Media and Google:

The Impact of Information Supply and Demand on Stock Returns

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Abstract

Media news is a proxy for attention from the information supply side, and the Google search is a proxy for attention from the information demand side. I show that that the attention has the biggest impact on financial markets when the supply side attention and demand side attention move in the same direction. A portfolio of buying stocks with both attentions up and short-selling stocks with both down generates 17% annual abnormal returns. The finding indicates that media is important to financial market only when the investors are willing to be affected. Furthermore, the attention measure is less subject to the estimation bias.

Keywords: Stock returns, Information Supply, Information Demand, Estimation Bias, Media, Google, Wikipedia, Web Traffic, News, Search Volume

JEL Codes: G12, G14

I. Introduction

In the information market, news is essentially initiated or generated by companies in the form of press releases and filing with regulators, and then information is disseminated by media in the form of news coverage. The release and dissemination steps form the supply side of the information market. The news are subsequently received and digested by investors, which forms the demand side of the information market. The path of the information transmission in the information market is well described by the chain of information release, dissemination and reception. For the information to pass through the whole path and affect stock prices, both media outlets and investors have to pay attentions. This study proposes a new measure of attention which incorporates attentions from both information supply and demand sides. I use the number of news articles and Google search volume as proxies for information supply side attention and demand side attention to study their joint impact on stock returns.

Attention can affect the stock price. For one thing, an increase in the attention implies an increase in participation of investors, individual investors in particular. These individual investors are chasing after attention grabbing stocks. They tend to buy rather than sell those stocks, which drives up the stock prices (Barber and Odean (2008) and Da, Engelberg and Gao (2011)). For the other, when investors allocate more attention to learn about a stock, the risk of the asset payoff perceived by investors is lower. Lower risks make the stocks more attractive to existing investors and increase their demands and raise the price (Veldkamp (2006)).

The joint use of attentions from both information supply and demand sides is crucial in studying the impact of attention on stock prices. The increase in attention from the information demand side ensures that a surge in news coverage due to media attention succeeds in attracting investors' attention, and thus affects prices. I show that an econometric model with only media attention over-estimates the impact of media attention when investors' attention decreases. On the other hand, the increase in information supply side attention helps to differentiate whether real news or other forces (e.g. pure emotional sentiments and liquidity shock) cause an increase in investors' attention. I show that the estimated impact of an increase in investors' attention is bias upward when media attention decreases.

Investors’ attention is important to enable the media attention to have a significant impact on stock prices. Firstly, an increase in the media attention per se is no guarantee of attracting more investors to pay attention to the stock since it depends on its reception. If investors still have no interest because the news is not sufficiently attention grabbing or investors are busy with other activities, the news will have a limited impact on the stock prices. Attention from the information demand plays a crucial role to confirm that the link between information supply and investor interest is well established. Secondly, the risk perceived by investors is lower so that the price goes higher only if investors actively pay more attention to learn, i.e. acquire more information. In summary, an increase in investors’ attention is a necessary condition for an increase in media attention to raise the stock price. Empirically, I find that an increase in news coverage has a strong positive correlation to future stock returns only if the search volume also rises.

On the other hands, is investors’ attention alone sufficient to affect the stock price? The answer is no. An increase in investors’ attention per se cannot tell us whether investors are responding to important corporate news or to other things (e.g. their emotions, or liquidity shocks) – these different forces may predict future returns in entirely different directions. For example, Savor (2012) provides evidence that the stock market events which are driven by news exhibit price momentum while those driven by pure sentiment exhibit price reversal. If the rise in Google search coincides with media news, then the increase in investors’ attention may predict a subsequent price momentum. Otherwise, a rise in investors’ attention may predict a subsequent price reversal as the sentiment fades or liquidity shock ends. Empirically, the paper shows that an increase in search volume predicts positive stock returns only when it is accompanied by an increase in news coverage, which indicates that only investors’ attention induced by news raises the stock prices.

Therefore, separating out the effects of attentions from information supply and demand side is a crucial but overlooked aspect of the empirical literature on stock returns and information release, dissemination and reception through the attention channel. The average effect of a single-sided media attention (or investors' attention) is not good enough because I show that the stock return prediction of the information demand (or supply) side attention is, in fact, conditional on the other half of the shift “pair”. Only by making the distinction can I pin down the attention channels driving the relationship among the news coverage, search volume and stock returns.

In this paper, I propose a new framework for testing the relationship between stock returns and the joint shifts in attention from both information supply and demand sides. With a novel panel dataset consisting of news articles and Google search volumes, I employ an empirical approach to isolate various underlying forces that link information supply side attention and demand side attention to stock returns. Using an approach similar to Cohen, Diether, and Malloy (2007), I identify four scenarios of the shift in attentions from supply and demand sides. I define a shift as an increase (decrease) in the information supply (demand) side attention if the ratio of number of news articles (search volume) to its 8 weeks moving average is above 75 percentile (below 25 percentile) of the ratios in the cross section during the week. These shift "pairs" enable us to pin down the dynamics of media's attention and investors' attention.

I find that an upward (downward) shift in both media attention and investors’ attnetion is the strongest predictor of cross sectional outperformance (underperformance). The findings imply that there is lower (higher) price impact of an increase in media attetion (investors’ attention) when investors’ attention (media attention) decreases (increases). The regression coefficients imply a 16% risk-adjusted outperformance of stocks with both media attention and investors’ attention up against stocks with both down. The result is robust to controlling for price reversal, price momentum, trading volume, institutional ownership, analyst coverage, and news coverage. An attempt to disentangle the information supply side attention and demand side attention in the financial market is not only theoretically appealing but also practically meaningful. A portfolio strategy of buying stocks with the “upward shift pair” and short selling the stocks with the “downward shift pair” delivers a 17% abnormal returns per year.

I conduct some robustness tests. First, since Google search volume mainly captures the investors’ attention from individual traders (Da, Engelberg and Gao (2011)), I conjecture that the empirical finding will be stronger among stocks held by individual investors. Barber, Brad, and Odean (2000) found that individual investors tilted their common stock investment towards high-beta, small and value stocks. Consistent with this hypothesis, I find that the outperformance increases to 25% and 34% per year in the small size subsample and the above-median return volatility subsample. Secondly, I eliminate the possibility that the price movement is solely driven by the price momentum and reversal. To do that, I treat the effect of the shift pairs as a function of the past return, and find that the impact of the information shift pairs persists. Thirdly, I show that the phenomenon is not fundamental driven. If an abnormal return is driven by fundamentals (i.e. good news, or bad news), it should not reverse over time but be a persistent component in the stock price. I follow Jegadeesh and Titman (1993) to form the overlapping portfolio. The abnormal returns of 2 weeks overlapping portfolio is only half of the non-overlapping portfolio, and the significantly positive abnormal returns vanished beyond an overlapping portfolio of 4 weeks.

The stock price goes up because these investors tend to buy rather than sell the attention grabbing stocks. If this explanation is true, I should observe that investors intensively buy stocks with good news, but less intensively sell stocks with bad news when both information supply and demand rise. I use the news tone as the proxies for good and bad news. The result shows a significantly large outperformance of stocks with good news and a marginally moderate underperformance of stocks with bad news among stocks with an upward shift in both media attention and investors' attention. On the other hands, I observe a big underperformance of stocks with bad news for stocks with media attention and investors' attention down.

I use the web traffic to the company page on Wikipedia to address the difficulty partially. If the assumption that the traffic to Wikipedia is a proxy for the learning of investors who have little general knowledge about the firm holds, then the Google search volume net of the Wikipedia traffic should capture the learning of investors who already have some basic knowledge of the stock (i.e. investors who have the stock in their mind). For each firm, I run the regression of the search volume on Wikipedia traffic and use the sum of the constant term and residual term as the measure of search volume net of Wikipedia traffic. I show that the upward shift "pair" predicts positive stock returns when I use either Wikipedia traffic or Google search volume net of Wikipedia traffic as the proxy for information demand. This implies that both the current explanation and the previous explanation are driving the phenomenon.

The remainder of the paper is organized as follows. I review the related literature in session II. Section III describes the data collection procedure and the research design. Section IV and V present and explain the empirical findings. In Section VI, I draw conclusions.

II. Related Literature

The information supply literature related to my study is on media and stock returns. For example, Chan (2003) examines momentum and reversal patterns following large price moves with or without news, finding that price events without news exhibit a reversal, while price events with accompanying news exhibit price momentum. Antiweiler and Frank (2004) document that stock messages predict market volatility. Tetlock (2007) does a linguistic analysis of news articles and reports that pessimistic tone predicts downward pressure on price and a subsequent reversal. Tetlock, Tsechansky, and Sofus

Macskassy (2008) find that the fraction of negative words in the news articles predicts earnings and stock returns. Fang and Peress (2009) document a persistent no-media-coverage premium whereby stocks without media coverage have a higher cross-sectional stock returns. I add to this literature by arguing that whether news (information supply) has an impact on stock return depends on whether there is a demand for information. If investors show no interest in the news, then it will have little impact on stock returns via the investors' attention channel. Information demand plays a crucial role to ensure that the link between information supply and attention is well established. The empirical findings also imply that the information demand (Google search volume) is a new metric on the information supply (news) which is different from the existing measures such as the news counts and news tone.

This research is also related to the information demand literature. Drake, Roulstone, and Thornock (2012) study the dynamics of the information demand by investors around earnings announcements. They document that abnormal Google search increases about two weeks prior to the earnings announcement, spikes markedly at the announcement, and continues at high levels for a period after the announcement. They also find that when investors search for more information in the days just prior to the announcement, preannouncement price and volume changes reflect more of the upcoming earnings news. Investors indeed demand more information during important corporate events (e.g. pre-earning announcement), and Google search seems an effective tool for investors to find extra information (evidenced by the finding that a higher Google search volume is accompanied by a stronger alignment between the pre-announcement price and the upcoming earnings news). Vlastakis and Markellos (2012) find that the information supply (measured by return volatility and trading) drives information demand (measured by Google search volume) among a sample of 30 largest NYSE stocks, although their study is not about the relationship between stock returns and the interaction of information supply and demand. In fact, the literature on information demand focuses on the determinants of the information demand either in time series or cross section. This paper's contribution to the literature is to differentiate whether company news or pure emotional sentiment drives an increase in information demand. The empirical finding shows that the former predicts positive future return, and the later has no prediction power.

One explanation of the documented phenomenon is related to the breadth of investors' participation, and the other explanation is related to the in-depth of investors' participation. When a rise in information supply causes an increase in awareness of a stock and a rise in information demand confirms it, more investors start considering investing in the stock (i.e., an increase in breath). Barber and Odean (2008) show that individual investors are net buyers of attention grabbing stocks. Therefore, there is a positive price pressure when more individual investors are aware of a stock. Da, Engelberg, and Gao (2011), for the first time, use Google search volume to measure investors' attention directly and document a strong predictability of search volume on future stock returns by arguing the similar channel of an increase in individual investors presence. The second explanation is that when a rise in information supply induces an increase in learning of a stock and a rise in information demand provides supportive evidence, existing investors know more about the stock (i.e. an increase in in-depth). Veldkamp (2006) shows that when more information is provided to the market, the posterior variance of the asset payoff conditional on the abundant information is lower. Lower risk makes the asset more attractive to investors, increases demand and raises the price. Therefore, both channels drive the stock price up. Empirically, I show that both channels are likely to play a role in driving the result.

III. Research Design

A. Data

A1. Company and Security Data

I limit the sample to Russell 3000 stocks. I obtain the current list of Russell 3000 stocks from CapitalIQ and add back the stocks which were dropped from Russell between 2004 and 2012 according to the CapitalIQ key development data. I obtain the accounting data from Compastat and stock data from CRSP. I keep firms that have both returns and accounting data between 2004 and 2012. I obtain the DGTW stock deciles by Daniel, Grinblatt, Titman, and Wermers (1997) from Wermers' website. The analyst coverage data is from IBES, and the institutional ownership data is from Thomson Reuters.

A2. News Article (Supply of Information)

I follow Veldkamp (2006) to use the number of news articles as proxy for information supply. Following Von Beschwitz, Keim, and Massa (2013), I use RavenPack for news data. RavenPack provides news analytics product based on Dow Jones Newswire archive. Each news is assigned a relevance score with respect to a company mentioned in the text. Von Beschwitz, Keim, and Massa (2013) find that highly relevant articles have impact on stock prices while there is almost no reactions to articles with a low relevance scores. Based on their finding, I only keep the news with the relevance score of 100% in the sample. RavenPack news analytics also differentiates news articles from press releases. The sentiment score derived from the news tone is also available. Both the news sources and the tone are used in this study.

A3. Google Search Volume (Demand for Information)

I follow Drake, Roulstone and Thornock (2012) to use Google search volume as the proxy for information demand. The search volume data is from Google Trends, which provides the time series of the search volume of the queried keywords, starting from 2004. The value of Google Trends is the percentage of the total search volume, and is further scaled by the maximum percentage of the keyword over time. Similar to the news article case, I searched for the firm by stock ticker. The search volume by stock ticker ensures that the search volume for a company most likely come from investors. I limited the geographical location of the search to "United States". Google Trends returned the message "Not enough search volume to show graphs" when the search volume was too low to form meaningful statistics. In this situation, I set the search volume of the entire time series to 0. The value 0 does not mean no search at all, but that the search volume is extremely low.

I am studying the stocks that are properly covered by media and have meaningful search volume statistics. Therefore, I dropped the stocks without news articles and non-zero search volume statistics over the entire sample periods. I ended up with 1946 stocks.

B. Supply and Demand "Pairs"

My empirical strategy is to identify four scenarios of the information supply and demand shift and use them to test the theoretical predictions.

Using an approach similar to Cohen, Diether, and Malloy (2007), I identify four scenarios of the shift in supply and demand for information. Differently from their variable definition, I define the shift by comparing company's current information supply (demand) against its past eight weeks moving average. The reason for doing so is that the information supply and demand variables are not smooth. For example, a large number of firm weeks have zero news article, and defining the news shift against its previous week news coverage is going to yield many invalid numbers because of being divided by zero. I further smoothen the time series of information supply and demand by using wavelet analysis to remove the noise component but all the smoothing is done only using the past information supply and demand to avoid forward looking bias. I define a shift as an increase (decrease) in information supply (demand) if the ratio of its current value to its 8 weeks moving average is above 75 percentile (below 25 percentile) of the ratios in the cross section during the week. I then define a supply and demand shift "pair" by combing any supply shift and any demand shift, which yields four supply and demand "pairs". I denote UU=1 (DD=1) if both information supply and demand shift upwards, and 0 otherwise. I denote UD=1 (DU=1) if information supply (demand) shifts upwards, but information demand (supply) shifts downwards, and 0 otherwise.

Table 1 reports the summary statistics. Table 1 Panel A reports the summary of firms' number of news articles and search volume as well as the ratio to their 8 weeks moving average. I deliberately dropped the no news firm week in the table of summary statistics. There are 352682 firm week with at least one news article out of the sample size of half million observations. This implies that about 70% of the firm weeks in sample has news coverage, i.e. majority of the firms are properly covered by media, and the key questions is what will happen if the intensity of the coverage shift upwards and downwards. The median of the news to its 8 weeks moving average ratio is 0.91 which implies that the distribution of the news is negatively skewed, and the same median ratio is 1 for Google search volume. Panel B summarizes the key variables by information supply and demand pair deciles. The firm week with UU=1 has larger market capitalization and more analyst and media coverage. If the distribution is driving the empirical findings of this study, then stock with DD=1 should outperform due to the size and media coverage effect. However, the opposite effect is observed. Therefore, this distribution cannot drive the empirical findings of this study.

C. Cross-Sectional Regressions

I follow Cohen, Diether, and Malloy (2007) for the econometrics specification. They use both pooled panel regression with monthly fixed effects and a Fama Macbeth regression. They report their results in pooled panel regressions and note that Fama Macbeth results are robust. Their reason for reporting pooled panel regressions is that there are time periods when all their shift dummies are 0. Since I have no such constraint, I report Fama Macbeth regression results in the main tables and run a robustness check for pooled panel regression in the unreported tables.

My baseline test model is a Fama Macbeth regression with Newey-West for 8 lags. DGTW adjusted return is used to measure stock abnormal returns. Following Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2003), I subtract the corresponding DGTW portfolio return from the raw return of the stock. In the unreported robustness check, I also use CAPM, 3 Factor and 4 Factor alphas to measure abnormal returns, and the result is robust. In addition to the abnormal return, I also use the past 1 week return to control for reversal and control the return between the lagged 52 and the lagged 2 week for momentum on the right hand side.

More specifically, I regress the abnormal return at time *t* on , , ,, (last week's return), (the return from week to week), (the institutional ownership measured as the percentage of shares held by intuitional investors in the previous quarter), (the average daily trading volume scaled by the total number of shares outstanding from week to), analyst coverage of the previous month and news coverage of the previous year.

The base line model takes the form:

where is the DGTW adjusted return.

IV. Empirical Results

A. Shift in Information Supply and Demand on Stock Return

Table 2 reports the main hypothesis tests. I regress DGTW returns on the lagged shift pair indicators on information supply and demand. Model 1 includes only the four information shift pairs as the independent variable. Model 2-6 include additional control variables sequentially. The regression results show that the UU=1 (DD=1) is the strongest predictor of an upward (downward) price movement. The finding indicates that the impact of information supply and demand is more salient when they move in the same direction. Specifically, the finding shows that the news that stimulates the information demand (rather than the non-attention-grabbing news) affects the stock prices the most. On the other hand, the information demand that is induced by the relevant news (instead of information demand due to other forces such as pure emotional sentiment) affects the stock prices the most. Although UD=1 is positively significant, the confidence level is much weaker at only 5% (the confidence level for UU=1 is 1%), and the economic magnitude is only about half of the economic magnitude for UU=1. Therefore, the shift in information demand (i.e. Google search volume) is still important to the magnitude and statistical confidence of the impact of the information supply despite of the significance of UD=1. Furthermore, when I do the same test conditional on the price reversal and momentum in Table 6, the significance of UD=1 totally disappears. Therefore, UD=1 is not a strong and robust predictor for stocks' outperformance. Moreover, DU=1 is entirely insignificant.

Since UU and DD are dummy variables, the coefficient can be simply interpreted as the weekly outperformance/underperformance of the stocks with a specific shift pair against the other stocks. For example, in Model 6, the coefficient for UU is 16.38 which implies 16.38 basis points outperformance of stocks with UU=1 against the other stocks per week. Similarly, the coefficient for DD is 15.40 so the stocks with DD=1 underperform the other stocks for 15.40 basis points per week. The weekly number of 16.38 and 15.40 basis points can be translated into 8.52% and 8% per year (i.e. and). If we compare the performance of stocks with UU=1 and DD=1, then the performance gap is 16.52% per year. The rest of the models implies a similar economic scale.

Since only the shift pairs UU and DD (i.e. information supply and demand move in the same direction) strongly predicts stock returns, I focus on these two "pairs" and conduct portfolio analysis in the next section.

B. Portfolio Strategy

To demonstrate that the predictability is tradable, I conduct a portfolio analysis, and find that the economic scale of the portfolio strategy is striking. The portfolio analysis is summarized in Table 3. I form a long-short portfolio of buying the stocks with an upward shift in both information supply and demand and short selling the stocks with both information supply and demand down. The result shows that stocks with UU=1 outperform the stocks with DD=1 in various risk adjusted performance measures. The economic significance is stunning. The long-short portfolio generates abnormal returns of 17% per year. The sharp ratio is about 0.3, which is much higher than S&P500 Sharpe ratio of 0.035 in the same period. This implies that the portfolio delivers a higher return NOT at the cost of higher return volatility.

C. Supply and Demand Shift on Stock Returns in Various Subsamples

Barber, Brad, and Odean (2000) demonstrate that individual investors tilt their common stock investment toward high-beta, small, and value stocks. I expect the individual investors to heavily rely on news and Google search for information. Therefore, the effect I find should be more salient in the subsample of small stocks, high market-equity to book-equity ratio stocks, high beta stocks and the high return volatility stocks.

I test this conjecture by doing portfolio analysis within each subsample by size, market equity to book equity ratio, beta and return volatility. Table 4 reports the results. Panel A splits the sample into large size and small size subsamples. I directly obtain the size decile from Wermers' website and classify deciles 1 and 2 as the small size subsample and the rest as the large size sample. The result shows that the stocks with UU=1 outperform DD=1 in both the small and large size sample. However, the economic significance in the small size subsample (25% per year) is much larger than that in the large size subsample (only 7% per year). Panels B reports the results for book-equity to market equity deciles and beta deciles respectively, where the BE/ME decile is obtained from Wermer's website. I found high book to market ratio sample has much higher economic magnitude. Panel C reports the test in volatility deciles which are obtained from CRSP. The high volatility decile shows an annual impact of 34% while the low volatility decile has a performance impact of 19% per year. Panel D shows that the economic magnitude is slightly higher in the high beta subsamples.

D. Robustness Checks on News Sources

In the main test, I use the news article (i.e. media news) as the proxy for information supply. Another information supply is press releases, which is essentially originated from the company, and disseminated either by the company itself or with the help of the newswires. I conduct the robustness check about the news sources. The prior is that the sources of information supply should not affect the testing result. No matter what is the source of the information (disseminated by media or released by companies), the information is reflected into price through investors' interpretation which manifest itself in investors information demand. Therefore, the sources of the information should not affect the result. I use the press releases as an alternative proxy for information supply. Furthermore, since the press releases are news by company, the component of the media news that is not correlated to the press releases is more likely initiated by media per ser. Assuming this logic holds, I can separate out the component of media news that is less likely stimulated by the company. Specifically, for each firm, I run the following regression , and should be less likely to be correlated to the press releases. I denote it as the news articles net of press releases. Then I use both press releases and news articles net of press releases as the proxy for information demand to conduct the main test. I report the result in Table 5. The finding shows that both the information supplied by companies and the information by media net of companies affect the stock prices conditional on the information demand, i.e. the result is robust to the choice of the sources of information supply.

F. Robustness Check on Price Reversal and Momentum

Chan (2003) and Tetlock (2010) have shown that when stock prices exhibit price momentum in presence of news, and exhibit price reversal in absence of news. Chan (2003) explanation is that a large price movement in a news day is due to informational trading which tends to continue the trend in the next period, while a large price jump in the no news day is most likely to be liquidity driven, and the price reversal is most expected as the compensation to the liquidity provider. Tetlock (2010) employ a model about information asymmetry to formulate the hypothesis. The model predicts that news resolves the information asymmetry. The uninformed gain the same information as the informed, and thus trade in the same direction as the informed did in the previous period, creating the price momentum.

To eliminate the possibility that the finding about the information supply and demand is only a paraphrase of the price momentum as in Chan (2003) and Tetlock (2010), I run the following regression model:

If the price momentum fully explain the phenomenon, then the interaction term between the past return and the information shift indicator should capture the full effect, and the coefficients of the shift indicators should not be significant. I report the regression results in Table 6. The result shows that both UU and DD are highly significant, and the magnitude of the coefficients are almost intact. Even better, the significance of UD in Table 2 disappears entirely. The result implies that information supply and demand have impact only when supply and demand move in the same direction after stripping off the effect of price reversal and momentum. The finding indicates that the joint impact of the information supply and demand has its own life beyond being a rephrase of the price reversal and momentum.

V. Explaining the Phenomenon

In this section, I discuss the possible causes of the documented phenomenon: the increase in new investors' awareness (i.e. the breadth of investors' participation), the increase in existing investors' learning effort (i.e. the in-depth of investors' participation), and news content driven. Awareness and learning can push stock prices up even when the odd to have good and bad news of equal importance is 50% to 50%, while news content driven channel works if the odds to have good news are higher.

A. The Increase in Investors' Awareness

An individual has limited cognitive resources and is unlikely to be able to consider every stock in the stock market. Barber and Odean (2008) argue that investors only include the first few stocks that catch their attention for their consideration. An upward shift in both information supply and demand implies that more investors have noticed the existence of the stock as a potential investment opportunity. Furthermore, the investors that are attracted by news tend to buy rather than sell the stocks that grab their attention. The asymmetric behavior will drive the price up even when the information content is neutral (i.e., neither good nor bad on average).

If this channel is true, individual investors would intensively buy stocks with good news, but less intensively sell stocks with bad news when both information supply and demand rise. The buy-sell asymmetry would cause the outperformance if investors exhibited such behavior to a less extent in the other shift "pairs". I use the news tone as the proxy for good news and bad news. RavenPack compiles the news archive and calculate the average news tone for each firm day. I take the average over the daily tone to form the weekly news tone and add the maximum sentiment score to make all the score positive. Then I define if the sentiment score score is above its eight weeks moving average and 0 otherwise. Moreover, . Then I run the following Fama Macbeth regression with Newey-West for 8 lags.

Table 7 reports the regression results. When UU=1, the market strongly react to good news, but is insensitive to bad news, which confirms that individual investors exhibit significant asymmetric buy-sell behavior when both information supply and demand rise. On the other hands, when DD=1, the individual investors' attention decrease too much which put a downward pressure to the stock price. Even the good news cannot compensate the drop in the stock price due to downward shift in both information supply and demand. Furthermore, the decline in both information supply and demand accelerates the drop in stock price due to bad news. When UD=1, the stock price exhibits a similar behavior to UU=1 but at a much smaller economic magnitude. Therefore, the finding that UU=1 corresponds to the strongest asymmetric buy-sell behavior still holds.

B. The Increase in Existing Investors' Learning

When the information supply is abundant and less costly to search and access, existing investors learn more about the stock and thus investors' posterior variance of the payoff is lower, which makes the asset more attractive to investors. Therefore, the demand for the stock increases and stock price rises. Veldkamp (2006) shows empirically that price goes up when the number of news goes up at the country level.

However, it is difficult to verify the channel of existing investors' learning at stock level because it is hard to differentiate whether the increase in search volume (information demand) comes from the new investors who are not aware of the stock or from the existing investors. I use the web traffic to the company page on Wikipedia to address the issue partially. The Wikipedia page for a firm usually appears in the first page of the search result when I search the company name on Google. Differently from new investors who do not have the stock in mind and even lack the basic information about the firm, existing investors already possess some basic knowledge about the firm. Therefore, I assume that the existing investors are less likely to click the link to the Wikipedia page from the result page of a Google search than new investors who are just aware of the stock and resort to Wikipedia link for some mere basic information about the company. If this assumption holds, then the Wikipedia traffic is a proxy for the learning of new investors and the Google search volume net of Wikipedia traffic captures more about the learning of the existing investors.

I managed to obtain the Wikipedia web traffic data from 2008 to 2012 for companies which have Wikipedia page and are listed in NYSE and Nasdaq. For each firm, I run the time series regression , and define Google search volume net of Wikipedia traffic as . Then I use Google search volume net of Wikipedia traffic and Wikipedia traffic as the proxies for information demand of investors who have already known some basic information about the stock and those who have not even possess such basic knowledge respectively. Table 8 reports the results for both Wikipedia traffic and Google search volume net of Wikipedia traffic. The results show that both measures exhibit similar pattern to the main test, which implies that both the learning of new investors and the learning of the existing investors play a partial role in driving the main result.

C. News Content Driven

Loewenstein and Seppi (2005) document that investors monitor their portfolios more frequently in rising markets than when markets are flat or falling. If this ostrich effect applies to individual stocks, the upward shift "pair" implies that investors embracing good news for the stock and therefore learn more, and the good fundamentals push up the prices. However, an abnormal return driven by fundamentals should not reverse over time but be a persistent component in the stock prices. I study the relationship between the shift and the accumulated abnormal return over various time horizons, and observe that the price gain/loss due to the shift in information supply and demand are short lived. Specifically, I follow Jegadeesh and Titman (1993) to form an overlapping portfolio over different time horizons. Taking a 8 weeks overlapping portfolio as an example, in each week, I rebalance 1/8 of the portfolio to buy stocks with an upward shift in both information supply and demand and short sell the stocks with both down, while keeping the rest of 7/8 portfolio intact. Table 9 reports the results up to 8 weeks overlapping portfolios in various risk adjusted returns. The result indicates that the portfolio has no persistent abnormal return component. For instance, the weekly abnormal return of the non-overlapping portfolio is about 33 basis points per week, while the weekly abnormal returns for the 2 weeks overlapping portfolio decreases to about 17 basis points. The abnormal return of the 5 weeks overlapping portfolio is insignificant at all. The result shows that good fundamentals are not likely to contribute to the documented phenomenon.

VII. Conclusion

The key message of the paper is that it is important to incorporate both information supply and demand to study the impact of information on stock prices. Information affects stock prices in two aspects. For one thing, the information contents (e.g. good news and bad news) affect stock prices. For another, the cognitive impact of the information on investors (e.g. investors' awareness and learning) can also affect stock prices even when the news is neutral (i.e. the odds to have good versus bad news of equal importance are 50% to 50%). The focus of the paper is the latter aspect. Both channels involve an occurrence of news and the simultaneous actions of investors to digest the news, making both information supply and demand jointly important.

I propose to use the joint shifts in information supply and demand to isolate the channel through which the information affects stock prices. Employing an identification strategy of using information supply and demand shifts "pairs", I am able to determine whether an information supply shift (or an information demand shift) goes through the right channel which can affect stock returns. Specifically, for the cognitive channels, an information demand shift helps to determine whether an information supply shift indeed succeeds in increasing investors' awareness and information learning effort and, therefore, predict positive future returns.

Empirically, I show that information has the strongest impact on the stock prices when the information supply and demand move in the same direction. This implies that the information supply affects stock return only if there is a demand for information. The result is robust after controlling for price reversal, price momentum, trading volume, institutional ownership, analyst coverage, and news coverage.

I demonstrate that the cross sectional difference in return is tradable. A weekly rebalanced portfolio to buy stocks with this shift "pair" and short sell the other stocks delivers an abnormal return of 17% per year with a Sharpe ratio of 0.3 (S&P500 sharp ratio is 0.035 in the same period). The abnormal return increases to 25% and 34% per year in the small stocks and high volatility stocks respectively.

There are three explanations for the documented observation. The first explanation is that the rise in information supply increases the awareness of the stock. The increase in information demand confirms that individual investors who do not have this stock in their mind start considering investing in the stock. The stock price is pushed up because these investors tend to buy rather than sell the attention grabbing stocks. Consistent with the explanation, I observe that investors intensively buy stocks with good news but less intensively sell stocks with bad news when both information supply and demand rise. The second explanation is that an increase in the information supply induces the existing investors (i.e. investors with this particular stock in their mind) to learn more and thus reduces their posterior variance of the asset payoff conditional on the abundant information. Therefore, lower risk makes the asset more attractive to investors, increases demand and raises the price. The result shows that the upward shift with Google search volume net of the Wikipedia traffic as information demand proxy also predict stock returns, which implies that the learning of existing investors (who already possess some basic knowledge of the firm and less likely to visit Wikipedia) play a role in the predictability. The third explanation is that upward shift implies higher likelihood of good news because of ostrich effect (investors monitor their portfolio more closely when the market is good). However, I assume that the rise in price due to fundamentals do not reverse over time and show that the price run up is short lived. Therefore, the good fundamental cannot explain the phenomenon.

The result shows that the attempt to disentangle the information supply and demand in the financial market is not only theoretically appealing but also practically meaningful.

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Table 1: Summary Statistics

Panel A reports the summary statistics of news and search volume. #News Article is the number of news articles for a firm in the month. Search volume is the search volume value from Google Trends. The search volume is constructed by normalizing the search by the total search in a region. Then it is also scaled by the maximum value of the entire time series of the keyword. #News/8W #News MA is the ratio of the #News and its 8 weeks moving average. Search/8W Search MA is the ratio of Search Volume and its 8 weeks moving average. Panel B summarizes the statistics by supply and demand shift deciles which are defined as a combination of a supply shift and a demand shift, where UU=1 if "News Up" (i.e. Supply Up) and "Search Up" (i.e. Demand Up), UD= 1 if "News Up" and "Search Down", DU=1 if "News Down" and "Search Up", DD=1 if "News Down" and "Search Down", ME is the market equity value in Millions, #Analyst is the number of analysts who cover the stock, #News Article and Search Volume are the number of news articles and Google search volume. The sample period is from 2005 to 2012.

Panel A: Summary Statistics for News and Search Volume

	Observation	Mean	Median	STD	P1	P25	P75	P99
# News Article	352682	15.2	3	66.83	1	1	8	225
Search Volume	515331	40.3	40	22.13	0	24	56	90
#News Article/8W #News Article MA	546359	0.9	0.91	0.514	0	0.61	1.17	1.87
Search/8W Search MA	501917	1	1	0.177	0.4	0.96	1.03	1.36

Panel B: Summary Statistics by Supply and Demand Shift Deciles

	ME	# Analyst	#News Article	Search Volume
UU	7118	8.28	18.26	42.56
UD	4368	7.27	10.86	31.45
DU	2503	5.98	3.54	43.35
DD	3236	6.73	4.00	30.70

Table 2: Information Supply and Demand on Stock Return

The table reports the relationship between the abnormal return and the lagged shift in both supply and demand for information. The regression model is Fama Macbeth regression with Newey-West for 8 lags: , where is measured by DGTW adjusted returns in basis points, UU=1 if “News Up, Search Up”, UD=1 if “News Up, Search Down”, DU=1 if “News Down, Search Up”, DD=1 if “News Down, Search Down”. The control variables include past week return, past returns between week t-52 and t-2, average daily trading volume between week t-52 and week t-1, institutional ownership of the previous quarter, log number of news articles in the past year, and log number of analyst in the past month. The sample period is between 2005 and 2012.

Impact of Information Supply and Demand on Stock Returns						
	DGTW Returns					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
UU, t-1	15.5840***	16.4192***	16.3848***	16.5811***	16.4552***	16.3831***
	(4.14)	(4.36)	(4.39)	(4.48)	(4.40)	(4.38)
UD, t-1	9.3213**	9.0517**	8.8588**	8.9674**	8.3561**	8.4640**
	(2.44)	(2.32)	(2.29)	(2.33)	(2.14)	(2.17)
DU, t-1	1.6398	0.9937	0.5386	0.9145	-0.1874	-0.3668
	(0.42)	(0.25)	(0.14)	(0.24)	(-0.05)	(-0.09)
DD, t-1	-14.9261***	-15.1407***	-14.4423***	-14.2764***	-15.3376***	-15.4024***
	(-4.58)	(-4.58)	(-4.44)	(-4.37)	(-4.58)	(-4.51)
Ret, t-1		-0.0266***	-0.0270***	-0.0268***	-0.0267***	-0.0267***
		(-7.34)	(-7.30)	(-7.22)	(-7.22)	(-7.26)
Ret, t-52 to t-2		-0.0007	-0.0006	-0.0006	-0.0006	-0.0007
		(-0.58)	(-0.47)	(-0.47)	(-0.49)	(-0.52)
Volume, t-52 to t-1			-406.7434	-454.8469	-404.4357	-387.779
			(-1.40)	(-1.53)	(-1.34)	(-1.27)
IO, t-1Q				3.2462	3.1389	5.4259
				(0.81)	(0.77)	(1.03)
Log(1+News)					-0.0045***	-0.0040***
					(-3.81)	(-3.13)
Log(1+Analyst)						-1.0254
						(-0.70)
Constant	5.4245***	0.5296	3.8792	2.1159	3.3659	3.68
	(4.99)	(0.16)	(0.87)	(0.50)	(0.81)	(0.90)
Observations	485,708	485,642	485,642	485,642	485,642	485,642
R-squared	0.001	0.02	0.029	0.03	0.031	0.031

Table 3: Portfolio Analysis on Supply and Demand for Information

Table 3 reports the abnormal return of a portfolio to go long the stocks with the increase in both information supply and demand (i.e. UU=1) and go short the stocks with the decrease in both information supply and demand (i.e. DD=1). The long and short portfolio is an equal weight portfolio and weekly rebalanced based on the information supply and demand in the previous week. The table reports the weekly abnormal returns in basis points. For example, the weekly average raw return of 33.72 basis points is translated into 17.53% annualized raw return (i.e. . The sample period is from 2005 to 2012.

Portfolio Performance of Buying UU and Shorting DD				
	Raw	MKT	3 Factor	4 Factor
Return/Alpha	33.7189***	33.6840***	34.0318***	34.0329***
	(6.17)	(6.12)	(6.20)	(6.19)

Table 4: Portfolio Analysis for Subsamples by Size, BE/ME, Beta and Volatility

Table 4 reports the abnormal return of a portfolio to go long the stocks with the increase in both information supply and demand (i.e. UU=1) and go short the stocks with DD=1. The protfolio analysis is conducted in various subsamples. The long and short portfolio is an equal weight portfolio and weekly rebalanced based on the information supply and demand in the previous week. Panel A reports the result by size deciles. Panel B presents the findings for book equity to market equity deciles. Panel C shows the relationship by beta deciles. Panel D reports the result for volatility deciles. The sample period is from 2005 to 2012.

Panel A: Size Subsample							
SmaDD Size				Large Size			
Raw	MKT	3 Factors	4 Factors	Raw	MKT	3 Factors	4 Factors
49.2195***	49.1864***	49.2523***	49.2761***	13.6737**	14.0261**	14.4754**	14.4588**
(6.32)	(6.28)	(6.29)	(6.30)	(2.20)	(2.24)	(2.32)	(2.32)
Panel B: Book to Market Subsample							
Low Book to Market				High Book to Market			
Raw	MKT	3 Factors	4 Factors	Raw	MKT	3 Factors	4 Factors
19.8783***	19.9879***	20.3570***	20.3514***	46.5083***	46.4842***	46.8097***	46.8202***
(2.61)	(2.61)	(2.65)	(2.65)	(6.21)	(6.18)	(6.21)	(6.21)
Panel C: Volatility Subsample							
Low Volatility				High Volatility			
Raw	MKT	3 Factors	4 Factors	Raw	MKT	3 Factors	4 Factors
38.4581**	37.7955**	38.5144**	38.5435**	66.7913***	66.4244***	66.4554***	66.4525***
(2.12)	(2.07)	(2.10)	(2.10)	(3.79)	(3.74)	(3.73)	(3.73)
Panel D: Beta Subsample							
Low Beta				High Beta			
Raw	MKT	3 Factors	4 Factors	Raw	MKT	3 Factors	4 Factors
37.3510**	36.0790**	37.3964**	37.3592**	46.0261***	46.0255***	45.9866***	45.7004***
(2.30)	(2.22)	(2.31)	(2.30)	(4.20)	(4.17)	(4.15)	(4.11)

Table 5: Press Releases as the Measure of Information Supply

The table reports the relationship between the abnormal return and the lagged shift in both supply and demand for information, where the press releases and the news articles net of press releases are used as the proxy for information supply. The news articles net of the press release are the residual of the time series regression of news articles on press releases for each company. The regression model is Fama Macbeth regression with Newey-West for 8 lags: , where is measured by DGTW adjusted returns in basis points, UU=1 if "Press Releases (or News Articles net of Press Releases) Up, Search Up", UD=1 if "Press Releases (or News Articles net of Press Releases) Up, Search Down", DU=1 if "Press Releases (or News Articles net of Press Releases) Down, Search Up", DD=1 if "Press Releases (or News Articles net of Press Releases) Down, Search Down". The control variables include past week return, past returns between week t-52 and t-2, average daily trading volume between week t-52 and week t-1, institutional ownership of the previous quarter, log number of news articles in the past year, and log number of analyst in the past month. The sample period is between 2005 and 2012.

Impact of Information Supply and Demand on Stock Returns						
	DGTW Returns					
	Press Releases			News Article Net of Press Releases		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
UU, t-1	20.0027***	20.3964***	19.7741***	15.0589***	16.6812***	16.5431***
	(5.31)	(5.29)	(5.17)	(3.76)	(4.21)	(4.23)
UD, t-1	7.3780*	7.8758**	7.4046**	6.7034*	7.7048**	7.2981*
	(1.94)	(2.12)	(1.98)	(1.78)	(2.01)	(1.89)
DU, t-1	-1.2433	-2.0744	-3.3338	-0.838	-0.4641	-1.0683
	(-0.41)	(-0.65)	(-1.05)	(-0.24)	(-0.13)	(-0.30)
DD, t-1	-14.0348***	-13.8957***	-15.1275***	-10.0916***	-9.4463***	-9.7125***
	(-3.56)	(-3.49)	(-3.68)	(-3.37)	(-3.15)	(-3.25)
Ret, t-1		-0.0268***	-0.0268***		-0.0273***	-0.0273***
		(-7.24)	(-7.29)		(-7.09)	(-7.12)
Ret, t-52 to t-2		-0.0006	-0.0006		-0.0007	-0.0007
		(-0.46)	(-0.50)		(-0.52)	(-0.56)
Volume, t-52 to t-1		-490.8785*	-428.521		-509.3553*	-459.639
		(-1.67)	(-1.42)		(-1.68)	(-1.48)
IO, t-1Q		3.1556	5.0235		3.5769	4.3986
		(0.77)	(0.94)		(0.89)	(0.80)
Log(1+News)			-0.0040***			-0.0035***
			(-3.12)			(-2.67)
Log(1+Analyst)			-0.8817			-0.3189
			(-0.63)			(-0.21)
Constant	5.2158***	2.2623	3.8107	5.2775***	1.7642	2.9068
	(4.81)	(0.53)	(0.92)	(4.60)	(0.40)	(0.67)
Observations	485,704	485,639	485,639	437,620	437,557	437,557
R-squared	0.001	0.03	0.03	0.001	0.031	0.031

Table 6: Lagged Returns and Information Supply/Demand on Stock Returns

The table reports the relationship between the abnormal return and the lagged shift in both supply and demand for information conditional on the past returns. The regression model is Fama Macbeth regression with Newey-West for 8 lags: , where is measured by DGTW adjusted returns in basis points, UU=1 if "News Up, Search Up", UD=1 if "News Up, Search Down", DU=1 if "News Down, Search Up", DD=1 if "News Down, Search Down", and is the past week return. The control variables include past week return, past returns between week t-52 and t-2, average daily trading volume between week t-52 and week t-1, institutional ownership of the previous quarter, log number of news articles in the past year, and log number of analyst in the past month. The sample period is between 2005 and 2012.

Past Returns and Impact of Information Supply and Demand					
	Model 1	Model 2	Model 3	Model 4	Model 5
UU, t-1	16.1124***	16.0479***	16.1344***	15.9859***	15.9115***
	(3.65)	(3.66)	(3.70)	(3.62)	(3.60)
UD, t-1	6.701	6.642	6.8679	6.2335	6.353
	(1.44)	(1.44)	(1.49)	(1.34)	(1.37)
DU, t-1	2.8254	2.2283	2.6516	1.5254	1.2862
	(0.61)	(0.47)	(0.57)	(0.33)	(0.27)
DD, t-1	-13.7074***	-13.3138***	-13.1037***	-14.1942***	-14.3662***
	(-3.71)	(-3.65)	(-3.54)	(-3.75)	(-3.71)
UU*Ret, t-1	0.0359***	0.0355***	0.0355***	0.0358***	0.0358***
	(5.19)	(5.04)	(5.05)	(5.08)	(5.07)
UD*Ret, t-1	0.00	0.00	0.00	0.00	0.00
	(0.08)	(0.11)	(0.13)	(0.13)	(0.13)
DU*Ret, t-1	-0.0256**	-0.0256**	-0.0255**	-0.0256**	-0.0258**
	(-2.37)	(-2.39)	(-2.37)	(-2.37)	(-2.40)
DD*Ret, t-1	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	(-1.38)	(-1.41)	(-1.42)	(-1.40)	(-1.40)
Ret, t-1	-0.0279***	-0.0284***	-0.0282***	-0.0282***	-0.0282***
	(-7.33)	(-7.39)	(-7.31)	(-7.33)	(-7.38)
Ret, t-52 to t-2	-0.0008	-0.0006	-0.0006	-0.0006	-0.0007
	(-0.60)	(-0.49)	(-0.49)	(-0.51)	(-0.54)
Volume, t-52 to t-1		-397.073	-444.848	-394.381	-379.534
		(-1.35)	(-1.48)	(-1.30)	(-1.23)
IO, t-1Q			3.2062	3.0957	5.3791
			(0.80)	(0.77)	(1.02)
Log(1+News)				-0.0045***	-0.0041***
				(-3.80)	(-3.12)
Log(1+Analyst)					-1.006
					(-0.68)
Constant	0.3887	3.7164	1.9635	3.2321	3.5346
	(0.11)	(0.81)	(0.45)	(0.77)	(0.84)
Observations	485,642	485,642	485,642	485,642	485,642
R-squared	0.023	0.032	0.034	0.034	0.034

Table 7: Good/Bad News and Information Supply/Demand on Stock Returns

The table reports the relationship between the abnormal return and the lagged shift in both supply and demand for information conditional on whether the news is good or bad on average. The regression model is Fama Macbeth regression with Newey-West for 8 lags: , where is measured by DGTW adjusted returns in basis points, UU=1 if “News Up, Search Up”, UD=1 if “News Up, Search Down”, DU=1 if “News Down, Search Up”, DD=1 if “News Down, Search Down”, is 1 if the news tone is above its 8 weeks moving average, and . The control variables include past week return, past returns between week t-52 and t-2, average daily trading volume between week t-52 and week t-1, institutional ownership of the previous quarter, log number of news articles in the past year, and log number of analyst in the past month. The sample period is between 2005 and 2012.

Good/Bad News and Impact of Information Supply and Demand						
	DGTW Returns					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
UU*Good News, t-1	34.4475***	35.7081***	35.7374***	36.1506***	35.9957***	35.8888***
	(6.53)	(6.75)	(6.71)	(6.74)	(6.66)	(6.65)
UD*Good News, t-1	20.3150***	21.2059***	20.6497***	20.8283***	20.1725***	20.4562***
	(3.87)	(3.89)	(3.86)	(3.86)	(3.71)	(3.75)
DU*Good News, t-1	2.1554	1.2744	1.0271	1.3541	0.2494	-0.1862
	(0.44)	(0.26)	(0.21)	(0.28)	(0.05)	(-0.04)
DD*Good News, t-1	-7.3989	-7.9874*	-7.3559	-7.6363*	-8.6690*	-8.6612*
	(-1.63)	(-1.78)	(-1.62)	(-1.69)	(-1.89)	(-1.88)
UU*Bad News, t-1	(5.83)	(5.94)	(6.13)	(6.23)	(6.42)	(6.53)
	(-1.07)	(-1.08)	(-1.13)	(-1.15)	(-1.19)	(-1.21)
UD*Bad News, t-1	(0.74)	(2.37)	(1.99)	(2.20)	(2.78)	(2.90)
	(-0.13)	(-0.40)	(-0.34)	(-0.38)	(-0.48)	(-0.50)
DU*Bad News, t-1	(0.80)	(0.73)	(0.86)	(0.79)	(1.77)	(1.86)
	(-0.17)	(-0.16)	(-0.19)	(-0.18)	(-0.39)	(-0.40)
DD*Bad News, t-1	-24.6674***	-24.8099***	-24.2446***	-24.3279***	-25.2815***	-25.5102***
	(-5.06)	(-5.00)	(-5.08)	(-5.04)	(-5.21)	(-5.20)
Ret, t-1		-0.0267***	-0.0270***	-0.0269***	-0.0268***	-0.0268***
		(-7.06)	(-7.08)	(-6.98)	(-6.98)	(-7.04)
Ret, t-52 to t-2		-0.0011	-0.001	-0.0009	-0.001	-0.001
		(-0.86)	(-0.74)	(-0.72)	(-0.73)	(-0.77)
Volume, t-52 to t-1			-366.692	-310.466	-264.479	-221.521
			(-1.25)	(-1.02)	(-0.86)	(-0.70)
IO, t-1Q				-5.406	-5.2696	-0.954
				(-1.09)	(-1.05)	(-0.16)
Log(1+News)					-0.0044***	-0.0035***
					(-4.05)	(-2.75)
Log(1+Analyst)						-2.187
						(-1.40)
Constant	6.1554***	1.1891	3.9484	6.9017	8.0150*	8.6719**
	(5.79)	(0.34)	(0.85)	(1.59)	(1.89)	(2.08)
Observations	445,810	445,745	445,745	445,745	445,745	445,745
R-squared	0.003	0.022	0.031	0.033	0.033	0.033

Table 8: Wikipedia Traffic as the Measure of Information Demand

The table reports the relationship between the abnormal return and the lagged shift in both supply and demand for information, where the Wikipedia traffic and the Google search volume net of Wikipedia traffic are used as the proxy for information demand respectively. Wikipedia traffic is the number of page views of the company page on Wikipedia. The Google search volume net of Wikipedia traffic is the residual of the time series regression of Google search volume on Wikipedia traffic for each company. The regression model is Fama Macbeth regression with Newey-West for 8 lags: , where is measured by DGTW adjusted returns in basis points, UU=1 if "News Up, Wiki (or Google net of Wiki) Up", UD=1 if "News Up, Wiki (or Google net of Wiki) Down", DU=1 if "News Down, Wiki (or Google net of Wiki) Up", DD=1 if "News Down, Wiki (or Google net of Wiki) Down". The control variables include past week return, past returns between week t-52 and t-2, average daily trading volume between week t-52 and week t-1, institutional ownership of the previous quarter, log number of news articles in the past year, and log number of analyst in the past month. The sample period is between 2005 and 2012.

Impact of Information Supply and Demand on Stock Returns

	DGTW Returns					
	Wikipedia Traffic			Google Search Net of Wikipedia Traffic		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
UU, t-1	20.7712***	22.9130***	22.3089***	12.5590**	14.9038***	15.0648***
	(3.70)	(4.05)	(3.96)	(2.38)	(2.78)	(2.83)
UD, t-1	2.9096	3.9039	3.6282	5.274	5.6131	5.0131
	(0.59)	(0.77)	(0.74)	(0.84)	(0.87)	(0.77)
DU, t-1	-2.0666	-0.3946	-2.1504	6.5766	8.3351	6.393
	(-0.39)	(-0.07)	(-0.40)	(1.20)	(1.38)	(1.02)
DD, t-1	-11.9659**	-11.0778**	-12.6171**	-13.2381***	-11.5589**	-13.4794***
	(-2.46)	(-2.25)	(-2.60)	(-3.07)	(-2.59)	(-3.01)
Ret, t-1		-0.0207***	-0.0207***		-0.0200***	-0.0199***
		(-3.06)	(-3.12)		(-2.96)	(-3.01)
Ret, t-52 to t-2		-0.0027	-0.0027		-0.0029	-0.003
		(-0.98)	(-1.01)		(-1.05)	(-1.08)
Volume, t-52 to t-1		-62.5173	32.1127		-73.2484	47.0283
		(-0.15)	(0.07)		(-0.17)	(0.11)
IO, t-1Q		9.4664	9.9377		6.0655	8.5878
		(1.19)	(1.30)		(0.78)	(1.09)
Log(1+News)			-0.0042***			-0.0040**
			(-2.74)			(-2.50)
Log(1+Analyst)			-1.5609			-2.8218
			(-0.59)			(-1.19)
Constant	4.2058**	-16.6375	-11.9082	4.1100**	-14.0377	-8.3721
	(2.30)	(-1.43)	(-1.01)	(2.18)	(-1.18)	(-0.70)
Observations	163,197	163,197	163,197	160,357	160,357	160,357
R-squared	0.002	0.04	0.042	0.002	0.04	0.042

Table 9: Impact of Information Supply and Demand over Various Time Horizons

Table 9 reports the abnormal return of a portfolio to go long the stocks with the increase in both information supply and demand (i.e. UU=1) and go short the stocks with DD=1 over various holding horizons. The long and short portfolio is an equal weight portfolio. I follow Jegadeesh and Titman (1993) to form overlapping portfolio over different time horizon. Taking 12 weeks overlapping portfolio as an example, in each week, I rebalance 1/12 of the portfolio based on the information supply and demand in the previous month and the rest of the 11/12 portfolio is intact. The sample period is from 2005 to 2012.

Impact of Information Supply and Demand over Various Horizons				
Overlapping Week	Raw	MKT	3 Factor	4 Factor
No Overlapping	33.7189***	33.6840***	34.0318***	34.0329***
	(6.17)	(6.12)	(6.20)	(6.19)
2 week	17.5975***	17.5648***	17.8697***	17.8726***
	(3.86)	(3.83)	(3.91)	(3.90)
3 week	11.2008***	10.9964***	11.3014***	11.3019***
	(2.67)	(2.60)	(2.69)	(2.68)
4 week	7.6222*	7.3949*	7.7393*	7.7372*
	(1.91)	(1.84)	(1.94)	(1.94)
5 week	5.4996	5.2451	5.5534	5.5434
	(1.43)	(1.36)	(1.45)	(1.45)
6 week	4.4588	4.2474	4.55	4.538
	(1.22)	(1.16)	(1.25)	(1.25)
7 week	3.5924	3.3806	3.6655	3.6531
	(1.05)	(0.98)	(1.07)	(1.07)
8 week	3.1923	2.967	3.2429	3.2324
	(0.97)	(0.90)	(0.99)	(0.99)
9 week	2.8891	2.6983	2.9866	2.9766
	(0.92)	(0.85)	(0.95)	(0.95)
10 week	2.6994	2.5055	2.819	2.8093
	(0.89)	(0.82)	(0.94)	(0.93)
11 week	2.1356	1.9545	2.2743	2.2643
	(0.72)	(0.65)	(0.77)	(0.77)
12 week	2.2348	2.0639	2.3772	2.3668
	(0.78)	(0.72)	(0.84)	(0.84)