 2012 unless limited by the variable availability.

Decile	E[IVOL]	IVOL	Beta	Size	BM	Mom	Rev	Illiq	ISkew	Disp	Turn	Age	IncVol	β^{VXO}	GKM_H	GKM_L	AM	Max	Mkt.shr.	Prc
1 (Low)	20.15%	10.74%	1.71	192	1.18	34.83%	-1.52%	6.20	0.08	0.37	0.66	140.21	0.04	0.0008	0.08	0.21	4.51	5.75%	1.47%	10.11
2	13.72%	8.93%	1.49	695	0.99	20.64%	-0.30%	2.52	0.13	0.27	0.71	172.23	0.03	0.0009	0.09	0.19	3.49	4.97%	4.99%	19.75
3	11.53%	8.31%	1.34	1,346	0.93	17.13%	0.21%	1.90	0.14	0.21	0.70	198.98	0.02	0.0009	0.09	0.17	3.49	4.70%	9.57%	31.45
4	10.30%	8.12%	1.26	1,901	0.90	15.44%	0.52%	1.53	0.15	0.18	0.69	220.76	0.02	0.0010	0.10	0.16	3.52	4.64%	13.69%	37.98
5	9.62%	8.30%	1.20	2,319	0.89	14.49%	0.76%	1.31	0.17	0.16	0.69	235.51	0.02	0.0009	0.10	0.15	3.47	4.75%	16.66%	45.82
6	9.33%	8.85%	1.17	2,441	0.90	14.00%	0.96%	1.50	0.19	0.17	0.70	245.07	0.02	0.0009	0.10	0.15	3.38	5.07%	17.96%	42.50
7	9.58%	10.04%	1.19	2,170	0.91	13.72%	1.31%	1.91	0.23	0.18	0.74	237.98	0.02	0.0012	0.11	0.14	3.38	5.76%	16.20%	38.09
8	10.58%	12.35%	1.28	1,568	0.93	12.75%	1.67%	2.49	0.29	0.22	0.82	214.48	0.02	0.0012	0.12	0.14	3.42	7.10%	11.71%	26.74
9	12.48%	16.67%	1.41	756	1.00	9.72%	2.46%	4.92	0.38	0.31	0.94	182.85	0.03	0.0013	0.13	0.14	3.60	9.67%	5.86%	21.19
10 (High)	16.72%	32.01%	1.58	247	1.17	-2.43%	7.15%	22.19	0.63	0.54	1.43	150.62	0.03	0.0019	0.16	0.14	4.65	20.25%	1.89%	10.23

Table A3
Portfolio factor loadings

This table reports alphas and factor loadings of *IVOL*$^{\text{shock}}$-sorted decile portfolios, corresponding to Table 1, Panel A, with respect to the five-factor model that in addition to the four Fama-French factors includes the *IVOL* factor, computed as the return differential between the high- and low-*IVOL* portfolios, as described in Ang, Hodrick, Xing, and Zhang (2006). For the equal-weighted portfolios, the *IVOL* factor is constructed using equal-weighted returns; for the value-weighted portfolios, the *IVOL* factor is constructed using value-weighted returns. The corresponding Newey-West-adjusted *t*-statistics are reported in parentheses. The sample period is October 1964–December 2012.

Equal-weighted portfolios					
Intercept	MKT	SMB	HML	MOM	IVOL
-1.17	0.10	0.24	0.08		
(-11.20)	(1.95)	(3.15)	(0.98)		
-0.93	0.05	0.24	-0.01	-0.27	
(-7.99)	(1.24)	(2.61)	(-0.15)	(-4.48)	
-0.84	-0.02	-0.17	0.03	-0.16	0.26
(-7.98)	(-0.70)	(-2.36)	(0.51)	(-4.52)	(13.10)

Value-weighted portfolios					
Intercept	MKT	SMB	HML	MOM	IVOL
-1.06	0.16	-0.19	0.18		
(-4.81)	(2.37)	(-2.64)	(1.81)		
-0.98	0.14	-0.19	0.16	-0.08	
(-4.56)	(2.20)	(-2.47)	(1.62)	(-1.36)	
-0.80	0.10	-0.44	0.17	-0.02	0.16
(-3.46)	(1.61)	(-3.42)	(1.57)	(-0.23)	(2.23)

Table A4
Characteristic-adjusted returns

The table reports characteristic-adjusted returns of $IVOL^{\text{shock}}$-sorted portfolios and the return differentials between the extreme deciles. Following Daniel and Titman (1997), we form characteristic matched portfolios at the end of June of year k. All stocks in our sample are sorted into size quintiles based on the NYSE size breakpoints; stocks within each size quintile are then sorted into BM quinitles using the NYSE BM breakpoints; stocks within each of the 25 size and BM groupings are further sorted into momentum quintiles based on the CRSP momentum breakpoints. The intersection of the size, BM, and momentum quintiles generates 125 benchmark portfolios at the end of June of year k. The equal-weighted monthly benchmark returns for the 125 portfolios are calculated over the following 12 months from July of year k to June of year k+1. A stocks monthly characteristic-adjusted return is defined as the difference between its raw monthly stock return and the monthly benchmark return of one of the 125 benchmark portfolios to which the stock belongs as of the end of June of year k. Newey and West (1987) adjusted *t*-statistics are reported in parentheses. Returns are in percent. The sample period is October 1964–December 2012.

$IVOL^{\text{shock}}$ Decile	Characteristic-adjusted return
1 (Low)	0.24
	(3.30)
2	0.19
	(5.08)
3	0.14
	(4.07)
4	0.09
	(2.59)
5	0.07
	(2.01)
6	0.09
	(2.45)
7	0.05
	(1.19)
8	-0.03
	(-0.78)
9	-0.19
	(-5.41)
10 (High)	-0.59
	(-7.71)
High-Low	-0.83
	(-8.73)

Table A5
Bivariate portfolio sorts

The table presents the equal- and value-weighted returns, as well as return differentials between high- and low-volatility-shock-sorted portfolios and the corresponding four-factor alphas. In Panel A, stocks are first sorted into size quintiles and then into further $IVOL^{\text{shock}}$ quintile portfolios. In panel B, stocks are first sorted into deciles based on each characteristic of interest and then, within each decile, into $IVOL^{shock}$ deciles. The control variables are described in Section A3 of the Online Appendix. The reported returns are averaged across the control-variable-sorted deciles for each of the $IVOL^{shock}$ deciles to produce portfolios with dispersion in $IVOL^{shock}$ and with near-identical levels of the control variable. The Newey and West (1987) adjusted t-statistics of the four-factor alphas for the return differentials are reported in parentheses. Returns are in percent. The sample period is October 1964–December 2012 or shorter, as limited by the control variable availability.

Panel A: Size and volatility-shock-sorted portfolios

Equal-weighted portfolios

$IVOL^{\text{shock}}$ quintile	Size quintile 1 (small)	2	3	4	5 (large)
1 (Low)	2.08	1.65	1.39	1.32	1.07
2	1.95	1.49	1.40	1.31	1.04
3	1.92	1.39	1.34	1.26	1.03
4	1.75	1.11	1.25	1.23	0.96
5 (High)	1.22	0.19	0.55	0.83	0.82
High-Low	-0.86	-1.46	-0.84	-0.49	-0.25
	(-4.69)	(-12.87)	(-7.32)	(-5.31)	(-3.14)
4-factor alpha	-0.70	-1.41	-0.83	-0.47	-0.24
	(-3.45)	(-10.03)	(-6.66)	(-5.08)	(-3.06)

Value-weighted portfolios

$IVOL^{\text{shock}}$ quintile	Size quintile 1 (small)	2	3	4	5 (large)
1 (Low)	1.84	1.63	1.38	1.29	0.93
2	1.71	1.48	1.39	1.29	0.95
3	1.62	1.40	1.31	1.24	0.84
4	1.35	1.10	1.24	1.23	0.84
5 (High)	0.14	0.18	0.57	0.84	0.73
High-Low	-1.71	-1.45	-0.82	-0.45	-0.20
	(-11.39)	(-11.94)	(-7.20)	(-4.77)	(-1.70)
4-factor alpha	-1.57	-1.39	-0.81	-0.44	-0.18
	(-9.54)	(-9.31)	(-6.36)	(-4.57)	(-1.47)

Panel B: Control variable- and volatility-shock-sorted portfolios

Equal-weighted portfolios

Decile	E[IVOL]	Beta	BM	Mom	Rev	Illiq	ISkew	Disp	Turn	Age	IncVol	β^{VXO}	AM	Max	GKM_H	GKM_L
1 (Low)	1.36	1.67	1.59	1.62	1.54	1.60	1.67	1.52	1.70	1.57	1.77	1.54	1.59	1.60	2.01	1.27
2	1.47	1.54	1.47	1.50	1.48	1.59	1.53	1.49	1.50	1.47	1.62	1.40	1.51	1.43	1.79	1.25
3	1.46	1.39	1.38	1.36	1.39	1.45	1.37	1.32	1.36	1.40	1.48	1.26	1.34	1.35	1.60	1.11
4	1.43	1.34	1.33	1.33	1.33	1.42	1.32	1.33	1.31	1.29	1.40	1.21	1.27	1.29	1.61	1.08
5	1.38	1.31	1.29	1.27	1.35	1.36	1.30	1.23	1.29	1.23	1.38	1.17	1.33	1.21	1.49	1.09
6	1.32	1.26	1.24	1.25	1.29	1.32	1.28	1.25	1.28	1.27	1.37	1.12	1.22	1.18	1.44	1.08
7	1.33	1.26	1.23	1.18	1.32	1.23	1.22	1.20	1.16	1.22	1.37	1.12	1.24	1.19	1.55	1.02
8	1.19	1.20	1.15	1.17	1.17	1.17	1.20	1.15	1.18	1.17	1.30	1.04	1.16	1.14	1.38	0.92
9	1.02	1.02	1.06	1.07	1.13	0.97	1.05	1.06	0.98	0.98	1.14	0.94	1.05	1.09	1.26	0.80
10 (High)	0.63	0.61	0.69	0.86	0.58	0.30	0.71	0.53	0.64	0.68	0.76	0.62	0.72	1.12	0.55	0.40
High-Low	-0.73	-1.06	-0.90	-0.76	-0.97	-1.31	-0.96	-0.99	-1.06	-0.89	-1.02	-0.92	-0.87	-0.48	-1.46	-0.87
	(-6.98)	(-11.60)	(-9.34)	(-7.50)	(-9.42)	(-12.79)	(-9.12)	(-8.16)	(-10.38)	(-6.56)	(-8.41)	(-7.39)	(-8.67)	(-2.52)	(-9.45)	(-6.35)
4-factor	-0.69	-1.05	-0.79	-0.83	-0.89	-1.22	-0.84	-0.91	-0.92	-0.81	-0.86	-0.86	-0.75	-0.32	-1.34	-0.77
alpha	(-8.79)	(-12.16)	(-9.75)	(-7.53)	(-9.96)	(-13.40)	(-9.84)	(-8.76)	(-10.94)	(-7.29)	(-10.05)	(-7.74)	(-9.28)	(-2.32)	(-10.00)	(-6.92)

Value-weighted portfolios

Decile	E[IVOL]	Beta	BM	Mom	Rev	Illiq	ISkew	Disp	Turn	Age	IncVol	β^{VXO}	AM	Max	GKM_H	GKM_L
1 (Low)	1.20	1.28	1.23	1.06	1.16	1.41	1.24	1.22	1.18	1.16	1.38	1.14	1.34	1.06	1.42	0.89
2	1.17	1.12	1.23	1.09	1.17	1.36	1.14	1.28	1.10	1.14	1.35	1.16	1.14	1.09	1.09	0.84
3	1.16	1.13	1.12	0.99	1.15	1.27	1.13	1.09	1.05	1.13	1.18	1.09	1.07	1.09	1.26	0.91
4	1.13	1.03	1.16	0.99	1.07	1.27	0.99	1.13	1.09	1.06	1.14	1.03	1.07	0.97	1.07	0.90
5	0.96	1.00	1.09	0.97	1.13	1.18	0.99	0.94	0.98	1.01	1.08	1.07	1.11	1.00	1.01	0.83
6	0.96	0.91	0.97	0.80	0.95	1.07	1.01	1.01	0.99	1.01	1.04	0.85	0.96	0.90	0.84	0.82
7	0.87	0.90	1.01	0.77	1.02	1.01	0.94	1.00	0.86	0.90	1.09	0.87	0.97	0.90	1.08	0.75
8	0.80	0.90	0.98	0.71	0.80	0.94	0.84	0.94	0.80	0.85	1.02	0.81	0.97	0.84	0.91	0.64
9	0.48	0.77	0.88	0.57	0.85	0.71	0.75	0.84	0.75	0.65	0.77	0.61	0.83	0.70	0.88	0.66
10 (High)	0.05	0.21	0.40	0.32	0.36	0.12	0.15	0.54	0.34	0.27	0.51	0.28	0.38	0.58	0.04	-0.09
High-Low	-1.15	-1.07	-0.82	-0.74	-0.81	-1.29	-1.10	-0.69	-0.84	-0.89	-0.87	-0.86	-0.96	-0.47	-1.38	-0.98
	(-6.86)	(-7.52)	(-4.93)	(-5.75)	(-4.49)	(-12.67)	(-6.69)	(-3.77)	(-6.10)	(-5.11)	(-5.07)	(-4.09)	(-6.44)	(-2.40)	(-5.57)	(-4.57)
4-factor	-1.08	-1.11	-0.78	-0.80	-0.71	-1.21	-1.05	-0.68	-0.73	-0.90	-0.77	-0.83	-0.88	-0.25	-1.42	-0.98
alpha	(-8.09)	(-8.17)	(-5.30)	(-5.73)	(-4.51)	(-12.66)	(-6.98)	(-4.26)	(-5.92)	(-5.66)	(-5.42)	(-3.98)	(-6.78)	(-1.91)	(-5.71)	(-4.74)

Table A6
Within-industry portfolio sorts

The table presents the equal- and value-weighted returns (Panels A and B), as well as return differentials between high- and low-volatility-shock-sorted portfolios and the corresponding four-factor alphas of within-industry-sorted portfolios. Stocks are sorted within each of the 10 Fama-French industries. In the "Combined" columns, the resulting $IVOL^{shock}$-decile portfolios are combined across industries to create a near-identical industry representation for each portfolio. The Newey and West (1987) adjusted t-statistics of the four-factor alphas for the return differentials are reported in parentheses. Returns are in percent. The sample period is October 1964–December 2012.

Panel A: Equal-weighted portfolios

$IVOL^{shock}$ Decile	Consumer durables	Consumer nondur.	Manufact.	Energy	HiTec	Telecom	Shops	Health	Utilities	Other	Combined
1 (Low)	1.37	1.49	1.59	1.44	1.98	2.04	1.53	2.18	1.16	1.60	1.64
2	1.56	1.41	1.44	1.38	1.91	1.67	1.33	2.04	1.12	1.50	1.54
3	1.29	1.30	1.32	1.67	1.43	1.59	1.61	1.73	0.98	1.32	1.42
4	1.23	1.41	1.31	1.53	1.46	1.34	1.40	1.68	1.04	1.27	1.37
5	1.29	1.11	1.33	1.33	1.34	1.34	1.26	1.73	0.93	1.20	1.29
6	1.27	1.48	1.36	1.25	1.42	1.26	1.20	1.46	0.99	1.22	1.29
7	1.24	1.30	1.39	1.33	1.59	1.33	1.19	1.33	0.97	1.14	1.28
8	0.98	1.00	1.19	1.34	1.35	1.23	1.07	1.36	1.00	1.19	1.17
9	1.08	1.00	1.12	1.10	1.24	1.19	1.03	1.10	0.99	1.01	1.09
10 (High)	0.75	0.15	0.57	0.76	1.23	0.84	0.58	1.11	0.94	0.38	0.73
High-Low	-0.63	-1.34	-1.03	-0.67	-0.75	-1.20	-0.95	-1.06	-0.21	-1.22	-0.91
	(-2.25)	(-3.44)	(-5.93)	(-1.95)	(-3.33)	(-2.46)	(-3.78)	(-3.08)	(-1.08)	(-6.58)	(-7.89)
4-factor alpha	-0.49	-1.34	-0.88	-0.53	-0.58	-0.49	-0.65	-0.89	-0.22	-1.01	-0.68
	(-1.75)	(-3.21)	(-4.90)	(-1.47)	(-2.43)	(-0.91)	(-2.09)	(-2.46)	(-1.03)	(-5.58)	(-6.26)

Panel B: Value-weighted portfolios

$IVOL^{shock}$ Decile	Consumer durables	Consumer nondur.	Manufact.	Energy	HiTec	Telecom	Shops	Health	Utilities	Other	Combined
1 (Low)	1.07	0.99	1.06	1.20	1.37	1.81	1.08	1.68	1.14	1.28	1.27
2	1.28	1.36	0.96	1.15	1.42	1.43	1.30	1.31	0.85	1.18	1.22
3	1.03	0.92	0.85	1.13	1.20	1.40	1.18	1.05	0.87	0.98	1.06
4	1.04	1.12	0.85	1.18	1.22	1.31	1.10	0.97	0.92	1.06	1.08
5	1.32	0.83	0.99	1.28	1.15	1.00	1.19	1.23	0.83	0.88	1.07
6	1.05	0.99	0.87	1.18	0.80	0.85	0.94	1.00	0.92	0.95	0.95
7	1.13	0.60	1.16	1.05	1.05	0.84	0.89	1.12	0.73	0.88	0.94
8	1.12	0.45	0.89	1.29	0.92	0.68	0.84	1.05	0.91	0.88	0.90
9	1.03	0.82	0.96	0.43	0.57	0.63	0.97	0.71	0.73	0.94	0.78
10 (High)	0.49	0.01	0.69	0.66	0.25	0.17	-0.08	0.53	0.66	0.24	0.36
High-Low	-0.59	-0.98	-0.37	-0.54	-1.12	-1.64	-1.17	-1.15	-0.47	-1.04	-0.91
	(-1.79)	(-2.41)	(-1.39)	(-1.16)	(-3.05)	(-2.96)	(-3.20)	(-2.83)	(-2.11)	(-3.48)	(-5.54)
4-factor	-0.49	-0.98	-0.32	-0.56	-0.97	-1.32	-1.11	-1.26	-0.63	-1.03	-0.85
alpha	(-1.49)	(-2.12)	(-1.06)	(-1.20)	(-2.54)	(-2.39)	(-2.62)	(-2.96)	(-2.48)	(-3.53)	(-5.28)

Table A7
Predictors of the short selling demand

The table reports pooled regressions of the end-of-month short selling demand measures (Utilization, which is the percentage of lendable shares on loan to short sellers, and Shares Borrowed) on the idiosyncratic volatility shock and a set of other variables computed during the month. The standard errors are double clustered by stock and month. The sample period is June 2002–December 2012.

	Measure of short selling demand:															
	Utilization								Shares Borrowed							
$IVOL^{shock}$	-0.0720	-0.0830	-0.0639	-0.0733	-0.0560	-0.0545	-0.2449	-0.2412	-0.0253	-0.0314	-0.0168	-0.0219	-0.0165	-0.0205	-0.0318	-0.0419
	(-6.01)	(-6.36)	(-5.57)	(-5.91)	(-5.06)	(-4.85)	(-4.86)	(-5.11)	(-7.32)	(-7.58)	(-6.83)	(-7.26)	(-6.38)	(-6.92)	(-4.76)	(-4.94)
Size			0.4083	0.4357	-0.3190	-0.2058	0.3335	0.4530			0.4284	0.4273	0.3343	0.3361	0.3697	0.3970
			(3.05)	(3.48)	(-2.24)	(-1.54)	(2.32)	(3.36)			(11.68)	(12.27)	(9.04)	(9.61)	(9.28)	(10.19)
BM					-5.0081	-4.7695	-4.8505	-4.4448					-0.6148	-0.6398	-0.6036	-0.6056
					(-14.32)	(-14.37)	(-14.57)	(-14.31)					(-8.05)	(-8.56)	(-7.93)	(-8.20)
Rev					0.0116	0.0112	-0.0386	-0.0416					-0.0024	-0.0012	-0.0110	-0.0111
					(1.28)	(1.17)	(-3.82)	(-3.95)					(-1.04)	(-0.49)	(-4.02)	(-3.63)
Mom					0.0053	0.0058	0.0029	0.0024					-0.0011	-0.0004	-0.0011	-0.0007
					(2.15)	(2.30)	(1.20)	(0.95)					(-1.94)	(-0.70)	(-2.18)	(-1.29)
IVOL							0.3207	0.3314							-0.0067	0.0101
							(6.12)	(6.53)							(-0.69)	(0.98)
Max							0.1579	0.1556							0.0577	0.0562
							(4.41)	(4.08)							(6.47)	(5.86)
Ind. dummies	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N	Y	N
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	9.35%	6.73%	9.49%	6.90%	12.82%	10.56%	14.32%	12.22%	17.79%	14.54%	20.02%	16.98%	20.86%	17.84%	21.08%	12.22%