Demand for Information and Stock Returns: Evidence from EDGAR

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Abstract

This paper empirically shows that information acquisition affects stock returns by reducing information asymmetry of the firm. When firms disclose material information that was known by insiders, demand for information transforms private information into public information, drives up the contemporaneous price, and predicts persistent and negative abnormal returns. The supply of information has no direct effect on information asymmetry, but acts as a catalyst, through which the demand for information magnifies its effect. Moreover, demand for information has stronger effects when investors are geographically close to firm headquarters or have experience in collecting information, suggesting that the cost of information acquisition affects information asymmetry.

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1 Introduction

Information demand affects asset prices through two channels. First, when a firm discloses unanticipated material information, investors collect, process, and trade on the information. As a result, demand for information transforms private information into public information, reduces information asymmetry (Grossman and Stiglitz (1980)), and decreases the cost of capital (Easley and O'Hara (2004)). Therefore, contemporaneous price increases to reflect the reduced risk premium in the future. Second, when making investment decisions, investors choose from a small pool of assets because of their limited attention (Barber and Odean (2007)), and acquire information about the selected assets. Demand for information reveals asset preferences, predicts increased demand for assets, and leads to higher stock returns. The two channels have opposite predictions of future stock returns, yet the empirical literature has only pointed to asset selection channel (Da, Engelberg, and Gao (2011); Ben-Rephael, Carlin, Da, and Israelsen (2017)), and ignored information asymmetry channel. This paper is the first to empirically test the effect of information acquisition on stock returns through information asymmetry channel. Moreover, the paper highlights heterogeneous effects of information asymmetry channel by exploring variations in investors' geographical proximity to firm headquarters, and shows that the effect is stronger when firms and investors are close. The result suggests that the cost of information acquisition affects price informativeness, and provides empirical support to Verrecchia (1982).

To proxy demand for information through information asymmetry channel, I use the number of 8-K downloads in the SEC's EDGAR log data, which track individual level requests to the EDGAR system. Firms use form 8-Ks to notify investors with event-specific material information, which was privately known by insiders.[1] Starting 2003, the SEC requires 8-Ks to be filed mandatorily within four business days after the triggering event. The timely disclosure of unanticipated events makes 8-K filing a valid source for investors to acquire new information, which is crucial for information asymmetry channel.

[1] Table A3 lists various sections of 8-K forms.

I show that the effect of demand for 8-K is consistent with the prediction of information asymmetry channel. Using Fama-Macbeth regression and controlling for media coverages and a set of well known risk factors, I show that demand for 8-K predicts a significant and negative abnormal return of -12 basis points (bps) for the subsequent month. Information asymmetry channel not only implies a lower return over the short-term, but also has predictability over the long-term. If demand for information reduces information asymmetry, current price will increase, followed by a lower expected returns in the future. To study the long-term predictability of information asymmetry channel, I show that the long/short portfolio sorted on size-adjusted 8-K demand yields a positive return of 43 bps in the formation month and a persistent and negative return of -27 bps per month throughout the next 12 months.[2]

To further sharpen my hypothesis that demand for 8-K affects returns through information asymmetry channel, I decompose demand for 8-K into two parts: demand for unscheduled and scheduled 8-K. Scheduled 8-K filings contain little new information, while unscheduled 8-Ks disclose material information only known by insiders.[3] Therefore, only demand for unscheduled 8-K can potentially decrease information asymmetry between insiders and investors and affect stock returns. The results are consistent with this hypothesis. Specifically, demand for unscheduled 8-K filings predicts negative abnormal returns, whereas demand for scheduled 8-K filings has no predictability.

Having demonstrated the effect of demand for 8-K on returns, I then directly test whether demand for 8-K reduces information asymmetry of the firm. Using the price impact measure to proxy information asymmetry (Huang and Stoll (1996)), I show that firm disclosures act as a catalyst, through which demand for information reduces firms' information asymmetry. In a weekly panel regression, the supply of 8-K has no direct effect on future information

[2]Throughout the paper, I use Fama-French five factors and UMD factor as the testing model unless specified otherwise. When conducting portfolio sort analysis, I use the size-adjusted information demand, because large firms have larger downloads volume in EDGAR. Similar procedure is also used in Nagel (2005).

[3]Around 10% of the total 8-K filings are scheduled filings. Such filings are typically categorized by the SEC under Item 2.02. A typical example is the announcement of the recent conference calls to discuss its earnings. All the non-public information is transmitted to the public during the conference calls, leaving the scheduled 8-K filing with no additional information to be learned by investors.

asymmetry. Demand for 8-K reduces information asymmetry, and its effect increases when there is information disclosure.

Consistent with the mechanism, I show that information asymmetry channel is concentrated in firms with high ex-ante information asymmetry. In other words, information acquisition has more potential in reducing the information asymmetry when firms have high information asymmetry. For example, the low media and analyst coverage makes it more difficult for small firms to disseminate information, resulting in a high cost of external financing. Therefore, firms and investors rely more heavily on the EDGAR platform, and the timely information acquisition has larger effects on stock returns.

Verrecchia (1982) proposes that the cost of information acquisition increases with information asymmetry. Using cross-section variation in demographics of investors and their past visiting patterns, I show that demand for 8-K has stronger effects when investors are geographically close to firm headquarters, or when they are more experienced in collecting information. Local viewers and frequent viewers tend to have an information advantage in terms of collecting and processing information (Nieuwerburgh and Veldkamp (2009)), thus having a lower cost of information acquisition. To the best of my knowledge, my paper is the first to empirically test how cost of information acquisition affects information asymmetry using individual-level data, which complements the theoretical claim in Verrecchia (1982).

Furthermore, I show that the effect of information acquisition through information asymmetry channel increases with the unexpectedness of the 8-K filing event, regardless of whether the event is good or bad news. I construct two measures to quantify the unexpectedness of the event. The first measure is the abnormal returns three days around event date. While abnormal returns capture market reactions to the event, it may also reflect investors' belief updating on future cash flows. The second measure is based on textual analysis and machine learning method. I create an unexpected abnormal return measure, which is the difference between the abnormal return of the event and the average abnormal return of 8-Ks with similar contexts. The larger the magnitude of the abnormal return is, the more unexpected the event is. The sign of the abnormal return indicates whether the news is good or bad. I show that the effect of the 8-K demand on stock returns is the strongest when the event is unexpected. That is, the 8-K portfolio yields large negative future returns/alphas, conditional on events with a large magnitude of abnormal return, regardless of whether the event is good or bad. The result also alleviates the concern that the underperformance of the 8-K portfolio is driven by bad news.

However, if information is already incorporated in the market, demand for information reflects investors' interest in the assets, which is captured by the asset selection channel. I use the number of 10-K downloads to proxy the demand for information in the asset selection channel. The Form 10-Ks provide investors with comprehensive financial and operational statements, which are useful for fundamental investment. For example, Deaves, Dine, and Horton (2006) surveys 1,600 retail investors and finds that the majority of shareholders read and use financial statements to make investment decisions. Such interests of assets are tilted towards the purchasing decisions because of the short-selling constraint faced particularly by retail investors. Unlike 8-K filings, there is a significant report lag between the fisical end date and disclosure date.[4] The long reporting lag of 10-Ks discourages investors who trade on time-sensitive information, most of which is previewed to the market either through earnings announcements or previous 8-K filings. As a result, demand for 10-K is likely to affect stock returns through the asset selection channel, rather than the information asymmetry channel, where timely processing of information is more valued.

The predictability of demand for information on stock returns through asset selection channel should be short-lived. In a perfectly efficient market, a demand shock will only lead to an increase in the contemporaneous price. Under certain frictions, the demand shock will be incorporated into prices in a short period, resulting in an alpha decay pattern.[5] Consistent with the intuition, I show that the long/short portfolio sorted on size-adjusted

[4]Starting 2003, the filing deadline for 10-Ks is 75 days for accelerated filers and 90 days for non-accelerated filers. The average report lag in my sample is 81 days.

[5]For example, the time lag between information acquisition and investment decision making can introduce the decay pattern.

10-K demand earns an alpha of 82 bps in the formation month, 65 bps in the first holding month, and 20 bps in the second holding month. Although demand for 10-K and demand for 8-K have similar prediction in contemporaneous prices, they have opposite predictions of future returns.

One important driving force of the difference in effects between 8-K and 10-K demand is that, 10-Ks are filed only once a year, so that the majority of the downloads happen outside the short time window around the disclosure date.[6] It does not mean that there is nothing to be learned from annual filings to reduce information asymmetry. In fact, when I limit the sample to the weeks when firms just disclose 10-Ks, demand for newly disclosed 10-Ks has similar effect with demand for 8-K. That is, the effect of 10-K demand flips from asset selection channel to information asymmetry channel if information acquisition happens during this limited time window. The result simply points out that, given the nature of low disclosure frequency, the asset selection channel dominates demand for 10-K most of the time.

This paper contributes to the literature in several ways. This paper is the first to empirically test the role of information acquisition in reducing information asymmetry, examine its effect on stock returns, and explore its heterogeneous effect through the cost of information acquisition channel, which complements a stream of theoretical work starting from Grossman and Stiglitz (1976). The fact that the information asymmetry channel is more pronounced in small firms with low liquidity has important implications. These firms face higher costs of external financing and have disadvantages to timely communicate with investors due to low coverages. Finding ways to lower the communication cost becomes an important challenge. As a result, firms and investors rely heavily on the EDGAR to timely disseminate information.

The paper also contributes to the recent and growing literature on investor attention. This paper highlights the different aspects of investor attention on stock returns. Prior lit-

[6]Loughran and McDonald (2017) shows that over 78% of 10-K downloads happen after the first filing month.

erature has focused on the asset selection channel by examining Google Trends (Da et al. (2011)) or Bloomberg news search (Ben-Rephael et al. (2017)). These measures do not differentiate sources of information, so that the dominant force (asset selection channel in this case) drives results. I show that, by taking into account different aspects of information acquisition, both asset selection channel and information asymmetry channel can be estimated simultaneously.

The paper is also one of the first to explore individual level geographical variation in information acquisition, which contributes to the literature on the home bias (Nieuwerburgh and Veldkamp (2009), Bernile, Kumar, and Sulaeman (2015)). The results suggest that local investors have an information advantage, and their demand for information has larger effects on prices through the information asymmetry channel.

The paper also informs the debate on whether the supply side of information reduces information asymmetry. For example, Amiram, Owens, and Rozenbaum (2016) finds that analyst forecast disclosure reduces information asymmetry during the announcement-period, whereas Coller and Yohn (1997) shows that earnings announcements and management forecasts increase information asymmetry. I show that the supply of information has no direct effect on future information asymmetry, but acts as a catalyst through which demand for information reduces information asymmetry. Therefore, the seemingly contradicted evidence of information supply on information asymmetry could be driven by the omitted demand for information.

The paper proceeds as follows. Section 2 discusses the sample selection and provides an overview of EDGAR log data. Section 3 jointly test the asset selection channel and the information asymmetry channel. Section 4 discusses the mechanisms of 8-K demand on prices. Section 5 shows the differential effects of 8-K demand. Section 6 shows that demand for 10-K captures investors' preference for assets. Section 7 concludes.

2 Data and Sample Selection

The paper uses data from several sources. I use CRSP, Compustat, I/B/E/S, and TAQ 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[7], and the EDGAR Master File to obtain filing type and date. To control for media coverage, I use Ravenpack news data. Ravenpack news data provide news coverage for a large sample of public companies[8]. I also control for Google Trends and Bloomberg News Heat Index. Google Trends data provide within-firm daily Google search volume index and are often used to capture retail investors' attention. Bloomberg index captures the news search volume by Bloomberg users and are used to capture institutional investors' attention. The data start from 2010/02/17.

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 EDGAR 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[9], the index page

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

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

[9]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.

flag[10], server status code[11], 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, Ma, and Wang (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. 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. I then aggregate the file requests at the firm and 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 sea-

[10] 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.

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

sonality 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 2 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 3 shows the number of filing downloads by IPs' proximity to firm headquarters. I classify a filing view into the home group if the distance between the IP's physical location 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 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 4 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.

3 The Two Channels of Information Demand

In this section, I use three approaches to test the asset selection channel and the information asymmetry channel. First, I run monthly Fama-Macbeth (1973) cross-section regression of returns on heterogeneous measures of information demand. Second, I use non-parametric approach by forming long/short portfolios and regressing portfolio returns on factors. Third, I use weekly level data to disentangle the information supply from the information demand. Since an average firm files one 8-K filing per month, the weekly level setting allows me to better control the supply of information, whereas the monthly level analyses are widely used in the literature.

3.1 Fama-Macbeth (1973) Approach

I first study the relation between future stock returns and the overall demand on EDGAR. I run Fama-Macbeth (1973) regression of monthly individual stock returns from month $t+1$ on information demand 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 demand 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 demand 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 the past 12-month trading volume. Since many of my information demand variables capture investor demand 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 1 shows the baseline result. Asset growth, firm size, operating profit, unexpected earnings, abnormal trading volume, and abnormal earning announcement returns can explain cross-section stock returns. I then add the aggregated demand for 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). The effect of aggregated demand for information is consistent with the finding in the literature, that the asset selection channel plays a dominant role in determining stock returns.

To disentangle the asset selection channel and information asymmetry channel, I split the aggregated views by their filing types. Demand for 10-K and 10-Q is more likely to capture the general demand for the asset, as forms 10-K and 10-Q provide investors with a comprehensive overview of the firm. Information on the firm's balance sheet is also widely used to make fundamental investing decisions. 10-K/Qs are often filed with significant delays, so that the demand for these filings responds to information that is relatively time-insensitive. Forms 8-K, on the other hand, are filed irregularly and contains information that is privately known by insiders. Under the SEC disclosure regulation, the material information needs to be disclosed within four business days. Demand for 8-K transforms the disclosed information into public information and reduces the information asymmetry between insiders and investors.

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, which is consistent with 10-K views capturing the asset demand. The coefficient of *log* $views_{10Q}$ is insignificant, and its magnitude is relatively small. There are two driving forces of the result. First, the correlation between 10-K views and 10-Q views is 0.91 over the full panel. As a result, 10-Q views do not provide additional variation beyond 10-K views in explaining stock returns in the future. Second, the substance and quality of forms 10-K and 10-Q differ. Forms 10-K are required to be audited, whereas Forms 10-Q are not. In addition, the MD&A section in Forms 10-K are much more detailed than in Forms 10-Q[12]. As a result, Form 10-K is a more reliable source for investment reference than Form 10-Q.

The demand for 8-K captures the information asymmetry channel. Demand for 8-K filings reduces the information asymmetry of the firm. As a result, investors require a lower risk premium to hold the asset. Firms with high 8-K demand earn less return in the future (12 bps per month), as can be seen from the negative and significant coefficient estimates of $log\ views_{8K}$. To further sharpen the result, I split the 8-K views into the scheduled and unscheduled 8-K views. The scheduled 8-K filing includes pre-scheduled event, such as earnings announcements and annual shareholder meetings. These scheduled reports typically contain information that is known by the market. Therefore, the demand for scheduled 8-K should have no predictability under the information asymmetry channel. Unscheduled filings disclose material information that was only known by insiders. It requires investors to timely collect, process, and incorporate the information into the market. Therefore, the demand for unscheduled 8-K should drive the result. In Column (4), the results are consistent with the hypothesis. The coefficient of unscheduled 8-K views is negative and significant, and the coefficient of schedule 8-K is insignificant.

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 demand for firm filings using a portfolio sorting approach. Since large firms naturally receive higher views than small firms, it is important to control for firm sizes when sorting on views, especially for the 10-K views[13]. At each month, I first run a cross-section regression of the natural log views on the natural log of lag

[12]For example, MD&A section of IBM Form 10-K spans 50 pages in 2018, and only 20 pages in 2019Q1.

[13]The correlation between the log of 10-K views and firm size is 0.56, and the correlation between the log of 8-K views and firm size is 0.34.

firm size and extract regression residuals as the size-adjusted demand for information. I then sort stocks into quintiles by the size-adjusted demand. Such procedure is also used in Nagel (2005). 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 2 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. Moreover, the effect of 10-K demand is short-termed, which can be seen from the insignificant alphas with three or twelve holding months.

Panel B of Table 2 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 demand is long-lasting. The 12-month holding alpha is around -0.6% per month and highly significant.

Panels C and D of Table 2 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.

The two channels of information demand have not only opposite predictions in the short term, but also suggest distinct patterns in the long term. For the asset selection channel, we should see the strongest evidence of positive contemporaneous return spread, followed by an alpha decay pattern. The speed of the alpha decay process relies on the liquidity of the underlying asset and the time lag between information acquisition and investment decision making. For the information asymmetry channel, the contemporaneous price should increase to reflect the risk reduction going forward, followed by a permanent decrease in risk premium. Therefore, the contemporaneous return spread is positive, and future return spread is negative and persistent.

Figure 6 shows the persistence of long/short portfolio return and alpha. I sort stocks by size-adjusted 10-K (8-K) demand 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 portfolio formation month and decay very quickly. The average alpha is 86 bps at month 0, 24 bps at month 2, and only 6 bps at month 4. The 8-K portfolio shows the opposite pattern. The portfolio return at formation month is positive and then becomes negative and highly persistent over the next 12 months. The distinct long term return patterns of 10-K and 8-K portfolios strongly support the hypothesis, that the demand for 10-K filings captures the general asset demand and the demand for 8-K filings reduces the information asymmetry of the firm.

Since I use size-adjusted views as the sorting variables, it is interesting to see how 10-K and 8-K portfolios perform under different size groups. At each month, I first sort stocks by their previous month market capitalization into quintiles. Conditional on each size quintile, I then sort stocks by the size-adjust 10-K (8-K) views into quintiles and form the long/short portfolio by buying the top quintile stocks and selling the bottom quintile stocks.

Figure 7 shows the result. Portfolios sorted on size-adjusted 10-K views yield positive and significant alphas across all size quintiles. The result is the strongest in the small size quintile, yielding 1.2% alpha per month. The magnitude of the alpha decreases with firm size. Both the liquidity and the short-selling constraint contribute to the result. Small firms are more illiquid than large firms. When facing a demand shock, small stocks face a larger price impact than large stocks. Moreover, small stocks have a tighter short-selling constrain than large stocks, which also limits the potential arbitrage opportunities and results in a large price increase.

Portfolios sorted on size-adjusted 8-K views yield negative alphas across all size quintiles, but alphas are significant for the bottom three size quintiles and insignificant for large stocks. For example, the 8-K portfolio yields an average alpha of -40 bps per month for the bottom three size quintiles, and -10 bps for the top two quintiles. The result is consistent with the information asymmetry reduction hypothesis. Small firms have less media/analyst coverage and institutional holding than large firms. Investors of small firms face a higher degree of information asymmetry and rely more on themselves in processing and incorporating the disclosed information. Therefore, demand for 8-K filings has a stronger effect in small firms than in large ones.

3.3 Weekly Frequency Result

This section demonstrates the heterogeneous effect of information acquisition on stock prices at the weekly frequency. Forms 10-K (10-Q) are filed once (three times) a year in general. Forms 8-K are filed irregularly, but once a month on average. Therefore, weekly level analysis allows me to study the interaction between the supply and the demand for information and their effects on prices.

I aggregate the daily stock returns and daily views to weekly frequency (Friday close to Friday close). My main variable of interest is $\log(views_t^k)$, which is the natural logarithm of total views of filing type k in week t. I then create a set of dummies to capture the information supply. The dummy variable $Filing\ k_t$ is equal to one if the firm has issued filings of type k in week t. The dummy variable $News_t$ is equal to one if the firm appears in the Ravenpack news database in week t. The dummy variable $Earnings\ Release_t$ is equal to one if the firm releases its earnings in week t. For a subset of the analysis[14], I also control for the Bloomberg search index and Google Trends, which capture the institutional and retail demand studied in the previous literature (Ben-Rephael et al. (2017), Da et al. (2011)). The dummy variable AIA_t is equal to one if the Bloomberg News Heat daily index has a maximum of 3 or above in week t. The dummy variable $DADSVI_t$ is equal to one if the Google Trends daily index in any day of the week is above its 90 percentile in the past month.

[14] Bloomberg News Heat index is only available after 2010/02/17.

Table 4 shows the weekly regression result. I regress the weekly stock returns on the demand for filings, controlling for the supply side of information, firm characteristics, lag returns, and time fixed effects. To capture the interaction between supply and demand of information under information asymmetry channel, I add the interaction term between the supply and demand of 8-K filings. Columns (1) and (3) study the contemporaneous relation between stock returns and demand for information, where the dependent variable is the current week stock returns. The dependent variables in Columns (2) and (4) are the next week stock returns.

As shown in Columns (1) and (2) of Table 4, the coefficient estimates of $\log(views_t^{10K})$ are all positive and significant, consistent with the asset selection hypothesis. The coefficient estimate of the interaction term between 8-K supply and demand is positive and significant in Column (1), and is negative and significant in the Column (2). The results support the information asymmetry channel. When firms release new information through 8-K filings, it relies on investors to acquire the information, thus reducing the information asymmetry. Therefore, the contemporaneous price increases, and future risk premium decreases. Both the asset selection channel and information asymmetry channel are robust after controlling for the Bloomberg and Google Trends search indexes, which are shown in Columns (3) and (4).

Figure 8 replicates the analysis in Figure 6 using weekly data, and the results are consistent. At the end of each week, I sort stocks by the size-adjusted weekly 10-K and 8-K views into quintiles, and form long/short portfolios. Portfolios are held throughout the next 24 weeks. The alphas of portfolios at each holding week is plotted. For 8-K portfolios, I limit the set of stocks that filed 8-K filings in the week, as the evidence suggested in Table 4 shows that the effect of 8-K demand is stronger, conditional on the supply of information.

The results do not imply that the demand for 10-K filings does not reduce information asymmetry. It merely states that the asset selection channel dominates, and it is hard to empirically disentangle the two channels because of the low disclosing frequency. To test whether demand for newly disclosed 10-K filings reduces information asymmetry, I limit my sample to a set of stocks that just disclosed 10-Ks in a week. I then sort these stocks on the size-adjusted view counts of the newly issued 10-K filings into quintiles. The result is plotted in Figure 9. Conditional on firms just issued 10-Ks in week 0, firms with high demand for new document yield higher returns in the contemporaneous week, and lower returns in the upcoming weeks. The effect of 10-K demand flips to the information asymmetry channel in this small subset. The long-term return pattern is comparable to the one found in 8-K filings. However, the alpha is noisily estimated, since only a small portion of firms file 10-K in a given week.

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 demand 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 demand underperform stocks with low 8-K demand and the underperformance is highly persistent over time. Moreover, the effect of 8-K demand should also depend on the ex-ante information asymmetry the firm is facing.

To test whether demand for information reduces the information asymmetry, I run a weekly panel regression of future information asymmetry on information acquisition, controlling for firm characteristics and information disclosure. The result is shown in Table 5. I use the price impact measure estimated following Holden and Jacobsen (2014) to proxy information asymmetry of the firm. For a given stock, the price impact on the k^{th} trade is defined as

$$Price\ Impact_k = \frac{2D_k(M_{k+5} - M_k)}{M_k}, \tag{1}$$

where M_{k+5} is the midpoint five minutes after the midpoint M_k, and D_k is the buy-sell indicator of the trade. The price impact measure captures the permanent component of the effective spread, and captures the information asymmetry of the firm. In column (1), the coefficient estimates of $log\ views_{8K}$ is negative and significant, suggesting that higher information acquisition of 8-K is associated with lower information asymmetry in the next month. The supply of 8-K also reduces the information asymmetry, as can be seen by the negative coefficient estimates of *Filing 8K*. However, once we interact the demand and supply of 8-K filing, the supply of 8-K does not have any significance, which is shown in column (2). The interaction term between 8-K demand and supply is negative and significant, showing that the demand for 8-K has a stronger effect in reducing information asymmetry, conditional on new information arrivals.

The effect of 8-K demand on stock returns should be larger when the ex-ante information asymmetry is higher. To proxy 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 demand into quintiles. Table 6 shows the portfolio double-sort results for 8-K demand and information asymmetry. When Amihud measure is low, the alpha of long/short 8-K demand 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 effects 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 an information advantage to collect and process information over non-local investors. Therefore, holding the level of information acquisition fixed, firms with more local demand for information have a 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 4 can be used as a 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 7 shows the portfolio double-sort results by 8-K demand 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 demand 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 7 studies the effect of 8-K demand on prices, 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 demand 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 demand 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 reports about the pre-scheduled meetings, do not convey any private information. Others, such as material agreement and change of officers, require investors' attention to interpret the information. Therefore, it is important to see how the effect of information demand interacts 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[15]. 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 represents 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

[15] 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 the 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 demand 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 8. 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 a similar result. The relation between 8-K demand and abnormal return exhibits a "V-shape". The effect of 8-K demand 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 demand does not predict future returns.

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 demand for 10-Ks on stock prices is a byproduct of demand shocks to assets. That is, the demand for asset drives up the demand for 10-K filings and stock prices. As a result, we should expect the effect of 10-K demand 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 attention-grabbing stocks. Abnormal trading volume and daily absolute returns are constructed as the following,

$$abvol_{i,t} = \frac{vol_{i,t} - \bar{vol}_{i,t-1,t-12}}{std\_vol_{i,t-1,t-12}}, \tag{2}$$

$$max\_dret_{i,t} = \max_{d \in t} \mid ret_{i,t,d} \mid \tag{3}$$

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 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 demand into quintiles.

Panel A of Table 9 show the alphas of double-sorted portfolios for abnormal trading volume and 10-K views. The last column shows the alphas of long/short 10-K demand 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 stocks with high 10-K demand.

7 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 a general demand for the asset, so that a spike in 10-K demand predicts short-term positive future returns. The effect of 10-K demand is stronger among attention-grabbing stocks. The alpha of the 10-K demand 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 demand stocks persistently underperform low 8-K demand stocks due to the reduced risk premium.

The effect of 8-K demand on stock returns is stronger for small firms. Small firms have lower institutional holdings, analyst coverage, and media exposure. Therefore, the communication through the EDGAR play a more important role for management teams of small firms to deliver their messages to investors. Investors of small firms also rely more heavily on the EDGAR to gain insights of the firm's operations. Timely processing the disclosed information reduces the information asymmetry between insiders and investors, leading to a reduction in the cost of capital. Such channel is more valuable for small firms, as they are the ones facing higher financing costs.

The paper also finds that, the effect of 8-K demand is higher when the cost of information acquisition is lower. The cost of information acquisition is not just about collecting information, but also about processing and interpreting the information. Local investors and investors who frequently download firm filings have such information advantages, and their information demand has a higher effect on stock returns than non-local and inexperienced investors. Although firms cannot choose the composition of their investors, they have controls over how to efficiently disclose the information and lower the cost. For example, various studies have shown that disclosure quality and readability affect the information environment.

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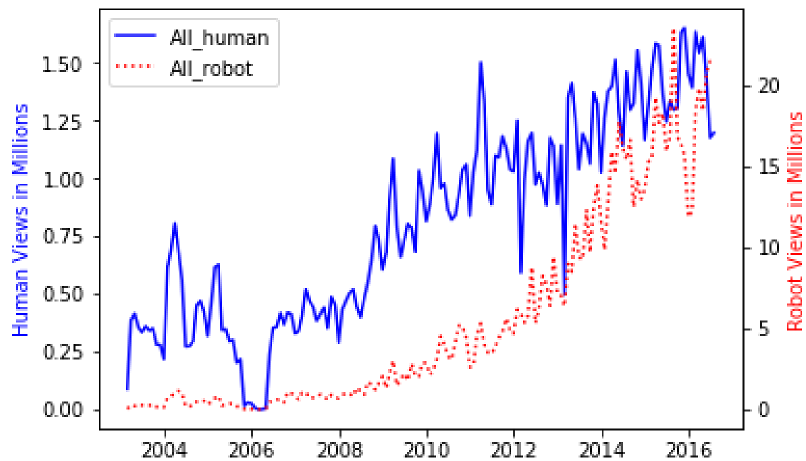
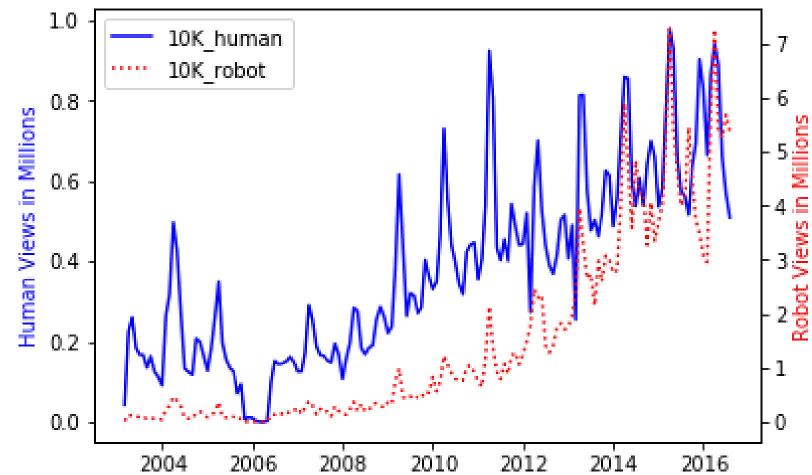
Figure 1

Time-series EDGAR Viewing Activity

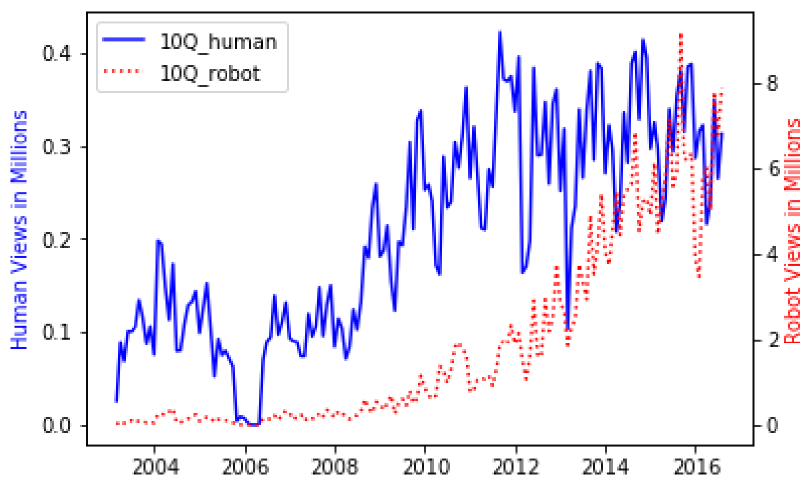
The figure shows the monthly aggregated number of views on EDGAR Log system. Following Lee et al. (2015), I separate crawling activities ("robot") from human viewing activities ("human"). Figures (b) to (d) show the number of views for 10-K, 10-Q, and 8-K filings, respectively.



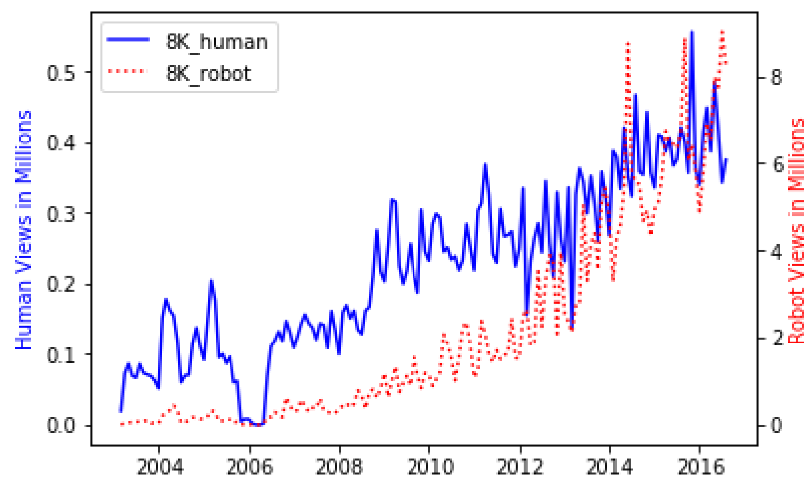
(a) All Filings



(b) 10-K Filings



(c) 10-Q Filings



(d) 8-K Filings

Figure 2

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. $views^{only}_{10K}$ is the total number of 10-K views by visitors who have not downloaded any 8-K filings of the firm. $views^{both}_{10K}$ is the total number of 10-K views by visitors who have downloaded one or more 8-K filings of the firm.

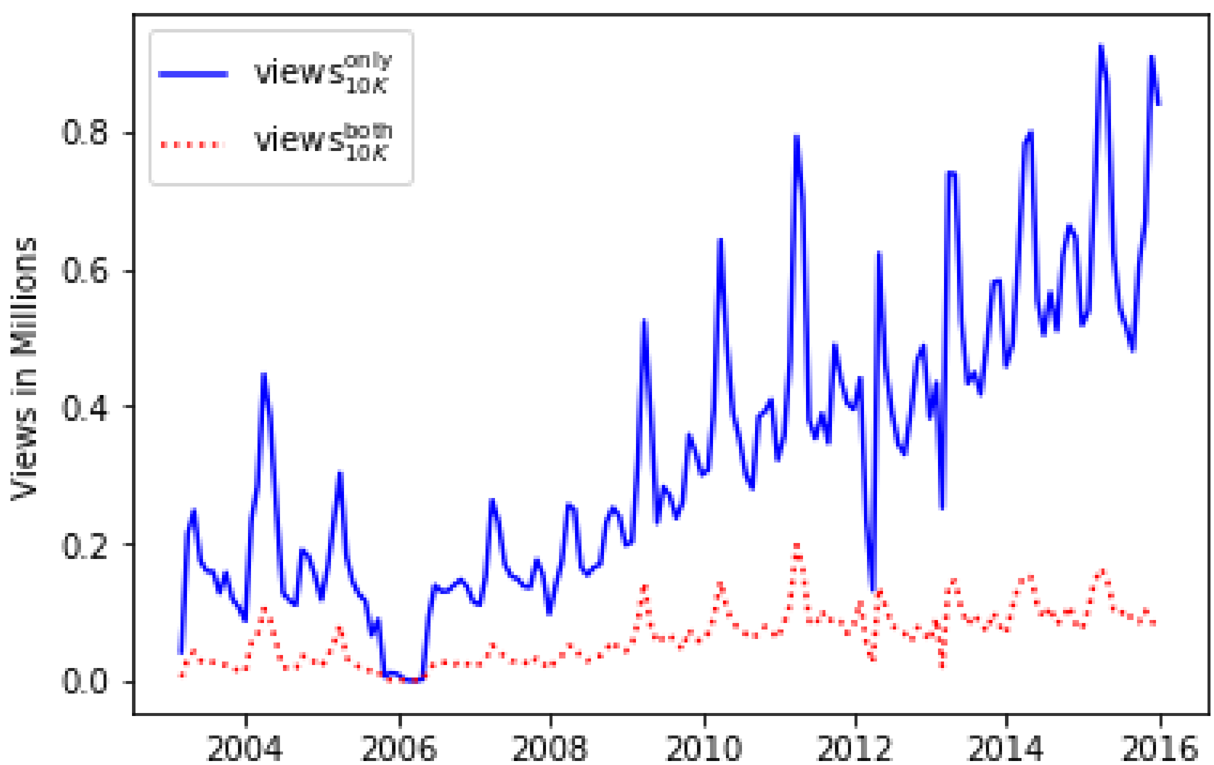
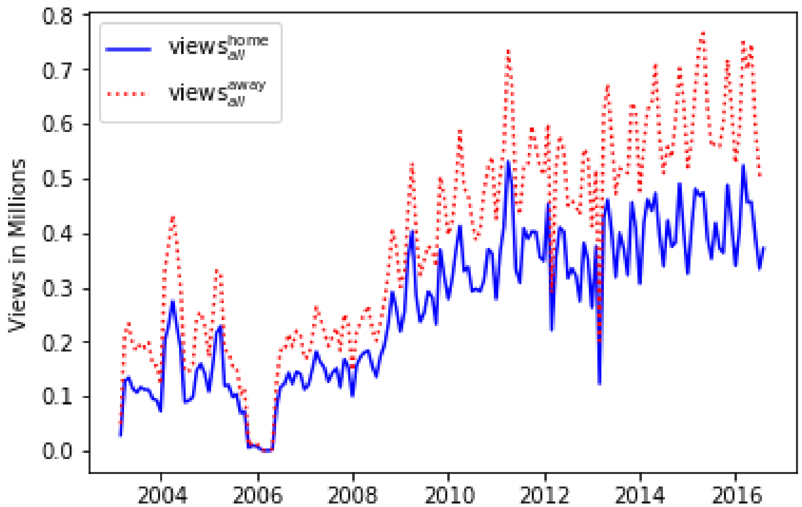


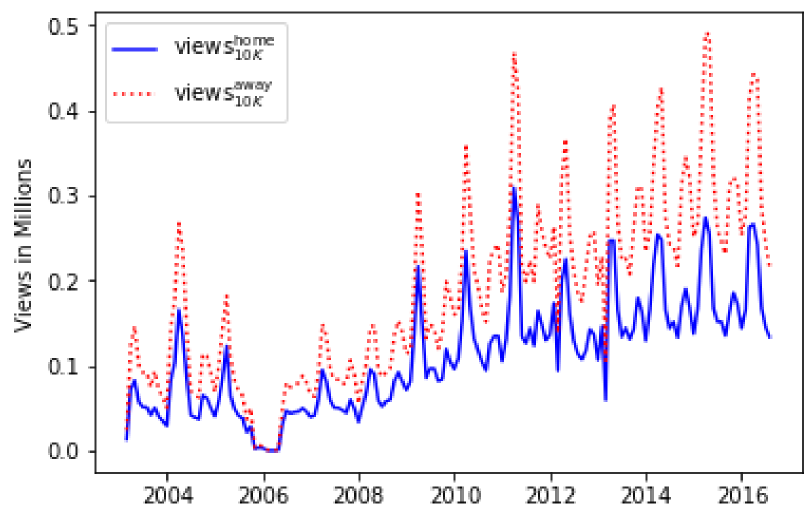
Figure 3

Viewing Activities by Geographical Distance

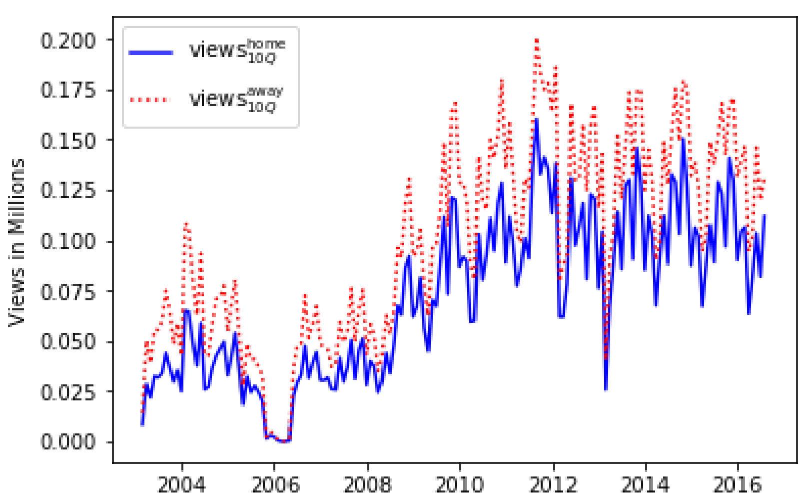
The figure shows the number of views by geographical distance. I classify a filing view as home if the distance between the locations of viewing IP and headquarter is less than 400 miles.



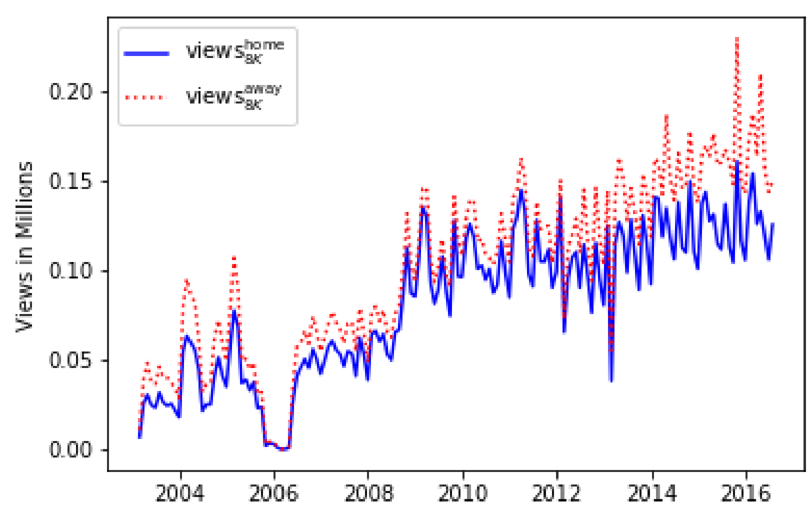
(a) All Filings



(b) 10-K Filings



(c) 10-Q Filings



(d) 8-K Filings

Figure 4

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.

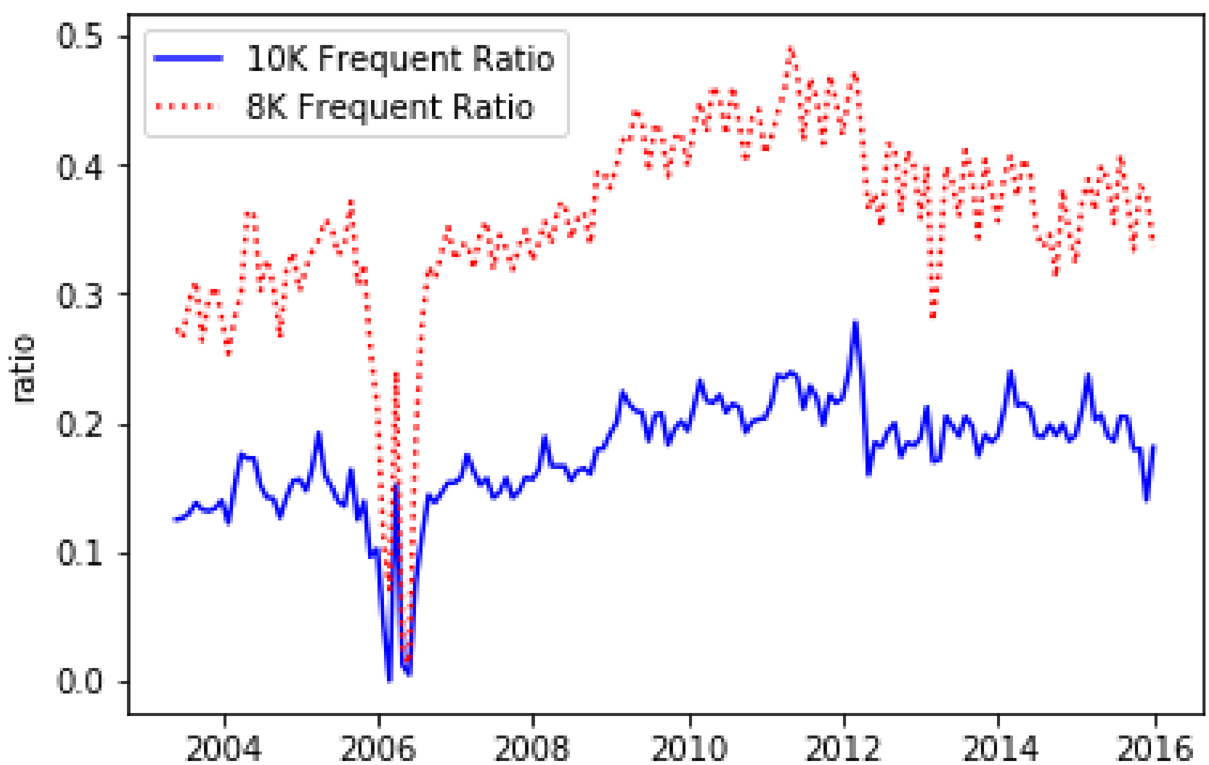


Figure 5

Investors' Demand for Filings Histogram by Firm Sizes

The figure shows the histogram of investor demand for filings 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.

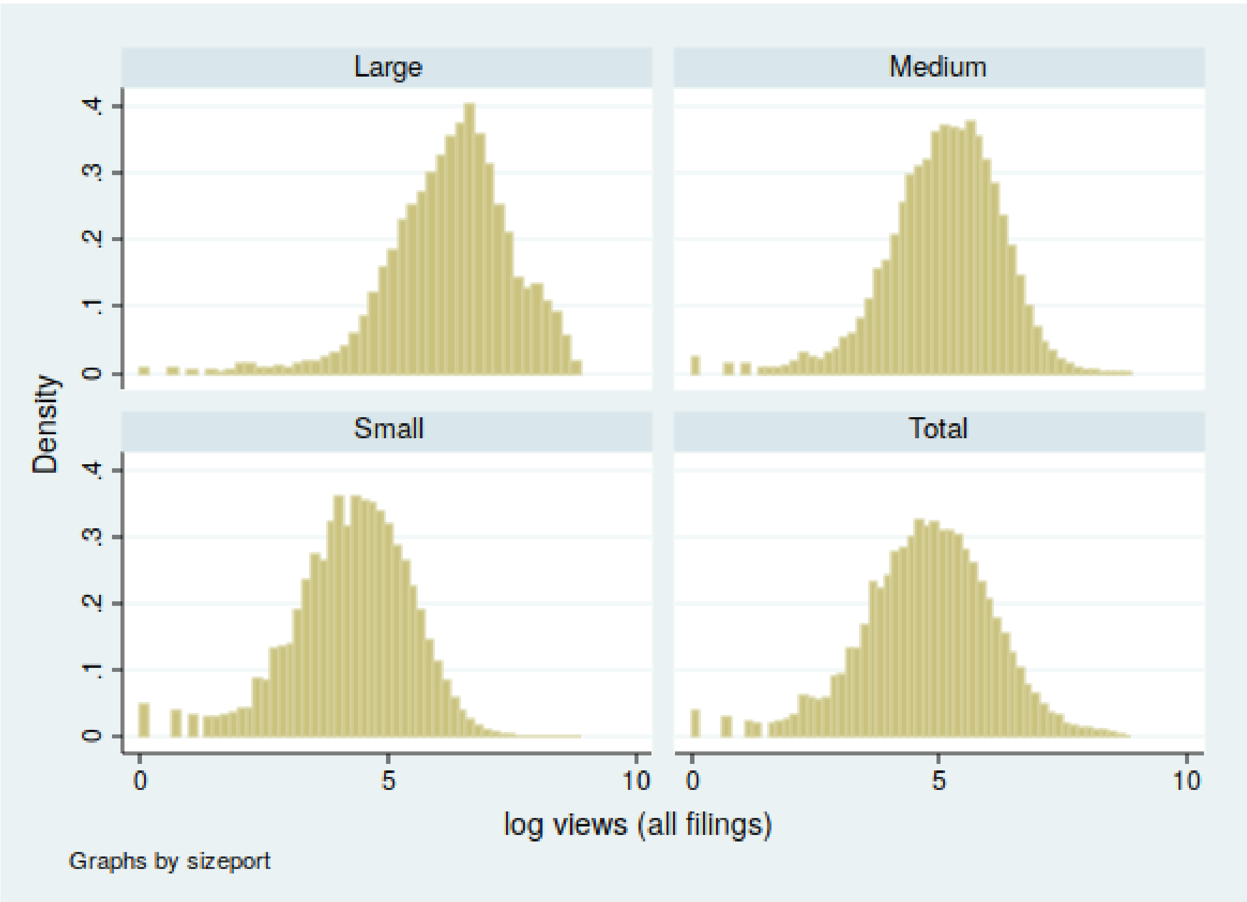


Figure 6

Long/Short 10-K (8-K) Demand 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.

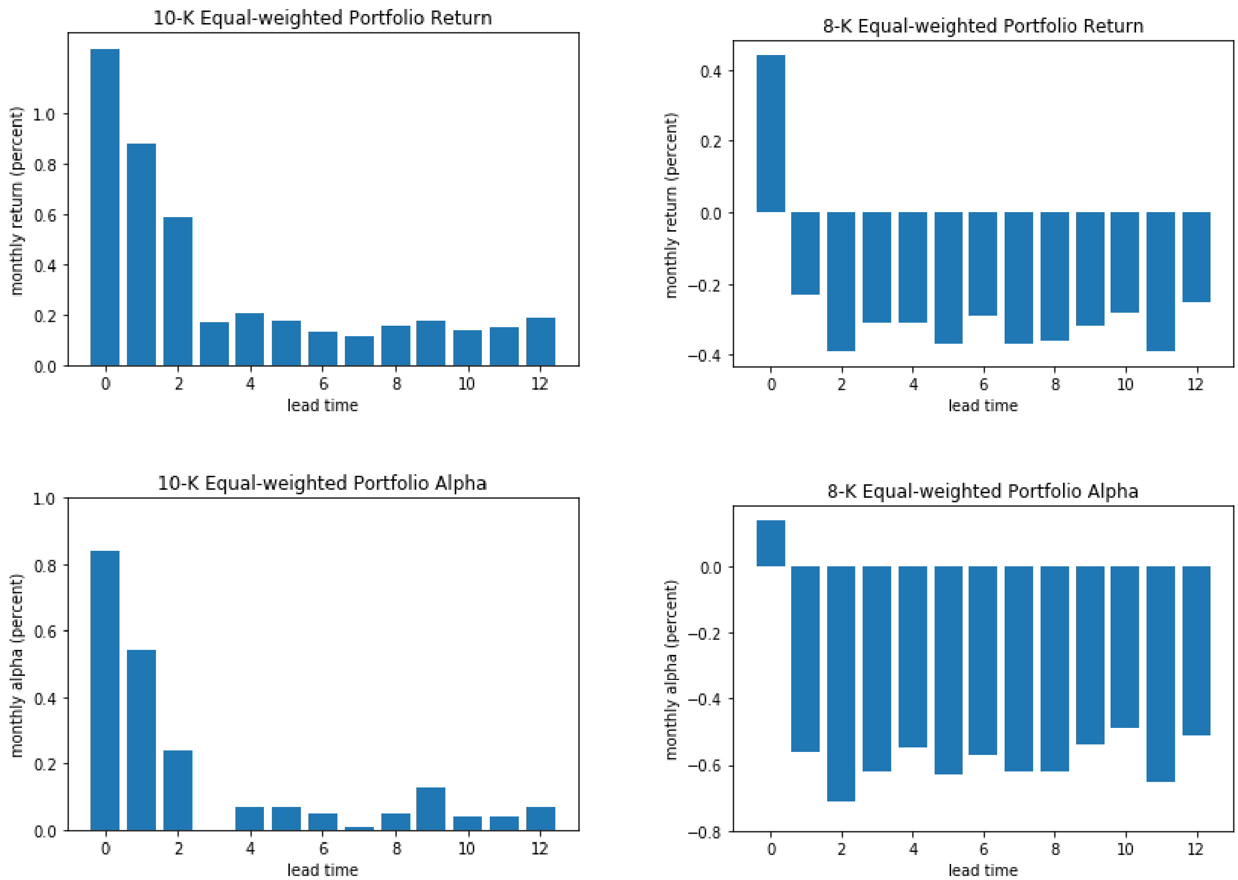


Figure 7

10-K (8-K) Portfolio Alpha and Firm Size

The figure shows the monthly size-adjusted 10-K (8-K) portfolio alpha, conditional on size quintiles. Stocks are sorted by the size-adjusted 10-K (8-K) views and the lag firm size into quintiles. Conditional on each size quintile, I form long/short portfolios and regress portfolio return on Fama-French five-factor and UMD. I then plot the average alpha of long/short portfolio for each size quintile, with t-statistics in parenthesis.

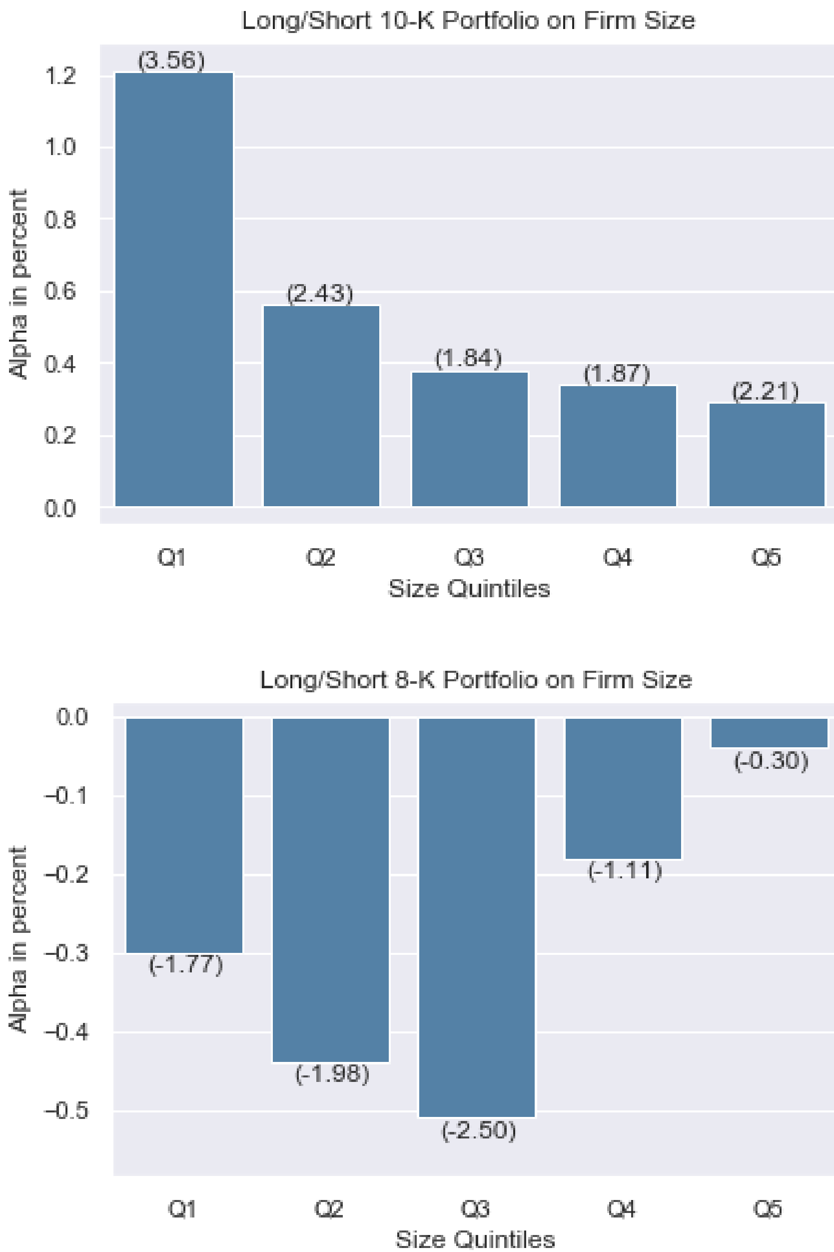
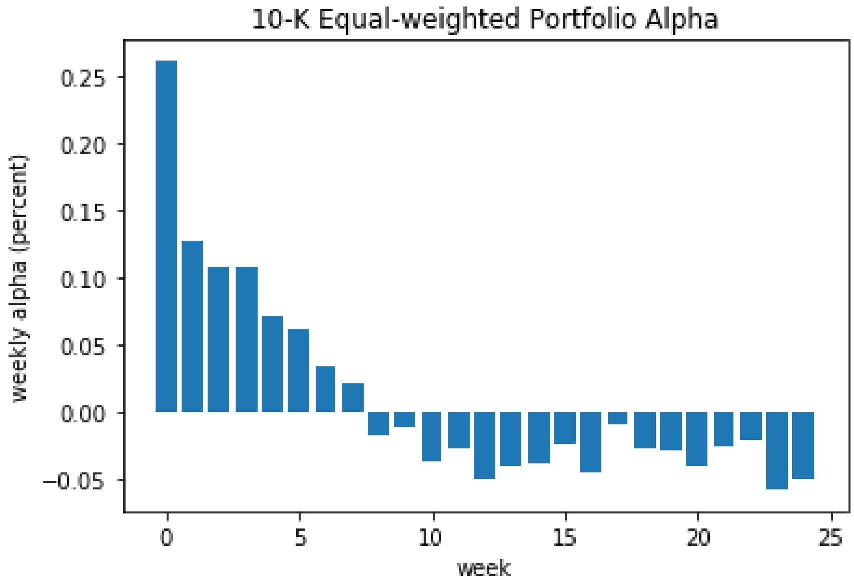


Figure 8

Long/Short 10-K (8-K) Demand Portfolio - Weekly Returns

The figure shows the weekly Fama French 5-factor alphas of 10-K and 8-K portfolios. Stocks are sorted by the size-adjusted weekly views at the end of Friday. Long/short portfolios are held throughout the next 24 weeks.



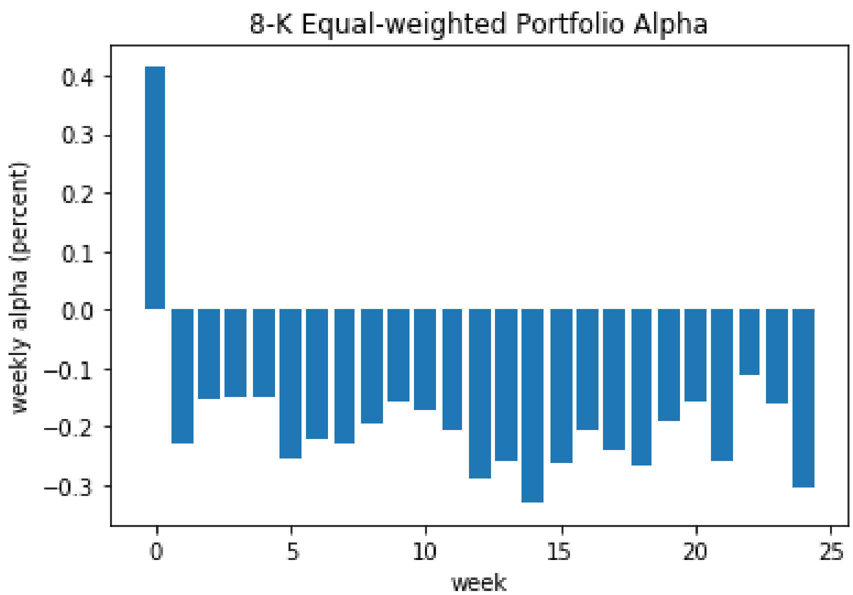


Figure 9
Newly Disclosed 10-K Portfolios
The figure shows the weekly Fama French 5-factor alphas of 10-K portfolios, conditional on a set of firms just disclosed 10-K in a week. At each week, I limit the sample to firms just disclosed 10-K in the week. Stocks are then sorted by the size-adjusted view counts of the newly disclosed 10-K filing into quintiles. Long/short portfolios are held throughout the next 24 weeks.

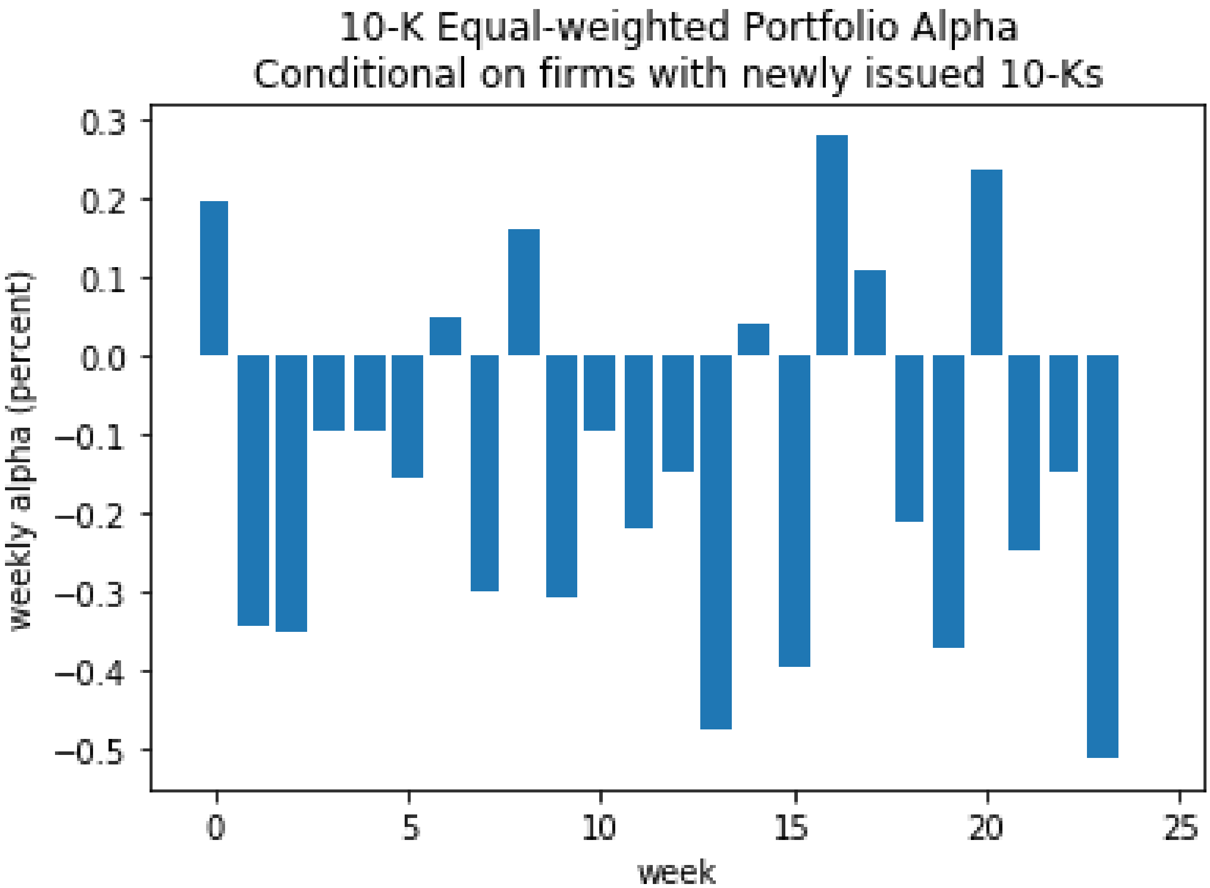


Figure 10
Demand for 8-K and Abnormal Return around Events
The figure studies the long/short portfolio of size-adjusted 8-K demand and abnormal returns around 8-K filing and event date. For each unscheduled 8-K filings, I calculate the cumulative abnormal return relative to the market around event and filing date. I then double sort stocks by the size-adjusted 8-K demand 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.

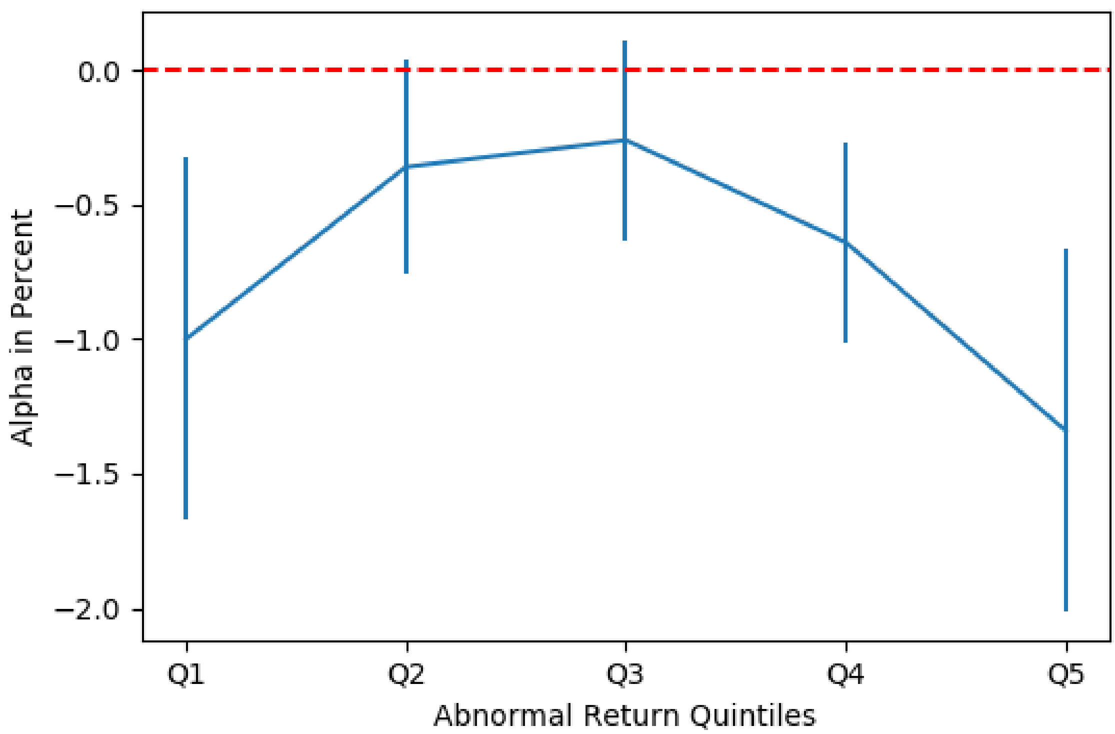


Table 1

Fama-Macbeth Regression on EDGAR Demand for Filings

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_{t+1}	Ret_{t+1}	Ret_{t+1}	Ret_{t+1}	Ret_{t+1}
$log\ views_{all}^{full}$		0.183^{*}			
		(1.75)			
$log\ views_{10K}^{full}$			0.390^{***}	0.388^{***}	0.347^{***}
			(7.42)	(7.35)	(5.89)
$log\ views_{10Q}^{full}$			-0.0691	-0.0697	-0.0531
			(-1.15)	(-1.15)	(-1.09)
$log\ views_{8K}^{full}$			-0.120^{**}		
			(-2.23)		
$log\ views_{8K}^{unscheduled}$				-0.117^{**}	-0.174^{***}
				(-2.32)	(-3.10)
$log\ views_{8K}^{scheduled}$				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 2
Long/Short Portfolio by 10-K and 8-K Demand
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) demand, 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 3
Double Sort on 10-K and 8-K Demand
The table shows monthly alphas of portfolios double sorted by size-adjusted 10-K and 8-K demand. 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 4
Weekly Regression of Stock Returns on EDGAR Demand for Filings

The table shows results from regressions of weekly individual stock returns on EDGAR views. The dependent variable in columns (1) and (2) is the current week stock returns in basis points. The dependent variable in columns (3) and (4) is the next week stock returns in basis points. $views_t^k$ is the cumulative views of filing type k at week t. *Filing* k_t is a dummy variable, which is equal to one if the firm issued any filings with type k at week t. $News_t$ is a dummy variable, which is equal to one if there is any news coverage of the firm in Ravenpack at week t. *Earnings Release*$_t$ is a dummy variable, which is equal to one if the firm releases its earnings at week t. AIA_t is a dummy variable, which is equal to one if the Bloomberg News Heat daily index has a maximum of 3 or above in week t. $DADSVI_t$ is a dummy variable, which is equal to one if the Google Trend daily index in any day of the week is above its 90 percentile in the past month. Firm controls include the log of firm market capitalization, and the book-to-market ratio. Time fixed effects are included, and standard errors are clustered by week.

	(1)	(2)	(3)	(4)
	ret_t	ret_{t+1}	ret_t	ret_{t+1}
$\log(views_t^{10K})$	14.11***	11.68***	6.809***	4.523***
	(8.58)	(7.69)	(4.27)	(2.95)
$\log(views_t^{8K})$	-0.405	-2.046	-1.955	-1.691
	(-0.26)	(-1.53)	(-0.88)	(-1.42)
Filing 10K$_t$ $\times \log(views_t^{10K})$	-1.504	5.867	-2.450	-0.0753
	(-0.23)	(1.01)	(-0.39)	(-0.01)
Filing 8K$_t$ $\times \log(views_t^{8K})$	11.54***	-3.262*	16.09***	-4.804*
	(4.79)	(-1.82)	(3.81)	(-1.79)
Filing 10K$_t$	-28.96	-25.01	0.292	0.375
	(-1.18)	(-1.27)	(0.01)	(0.01)
Filing 8K$_t$	-5.198	8.463*	-32.67**	11.28
	(-0.86)	(1.86)	(-2.51)	(1.16)
Media Coverage$_t$	34.38***	5.645***	24.83***	2.975
	(16.84)	(3.29)	(7.33)	(0.92)
Earning Release$_t$	36.70***	14.36***	1.390	17.51***
	(6.20)	(3.39)	(0.17)	(3.18)
AIA_t			51.67***	0.999
			(11.19)	(0.34)
$DADSVI_t$			21.89***	2.301
			(11.05)	(1.32)
lag returns	Yes	Yes	Yes	Yes
firm controls	Yes	Yes	Yes	Yes
week fe	Yes	Yes	Yes	Yes
N	2308554	2305463	529874	528806
r2	0.115	0.113	0.154	0.172
F	63.31	21.04	27.70	3.784

t statistics in parentheses

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

Table 5
Panel Regression of Information Asymmetry
The table shows the weekly panel regression of next-month information asymmetry proxy on current month investor demand for filings. The dependent variable is the price impact measure estimated following Holden and Jacobsen (2014). $views_t^k$ is the cumulative views of filing type k at week t. *Filing* k_t is a dummy variable, which is equal to one if the firm issued any filings with type k at week t. $News_t$ is a dummy variable, which is equal to one if there is any news coverage of the firm in Ravenpack at week t. *Earnings* $Release_t$ is a dummy variable, which is equal to one if the firm releases its earnings at week t. Firm controls include the log of firm market capitalization, and the book-to-market ratio. Time and firm fixed effects are included. Standard errors are two-way clustered by time and firm.

	(1)	(2)
	Price $Impact_{t+1}$	*Price* $Impact_{t+1}$
$\log(views_t^{10K})$	-0.00120*	-0.00109*
	(-1.83)	(-1.74)
$\log(views_t^{8K})$	-0.00352***	-0.00324***
	(-3.41)	(-3.19)
Filing $10K_t$	0.00625	0.0373**
	(0.63)	(1.99)
Filing $8K_t$	-0.00284*	0.00217
	(-1.79)	(0.68)
Filing $10K_t \times \log(views_t^{10K})$		-0.00331*
		(-1.79)
Filing $8K_t \times \log(views_t^{8K})$		-0.00508**
		(-1.97)
Media $Coverage_t$	0.00605**	0.00598**
	(2.50)	(2.46)
Earning $Release_t$	-0.00957**	-0.00983**
	(-1.98)	(-2.04)
Firm and Time FE	Yes	Yes
firm controls	Yes	Yes
N	2022081	2022081
r2	0.485	0.485
F	234.5	188.0

t statistics in parentheses

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

Table 6
8-K Demand 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 7
8-K Demand, 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 8

8-K Demand 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 demand 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 9
10-K Demand 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 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 Demand, 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
Demand for Filings 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