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Public news arrival and the idiosyncratic volatility puzzle☆

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ABSTRACT

This paper analyzes the effects of news and its sentiment on the idiosyncratic volatility (*IVOL*) — expected return relation. We postulate that the perceived negative *IVOL*-expected return relation could be the artifact of the confounding effect of public news arrivals. Using the stock return data from the Center for Research in Security Prices (CRSP) database and the news database from the RavenPack News Analytics over the period from 2000 to 2011, we show that the strength of the positive relation is reduced systematically by 50% after accounting for the arrivals of good and bad news releases, which are defined by their sentiment scores. This finding is robust to numerous model specifications, and the inclusion of firm-level characteristics, liquidity risk and information risk. When we restrict the firm-specific news to value-relevant news, the positive relation disappears. We conclude that that the public arrivals of firm-specific news play a significant role in explaining the *IVOL* puzzle.

1. Introduction

Modern portfolio theory asserts that, in the absence of market imperfections, rational investors should hold diversified portfolios, and therefore idiosyncratic volatility (*IVOL*) or risk should not be priced. However, this assertion is subsequently challenged by many researchers who argue that, in the presence of market imperfections, investors under-diversify, and such under-diversification could lead to a positive relation between *IVOL* and expected stock returns in the cross-section (Levy, 1978; Malkiel and Xu, 2002; Merton, 1987). While the argument has received support from a number of empirical studies including Spiegel and Wang (2005), Malkiel and Xu (2006), Fu (2009) and Chua et al. (2010), recent work by Ang et al. (2006) documents an opposite and puzzling result; they find that portfolios with high *IVOL* have abnormally low returns. This result is generally regarded as the idiosyncratic volatility puzzle since it suggests high *IVOL* commands a negative risk premium.[1]

Many studies have emerged in the past decade to address the puzzling results of Ang et al. (2006). Studies such as Saryal (2009) and Fu (2009) point out that the puzzle is in part caused by the method of *IVOL* measurement.

☆ Abbreviations defined in this paper: Center for Research in Security Prices (CRSP), Mixture of Distribution Hypothesis (MDH), Exponential GARCH (EGARCH), New York Stock Exchange (NYSE) and American Stock Exchange (AMEX).

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[1] Bali and Cakici (2008) question the robustness and significance of a cross-sectional relation between volatility and expected returns. They show that the data frequency used to estimate idiosyncratic volatility, weighting scheme used to compute average portfolio returns, breakpoints utilized to sort stocks into quintile portfolios, and using a screen for size, price and liquidity play a critical role in determining the existence and significance of a relation between idiosyncratic risk and the cross-section of expected returns. We thank one of the referees for pointing out the results of Bali and Cakici (2008) to us.

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Grullon et al. (2012) and Bali et al. (2011b) find that innovations in *IVOL* are positively related to contemporaneous stock returns, which further causes the negative relation temporally. More specifically, any innovation in the *IVOL* could increase the growth option value of the firm, but as the firm hedges against rising volatility, expected returns fall. Boyer et al. (2010) assert that the negative relation can be explained by the expected idiosyncratic skewness, while Bali et al. (2011a) show that the relation can be explained by the maximum daily return over the previous month. Han and Kumar (2013) assert that the puzzle is mainly driven by retail trading. Jiang et al. (2014) argue that investor overconfidence and costly arbitrage leads to an overpricing of *IVOL*, and upon the lifting of the short-sale constraints, arbitrageurs act to dampen the price, reinforcing the negative relation between *IVOL* and future returns. They use three natural experiments involving changes to the short-sale constraints (including the expiration of the IPO lockup period, the introduction of tradable options and the expiration of the short-selling ban in October 2008) and find support for their hypotheses. Chen and Petkova (2012) argue that the average variance component of the aggregate market offers an alternative explanation for the puzzling relation. Finally, Fu (2009) and Huang et al. (2010) present evidence that return reversals in stocks with high *IVOL* can explain the perceived negative price of idiosyncratic risk.

The primary focus of these studies is on how the different characteristics of *IVOL*, as well as the market conditions, contribute to the *IVOL*-expected return relation. In this paper, we offer an alternative explanation for this relation. We postulate that the perceived negative *IVOL*-expected return relation could be the artifact of the confounding effect of public news arrivals. First, the arrival of bad (good) news is associated with both contemporaneous and future negative (positive) returns (Chan, 2003). Second, because of the leverage effect, bad news increases the expected *IVOL* (Black, 1976). However, the impact of good news on the expected *IVOL* is less clear. Studies by Chen and Ghysels (2011) show that good news reduces expected volatility but very good news (and very bad news) increase expected volatility. Such asymmetric effect is somewhat loosely in line with results documented by Engle and Ng (1993), who find that the impact of negative stock return on volatility is much greater than that of positive stock return. In this paper, we argue that mixing these two effects, i.e. the effects of news type on *IVOL* and stock return could lead to a perceived negative *IVOL*-expected return relation documented by Ang et al. (2006).

More specifically, we present evidence showing that both the intensity and the quality (good versus bad) of news flow can contribute to the negative relation between *IVOL* and expected return. To address one of the criticisms on Ang et al.'s (2006) results by Fu (2009) that *IVOL* is time-varying, we employ the Exponential GARCH (EGARCH) model to estimate the expected *IVOL*, i.e. the expected *IVOL* at time t conditional on the information set at time $t-1$ and examine its relation to excess return at time t with and without controlling for the impact of public news in the estimation of the expected *IVOL*. If the news explains the level of expected *IVOL*, the inclusion of news would significantly reduce the positive relation documented by Fu (2009). Our stock sample consists of stocks traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ from January 2000 to December 2011.[2] Our news datasets are obtained from the RavenPack News Analytics Dow Jones Edition (RavenPack), which is a comprehensive database covering more than 1200 types of firm-specific and macroeconomic news events. RavenPack automatically tracks and monitors relevant information on tens of thousands of companies, government organizations, influential people, key geographical locations, and all major currencies and traded commodities. The service includes analytics on more than 170,000 entities in over 100 countries, and it covers over 98% of the investable global market. Among its many benefits, RavenPack delivers sentiment analysis and event data that are most likely to affect financial markets and trading around the world — all in a matter of milliseconds. It continuously analyzes relevant information from major real-time newswires and trustworthy sources such as Dow Jones Newswires, regional editions of the Wall Street Journal and Barron's, and Internet sources including financial sites, blogs, and local and regional newspapers, to produce real-time news sentiment scores. All relevant news articles about entities are classified and quantified according to their sentiment, relevance, topic, novelty and market effect. In terms of the sentiment, RavenPack uses a proprietary computational linguistic analysis algorithm[3] to quantify the positive and negative perceptions on facts and opinions reported in the news textual content. The core of the algorithm can be divided into two steps. First, RavenPack builds up a historical database of words, phrases, combinations and other word-level definitions that have affected the target company, market or asset class; and second, the text in the specific news story is compared with the historical database, and the sentiment score is generated accordingly. In this paper, we use the sentiment score to classify news type.

To examine our conjecture empirically, we first estimate *IVOL* without including news in the estimation of the expected *IVOL*. The expected *IVOL* is fitted against the excess return after controlling for the Fama and French Three Factors including the premiums for the market risk, book-to-market and firm size (Fama and French, 1993, 1996) in a panel regression framework. Consistent with Fu (2009), we find the relation to be positive and statistically significant. We then construct a group of news variables that take into consideration the number, relevance and/or sentiment of news, and incorporate them into the EGARCH specification. We re-estimate the expected *IVOL* and regress it against the excess return under the same framework. After we account for the news type (good news and bad news), the strength of the positive relation is reduced systematically by about 50%. We further check to see if this finding is robust to various model specifications, the inclusion of other firm-level characteristics such as momentum factor, liquidity risk and information risk, in explaining the cross-section of the stock returns. Our baseline result remains unchanged. Since not all types of news are value-relevant, we restrict firm-specific news to earnings-related as well as non-earnings news releases that are value-relevant, including, *inter alia*, mergers and acquisitions, bankruptcy, releases of new products and services, asset sale or acquisition, equity issuing decisions, labor issues, partnerships, industrial

[2] The starting date of the RavenPack database is January 2000 and no news data are available before this date.
[3] See Appendix A for details of how the sentiment scores are constructed by RavenPack.

accidents and exploration. This restriction also serves as a robustness check of our baseline results. With this restriction in place, the positive *IVOL*-expected return relation disappears.[4]

The rest of this paper is organized as follows. Section 2 describes the methodology used to estimate the idiosyncratic volatility and the news variables constructed from RavenPack. Section 3 discusses the empirical results from our models and describes our sample. Section 4 discusses various robustness checks, and Section 5 concludes.

2. Idiosyncratic volatility and news variables

2.1. Estimation of idiosyncratic volatility

In his critique of Ang et al. (2006) methodology, Fu (2009) contends that lagged *IVOL* may not be appropriate to serve as proxy for expected *IVOL* because of the return reversal and the time-varying property of *IVOL*. Fu uses EGARCH to estimate the expected (conditional) *IVOL*, and finds evidence that is opposite to the Ang et al.'s *IVOL* puzzle; he shows that the expected *IVOL* is significantly and positively related to the contemporaneous monthly stock returns. In light of Fu's finding, we follow his methodology and estimate the monthly *IVOL* using EGARCH:

$$r_{i,\,t} = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + \varepsilon_{i,\,t} \text{ and } \varepsilon_{i,\,t} \sim N\left(0,\ \sigma^2_{i,\,t}\right)$$

$$\ln\left(\sigma^2_{i,\,t}\right) = a_i + \sum_{l=1}^{p} b_{i,\,l} \ln\left(\sigma^2_{i,\,t-1}\right) + \sum_{k=1}^{q} c_{i,\,k}\left\{\theta\left(\frac{\varepsilon_{i,\,t-k}}{\sigma_{i,\,t-k}}\right) + \gamma\left[\left|\frac{\varepsilon_{i,\,t-k}}{\sigma_{i,\,t-k}}\right| - (2/\pi)^{1/2}\right]\right\}$$

$$\text{where } 1 \le p \le 3 \text{ and } 1 \le q \le 3 \tag{1}$$

where $r_{i,\,t}$ is the excess return of firm *i* at month *t*. MKT_t, SMB_t and HML_t are the Fama–French Three Factors (Fama and French, 1993, 1996): the excess return on a broad market portfolio, the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks, and the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks, respectively. $\varepsilon_{i,\,t}$ is an independently and identically distributed innovation for firm *i* at month *t*, which follows a normal distribution with mean 0 and standard deviation $\sigma_{i,\,t}$. Following Fu's (2009) methodology, for each month, we estimate nine EGARCH models with different permutations of *p* and *q* ($p + q + 3$) and select a model that has the lowest AIC. The expected *IVOL* in month *t* is given by $E_{t-1}(\sigma_{i,\,t})$, where the expectation is taken with respect to all information available up to the month $t-1$. Similar to Fu (2009), our estimation window begins at 30 months (i.e. a minimum of 30 observations) with an expanding window up to month $t-1$.

2.2. Construction of news variables

To construct the news variables, we use the RavenPack,[5] which captures more than 1,200 types of intraday firm-specific and macroeconomic news events from January 2000 onwards. To account for the qualitative effect of these news releases, RavenPack offers an analytical output for each firm-specific and macroeconomic news release on a global basis. These news releases are obtained from Dow Jones Newswires, the Wall Street Journal and the Barron's. Among dozens of the analytical outputs in the database, we use the *REL*, *CSS*, *ESS* and *ENS*.[6]

The *REL* is the relevance score which indicates how strongly the news story is related to a particular company. It ranges from 0 to 100. A high *REL* suggests that the news story is highly relevant to the corresponding stock.

The *CSS* is a sentiment score that ranges from 0 to 100. It represents the news sentiment of a given story by combining various sentiment analysis techniques. The direction of the score is determined by emotionally charged words and phrases embedded in the news story, which is typically rated by experts as having a short-term positive or negative share price effect. A high score (above 50) indicates a positive intraday stock price effect, while a low score (below 50) indicates a negative effect.

The *ESS* is a granular score that ranges from 0 to 100. It specifies whether the news story conveys positive or negative sentiment about the stock. The score is constructed as follows. First, a set of news (training set) is categorized by a group of financial experts based on the degree to which they have a short-term positive or negative macroeconomic effect. Second, their classification is encapsulated in an algorithm that generates a score ranging from 0 to 100. A high score (above 50) indicates positive sentiment, while a low score (below 50) indicates negative sentiment.

The *ENS* is a score that ranges from 0 to 100. It measures how 'new' or 'novel' a news story is in the previous 24-hour period. The first story reporting a categorized event about the macroeconomy is considered the most novel and receives a score of 100.

According to the Mixture of Distribution Hypothesis (MDH) originally proposed by Clark (1973), and later extended by Tauchen and Pitts (1983) and Harris (1986, 1987), asset return volatility is proportional to the rate of information arrival. Using

[4] Our finding is loosely related to Shen (2008) who shows that the cross-sectional variation in *IVOL* is due to firm-specific information. While he shows that private information is the dominant factor driving the variation in *IVOL*, we show how the public arrival of different news types explains the *IVOL*-return relation.

[5] Details of the RavenPack can be found in Mitra and Mitra (2011).

[6] See Appendix A for details on how the scores are calculated.

the number of news articles as proxy for the rate of information arrival, Kalev et al. (2004) show that the clustering nature of information arrival explains one stylized feature of asset return volatility — volatility persistence. Drawing from the argument of MDH, one might argue that news releases can induce *IVOL*, and thus, we construct a variable based on the raw number of news articles $N_{i,t}$, which is the number of news articles for firm *i* received between month $t-1$ and month *t*.

Since not all news releases are highly relevant, we regenerate the number of news articles weighted by *REL*:

$$RN_{i,\,t} = \sum_{all\quad \tau} \frac{REL_{i,\,\tau}}{100}. \tag{2}$$

The sentiment of news, i.e. news type, can also affect *IVOL*. Veronesi (1999) argues that the impact of news on volatility depends on whether the news is good or bad. In the presence of asymmetric information, Veronesi (1999) shows that investors overreact to bad news in good times and underreact to good news in bad times, which in turn affects return volatility differently. Veronesi's (1999) argument is tested and supported by numerous empirical papers, including Laakkonen and Lanne (2009), Mitra et al. (2011), Chen and Ghysels (2011) and Ho et al. (2013). To encapsulate the impact of news type (good and bad news), we construct the number of negative and positive news articles weighted by *REL* and *CSS* for firm *i* in month *t* as follows:

$$WNN_{i,\,t} = \sum_{all\quad \tau} \frac{I\left(CSS_{i,\,\tau} < 50\right)\left|CSS_{i,\,\tau} - 50\right| REL_{i,\,\tau}}{100} \tag{3}$$

$$WNP_{i,\,t} = \sum_{all\quad \tau} \frac{I\left(CSS_{i,\,\tau} > 50\right)\left|CSS_{i,\,\tau} - 50\right| REL_{i,\,\tau}}{100} \tag{4}$$

where $I(\cdot)$ is the indicator function that gives 1 when the condition inside the parentheses is true and 0 otherwise.

It has been argued in the literature that news sentiment can significantly affect stock return (Hafez, 2009; Leinweber and Sisk, 2011; Moniz et al., 2011; Veronesi, 1999). To control for such an impact, we construct the weighted event score to measure the average sentiment of news at time *t*. For firm *i* at month *t*, the weighted event score (*WESS*) is given by the following:[7]

$$WESS_{i,\,t} = \frac{1}{T} \sum_{all\quad \tau} \frac{\left(ESS_{i,\,\tau} - 50\right) ENS_{i,\,\tau}}{100} \tag{5}$$

where *T* is the total number of news stories in the monthly interval $[t-1, t]$.[8]

The rationale behind the above weighting system is simple. In the case of *RN*, *WNN* and *WNP*, news is weighted by the relevance score. We expect investors to react less on news that is remotely relevant to the stock. Hence, a lower weight is given to news with a low relevance score. In the case of *WESS*, the *ESS* is weighted by the novelty score. News that has already been reported by other news sources, or news that belongs to a chain of related news stories, are expected to have a lower effect on the stock return volatility. Thus, they are assigned a lower weight because they are not 'new' to the market.

3. Empirical results

3.1. Data and sample

Our data include the monthly returns of the NYSE, AMEX and NASDAQ common stocks from January 2000 to December 2011. The stock return data is obtained from the Center for Research in Security Prices (CRSP) while the book value of each company is obtained from Compustat. Fama–French Three Factors (FF3F) are downloaded from Kenneth French's website.[9][10] *IVOL* and news variables are constructed as discussed in Section 2.

We follow Fu's (2009) stock selection criteria. More specifically, we include stocks that have at least 30 monthly observations, and in each month, we require a minimum of 15 trading days for which they have non-zero trading volume. Furthermore, we require that for each selected stock, at least one news variable has non-zero value for the first 30 months. Based on these criteria, our sample consists of 5,152 stocks. The descriptive statistics of the variables are presented in Table 1.

Table 1 shows that both the average excess and raw returns for individual stocks are positive (0.8901% and 1.0412%, respectively). After being weighted by *REL* and *CSS*, the average weighted number of negative news articles is slightly greater than the average weighted number of positive news articles, with values of 25.9463 and 22.6327, respectively. The average news sentiment, as captured by *WESS*, is positive (2.7455). *E*(*IVOL*) is estimated using Eq. (1) and has a mean of 11.2241%. After we include the raw number of news or the number of news weighted by relevance score, ($E(IVOL)_N$ and $E(IVOL)_{RN}$, respectively) the

[7] Note that *ESS* is only available when *REL* is 100, so *REL* is not used to construct the weighted event score.
[8] We also estimate the EGARCH models without *WESS* in the mean equation, and the results are consistent.
[9] In EGARCH models, the starting period is 30 months, so the actual data coverage is from July 2002 to December 2011.
[10] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We thank Kenneth French for making these data available.

Table 1
Descriptive statistics of variables.

Variables	Mean	Std dev.	Median	Q1	Q3	Skew
r_t	0.8901	15.5465	0.2514	−6.1360	6.7491	2.2299
R_t	1.0412	15.5411	0.4228	−5.9777	6.8911	2.2245
WNN_t	25.9463	59.3427	5.2200	0.0000	25.6000	5.1038
WNP_t	22.6327	46.6571	9.0000	2.0000	23.9300	5.6244
$E(IVOL)$	11.2241	8.9552	8.8376	5.5312	14.0502	2.6203
$E(IVOL_N)$	10.2764	8.4560	8.0236	4.9839	12.7853	2.7229
$E(IVOL_{RN})$	10.3395	8.5192	8.0716	5.0221	12.8639	2.7550
$E(IVOL_{WN})$	11.4493	11.2157	8.4237	5.0888	13.8567	3.6386
$WESS_t$	2.7455	7.6491	0.5000	−0.1667	7.1000	0.2946

Note: This table presents the descriptive statistics of variables involved in this study. The summary statistics include mean value (Mean), standard deviation (Std dev.), 25 percentile (Q_1), 75 percentile (Q_3) and skewness (Skew) for each variable. The sample period is from January 2000 to December 2011. r_t is the monthly excess return. R_t is the monthly raw return. Both r_t and R_t are reported in percentage. $WNN_t(WNP_t)$ is the monthly contemporaneous number of negative (positive) news weighted by relevant and sentiment. $E(IVOL_N)$, $E(IVOL_{RN})$ and $E(IVOL_{WN})$ are the one-month-ahead idiosyncratic volatility estimated by EGARCH models with raw number of news, number of news weighted by relevance and number of news weighted by relevance and sentiment in the conditional variance equation, respectively and with $WESS_t$ in the mean equation in all cases.

expected *IVOL* falls to 10.2764 and 10.3395, respectively. When we separate out the news into good news and bad news, each weighted by *REL* and *CSS*, the expected *IVOL* increases and becomes more skewed.

Table 2 reports the correlations between these variables, and based on the correlation statistics, there seems to be some evidence of the confounding effect of news: while $E(IVOL)$ is positively related to stock return (excess return r_t and raw return R_t), *WESS* is positively associated with stock return but it is negatively associated with $E(IVOL)$.

3.2. IVOL, excess returns and news

In this study, we contend that the perceived negative *IVOL*-expected return relation could be driven by the confounding effect of the arrival of good news and bad news. When bad news arrives, we expect a contemporaneous negative stock return. When good news arrives, we expect a contemporaneous positive stock return. Meanwhile, because of the leverage effect, bad news drives up the expected *IVOL*, while the impact of good news on the expected *IVOL* is less clear. To examine the interrelation between *IVOL*, excess return and news, we sort portfolios of lagged *IVOL*, lagged weighted number of negative news, and lagged weighted number of positive news by quintiles. panel A of Table 3 reports the average excess returns by each quintile portfolio. It can be seen that as the lagged *IVOL* rises, the average excess return falls, and the average excess return falls with the number of weighted negative news, while it rises with the number of weighted positive news. The return differences between the top and the bottom quintile portfolios across *IVOL*, *WNN* and *WNP* are statistically significant at the 1% level.

In panel B, we report the average *IVOL* by portfolios of good news and bad news. For the portfolio of stocks that have the top quintile of (weighted number of) bad news, the average *IVOL* is 11.3185%, while the average *IVOL* for the corresponding portfolio with the bottom quintile of bad news is 10.3412%. The difference is statistically significant (t-statistic $= 20.6111$). For good news, the pattern is in the opposite direction. A high weighted number of good news tends to be associated with low *IVOL* and vice versa. The difference between the top and the bottom quintiles is also statistically significant (t-statistic $= -56.2292$). Overall, Table 3's result highlights that the *IVOL* puzzle may be caused by the potential confounding effect of news. High intensity of news arrival may exacerbate the negative relation documented by Ang et al. (2006), which implies that the presence of news arrival may reduce the positive relation documented by Fu (2009).

Table 2
Correlations between variables.

	r_t	R_t	$E(IVOL)$	$E(IVOL_N)$	$E(IVOL_{RN})$	$E(IVOL_{WN})$	$WESS_t$
r_t	1.0000	0.9999*	0.0272*	0.0245*	0.0237*	0.0189*	0.0820*
R_t		1.0000	0.0264*	0.0239*	0.0231*	0.0183*	0.0822*
$E(IVOL)$			1.0000	0.4977*	0.4989*	0.4105*	−0.0238*
$E(IVOL_N)$				1.0000	0.5654*	0.3814*	−0.0195*
$E(IVOL_{RN})$					1.0000	0.3825*	−0.0193*
$E(IVOL_{WN})$						1.0000	−0.0212*
$WESS_t$							1.0000

Note: This table presents the correlations between return, news variables and control variables. The symbol * indicates that the correlation is significant at 5% level. For explanations of the variables, please see Table 1.

Table 3
Portfolios analysis based on the news variables.

Portfolios	$IVOL_{t-1}$	WNN_{t-1}	WNP_{t-1}
Panel A: Average excess return			
1	0.6754	0.7509	0.4305
2	0.6967	0.7094	0.6176
3	0.7001	0.6900	0.7006
4	0.8566	0.6951	0.8403
5	0.4915	0.5748	0.8314
5 − 1	−0.1836	−0.1774	0.3997
	(−2.3633)	(−2.8283)	(6.5306)
Panel B: Average $IVOL_{t-1}$			
1		10.3412	11.7187
2		11.0039	10.7637
3		10.3093	10.7918
4		10.2289	10.5023
5		11.3185	9.4250
5 − 1		0.9773	−2.2937
		(20.6111)	(−56.2292)

Note: This table presents the average excess return and $IVOL_{t-1}$ of each portfolio constructed using quintiles of $IVOL_{t-1}$, WNN_{t-1} and WNN_{t-1}, respectively. 5 − 1 is the difference between the average of the portfolios 1 and 5. The values in the brackets are the corresponding Newey–West *t*-test statistics. $IVOL_{t-1}$ is the realized volatility constructed using daily returns at time $t-1$ as done in Ang et al. (2006). For explanations of other variables, please see Table 1.

3.3. Effect of idiosyncratic volatility on excess return

To examine our conjecture, we run panel regressions of excess returns against the expected *IVOL*. The expected *IVOL* is estimated using Eq. (1). In the panel regression, we include the FF3F and *WESS* with the standard error clustered by firm and month–year (Petersen, 2009):

$$r_t = \beta_0 + \beta_1 E(IVOL)_t + \beta_2 WESS_t + \beta_3 MKT_t + \beta_4 SMB_t + \beta_5 HML_t + \varepsilon_t. \tag{6}$$

Table 4 presents the baseline results. In the first row, we report the estimated coefficient of β_1 without the inclusion of the news variable. The impact of the expected *IVOL* at *t* on excess return at *t* is 0.0406 and it is statistically significant at the 1% level (*t*-statistic = 2.3473). When we include in the estimation of $E(IVOL)$ the number of news ($E(IVOL)_{WN}$), the number of news weighted by its relevance ($E(IVOL)_{RN}$), and the weighted number of good news and bad news ($E(IVOL)_{WN}$), the impact of *IVOL* falls. In particular, the impact reduction is the highest for $E(IVOL)_{WN}$, where news releases are divided into good news and bad news. Comparing with the base case of no news, the size of the coefficient is reduced by 49% to 0.0207 and it is marginally significant (*t*-statistic = 1.7503). This result supports our earlier conjecture that the impact of news arrival could reinforce the perceived negative *IVOL*-return relation. Furthermore, by including good news and bad news in the estimation of the expected *IVOL*, the positive relation documented by Fu (2009) diminishes.[11]

We further examine the returns of portfolios based on sorting stocks into quintiles of expected *IVOL*, both with and without the news variables in the EGARCH estimation. Table 5 presents the results. Without the inclusion of news, the average excess return not explained by the Fama French Three Factors (FF3F alpha) almost monotonically increases in the expected *IVOL*. The difference between the top and the bottom quantiles is 0.2335% per month (*t*-statistic = 2.7314). When we include the raw number of news, FF3F alpha falls to 0.1614%, and so does its significance (*t*-statistic = 1.9715). Once we allow news to be separated into good news and bad news, the alpha falls to 0.0938% and it becomes statistically insignificant (*t*-statistic = 1.1420). Consistent with Table 4, raw return R_t in the top quintile portfolio of *IVOL* falls from 1.4201%(no news) to 1.2883%, which is driven by the fact that more (less) bad (good) news increases the expected *IVOL* as well as lowers the stock return. The lack of significance of alpha in the final column also suggests that the cross-sectional variation of excess returns can be better explained by *IVOL*, which is in part caused by both the intensity of news flows and the news type.

[11] We have also considered Hou and Loh's (2014) covariance decomposition approach to estimate the fraction of *IVOL* relation explained by the news variables. The estimated fraction is 73%, suggesting that 73% of coefficient of $E(IVOL)$ on return is caused by news effects. After controlling for the above five control variables, the estimated fraction falls to about 48%, which is in line with our main finding that the news effects contribute to roughly 50% of the expected *IVOL*-return relation.

Table 4
Average effect of idiosyncratic volatility on excess return controlled for Fama–French Three Factors (FF3F) and *WESS*.

$E(IVOL)$	$E(IVOL_N)$	$E(IVOL_{RN})$	$E(IVOL_{WN})$	% Reduc.	$WESS$	MKT	SMB	HML
0.0406				–	0.1808	1.0220	0.7364	0.2001
(2.3473)					(26.3139)	(32.2920)	(12.9453)	(2.3570)
	0.0367			9.61%	0.1804	1.0220	0.7368	0.2001
	(2.2242)				(26.3011)	(32.2229)	(12.8965)	(2.3498)
		0.0367		9.61%	0.1804	1.0221	0.7370	0.2000
		(2.2046)			(26.3280)	(32.2280)	(12.8994)	(2.3496)
			0.0207	49.01%	0.1803	1.0222	0.7375	0.1996
			(1.7503)		(26.3593)	(32.1615)	(12.8754)	(2.3343)

Note: This table presents the estimated coefficients for panel robust regressions with FF3F and *WESS*. MKT_t, SMB_t and HML_t are the Fama–French Three Factors: the excess return on a broad market portfolio, the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks, and the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks, respectively. % Reduc. is the reduced percentage of the coefficient of $E(IVOL_N)$, $E(IVOL_N)$ and $E(IVOL_{WN})$ compared with the coefficient of $E(IVOL)$. The values in the brackets are the corresponding t-test statistics. For explanations of other variables, please see Table 1.

4. Robustness checks

4.1. Model specification, information risk and liquidity risk

To check for the robustness of our results, we consider numerous alternative model specifications. First, we consider taking the time-series average of the slopes in cross-sectional regressions based on the standard Fama–Macbeth methodology. For each month t, we regress the raw return R_t against $E(IVOL)_t$ and a number of control variables:

$$R_t = \beta_0 + \beta_1 E(IVOL)_t + \beta_2 \ln(BE/ME) + \beta_3 \ln(ME) + \beta_4 \ln(TURN) + \beta_5 \ln(CVTURN) + \beta_6 RET(-2,-7) + \varepsilon_t. \tag{7}$$

BE/ME is the book-to-market equity. It is calculated by dividing the fiscal year-end book value of common equity by the calendar year-end market value of equity. *ME* is the market value of equity, which is the product of the monthly closing price and the number of outstanding shares in June of the relevant year. *TURN* is the average dollar value turnover, and *CVTURN* is the coefficient of the variation of turnovers over the past 36 months. $RET(-2,-7)$ is the compound gross return from month $t-7$ to $t-2$ (inclusive). As argued by Fu (2009), the return in month $t-1$ is excluded to avoid any spurious association between subsequent monthly returns caused by thin trading or the bid-ask spread effects. Both *TURN* and *CVTURN* are used to capture the level of liquidity. Second, we replace the FF3F in the original model with firm fixed effects plus the above controls. Finally, the market microstructure literature asserts that investors demand a premium when investing in firms with high information asymmetry (Easley and O'Hara, 2004) and high liquidity risk (Acharya and Pedersen, 2005; Amihud and Mendelson, 1986; Sadka, 2006; Stambaugh, 2003). Easley et al. (1996) develop a structural model known as the *PIN* model that provides an estimate of the risk associated with information asymmetry at the firm level. Easley et al. (2002) show that differences in *PIN*, or differences in the level of information asymmetry, can explain their differences in the expected stock return. Duarte and Young (2009) extend

Table 5
Portfolio analysis based on the expected IVOL.

	$E(IVOL)$			$E(IVOL_N)$			$E(IVOL_{RN})$			$E(IVOL_{WN})$		
Portfolios	$E(IVOL)$	R_t	$FF3-\alpha$	$E(IVOL_N)$	R_t	$FF3-\alpha$	$E(IVOL_{RN})$	R_t	$FF3-\alpha$	$E(IVOL_{WN})$	R_t	$FF3-\alpha$
1	3.5387	0.7482	0.1082	3.1309	0.7934	0.1269	3.1465	0.7837	0.1212	3.1254	0.7930	0.1319
			(3.1547)			(3.5092)			(3.3475)			(3.7051)
2	6.1740	0.8372	0.0749	5.5707	0.8587	0.0948	5.6064	0.8276	0.0643	5.7354	0.9320	0.1640
			(1.9630)			(2.3832)			(1.6175)			(4.0792)
3	8.8732	1.0489	0.1807	8.0614	1.0211	0.1539	8.1082	1.0507	0.1867	8.4570	0.9997	0.1288
			(3.8763)			(3.2805)			(3.9907)			(2.7113)
4	12.8317	1.1514	0.1750	11.6641	1.1681	0.2166	11.7503	1.2042	0.2437	12.5584	1.1928	0.2302
			(3.1186)			(3.9204)			(4.3991)			(3.9812)
5	24.7042	1.4201	0.3417	22.9563	1.3645	0.2883	23.0873	1.3395	0.2646	27.3715	1.2883	0.2256
			(4.4221)			(3.9606)			(3.5836)			(3.0820)
5 − 1		0.6719	0.2335		0.5710	0.1614		0.5558	0.1434		0.4954	0.0938
		(4.6543)	(2.7314)		(4.0001)	(1.9715)		(3.8657)	(1.7289)		(3.4788)	(1.1420)

Note: This table presents the average expected idiosyncratic volatility, average raw return and Fama–French 3-factor alpha of each portfolio constructed using quintiles of $E(IVOL)$, $E(IVOL_N)$, $E(IVOL_{RN})$ and $E(IVOL_{WN})$, respectively. R_t is the raw return. $FF3-\alpha$ is the Fama–French 3-factor alpha. The values in the brackets are the corresponding Newey–West t-test statistics. For explanations of other variables, please see Table 1.

Table 6
Robustness check without *WESS*.

Additional control in the return	$E(IVOL)$	$E(IVOL_N)$	$E(IVOL)_{RN}$	$E(IVOL_{WN})$	% Reduc.	Control variables	Liquidity risk and information risk
–	0.0795	0.0736	0.0695	0.0472	40.63%	No	–
	(3.2066)	(2.9972)	(2.9630)	(2.6081)			
FF3	0.0648	0.0588	0.0559	0.0351	45.83%	No	–
	(3.5969)	(3.2999)	(3.2329)	(2.6800)			
FF3	0.0631	0.0572	0.0543	0.0340	44.54%	No	*PIN*
	(3.4670)	(3.1791)	(3.0986)	(2.5622)			
FF3	0.0583	0.0526	0.0497	0.0308	47.17%	No	*PSOS*
	(3.2109)	(2.9420)	(2.8587)	(2.3211)			
FF3	0.0576	0.0517	0.0489	0.0306	46.88%	No	*Spread*
	(3.3201)	(2.9897)	(2.9127)	(2.3837)			
FF3	0.0612	0.0552	0.0525	0.0330	46.08%	No	*Amihud*
	(3.4465)	(3.1261)	(3.0583)	(2.5260)			
FM	0.0394	0.0373	0.0344	0.0159	59.64%	Yes	–
	(4.5553)	(4.4373)	(4.0348)	(2.5781)			
FM	0.0394	0.0375	0.0343	0.0160	59.39%	Yes	*PIN*
	(4.5744)	(4.5032)	(4.0643)	(2.6155)			
FM	0.0390	0.0373	0.0336	0.0151	61.28%	Yes	*PSOS*
	(4.5575)	(4.4733)	(4.0149)	(2.5018)			
FM	0.0350	0.0334	0.0311	0.0137	60.85%	Yes	*Spread*
	(4.1914)	(4.0686)	(3.7706)	(2.3107)			
FM	0.0370	0.0347	0.0323	0.0149	59.73%	Yes	*Amihud*
	(4.3416)	(4.1514)	(3.8387)	(2.4405)			
FE	0.0562	0.0489	0.0457	0.0263	53.20%	Yes	–
	(4.3483)	(3.8720)	(3.7985)	(2.6715)			
FE	0.0565	0.0492	0.0459	0.0265	53.10%	Yes	*PIN*
	(4.3576)	(3.8874)	(3.8120)	(2.6865)			
FE	0.0558	0.0488	0.0454	0.0259	53.58%	Yes	*PSOS*
	(4.3446)	(3.8736)	(3.7863)	(2.6410)			
FE	0.0530	0.0459	0.0427	0.0248	53.21%	Yes	*Spread*
	(4.2230)	(3.6884)	(3.6351)	(2.5421)			
FE	0.0546	0.0473	0.0442	0.0255	53.30%	Yes	*Amihud*
	(4.2567)	(3.7526)	(3.6816)	(2.5917)			

Note: This table presents the results of robustness check without controlling for *WESS* for the reduced dataset (firms with non-missing *PIN*, *PSOS*, *Spread* and *Amihud* values). *FF*3 is the Fama–French Three Factors fitted by the panel robust regression. *FM* is the Fama–Macbeth model. *FE* is the panel robust regression with fixed effects factors. Control variables include BE/ME, ME, *TURN*, *CTURN* and $RET(-2,-7)$. BE/ME is book-to-market equity, which is the fiscal year-end book value of common equity divided by the calendar year-end market value of equity. *ME* is the market value of equity, which is the product of monthly closing price and the number of outstanding shares in June. *TURN* is the average turnover and *CVTURN* is the coefficient of variation of turnovers in the past 36 months. $RET(-2,-7)$ is the compound gross return from month $t-7$ to $t-2$. % Reduc. is the reduced percentage of the coefficient of $E(IVOL_{WN})$ compared with the coefficient of $E(IVOL)$. Liquidity risk and information risk include *PIN*, *PSOS*, *Spread* and *Amihud*. *PIN* is the lagged probability of information-based trading using Duarte and Young's (2009) approach. *PSOS* is the lagged probability of symmetric order flow shocks constructed using Duarte and Young's framework. *Spread* is the lagged quoted spreads. *Amihud* is the lagged Amihud illiquidity measure. The values in the brackets are the corresponding *t*-test statistics. For explanations of other variables, please see Table 1.

the *PIN* model to accommodate the positive correlation between buys and sells, as well as develop a measure of illiquidity unrelated to information asymmetry known as *PSOS* (probability of symmetric order-flow shock), and find that only *PSOS*, i.e. liquidity risk, explains the cross section of expected returns. In light of Duarte and Young's findings, we estimate Duarte and Young's (2009) adjusted *PIN* and *PSOS* for each stock and for each quarter, and we include the lagged estimates, i.e. estimates from the prior quarters into the regression model (7).[12] For robustness, we also consider other liquidity measures, including the quoted spread and the Amihud measure in the prior month, to see if our baseline conclusion continues to hold.

Table 6 reports results of the above model specifications. In Table 7, we include *WESS* in the specification (7). Both Tables 6 and 7 show that our conclusion remains largely unchanged. While the size of the reduction in the estimated coefficient of β_1 generally increases when additional control variables are included, the range of the reduction is between 40% and 60%. Liquidity risk seems to have little impact on the *IVOL*-return relation. This corresponds to Spiegel and Wang's (2005) result, which shows that liquidity risk plays a relatively minor role in explaining cross-section of returns compared with *IVOL*.

4.2. News categories

Not all news is value-relevant. Some news such as the release of earnings reports, mergers and acquisitions, change of the board, purchase of important assets and the release of new products and services, have significant implications for the

[12] Our intraday trade data is sourced from Thomson Reuters Tick History through SIRCA. Due to data availability, we are able to compute the estimates for 4128 firms, which captures about 80% of the original sample.

Table 7
Robustness check with *WESS*.

Additional control in the return	$E(IVOL)$	$E(IVOL_N)$	$E(IVOL)_{RN}$	$E(IVOL_{WN})$	% Reduc.	Control variables	Liquidity risk and information risk
–	0.0811 (3.2508)	0.0746 (3.0195)	0.0710 (3.0090)	0.0486 (2.6764)	40.07%	No	–
FF3	0.0665 (3.6461)	0.0598 (3.3178)	0.0575 (3.2918)	0.0366 (2.7722)	44.96%	No	–
FF3	0.0650 (3.5273)	0.0584 (3.2066)	0.0560 (3.1674)	0.0356 (2.6622)	45.23%	No	*PIN*
FF3	0.0603 (3.2769)	0.0539 (2.9741)	0.0515 (2.9316)	0.0324 (2.4256)	46.27%	No	*PSOS*
FF3	0.0591 (3.3697)	0.0525 (3.0049)	0.0503 (2.9700)	0.0319 (2.4762)	46.02%	No	*Spread*
FF3	0.0628 (3.4945)	0.0561 (3.1428)	0.0540 (3.1156)	0.0344 (2.6171)	45.22%	No	*Amihud*
FM	0.0399 (4.6144)	0.0371 (4.4019)	0.0348 (4.1124)	0.0167 (2.7338)	58.15%	Yes	–
FM	0.0398 (4.6254)	0.0372 (4.4606)	0.0347 (4.1380)	0.0168 (2.7659)	57.79%	Yes	*PIN*
FM	0.0395 (4.6195)	0.0371 (4.4393)	0.0340 (4.0924)	0.0159 (2.6611)	59.75%	Yes	*PSOS*
FM	0.0355 (4.2537)	0.0332 (4.0309)	0.0315 (3.8481)	0.0145 (2.4716)	59.15%	Yes	*Spread*
FM	0.0375 (4.3982)	0.0345 (4.1127)	0.0327 (3.9095)	0.0156 (2.5940)	58.40%	Yes	*Amihud*
FE	0.0564 (4.3360)	0.0482 (3.7854)	0.0457 (3.7962)	0.0268 (2.7166)	52.48%	Yes	–
FE	0.0566 (4.3402)	0.0484 (3.7957)	0.0458 (3.8052)	0.0269 (2.7269)	52.47%	Yes	*PIN*
FE	0.0561 (4.3331)	0.0481 (3.7874)	0.0454 (3.7849)	0.0264 (2.6877)	52.94%	Yes	*PSOS*
FE	0.0533 (4.2156)	0.0452 (3.6050)	0.0428 (3.6358)	0.0253 (2.5919)	52.53%	Yes	*Spread*
FE	0.0549 (4.2436)	0.0466 (3.6664)	0.0442 (3.6783)	0.0260 (2.6367)	52.64%	Yes	*Amihud*

Note: This table presents the results of robustness check with controlling for *WESS* for the reduced dataset (firms with non-missing *PIN*, *PSOS*, *Spread* and *Amihud* values). *FF3* is the Fama–French Three Factors fitted by the panel robust regression. *FM* is the Fama–Macbeth model. *FE* is the panel robust regression with fixed effects factors. Control variables include *BE/ME*, *ME*, *TURN*, *CTURN* and *RET*(−2, −7). *BE/ME* is book-to-market equity, which is the fiscal year-end book value of common equity divided by the calendar year-end market value of equity. *ME* is the market value of equity, which is the product of monthly closing price and the number of outstanding shares in June. *TURN* is the average turnover and *CVTURN* is the coefficient of variation of turnovers in the past 36 months. *RET*(−2, −7) is the compound gross return from month $t-7$ to $t-2$. % Reduc. is the reduced percentage of the coefficient of $E(IVOL_{WN})$ compared with the coefficient of $E(IVOL)$. Liquidity risk and information risk include *PIN*, *PSOS*, *Spread* and *Amihud*. *PIN* is the lagged probability of information-based trading using Duarte and Young's (2009) approach. *PSOS* is the lagged probability of symmetric order flow shocks constructed using Duarte and Young's framework. *Spread* is the lagged quoted spreads. *Amihud* is the lagged Amihud illiquidity measure. The values in the brackets are the corresponding *t*-test statistics. For explanations of other variables, please see Table 1.

value of the firm. For example, the announcement of a new product/service or upgrade of an existing product/service provides information about the firm's innovation that is arguably the fundamental determinant of growth.

In RavenPack, all news items are classified into various broad categories. There are more than 30 categories including, among others, product and services, labor issues, acquisitions and mergers, equity actions, assets, and partnerships. For the purpose of the analysis, we divide these news items into two broad groups: (i) earnings news, which covers the announcement of earnings figures, dividend payout or change of dividend payment; and (ii) non-earnings news, which covers nine categories which we believe are significant enough to affect share values, but which we restrict to those that are considered to be value-relevant. They are the following:[13]

1. Acquisitions and mergers. It contains news reporting the acquisition or merger of the company, and whether the acquisition or merger is officially announced, completed, or failed.
2. Assets. It contains news reporting about the sale or acquisition of a company's tangible assets (such as offices or plants) or intangible assets (such as patents).
3. Bankruptcy. It contains news reporting that the company files a bankruptcy exit plan, declares insolvency or the inability to discharge all its debts.

[13] The definitions are obtained from https://ravenpack.com/rpna/newsanalytics-dj-edition/3.0/resources/RPNA_DJEdition_categories_3.0.csv. Similar news categories are also used in Boudoukha et al. (2015) to examine the relation between news and stock price changes.

Table 8
Stocks with earnings and non-earnings news.

Additional control in the return	$E(IVOL)$	$E(IVOL_{WN})$	% Reduc.	$E(IVOL^E_{WN})$	% Reduc.	$E(IVOL^N_{WN})$	% Reduc.	$E(IVOL^B_{WN})$	% Reduc.	Control variables
FF3	0.0559	0.0311	44.29%	0.0002	99.65%	−0.0001	99.80%	0.0009	98.34%	No
	(3.2760)	(2.5305)		(0.8488)		(−1.2420)		(0.8188)		
FM	0.0379	0.0161	57.48%	0.0110	71.04%	0.0129	65.82%	0.0073	80.72%	Yes
	(4.2694)	(2.6883)		(3.0387)		(2.8806)		(2.5011)		
FE	0.0513	0.0248	51.66%	0.0002	99.61%	−0.0001	99.81%	0.0006	98.83%	Yes
	(4.3102)	(2.7857)		(0.8128)		(−1.2852)		(0.5991)		

This table presents the results of the stocks with earnings and non-earnings news and controlling for *WESS* for the reduced dataset (firms with non-missing earnings and non-earnings news). *FF*3 is the Fama–French Three Factors fitted by the panel robust regression. *FM* is the Fama–Macbeth model. *FE* is the panel robust regression with fixed effects factors. Control variables include *BE*/*ME*, *ME*, *TURN*, *CTURN* and *RET*(−2, −7). *BE*/*ME* is book-to-market equity, which is the fiscal year-end book value of common equity divided by the calendar year-end market value of equity. *ME* is the market value of equity, which is the product of monthly closing price and the number of outstanding shares in June. *TURN* is the average turnover and *CVTURN* is the coefficient of variation of turnovers in the past 36 months. *RET*(−2, −7) is the compound gross return from month $t-7$ to $t-2$. $E(IVOL^E_{WN})$ is the $E(IVOL_{WN})$ calculated using earnings news only. $E(IVOL^N_{WN})$ is the $E(IVOL_{WN})$ calculated using non-earnings news only. $E(IVOL^B_{WN})$ is the $E(IVOL_{WN})$ calculated using both earnings and non-earnings news. % Reduc. is the reduced percentage of the coefficient of $E(IVOL_{WN})$, $E(IVOL^E_{WN})$, $E(IVOL^N_{WN})$ and $E(IVOL^B_{WN})$ compared with the coefficient of $E(IVOL)$. The values in the brackets are the corresponding *t*-test statistics. For explanations of other variables, please see Table 1.

4. Equity actions. It contains news reporting about the company's equity issuing decision (initiation, postponement or termination) such as IPOs, private placements, seasoned offerings, and rights issues. It also contains news about the company's listing decision, share buyback, reorganization decisions, new investments or capital expenditure (CAPEX).
5. Exploration. It contains news reporting that the company begins, suspends or terminates extraction of a commodity.
6. Industrial accidents. It contains news reporting that the company experiences an industrial accident, for example, an accident that occurs at a general building or place where it stores or processes its products.
7. Labor issues. It contains news reporting when the company appoints or promotes an executive, discloses the wage or compensation or any additional pay or bonuses paid to an executive, or the departure of an executive. It also contains news in relation to job cuts, agreements with the workers' union or work strikes.
8. Partnerships. It contains news reporting about the company's decision to start or end a business alliance with another entity such as joint venture.
9. Product and services. It contains news reporting when a company releases a new product or service, or an upgrade to an existing one, signs or receives a new contractual agreement for a product or service, or terminates an existing agreement, or any other information about its product or service such as price increase/decrease, product recall or regulatory approval to develop or market the product. It also contains news reporting when a company completes a phase in the clinical trial process or the development of a new drug, files to commence a clinical trial, discloses results about a clinical trial, starts or suspends the development of a drug or clinical trial, or discloses information about its clinical trials such as patient enrolment.

Table 8 presents results based on these two news groups. For both the FF3F model and the panel robust model with firm/month fixed effects, the reduction reaches 99%. The estimated β_1 falls to around 0 and it is not statistically different from 0. For the Fama–MacBeth specification, while the reduction is less substantial, it falls from 0.0379 to around 0.011 (statistically significant at the 1% level). If we include non-earnings news only, the reduction is slightly less (66%), but if both categories of news are considered, the reduction reaches 80%.

Overall, our original conclusion remains intact under different model specifications. It does not vary with the inclusion of liquidity risk or information risk. The presence of good news and bad news creates a confounding effect on the relation between expected *IVOL* and returns. Our results are even stronger after we include only value-relevant news.[14]

5. Conclusion

In his seminal paper, Merton (1987) argues that *IVOL* is priced when investors are under-diversified. However, recent empirical evidence shows that the relation between *IVOL* and the expected return is unclear. Ang et al. (2006, 2009) identify a puzzle that contradicts Merton's hypothesis. They find that portfolios with high *IVOL* have low subsequent returns, which implies the negative price of risk. Ang et al.'s finding is criticized by Fu (2009), who argues that the model is specified incorrectly

[14] One alternative explanation to our empirical results is that firms with little or no news have a stronger (positive) *IVOL*-return relation because investors demand a higher return for stocks that suffer a greater level of information asymmetry. But such explanation is ruled out because (1) our results hold when other proxy for information asymmetry (*PIN*) is included as a control variable; and (2) such explanation offers no role for explaining the differential impact of good news and bad news on the *IVOL*-return relation (as highlighted in Table 3 (panel B) and Table 4).

because *IVOL* is time-varying and stock returns exhibit reversals. Using the EGARCH model to estimate the expected *IVOL*, Fu shows that expected *IVOL* is positively related to the expected return.

In this study, we present evidence showing that both the intensity and the quality of news flow can contribute to the perceived negative relation between *IVOL* and expected return. More specifically, we argue that the arrival of news serves as a confounder to the *IVOL*-return relation. The perceived negative relation may be driven by (i) the positive (negative) relation between the intensity of bad (good) news arrivals and *IVOL*; and (ii) the negative (positive) relation between the intensity of bad (good) news arrivals and stock return. To test this conjecture, we construct a group of news variables using the news database from RavenPack. These news variables include the raw number of news articles, the number of news articles weighted by their relevance, the number of good and bad news articles weighted by relevance and the sentiment score of the news. To examine the impact of news on the relation, we use Fu's (2009) EGARCH framework to account for the time-varying nature of *IVOL* and include the news variables in the estimation of the expected *IVOL*. While the average positive effect of expected *IVOL* on the expected return is substantial, the average effect is reduced by roughly 50% after the confounding effect of news is taken into consideration. This result is robust to the inclusion of other risk factors such as information risk and liquidity risk, and different model specifications including the Fama–MacBeth model with firm-level controls and the robust panel fixed effects model. Since not all firm-specific news releases are equally important, we focus exclusively on the value-relevant ones and find that the positive *IVOL*-return relation disappears as a result. This finding further suggests that the public arrival of firm-specific news plays a significant role in explaining the *IVOL* puzzle.

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Appendix A. RavenPack algorithm

A.1. Expert consensus tagging methodology

RavenPack's Expert Consensus Methodology underpins the *ESS* score and entails a group of financial experts manually tagging a set of stories that is later used as a basis for automated computer classification using a Bayes Classifier.

<u>Step one: a Classification Base is defined</u>
When developing a new sentiment series that uses the Expert Consensus methodology, the first step is to develop a Classification Base, or define the types of stories that contain the content relevant for tagging. The ideal Classification Base contains only stories that contain news that affect the target market or asset class.
<u>Step two: experts build an internal Tagging Guide</u>
When developing a new sentiment series that requires manual tagging, a team of in-house experts with extensive backgrounds in linguistics, finance, and economics first develop and agree upon a set of parameters and basic assumptions that will guide sentiment tagging. This Tagging Guide ensures that the assumptions used in identifying story sentiment are consistent and agreed upon. It provides rules for when to identify stories as positive, negative or neutral.
<u>Step three: a large sample is tagged</u>
A sample of up to 28,000 stories in the Classification Base developed in step one is drawn from RavenPack's news database for a fixed date range. Stories are randomly selected for tagging. Up to ten experts read and classify all story headlines in the sample using the Tagging Guide developed in step two.
The Tagging Guide is built to avoid disagreements in story sentiment among experts. Even so, stories that were not classified by 80% of expert taggers as having the same sentiment are automatically given the NA code. Stories that contain both positive and negative sentiment are judged based on the story's overall effect on the market. Stories with equal amounts of positive and negative sentiment are tagged as neutral.
<u>Step four: software is trained from sample to automate tagging</u>
Once an appropriate sample of stories has been tagged, a Bayes Classifier uses supervised learning to discern patterns in expert tagging and establish rules for future automation. This automated tagging process must meet exceptional levels of accuracy in order to be made available to clients. In cases when accuracy is not sufficiently high, step three is repeated with a larger sample set. Accuracy levels vary by classifier but range from 80% to 96%.

Step five: generate historical analysis and enable real-time tagging

After the classifier has been trained to reach acceptable levels of accuracy, historical analysis is generated and real-time tagging is enabled. This process involves several consistency checks of historical data and generation of volume statistics. When this process is complete, the series is published.

Step six: quarterly re-evaluation

Because training is based on a limited data range, there always exists the possibility that new economic terminology, trends, types of reporting, market forces, etc. may emerge after the sample period used in step three. In order to account for these trends, classifiers are re-evaluated on a quarterly basis. This process involves completing step three for stories sampled outside of the date range of the original sample or most recent quarterly re-evaluation. The results of this expert classification are compared to the results of automated classification. If the accuracy level is 10% lower than the level when the series was originally released, a new series is developed.

A.2. Market Response methodology

RavenPack's Market Response methodology underpins the *CSS* score and is based on a Rule Base that identifies and maps individual words or word combinations in the story headline to the price impact on stocks of companies mentioned in the headline. The price impact is measured in the hours ahead of the arrival of the news item and is transformed into an Impact Score using advanced machine learning techniques.

Step one: a Classification Base is defined

When developing a new impact series that uses the Market Response methodology, the first step is to develop a Classification Base, or define the types of stories that contain the content relevant for measuring the market impact. The ideal Classification Base contains only stories that contain news that affect the target market or asset class.

Step two: a large sample is analyzed to create a Rule Base

A sample of up to 30,000 headline stories in the Classification Base developed in step one is drawn from RavenPack's news database for a fixed date range. The headlines of these stories are extracted and parsed into words to form a list of candidates of individual words and word combinations that are typical for such headline stories. Based on statistical measures, about 4,000 of these words and word combinations have been identified as promising in relations to predicting market impact.

Step three: create an Impact Score using the Rule Base

Once a Rule Base has been established, different advanced machine learning techniques are applied with the objective of creating an Impact Score that identifies the probability of the volatility of a particular stock to be either higher or lower than the volatility of the market.

Step four: generate historical analysis and enable real-time tagging

Applying step two and three on the target story type, historical analysis is generated and the real-time creation of Impact Scores is enabled. This process involves several consistency checks of historical data. When this process is complete, the series is published.

Step five: quarterly re-evaluation

Because story sampling is based on a limited data range, there always exists the possibility that new economic terminology, trends, types of reporting, market forces, etc. may emerge after the sample period used in step two and three. In order to account for these trends, scores are re- evaluated on a quarterly basis.

This process involves completing step two for stories sampled outside of the date range of the original sample or most recent quarterly re-evaluation. Statistical measures are used with the purpose of identifying additional words or word combinations that, from a statistical perspective, seem promising in terms of market impact. Such words and word combinations are added to the Rule Base and are then used under step three to continuously maintain and improve the impact series to reflect current market conditions.

A.3. Factors in the Event Sentiment Score

In addition to the expert consensus survey data, the Event Sentiment Score (*ESS*) has a strength component that is influenced by a variety of factors, depending on the type of event. RavenPack systematically extracts information from every news story to model these factors and determine how positive or negative each event should be. Here is a list of some of these factors:

Emotional factor:

There are 5 scales containing groups of words and phrases in the RavenPack emotional magnitude component of *ESS*. Each component contains words that signify the magnitude of an event as described by the author of the story.

(a) Low magnitude: Contains adjective words such as 'low, minor, small, or inconsequential' and phrases such as 'below the mark or not meaningful'

(b) Moderate magnitude: Contains words such as 'moderate, mellow, or dainty' and phrases such as 'nothing much or fairly flat'

(c) Substantial magnitude: Contains words such as 'substantial, durable, considerable or extensive' and phrases such as 'fairly considerable or significantly large'
(d) Severe magnitude: Contains words such as 'severe, commanding, destructive, or excruciating' and phrases such as 'extremely high or highly elevated'
(e) Critical magnitude: Contains words such as 'critical, devastation, massacre, or catastrophic' and phrases such as 'super colossal or most damaging'

Analyst rating factor

Covers over 150 different broker and analyst rating scales for stocks (e.g. strong buy, buy, hold, sell, and strong sell).

Credit rating factor

Consolidates the three main credit ratings scales by Moody's, Fitch, and S&P (e.g. AAA, AA, BB, and C) into one normalized scale.

Fundamental comparison factor

Extracts and calculates numerical differences between actual or estimated values in earnings, revenues, dividends, and any other financial or economic announcement. Performs arithmetic, and translates fundamental percentage changes into a normalized score within the *ESS* ranges.

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