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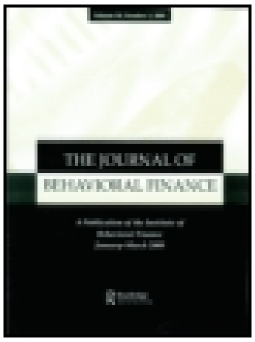

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Crash Fears and Stock Market Effects: Evidence From Web Searches and Printed News Articles

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ABSTRACT
The authors studied the complex relationship between information supply and demand using newspaper articles and web searches that reflect investors' crash fears. They report that more web searches lead to more news, whereas more news does not have that effect on web search in the future. The authors show also that web searches have an immediate effect on stock market returns and the VIX implied volatility, whereas the effect of news articles lasts longer, up to 11 weeks. The results suggest collectively that the web searches related to market crashes lead both the printed news stories about market crashes.

KEYWORDS
Crash fear; Volatility; Information supply and demand; Web search

Introduction

The quick reaction of security prices to new information is a focal characteristic of well-functioning and efficient capital markets, as the efficient-market hypothesis by Fama (1970) proclaims. Typically, news is assumed to be new information, but the quick reaction of security prices presumes investors' pay attention to the news, which is a scarce resource (see Kahneman, 1973). Thus, it is the designation of news, but also investors' attention to it, which moves asset prices in a dynamic process. The extant literature shows increasing evidence of the relevance of investor attention explaining market volatility (Vlastakis & Markellos, 2012; Goddard, Kita, & Wang, 2015; Andrei & Hasler, 2015; Moussa, Delhoumi, & Ouda, 2017). We follow this stream of the literature and touch on an alternative view that the information dissemination process for market volatility does not necessarily originate in information supply, which the news itself represents. Motivated by the widespread use of the VIX implied volatility index, the "investor fear gauge" (see Whaley 2000), as the focal market bellwether, we focus in our analysis on the VIX implied volatility and market crash fears.

Information searches by investors, as investor attention and information demand, can reflect the market's anticipation of new information. For example, Billings amnd Jennings (2011) proposed a measure of anticipated information content that explains the ex post responsiveness of stock prices to earnings information. Moreover, in line with the presumption regarding anticipation, Easton, Geo, and Gao (2010) found evidence for a predictable drift in stock prices before the earnings announcements related to the earnings announcements of earlier reporting firms. This anecdotal evidence and the market-borne events such as the Market Crash of 1987 and the 2010 Flash Crash, which could not have been related to specific news, raise the question of how market reactions, information supply, and information demand in the price discovery process lead and relate to one another.

The research of Vlastakis and Markellos (2012) relates to this question, reporting that the dynamic interactions between information supply and demand do not allow conclusive inferences about the information discovery process. The objective of our study is to follow this stream of research and address the dynamic relationship between information supply, information demand and stock market effects in a novel way. We model the lag structure of information supply and demand in predicting each other using a state space model. This enables us to specifically analyze interactions between information supply and demand. In addition, we use the distributed lag model to measure the effects of information supply and demand on realized stock prices and on investors' expectations about future stock market uncertainty in the stock market. To proxy the information supply

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and demand, we utilize frequencies of news articles that appear in newspapers during 1 week as well as weekly online Google search volumes. Using these measures for information supply and demand, we are able to examine the mechanism of how online searchers vis-à-vis the traditional media affect realized stock returns and the anticipated risk in the stock market.

We use negative information search words *market crash* to reflect information supply and demand related to investor fear (see Da, Engelberg, & Gao, 2015). Our measures of information supply and demand represent investor sentiment inferred from the traditional media and online search activity. We focus on the U.S. market including the S&P 500 returns and measures of investors' expectations of future volatility and the volatility of volatility, namely the VIX implied volatility index and the VVIX index of the volatility of volatility; in our analysis over the period 2004–2015. Of these market-based measures, the S&P 500 returns measure the actual realizations in the stock market, whereas the VIX and VVIX volatility indices can provide further insight into investors' expectations because as forward-looking measures they reveal information about investors' expectations of stock market uncertainty.

We expect that the impact of the information demand for stock market returns and volatility is instant relative to information supply, because information demand reflects private information, which can spread by word of mouth (e.g., Hong, Kubik, & Stein, 2005), and investor anticipation. Based on gatekeeping theory (e.g., White, 1950), the news as an information supply can be selective and learning investors should be able to anticipate and update their beliefs that have not yet reached the information supply side (e.g., the pre-earnings announcement drift in Easton et al., 2010).

We contribute to the literature in several different ways. First, our methodological approach allows for interactions between information supply and demand and market effects, which enables us to address the complex relationship between information supply and demand, as stressed by Vlastakis and Markellos (2012). Furthermore, Ben-Rephael, Carlin, Da, and Israelsen (2018) studied how information demand and supply affect market prices and find that it is rather institutional demand than supply that is associated with risk premium. With respect to these studies, we analyze the complex relationship between information demand and supply in a dynamic setting using the state space model, which yields more precise information on the nature of the interaction between information supply and demand.

Second, we take into consideration changes in investors' expectations of the volatility of volatility and its relationship with information supply and demand. For that purpose, we use the VVIX volatility of volatility index, which was not considered apart from volatility in previous related studies on investor attention and market volatility (e.g., Vlastakis & Markellos, 2012; Aouadi, Arouri, & Teulon, 2013; Goddard et al., 2015; Andrei & Hasler, 2015). The inclusion of the VVIX volatility of volatility index as an additional volatility indicator was motivated, for example, by Park (2015) for the relevance of VVIX in measuring the market's perception of tail risk.

Our results on the interaction between supply and demand for market crash related information show that an expected increase in information supply has a tendency to decelerate future information demand. However, an expected increase in information demand always tends to accelerate future information supply. This result implies that information diffusion and changes in volatility in the financial market has its origins in information demand rather than information supply. Our further evidence shows that this feature of information diffusion can be seen as a more instantaneous effect of information demand on stock market returns and volatility.

The remainder of the article is organized as follows. The second section presents the background and hypotheses of our study. In the third section, we present the data. In the fourth section, we present the methodology. The fifth section is for the empirical findings of our study. We conclude our study in the sixth section.

Background and hypotheses

Literature review

The Google Search Volume Index (GSVI) has become a much-used tool in financial market research. Several studies, such as those by Da, Engelberg, and Gao (2011); Vozlyublennaia (2014), Da et al. (2015), Klemola, Nikkinen, and Peltomäki (2016), Chronopoulos, Papadimitriou, and Vlastakis (2018), and Yin and Feng (2019), have utilized the GSVI when explaining stock returns. Studies such as those by Vlastakis and Markellos (2012), Aouadi et al. (2013), Andrei and Hasler (2015), Goddard et al. (2015), and Moussa et al. (2017) have utilized the GSVI when explaining market volatility.

Interestingly, the extant research on financial markets has started to view news as the information supply side and investor attention, measured using Internet search volumes, as the information demand side (e.g., Vlastakis & Markellos, 2012; Moussa et al., 2017). Following this approach, Vlastakis and Markellos found that information demand is positively related to historical and implied measures of volatility, trading volume, periods of higher returns, and investor risk aversion. Importantly, they argued that the dynamic interactions between information supply and demand do not allow conclusive interferences about the information discovery process, although they are positively correlated. Moussa et al. found that the impact of public information on stock return volatility and returns is mixed depending on the companies.

In relation to measuring information supply and demand using news and online search volumes, it is notable from the information diffusion perspective that the news' information content may not be from the original source and can be biased. For example, the media's gatekeeping function theory implies that the news' information content can be selective and biased. Soroka (2012) addressed the media's gatekeeping function (see White, 1950 as a classical study of gatekeeping) and pointed out that the representation of various topics in the media differs from the distribution of information in the real world. The study shows evidence that the media overpresent negative economic trends. Moreover, Ahern and Sosyura (2015) presented evidence on how several factors affect the accuracy of media coverage, while Solomon's (2012) evidence shows that firm publicity can be selective because of investor relation activities.

Hypotheses

The research by Hong et al. (2005) presents evidence that investors spread information about stocks by word of mouth, which means that private information from other investors can be a significant source of information. It is notable that this information may not always reach the public news (information supply) accurately according to the gatekeeping theory. In line with Bayes' rule, rational agents update their beliefs after receiving new information, which may explain various financial market phenomena (Pastor & Veronesi, 2009). Thus, changes in beliefs, which can be detected in online information searches by anticipating investors, can reflect new and updated information that is available to the public even though it is not published news.

The previous feature of dynamic information use implies that there is an interactive relationship between information supply and demand. In their study on information diffusion and external information influence, Myers, Zhu, and Leskovec (2012) presented that external influences are instant, while the influence of information in the network of already affected participants increases slowly. It follows from these pieces of evidence that it is reasonable to assume that information demand should affect information supply instantly, especially if the information is negative (considering the negative bias in the media). Therefore, information demand, which can be external and should be continuously updated based on the market participants' beliefs, should alter information supply, which leads to the following hypothesis:

> Hypothesis 1 (H1): The relationship between information supply and demand is interactive.

Our first hypothesis is related to the previous literature, in particular to Vlastakis and Markellos' (2012) novel finding that the relationship between information supply and demand is bidirectional. Our first hypothesis does not imply one direction for this interaction, but rather the more driving variable of information supply and demand should exhibit more instant stock market effects.

If the media act as gatekeepers of information, more original sources of information would be stock market information and investor anticipation measured as information searches. In a seminal study, Tetlock (2007) did indeed find evidence against the use of media content as a proxy for new information. In addition, investor anticipation that is not reflected in the public news is found to be a significant explanatory variable of stock price changes. Billings and Jennings (2011) and Easton et al. (2010) presented evidence that investor anticipation ahead of earnings announcements to the public can drive stock prices. Drake, Roulstone, and Thornock (2012) suggested that information diffusion is not instantaneous, as earnings announcements are spread over the earnings announcement period. Thus, we argue that information demand is a leading factor in the information diffusion process for market volatility and present the following hypotheses:

> H2: Information demand leads to immediate stocks market effects.

> H3: Information supply leads to gradual stock market effects.

Data and measurements

Measurement of information supply and demand

We utilize weekly frequencies of published newspaper articles and online Google searches to proxy the information supply and demand. We measure information demand on a weekly basis, from Sunday to Saturday, using the GSVI from the Google Trends database for the search words *market crash* collected in January 2016. The GSVI measures the search frequency of the search words relative to their total number of searches. It has been used in several financial studies, for example, by Da et al. (2011), to measure investor attention. Vlastakis and Markellos (2012) then used the GSVI to measure information demand along with information supply, measured as news headlines from the Thomson Reuters NewsScope Archive database.

The use of the search words *market crash* in this type of research is motivated for several reasons: First, severe market declines such as Black Monday on October 19, 1987, or the Wall Street Crash on October 24, 1929, are known as market crashes. The concept of a market crash thus provides a context for severe market declines reflecting investor fear and market volatility. Second, from the behavioral finance perspective, market crashes should be at the forefront of investors' attention, as market crashes are obstacles for investors with respect to their survival. Lo's (2004) adaptive market hypothesis posits that survival is the only objective that matters for every financial market participant and argues that fear and greed are linked to evolutionary forces, which in turn are linked to the probability of survival. Moreover, the financial literature describes the severity of market crashes for investors with phrases such as "blood on the streets," which fit well with the survival aspect of market crashes. Third, based on negative attention bias (see Smith et al., 2006), people are likely to pay more attention to negative information. Because of this reason, search words oriented toward negative market outcomes should be more suitable for research on information processing de facto than other commonly used search words in equity market research such as index-related search words like *Dow* (e.g., Vozlyublennaia, 2014; Hamid & Heiden, 2015), stock tickers (e.g., Da et al., 2011; Joseph, Wintoki, & Zhang, [2011]), and company names (e.g., Bijl, Kringhaug, Molnar, & Sandvik, 2016). Klemola et al. (2016) used negative and positive search words such as *market crash* and *market rally* as potential gauges of investor sentiment. They found that negative search terms in particular predict short-term stock market returns and suggest, in line with negative attention bias (Smith et al., [2006]), that the attention paid to negative information is more effectively transmitted to prices. Thus, the possibility of a market crash as a negative prospect is a focal object for investor attention. Fourth, the concept of a market crash is well known among investors and academics. Several studies focus on "market crashes" or "crash risk" (e.g., Hong & Stein, 2003; Huang and Wang, 2009; Bates, 2012).

Instead of using the search words *market crash*, another more comprehensive approach would be to use the approach of Da et al. (2015), which chooses from an extensive set of negative words in a dictionary by running backward-rolling regressions on market returns to select the most significant market returns. This approach, however, does not enable us to precisely match information supply and demand due to different search words on the news and used by online searchers. Also, we would not be able to address the causality between information supply and demand if we were to choose to conduct information demand variables by running backward regressions. Furthermore, many of the search words in the study by of Da et al. (2015) do not directly relate to investors' fears and market volatility. As top search words for investor fear, their methodology leads them to use *gold prices* and *gold*, which reflect information supply and demand for gold.[1]

To construct a proxy for information supply, we utilize the LexisNexis database, which is used in other similar studies (e.g., Yang, Lim, Oh, Animesh, & Pinsonneault, 2012; Goddard et al., 2015), and collect weekly news stories that match the search words *market crash*. Thus, we use the number of news stories that match the search words *market crash* as the measure of information supply. The frequency of the news stories is limited to newspaper stories. These data are available on a daily basis but we construct the data based on news stories matching weekly periods with our GSVI-based proxy for information demand.

Stock market returns and measures of investor expectations

To measure the impact of information supply and demand on the financial market, we focus on the concept of a "market crash" and measure the impact on the equity market volatility using the VIX implied volatility index, the VVIX index of the volatility of volatility and the S&P 500 returns. This set of research variables is well aligned, as a market crash implies a negative market state, while the VIX is well known as a market state variable that is oriented toward stock market outcomes. We relate the VIX and our information supply and demand variables to investor sentiment. For example, the VIX is commonly called the investor fear gauge, after Whaley (2000). The VVIX is a more recent measure of risk, and Park (2015) suggested it impounds the market's perception of so-called tail risk, linking it to investors' anticipation of market crashes. The S&P 500 returns act as a proxy for market returns.

Summary statistics

Table 1 reports the descriptive statistics for the variables of the empirical analyses. *D* and *S* denote information demand and supply, respectively. We define that $\Delta D_t \equiv D_t - D_{t-1}$ and $\Delta S_t \equiv S_t - S_{t-1}$. The stock index return of the S&P 500 index, *ret*, is defined conventionally as the log of the price relative (i.e., $ret_t \equiv \log(S\&P\ 500\ index_t / S\&P\ 500\ index_{t-1})$). ΔVIX and $\Delta VVIX$ denote changes in the VIX and VVIX indices defined as $\Delta VIX_t \equiv VIX_t - VIX_{t-1}$ and $\Delta VVIX_t \equiv VVIX_t - VVIX_{t-1}$, respectively.

Table 1 demonstrates that the average (median) weekly return for the S&P index is 0.104% (0.267%), with a standard deviation of 2.79% during the sample period. The annualized standard deviation is thus approximately 20%, which corresponds to a typical volatility level in stock markets. The sample contains bullish weeks (the stock index up by 12.95%) and bearish weeks (the stock index down by 14.91%).

Both uncertainty measures show considerable variation. The changes in the VIX index range from –26.38 to 27.72 and the changes in VVIX range from –41.47 to 81.40. The standard deviations of ΔVIX and $\Delta VVIX$ are 3.93 and 9.93, respectively. The Dickey–Fuller and Phillips–Perron tests confirm that all the differenced time series are stationary.

Table 1. Descriptive statistics of the supply and demand of crash-related information and key stock market variables.

Variable	Mean	Median	St dev	Min	Max
D	10.53	9.00	8.02	4.00	100.00
S	84.76	64.00	82.94	22.00	784.00
Δ*D*	0.00	0.00	7.32	–78.00	75.00
Δ*S*	0.04	0.00	59.28	–354.00	573.00
ret	0.104	0.267	2.79	–14.91	12.95
Δ*VIX*	–0.005	–0.110	3.93	–26.38	27.72
Δ*VVIX*	0.019	–0.450	9.93	–41.47	81.40

Note. This table reports descriptive statistics for the variables of the empirical analyses from 2004 to 2015. D and S denote information demand and supply, respectively. D is inferred from weekly online Google search volumes using the search term market crash. S is obtained from the LexisNexis database, by collecting the weekly frequency of news articles that match the same search term. $\Delta D_t \equiv D_t - D_{t-1}$ and $\Delta S_t \equiv S_t - S_{t-1}$. The stock index return of the S&P 500 index, $ret_t \equiv \log(S\&P\ 500\ index_t / \log(S\&P\ 500\ index_{t-1})$. Δ VIX and Δ VVIX denote changes in the VIX and VVIX indices defined as $\Delta VIX_t \equiv VIX_t - VIX_{t-1}$ and $\Delta VVIX_t \equiv VVIX_t - VVIX_{t-1}$, respectively.

Table 2. Pearson correlation coefficients of the supply and demand of crash-related information and key stock market variables.

	Δ*D*	Δ*S*	*Ret*	Δ*VIX*
Δ*S*	0.742			
	<0.0001			
Ret	–0.238	–0.247		
	<0.0001	<0.0001		
Δ*VIX*	0.389	0.344	–0.834	
	<0.0001	<0.0001	<0.0001	
Δ*VVIX*	0.346	0.307	–0.534	0.673
	<0.0001	<0.0001	<0.0001	<0.0001

Note. This table presents the Pearson correlation coefficients for the variables of the empirical analyses from 2004 to 2015. D and S denote information demand and supply, respectively. D is inferred from weekly online Google search volumes using the search term market crash. S is obtained from the LexisNexis database by collecting the weekly frequency of news articles that match the same search term. $\Delta D_t \equiv D_t - D_{t-1}$ and $\Delta S_t \equiv S_t - S_{t-1}$. The stock index return of the S&P 500 index, $ret_t \equiv \log(S\&P\ 500\ index_t / S\&P\ 500\ index_{t-1})$. Δ VIX and Δ VVIX denote changes in the VIX and VVIX indices defined as $\Delta VIX_t \equiv VIX_t - VIX_{t-1}$ and $\Delta VVIX_t \equiv VVIX_t - VVIX_{t-1}$, respectively.

Table 2 reports the Pearson correlation coefficients for the variables used in the empirical analyses. The changes in the information measures seem to be closely correlated with the correlation coefficient of 0.742. This indicates that although the variables come from different data sources, they measure the same phenomenon. The close correlation is consistent with previous evidence, for example, that of Drake et al. (2012), that information demand and news are positively associated. Furthermore, the contemporaneous correlations of the information measures with stock returns are negative (i.e., an increase in stock market crash–related news has a contemporaneous negative relationship with stock returns). The correlation coefficients are –0.238 and –0.247, respectively. Logically, the relationships with both uncertainty measures are positive, and the correlations of stock returns with the uncertainty measures are negative. All the correlation estimates are statistically significant with *p* values lower than 0.01%. Although the analysis of the correlation coefficients shows a significant association between the variables, it does not provide any evidence of how the 2 information measures interact or how the information is processed in the stock market. We next turn our attention to these research issues.

Methodology

This study relies on 2 statistical methodologies, the first of which is intended to capture the dynamic interactions between information supply and demand.

For the second methodology, the objective is to model the processing of news on the stock markets (the S&P 500 stocks) and with regard to investors' expectations of uncertainty in the stock market (the VIX and VVIX indices). These methodologies are discussed in the following subsections.

State space model

We perform our analyses on the dynamic interactions of the GSVI and news flow by estimating a state space model, which is applied to test H1. The model describes multivariate time series through the state vector which summarizes all the relevant information from the current and past values of the series. In this study, we assume that the dynamic interactions of the variables ΔD and ΔS are characterized by the following simple transition equation:

$$z_{t+1} = Fz_t + Ge_{t+1}, \tag{1}$$

where $\mathbf{z}_t$ is a (4×1) state vector defined as $\mathbf{z}'_t = \begin{bmatrix} \Delta D_t & \Delta S_t & \Delta D_{t+1|t} & \Delta S_{t+1|t} \end{bmatrix}$, $\mathbf{F}$ is a (4×4) transition matrix, $\mathbf{G}$ is an (4×2) input matrix and $\mathbf{e}_t$ is an (2×1) innovation vector (SAS Institute, 1996). The transition matrix $\mathbf{F}$ exposes the dynamic properties of the state space model and is therefore our issue of interest; to simplify the presentation, we are not presenting the observation equation of the system. The parameters of the model are estimated via the approximate maximum likelihood estimation. Finally, the robustness of the chosen specification is verified by estimating the model excluding the years 2006 and 2007. The untabulated results are similar to the reported ones. Thus, we therefore conclude that our model specification is feasible.

Distributed lag model

The distributed lag effects are modeled to examine the processing of the GSVI and news flow in the stock market, and to test H2 and H3. The lag effects are examined by estimating the following model:

$$f_t(S\&P500) = \mu + \sum_{i=0}^{p} \alpha_i \Delta D_{t-i} + \sum_{i=0}^{q} \beta_i \Delta S_{t-i} + \epsilon_t, \tag{2}$$

where the dependent variable is a function of the $S\&P500$ (i.e., the stock market return, the change in implied volatility [VIX], or the change in implied volatility on VIX [VVIX]), and the explanatory variables are the current and lagged values of ΔD_t and ΔS_t.

The distribution of the lag effects is modeled by applying the Almon, (1965) type of lag model, using Emerson's (1968) orthogonal lag polynomials: $\alpha_i = a_0 + \sum_{j=0}^{n} a_j h_j(i)$ and $\beta_i = b_0 + \sum_{j=0}^{m} b_j g_j(i)$ (SAS Institute, 1996). As the residuals are serially correlated, the model is estimated with a correction for autocorrelation. Based on the analysis of the orthogonal polynomials, the lag length of 12 and the polynomial degree of 2 are chosen for both variables ΔD_t and ΔS_t. The selection is also supported by the adjusted R^2 criteria. Finally, we also verify that our results are insensitive to the selection of the lag length.

Empirical findings

Dynamic interactions between information supply and demand

Table 3 presents the results of the analysis of the dynamic interactions of information demand and supply. This analysis is denoted for testing H1 that the relationship between information supply and demand is interactive. The main results of the estimation can be summarized in the following transition equation, which includes a presentation of the composition of the transition matrix (the corresponding estimates with t values and p values can be found in Table 3):

$$\begin{bmatrix} \Delta D_{t+1|t+1} \\ \Delta S_{t+1|t+1} \\ \Delta D_{t+2|t+1} \\ \Delta S_{t+2|t+1} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -0.26 & 0.05 & 0.73 & -0.03 \\ -1.98 & 0.24 & 3.51 & 0.29 \end{bmatrix}$$

$$\begin{bmatrix} \Delta D_t \\ \Delta S_t \\ \Delta D_{t+1|t} \\ \Delta S_{t+1|t} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ -0.15 & -0.04 \\ 3.40 & -0.58 \end{bmatrix} \begin{bmatrix} e_{t+1} \\ n_{t+1} \end{bmatrix} \tag{3}$$

The statistically significant estimate values for all the estimates, at least at the 5% level, lends support to

Table 3. Dynamic interactions of supply and demand.

Element	Estimate	t value	p value
F(3,1)	−0.264	−3.35	0.0009
F(3,2)	0.050	5.43	0.0000
F(3,3)	0.726	9.43	0.0000
F(3,4)	−0.027	−2.44	0.0151
F(4,1)	−1.980	−3.24	0.0013
F(4,2)	0.242	3.31	0.0010
F(4,3)	3.512	5.91	0.0000
F(4,4)	0.288	3.25	0.0012
G(3,1)	−0.148	−2.43	0.0155
G(3,2)	−0.037	−4.86	0.0000
G(4,1)	3.397	7.05	0.0000
G(4,2)	−0.582	−9.38	0.0000

Note. This table reports the estimation results of the state space model defined by the following state transition equation: $z_{t+1} = Fz_t + Ge_{t+1}$, where z'_t is a state vector $\begin{bmatrix} \Delta D_t & \Delta S_t & \Delta D_{t+1|t} & \Delta S_{t+1|t} \end{bmatrix}$, F is a transition matrix, G is an input matrix and e_t is an innovation vector.

Table 4. Contemporaneous and lagged effects of supply and demand on stock market returns, VIX, and VVIX.

Panel A. Demand

Lag(n) in	Stock returns			Uncertainty			VVIX		
Weeks	Estimate	*t* value	*p* value	Estimate	*t* value	*p* value	Estimate	*t* value	*p* value
$\Delta D(0)$	−0.105*	−4.18v	<0.0001*	0.223*	7.98*	<0.0001*	0.529*	6.48*	<0.0001*
$\Delta D(1)$	−0.076*	−3.44*	0.001*	0.170*	7.10*	<0.0001*	0.374*	5.33*	<0.0001*
$\Delta D(2)$	−0.050*	−2.25*	0.025*	0.122*	5.17*	<0.0001*	0.240*	3.42*	0.001*
$\Delta D(3)$	−0.029	−1.18	0.237	0.081*	3.18*	0.002*	0.126*	1.66*	0.098*
$\Delta D(4)$	−0.012	−0.44	0.657	0.046*	1.67*	0.096*	0.033	0.39	0.694
$\Delta D(5)$	0.001	0.03	0.976	0.017	0.59	0.553	−0.040	−0.46	0.646
$\Delta D(6)$	0.009	0.32	0.749	−0.005	−0.17	0.865	−0.093	−1.04	0.300
$\Delta D(7)$	0.013	0.47	0.639	−0.021	−0.72	0.470	−0.126	−1.42	0.156
$\Delta D(8)$	0.013	0.49	0.628	−0.031	−1.11	0.267	−0.138	−1.63	0.103
$\Delta D(9)$	0.009	0.34	0.733	−0.035	−1.32	0.186	−0.129	−1.64	0.102
$\Delta D(10)$	0.000	−0.01	0.994	−0.032	−1.28	0.202	−0.101	−1.33	0.183
$\Delta D(11)$	−0.013	−0.54	0.590	−0.024	−0.88	0.377	−0.052	−0.66	0.513
$\Delta D(12)$	−0.031	−1.07	0.287	−0.009	−0.27	0.786	0.018	0.19	0.847
Sum of lags	−0.271			0.502			0.641		

Panel B. Supply

Lag(n) in	Stock returns			Uncertainty			VVIX		
Weeks	Estimate	*t* value	*p* value	Estimate	*t* value	*p* value	Estimate	*t* value	*p* value
$\Delta S(0)$	0.000	−0.10	0.920	−0.003	−0.92	0.359	−0.012	−1.31	0.190
$\Delta S(1)$	−0.003	−1.11	0.269	0.001	0.48	0.628	−0.003	−0.41	0.679
$\Delta S(2)$	−0.005*	−1.91*	0.057*	0.005*	1.80*	0.072*	0.004	0.48	0.630
$\Delta S(3)$	−0.006*	−2.36*	0.019*	0.007*	2.72*	0.007*	0.009	1.13	0.259
$\Delta S(4)$	−0.007*	−2.55*	0.011*	0.009*	3.27*	0.001*	0.013	1.52	0.130
$\Delta S(5)$	−0.008*	−2.60*	0.010*	0.011*	3.58*	0.000*	0.015*	1.72*	0.085*
$\Delta S(6)$	−0.007*	−2.56*	0.011*	0.011*	3.76*	0.000*	0.016*	1.81*	0.071*
$\Delta S(7)$	−0.007*	−2.43*	0.016*	0.011*	3.84*	0.000*	0.016*	1.78*	0.076*
$\Delta S(8)$	−0.006*	−2.18*	0.030*	0.011*	3.79*	0.000*	0.014	1.63	0.104
$\Delta S(9)$	−0.004*	−1.73*	0.084*	0.009*	3.53*	0.001*	0.010	1.29	0.199
$\Delta S(10)$	−0.002	−0.98	0.329	0.007*	2.87*	0.004*	0.005	0.67	0.502
$\Delta S(11)$	0.000	0.08	0.936	0.005*	1.71*	0.088*	−0.002	−0.20	0.842
$\Delta S(12)$	0.003	1.13	0.257	0.001	0.36	0.721	−0.010	−1.06	0.289
Sum of lags	−0.052			0.086			0.076		

Panel C. Polynomial estimates

	Estimate	*t* value	*p* value	Estimate	*t* value	*p* value	Estimate	*t* value	*p* value
Intercept	0.116	1.15	0.252	−0.020	−0.19	0.846	0.013	0.04	0.968
ΔD^0	−0.075	−1.02	0.310	0.139*	1.80*	0.072*	0.178	0.77	0.442
ΔD^1	0.084*	2.05*	0.041*	−0.261*	−5.82*	<0.0001*	−0.575*	−4.37*	<0.0001*
ΔD^2	−0.096*	−2.41*	0.016*	0.140*	3.26*	0.001*	0.456*	3.60*	0.000*
ΔS^0	−0.014*	−1.86*	0.063*	0.024*	2.96*	0.003*	0.021	0.88	0.381
ΔS^1	0.004*	0.94	0.347	0.004	0.96	0.336	0.002	0.17	0.866
ΔS^2	0.011*	2.86*	0.004*	−0.015*	−3.67*	0.000*	−0.034*	−2.74*	0.006*
R^2	0.14			0.35			0.22		

Note. This table presents the results from the Almon (1965) model estimations, which measures the effects of demand and supply on stock market returns (S&P 500 index), stock market uncertainty measured using the forward-looking VIX index of CBOE, and the volatility of stock market uncertainty measured using the VVIX index of CBOE. Panel A shows the results for demand and Panel B shows the results for supply. Panel C reports the orthogonal lag polynomials. *Indicates estimates that are statistically significant at the 10% level.

H1. Thus, the results in Table 3 suggest that information supply and demand are not 1-directional and that information demand affects information supply. This finding is in line with Vlastakis and Markellos (2012) that the relationship between information supply and demand is bidirectional. However, the estimates from our state space model reveal more of the complex interaction between information supply and demand. The coefficients for the information demand variables $\Delta D_{t+1|t}$ and ΔD_t suggest that an increase in a conditional expectation of information demand increases both future expected information supply and demand, but an increase in information demand decreases both of them. With regard to the impact of information supply, the positive coefficients for ΔS_t suggest that a change in information supply decreases future expected information supply, similar to a change in information demand.

The results in Table 3 reveal a notable difference between information demand and supply. The positive and negative coefficients for $\Delta S_{t+1|t}$ when explaining future expected information supply and demand, respectively, imply that an increase in conditional expectation of information supply decreases future expected information demand, but increases future expected information supply. An interpretation of this result is that the positive effect for information supply indicates that the expectation of more news increases future news. Intuitively, the negative effect for information demand supports the view that public news in the financial market eventually satisfies investors' demand for new information. The results are also evidence of a noninstantaneous information diffusion in line with studies such as by Drake et al. (2012), which shows that information demand associated with earnings announcements is spread over a period surrounding the earnings announcement. In relation to Vlastakis and Markellos (2012), the interactive relationship between information supply and demand can be bidirectional in a dynamic setting. All in all, these results suggest that information supply decelerates the interaction between information supply and demand, while information demands it.

Shape of the lag structure

Table 4 presents the results on the effects of information supply and demand on changes in stock market returns, the VIX implied volatility index and the VVIX index of the volatility of implied volatility. These results, which are depicted in Figures 1–3, are denoted for testing our second and third hypotheses that information demand leads to immediate stock market effects (H2) and information supply leads to eventual stock market effects (H3). The statistically significant estimates at the 5% level for information demand lagged in 0–2 weeks show that a greater information demand is associated immediately with lower stocks returns and increases in VIX and VVIX. This result is logical, considering the pessimistic nature of the search words *market crash* and the negative relationship between changes in implied volatility and market returns (e.g., Whaley, 2000).

Our results in Table 4 on the effects of information supply differ from the results on information demand in 2 notable ways. First, the estimates for information supply lagged in 0–2 weeks are not statistically significant at the 10% level when explaining stock returns and changes in VIX, which shows that information supply does not have an immediate effect on stock returns and volatility. However, the estimates for information supply are negative (positive) for stock returns (volatility) and statistically significant at the 10% level for lags from 2 to 9.

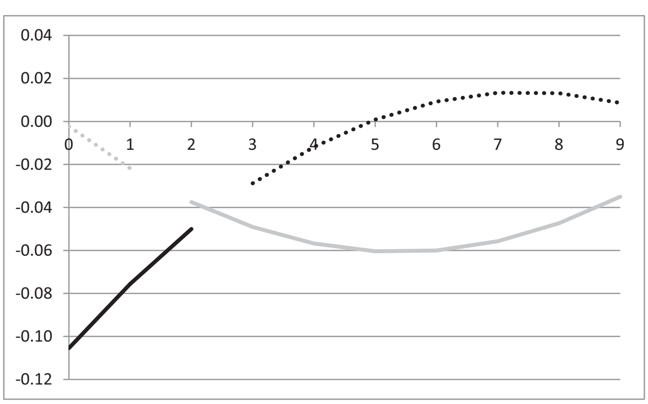

Figure 1. Effects of demand and supply on stock market returns.
This figure illustrates the effects of demand (black line) and supply (dark line) on stock market returns. The solid line indicates the statistical significance of the relationship at the 10% level.

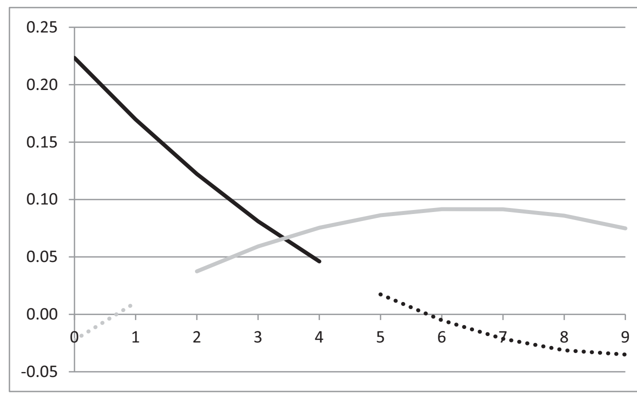

Figure 2. Effects of demand and supply on stock market uncertainty (VIX).
This figure illustrates the effects of demand (black line) and supply (dark line) on stock market uncertainty measured using the forward-looking VIX index. The solid line indicates the statistical significance of the relationship at the 10% level; the dashed line indicates a statistically insignificant relationship.

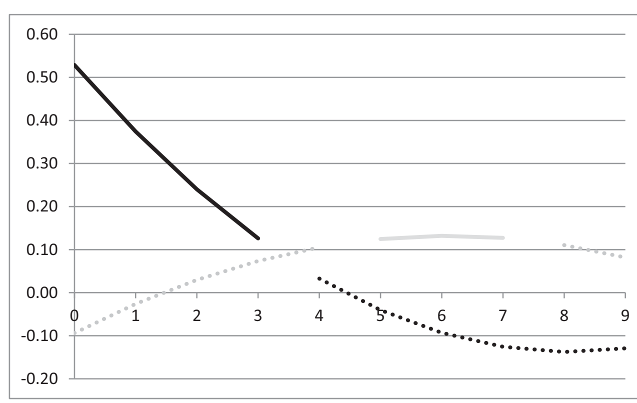

Figure 3. Effects of demand and supply on the volatility of volatility (VVIX).
This figure illustrates the effects of demand (black line) and supply (dark line) on the volatility of the stock market uncertainty. The volatility of volatility is measured using the forward-looking VVIX index. The solid line indicates the statistical significance of the relationship at the 10% level; the dashed line indicates a statistically insignificant relationship.

The signs of the estimates are similar to those of information demand, which is natural due to the object of the information, and the results are line with our third hypothesis, as the significance of the coefficient clearly indicates the long-term effects of information supply. The results on information demand and supply show collectively that the demand effect dominates at first, but then decays when information supply takes on the more dominant role. Thus, our analysis of the effects of information demand lend support to our second and third hypotheses, and they are in line with the evidence of Tetlock (2007) that the use of media content as a proxy for new information may not be warranted. This evidence for information supply is similar to Liu, Sherman, and Zhang (2014), who found that media coverage without genuine news affects a stock's long-term value.

Second, relative to the results for VIX, the effects of information supply are considerably weaker for VVIX, as only a few coefficients are statistically significant at the 10% level. Further, the weak effects of information supply can be observed in Figure 3, where it can be clearly seen that the coefficient values for information supply are very weak compared with information demand. This is a novel finding, showing that information supply has relatively little impact on the implied volatility of volatility. A reasonable explanation for this finding is that the VVIX index reflects the demand side but not the supply of information because the volatility of volatility may be related to the uncertainty of future market states, which is anticipated by investors rather than revealed in the public news.

Conclusion

In this study, we focus on investors' crash fears and utilize data on published newspaper articles and web search volumes to address the complex association between information supply and demand related to investor fear and their effects on realized stock market returns, implied volatility (VIX), and the volatility of implied volatility (VVIX) using 2 methodologies. First, we use the state space model to study the interactions between information supply and demand, which are closely correlated variables. This analysis reveals novel findings for the extant literature (see Vlastakis & Markellos, 2012) that information demand increase future information supply and demand, while information supply mainly increases information demand. Our evidence shows that information demand rather than information supply leads to more instantaneous effects in the financial markets and drives the interaction between the supply and demand sides, whereas the information supply side plays an important concluding role in the relationship between the 2. These findings show that the role of the public news as the origin of information processing in the financial markets should be reconsidered and more attention should be paid to the gatekeeping role of the media (White, 1950). Thus, our study, together with Drake et al. (2012), suggests that information demand leads the information diffusion process.

Second, we use the distributed lag model to investigate the effects of information supply and demand on stock returns, on volatility and on the volatility of volatility. Our study shows that the effects of information demand on realized stock returns and the VIX index are instantaneous, while the effects of information supply on stock returns and volatility are gradual. Moreover, our results on the effects of information supply suggest that it tends to act in the long term, which is consistent with the study by Liu et al. (2014), who linked their evidence to the long-term effect of investor recognition. These findings suggest that the novelty of media content is weak, although it plays a concluding role in the dynamic relationship between information supply and demand. Our evidence is consistent with that of Peress (2014) that the media contribute to the efficiency of the stock market by improving the dissemination of information, although with a lag. The effects of information supply on the VVIX index are weak, which implies that the VVIX index for the volatility of implied volatility is informationally an excellent market indicator that is not exposed to the public news. These findings on the explicit nature of the lag effects of information supply and demand add on the evidence of Ben-Rephael et al. (2018) who found that it is not supply, but rather institutional demand that is associated with risk premium.

Our study casts doubt on understanding media content as new information, which is in line with the evidence of Tetlock (2007). Therefore, investors and the financial news production industry should closely follow information demand to provide investors with contemporaneous information. In other words, web searches can reveal which news topics have an audience and are attracting news followers' attention. For investors and the financial industry, our study suggests that the process of monitoring investment opportunities can significantly benefit from actively analyzing the information demand side, not just the information supply side (i.e., the news). Our study calls for further research on this topic.

Note

1. We also considered the search word *recession* in the study by Da et al. (2015), but we found that the information supply and demand for *recession* exhibits relatively lower correlation with changes in the VIX index than does the information supply and demand for *market crash.*

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References

Ahern, K. R., & Sosyura, D. (2015). Rumor has it: Sensationalism in financial media. The Review of Financial Studies, 28(7), 2050–2093.

Almon, S. (1965). The distributed lag between capital appropriations and net expenditures. *Econometrica*, 33(1), 178–196.

Andrei, D., & Hasler, M. (2015). Investor attention and stock market volatility. *Review of Financial Studies*, 28(1), 33–72.

Aouadi, A., Arouri, M., & Teulon, F. (2013). Investor attention and stock market activity: Evidence from France. *Economic Modelling*, 35(C), 674–681.

Bates, D. S. (2012). U.S. stock market crash risk, 1926-2010. *Journal of Financial Economics*, 105(2), 229–259.

Ben-Rephael, A., Carlin, B. I. Da, Z., & Israelsen, R. D. (2018). Demand for Information and asset pricing. Kelly School of Business at Indiana University, Working Paper.

Bijl, L., Kringhaug, G., Molnar, P., & Sandvik, E. (2016). Google searches and stock returns. *International Review of Financial Analysis*, 45(May), 150–156.

Billings, B., & Jennings, R. (2011). The option market's anticipation of information content in earnings announcements. *Review of Accounting Studies*, 16(3), 587–619.

Chronopoulos, D. K., Papadimitriou, F. I., & Vlastakis, N. (2018). Information demand and stock return predictability. *Journal of International Money and Finance*, 80(February), 59–74.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance*, 66(5), 1461–1499.

Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *Review of Financial Studies*, 28(1), 1–32.

Drake, M. S., Roulstone, D. T., & Thornock, J. R. (2012). Investor information demand: Evidence from Google searches around earnings announcements. *Journal of Accounting Research*, 50(4), 1001–1040.

Easton, P. D., Geo, G., & Gao, P. (2010). Pre-earnings announcement drift. University of Notre Dame, Working Paper.

Emerson, P. L. (1968). Numerical construction of orthogonal polynomials from a general recurrence formula. *Biometrics*, 24(3), 695–701.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2), 383–417.

Goddard, J., Kita, A., & Wang, Q. (2015). Investor attention and FX market volatility. *Journal of International Financial Markets, Institutions and Money*, 38(September), 79–96.

Hamid, A., & Heiden, M. (2015). Forecasting volatility with empirical similarity and Google trends. *Journal of Economic Behavior & Organization*, 117(September), 62–81.

Huang, J., & Wang, J. (2009). Liquidity and market crashes. *Review of Financial Studies*, 22(7), 2607–2643.

Hong, H., & Stein, J. C. (2003). Differences in market opinion, short-sale constraints, and market crashes. *Review of Financial Studies*, 16(2), 487–525.

Hong, H., Kubik, J. D., & Stein, J. C. (2005). Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers. *The Journal of Finance*, 60(6), 2801–2824.

Joseph, K., Wintoki, M. B., & Zhang, Z. (2011). Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal of Forecasting*, 27(4), 1116–1127.

Kahneman, D. (1973). *Attention and effort*. Englewood Cliffs: Prentice-Hall.

Klemola, A., Nikkinen, J., & Peltomäki, J. (2016). Changes in investors' market attention and near-term stock market returns. *Journal of Behavioral Finance*, 17(1), 18–30.

Liu, L. X., Sherman, A. E., & Zhang, Y. (2014). The long-run role of the media: Evidence from initial public offerings. *Management Science*, 60(8), 1945–1964.

Lo, A. W. (2004). The adaptive markets hypothesis. The Journal of Portfolio Management, 30(5), 15–29.

Myers, S., Zhu, C., & Leskovec, J. (2012). *Information diffusion and external influence in networks*. Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 33–41

Moussa, F., Delhoumi, E., & Ouda, O. B. (2017). Stock return and volatility reactions to information demand and supply. *Research in International Business and Finance*, 39(A), 54–67.

Park, Y.-H. (2015). Volatility-of-volatility and tail risk hedging returns. *Journal of Financial Markets*, 26(November), 38–63.

Pastor, L., & Veronesi, P. (2009). Learning in financial markets. *Annual Review of Financial Economics*, 1(1), 361–381.

Peress, J. (2014). The media and the diffusion of information in financial markets: Evidence from newspaper strikes. The Journal of Finance, 69(5), 2007–2043.

SAS Institute. (1996). *Forecasting examples for business and economics using the SAS® system*. Cary, NC: SAS Institute Inc.

Solomon, D. H. (2012). Selective publicity and stock prices. *The Journal of Finance*, 67(2), 599–638.

Soroka, S. N. (2012). The gatekeeping function: Distributions of information in media and the real world. *The Journal of Politics*, 74(2), 514–528.

Smith, N. K., Larsen, J. T., Chartrand, T. L., Cacioppo, J. T., Katafiasz, H. A., & Moran, K. E. (2006). Being bad isn't always good: Affective context moderates the attention bias towards negative information. *Journal of Personality and Social Psychology*, 90(2), 210–220.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, 62(3), 1139–1168.

Vlastakis, N., & Markellos, R. N. (2012). Information demand and stock market volatility. *Journal of Banking & Finance* 36(6), 1808–1821.

Whaley, R. E. (2000). The investor fear gauge. *The Journal of Portfolio Management*, 26(3), 12–17.

White, D. M. (1950). The 'gate keeper': A case study in the selection of news. *Journalism Bulletin* 27(3), 383–390.

Vozlyublennaia, N. (2014). Investor attention, index performance, and return predictability. *Journal of Banking & Finance*, 41(April), 17–35.

Yang, S.-B., Lim, J. H., Oh, W., Animesh, A., & Pinsonneault, A. (2012). Using real options to investigate the market value of virtual world businesses. *Information Systems Research*, 23(3-part-2), 1011–1029.

Yin, L., & Feng, J. (2019). Can investors attention to oil markets predict stock returns? *The North American Journal of Economics and Finance*, 48(C), 786–800.