Demand for Information and Stock Returns: Evidence from EDGAR

Pingle Wang*

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Abstract

This paper studies the information acquisition process by investors using a novel dataset that tracks filing downloads on the SEC's EDGAR. Demand for 10-K filings predicts short-term positive return spread, and demand for 8-K filings predicts long-term negative return spread. The striking difference in the effects of 10-K and 8-K attention on stock prices can be contributed to the different viewing patterns. Demand for 10-K filings represents a general demand for assets, where 10-K visitors are typically infrequent visitors who never download any filings of the firm in past quarters. The effects are higher for attention-grabbing stocks. In the meanwhile, the demand for 8-K filings comes from frequent and local viewers with a potential information advantage. Such attention reduces information asymmetry of the firm, which decreases the cost of capital and explains the persistent underperformance of high 8-K attention stocks.

*Simon Business School, University of Rochester, Rochester, NY 14627. Phone: (505) 273-1067. E-mail: pingle.wang@simon.rochester.edu.

1 Introduction

Information plays a central role in determining asset prices. There is a large and extensive literature on how the supply side of information affects prices. Recent papers have focused on the economic announcement (Savor and Wilson (2013), Lucca and Moench (2015)), corporate disclosures (Lawrence (2013),Hwang and Kim (2017)), and media coverage (Fang and Peress (2009)). However, how investors acquire and process the information and its effect on asset prices is less well understood.

Information demand affects asset prices in two completely different channels. On the one hand, the demand for information is driven by the demand for assets. Since investors have limited attention (Barber and Odean (2007)), the demand for information reflects their asset selection preference. As a result, the information demand can predict positive future returns. On the other hand, investors who frequently search for and study information of a firm reduce the proportion of private information and reduce information asymmetry (Grossman and Stiglitz (1980)) through a better grasp of the less public information. Therefore, it becomes less risky for an uninformed investor to hold the asset, the cost of capital reduces (Easley and O'Hara (2004)), prices increase contemporaneously, and the demand for information predicts lower future returns. Current literature points uniformly to the evidence of asset selection channel (see Da, Engelberg, and Gao (2011) and Ben-Rephael, Carlin, Da, and Israelsen (2017)). However, the empirical evidence on how demand for information reduce information asymmetry is still lacking. It is hard to empirically disentangle the two channels and quantify their effects, as it requires measures on heterogeneous information demand, which are lacked in the current literature.

In this paper, I study how information acquisition by investors on the EDGAR filing system affects stock prices using a large sample of the U.S. public firms from 2003 to 2016. The U.S. Securities and Exchange Commission (SEC) made the EDGAR server log files publicly available recently. Unlike Google/Bloomberg search index, the log data keep track of filing download by each visitor with a unique identifier, so that I can measure not only the level of overall demand for information but also the information content and individual viewing patterns. Among a large set of filing types in EDGAR, I focus on the three most important filings regarding firms' financial and operational conditions, the annual report 10-K, the quarterly report 10-Q, and material information disclosure 8-K[1]. The Form 10-K/Qs and 8-Ks differ in the information content and reporting frequencies. The Form 10-K/Qs provide investors comprehensive financial and operation statements periodically, which is useful for investors to make investment decisions. The Form 8-Ks are filed irregularly[2], and material information is disclosed either mandatorily or voluntarily. Therefore, the asset preference channel is more likely to dominate for 10-K/Q demand, and the reduction of information asymmetry channel is likely to dominate for 8-K demand.

I show that the aggregated demand for firm filings predicts higher future returns, which is consistent with the general findings in the literature (Barber and Odean (2007); Da et al. (2011); Ben-Rephael et al. (2017)). That is, the asset selection channel is the dominant force of the demand for information. By focusing on the heterogeneous information content, I find that the demand for 10-K filings predicts higher future returns, the demand for 8-K filings predicts lower future returns, and the demand for 10-Q filings does not predict future returns. Furthermore, I show that the demand for unscheduled 8-K filings predicts future returns, and the demand for scheduled 8-K filings does not have any predictability. The result is consistent with the reduction in information asymmetry, since unscheduled filings contain information that was previously private only to the management team. Demand for unscheduled filings transforms the previously private information into public information, decreases information asymmetry, and reduces the future cost of capital. The long/short portfolio sorted on 10-K views earns around 65 basis points equal-weighted alpha per month, and the portfolio sorted on 8-K views earns -50 basis points equal-weighted alpha[3].

[1]Previous studies on information disclosure also focuses extensively on 10-K/Q and 8-K filings. See Livnat and Zhang (2012) and Gibbons, Iliev, and Kalodimos (2019), for example.

[2]Items 2.02 of 8-K filings contain information on pre-scheduled events.

[3]Throughout the paper, I use Fama-French five factors and UMD factor as the testing model, unless specified otherwise.

Besides the difference in return directions the two channels can predict, they also imply drastically different return patterns in the long-term. For the asset selection channel, the predictability of information demand should be short-lived. In a perfectly efficient market, a demand shock will only impact prices contemporaneously. Under certain frictions, the demand shock will be incorporated into prices in a short period of time, resulting in an alpha decay pattern. The alpha of the 10-K portfolio is consistent with such pattern, starting from an average of 82 basis points (bps) in the formation month and decreasing to around 20 bps in the second holding month.

On the contrary, if demand for information reduces information asymmetry and firms' cost of capital, then contemporaneous price should go up to reflect the permanent decrease in risk adjusted returns in the future. Therefore, the portfolio that captures the spread in information demand will have a positive alpha in the formation period, followed by a persistent and negative alpha in the holding periods. The long/short portfolio sorted by 8-K attention exhibits such return pattern. At the formation month, the 8-K portfolio yields a positive alpha of 18 bps. The alpha of the 8-K portfolio then becomes and remains negative (around -60 bps) throughout the next 12 months.

The differential effects between 10-K and 8-K attention are due to the fact that, they represent two different underlying mechanisms. Therefore, there are substantial differences between 10-K and 8-K viewers. First, by tracking the viewing histories of each 10-K investors, I find that 80% of 10-K investors never visited any 8-K filings of the firm over the past three months. Second, the geographical distributions of 10-K and 8-K investors are different in the sense that, 8-K investors are more concentrated near the firm headquarters than 10-K investors. Third, infrequent visitors constitute a large proportion of 10-K investors, as over 90% 10-K visitors never downloaded any filings of the firm in the past three months. 8-K investors, on the contrary, have a much larger population of frequent visitors.

Next, I directly test the effect of information demand through information asymmetry reduction channel. In a monthly panel regression, I show that a standard deviation increase in the 8-K attention reduces the next month Amihud (2002) measure by 25 percentiles. The result is robust using Corwin and Schultz (2012) quote spread measure and Easley, Kiefer, and O'Hara (1997) probability of informed trading measure[4]. On the contrary, the demand for other filing types have no significant effects on information asymmetry proxies. Moreover, I show that the magnitude of alpha is greater when the level of ex-ante information asymmetry is high. Using the previous quarter analyst forecast dispersion as a proxy for ex-ante information asymmetry, I find that the 8-K portfolio earns -71 bps per month in alpha for firms with high forecast dispersion and only -13 bps for firms with low dispersion, with the difference being highly significant as well.

I also document the heterogeneous effect of 8-K demand on prices through the cost of information acquisition channel. Verrecchia (1982) extends Grossman and Stiglitz (1980) and provides comparative statics regarding the cost of information acquisition. In particular, ceteris paribus, the informativeness of price is nondecreasing as information acquisition costs are reduced. I use the firm-level share of local viewers and the share of frequent viewers to capture the variation in cost of information acquisition. Local viewers and frequent viewers tend to have information advantage in terms of collecting and processing information. Firms that have a higher level of local viewers and frequent viewers have the lower cost of information acquisition. My finding is supportive to Verrecchia (1982). The effect of information demand on prices is larger when more demand comes from local and frequent viewers who have relatively low cost of information acquisition.

Moreover, I show that the effect of 8-K attention is a function of the information content provided in the filings. The demand for 8-K filings only predicts stock returns through the information asymmetry channel, if the information disclosed was not previously known to the general public. I use the three-day abnormal return around filing/event date as a proxy for the importance of information content. If the abnormal return is large and positive (negative), it is likely that the firm disclosed private and good (bad) news that is

[4]I obtain quarterly PIN measure from Brown and Hillegeist (2007) and aggregate my attention variables into quarterly frequency. The result is available upon request.

not foreseen by the public. Using abnormal return around event date, I show that the effect of 8-K attention on stock returns exhibits a "v-shape" relative to the abnormal returns. That is, demand for 8-K information predicts stock returns better when the information disclosed is private, regardless of whether it is good or bad. When the information contained in the filing is anticipated by the market, investors do not have much to learn, leading to a poorer performance of 8-K portfolio.

Lastly, I test the demand for asset channel, where investors' demand for 10-K filings reflects their preference for the assets. Barber and Odean (2007) shows that investors consider purchasing stocks that are highly visible. Therefore, the demand for 10-K filings should capture the demand for assets better among high visible stocks than among low visible ones. I use the maximum daily return during the month and abnormal trading volume to proxy for stock visibility. I find that the long/short portfolio sorted by 10-K attention earns a monthly alpha of 87 basis points (bps hereafter) among high visible stocks and only 31 bps among low visible stocks. Moreover, the spread in alpha is concentrated among firms with a large population of new visitors who have not downloaded any filings of the firms in the past three months. These new visitors are more likely to be the ones who consider buying the assets. Note that, the results do not imply that the attention to 10-K filings does not reduce information asymmetry. It simply points out that, the asset selection channel is the dominant force here in determining asset returns, given the infrequent disclosure requirement and investors' visiting patterns. Besides the standard financial and operation statement, management forecast and risk evaluation are also included in the Form 10-K. Investors who pay attention to these sections could potentially learn important aspects of firms from the managers' perspective and reduce information asymmetry. In some later test, I show that the effect of 10-K attention flips to the information asymmetry reduction channel, conditional on the firms just file the Form 10-K. In this case, the spread in 10-K attention predicts an alpha of -57 bps. However, the alpha is noisily estimated, since only a small portion of firms file 10-K in a given month.

My paper contributes to the literature that analyzes cross-section stock returns and investor attention. Da et al. (2011) and Ben-Rephael et al. (2017) show that spikes in Google and Bloomberg search volumes can predict positive future stock returns. Different from their papers, my paper focuses on the heterogeneous information content acquired by investors and investors' patterns of information acquisition. Demand for information not only predicts positive and short-term cross-section stock returns through the asset demanding channel but also predicts negative and long-term returns through the reduction in information asymmetry channel.

The paper also fits into the literature that studies information asymmetry. Easley and O'Hara (2004) builds a theoretical model and shows information asymmetry increases the cost of capital. Brown, Hillegeist, and Lo (2004) and Brown and Hillegeist (2007) show empirically that firm disclosures reduce information asymmetry. In this paper, I show that the demand for information also reduces information asymmetry, which affects the cross-section stock returns.

A few recent papers also use the EDGAR log data. Lee, Ma, and Wang (2015) identifies peer firms through a "co-search" algorithm. Loughran and McDonald (2017) shows that investor attention to firm filings is a scarce resource. Bauguess, Cooney, and Hanley (2018) uses EDGAR log data and studies IPO pricing. They focus on Form S-1 (IPO's initial registration statement) and show that investor attention can predict IPO success and initial stock returns. Chen, Cohen, Gurun, Lou, and Malloy (2018) studies how mutual fund managers acquire information on firms and insiders. Gibbons et al. (2019) shows that analysts rely on EDGAR filings to make forecasts.

The paper proceeds as follows. Section 2 discusses the sample selection and provides an overview of EDGAR log data. Section 3 provides my main results on heterogeneous effects of information demand on stock prices. Section 4 discusses the mechanisms of 8-K demand on prices. Section 5 shows the differential effects of 8-K through the cost of information acquisition and information content channels. Section 6 shows that demand for

10-K captures investors' preference for assets. Section 7 provides a set of robustness checks. Section 8 concludes.

2 Data and Sample Selection

I combine data from several sources to execute the paper. I use CRSP, Compustat, and I/B/E/S to obtain stock related information, the Thompson Reuters to obtain institutional ownership data, the EDGAR server log to obtain daily log of page requests for SEC filings[5], and the EDGAR Master File to obtain filing type and date. To control for media coverage, I use Google Trends data and Ravenpack news data. Google Trends data provide within-firm monthly Google search volume index, which ranges from 0 to 100. Ravenpack news data provide news coverage for a large sample of public companies[6].

The sample starts in 2003 and ends in 2016. I use all domestic equity stocks with share code 10 or 11. I require stocks with a valid market value at month-end in the CRSP, valid financial statement data in Compustat, and valid earning announcement data in I/B/E/S. I also require that stocks in the CRSP have matched identifiers in the SEC EDGAR. The matched sample has 5,989 unique stocks. After merging with Ravenpack and Google Trends data, the sample reduces to 4,106 unique stocks, where most of the sample loss occurs for microcap stocks. For the main analysis, I will use the larger sample. All my results are robust when using the smaller sample.

2.1 The EDGAR Server Log

The SEC EDGAR server log is publicly available and can be obtained from its website. The data contain daily log files from 2003 forward. The log file contains the timestamps of page requests, the firm identifier, the filing accession number, the IP address of the request[7],

[5]I use the link file provided by WRDS to link stock identifiers "permno" in CRSP and "cik" in SEC.

[6]I match Ravenpack data with the CRSP data using 8-digit CUSIP, ticker symbol, and company names.

[7]Only the first three octets of the IP address are available, and the last octet is replaced with random characters, so that the IP address is uniquely identifiable.

the index page flag[8], server status code[9], the crawler flag, and so on. Log files between September 24, 2005, and May 10, 2006, were labeled by the SEC as "lost or damaged", and are excluded from the empirical analysis. Some users use automated programs to crawl and download SEC filings, and the EDGAR log files flag not all crawling activities. Following Lee et al. (2015), I label an IP address as a crawler if it is associated with more than 50 daily requests.

The sample starts with over 21.89 billion records. I first reduce the sample by excluding requests with the index page flag or server status code above 300, which leaves me with 9.84 billion records. I then link the Central Key Index (CIK) provided by EDGAR with the stock identifier in CRSP. After the merge, the sample reduces to 3.36 billion records. I further reduce the sample by focusing on filings of the following three types, Forms 10-K, 10-Q, and 8-K, which leaves me with 1.36 billion records. Forms 10-K and 10-Q contain comprehensive reports of the firm performance for the recent fiscal year and quarter, respectively. Form 8-K is a report of unscheduled material events that are important to the shareholders and the SEC. These set of forms represent the most relevant information of a firm's operation and performance and are important to investors and financial analysts. I then get the physical locations of IP addresses in the record. Finally, I have a sample of log requests with 1.36 billion records.

For each filing request, I classify it along three dimensions, the filing type (Forms 10-Q, 10-K, and 8-K), the geographical distance between the requested IP and firm headquarters, and whether the IP is a frequent visitor of the firm.

Classifying filing requests by filing types has several advantages. First, different filing types represent different information flows. Forms 10-K/Q are filed periodically, containing financial and operational statements of the firm over the past year/quarter. Thus, they provide investors with a comprehensive overview of the firm. Forms 8-K are filed whenever

[8] There is an index page containing all documents for a filing. The index page flag indicates that the user simply visits the index page without downloading any documents.

[9] The server status code indicates whether the request is successful, which is typically below 300.

firms are required to disclose material information, or managers judge it necessary to disclose voluntarily[10]. Therefore, 8-K filings contain the most up-to-date information.

Furthermore, if the distance between the locations of the IP address and the firm headquarter is less (greater) than 400 miles, I classify the request as a home (away) request. I then aggregate the file requests at the firm and the month level.

2.2 Overview of EDGAR Downloads

Figure 1 shows the monthly aggregated file downloads in my final sample. I separate crawling activities ("robots") from human viewing activities ("human"). Figure 1a shows the plot for all filing types. There has been an increasing trend for viewing activities on EDGAR. The number of human downloads starts at 0.25 million in 2003 and ends at 1.5 million in 2016. The number of crawling requests is about 15 times greater than the number of human downloads. Figures 1b to 1d show the monthly aggregated plot by file types. The strong seasonality in 10-K and 10-Q downloads are driven by the filing cycles. 10-K downloads consist around half of all downloads, with the remaining half split by 8-K and 10-Q downloads.

2.3 Difference in 10-K and 8-K Views

The EDGAR log data keep track of each IP visit so that I can distinguish viewing patterns of 10-K and 8-K visitors. Figure 4 shows that the majority of 10-K visitors never downloaded any 8-K filings of the firm in the past quarter. Moreover, 10-K visitors are different from 8-K visitors in terms of geographical distance to headquarters and the visiting frequency.

Figure 5 shows the number of filing downloads by geographical distance groups. I classify a filing view into the home group if the distance between the location of the IP address and the firm headquarter is less than 400 miles. Otherwise, I classify it into the away group. The cut-off of 400 miles is about the diameter of an average state in the U.S. I denote the number of home (away) filing views as $views_k^{home}$ ($views_k^{away}$). The result suggests that a

[10] Voluntary disclosures are often categorized by the SEC into Item 8.01 and Item 7.01.

large proportion of downloads are made by users geographically close to the firm headquarter, especially for 8-K filings. 10-K filings, on the other hand, face a wider range of audience, as the gap between away $views_{10K}^{away}$ and $views_{10K}^{home}$ widens.

Figure 6 plots the time-series averages of frequent visitor ratios by 10-K and 8-K visitors. I classify a filing download as frequent if the IP address has downloaded one or more filings of the firm in the past three months. Frequent visitors constitute around 15% of 10-K visitors, and around 35% of 8-K visitors.

2.4 Determinants of 8-K Attention

This section studies the determinants of 8-K demand. For each unscheduled 8-K filings, I collect the total views from the posted date to the 30th day after the post. The total views provide us a sense of the level of information demand. To proxy for the speed of information diffusion, I count the number of days it requires for the cumulative views to reach 50% of the total views. The shorter the number of days it is, the faster the information diffuses. The intuition for the measure is similar to the half-life used in the fields of physics and biology.

Table 1 shows the determinants of unscheduled 8-K views. The dependent variable is the natural logarithm of the 30-day total views of each filing. In the baseline specification, I control for the firm's characteristics, such as size, book-to-market, asset growth, profitability, past stock returns and the number of analysts covering the firm. For each firm, I also calculate the past 12-month local visitor ratio and frequent visitor ratio.

As shown in column 1 of Table 1, large and value firms tend to have a higher level of information demand. The coefficient of local visitor ratio is negative and highly significant, suggesting that firms with a higher proportion of local viewers receive less overall attention. As local investors are more efficient in collecting and processing the information than non-local investors, and the market endogenizes such information choice, the overall demand for information will be lower for firms with high composition of local viewers.

In column 2, I control for the absolute magnitude of 3-day cumulative abnormal return

(CAR) around the event date of the filing. The abnormal return is measured as the market excess return. The absolute value of CAR shows how unexpected the event is. Events that are unexpected by the market draw more attention from investors, as the coefficient of $\mid CAR \mid$ is positive and significant. In column 3, I add a positive news dummy, which is equal to one if CAR is positive, and zero otherwise. I also interact the positive news dummy with the absolute value of CAR. The result suggests that there is asymmetry in responses to negative versus positive information (Soroka (2006)).

Table 2 studies the speed of information diffusion. The dependent variable is the half-life $t_{\frac{1}{2}}$, the number of days it needs for views to reach 50% of total views. Contrary to the level of information demand, the more local viewers there are to pay attention to the firm, the faster the information diffuses, as the coefficient on local viewer ratio is negative and significant. Information also diffuses faster for larger firms. Surprisingly, the coefficient on the number of analysts is positive but insignificant, suggesting that firms with more analyst coverage have a lower rate of information diffusion. It could be that, investors outsource the information acquisition to analysts and rely on analysts' interpretation, so that they pay less attention to firms' filings directly. Similar to the level of information demand, unexpected news diffuses fast, and the sensitivity to unexpectedness is asymmetrically large for bad news than for good news.

3 Heterogeneous Effects of EDGAR Attention on Stock Returns

In this section, I use two approaches to study how demand for information affects asset prices. First, I use Fama-Macbeth (1973) cross-section regression. Second, I form long/short portfolios based on their attention levels.

3.1 Fama-Macbeth (1973) Approach

I first study the relation between future stock returns and the overall attention on EDGAR. I run Fama-Macbeth (1973) regression of monthly individual stock returns from month $t+1$ on investor attention variables from month t. *log views*$_k$ is the monthly natural logarithm of form k's total viewing counts. I consider forms 10-K, 10-Q, and 8-K.

All regressions control for the following characteristics. For firms' fundamental variables, I include *Asset Growth*, *log(BM)*, *log(ME)*, and *Operating Profit*. *Asset Growth* is the annual growth rate of assets; *log(BM)* is the natural log of the book-to-market ratio; *log(ME)* is the natural log of the firm market capitalization; *Operating Profit* is the ratio of operating profits to book equity. I include the current month stock return $r_{1,0}$ and the past-12 month stock return $r_{12,2}$ to control for firms' past performance, which may drive both investor attention and future returns. Gervais, Kaniel, and Mingelgrin (2001) and Barber and Odean (2007) document that abnormal trading volume increases a firm's visibility, which could affect both attention and future stock returns. Therefore, I include *Abnormal Trading Volume*, which is the difference between monthly trading volume and past 12-month average trading volume, scaled by the standard deviation of past 12-month trading volume. Since many of my attention variables capture investor attention to firms' annual and quarterly filings, I include earning surprise and earning drift from the most recent earnings announcement. *SUE* is the unexpected quarterly earnings scaled by market cap; *Earning Drift* is the sum of daily returns in three days around earning announcement. Lastly, I control for firm disclosure. *file 8K*, *file 10K*, and *file 10Q* are the numbers of form 8-K, 10-K, and 10-Q issued by the firm on the EDGAR, respectively.

Column 1 of Table 3 shows the baseline result. Asset growth, firm size, operating profit, unexpected earnings, abnormal trading volume, and abnormal earning announcement returns are able to explain cross-section stock returns. I then add the overall investor attention to EDGAR filings, *log views*$_{all}$, to the previous specification. *log views*$_{all}$ is the natural log of all filing views of the firm in the current month. Column (2) shows the regression result.

The estimate of *log* $views_{all}$ is positive and significant. Firms with high filing views earn a premium of roughly 18.3 basis points per month (2.2% per year).

To study the heterogeneous effect of filing views, I split the overall views by their filing types into three parts, and the result is shown in Column (3). The coefficient estimates of *log* $views_{10K}$ are positive (39 bps per month) and highly significant with t-stat of 7.42. Firms with high 8-K filing attention earn less return in the future (12 bps per month), as can be seen from the negative and significant coefficient estimates of *log* $views_{8K}$. Lastly, there is no effect of 10-Q views on stock returns. The coefficient of *log* $views_{10Q}$ is insignificant, and its magnitude is relatively small. In Column (4), I further split the 8-K views into the scheduled and unscheduled 8-K views. The effect is entirely driven by the unscheduled 8-K views. In Column (5), I control for the change in Google Trends and media news coverage. The result is robust, but the sample is smaller than the ones in previous columns.

3.2 Portfolio Sort Approach

In this section, I study the effect of investor attention to firm filings using a portfolio sorting approach. At each month, I first run a cross-section regression of the natural log views on the natural log of lag firm size and extract regression residuals as the size-adjusted attention. I then sort stocks into quintiles by the size-adjusted attention[11]. Finally, I form a long/short portfolio by buying the top quintile stocks and selling the bottom quintile stocks and regress the monthly portfolio returns on benchmark factors. The factor models include CAPM, Fama-French three-factor (FF3), Fama-French-Carhart (FFC), Fama-French five-factor plus momentum (FF5+UMD), and an eight-factor model by including betting-against-beta and liquidity factors.

Panel A of Table 4 shows the portfolio sort result for 10-K views. The monthly one-month holding return of the equal-weighted long/short portfolio is 0.9% and highly significant. After controlling for common pricing factors, the average alpha is around 0.65% per month. More-

[11] I control for their firm sizes because large firms tend to receive higher views. The result is robust if I sort stocks by the unadjusted views.

over, the effect of 10-K attention is short-termed, which can be seen from the insignificant alphas with three or twelve holding months.

Panel B of Table 4 shows the portfolio sort result for 8-K views. Consistent with the result in Fama-Macbeth (1973) regression, the equal-weighted long/short portfolio earns a monthly alpha of -0.56%. Moreover, the effect of 8-K attention is long-lasting. The 12-month holding alpha is around -0.6% per month and highly significant.

Panels C and D of Table 4 shows the factor loadings of one-month 10-K and 8-K portfolios. The alphas of 10-K (8-K) portfolios are monotonically increasing (decreasing) with the level of 10-K (8-K) views.

Figure 2 shows the persistence of long/short portfolio return and alpha. I sort stocks by size-adjusted 10-K (8-K) attention into quintiles at month t, and study the long/short portfolio returns at month $t + k$, where k ranges from 0 to 12. For the 10-K portfolio, the return and alpha are pronounced the most in the first holding month and decay very quickly. The 8-K portfolio shows the opposite pattern. The contemporaneous return at formation month (month 0) is positive. Then the portfolio returns become negative and highly persistent over time.

4 Mechanisms of 8-K Demand on Stock Returns

Easley and O'Hara (2004) documents that investors demand higher returns for stocks with more private information. Boot and Thakor (2001) suggests that disclosing information that is only known to informed investors decreases the information advantage informed investors have over the uninformed. However, little study has shown the effect of information demand on information asymmetry, as past literature mainly focuses on the supply side. In this section, I show that investors' 8-K attention decreases the proportion of private information, which then leads to a reduction in information asymmetry. As a result, stocks become less risky for uninformed investors to hold and expected returns decrease. Therefore, we observe that stocks with high 8-K attention underperform stocks with low 8-K attention and the underperformance is highly persistent over time. Moreover, the effect of 8-K attention should also depends on the ex-ante information asymmetry the firm is facing, and the information content provided in the filing itself.

Table 6 shows the monthly panel regression results of future information asymmetry on investor attention to firm filings, controlling for firm characteristics and information disclosure. I use Amihud (2002) measure and quote spread estimated following Corwin and Schultz (2012). The coefficient estimates of $log\ views_{8K}$ is negative and significant, suggesting that higher 8-K attention is associated with lower information asymmetry in the next month. Moreover, the economic magnitude of the coefficient is large. One standard deviation of 8-K attention can move Amihud measure by 25 percentiles.

The effect of 8-K attention on stock returns should be larger when the ex-ante information asymmetry is higher. To proxy for ex-ante information asymmetry, I use Amihud illiquidity measure and previous quarter analyst forecast dispersion. I first sort stocks by information asymmetry measures into terciles. Conditional on each tercile, I sort stocks by size-adjusted 8-K attention into quintiles. Table 7 shows the portfolio double-sort results for 8-K attention and information asymmetry. When Amihud measure is low, the alpha of long/short 8-K attention portfolio is -12 bps per month. When Amihud measure is high, the magnitude of alpha increases to -72 bps per month. The result is similar using analyst forecast dispersion.

5 Heterogeneous Effect of 8-K Demand

This section shows heterogeneous effect of 8-K demand on stock returns. The heterogeneity stems from the cost of information acquisition and the information contents of the filings.

5.1 Cost of Information Acquisition

The cost of information acquisition plays an important part in reducing information asymmetry. In Verrecchia (1982) Corollary 4, the informativeness of price is nondecreasing as information acquisition costs are reduced. Although I do not directly observe the cost of information acquisition of each investor, an investor's past information acquisition history and his/her geographical location are observed in the data. I use the firm-level share of local demand and share of frequent viewers to capture the cost of information acquisition.

Local investors have information advantage to collect and process information over non-local investors. Therefore, holding the level of information acquisition fixed, firms with more local demand of information have lower cost of information acquisition. Moreover, I make the explicit assumption that, the cost of information acquisition is lower for an investor who acquired information of the firm in the past quarter than one who did not. Therefore, frequent visitor ratio defined in Figure 6 can be used as an proxy for the cost of information acquisition. The higher the frequent visitor ratio is, the lower the cost of information acquisition.

Panel A of Table 8 shows the portfolio double-sort results by investor attention and the average distance of viewer location to firms' headquarters. For each stock at each month, I calculate the average distance between IP addresses and firm headquarters for each filing type. I then double sort stocks by the average distance into terciles and by the size-adjusted views into quintiles. The effect of 8-K attention is mainly concentrated in the low (-48 bps/month) and medium (-65 bps/month) distance terciles, and much weaker in the high (-18 bps/month) distance tercile. Moreover, the difference between high and low terciles is statistically significant.

Panel B of Table 8 studies the attention effects, conditional on visitors' past visiting patterns. For each firm-month, I calculate the proportion of frequent visitors. I then double sort stocks by the frequency ratio into terciles and by size-adjusted 8-K views into quintiles. Portfolios sorted by 8-K attention show significant and negative alphas when views are from frequent visitors (-42 bps/month). When the frequent ratio is low, however, the 8-K portfolio yields an insignificant alpha of -25 bps per month.

5.2 Information Content

Moreover, the effect of 8-K attention should be a function of the information content provided in the filings. The demand for information only reduces the information asymmetry, if the information provided by the firm was previously private. Some filings, such as report about the pre-scheduled meetings, do not convey any private information. Others, such as material agreement and change of officers, require investor attention to interpret the information. Therefore, it is important to see how the effect of information demand interact with the information content provided in the filings.

I extract the "event date" and "post date" for each filing and calculate the three-day market excess abnormal return of the firm around both dates[12]. Two measures are then used to quantify the importance of each filing. The first measure is simply the maximum of absolute abnormal returns around event and post dates. This measure captures the market response to the information provided in the filing. If the new information is good (bad) news, the measure is high (low). If the information conveyed in the filing is already anticipated or even well understood by the market, the measure should be small in absolute terms. In my sample, the measure has a mean of 0.4% and standard deviation of 12%.

The second measure is constructed using textual analysis. For each filing i, I build a document classifier based on the past one-year 8-K filings of all firms in my sample. I then compute the document similarity vector between the filing i and all past year filings. The similarity vector represent how similar the pair of documents is. I calculate the expected market response to the filing i as the weighted average of three-day abnormal returns of filings in the past year, with the weight determined by the similarity vector. The expected market response captures what the abnormal return level should be, given the similarity of

[12]Starting 2004, the SEC requires firms to disclose any material information within four days of the event. In practice, however, the lag can be more than four days as firms can ask for some additional grace periods.

information content between the filing i and past filings. Lastly, I calculate the difference between the realized market response and the expected market response, and use this "unexpected market response" as a proxy for information importance. The measure has a mean of 0.1% and standard deviation of 10%. The difference between two measures is that, the second measure captures the shock in information content beyond the part expected by the market.

To see how the effect of 8-K attention varies with the importance of information content of the filing, I double sort stocks by the size-adjusted 8-K views and the above two measures. The result is shown in Table 9. In Panel A, the information importance measure is the raw abnormal cumulative return around the event. In Panel B, the information importance measure is the unexpected abnormal return. Both panels yield similar result. The relation between 8-K attention and abnormal return exhibits a "V-shape". The effect of 8-K attention is concentrated in the low and high abnormal return terciles, and relatively weak in the middle tercile, where the average abnormal return is around zero. When abnormal returns are high (low), firms are likely to have disclosed good (bad) private information. The demand for 8-K filings then plays an important role in interpreting the piece of information and reduce information asymmetry, which leads to a negative spread in future returns, regardless of whether the information itself is good or bad. However, when there is little abnormal return around event/post date, it is likely that the market has already taken into account the information content, which leaves investors not too much to learn in the first place. As a result, the spread in 8-K attention does not predict future returns well.

6 Mechanism of 10-K Demand on Stock Returns

Barber and Odean (2007) documents that attention is a scarce resource, and demand for assets is rooted from the stocks that grab investor attention. When investors make purchasing decisions for a stock, 10-K filings provide the most comprehensive coverage of the operational and financial details of a firm. Therefore, the effect of attention to 10-K filings on stock prices is a byproduct of demand shocks to assets. That is, the demand for asset drives up demand of information to 10-K filings and stock prices. As a result, we should expect the effect of 10-K attention on stock prices to be higher for attention-grabbing stocks, where the demand shock is potentially higher.

I use stocks with high abnormal trading volume and high daily absolute returns to proxy for attention-grabbing stocks. Abnormal trading volume and daily absolute returns are constructed as the following,

$$abvol_{i,t} = \frac{vol_{i,t} - \bar{vol}_{i,t-1,t-12}}{std\_vol_{i,t-1,t-12}}, \tag{1}$$

$$max\_dret_{i,t} = \max_{d \in t} \mid ret_{i,t,d} \mid \tag{2}$$

where $\bar{vol}_{i,t-1,t-12}$ and $std\_vol_{i,t-1,t-12}$ are the mean and standard deviation of monthly trading volume during the past 12 month, respectively. $ret_{i,t,d}$ is the daily return of stock i on month t and day d. Gervais et al. (2001) first documents that stocks with abnormally high trading volume earn return premiums in the future. The argument is that shocks to the trading volume of a stock increase its visibility, which draws investor attention and drives up stock prices. Barber and Odean (2007) uses abnormal trading volume and daily maximum return to proxy for attention-grabbing. I first sort stocks by abnormal trading volume (daily absolute returns) into terciles. Conditional on each tercile, I then sort stocks by the size-adjusted 10-K attention into quintiles.

Panel A of Table 11 show the alphas of double-sorted portfolios for abnormal trading volume and 10-K views. The last column shows the alphas of long/short attention portfolios conditional on abnormal volume terciles. For low abnormal trading volume tercile, the spread in alpha is 31 bps per month. The spread in alpha increases to 87 bps per month for stocks in high abnormal trading volume tercile. Panel B shows the result using the maximum daily return as a proxy for attention-grabbing. The result is very similar to Panel A. Moreover, the spread is mostly driven by the outperformance of high attention stocks.

7 Robustness Check

7.1 Robustness Check: Information Supply

An alternative explanation for the attention effect is that information supply drives both attention and stock prices. When a firm announces an earnings announcement or files a filing on EDGAR, investors pay attention to its information content and trade on it. Therefore, it is important to separate information demand from the information supply. In this section, I study the long/short portfolio returns conditional on whether there is an event of information supply, such as earnings announcements and EDGAR filings.

Panel A of Table 12 shows the long/short portfolio alphas sorted by 10-K views, conditional on whether the firm filed any Form 10-Ks in the month. When firms do not file any filings on the portfolio formation month, stocks with high size-adjusted 10-K views outperform stocks with low size-adjusted 10-K views by 0.66% per month with a t-stat of 3.65. However, conditional on the set of firms filed Form 10-K in the formation month, the portfolio yields an alpha of -57 bps but insignificant. When firms file 10-K, two channels of information demand are working in the opposite directions. Meanwhile, around 45% of firms file 10-K in March, and the number of firms in the portfolios varies a lot throughout the year, leading to an imprecise estimate. Therefore, conditional on 10-K filing, the long/short portfolio does not generate positive return spread.

Panel B of Table 12 shows the long/short portfolio alphas sorted by 8-K views, conditional on whether the firm files an unscheduled 8-K filing on EDGAR. The long/short portfolio of stocks sorted by unscheduled 8-K views earns a monthly alpha of -0.62% when there is information supply, and -0.36% when there is no filings.

Overall, the findings suggest that the effect of investor attention to firms' EDGAR filings on stock prices is not driven merely by new filings.

7.2 Robustness Check: Media Coverage

Earnings announcement and EDGAR filings may not fully capture the supply of information, as some events are covered by the media but not necessarily reported to the SEC. These shocks in information supply may drive stock prices and investor attention, which leads to the co-movement of EDGAR views and stock returns. Therefore, it is important to show that investor attention to firm filings has effects on stock prices even in the absence of media coverage.

I use the number of news mentioned on Ravenpack to proxy for media coverage. Since firms have heterogeneous exposure to the media, I first compute the past 12-month rolling median of the number of news. I then create a high media coverage dummy, which is equal to one if the current month news coverage is greater than the past 12-month median, and zero otherwise. Conditional on the high media coverage dummy, I sort stocks by size-adjusted 10-K (8-K) attention into quintiles. Table A5 shows that the effect of attention exists in both high and low coverage stocks.

8 Conclusion

In this paper, I empirically test two channels where demand for information affects asset prices using EDGAR log data. On the one hand, investor attention to form 10-Ks is associated with general demand for the asset, so that a spike in 10-K attention predicts short-term positive future returns. The effect of 10-K attention is stronger among attention-grabbing stocks. The alpha of 10-K attention portfolio decays sharply after the first month, consistent with the demand shock. On the other hand, investor attention to form 8-Ks decreases information asymmetry. As a result, high 8-K attention stocks persistently underperform low 8-K attention stocks due to the reduced risk premium. The effect of 8-K attention is stronger when firms have high ex-ante information asymmetry.

This paper also sheds lights on the micro-level information acquisition patterns. The striking difference in 10-K and 8-K attention is contributed to the heterogeneous viewing patterns of investors. Investors who pay attention to form 10-Ks are different from the ones who view 8-Ks, as 80% of 10-K viewers did not download any 8-K filings over the previous quarter. Moreover, 10-K investors are typically one-time viewers, in the sense that they seldom visit company filings in the past. On the contrary, 8-K investors are frequent visitors who regularly review both old and new filings. Lastly, 8-K investors have a larger proportion of local investors, who presumably have an advantage to acquire information.

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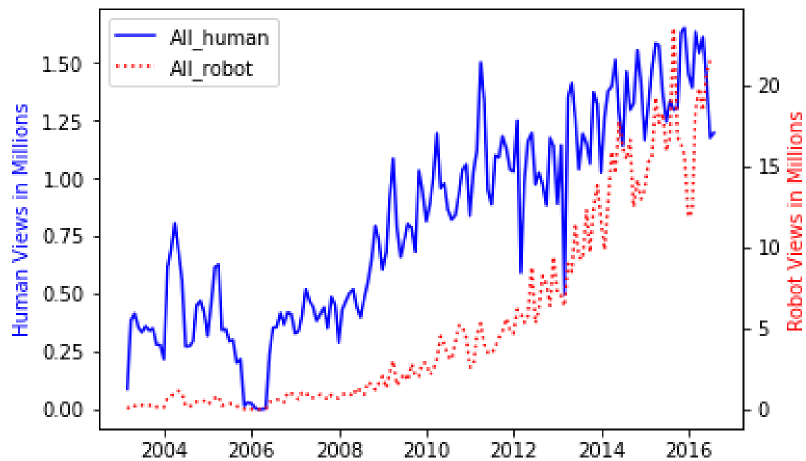
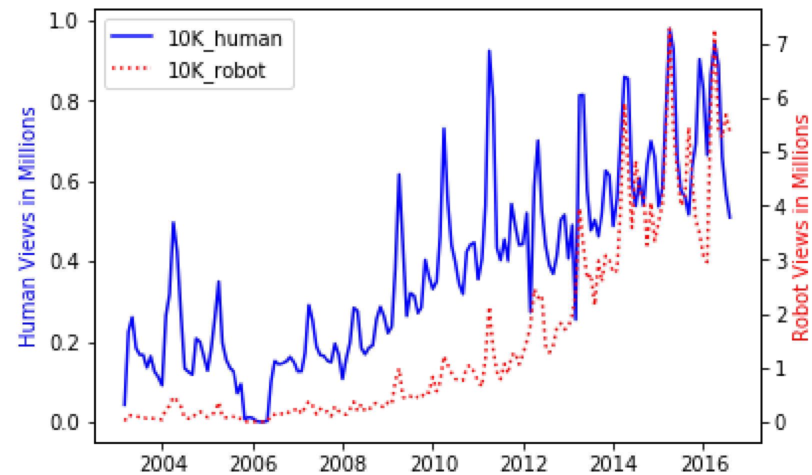
Figure 1

Time-series EDGAR Viewing Activity

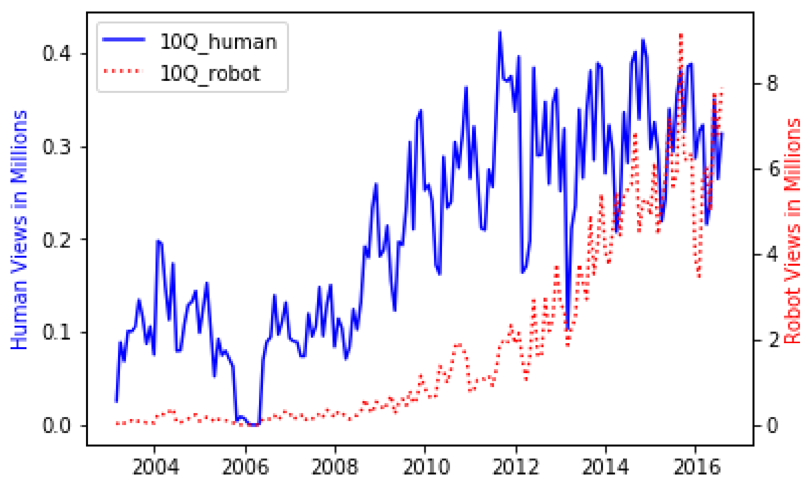
The figure shows the monthly aggregated number of views on EDGAR Log system. Following Lee et al. (2015), I separate crawling activities (“robot”) from human viewing activities (“human”). Figures (b) to (d) show the number of views for 10-K, 10-Q, and 8-K filings, respectively.



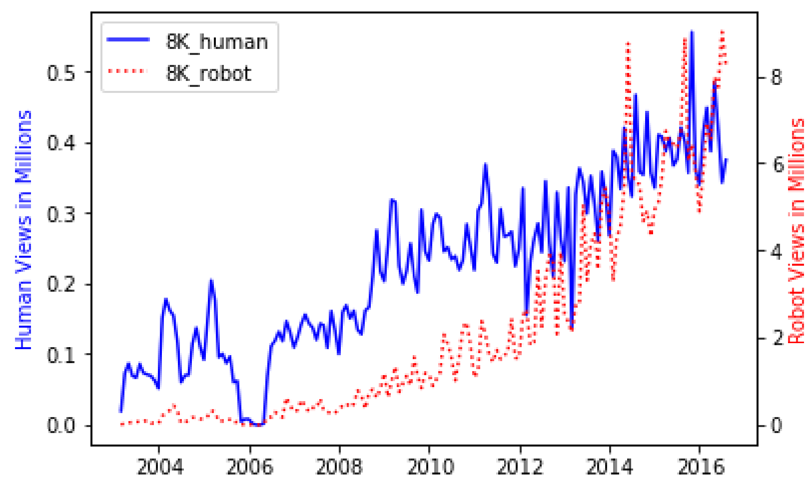
(a) All Filings



(b) 10-K Filings



(c) 10-Q Filings



(d) 8-K Filings

Figure 2
Long/Short Investor Attention Portfolio Return
The figure shows the monthly long/short portfolio returns and alphas for up to 12 months. Stocks are sorted by the size-adjusted 10-K (8-K) views into quintiles. I then form long/short portfolios and plot the next 12 month average portfolio return and Fama French five-factor alphas. For 8-K views, I only focus on the views on unscheduled filings.

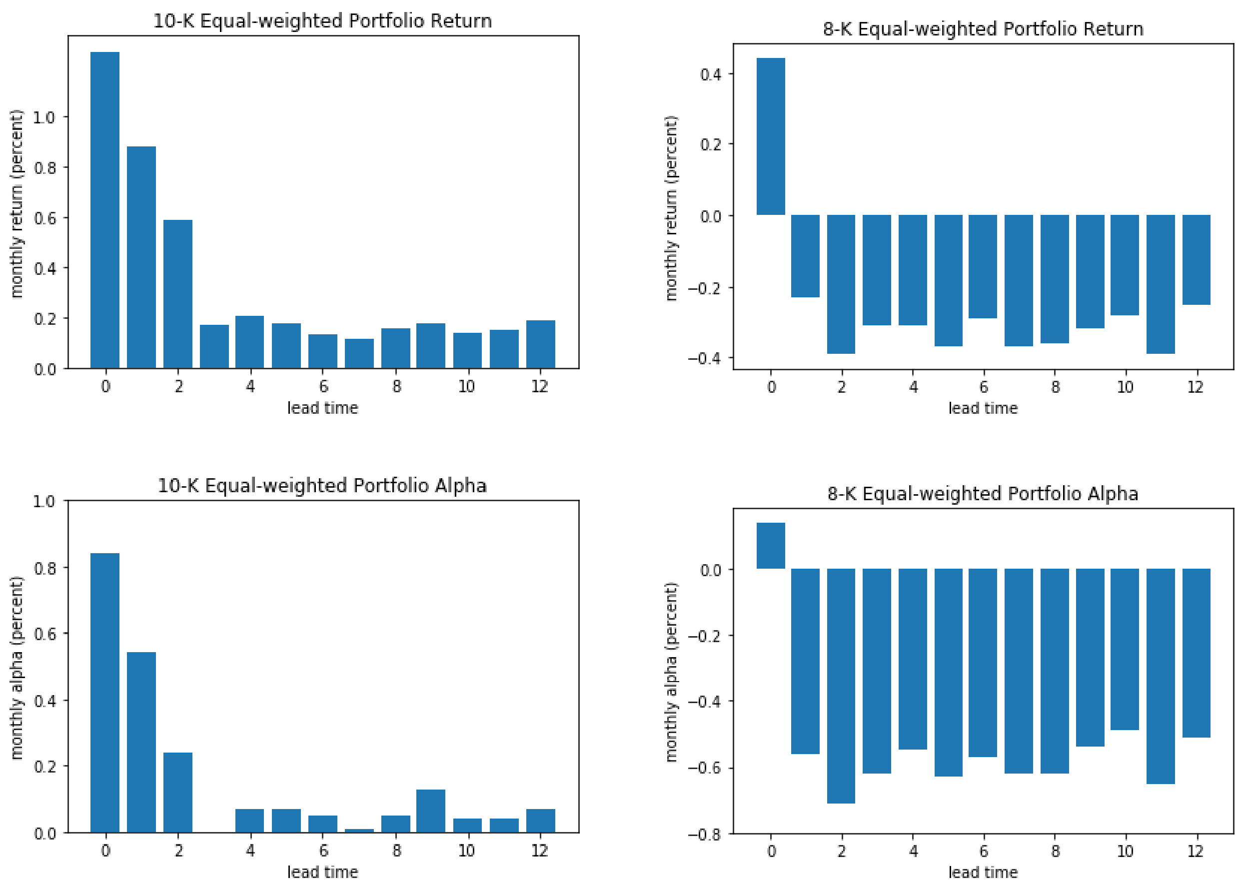


Figure 3
Long/Short Investor Attention and Volatility
The figure shows the monthly volatility difference between the top and the bottom attention stocks from the formation month to the next 12 months. Stocks are sorted by the size-adjusted 10-K (8-K) views into quintiles. I then form long/short portfolios and plot the next 12 month average volatility difference. For 8-K views, I only focus on the views on unscheduled filings.

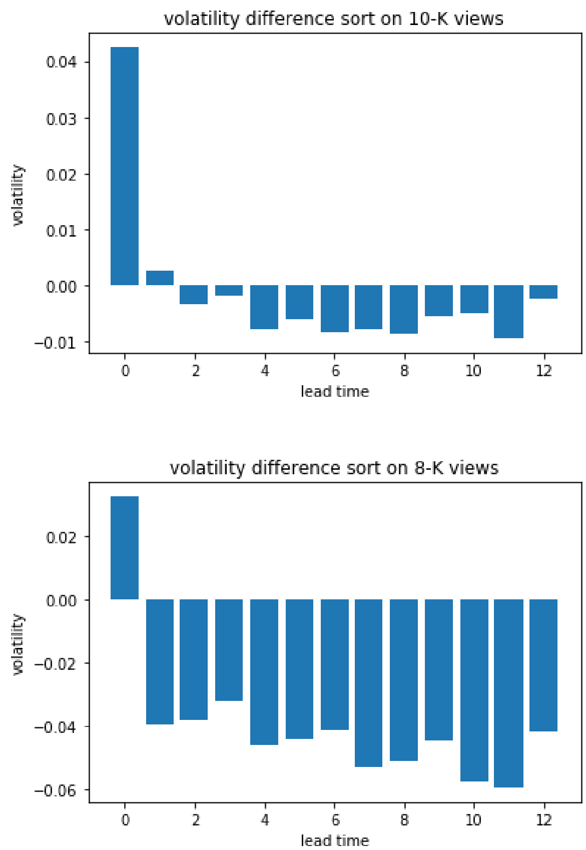


Figure 4

10-K Views Conditional on 8-K Views

The figure shows the time-series of 10-K viewing activity, conditional on whether the visitor also viewed any 8-K filings of the firm in the past three months. $views_{10K}^{only}$ is the total number of 10-K views by visitors who have not downloaded any 8-K filings of the firm. $views_{10K}^{both}$ is the total number of 10-K views by visitors who have downloaded one or more 8-K filings of the firm.

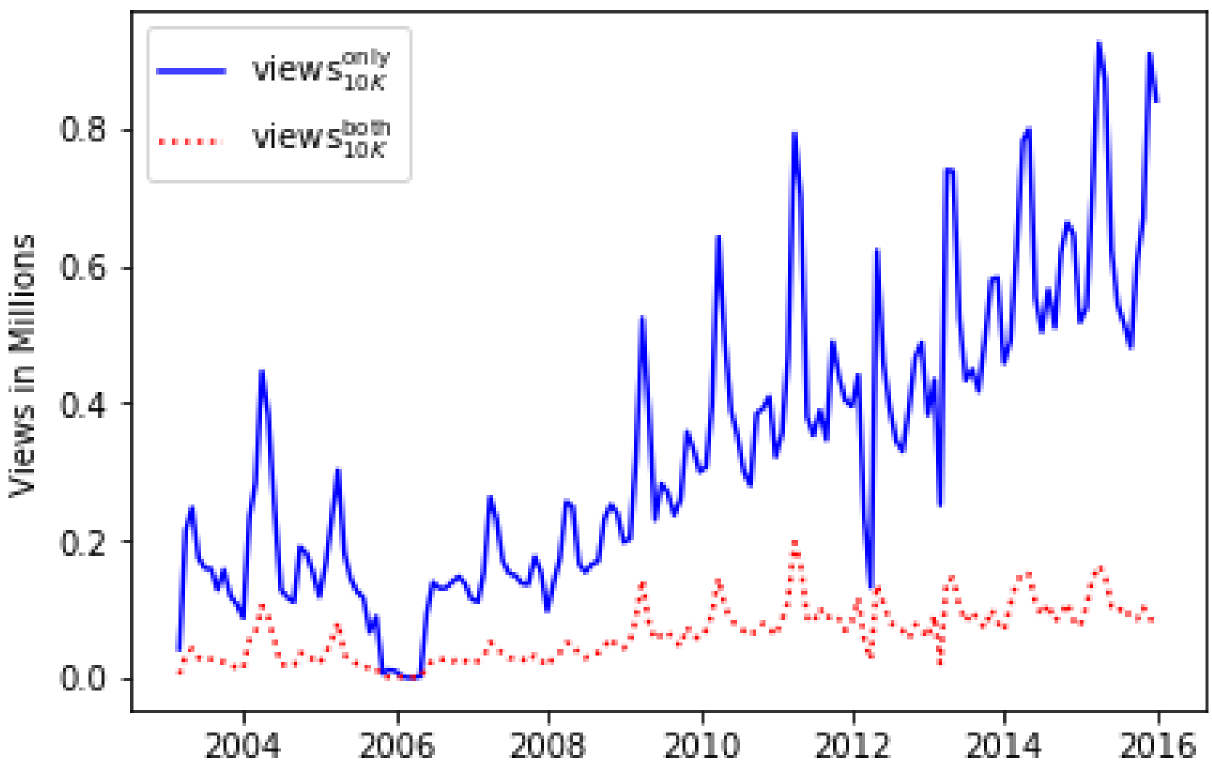
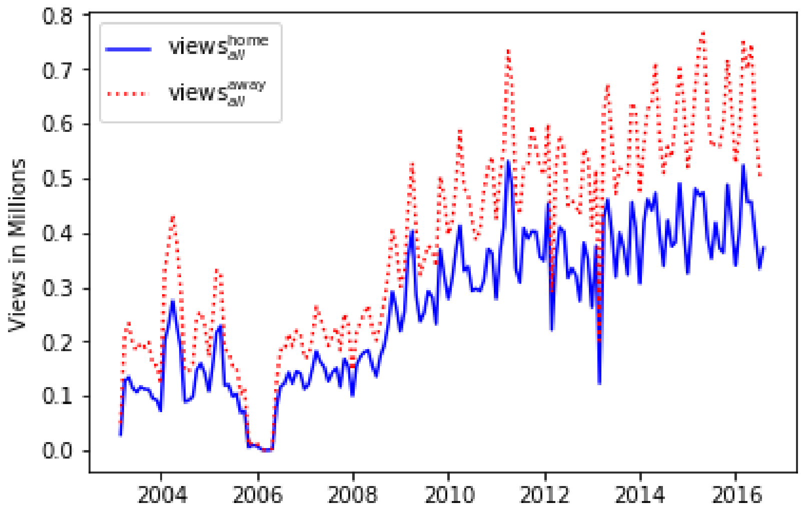


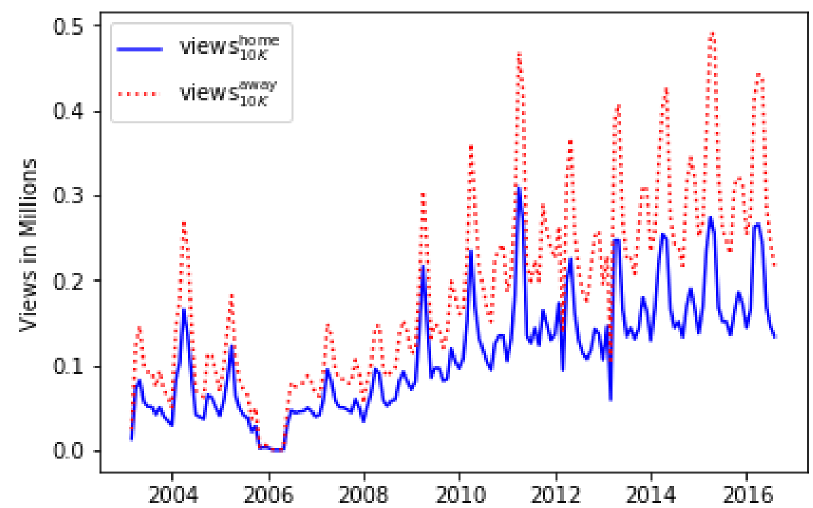
Figure 5

Viewing Activities by Geographical Distance

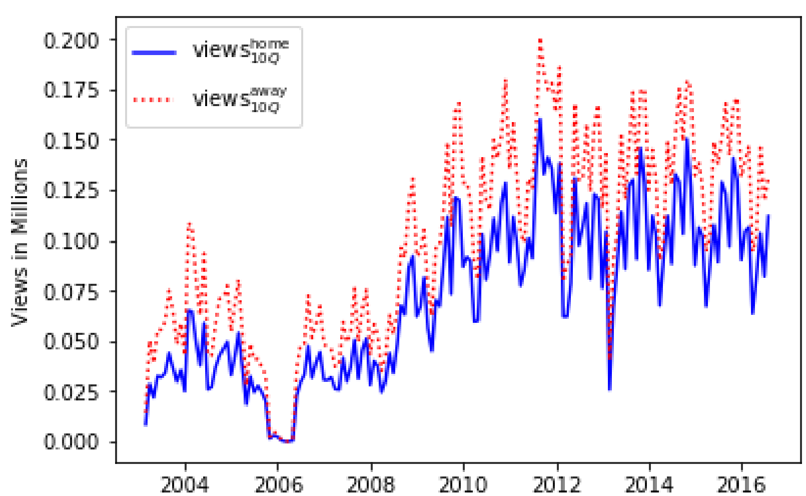
The figure shows the number of views by geographical distance. I classify a filing view as home if the distance between the locations of viewing IP and headquarter is less than 400 miles.



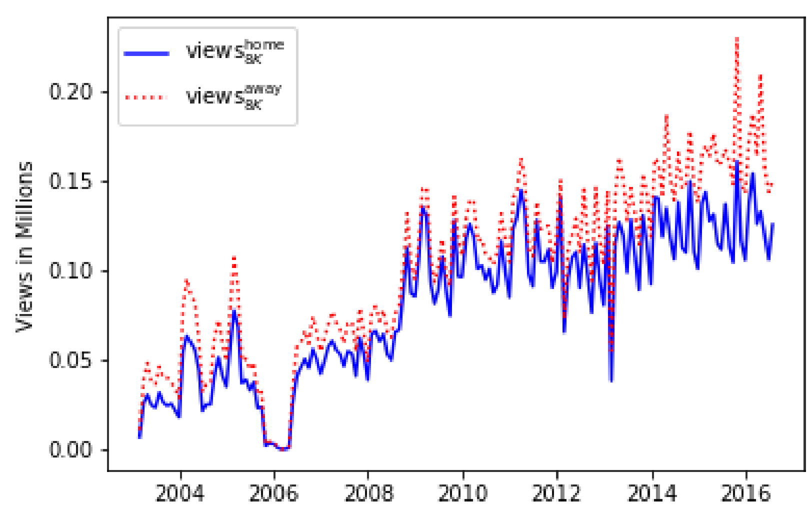
(a) All Filings



(b) 10-K Filings



(c) 10-Q Filings



(d) 8-K Filings

Figure 6

Time-series Frequent Visitor Ratios

The figure shows the time-series plot of frequent visitor ratios by 10-K and 8-K visitors. For each firm and IP address, I classify a filing view as frequent if the IP address submitted requests to view the company filings during the past three months. At each month, I then calculate the cross-section average of frequent ratios by 10-K and 8-K filings.

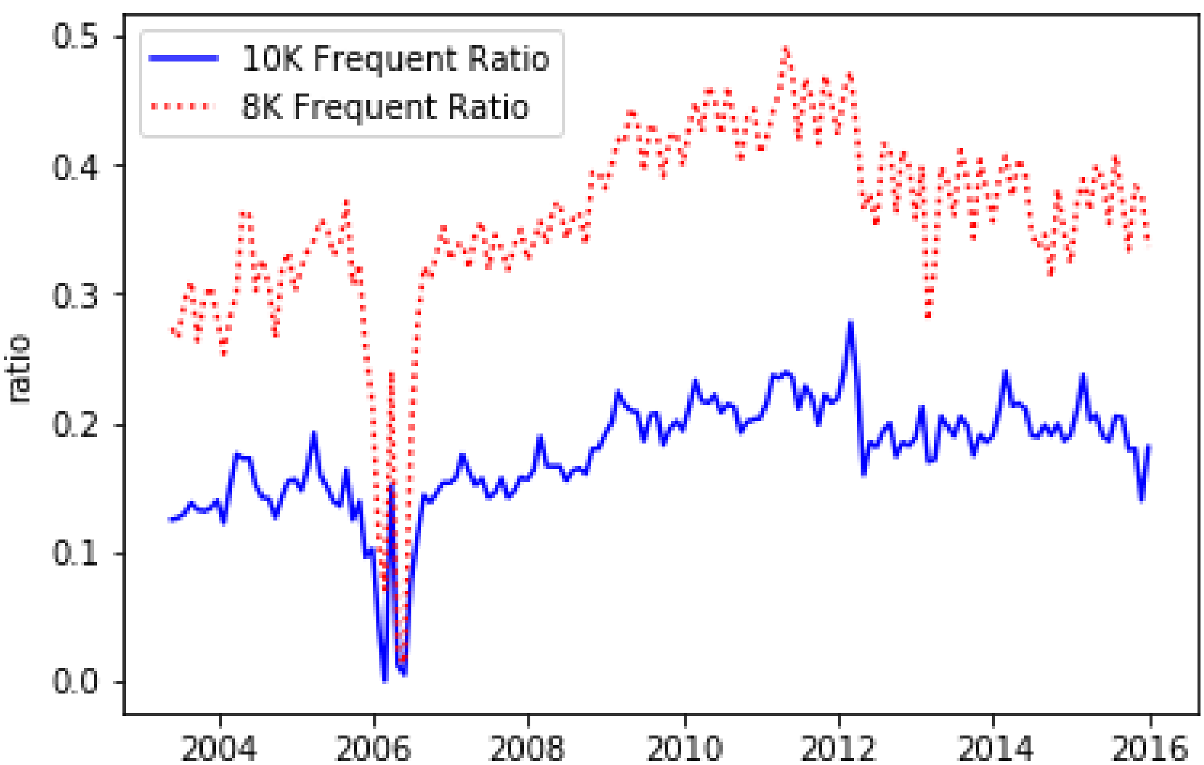


Figure 7

Investor Attention Histogram by Firm Sizes

The figure shows the histogram of investor attention on EDGAR, grouped by firm sizes. The horizontal axis is the natural log of monthly filing views of a firm. A small firm is defined with a firm market cap below 20% NYSE percentile. A large firm is defined with a firm market cap above 80% NYSE percentile. A medium-size firm is defined with a firm market cap between 20% and 80% NYSE percentile.

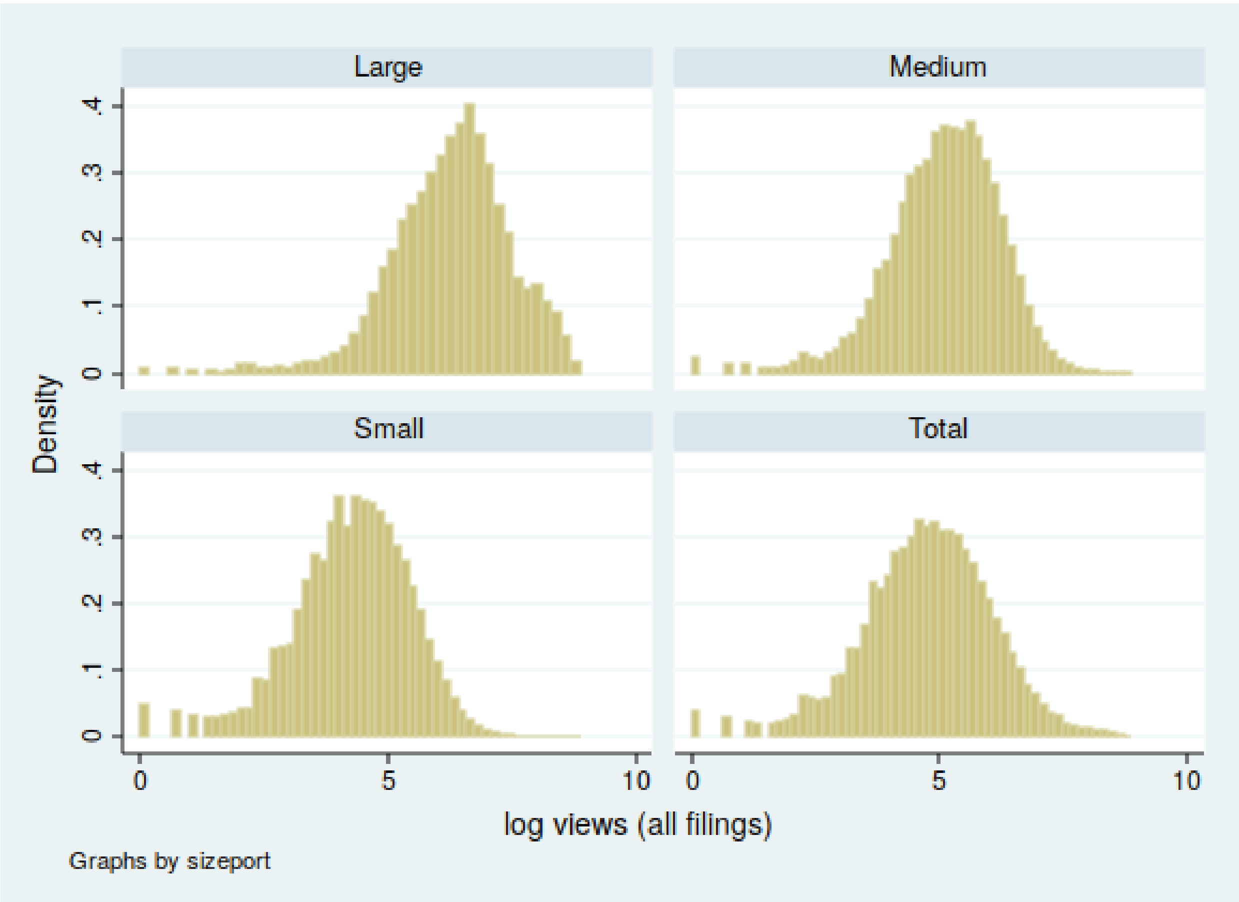


Figure 8
Demand for 8-K and Abnormal Return around Events

The figure studies the long/short portfolio of size-adjusted 8-K attention and abnormal returns around 8-K filing and event date. For each unscheduled 8-K filings, I calculate the cumulative abnormal return relative to the market around event and filing date. I then double sort stocks by the size-adjusted 8-K attention and the cumulative abnormal return into 5-by-5 blocks. Conditional on each abnormal return quintile, I regress the long/short size-adjusted 8-K portfolio return on Fama French five factors and momentum factor, and plot the alphas and 95% confidence intervals. For stocks with multiple unscheduled filings in a month, I choose the one with the highest absolute abnormal return.

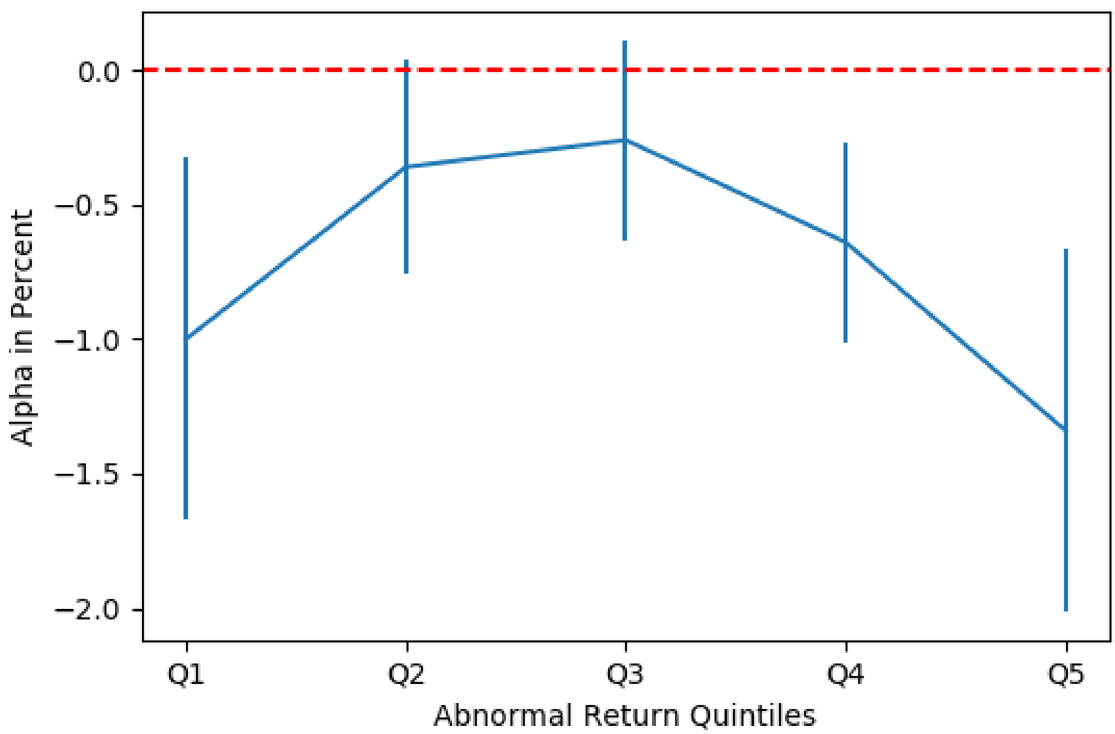


Table 1
Determinants of 8-K Views

The table shows the determinants of 8-K filing views. The unit of observation is at filing level. The dependent variable is the log of total views of an 8-K filing after 30 days. $CAR_{-1,1}^{event\ day}$ is the firm's 3-day cumulative abnormal return excess the market around the event day. The dummy variable *pos news* is equal to one if the CAR is positive, and zero otherwise. The variable *local visitor ratio* is the past 12-month average proportion of local 8-K views. The variable *frequent visitor ratio* is the past 12-month average proportion of frequent 8-K viewers. I include 8-K category dummies in columns (4) and (5).

	(1)	(2)	(3)	(4)	(5)
	log(views)	log(views)	log(views)	log(views)	log(views)
$\mid CAR_{-1,1}^{event\ day} \mid$		2.149***	3.094***	3.120***	3.151***
		(25.60)	(40.18)	(40.93)	(41.45)
pos news			0.0350***	0.0370***	0.0365***
			(5.46)	(5.81)	(5.70)
$\mid CAR_{-1,1}^{event\ day} \mid \times$ pos news			-1.296***	-1.358***	-1.362***
			(-12.46)	(-13.13)	(-13.04)
local visitor ratio	-0.349***	-0.317***	-0.313***	-0.306***	-0.303***
	(-7.55)	(-6.99)	(-6.91)	(-6.93)	(-6.86)
frequent visitor ratio	1.577***	1.575***	1.576***	1.493***	1.481***
	(23.15)	(23.54)	(23.59)	(22.95)	(22.81)
asset growth	-0.131***	-0.133***	-0.135***	-0.133***	-0.133***
	(-6.84)	(-7.04)	(-7.19)	(-7.24)	(-7.24)
book-to-market	0.184***	0.190***	0.192***	0.196***	0.196***
	(12.87)	(13.73)	(13.89)	(14.46)	(14.42)
log(ME)	0.0770***	0.0989***	0.101***	0.108***	0.109***
	(8.84)	(11.46)	(11.75)	(12.80)	(12.89)
operating profit	0.0184***	0.0191***	0.0194***	0.0203***	0.0203***
	(2.72)	(2.90)	(2.95)	(3.12)	(3.14)
ret_{t-1}	-0.154***	-0.132***	-0.124***	-0.116***	-0.117***
	(-6.29)	(-5.77)	(-5.48)	(-5.31)	(-5.33)
$ret_{t-2,t-12}$	-0.133***	-0.123***	-0.122***	-0.106***	-0.109***
	(-12.24)	(-11.67)	(-11.70)	(-10.27)	(-10.62)
num of analysts	0.0323***	0.0305***	0.0303***	0.0299***	0.0296***
	(14.14)	(13.55)	(13.47)	(13.61)	(13.49)
itemFE	No	No	No	Broad Sections	Detailed Sections
adjusted R^2	0.119	0.137	0.139	0.162	0.165
F	212.1	265.7	324.8	386.8	397.1

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2
Speed of 8-K Information Diffusion

The table shows the determinants of 8-K diffusion speed. The unit of observation is at filing level. The dependent variable is the speed of information diffusion of the 8-K filing. For each 8-K filing, I calculate the number of days needed to reach the 50% of total views at the end of the 30th day. The dependent variable is the difference between 30 and the number of day needed (the higher the difference is, the faster the information diffuses). $CAR^{event\ day}_{-1,1}$ is the firm's 3-day cumulative abnormal return excess the market around the event day. The dummy variable *pos news* is equal to one if the CAR is positive, and zero otherwise. The variable *local visitor ratio* is the past 12-month average proportion of local 8-K views. The variable *frequent visitor ratio* is the past 12-month average proportion of frequent 8-K viewers. I include 8-K category dummies in columns (4) and (5).

	(1)	(2)	(3)	(4)	(5)
	$t_{\frac{1}{2}}$	$t_{\frac{1}{2}}$	$t_{\frac{1}{2}}$	$t_{\frac{1}{2}}$	$t_{\frac{1}{2}}$
$\mid CAR^{event\ day}_{-1,1} \mid$		-3.769***	-5.803***	-5.090***	-4.758***
		(-20.07)	(-26.04)	(-23.07)	(-21.57)
pos news			-0.108***	-0.0863***	-0.0822***
			(-4.53)	(-3.65)	(-3.51)
$\mid CAR^{event\ day}_{-1,1} \mid \times$ pos news			2.803***	2.245***	2.138***
			(10.06)	(8.22)	(7.99)
local visitor ratio	-0.150*	-0.206**	-0.215**	-0.188**	-0.152*
	(-1.71)	(-2.36)	(-2.45)	(-2.09)	(-1.67)
frequent visitor ratio	-2.043***	-2.040***	-2.041***	-2.023***	-2.038***
	(-15.00)	(-15.04)	(-15.05)	(-14.71)	(-14.69)
asset growth	-0.0104	-0.00742	-0.00223	-0.00591	-0.00624
	(-0.29)	(-0.21)	(-0.06)	(-0.17)	(-0.17)
book-to-market	-0.0118	-0.0228	-0.0262	-0.0214	-0.0270
	(-0.44)	(-0.86)	(-1.00)	(-0.79)	(-0.99)
log(ME)	-0.121***	-0.160***	-0.164***	-0.157***	-0.159***
	(-8.81)	(-11.56)	(-11.92)	(-10.74)	(-10.65)
operating profit	0.0432***	0.0418***	0.0413***	0.0515***	0.0516***
	(3.61)	(3.52)	(3.49)	(4.29)	(4.27)
ret_{t-1}	-0.128**	-0.166***	-0.183***	-0.186***	-0.168***
	(-2.06)	(-2.69)	(-2.98)	(-3.02)	(-2.72)
$ret_{t-2,t-12}$	0.142***	0.125***	0.125***	0.112***	0.109***
	(6.28)	(5.54)	(5.54)	(4.86)	(4.73)
num of analysts	0.00231	0.00548	0.00595	0.00529	0.00519
	(0.61)	(1.45)	(1.58)	(1.34)	(1.30)
itemFE	No	No	No	Broad Sections	Detailed Sections
adjusted R^2	0.00388	0.00652	0.00683	0.0116	0.0150
F	53.56	87.73	106.5	117.6	121.4

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3
Fama-Macbeth Regression on EDGAR Attention
The table shows results from Fama-Macbeth regressions of monthly individual stock returns on EDGAR views. The variable *log views*$_k$ is the natural log of human views of the firm for filing type k. Regressions include controls for other variables that are known to predict cross-section variation in returns. Independent variables are winsorized at one and 99% levels. The sample covers from 2003 to 2016, with the dates determined by the availability of EDGAR Log data. Asset Growth is the annual percentage change in total assets. log(BM) is the natural logarithm of the book-to-market ratio. log(ME) is the natural logarithm of market capitalization. Operating Profit is the revenue minus cost of goods sold, SG&A expenses, and interest expense, divided by lagged common shareholders' equity. Abnormal Trading Volume is the difference between trading volume and previous 12-month average trading volume, scaled by the standard deviation of previous 12-month trading volume. SUE is the unexpected quarterly earnings (adjusted by median forecast earnings) divided by fiscal-quarter-end market capitalization. Earning Drift is the sum of daily returns in three days around the earnings announcement. Media Coverage is the total number of news covered by Ravenpack. Count Variables file 10K/10Q/8K are the number of 10-K/10-Q/8-K filings in the month.

	(1)	(2)	(3)	(4)	(5)
	Ret	Ret	Ret	Ret	Ret
$log\ views^{full}_{all}$		0.183*			
		(1.75)			
$log\ views^{full}_{10K}$			0.390***	0.388***	0.347***
			(7.42)	(7.35)	(5.89)
$log\ views^{full}_{10Q}$			-0.0691	-0.0697	-0.0531
			(-1.15)	(-1.15)	(-1.09)
$log\ views^{full}_{8K}$			-0.120**		
			(-2.23)		
$log\ views^{unscheduled}_{8K}$				-0.117**	-0.174***
				(-2.32)	(-3.10)
$log\ views^{scheduled}_{8K}$				0.0237	0.0128
				(0.70)	(0.30)
file 10K	0.222*	0.149	-0.0693	-0.0729	-0.0797
	(1.87)	(1.22)	(-0.55)	(-0.58)	(-0.52)
file 8K	-0.0760***	-0.120***	-0.0584	-0.0585	-0.0417
	(-2.99)	(-4.79)	(-1.13)	(-1.20)	(-1.37)
file 10Q	-0.0725*	-0.0873*	-0.0531	-0.0441	-0.0471
	(-1.75)	(-1.90)	(-1.44)	(-1.49)	(-1.55)
Asset Growth	-0.723***	-0.680***	-0.622***	-0.625***	-0.527***
	(-4.76)	(-4.70)	(-4.30)	(-4.32)	(-3.56)
log(BM)	0.134	0.108	0.0946	0.0937	0.0503
	(0.87)	(0.70)	(0.62)	(0.61)	(0.32)
log(ME)	-0.0696	-0.133*	-0.178**	-0.178**	-0.0658
	(-1.39)	(-1.81)	(-2.48)	(-2.49)	(-0.90)
Operating Profit	0.0834**	0.0654*	0.0482	0.0477	0.0475
	(2.31)	(1.74)	(1.30)	(1.29)	(1.39)
$r_{1,0}$	-2.319***	-2.397***	-2.398***	-2.394***	-2.224***
	(-3.49)	(-3.71)	(-3.72)	(-3.71)	(-3.07)
$r_{12,2}$	-0.608	-0.498	-0.496	-0.495	-0.415
	(-1.41)	(-1.30)	(-1.30)	(-1.29)	(-1.04)
Abnormal Trading Volume	0.141***	0.132***	0.135***	0.136***	0.128***
	(4.08)	(3.90)	(4.02)	(4.02)	(3.35)
SUE	3.930***	3.900***	3.861***	3.860***	3.945***
	(4.88)	(4.90)	(4.86)	(4.86)	(4.24)
Earning Drift	1.250***	1.261***	1.244***	1.240***	1.116***
	(3.30)	(3.38)	(3.34)	(3.33)	(2.73)
Change in Google Trend					-0.108
					(-0.82)
Media Coverage					0.00314
					(0.69)
Constant	1.719**	1.801**	2.399***	2.395***	1.052
	(2.06)	(2.12)	(2.63)	(2.62)	(1.14)
N	502662	502662	502662	502662	347381
r2	0.0351	0.0385	0.0402	0.0403	0.0431
F	11.87	11.55	14.10	13.11	8.328

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4
Long/Short Portfolio by 10-K and 8-K Attention

The table shows monthly alphas and factor loadings of portfolios sorted by the 10-K/8-K viewing activity. To control for firm sizes, I first run a cross-section regression of $log\ views_{10K}$ ($log\ views_{8K}$), the natural log of 10-K (8-K) views, on the natural log of lag firm size. The residuals of the regression can be interpreted as the level of 10-K (8-K) attention, after controlling for firm size. I then sort stocks by the size-adjusted log views into quintiles and form equal-weighted portfolios. Panel A and B show the long/short portfolio returns and alphas with one, three, and twelve holding months for the 10-K and 8-K portfolios. Panel C and D show the factor loadings of 10-K and 8-K portfolios. For 8-K views, I only focus on the views on unscheduled filings.

Panel A: Size-adjusted 10-K Views Equal Weighted L/S Alpha

Holding Months	Raw Return	$Alpha^{CAPM}$	$Alpha^{FF3}$	$Alpha^{FFC}$	$Alpha^{FF5+UMD}$	$Alpha^{8-factor}$
1	0.90***	0.65***	0.65***	0.73***	0.67***	0.58***
	(3.72)	(2.93)	(2.94)	(4.17)	(3.81)	(3.27)
3	0.62***	0.38*	0.38*	0.45***	0.38**	0.29*
	(2.81)	(1.88)	(1.9)	(2.9)	(2.43)	(1.82)
12	0.50***	0.28	0.27	0.33**	0.26*	0.19
	(2.67)	(1.64)	(1.63)	(2.33)	(1.83)	(1.29)

Panel B: Size-adjusted 8-K Views Equal Weighted L/S Alpha

Holding Months	Raw Return	$Alpha^{CAPM}$	$Alpha^{FF3}$	$Alpha^{FFC}$	$Alpha^{FF5+UMD}$	$Alpha^{8-factor}$
1	-0.23	-0.56***	-0.56***	-0.51***	-0.56***	-0.47***
	(-1.18)	(-4.11)	(-4.09)	(-4.47)	(-4.78)	(-4.01)
3	-0.28*	-0.63***	-0.63***	-0.58***	-0.62***	-0.52***
	(-1.75)	(-4.91)	(-4.88)	(-5.48)	(-5.63)	(-4.83)
12	-0.27*	-0.63***	-0.63***	-0.58***	-0.61***	-0.52***
	(-1.83)	(-5.57)	(-5.56)	(-6.32)	(-6.4)	(-5.52)

Panel C: Factor Loadings of 10-K Portfolio

level	alpha	mktrf	smb	hml	umd	rmw	cma
Low	-0.01	0.835***	0.635***	0.185***	-0.015	-0.306***	-0.209***
	(-0.14)	(33.23)	(15.33)	(4.53)	(-0.73)	(-5.53)	(-3.1)
2	0.02	0.944***	0.734***	0.098***	-0.049***	-0.311***	-0.155***
	(0.34)	(54.89)	(25.88)	(3.52)	(-3.59)	(-8.19)	(-3.35)
3	0.12	0.977***	0.753***	0.085**	-0.138***	-0.218***	-0.096*
	(1.64)	(45.98)	(21.5)	(2.48)	(-8.11)	(-4.64)	(-1.67)
4	0.39***	1.017***	0.755***	0.057	-0.236***	-0.153**	0.025
	(4.12)	(36.47)	(16.43)	(1.25)	(-10.58)	(-2.48)	(0.33)
High	0.66***	1.001***	0.751***	-0.038	-0.437***	-0.262**	0.246*
	(3.79)	(19.79)	(9.01)	(-0.47)	(-10.81)	(-2.35)	(1.81)
H-L	0.67***	0.167***	0.117	-0.223***	-0.422***	0.044	0.456***
	(3.81)	(3.25)	(1.38)	(-2.68)	(-10.32)	(0.39)	(3.3)

Panel D: Factor Loadings of 8-K Portfolio

level	alpha	mktrf	smb	hml	umd	rmw	cma
Low	0.47***	0.746***	0.62***	0.116**	-0.103***	-0.365***	-0.071
	(4.44)	(24.04)	(12.12)	(2.31)	(-4.16)	(-5.33)	(-0.85)
2	0.34***	0.87***	0.737***	0.099**	-0.152***	-0.29***	-0.092
	(3.24)	(28.49)	(14.62)	(2.01)	(-6.22)	(-4.31)	(-1.12)
3	0.37***	0.979***	0.803***	0.01	-0.145***	-0.282***	-0.025
	(3.98)	(36.0)	(17.89)	(0.23)	(-6.67)	(-4.71)	(-0.34)
4	0.19*	1.02***	0.763***	0.049	-0.206***	-0.266***	0.003
	(1.83)	(33.23)	(15.07)	(0.98)	(-8.41)	(-3.95)	(0.03)
High	-0.08	1.097***	0.69***	0.025	-0.338***	-0.24***	-0.007
	(-0.65)	(31.17)	(11.88)	(0.43)	(-12.02)	(-3.1)	(-0.07)
H-L	-0.56***	0.353***	0.075	-0.095*	-0.233***	0.127*	0.06
	(-4.78)	(10.29)	(1.33)	(-1.7)	(-8.49)	(1.68)	(0.65)

t statistics in parentheses

Table 5
Double Sort on 10-K and 8-K Attention
The table shows monthly alphas of portfolios double sorted by size-adjusted 10-K and 8-K attention. For each portfolio, I regress portfolio return on Fama French five factors and momentum factor. For 8-K views, I only focus on the views on unscheduled filings.

8-K / 10-K	Low	2	3	4	High	H-L
Low	0.04	0.05	0.20	0.40**	0.67***	0.63**
	(0.43)	(0.55)	(1.52)	(2.37)	(2.67)	(2.48)
2	-0.18	-0.03	0.12	0.23	0.68***	0.86***
	(-1.52)	(-0.29)	(1.16)	(1.6)	(3.12)	(3.49)
3	-0.20	-0.06	0.06	0.34**	1.00***	1.21***
	(-1.6)	(-0.62)	(0.57)	(2.59)	(4.57)	(4.61)
4	-0.16	-0.17	-0.11	0.22*	0.44**	0.60**
	(-0.91)	(-1.59)	(-1.07)	(1.7)	(2.31)	(2.37)
High	-1.16***	-0.45***	-0.18	-0.08	-0.02	1.14***
	(-4.8)	(-2.85)	(-1.52)	(-0.64)	(-0.12)	(4.05)
H-L	-1.21***	-0.51***	-0.39**	-0.49***	-0.72***	
	(-5.03)	(-2.89)	(-2.35)	(-2.84)	(-2.94)	

t statistics in parentheses

Table 6
Panel Regression of Private Information
The table shows the monthly panel regression of next-month information asymmetry proxy on current month investor attention to filings. The dependent variables are the next-month quote spread (Corwin and Schultz (2012)) and Amihud (2002) measure. Independent variables include the log views of filings, current information asymmetry measure, and firm characteristics shown in Table 3. Time and firm fixed effects are included. Standard errors are two-way clustered by time and firm.

	(lead asy proxy)	
	(1)	(2)
	spread	amihud
log views$_{10K}$	-0.00742	-0.113
	(-1.48)	(-1.06)
log views$_{8K}$	-0.00626*	-0.172***
	(-1.82)	(-2.69)
log views$_{10Q}$	0.00698	0.0641
	(1.54)	(0.71)
asy proxy	0.283***	0.441***
	(14.71)	(6.16)
Asset Growth	-0.0197***	0.0501
	(-2.87)	(0.55)
log(BM)	0.0145	-0.198
	(1.52)	(-0.76)
log(ME)	-0.213***	-1.843***
	(-15.76)	(-5.68)
Operating Profit	-0.00167	-0.0675
	(-0.85)	(-1.44)
$r_{1,0}$	0.0386	-0.203
	(1.42)	(-0.19)
$r_{12,2}$	-0.0384***	0.0766
	(-5.73)	(0.84)
Abnormal Trading Volume	-0.00438***	-0.0614***
	(-3.36)	(-3.84)
SUE	-0.0466	-0.740**
	(-1.54)	(-2.13)
Earning Drift	0.0214	0.556**
	(1.09)	(2.31)
file 10K	0.0116	0.00526
	(0.90)	(0.04)
file 8K	0.0268***	0.142***
	(2.93)	(2.69)
file 10Q	0.0172***	0.169**
	(2.94)	(2.15)
Time and Firm FE	Yes	Yes
N	449278	448647
adjusted R^2	0.389	0.352
F	56.97	21.78

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7
8-K Attention and Information Asymmetry
The table shows monthly alphas of portfolios sorted by size-adjusted 8-K views and information asymmetry. I use Amihud illiquidity measure and previous quarter earning forecast dispersion to measure ex-ante information asymmetry. For each portfolio, I regress portfolio return on Fama French five factors and momentum factor. For 8-K views, I only focus on the views on unscheduled filings.

Panel A: Double Sort by Size-adjusted 8-K Views and Amihud

Amihud/Views	Low	2	3	4	High	H-L
Low	0.09	0.01	0.10	0.10	-0.03	-0.12
	(1.17)	(0.12)	(1.33)	(1.32)	(-0.32)	(-1.08)
2	0.21**	0.12	0.21**	0.26**	-0.12	-0.34*
	(2.22)	(1.11)	(2.01)	(2.22)	(-0.69)	(-1.71)
High	0.81***	0.72***	0.67**	0.45***	0.04	-0.72**
	(4.2)	(3.3)	(2.58)	(3.46)	(0.1)	(-2.31)
H-L	0.73***	0.71***	0.57**	0.35**	0.07	-0.6**
	(3.36)	(2.94)	(2.11)	(2.13)	(0.18)	(-2.12)

Panel B: Double Sort by Size-adjusted 8-K Views and Past Forecast Dispersion

Forecast Dispersion/Views	Low	2	3	4	High	H-L
Low	0.32***	0.08	0.21**	0.22**	0.18**	-0.13
	(3.68)	(0.97)	(2.6)	(2.57)	(2.07)	(-1.16)
2	0.15*	0.19**	0.20**	0.06	-0.09	-0.24*
	(1.66)	(2.02)	(2.05)	(0.58)	(-0.74)	(-1.69)
High	0.17	-0.09	-0.14	-0.15	-0.54***	-0.71***
	(1.29)	(-0.61)	(-0.88)	(-0.93)	(-2.65)	(-3.27)
H-L	-0.15	-0.18	-0.34*	-0.37*	-0.72***	-0.58***
	(-0.87)	(-0.95)	(-1.85)	(-1.91)	(-3.2)	(-2.85)

t statistics in parentheses

Table 8
8-K Attention, Distance to Headquarters, and Frequent Viewers
The table shows monthly alphas of equal-weighted portfolios sorted by size-adjusted 8-K views, conditional on geographical distance distribution to headquarters and frequent viewer ratios. Geographical distance is the value-weighted distance between the location of viewing IP and the firm headquarter. I classify a view as a frequent view if the IP address visited any firm filings in the past three months. Frequent visitor ratio is the ratio between the numbers of frequent and infrequent views. For each stock at each month, I first sort stocks by geographical distance (frequent visitor ratio) into terciles. Conditional on each tercile, I then sort stocks by size-adjusted 8-K views into quintiles. For each portfolio, I regress portfolio return on Fama French five factors and momentum factor, and report the alphas.

Panel A: Double Sort by Size-adjusted 8-K Views and Distance

distance/8-K views	Low	2	3	4	High	H-L
Low	0.55***	0.37***	0.31**	0.12	-0.03	-0.48***
	(4.67)	(3.48)	(2.44)	(1.28)	(-0.24)	(-3.61)
2	0.54***	0.48***	0.20	0.06	-0.11	-0.65***
	(4.27)	(3.7)	(1.55)	(0.43)	(-0.75)	(-4.21)
High	0.44***	0.17	0.47***	0.41**	0.26	-0.18*
	(3.11)	(1.2)	(3.71)	(2.55)	(0.96)	(-1.73)
H-L	-0.12	-0.21	0.16	0.28*	0.29	0.31**
	(-0.95)	(-1.56)	(1.11)	(1.69)	(1.38)	(-2.32)

Panel B: Double Sort by Size-adjusted 8-K Views and 8-K Freq Ratio

$freq^{8K}$/8-K views	Low	2	3	4	High	H-L
Low	0.44***	0.38***	0.23*	0.45***	0.21	-0.25
	(3.17)	(3.15)	(1.77)	(3.95)	(1.64)	(-1.62)
2	0.47***	0.45***	0.30**	0.13	-0.02	-0.49***
	(3.57)	(3.63)	(2.4)	(0.94)	(-1.43)	(-2.95)
High	0.35***	0.28**	0.19	-0.11	-0.07	-0.42***
	(3.19)	(2.03)	(1.64)	(-0.82)	(-0.41)	(-2.8)
H-L	-0.06	-0.08	-0.01	-0.53***	-0.27*	-0.17*
	(-0.51)	(-0.55)	(-0.11)	(-4.02)	(-1.81)	(-1.77)

t statistics in parentheses

Table 9
8-K Attention and Information Content
The table shows monthly alphas of portfolios sorted by size-adjusted 8-K views and cumulative abnormal returns around filing and event date of unscheduled 8-K filings. For each unscheduled 8-K filings, I calculate the cumulative abnormal return relative to the market around event and filing date. I then double sort stocks by the size-adjusted 8-K attention and the cumulative abnormal return into 5-by-3 blocks. Conditional on each abnormal return tercile, I regress the long/short size-adjusted 8-K portfolio return on Fama French five factors and momentum factor. For stocks with multiple unscheduled filings in a month, I choose the one with the highest absolute abnormal return.

Panel A: Double Sort by Size-adjusted 8-K Views and Abnormal Returns

abret/views	Low	2	3	4	High	H-L
Low	0.36**	0.22	-0.05	-0.01	-0.38*	-0.76***
	(2.05)	(1.07)	(-0.23)	(-0.04)	(-1.77)	(-3.19)
2	0.32**	0.41***	0.18	0.36***	0.11	-0.23*
	(2.5)	(3.18)	(1.57)	(3.06)	(-0.11)	(-1.78)
High	0.65***	0.53***	0.36*	0.13	-0.33	-0.99***
	(3.66)	(3.07)	(1.74)	(0.61)	(-1.64)	(-4.39)
H-L	0.28	0.31	0.41**	0.14	0.05	-0.23
	(1.43)	(1.28)	(2.03)	(0.5)	(0.21)	(-0.72)

Panel B: Double Sort by Size-adjusted 8-K Views and Unexpected Abnormal Returns

unexpected abret/views	Low	2	3	4	High	H-L
Low	0.38**	0.20	-0.04	-0.05	-0.36*	-0.76***
	(2.2)	(0.96)	(-0.21)	(-0.21)	(-1.68)	(-3.15)
2	0.28**	0.40***	0.15	0.43***	0.02	-0.27
	(2.22)	(3.06)	(1.37)	(3.73)	(0.17)	(-1.65)
High	0.69***	0.48***	0.36*	0.11	-0.36*	-1.07***
	(3.94)	(2.8)	(1.82)	(0.53)	(-1.77)	(-4.69)
H-L	0.31	0.29	0.40*	0.16	0.00	-0.31
	(1.62)	(1.15)	(1.97)	(0.58)	(0.0)	(-1.45)

t statistics in parentheses

Table 10
8-K Attention and Speed of Information Diffusion

The table shows monthly alphas of portfolios sorted by size-adjusted 8-K views and firms' past speed of information diffusion. For each unscheduled 8-K filings, I calculate the number of days needed for the views to reach 50% of total views by the end of a 30th day. Therefore, the more days it needs, the lower the speed of information diffusion for the filing. For each firm and each month, I calculate the average number of days needed for all filings in the past 24-month and multiply it by -1 to proxy for speed of information diffusion. I then double sort stocks by the size-adjusted 8-K attention and the speed of information diffusion into 5-by-3 blocks. Conditional on each speed tercile, I regress the long/short size-adjusted 8-K portfolio return on Fama French five factors and momentum factor.

speed/views	Low	2	3	4	High	H-L
Low	0.57***	0.37***	0.27*	0.33**	-0.24	-0.82***
	(4.22)	(2.65)	(1.86)	(2.12)	(-1.27)	(-4.25)
2	0.32**	0.53***	0.12	0.01	-0.09	-0.41**
	(2.23)	(3.38)	(0.89)	(0.05)	(-0.59)	(-2.35)
High	0.30**	0.23*	0.37***	0.15	-0.05	-0.36*
	(2.49)	(1.71)	(2.94)	(0.87)	(-0.28)	(-1.72)
H-L	-0.27**	-0.15	0.10	-0.19	0.19	0.46*
	(-2.04)	(-0.89)	(0.66)	(-1.0)	(0.97)	(1.85)

t statistics in parentheses

Table 11
10-K Attention and Attention-Grabbing

The table shows monthly alphas of portfolios sorted by size-adjusted 10-K views and attention-grabbing measure. I use abnormal trading volume and maximum daily absolute return to measure attention-grabbing. Abnormal trading volume is the difference between monthly trading volume and past 12-month average trading volume, scaled by the standard deviation of past 12-month trading volume. For each portfolio, I regress portfolio return on Fama French five factors and momentum factor. For 8-K views, I only focus on the views on unscheduled filings.

Panel A: Double Sort by Size-adjusted 10-K Views and Maximum Return

Max Return/Views	Low	2	3	4	High	H-L
Low	0.29***	0.31***	0.38***	0.35***	0.60***	0.31**
	(2.9)	(3.84)	(4.58)	(4.09)	(5.86)	(2.31)
2	-0.03	-0.07	0.16*	0.33***	0.52***	0.55***
	(-0.26)	(-0.83)	(1.91)	(3.55)	(3.12)	(2.84)
High	-0.36**	-0.32**	-0.02	0.45**	0.51	0.87***
	(-2.17)	(-2.22)	(-0.11)	(2.16)	(1.63)	(3.14)
H-L	-0.65***	-0.63***	-0.40**	0.10	-0.09	0.56**
	(-3.3)	(-3.41)	(-2.18)	(0.49)	(-0.31)	(1.99)

Panel B: Double Sort by Size-adjusted 10-K Views and Abnormal Trading Volume

Abnormal Trading Volume/Views	Low	2	3	4	High	H-L
Low	-0.31***	-0.23**	-0.12	-0.19	0.06	0.38*
	(-2.7)	(-2.29)	(-1.05)	(-1.33)	(0.31)	(1.87)
2	0.01	0.03	0.27***	0.46***	0.63***	0.62***
	(0.07)	(0.35)	(2.76)	(4.04)	(3.34)	(3.31)
High	0.21*	0.09	0.31***	0.72***	1.16***	0.95***
	(1.85)	(0.9)	(2.91)	(5.5)	(5.49)	(4.16)
H-L	0.52***	0.32**	0.43***	0.91***	1.10***	0.57**
	(3.41)	(2.22)	(2.91)	(5.57)	(5.3)	(2.32)

t statistics in parentheses

Table 12
Investor Attention Portfolios Conditional on Filing Month
The table shows monthly equal-weighted alphas of size-adjusted 10-K (8-K) portfolios, conditional on whether the firm filed any 10-K (8-K) in the month. I then regress the portfolio return on Fama French five factors and momentum factor. For 8-K attention and filings, I only focus on the unscheduled filings.

Panel A: Double Sort by Size-adjusted 10-K Views and Filing Month

Filing Month/Views	Low	2	3	4	High	H-L
No	-0.04	-0.03	0.11	0.33***	0.62***	0.66***
	(-0.49)	(-0.48)	(1.43)	(3.1)	(3.45)	(3.65)
Yes	1.44	0.56	0.02	0.34	0.62***	-0.57
	(1.59)	(1.05)	(0.06)	(1.39)	(2.89)	(-0.64)

Panel B: Double Sort by Size-adjusted 8-K Views and Filing Month

Filing Month/Views	Low	2	3	4	High	H-L
No	0.49***	0.48***	0.24*	0.29**	0.08	-0.36**
	(3.79)	(3.66)	(1.8)	(2.11)	(1.35)	(-2.2)
Yes	0.42***	0.43***	0.20*	0.17	-0.20	-0.62***
	(3.79)	(4.01)	(1.88)	(1.4)	(-1.45)	(-4.23)

t statistics in parentheses

Table A1
Summary statistics

The table shows the summary statistics of main variables at the firm-month level. $views_{10K}$ is the number of 10-K filing views. $views_{10Q}$ is the number of 10-Q filing views. $views_{8K}$ is the number of 8-K filing views. Asset Growth is the annual percentage change in total assets. log(BM) is the natural logarithm of book-to-market ratio. log(ME) is the natural logarithm of market capitalization. Operating Profit is the revenue minus cost of goods sold, SG&A expenses, and interest expense, divided by lagged common shareholders' equity. Abnormal Trading Volume is the difference between trading volume and previous 12-month average trading volume, scaled by the standard deviation of previous 12-month trading volume. SUE is the unexpected quarterly earnings (adjusted by median forecast earnings) divided by fiscal-quarter-end market capitalization. Earning Drift is the sum of daily returns in three days around earnings announcement. Media Coverage is the total number of news in covered by Ravenpack. file 10K/10Q/8K is the number of 10-K/10-Q/8-K filings in the month.

Variable	Obs	Mean	Std. Dev.	Min	Max	P1	P25	P50	P75	P99
$views_{10K}$	502662	133.98	1032.961	0	370231	0	17	44	110	1478
$views_{10Q}$	502662	79.868	2547.154	0	1053239	0	13	32	75	587
$views_{8K}$	502662	75.786	336.343	0	133132	0	11	31	80	655
Asset Growth	502662	.103	.348	-.679	3.197	-.471	-.038	.047	.154	1.748
log(BM)	502662	.642	.622	-1.611	7.644	-.385	.29	.518	.829	3.055
log(ME)	502662	12.979	2.092	5.535	18.626	8.603	11.439	12.908	14.404	17.85
Operating Profit	502662	.694	1.182	-6.469	9.753	-3.027	.285	.537	.925	6.16
Abnormal Trading Volume	502662	.185	1.612	-2.826	19.255	-1.926	-.76	-.22	.647	6.916
SUE	502662	-.006	.16	-6.275	1.528	-.358	-.003	0	.003	.286
Earning Drift	502662	.002	.088	-.464	.524	-.24	-.04	.001	.042	.255
Media Coverage	397780	8.306	9.512	0	407	0	2	6	11	43
file 10K	502662	.089	.319	0	1	0	0	0	0	1
file 8K	502662	1.008	1.147	0	26	0	0	1	2	5
file 10Q	502662	.253	.478	0	1	0	0	0	0	1

Table A2
10-K Attention, Distance to Headquarters, and Frequent Viewers

The table shows monthly alphas of equal-weighted portfolios sorted by size-adjusted 10-K views, conditional on geographical distance distribution to headquarters and frequent viewer ratios. Geographical distance is the value-weighted distance between the location of viewing IP and the firm headquarter. I classify a view as a frequent view if the IP address visited any firm filings in the past three months. Frequent visitor ratio is the ratio between the numbers of frequent and infrequent views. For each stock at each month, I first sort stocks by geographical distance (frequent visitor ratio) into terciles. Conditional on each tercile, I then sort stocks by size-adjusted 10-K views into quintiles. For each portfolio, I regress portfolio return on Fama French five factors and momentum factor, and report the alphas.

Panel A: Double Sort by Size-adjusted 10-K Views and Distance

distance/10-K views	Low	2	3	4	High	H-L
Low	-0.10	-0.04	0.09	0.09	0.23*	0.33*
	(-0.93)	(-0.43)	(0.92)	(0.78)	(1.69)	(1.77)
2	-0.22**	-0.17*	-0.09	0.23**	0.28*	0.49**
	(-2.29)	(-1.94)	(-0.97)	(2.12)	(1.7)	(2.59)
High	-0.05	0.02	0.11	0.38***	0.63***	0.68***
	(-0.37)	(0.19)	(1.08)	(2.82)	(2.91)	(3.0)
H-L	0.05	0.04	0.02	0.28	0.39*	0.35*
	(0.34)	(0.34)	(0.13)	(1.18)	(1.77)	(1.78)

Panel B: Double Sort by Size-adjusted 10-K Views and 10-K Freq Ratio

$freq^{10K}$/10-K views	Low	2	3	4	High	H-L
Low	0.00	-0.08	0.11	0.26**	0.63**	0.63**
	(0.02)	(-0.81)	(1.11)	(2.21)	(3.38)	(3.14)
2	-0.23***	-0.03	0.08	0.14	0.27	0.50**
	(-2.65)	(-0.41)	(0.91)	(1.22)	(1.52)	(2.5)
High	-0.09	-0.09	-0.00	0.13	0.40*	0.49*
	(-0.85)	(-1.08)	(-0.04)	(1.02)	(1.67)	(1.83)
H-L	-0.10	-0.02	-0.11	-0.16	-0.26	-0.14
	(-0.95)	(-0.19)	(-0.99)	(-1.15)	(-1.35)	(-1.25)

t statistics in parentheses

Table A3
EDGAR 8-K Filing Counts

The table shows the number of 8-K filings by section for all firms in the sample from 1994 to 2016. A filing can be categorized into multiple sections/items.

Item Code	Description	Section Count	Item Count
Section 1	Registrant's Business and Operations	210636	
Item 1.01	Entry into a Material Definitive Agreement		198726
Item 1.02	Termination of a Material Definitive Agreement		18355
Item 1.03	Bankruptcy or Receivership		4320
Item 1.04	Mine Safety		182
Section 2	Financial Information	369770	
Item 2.01	Completion of Acquisition or Disposition of Assets		43560
Item 2.02	Results of Operations and Financial Condition		262011
Item 2.03	Creation of a Direct Financial Obligation		61905
Item 2.04	Triggering Events That Accelerate or Increase a Direct Financial Obligation		3701
Item 2.05	Costs Associated with Exit or Disposal Activities		5518
Item 2.06	Material Impairments		3119
Section 3	Securities and Trading Markets	66905	
Item 3.01	Notice of Delisting or Failure to Satisfy a Continued Listing Rule or Standard		14068
Item 3.02	Unregistered Sales of Equity Securities		45151
Item 3.03	Material Modification to Rights of Security Holders		12249
Section 4	Matters Related to Accountants and Financial Statements	31476	
Item 4.01	Changes in Registrant's Certifying Accountant		25642
Item 4.02	Non-Reliance on Previously Issued Financial Statements or a Related Audit Report or Completed Interim Review		5968
Section 5	Corporate Governance and Management	262237	
Item 5.01	Changes in Control of Registrant		16682
Item 5.02	Departure/Election/Appointment of Directors or Officers; Compensatory Arrangements of Certain Officers		194313
Item 5.03	Amendments to Articles of Incorporation or Bylaws; Change in Fiscal Year		37421
Item 5.04	Temporary Suspension of Trading Under Registrant's Employee Benefit Plans		1116
Item 5.05	Amendment to Registrant's Code of Ethics, or Waiver of a Provision of the Code of Ethics		1932
Item 5.06	Change in Shell Company Status		1719
Item 5.07	Submission of Matters to a Vote of Security Holders		38456
Item 5.08	Shareholder Director Nominations		340
Section 6	Asset-Backed Securities	1052	
Item 6.01	ABS Informational and Computational Material		199
Item 6.02	Change of Servicer or Trustee		660
Item 6.04	Failure to Make a Required Distribution		43
Item 6.05	Securities Act Updating Disclosure		105
Section 7	Regulation FD Disclosure	207540	
Section 8	Other Events	421676	
Section 9	Financial Statements and Exhibits	968550	

Table A4
EDGAR 8-K Views by Sections

The table shows the total number of 8-K views by section for all firms in the sample from 2003 to 2016. If a filing is categorized into multiple sections/items, a single view of the filing is counted into multiple sections/items.

Item Code	Description	Section Count	Item Count
Section 1	Registrant's Business and Operations	234569	
Item 1.01	Entry into a Material Definitive Agreement		228676
Item 1.02	Termination of a Material Definitive Agreement		21985
Item 1.03	Bankruptcy or Receivership		1568
Item 1.04	Mine Safety		199
Section 2	Financial Information	410335	
Item 2.01	Completion of Acquisition or Disposition of Assets		35479
Item 2.02	Results of Operations and Financial Condition		308484
Item 2.03	Creation of a Direct Financial Obligation		69664
Item 2.04	Triggering Events That Accelerate or Increase a Direct Financial Obligation		2552
Item 2.05	Costs Associated with Exit or Disposal Activities		11464
Item 2.06	Material Impairments		5017
Section 3	Securities and Trading Markets	56773	
Item 3.01	Notice of Delisting or Failure to Satisfy a Continued Listing Rule or Standard		8991
Item 3.02	Unregistered Sales of Equity Securities		35529
Item 3.03	Material Modification to Rights of Security Holders		18957
Section 4	Matters Related to Accountants and Financial Statements	12015	
Item 4.01	Changes in Registrant's Certifying Accountant		7407
Item 4.02	Non-Reliance on Previously Issued Financial Statements or a Related Audit Report or Completed Interim Review		4714
Section 5	Corporate Governance and Management	264116	
Item 5.01	Changes in Control of Registrant		3399
Item 5.02	Departure/Election/Appointment of Directors or Officers; Compensatory Arrangements of Certain Officers		207761
Item 5.03	Amendments to Articles of Incorporation or Bylaws; Change in Fiscal Year		50110
Item 5.04	Temporary Suspension of Trading Under Registrant's Employee Benefit Plans		1412
Item 5.05	Amendment to Registrant's Code of Ethics, or Waiver of a Provision of the Code of Ethics		3293
Item 5.06	Change in Shell Company Status		613
Item 5.07	Submission of Matters to a Vote of Security Holders		39600
Item 5.08	Shareholder Director Nominations		167
Section 6	Asset-Backed Securities	25	
Item 6.01	ABS Informational and Computational Material		0
Item 6.02	Change of Servicer or Trustee		7
Item 6.04	Failure to Make a Required Distribution		0
Item 6.05	Securities Act Updating Disclosure		16
Section 7	Regulation FD Disclosure	246470	
Section 8	Other Events	320659	
Section 9	Financial Statements and Exhibits	938448	

Table A5
Investor Attention Portfolios Conditional on Media Coverage
The table shows monthly equal-weighted alphas of portfolios sorted by size-adjusted views and high media coverage dummy, which is equal to one if the number of news is higher than the past 12-month median.

Panel A: Double Sort by Size-adjusted 10-K Views and Media Coverage

Media/10-K views	Low	2	3	4	High	H-L
Low	-0.11	-0.14**	0.00	0.16	0.53***	0.64***
	(-1.27)	(-2.04)	(0.01)	(1.54)	(2.89)	(3.33)
High	-0.09	-0.19**	-0.00	0.20*	0.17	0.26
	(-0.92)	(-2.12)	(-0.05)	(1.79)	(0.93)	(1.27)
H-L	0.02	-0.04	-0.01	0.04	-0.36**	-0.38
	(0.19)	(-0.39)	(-0.05)	(0.31)	(-2.58)	(-1.52)

Panel B: Double Sort by Size-adjusted 8-K Views and Media Coverage

Media/8-K views	Low	2	3	4	High	H-L
Low	0.55***	0.35***	0.42***	0.26**	-0.01	-0.56***
	(4.42)	(2.9)	(3.47)	(2.25)	(-0.09)	(-4.02)
High	0.37***	0.27**	0.24**	0.03	-0.23	-0.61***
	(3.19)	(2.36)	(2.34)	(0.25)	(-1.6)	(-3.8)
H-L	-0.18	-0.09	-0.18	-0.23**	-0.23*	-0.05
	(-1.39)	(-0.75)	(-1.39)	(-2.08)	(-1.94)	(-0.33)

t statistics in parentheses