Information Consumption and Asset Pricing[*]

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Abstract

We study whether firm and macroeconomic announcements that convey systematic information generate a return premium for firms that experience information spillovers. We use information consumption to proxy for investor learning during these announcements and construct ex ante measures of expected information consumption (EIC) to calibrate whether learning is priced. On days when there are information spillovers, affected stocks earn a significant return premium (5% annualized) and the CAPM performs better. The positive effect of FOMC announcements on the risk premia for individual stocks appears to be modulated by EIC. Our findings are most consistent with a risk-based explanation for the return premia we identify.

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Disclosure Statement: Azi Ben-Rephael

Azi Ben-Rephael declares that he has no relevant or material financial interests that relate to the research described in this paper.

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1. Introduction

How information becomes incorporated into asset prices is one of the most fundamental issues in finance. For a long time, it has been well-accepted that risk premia should accrue on days when the arrival of information gets processed, resolves uncertainty, and generates systematic price movements (e.g., Beaver, 1968; Kalay and Loewenstein, 1985). Yet, despite the longstanding importance of this idea, there has been a recent rebirth of interest in these risk premia and the performance of the CAPM during scheduled information events such as firm earnings announcements and macroeconomic announcements (Patton and Verardo 2012; Savor and Wilson, 2013, 2014, and 2016).[1]

According to Savor and Wilson (2016), a risk-based explanation for an announcement premium rests on the premise that information from issuing firms conveys signals about related firms and the general economy. Under this view, Bayesian investors learn from the news and are tasked with a signal extraction problem to determine how much of the announcing firm's information is systematic in nature. In turn, if information spillover occurs and a risk premium accrues to related firms, it should be lower than that of the announcing firm.

In this paper, we measure the effect of such cross-learning on the asset prices of related firms when investors solve this signal extraction problem. To fix ideas, we pose a parsimonious extension of the theoretical model in Savor and Wilson (2016) and show that the risk premium that is earned during cross-learning is monotonically increasing in its precision. We provide a rationale for why measuring this type of information processing should better identify when firms are more sensitive to peer-related and macroeconomic announcements.

Empirically, we show that information consumption for individual firms is often triggered by peer- and other aggregate news events, even when those firms do not release news themselves (AIA; Ben-Rephael, Da, and Israelsen, 2017). Such information consumption is likely to be a good proxy for cross-learning during announcements. To study how this affects prices, we construct an ex ante measure called Expected Information Consumption (EIC).[2] If the information consumption for a firm spiked frequently in the past when peer firms released news or there was a

[1] See also Ai and Bansal (2018) and Andrei, Cujean, and Wilson (2017) for recent theoretical analysis.
[2] Abnormal institutional attention (AIA) used by Ben-Rephael, Da, and Israelsen (2017) arises contemporaneously with returns. Using our EIC measures allows us to associate the excess returns that we observe with return premia that accrue to investors and avoid concerns of reverse causality and endogeneity that arise with AIA.

macroeconomic announcement, then we expect EIC to be positive when similar events are scheduled to occur in the future.

We confirm that positive EIC is associated with a return premium by using panel regressions similar to those in Engelberg, McLean, and Pontiff (2018), controlling for scheduled events and weighting each firm by its lagged daily gross return. Asparouhova, Bessembinder, and Kalcheva (2010, 2013) recommend this weighted least squares (WLS) approach as an effective way to alleviate the impact of microstructure noise in asset pricing tests. The results are economically and statistically significant. For example, when peer-firms release information, calendar-time trading strategies show that positive EIC firm-days are associated with daily excess returns of 7.06 basis points, compared to 4.60 basis points for firm-days unaffected by the spillover. The resulting annualized Sharpe ratio for positive EIC firm-days is 1.02 and is 0.68 for firm-days unaffected by the spillover.

Other previous studies have explored information spillovers (e.g., Hong, Torous, and Valkanov, 2007; Cohen and Frazzini, 2008; and Menzly and Ozabas, 2010) based on the release of information, but not its consumption. In contrast to these studies, our results show a predictable return premium that does not depend on the sign of the released information. More importantly, we compare our measure of EIC to other peer firm definitions such as SIC-based industry classifications (Fama and French, 1997), text-based industry classifications (Hoberg and Philips, 2010 and 2016), co-mentioning in the news (Schwenkler and Zheng, 2019), correlated trading volume (Lo and Wang, 2006, and Cremers and Mei, 2007), and customer-supplier links (Cohen and Frazzini, 2008). Even after controlling for these other definitions, EIC appears to be priced. Additionally, while positive EIC firms are sometimes also identified as peers according to other definitions, EIC firms are associated with a higher premium than would be found by using the other definitions alone.

EIC is also associated with a premium when macroeconomic events arise. On macroeconomic announcement days, EIC stocks earn a return that is 6.61 basis points higher than other stocks. On FOMC announcement days, the difference increases to 13.70 basis points. While there is a significant market risk premium associated with macroeconomic announcements, stocks vary considerably in their reaction to the announcement. The EIC measure identifies stocks that are most prone: stocks from more cyclical industries (energy, information technology and customer discretionary), from larger companies, with higher betas, and more leverage. Not surprisingly, they are the ones that are more affected by aggregate announcements and therefore are associated with a higher premium.

Next, we investigate whether the return premia we observe are consistent with a risk-based interpretation. We show that the CAPM beta is roughly 5% higher on days with positive EIC, even after controlling for scheduled firm-specific information events. In addition, we find that the CAPM performs better for stock-days when institutional investors are expected to consume information. Finally, subsample analyses confirm that our results are stronger among sub-groups in which we expect information spillover to be stronger.

We also confirm the findings of Savor and Wilson (2014) that the CAPM works in the set of days with important macroeconomic announcements. Though, we find that this result is conditional on information consumption. Overall, the estimated market risk premium on days with FOMC announcements is about 11 basis points. However, the estimated CAPM risk premium is 44 basis points for stocks with a positive EIC and not statistically significant for stocks with zero EIC.

While our collective evidence appears to support a risk-based explanation, there are other alternative explanations for our findings that we explore. One is price pressure, whereby the higher average return associated with EIC might simply reflect a transitory price pressure that eventually reverts instead of commanding a permanent risk premium. We test this using a calendar-time trading portfolio approach, which avoids clustering events. If price pressure accounts for our results, then any initial pressure should predict future reversals. We find no reversals at all during the first month, and the small reversals that we do identify beyond one month are not significant or robust. However, because we study a relatively short sample period, we acknowledge that we cannot completely exclude this explanation because we cannot rule out reversals in the long-run.

Another possible explanation is based on mispricing: the higher average return associated with EIC could reflect a correction to mispricing rather than a risk premium. However, this explanation requires an asymmetry such that only underpricing gets corrected, but that overpricing persists because of short-sale constraints. Also, under this explanation, we would expect to see no results among stocks that are correctly priced. To evaluate this, we use the mispricing score (MISP) of Stambaugh, Yu, and Yuan (2012) and do not find evidence in the data to support this explanation. The EIC coefficient is very similar across mispriced and correctly priced stocks based on the MISP measure.

We also acknowledge that it is often impossible to distinguish between rational and behavioral explanations for the return premia that we identify (Kozak, Nagel, and Santosh, 2018). Other alternative explanations also may include limited investor attention (e.g., Frazzini and Lamont, 2007, Hirshleifer, Lim, and Teoh, 2009), rational inattention, and biases in investor expectations (e.g., Linnainmaa and Zhang, 2018). Nevertheless, our findings do provide compelling evidence that a risk premium is earned when investors process public announcements and update their beliefs about affected firms and the general economy.

The remainder of the paper is organized as follows. In Section 2, we provide a parsimonious theoretical model based on Savor and Wilson (2016) and describe our raw measures of information consumption and supply. There we also outline how we construct our ex-ante expected measures of information consumption. In Section 3, we analyze how our measures of *EIC* are related to return premia, provide additional evidence consistent with a risk-based interpretation, and discuss alternative explanations. Section 4 concludes. The Appendix provides more details regarding the variables that we construct.

2. Theoretical Motivation and Information Consumption Measures

To motivate our empirical work, we start in Section 2.1 by providing a brief extension of the model in Savor and Wilson (2016) to include information consumption. Then, in Section 2.2, we summarize our raw measures of information consumption and events. In Section 2.3, we construct ex-ante measures of expected information consumption (*EIC*). Finally, Section 2.4 examines characteristics of stocks with positive EIC. The Appendix contains added details about our empirical measures.

2.1 Theoretical Motivation

Suppose there are N firms in the economy. On day t, firm i makes a scheduled announcement for its cash flow (CF) news:

$$CF_{i,t} = \eta_{i,t} + \nu_{i,t},$$

where η_i represents the component that is common to all firms in the peer group of firm i. The peer group is broadly defined to include P_i firms that share some economic links with firm i. The variable ν_i represents a firm-specific component. Assume η and ν are uncorrelated across all firms (asymptotically true when *N* becomes large). For simplicity, further assume that the variances of η and v are constant and are denoted as σ_η^2 and σ_v^2.

Macroeconomic announcements also fit this framework by re-interpreting *i* as a particular macroeconomic announcement rather than an individual firm. Peer firms in this case will be all firms that are expected to be affected by the announcement. As such, η_i represents the component that could affect other firms and v_i represents the component that does not affect firms directly.

Firm returns also involve discount rate (*DR*) news. As in Savor and Wilson (2016), we assume *DR* news are uncorrelated with *CF* news, have constant variance and identical pairwise correlation across all pairs of firms. Under these assumptions, all firms carry the same *DR* risk premium (denoted as *DRP*). The cross-sectional variation in total risk premium comes from the *CF* risk premium only.

After the announcement, the other firms fall into three groups: S_i EIC firms, P_i - S_i other peer firms, and $N - P_i - 1$ unrelated firms. In the case of a macroeconomic announcement, firms fall into three groups: S_i EIC firms, P_i - S_i other affected firms and $N - P_i$ unaffected firms.

EIC Firms: For these S_i firms, investors actively acquire (consume) more information about component η_i, and update their expectations about their *CF* news as:

$$\frac{A\sigma_\eta^2}{A\sigma_\eta^2 + \sigma_v^2} CF_{i,t}, \qquad A > 1.$$

Why would investors tend to search for news about some particular firms? First, by self-revealing preference, active information acquisition reveals that these firms are believed to be more "connected" to the announcing firm. Second, it may be that the quality or quantity of previous news releases by these S_i firms allow for better Bayesian updating, once there is an announcing firm.

As such, there are several ways to interpret the parameter *A*. First, *A* measures how much investors think (by self-revealing preference) that these S_i firms are connected to the announcing firm. Second, *A* may be a proxy for the information externality between news from the announcing firm and previous news that is available for related firms. Third, *A* measures how much active information acquisition makes signal η more precise relative to v. Last, for these firms, investors actively acquire *A-1* additional signals about η. More expected signal extraction effort (EIC) is captured by *A*, and as shown below, leads to a higher risk premium as information becomes incorporated into prices.

Other Peer Firms: For the remaining $P_i - S_i$ peer firms, investors update expectations about their *CF* news as:

$$\frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_v^2} CF_{i,t}.$$

Unrelated Firms: Investors do not learn about the remaining firms from the announcement, so that their *CF* news is zero.

Conditional Risk Premia: In aggregate, the CF news for the market on day *t* is

$$CF_{mkt,t} = \frac{1}{N}\left[1 + S_i \frac{A\sigma_\eta^2}{A\sigma_\eta^2 + \sigma_v^2} + (P_i - S_i)\frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_v^2}\right] CF_{i,t}.$$

Following Campbell and Vuolteenaho (2014), the conditional risk premium (as of day t-1) is

$$RP_{i.t-1} = \gamma Cov\left(CF_{i,t}, CF_{mkt,t}\right) + DRP.$$

Denote cash flow price (*CFP*) as

$$CFP = \frac{\gamma}{N}\left[1 + S_i \frac{A\sigma_\eta^2}{A\sigma_\eta^2 + \sigma_v^2} + (P_i - S_i)\frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_v^2}\right].$$

For the case of macroeconomic announcement,

$$CFP = \frac{\gamma}{N}\left[S_i \frac{A\sigma_\eta^2}{A\sigma_\eta^2 + \sigma_v^2} + (P_i - S_i)\frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_v^2}\right].$$

For the announcing firm *i*, the risk premium is

$$CFP + DRP.$$

But, for the EIC firms, the risk premium is

$$\frac{A\sigma_\eta^2}{A\sigma_\eta^2 + \sigma_v^2} CFP + DRP,$$

while for the other peer firms, the risk premium is

$$\frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_v^2} CFP + DRP.$$

For unrelated firms, the risk premium is simply DRP. This predicts that the risk premium should increase monotonically when moving from unrelated firms, to other peer firms, to EIC firms, and to announcing firms. We confirm this to be the case in our empirical tests.

2.2 Raw Measures of Ex Post Information Consumption and Events

Bloomberg provides data that include transformed measures of news reading and news searching activity on Bloomberg's terminals. The majority of Bloomberg terminal users are institutional investors who have both the incentives and financial resources to react quickly to important news about a firm (Ben-Rephael, Da, and Israelsen, 2017). Based on data availability, our sample period ranges from February 2010 to December 2017.[4] Following Da, Engelberg, and Gao (2011), we begin with the sample of all stocks that appeared in the Russell 3000 index during our sample period. We then require the stocks in our sample to satisfy the following conditions: (1) have measures of news-searching and news-reading activity on Bloomberg terminals and the Google search engine; (2) have a share code of 10 or 11 in the Center for Research in Securities Prices (CRSP) database; (3) have stock prices greater than or equal to \$5 at the end of the previous month; (4) have book-to-market information. After applying these conditions, we study 3,188 stocks and 4,046,190 day-stock observations.

Abnormal institutional attention (AIA): Our main variable of information consumption measures ex post spikes in attention by institutions (Ben-Rephael, Da, and Israelsen, 2017). Bloomberg records the number of times terminal users actively search for or read news articles on particular stocks, and places more emphasis on active demand for information for a specific firm by assigning a score of 10 when users search for news and 1 when users simply read a news article. These numbers are aggregated into hourly counts and Bloomberg creates an attention score by comparing the average hourly count during the previous 8 hours to all hourly counts over the previous month for the same stock. They assign a score of 0, 1, 2, 3 or 4 if the rolling average is in the lowest 80% of the hourly counts over the previous 30 days, between 80% and 90%, 90% and 94%, 94% and 96%, or greater than 96% of the previous 30 days' hourly counts, respectively.

[4] Bloomberg's historical attention measures begin on 2/17/2010. Historical data are missing for the periods of 12/6/2010 – 1/7/2011 and 8/17/2011 – 11/2/2011.

Bloomberg aggregates these scores up to a daily frequency by taking a maximum of all hourly scores throughout the day.[5] Using this daily measure and following Ben-Rephael, Da, and Israelsen (2017), we compute the abnormal institutional attention (*AIA*) as a dummy variable that takes a value of 1 if Bloomberg's daily maximum is 3 or 4, and 0 otherwise. The dummy variable allows easier interpretation of the differential impact of high vs. low institutional attention shocks on economic outcomes, and we confirm that alternative definitions of AIA do not alter our conclusions in the paper. Ben-Rephael, Da, and Israelsen (2017) provide evidence that *AIA* facilitates the incorporation of information into prices.

Abnormal Google Search Volume Index (*DADSVI*): Our second variable of information consumption measures ex post spikes in attention by retail investors. As described by Da, Engelberg, and Gao (2011), retail attention is measured using the daily Google Search Volume Index (*DSVI*). We calculate the abnormal *DSVI* by taking the natural log of the ratio of the *DSVI* to the average of *DSVI* over the previous month. To facilitate the comparison with a stock's *AIA*, we create a dummy variable version of *ADSVI*: for each day, we assign a score of 0, 1, 2, 3, or 4 scores using the firm's past 30 trading day *DSVI* values. Then, for each day, *DADSVI* is set to one if the score is 3 or 4, and 0 otherwise. Measures related to retail information consumption are included as controls and we find them to have no systematic implications whatsoever.

Information Events: Our three measures of scheduled events are based on earnings announcements, other scheduled firm events, and macroeconomic announcements. To facilitate a comparison with *AIA* and *DADSVI*, we construct a dummy variable *EDAY*, which is equal to one for a stock when the firm announces its earnings and zero otherwise. We obtain earnings announcement dates from I/B/E/S.

In our sample, there are 163,865 scheduled events from 2010 to 2017.[6] Bloomberg classifies each event into one of 9 categories. The most common category – making up 43% of all events – is "TV/Conference/Presentation", which consists primarily of investor conferences, but also includes prescheduled press conferences. The next two most common categories are

[5] Please see the online data appendix at the authors' websites for detailed instructions on downloading the Bloomberg search data: https://sites.google.com/site/abenreph/, http://www3.nd.edu/~zda/ or http://ryan.israelsen.com
[6] We gather these scheduled events from Bloomberg's Corporate Events Calendar Function (EVTS). These events are known in advance.

“Earnings Release” and “Earnings Call”, which make up 36% and 30% of events. Not surprisingly, these are typically scheduled on the same day (they make up 37% of events combined). The next two most common categories are “Shareholder Meeting” and “Corporate Access”, accounting for 12% and 6% of all events, respectively. The remaining 4% of events fall under the categories “Mergers and Acquisitions”, “Sales Result”, “Analyst Marketing”, and “Earnings Guidance”. We create two dummy variables *SEDAY* and *NESEDAY* to indicate the scheduled event day and non-earning scheduled event day (so *SEDAY* = *EDAY* + *NESEDAY*)

We also include several measures based on important macroeconomic news announcements. Because there are macroeconomic announcements almost every day, we limit ourselves to those that draw the most attention from institutional investors on Bloomberg terminals.[7] Those include announcements of nonfarm payroll (*NFP*), the producer price index (*PPI*), the Federal Open Market Committee rate decision (*FOMC*), the “advance” forecast of the U.S. Gross Domestic Product (*GDP*), and the Institute for Supply Management Manufacturing Index (*ISM*). Announcement dates and times are all from Bloomberg. For each of these five announcements, we create dummy variables equal to one on announcement days and zero on other days. In addition to the five individual dummy variables, we also create the dummy variable *MACRO* which is set equal to one on days when at least one of the five announcement dummies is equal to one and zero otherwise.

Finally, we obtain news coverage of our sample stocks from RavenPack. Likewise, we define *NDAY* as a dummy variable that is equal to one if a news article about the firm is published on the Dow Jones Newswire on a particular day and zero otherwise. Because we want to distinguish earnings announcements from other news, we set *NDAY* equal to zero on earnings announcement days. *USNDAY* is a dummy variable indicating unscheduled news days.

For each firm, we calculate the value-weighted averages of *NDAY* and *EDAY* for other firms in the same (Fama French 48) industry, which we call *FF48_NDAY* and *FF48_EDAY*, respectively. In addition, we create two similar variables, *AGG_NDAY*, and *AGG_EDAY*, which capture the value-weighted averages of *NDAY* and *EDAY* using all firms in the sample on a given day.

[7] For macro announcements, attention is measured based on Bloomberg’s “relevance score” which represents the number of “alerts” set on Bloomberg Terminals for an economic event relative to all alerts set for the 130 macro events in the U.S. Users can choose to be alerted to different types of announcement events.

Summary Statistics: According to Table 1, the average stock in our sample experiences an information consumption shock from institutional investors on 7.59% of all trading days. The average frequency of information consumption shocks by retail investors is similar at 7.64%.

Insert Table 1 about here.

Regarding scheduled firm events, firms have an average of four earnings announcement days per year, or 1.5% of all trading days. Other non-earnings scheduled events occur more frequently, about 2.4% of all trading days. Focusing on all non-earnings news events, for a typical firm in our sample, about one day out of five is a news day, on average. The average (median) firm size is around $6.2 ($1.1) billion. On average, $51.10 million dollars' worth of shares is traded per day for a given stock. Finally, the mean (median) daily return in our sample is 9.44 (7.26) basis points.

To examine what drives institutional information consumption, Table 2 presents the results of Logit panel regressions in which we regress *AIA* on measures of information supply at the firm, industry, and macroeconomic level. We include day-of-the-week dummies to capture seasonality in attention that been previously documented (DellaVigna and Pollet, 2009; Liu and Peng, 2015; and Ben-Rephael, Da, and Israelsen, 2017). Other controls include firm characteristics such as absolute returns, size, book-to-market, firm beta and leverage.

Insert Table 2 about here.

The results suggest that in periods with more firm-level news, institutional investors are more likely to consume information for a stock, especially when the events are pre-scheduled. But, the results in Table 2 also suggest that information consumption about a particular firm rises because of spillover effects from other firms. Industry-level news, especially earnings announcements made by competitors, are correlated with greater institutional information consumption. This is intuitive given that earnings news about firms in an industry may have important implications for other firms in the industry. Additionally, when there is more news about large firms in the market, institutional information consumption for individual stocks is more likely to be high. News about large firms may have systematic implications for other stocks, even when these firms are in different industries.

Focusing on macroeconomic news, specifications 5, 7, and 9 include the *MACRO* dummy variable. In general, institutional information consumption on individual stocks often coincides with macroeconomic announcements, even after controlling for other firm-, industry-, and market-level events. Among all five macroeconomic announcements, FOMC rate announcements appear to draw the most attention (specifications 6 and 8). Macroeconomic announcements estimates attenuate once we control for firm characteristics and absolute returns (specification 9 and 10). Note that we do not expect MACRO announcements to affect all firms in a similar manner. Later, we explore the effect of MACRO announcements on the affected stocks.

To summarize, *AIA* can be triggered not only by firm-specific events, but also via information events from other firms and from the macro-economy. These observations motivate us to construct measures of expected information consumption (*EIC)*, based on how investors had responded to various events in the past.

2.3. Expected Information Consumption (EIC)

In order to link information consumption to asset pricing outcomes, we construct several ex-ante measures of institutional consumption (*EIC*) and retail consumption (*ERIC*). All of the measures are dummy variables that take a value of one if the predicted frequency of consumption exceeds a threshold, and zero otherwise. Full details of the construction methodology for each measure are in the Appendix. Summary statistics about *EIC* measures are in Table 3.

Insert Table 3 about here.

Our first measure of expected institutional information consumption is based on information spillover from other firms' scheduled events (*EIC_PEER)*. If firm A's *AIA* often spikes on firm B's scheduled event in the past, we predict firm A's *EIC* to be 1 on firm B's next scheduled event day. We view this *EIC* measure as a novel measure empirically. For example, Savor and Wilson (2016) attribute the positive earnings announcement window return to a risk premium, since firm A's earnings announcement can affect other firms. Hence, the earnings announcement is systematic in nature. Their model would also predict a risk premium on the affected firms on that day, but the literature to date has not tested this prediction directly. *EIC_PEER* fills this void.

Column 1 of Table 3 reports the number of observations and percentage of AIA=1 cases conditioning on *EIC_PEER* = 1 or 0. The percentage of AIA=1 for the *EIC_PEER* = 1 subsample is around 24.1%, which is more than three times larger than the likelihood of a random draw of AIA=1. The percentage of AIA=1 in the case of *EIC_PEER* = 0 is only around 9.1%. The difference in frequencies is statistically significant, suggesting that *EIC_PEER* does a good job predicting ex-post AIA due to information spillover from peer firms' scheduled events.

Our second measure of expected institutional information consumption is based on information spillover on FOMC announcement days (*EIC_FOMC)*. If firm A's *AIA* often spikes during previous FOMC announcements, we can predict firm A's *EIC* to be 1 on the next FOMC announcements. While the previous literature focuses on the market risk premium around FOMC announcements, this analysis contributes by considering a cross-sectional dimension. Since not all stocks are affected equally, *EIC_FOMC* identifies stocks that are more likely to be associated with a risk premium during FOMC announcements. We also include the third measure *EIC_MACRO* to study the effects of information spillover on Macro announcement days using all five macro events defined in Table 2.

Column 2 and 3 of Table 3 report the number of observations and percentage of AIA=1 observations conditioning on *EIC_FOMC* and *EIC_MACRO* equal to 1 or 0. There are 59 (334) FOMC (MACRO) announcements days, with 11,159 (18,377) *EIC_FOMC*=1 (*EIC_MACRO=1*) observations from a sample of 126,223 (715,928) firm-announcement day observations. The percentage of AIA=1 observations is around 25.6% (30.9%) for *EIC_FOMC*=1 (*EIC_MACRO=1*). In contrast, the percentage of AIA=1 observations in the case of *EIC_FOMC* = 0 (*EIC_MACRO* = 0) is around 8.4% (7.5%).

Finally, we construct an overall spillover measure based on all three classes of expected information consumption (*EIC_ALL*), which aggregates *EIC_PEER*, *EIC_FOMC*, and *EIC_MACRO*. Column 4 of Table 3 reports the number of observations and percentage of AIA=1 cases conditioning on *EIC_ALL* equals to 1 or 0. In total, we are able to identify 270,054 *EIC_ALL =1* observations (from the full sample of 4,046,091 observations). The accuracy rate (or the percentage of *AIA* = 1 observations in the case of *EIC_ALL* = 1) is more than 24%, significantly higher than its counterpart in the case of *EIC_ALL* = 0 of around 6.7%.

To summarize and conclude this subsection, our various *EIC* measures speak directly to the recent literature that finds higher stock returns on scheduled information event days. Examples of such events include firm-level earnings announcements (Frazzini and Lamont, 2007; Barber, DeGeorge, Lehavy, and Trueman, 2013, among others) and macro announcements (Savor and Wilson, 2003, among others). We extend this literature in several important dimensions and add new insights. First, our *EIC* spillover measures allow us to identify events that are more likely to have important systematic implications, as they are designed to capture active information consumption from scheduled announcements.[8] Second, and even more important, this allows us to we directly examine information spillover. While the existing literature focuses on the return premium on the announcing firm, we also study return premium on other firms that are affected by the announcement. We also add an important cross-sectional dimension to macroeconomic announcements by ex-ante identifying stocks that are more likely to be affected. Finally, while we are not the first to explore information spillovers (e.g., Hong, Torous, and Valkanov, 2007; Cohen and Frazzini, 2008; and Menzly and Ozabas, 2010), our *EIC* measures allow us to examine information consumption rather than information releases. Moreover, our results show a predictable return premium that is not conditioned on the sign of the released information.

2.4. Characteristics of EIC=1 Stocks

In Table 4, we explore the characteristics of EIC=1 stocks. Similar to Table 2, we run logit panel regressions where *EIC_PEER*, *EIC_FOMC* and *EIC_MACRO* are the dependent variables. Panel A of Table 4 examines *EIC_PEER*. In our base specifications, we include value-weighted *SEDAY* measures at the Fama French 48 industry and market level, excluding the firm of interest (*"BASE"* specifications). Next, we include additional *SEDAY*-based measures based on various alternative peer measures. As expected, Specifications 1-3 indicate that both the industry and market scheduled events explain predicted spikes in *EIC_PEER*. Note however, that comparing the market-based measure with the industry-based measure, we find that the market-based measure is more economically significant (a coefficient of 4.623 vs. 0.927). This suggests that firms learn from scheduled events of major firms in the market, even if they belong to different industries.

[8] In contrast, when we explore *ERIC* as a dependent variable (as in Table 2), we find that it does not respond to industry or aggregate firm information, or macroeconomic events. Details available from the authors upon request.

Insert Table 4 about here.

Next, in Specifications 4-10 we explore the additional contributions from the scheduled events of alternatively defined peer firms. Specifications 4-6 capture the responses of *EIC_PEER* to scheduled events from the firm's three closest peers based on the Fama French 48 industry classification, the GICS2 sectors, and Hoberg and Phillips (2010, 2016) textual-based similarity scores (TINC3). Hoberg and Phillips' measure seems to contribute the most, with a coefficient of 0.235. Next, prior literature has found trading volume to have systematic implications (e.g., Lo and Wang, 2006, and Cremers and Mei, 2007). Thus, in specification 7, we replace AIA with abnormal trading volume and construct a similar expected abnormal volume measure (*EAVOL*). In other words, *EAVOL* predicts information spillover based on correlated trading volume spikes in the past. Interestingly, *EAVOL* seems to be economically significant, with a coefficient of 1.635, potentially because trading volume often spikes with information consumption. In Specifications 8, we include a Co-News measure (Schwenkler and Zheng, 2019) that identifies peer firms as those mentioned in the same news article. The measure is significant with a coefficient of 0.324. Finally, we examine "connected" firms sharing supplier-customer links (Cohen and Frazzini, 2008). However, scheduled events from these "connected" firms do not trigger *EIC_PEER* in a significant way.

While *EIC_PEER* is related to scheduled events of alternatively defined peer firms, scheduled events by other major firms in the economy (captured by *AGG_SEDAY*) seem to be more important. This reinforces our understanding that *EIC_PEER* captures consumption of information that is systematic in nature.

In Panel B, we analyze FOMC and macroeconomic announcements. We use the GICS2 sector classification and include sectors dummy variables. We set "*Customer Staples*" as our base (excluded) sector. We find that affected stocks tend to come from more cyclical industries (energy, and information technology and customer discretionary). We also find that they tend to be bigger and are associated with higher betas and leverage as well. Perhaps, it is not surprising that these are the stocks that are mostly affected by information contained in macroeconomic announcements. Importantly, our EIC measures (*EIC_FOMC* and *EIC_*MACRO) uniquely allow us to reveal such information spillovers.

3. EIC and Asset Prices

3.1 Return Premia

We now test whether firm-days with expected information consumption are associated with a return premium. To examine this, in Table 5, we run panel regressions of daily stock returns on various *EIC* measures, controlling for scheduled firm information events, expected retail information consumption (*ERIC*), scheduled events from alternatively defined peer firms, and other controls including *LnSize*, *LnBM* and 10 return lags of squared returns, and trading volume. Day fixed effects are also included and standard errors are clustered by firm and date. Finally, to correct for a possible microstructure bias, we follow Asparouhova, Bessembinder, and Kalcheva (2010, 2013) and employ a weighted-least-square (WLS) correction procedure, where we use lagged gross return as the weight for each observation. For consistency, we apply the same weighting scheme throughout the remaining analyses.

Insert Table 5 about here.

First, in many of the specifications in Table 5, there appears to be a significant return premium associated with earnings announcements (*EDAY*), which confirms the results that are present in Engelberg, McLean, and Pontiff (2018) and the presence of an earnings announcement premium (Frazzini and Lamont, 2007; Barber, De George, Lehavy and Trueman, 2013; Savor and Wilson, 2016). However, the earnings announcement premium is absent or only marginally significant when we analyze FOMC announcements and macroeconomic events (*MACRO*). Second, other (non-earnings) firm scheduled events carry a return premium, which is economically significant. This finding is novel as these firm scheduled events have not been systematically studied before. Third, the coefficients on *ERIC* are small and insignificant, possibly because retail investors consume information with a delay, when a significant portion of uncertainty has already been resolved in the market.

Exploring the risk premium associated with the EIC measures, in Specifications 1-7 we find a robust premium associated with *EIC_PEER*, which ranges between 2.1-2.3 basis points. The coefficient on *EIC_PEER* is smaller than those on scheduled events for two reasons. First, while scheduled events are known in advance, *EIC_PEER* needs to be estimated with errors and such errors can lead to an attenuation bias. More importantly, models in both Savor and Wilson (2016) and Section 2.1 predict the highest premium for the announcing firms because these firms have the highest exposure to the information contained in the announcements. Finally, we note that *EIC_PEER* is seven times more frequent than *EDAY*, and four times more frequent than *NESEDAY*, so the cumulative contribution of *EIC_PEER* to return premia is comparable.

Our extension of the model of Savor and Wilson (2016) in Section 2.1 also predicts a positive risk premium for firms that experience information spillovers, and that EIC firms are associated with higher risk premia than other peer firms. Specifications (3) to (7) confirm these predictions. In particular, we find that the *EAVOL* coefficient is virtually zero. Even for *FF48_SEDAY*, a one standard deviation increase in this measure is associated with 0.47 basis points higher returns.

In Specifications 8-11, we estimate the premium associated with our *EIC_FOMC* and *EIC_MACRO* measures. Consistent with macroeconomic announcements conveying systematic information, we find that *EIC_FOMC* (*EIC_MACRO*) is associated with an additional premium of 11.235 (7.187). Consistent with Table 4.B, the EIC measures identify firms that are most affected by macroeconomic information that earn a higher premium. Finally, in Specifications 12-14, we look at *EIC_ALL*, which combines all three measures. The estimated premium ranges between 3.6-3.8 basis points.

3.2 Calendar-time Trading Strategies and Economic Magnitudes

In Table 6, we examine the economic magnitude of the return premium using calendar-time trading strategies. The trading strategies are implementable since the *EIC* measures are constructed using only historical information. This allows us to calculate the excess returns and Sharpe ratios associated with various *EIC* measures.

Insert Table 6 about here.

Panel A of Table 6 explores calendar-time portfolios based on firm scheduled events. Our stylized model includes four types of firms: the *Announcing Firms*, *EIC firms*, *Other Peer* Firms, and *unrelated firms* (Benchmark). Consequently, in panel A, we construct the four corresponding non-overlapping portfolios on each event day. The first portfolio includes the "*Announcing Firms*," or firms with scheduled events (Specification 1). The second portfolio includes "*EIC Peer*

Firms," or firms with *EIC_PEER* =1 (Specification 2). The third portfolio includes the "*Other Peer Firms,*" or other firms in the same industries as the announcers with *EIC_PEER* =0 (Specification 3). The last portfolio is the "*Benchmark*" portfolio that includes all other firms (Specification 4). Detailed information regarding the construction of the four portfolios appear in the caption of Table 6.

Consistent with the stylized model in Section 2.1, we find that the average daily excess return (over the risk free rate) associated with these portfolios monotonically decreases from 10.28 basis points (the announcing firms) to 4.6 basis points (the benchmark). The risk-adjusted returns also decrease accordingly. In particular, the *EIC_PEER* portfolio has a Fama-French 5-Factor (DGTW) risk-adjusted return of 2.0 (1.7) basis points. The portfolio annualized Sharpe ratio is 1.02, representing an almost 50% increase from that of the benchmark portfolio. The returns and Sharpe ratio of the *EIC_PEER* portfolio also compare favorably against those of other peer firms. In other words, active information consumption is indeed associated with a higher premium that is economically significant.

Next, in Panel B, we explore calendar-time portfolios associated with macroeconomic announcements, where the portfolios of interest are based on *EIC_FOMC* = 1 and *EIC_MACRO* = 1. The benchmark portfolios are based on *EIC_FOMC* = 0 and *EIC_MACRO* = 0. Consistent with the regression analysis, we find significant return premia associated with the EIC=1 portfolios, which almost double those associated with the EIC=0 portfolios. Moreover, the annualized Sharpe ratio associated with the *EIC_FOMC*=1 (*EIC_MACRO*=1) portfolio is 102% (58.5%) higher than that of its benchmark. Finally, while the risk-adjusted returns of the EIC=1 portfolios are between 4.6-8.9 basis points, the risk-adjusted returns of the EIC=0 portfolios are around 0.

3.3 Support for a Risk-Based Explanation

In this subsection we further explore the relation between our EIC measures, the CAPM Beta, the performance of the CAPM, and across various subsamples. Table 7 reports these results, which provide support for a risk-based interpretation of the return premia we observe.

Insert Table 7 about here.

In Panel A of Table 7, we examine whether systematic risk is higher on days with *EIC*, *ERIC*, or other scheduled firm events. Given the systematic implications of trading volume, we also include *EAVOL* as a control. We estimate a time-varying factor loading CAPM beta model using variations of the following model:

$$\begin{aligned} ERET_{it} = \alpha_i &+ \beta_1 \times EIC_{it} + \beta_2 \times ERIC_{it} + \beta_3 \times NESEDAY_{it} + \beta_4 \times EDAY_{it} + \beta_5 \\ &\times EAVOL_{it} + \beta_6 \times MKTRF_t + \beta_7 \times MKTRF_t \times EIC_{it} + \beta_8 \times MKTRF_t \\ &\times ERIC_{it} + \beta_9 \times MKTRF_t \times NESEDAY_{it} + \beta_{10} \times MKTRF_t \times EDAY_{it} \\ &+ \beta_{11} \times MKTRF_t \times EAVOL_{it} + \varepsilon_{it} \end{aligned}$$

where *ERET* is the stock return minus the risk free rate (in basis points), *MKTRF* is the market return minus the risk free rate (in basis points), and EIC is based on *EIC_ALL*. As in Patton and Verardo (2012), stock fixed effects are included in each regression, which allows us to capture within-firm beta estimation. Given that this is a within-firm analysis and the fact that most of the spillover observations start from April 2011 (Column 1 of Table 3), we run our beta tests from April 2011. The results are reported in Panel A of Table 7.

The first five specifications in Table 7.A report the coefficients from panel regressions, controlling for the five information consumption and information supply measures separately. The first specification indicates that CAPM betas on days with *EIC* = 1 are about 0.047 higher than on days with no expected information consumption. The second specification shows no significant change in the CAPM betas on days with *ERIC* = 1. Specifications 3 and 4 examine the impact of scheduled events and earnings announcements on betas. Betas are about 0.14 higher on days with earnings announcements, which is consistent with Patton and Verardo (2012). Other scheduled firm-level news events increase the beta by 0.061. We also find that *EAVOL* has a coefficient of 0.041. Finally, Specifications 6 and 7 include all five measures as interactions with market returns. The impact of *EIC* is only slightly smaller than when it is included individually. The increase in beta on EIC days supports a risk-based interpretation of higher average returns on those days.

Next, we turn to tests of the Capital Asset Pricing Model. Savor and Wilson (2014) show that the CAPM performs well on macroeconomic announcement days (FOMC, unemployment, and inflation), and fails on other days. In the same spirit, we partition stock-day observations based on measures of *EIC* and carry out our tests. Each day, we run a cross sectional regression of excess stock returns on CAPM betas. Panel B of Table 7 examines the time-series means of these Fama-MacBeth (1973) regression coefficients.

Various measures of *EIC* paint a consistent picture that the CAPM performs better for stock-days when institutional investors are expected to consume information. When *EIC* = 0, the slope coefficient on the CAPM beta is never significant while the intercept term is often positive and significant, consistent with the well-documented failure of the CAPM in describing the cross-sectional variation in average returns. In contrast, when *EIC* = 1, the slope coefficient on the CAPM beta is always positive and significant and the intercept term is rarely significant. The risk premium estimate for *EIC* = 1 ranges from 8.166 to 43.852 basis points, and is always significantly higher than when *EIC* = 0.

For example, for the combined *EIC* (*EIC_ALL*) in specification 4, when institutional investors are expected to consume information, the CAPM does well with a significant risk premium estimate of 9.71 basis points and an insignificant intercept term close to zero. In contrast, when *EIC_ALL* = 0, the CAPM fails with an insignificant risk premium estimate close to zero and a significantly positive intercept term of 6.71 basis points. A risk premium of around 10 bps for *EIC*=1 is consistent with the sample statistics reported in Table 1 and the additional increase in risk premium documented in Table 5. Note that the increase in beta of around 5% is much lower than the increase in return of *EIC*=1 relative to *EIC*=0 which is around 40%. This suggests that this is not just an increase in the quantity of risk, but also an increase in the compensation per unit of risk as well. Our calendar time portfolios (see Table 6) are consistent with this view, where the Sharpe ratio for *EIC*=1 stocks is around 50% higher than that for *EIC*=0 stocks.

Insert Figure 1 about here.

Figure 1.A illustrates the CAPM result graphically. Each day, within *EIC_ALL* = 1 and *EIC_ALL* = 0 subsamples, we sort stocks into decile portfolios based on their CAPM betas, estimated over the previous 252 trading days using the same decile cutoffs for all stocks. Figure 1.A plots the average portfolio daily excess returns (over the risk-free rate) against their average CAPM betas, separately for the two subsamples. The figure confirms that the CAPM works better among *EIC_ALL* = 1 stocks. There is a positive relation between the average excess return and the

CAPM beta for stocks when institutional investors are expected to consume information. Among *EIC_ALL* = 0 stocks, the relation is in fact slightly negative.

Specification 2 in Panel B of Table 7 focuses on the interesting case of the FOMC announcements. Savor and Wilson (2014) find that the CAPM performs well on those days. We find their results to be modulated by *EIC*. On FOMC announcement days, the CAPM only works well among a subset of stocks where institutional investors are expected to consume information. For those stocks, the CAPM regression generates a significant risk premium estimate of 43.852 basis points. For the remaining stocks, the risk premium estimate is still small and insignificant.

Figure 1.B illustrates the FOMC results graphically. We observe the strongest positive relation between the average excess return and the CAPM beta among *EIC* = 1 stocks on FOMC announcement dates. On these dates, the relation between average excess returns and CAPM betas is much weaker among *EIC* = 0 stocks. Similar patterns apply to the broader set of macroeconomic announcements and *EIC_ALL* as well, as reported in specifications 3 and 4.

Finally, in Panel C of Table 7 we consider four subsamples in our data. The first two are based on firm characteristics: the relative size within the firm's Fama French 48 industry and number of analysts covering the firm. We hypothesize that *ceteris paribus*, smaller firms in an industry and firms with lower analyst coverage should respond more to information disseminated by other firms. The second two subsamples of firms are chosen based on the timing aspect of information releases. Specifically, we explore differences across 10-K and 10-Q reporting quarters and differences across the first half and second half of the earnings cycle. *Ceteris paribus*, we hypothesize that information released in the 10-K and information released during the first half of the earnings cycle should be more material and informative compared to information released in the 10-Q and the second half of the earnings cycle. As such, information consumption during the 10-K quarter and information consumption during the first half of the earnings cycle should command a higher risk premium.

Specifically, Panel C of Table 7 repeats the analyses in Tables 5 and 7.B and reports the risk premium and the CAPM regression slopes for all four subsamples using *EIC_ALL*. As with the previous analyses, the risk premia are statistically significant and the CAPM performs well for *EIC_ALL*=1. The differences across subsamples are economically significant and appear to be consistent with our conjectures. Smaller firms and those with lower analyst coverage have higher risk premia when *EIC* is equal to 1, and the CAPM slopes are steeper. This also appears to be the case for the 10-K quarter and for firms who report in the first half of earnings cycles.

3.4 Alternative Explanations

Our collective evidence seems to be consistent with a risk-based explanation. However, there are other alternative explanations for our findings. In this subsection, we explore two alternative explanations: price pressure and mispricing. Table 8 reports the results.

We first explore the existence of price pressure. That is, the higher average return associated with *EIC* could be transitory and subsequently revert. Panel A of Table 8 extends the calendar time portfolio analysis for the *EIC_ALL* portfolio from trading day 1 to trading day 90 after portfolio formation. We report results for cumulative risk-adjusted returns based on the Fama-French 5-Factor Model, and the Daniel, Grinblatt, Titman and Wermers (1997) characteristic-based adjustment.

Insert Table 8 about here.

Regardless of the risk-adjustment method used, the first thing to note is the large *p*-values associated with these cumulative abnormal portfolio returns. While the return point estimates range from -2 to 6 basis points, their standard errors are much wider, which cast doubts on any reliable inference from this analysis. Nevertheless, the short-term abnormal returns show no indication of an immediate reversal. The longer-term analysis does present negative point estimates around days 40 to 60, but they are not statistically different from zero and are not robust over time. They become positive again by day 90. However, while we do not find strong evidence for a return reversal, we acknowledge that we cannot completely rule it out, since our relatively short sample period may prevent us from documenting statistically significant reversals in the long run. Admittedly, we recognize the limitations of our empirical exercise in ruling out a price pressure explanation.

Next, we explore the existence of a potential mispricing explanation, where the higher average return associated with *EIC* reflects a correction to mispricing rather than a risk premium. Panel B of Table 8 extends the analysis conducted in Table 5 using the mispricing measure (MISP) of Stambaugh, Yu, and Yuan (2012). We match our sample with the MISP measure and rank the stocks based on their MISP scores into four quartiles. The mispriced stocks (Mispriced) are stocks with MISP values in the top and bottom quartiles (quartiles 1 and 4). Non-mispriced stocks (Non-Mispriced) are stocks with MISP values in the middle quartiles (quartiles 2 and 3). We find that the return of the two groups of stocks are almost identical with an associated return premium of 3.63 and 3.64 basis points, respectively. To the extent that MISP captures relative mispricing across stocks, this evidence suggests that mispricing does not likely account for our results.

In sum, we find measures of expected information consumption to be associated with higher average stock returns around scheduled announcements of systematic information. While it is impossible to completely rule out price pressure, mispricing and other potential alternative explanations, the collection of our results involving ex-ante measures, average returns, betas, and the performance of the CAPM does provide strong support for a risk-based interpretation.

4. Concluding Remarks

Understanding the relationship between information consumption and asset pricing is fundamentally important. Recent evidence suggests that the scheduled arrival of systematic information is associated with a risk premium (Savor and Wilson, 2013, 2014, 2016). We show that such scheduled announcements also generate a return premium for firms that experience information spillovers. Using institutional investors' news researching and reading activities, we construct novel measures of expected information consumption (EIC) on individual firms during such spillovers, when scheduled peer firm or macroeconomic announcements occur.

We confirm that expected information consumption is associated with a higher average return, that the CAPM performs well for individual stocks on days in which information consumption is expected to be high, and that expected information consumption appears to modulate the effect of FOMC announcements on asset prices (Savor and Wilson, 2014). Collectively, these evidence support a risk-based interpretation of the return premia.

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Appendix: EIC Construction

In this appendix, we give more details regarding the construction of our *EIC* measures. Table A provides a full list of the variables that we use in our regressions.

Using firms' earnings announcements from I/B/E/S and a list of scheduled events available to Bloomberg terminal users in advance, our first spillover measure of institutional investors' expected information consumption is based on the predicted response of AIA to peer-firm scheduled events. This ex-ante measure aims to capture *systematic* information spillovers from *peer-firm* scheduled events (*EIC_PEER*). In particular, we zoom in on two cases. The first is systematic information spillovers during earnings cycles from other firms' scheduled earnings announcements. The second is systematic information spillover from other firms' non-earnings scheduled events. The basic idea behind our method is intuitive and simple: if firm A's *AIA* often spikes during firm B's past earnings announcements (firm B's previous non-earnings scheduled events), we can predict its *AIA* will likely be 1 on firm B's next earnings announcement (non-earnings scheduled event). Our *EIC_PEER* measure is the combination of these two cases.

To identify systematic information spillovers during the earnings cycle, for each firm i in quarter q, we examine the set of J firms (excluding firm i) over the past four quarters and count the cases in which firm i's *AIA* spikes (i.e., *AIA*=1) on firm j's earnings announcement days. We then calculate the ratio between the number of *AIA*=1 spikes and the total number of firm j's earnings announcements. For example, if *AIA* for firm i spiked on three of firm j's announcements days, the score of pair i-j is set to 3/4. We repeat this calculation for all J firms. We then use these scores to predict information consumption for firm i that spills over from each firm j on their subsequent earnings announcement days. Returning to the previous example, the score 3/4 is assigned to firm i on the day firm j announces earnings in quarter q. Given that multiple firms may report their earnings on same day *t* of quarter q we examine the maximum and median scores for firm i across all firms announcing earnings.

We then construct an earnings spillover dummy variable that receives a value of 1 for firm i when the max score on a given day is equal or greater than 3/4 and the median score is greater than 1/4 (i.e., a minimum response to an earnings event out of 4 potential events). The median score requirement is geared toward revealing systematic signals from multiple firms. The earnings spillover dummy variable is set to zero otherwise. Finally, to reduce the noise and increase the possibility that investors learn from peer firm earnings announcements, for each firm i we include observations from the beginning of the quarter until the firm's own earnings announcement. We also make sure to exclude firm i's own earning announcement day.

To identify systematic information spillovers peer firm non-earnings scheduled events, we exclude earnings announcements and earning calls from the Bloomberg's scheduled list of events. Since the median number of non-earnings scheduled events per firm and year is around 6, we treat the non-earnings scheduled events as a one pooled category. We then use the same methodology. In particular, for each firm i in quarter q, we examine the set of J firms over the past four quarters and count the cases in which firm i's *AIA* spikes (i.e., *AIA*=1) on firm j's non-earnings scheduled event days. We then calculate the ratio between the number of *AIA*=1 spikes and the total number of firm j's non-earnings scheduled events. We repeat this calculation for all J firms. Next, the scores are placed in quarter q based on each firm j's quarter-q scheduled event days and calculate the maximum score. As in the case of earnings spillovers, we construct a non-earnings scheduled dummy variable that receives a value of 1 for firm i if the max score on a given day is equal to 1, and the median score is equal or greater than 1/6 (i.e., a minimum response to a scheduled event with a frequency of 6 events per year). The dummy variable is set to zero otherwise. Finally, to increase the possibility that investors learn from peer firm non-earnings scheduled events, we make sure to exclude firm i's own scheduled events. Finally, to construct *EIC_PEER* measure, we combine the two dummy variables (i.e., the earnings spillover dummy and the non-earnings scheduled event dummy) by taking the max of the two dummy variables.

The second set of measures is based on the predicted response of *AIA* to FOMC announcements and all MACRO announcements. We construct a predicted information consumption measure for each stock and FOMC announcement day (*EIC_FOMC*) and each stock and MACRO announcement day (*EIC_MACRO*). The measures are based on *firm AIA* behavior over the previous four FOMC announcements days or year's worth of MACRO announcement days.

For FOMC announcement days, if a given stock, If *AIA* is equal to one at least 50% of the previous four FOMC announcement days[9], we set *EIC_FOMC* to 1 on the current FOMC announcement day, and zero otherwise. During the first few months of our sample we allow for *up to* 4 announcements, to minimize loss of observations. For MACRO announcement days, since

[9] The Federal Reserve Open Market Committee (FOMC) holds 8 regularly scheduled meetings per year and additional meetings as needed.

there are macroeconomic announcements almost every day, we limit ourselves to the five categories that draw the most attention from institutional investors on Bloomberg terminals (see Table 2): Nonfarm Payroll (NFP), Producer Price Index (PPI), FOMC, the advance estimate for GDP (GDP), and the ISM manufacturing index (ISM). The Macroeconomic announcement dates are from Bloomberg. For each category, for a given stock, If *AIA* is equal to one at least 50% of the previous year, and set the category dummy variable to 1, and zero otherwise.[10] *EIC_MACRO* is then the max across five categories.

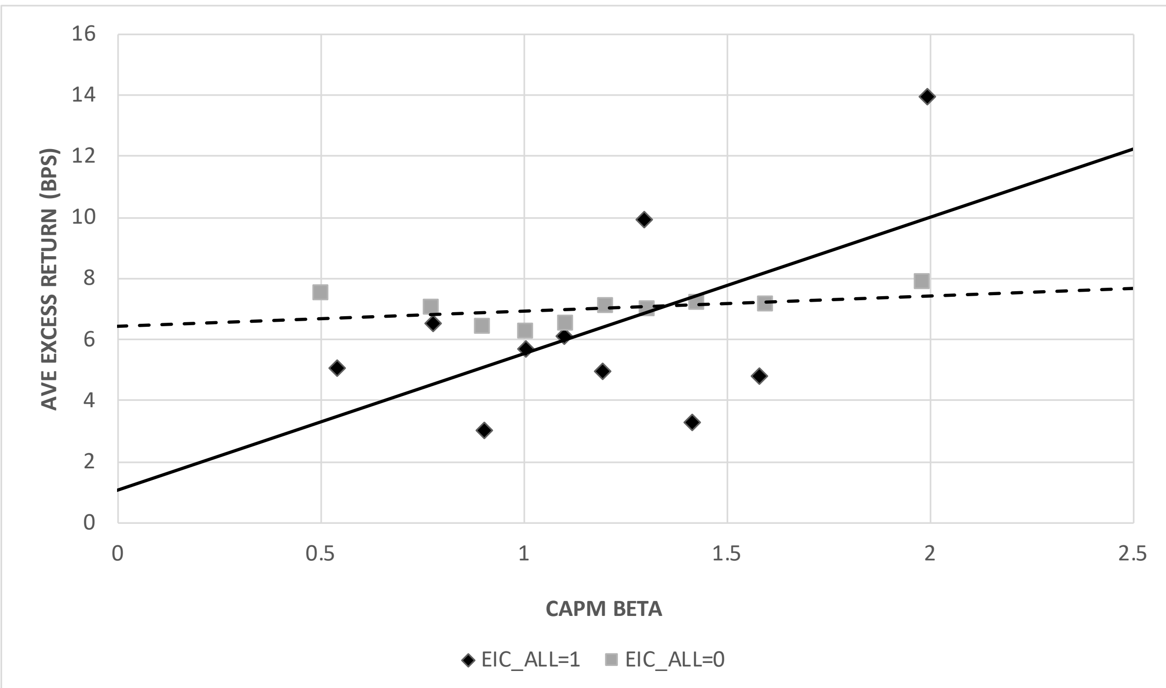
Finally, we construct an overall spillover measure based on the expected information consumption measures constructed (*EIC_ALL*). The measure is based on the aggregation of *EIC_PEER*, *EIC_FOMC* and *EIC_MACRO*. Summary statistics about all of these measures are provided in Table 3 together with additional discussions in Section 2.3 of the paper.

[10] As in the case of non-earnings firm scheduled events, since the number of macro announcements in general is not fixed, we look at a period of up to a year.

Figure 1. CAPM in Various Subsamples

Each day, we partition stocks in our sample into ten decile portfolios based on their CAPM betas, where for each day and stock, betas are estimated using the previous 252 trading days. Then, for each decile, we create two subsamples based on whether their *EIC_ALL* equal 1 or 0 on that day. Panel A plots the average portfolio daily excess returns (over the risk-free rate) against their average CAPM betas, separately for *EIC_ALL* = 1 (solid line) and *EIC_ALL* = 0 (dashed line) subsamples. In Panel B, we plot the average portfolio daily excess returns against their average CAPM betas separately for (1) *EIC* = 1 stocks over FOMC announcement dates (*EIC* = 1 & FOMC = 1, solid line); (2) *EIC* = 0 stocks over FOMC announcement dates (*EIC* = 0 & FOMC = 1, dotted line); (3) stocks over FOMC announcement dates (FOMC, dashed line).

Graph 1.A – Excess Return and CAPM Betas: *EIC_ALL* = 1 and *EIC_ALL* = 0 Subsamples



Graph 1.B – Excess Returns and CAPM Betas FOMC / *EIC* Subsamples

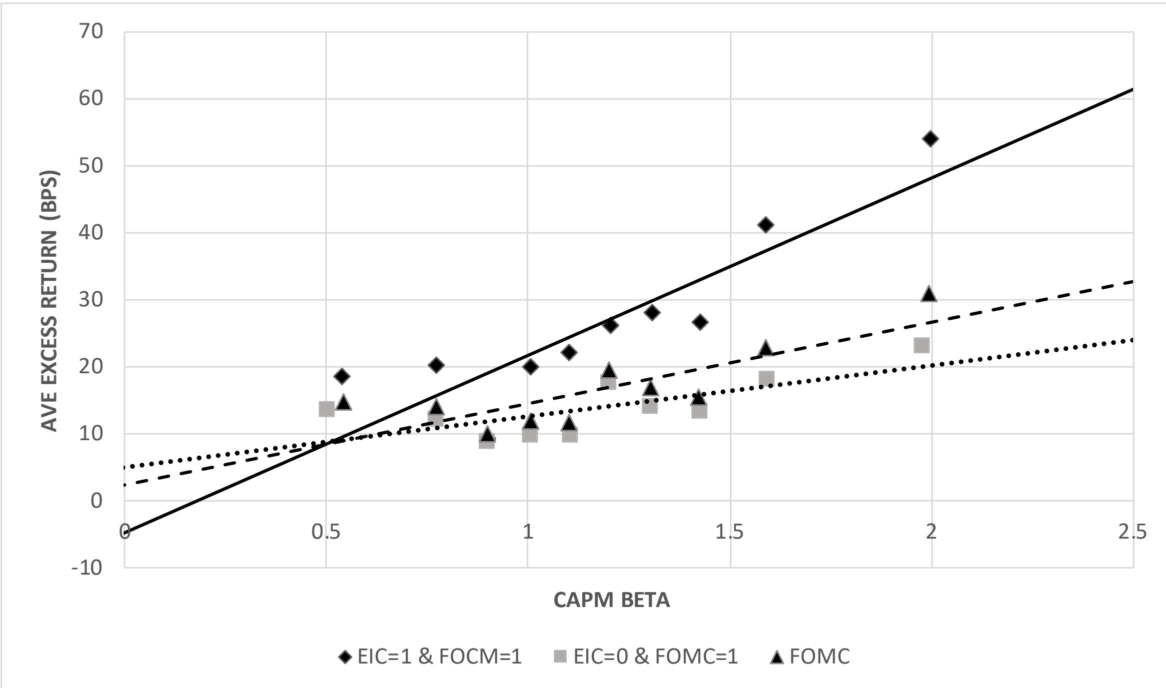


Table 1. Summary Statistics

This table reports the summary statistics of our Abnormal Institutional Attention measure (*AIA*) and other selected variables from February 2010-December 2017. Our full sample includes all stocks that appeared in the Russell 3,000 index during our sample period, with CRSP Share Codes 10 and 11, *AIA* and book-to-market information and price of at least $5. This results in 4,046,091 day-stock observations across 3,188 unique stocks. All variables are defined in Table A. *Num Firms* reports the number of unique firms. Mean, Median, and SD refer to the cross-sectional average, median, and standard deviation of the firms' time series averages. Due to data coverage, *DADSVI* statistics are based on 2,713,314 *DADSVI* day-stock observations. See Table A for information regarding the augmentation of *DADSVI's* sample with zeros when analyzing *AIA* and *DADSVI* together.

Variable	Mean	Median	SD
Num Firms	3,188		
AIA	0.0759	0.054	0.081
DADSVI	0.0764	0.0755	0.041
NDAY	0.218	0.222	0.128
NESEDAY	0.024	0.017	0.026
EDAY	0.015	0.016	0.004
RET	9.44	7.26	28.05
DolVol	51.10	10.27	173.18
BM	0.640	0.522	0.940
SizeInM	6,233	1,081	22,838
InstOwn	0.611	0.664	0.235

Table 2. Determinants of Institutional Information Consumption

This table reports results from Logit panel regressions of the Abnormal Institutional Attention measure (*AIA*) from Bloomberg on various measures of scheduled and unscheduled information events and additional control variables. All variables are defined in Table A. Specification 1 includes three firm information events: an unscheduled news day dummy (*USNDAY*), a non-earnings scheduled event dummy (*NESEDAY*), and an earnings announcement day dummy (*EDAY*). In Specifications 2-4, we also include the value weighted averages of *NDAY* (scheduled and unscheduled firm news excluding earnings) for firm *i*'’s Fama French 48 industry (excluding firm *i*) (*FF48_NDAY*), and a similar measure using earnings announcements (*FF48_EDAY*) as well as value weighted measures at the market level for news (*AGG_NDAY*) and earnings announcements (*AGG_EDAY)*. In Specifications 5-8, we explore macroeconomic announcement days. Macroeconomic announcement dates are from Bloomberg. Specifications 5 and 7 include a dummy variable indicating that that there was at least one of five major macroeconomic news announcements that day (*MACRO*). Specification 6 and 8, include individual dummy variables for each of the five macroeconomic news announcements: Nonfarm Payroll (*NFP*), Producer Price Index (*PPI*), the FOMC rate announcement (*FOMC*), the advance estimate for GDP (*GDP*), and the ISM Manufacturing index (*ISM*). In Specifications 9 and 10, we also include additional firm control variables: the natural logarithm of the firm’s market capitalization (*LnSize*); the natural logarithm of the firm’s book-to-market ratio (*LnBM*); the absolute return of the stock (*AbsRet*); firm CAPM beta using the previous 252 trading days; and firm leverage, calculated as the ratio between long-term debt and total assets. All specifications include day-of-the-week fixed effects. The sample includes 4,046,091 day-stock observations. Standard errors (in parentheses) are double clustered by firm and date. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively. *Pseudo R Squared* is the logistic model’s Max-rescaled R-Square.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
USNDAY	0.931 ***	0.926 ***	0.912 ***	0.913 ***			0.913 ***	0.913 ***	0.462 ***	0.462 ***
	(0.019)	(0.019)	(0.019)	(0.019)			(0.019)	(0.019)	(0.012)	(0.012)
NESEDAY	1.297 ***	1.300 ***	1.300 ***	1.302 ***			1.302 ***	1.303 ***	0.736 ***	0.737 ***
	(0.035)	(0.034)	(0.034)	(0.034)			(0.034)	(0.034)	(0.029)	(0.029)
EDAY	3.175 ***	3.147 ***	3.117 ***	3.113 ***			3.112 ***	3.114 ***	2.568 ***	2.571 ***
	(0.027)	(0.026)	(0.026)	(0.026)			(0.026)	(0.026)	(0.034)	(0.034)
FF48_NDAY		0.121 **		-0.052			-0.052	-0.051	-0.093 **	-0.093 **
		(0.055)		(0.064)			(0.064)	(0.064)	(0.037)	(0.037)
FF48_EDAY		0.813 ***		0.481 ***			0.482 ***	0.484 ***	0.415 ***	0.418 ***
		(0.095)		(0.085)			(0.085)	(0.085)	(0.077)	(0.077)
AGG_NDAY			0.586 ***	0.629 ***			0.631 ***	0.631 ***	1.092 ***	1.092 ***
			(0.092)	(0.108)			(0.108)	(0.108)	(0.116)	(0.116)
AGG_EDAY			2.011 ***	1.560 ***			1.501 ***	1.660 ***	1.864 ***	2.061 ***
			(0.408)	(0.424)			(0.428)	(0.432)	(0.489)	(0.495)
MACRO					0.084 ***		0.051 *		0.016	
					(0.026)		(0.027)		(0.033)	
FOMC						0.149 ***		0.106 **		0.069
						(0.048)		(0.047)		(0.078)
GDP						0.294 ***		-0.103		-0.144
						(0.054)		(0.070)		(0.088)
ISM						0.068		0.062		0.007
						(0.042)		(0.046)		(0.053)
PPI						-0.042		0.037		0.050
						(0.047)		(0.050)		(0.058)
NFP						0.078		0.044		0.007
						(0.055)		(0.060)		(0.071)
Day of Week FE?	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Other Controls?									YES	YES
Pseudo R Squared	0.095	0.095	0.096	0.096	0.005	0.006	0.096	0.096	0.236	0.236

Table 3. Institutional Investor Expected Information Consumption Measures and Subsamples

This table reports statistics for the four expected institutional information consumption measures (EIC) defined in the Appendix. *# of Observations* is the number of sample observations used in the analysis. *EIC=1 Obs* is the number of observations with expected institutional information consumption equal to 1. *% of EIC=1 Obs* is the percentage of these observations to total observations in that sample. Next, the table reports the percentage of AIA=1 observations conditioning on *EIC*=1 and *EIC*=0. *P-Value of diff*, is the *p*-Value of the difference in percentages. *Sample Range* indicates the first month and last month of the analyzed sample.

	EIC_PEER	EIC_FOMC	EIC_MACRO	EIC_ALL
	(1)	(2)	(3)	(4)
# of Observations	2,306,754	126,223	715,928	4,046,091
EIC = 1 Obs	252,476	11,159	18,377	270,054
% of *EIC*=1 Obs	10.95%	8.84%	2.57%	6.67%
EIC = 1 and *AIA* = 1	24.12%	25.61%	30.89%	24.17%
EIC = 0 and *AIA* = 1	9.12%	8.41%	7.46%	7.09%
P-Value of diff	<.0001	<.0001	<.0001	<.0001
Sample Range	Apr11-Dec17	Apr10-Dec17	Mar10-Dec17	Feb10-Dec17

Table 4. Determinants of *EIC_PEER*, *EIC_MACRO* and *EIC_FOMC*

This table reports results from Logit panel regressions of the expected institutional information consumption measures (EIC) defined in the Appendix, on various measures of scheduled information events and other control variables. All variables are defined in Table A. Panel A examines the *EIC_PEER* measure. Specifications 1-3 (*BASE*) include value weighted averages of *SEDAY* (all scheduled firm news) for firm *i*''s Fama French 48 industry (excluding firm *i*) (*FF48_SEDAY*), as well as value weighted measures at the market level (excluding firm *i*) (*AGG_SEDAY*). In Specifications 4-10, we explore additional *SEDAY*-based measures using alternative peer firm definitions. In Specification 4 - 6, we include measures based on the firm's three closest peers, where peers are defined within the FF48 industry (*FF48_3CLS*), the GICS2 sector (*GICS2_3CLS*), and the Hoberg and Phillips (2010, 2016) TINC3 classification (*HPTINC3_3CLS*), respectively. In Specifications 4 and 5, closest peers are define based on the smallest absolute difference in firm market cap. In Specification 6, closest peers are defined based on the highest textual-based similarity scores. In Specification 7, we include an equivalent *EIC_PEER* measure based on volume spikes, where we replace AIA with abnormal trading volume (*EAVOL*). In Specification 8, we include a measure based on co-mentioning in news articles. Finally, our last measure (Specification 9) is based on supplier-customer economic links, where we look at suppliers' top customers (*SUP-CUS*). We run a horserace across these measures in Specification 10. We control for *LnSize*, *LnBM*, *Beta* and *Leverage*. We also include day-of-the-week fixed effects. In Panel B we examine the *EIC_MACRO* (Specifications 1-2) and *EIC_FOMC* (Specifications 3-4) measures. We include ten (out of the eleventh) GICS2 sector dummy variables, where the removed "*Customer Staples*" serves as the base sector. We include the same control variables reported in Panel A. Standard errors (in parentheses) are double clustered by firm and date. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively. *Pseudo R Squared* is the logistic model's Max-rescaled R-Square.

Panel 4.A – *EIC_PEER*

	BASE			ALTERNATIVE PEERS						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
FF48_SEDAY	0.927 ***		0.134 **	0.051	0.107 **	0.084	0.140 ***	0.130 **	0.133 **	0.029
	(0.083)		(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.054)
AGG_SEDAY		4.623 ***	4.509 ***	4.423 ***	4.404 ***	4.430 ***	4.025 ***	4.389 ***	4.518	3.734 ***
		(0.423)	(0.424)	(0.424)	(0.426)	(0.422)	(0.374)	(0.424)	(0.424)	(0.374)
FF48_3CLS				0.135 ***						0.082 ***
				(0.015)						(0.013)
GICS2_3CLS					0.124 ***					0.080 ***
					(0.015)					(0.013)
HPTINC3_3CLS						0.235 ***				0.177 ***
						(0.022)				(0.020)
EAVOL							1.635 ***			1.633 ***
							(0.032)			(0.032)
CO-NEWS								0.324 ***		0.332 ***
								(0.042)		(0.040)
SUP-CUS									-0.043	-0.053
									(0.054)	(0.054)
LnSIze	0.645 ***	0.651 ***	0.651 ***	0.648 ***	0.648 ***	0.649 ***	0.694 ***	0.648 ***	0.652 ***	0.688 ***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
LnBM	0.147 ***	0.141 ***	0.142 ***	0.142 ***	0.142 ***	0.139 ***	0.140 ***	0.140 ***	0.146 ***	0.142 ***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)	(0.030)	(0.030)	(0.031)
Beta	0.659 ***	0.647 ***	0.646 ***	0.645 ***	0.645 ***	0.648 ***	0.703 ***	0.644 ***	0.638 ***	0.691 ***
	(0.043)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.043)	(0.044)	(0.045)
Leverage	0.723 ***	0.689 ***	0.691 ***	0.690 ***	0.692 ***	0.697 ***	0.717 ***	0.686 ***	0.692 ***	0.717 ***
	(0.117)	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)	(0.120)	(0.119)	(0.119)	(0.120)
Day of Week FE?	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Pseudo R Squared	0.184	0.193	0.193	0.193	0.193	0.194	0.236	0.194	0.193	0.237

Panel 4.B – *EIC_MACRO* and *EIC_FOMC*

	EIC_MACRO		*EIC_FOMC*	
Variable	(1)	(2)	(3)	(4)
Consumer_Discretionary	0.346 **	0.344 **	0.103	0.102
	(0.137)	(0.137)	(0.145)	(0.144)
Energy	0.398 ***	0.383 ***	0.509 ***	0.501 ***
	(0.133)	(0.133)	(0.170)	(0.169)
Financial	-0.057	-0.065	-0.171	-0.176
	(0.139)	(0.140)	(0.153)	(0.153)
Healthcare	0.188	0.168	0.073	0.066
	(0.115)	(0.114)	(0.147)	(0.146)
Information_Technology	0.320 **	0.302 **	0.286 *	0.274 *
	(0.136)	(0.137)	(0.150)	(0.150)
Industrials	-0.269 **	-0.281 **	-0.270 *	-0.279 *
	(0.122)	(0.122)	(0.150)	(0.149)
Materials	0.172	0.168	0.164	0.156
	(0.146)	(0.146)	(0.167)	(0.166)
Real_Estate	-0.034	-0.059	0.260	0.245
	(0.249)	(0.240)	(0.244)	(0.238)
Telecom	0.045	0.040	-0.022	-0.030
	(0.152)	(0.152)	(0.224)	(0.221)
Utilities	0.122	0.082	-0.226	-0.239
	(0.148)	(0.146)	(0.181)	(0.178)
LnSIze	0.756 ***	0.760 ***	0.658 ***	0.658 ***
	(0.033)	(0.033)	(0.023)	(0.023)
LnBM	0.272 ***	0.274 ***	0.155 ***	0.154 ***
	(0.059)	(0.059)	(0.044)	(0.044)
Beta	0.797 ***	0.799 ***	0.643 ***	0.645 ***
	(0.075)	(0.075)	(0.073)	(0.073)
Leverage	0.610 ***	0.609 ***	0.654 ***	0.651 ***
	(0.199)	(0.199)	(0.166)	(0.165)
Day of Week FE?	YES	YES	YES	YES
EDAY and NESEDAY?		YES		YES
Pseudo R Squared	0.199	0.211	0.201	0.203

Table 5. Expected Information Consumption and the Return Premium

This table reports results from panel regressions of daily returns on measures of expected institutional information consumption (EIC), controlling for scheduled firm information events, expected retail information consumption (*ERIC*), alternative *SEDAY*-based peer measures (see Table 4), and other firm characteristics. All variables are defined in Table A. Specifically; we analyze each of the four expected institutional information consumption measures described in Table 3 and the Appendix. Specifications 1-7 explore *EIC_PEER*, Specifications 8-9 (10-11) explore *EIC_FOMC* (*EIC_FOMC)* and Specifications 12-14 explore *EIC_ALL*. *NESEDAY* is non-earnings firm scheduled event day dummy. *EDAY* is firm earnings announcement day dummy. *ERIC* is the expected information consumption by retail investors constructed using *DADSVI*, using the same methodology defined in the Appendix. In a similar manner, *EAVOL* is a similar measure based on abnormal trading volume. Following Table 4, in Specifications 1-7 (*EIC_PEER)* we control for the other alternative peers measures based on *CO-NEWS*, *SUP-CUS*, *FF48_SEDAY*, *GICS2_3CLS* and *HPTINC3_3CLS* (see Table A for more details). Since *CO-NEWS*, *SUP-CUS* and *FF48_SEDAY* are value-weighted measures, we report their one standard deviation effect on returns. "*Other Controls*" include the natural logarithm of the firm's market capitalization (*LnSize*) and the natural logarithm of the firm's book-to-market ratio (*LnBM*) together with ten lags of returns, squared returns, news dummy, and trading volume. Date fixed effects are included in each specification and standard errors (in parentheses) are double clustered by firm and date. Finally, to correct for a possible microstructure bias, we follow Asparouhova, Bessembinder, and Kalcheva (2010, 2013) and employ a WLS correction procedure, where we use lagged gross return as the weight. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

	EIC_PEER							EIC_FOMC		EIC_MACRO		EIC_ALL		
					FF48 SEDAY	GICS2 3CLS	HPTINC3 3CLS							FF48 SEDAY
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
EIC	2.258 ***	2.116 **	2.118 **	2.121 **	2.107 **	2.120 **	2.119 **	11.063 ***	11.235 ***	7.230 ***	7.187 ***	3.613 ***	3.668 ***	3.777 ***
	(0.870)	(0.867)	(0.869)	(0.863)	(0.863)	(0.863)	(0.863)	(3.191)	(3.253)	(2.599)	(2.608)	(0.942)	(0.943)	(0.938)
NESEDAY		7.296 **	7.295 **	7.376 **	7.124 **	7.386 **	7.413 **		0.328		1.394		4.316 ***	4.281 ***
		(3.291)	(3.288)	(3.294)	(3.277)	(3.311)	(3.300)		(4.900)		(2.777)		(1.152)	(1.140)
EDAY		15.967 ***	15.968 ***	16.017 ***	15.995 ***	16.028 ***	16.068 ***		3.794		10.420 *		17.298 ***	17.395 ***
		(3.991)	(3.990)	(3.989)	(3.984)	(3.996)	(3.997)		(12.113)		(6.303)		(3.177)	(3.173)
ERIC		0.346	0.346	0.346	0.362	0.346	0.345		-0.545		0.312		0.358	0.385
		(0.565)	(0.564)	(0.564)	(0.564)	(0.564)	(0.564)		(3.411)		(1.308)		(0.500)	(0.500)
EAVOL			-0.017	-0.028	-0.013	-0.028	-0.029		-1.169		-3.387			-1.118
			(0.715)	(0.715)	(0.715)	(0.715)	(0.715)		(2.348)		(2.746)			(0.593)
CO-NEWS				0.171	0.171	0.171	0.170							0.107
				(0.169)	(0.169)	(0.169)	(0.169)							(0.149)
CUS-SUP				0.034	0.007	0.034	0.032							0.043
				(0.199)	(0.196)	(0.199)	(0.199)							(0.149)
OTHER PEERS					0.469	0.069	0.500							0.080
					(0.327)	(0.586)	(0.727)							(0.283)
Other Controls?	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Day FE?	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 6. Assessing the Economic Magnitude via Calendar Time Portfolios

This table reports results from calendar time portfolios based on firm scheduled events (Panel A) and macroeconomic announcements (Panel B). In panel A, we report results for four non-overlapping portfolios. The first portfolio includes the announcing firms, based on firms' own scheduled announcements ("*Announcing Firms*"). To be included in this portfolio, on any given day, we require firms to have at least one schedule event (i.e., SEDAY=1). The second portfolio includes *EIC Peer Firms*. To be included in this portfolio, on any given day, we require firms to have at least one *EIC_PEER* =1. The third portfolio includes *Other Peer Firms*. To be included in this portfolio, on any given day, we require a firm in a given FF48_IND to have *SEDAY*=0 and *EIC_PEER*=0. In addition, we require at least one scheduled announcement (i.e., *SEDAY*=1) by other firms in the relevant Fama-French 48 industry. The fourth portfolio is the benchmark, which includes all other firms. Specifically, to be included in the benchmark portfolio, on any given day, a firm in a given Fama French 48 industry must have *SEDAY*=0, *EIC_PEER*=0. In addition, we require *SEDAY*=0 for all firms in the same industry on that day. To calculate daily portfolio returns, we consider days with at least one event. To reduce noise, if the number of stocks on any given day of the second portfolio (*EIC Peer Firms*) drops below 2; we replace the portfolio return with the return of the third portfolio (*Other Peer Firms*). In panel B, we explore both the FOMC and MACRO economic announcements. To be included in the EIC=1 portfolios, we require on any given FOMC (MACRO) announcement day, a firm only to have *EIC_FOMC*=1 (*EIC_MACRO* = 1) events. The benchmark portfolio includes, on these days, all other stocks with *EIC_FOMC* = 0 (*EIC_MACRO* = 0). For each calendar-time portfolio, we report the average excess return (*ExPortRet*), together with the Fama-French 3- and 5- factor model risk adjusted returns, and Daniel, Grinblatt, Titman and Wermers (1997) characteristic- adjusted returns (*ExPortRet* - *FF3*, *ExPortRet – FF5* and *ExPortRet* - *DGTW*, respectively). All returns are in basis points. We also report portfolio annualized Sharpe Ratio (*Portfolio Ann. Sharpe Ratio* or *BM Ann. Sharpe Ratio*) and the percentage change in Sharpe Ratio relative to the benchmark (*% change*). The factors and the risk free rate are from Ken French's website. Standard errors (in parentheses) are estimated using Newey-West adjustment with 10 lags. Finally, to correct for a possible microstructure bias, we follow Asparouhova, Bessembinder, and Kalcheva (2010, 2013) and employ a WLS correction procedure, where we use lagged gross return as the weight. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel 6.A – Average Excess Return, Risk-Adjusted Returns and Sharpe Ratio of Firm Scheduled Events

	Announcing Firms (1)	EIC Peer Firms (2)	Other Peer Firms (3)	Benchmark (4)
ExPortRet	10.278 ***	7.063 ***	5.690 **	4.602 *
	(3.655)	(2.639)	(2.572)	(2.406)
ExPortRet - FF3	5.269 **	1.837 *	0.708	-0.272
	(2.407)	(0.997)	(0.451)	(0.676)
ExPortRet - FF5	5.243 **	2.003 **	0.802 *	-0.463
	(2.423)	(0.997)	(0.448)	(0.662)
ExPortRet - DGTW	5.037 **	1.704 **	0.761 **	0.136
	(2.222)	(0.813)	(0.360)	(0.577)
Portfolio Ann. Sharpe Ratio	1.211	1.018	0.820	0.682
BM Ann. Sharpe Ratio	0.682	0.682	0.682	0.682
% change	77.60%	49.26%	20.24%	0.00%
Ave. # of Stocks	92	160	859	400

Panel 6.B – Average Excess Return, Risk-Adjusted Returns and Sharpe Ratio of Macroeconomic Announcements

	FOMC		MACRO	
	EIC=1 (1)	EIC=0 (2)	EIC=1 (3)	EIC=0 (4)
ExPortRet	28.554 **	14.857	17.704 **	11.095
	(13.866)	(14.358)	(6.978)	(6.797)
ExPortRet - FF3	8.928 ***	-0.884	5.146 **	1.105 **
	(2.290)	(0.877)	(2.230)	(0.439)
ExPortRet - FF5	8.795 ***	-1.020	4.682 **	1.111 **
	(2.317)	(0.935)	(2.128)	(0.436)
ExPortRet - DGTW	6.884 **	-0.162	4.737 **	0.581
	(2.621)	(0.761)	(1.973)	(0.391)
Portfolio Ann. Sharpe Ratio	3.495	1.727	2.320	1.464
% change	102.36%		58.50%	
Ave. # of Stocks	170	1839	48	2006

Table 7. Additional Evidence from Firm Beta, the CAPM, and Subsample Analysis

This table explores the relation between our expected institutional information consumption measures (EIC) (described in Table 3 and the Appendix), the CAPM *Beta* (Panel A), the performance of the CAPM (Panel B), and across various subsamples (Panel C). All variables are defined in Table A. In Panel A, we report results from panel regressions of daily excess stock returns on excess market returns and on interactions of excess market returns with measures of expected information consumptions and scheduled information events. Excess return (*ERET*) is measured relative to the risk free rate (*RF)*. The market excess return (*MKTRF*) and the risk free rate are from Ken French's website. We interact *MKTRF* with *EIC_ALL (EIC)*, *ERIC_ALL (ERIC)*, *NESEDAY*, *EDAY* and *EAVOL* (i.e., *EAVOL_ALL*). Direct effects are included and not reported to conserve space. Following Patton and Verardo (2012), the specifications include firm fixed effects, which allow us to capture within-firm beta estimation. Standard errors (in parentheses) are double clustered by firm and date. In Panel B, we report time-series average coefficients from Fama-MacBeth (1973) cross sectional regressions of daily excess return (*ERET*) on CAPM betas for the four *EIC* measures. In particular, *EIC_PEER* is based on peer-firm scheduled events. *EIC_FOMC* and *EIC_FOMC* are based on FOMC and MACRO announcement days. *EIC_ALL* is the combination of measures 1, 2 and 3. *EIC=0* (*EIC=1*) includes sample observations where *EIC* is equal to 0 (1). *Diff 1-0* is the difference between the coefficient estimates of both samples. Given that the number of *EIC=1* observations can be very scarce on some days, we report value weighted time-series averages of the cross-sectional regression estimates, based on the daily number of cross sectional observations. Standard errors (in parentheses) are estimated using the Newey-West adjustment with 10 lags. In Panel C, we repeats the main analysis conducted in Tables 5 and Table 7.B, for subsamples based on firm relative size within Fama French 48 industry, analyst coverage, reporting quarter and time during the earnings cycle. Columns (1) and (2) repeat the analysis conducted in Specification 13 of Table 5 (*EIC_ALL*). In Specification 1, we rank firms based on their relative size within industry, where we keep industries with at least five firms in our sample. *Small* (*Large*) refers to firms with size below (above) the median industry size. In Specifications 2 we rank firms based on their analyst coverage, where *Low* (*High*) refers to firms with coverage below (above) the median level of analyst coverage. In Specification 3 we look at the difference between the first quarter (Q1) and other quarters (Q2-Q4). In Specification 4 we focus on the timing during the earnings cycle, where *First Half* (*Second Half*) captures the first (second) half of the cycle based on number reporting firms. Specifically, we count the number of reporting firms and define the first half as the period in the cycle where the cumulative number of reporting firms to total reporting firms is lower than 50%. For brevity, in Columns 1 and 2 only report the coefficient estimate of *EIC_ALL* from the full panel regression. Columns 3 and 4 only report the CAPM slope of *EIC_ALL*=1 subsample (see Beta Column in Specification 4 of Table 7.B). Finally, to correct for a possible microstructure bias, we follow Asparouhova, Bessembinder, and Kalcheva (2010, 2013) and employ a WLS correction procedure, where we use lagged gross return as the weight. In panel B, the correction is done in the cross-sectional regression step. In all panels Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Table 7.A. Expected Information Consumption and Firm Beta

	EIC_ALL						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MKTRF	1.148 ***	1.153 ***	1.150 ***	1.150 ***	1.149 ***	1.146 ***	1.144 ***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
MKTRF EIC*	0.047 **					0.048 **	0.043 **
	(0.018)					(0.018)	(0.018)
MKTRF ERIC*		-0.011				-0.015	-0.017
		(0.014)				(0.014)	(0.013)
*MKTRF*NESEDAY*			0.061 ***			0.065 ***	0.066 ***
			(0.020)			(0.020)	(0.020)
*MKTRF*EDAY*				0.139 ***		0.139 ***	0.136 ***
				(0.041)		(0.041)	(0.042)
MKTRF EAVOL*					0.041 ***		0.035 **
					(0.015)		(0.014)
Direct Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7.B Expected Information Consumption and the CAPM

	EIC_PEER		*EIC_FOMC*		*EIC_MACRO*		*EIC_ALL*	
	(1)		(2)		(3)		(4)	
	Intercept	Beta	Intercept	Beta	Intercept	Beta	Intercept	Beta
EIC = 0	4.865 ***	0.130	1.710	10.761	2.272	7.931	6.706 ***	0.034
	(1.716)	(2.615)	(7.381)	(9.211)	(3.356)	(6.209)	(1.302)	(2.111)
EIC = 1	0.527	8.166 **	-15.852	43.852 **	-13.482	29.812 ***	-0.318	9.709 ***
	(3.043)	(3.844)	(12.075)	(16.779)	(8.178)	(9.085)	(2.945)	(3.713)
Diff 1 - 0	-4.337	8.036 *	-17.561	33.091 *	-15.754 *	21.882 **	-7.024 **	9.676 **
	(3.493)	(4.649)	(14.152)	(19.141)	(8.840)	(11.003)	(3.220)	(4.271)

Table 7.C Risk Premium and CAPM Slope - Subsample Analysis

	Risk Premium		CAPM Slope	
	EIC_ALL Coefficient		*EIC_ALL* = 1 Subsample	
	(1)	(2)	(3)	(4)
Firm Characteristics:				
	Small	Large	Small	Large
Size IND	4.194 **	2.013 ***	9.546 *	9.202 **
	(2.094)	(0.770)	(5.185)	(3.810)
	Low	High	Low	High
Analyst Coverage	4.218 **	1.954 ***	11.949 *	9.293 **
	(1.735)	(0.752)	(6.571)	(3.738)
Timing:				
	Q1	Q2-Q4	Q1	Q2-Q4
Quarters	4.436 **	3.546 ***	18.420 ***	7.309 *
	(1.737)	(1.102)	(6.048)	(4.382)
	First Half	Second Half	First Half	Second Half
Announcing Firms	3.896 ***	3.037 **	17.787 ***	4.559
	(1.355)	(1.219)	(6.029)	(4.665)

Table 8. Alternative Explanations

This table examines two alternative explanations: price pressure (Panel A) and mispricing (Panel B). Panel A extends Table 6's calendar time portfolio analysis and reports results for *EIC_ALL* calendar time portfolios from trading day 1 to trading day 90 after portfolio formation (i.e., trading day 0). In particular, we hold the portfolios up to 90 trading days and calculate their average daily risk adjusted returns. We adjust for risk using the Fama-French 5-Factor Model (*FF-Factor-Adjustment*) and Daniel, Grinblatt, Titman and Wermers (1997) characteristic based risk adjustment (*DGTW Characteristics Adjustment*). For each horizon (*Days* in panel 8.A), we report the cumulative return (i.e., the average daily risk adjusted return *times* the number of days the portfolios are held) together with their corresponding standard errors and *p*-values. For example, "*Days*" 60 refers to the 60-day cumulative return, which is calculated as the daily average risk adjusted return of 60 formed portfolios times 60. All returns are in basis points. To reduce the effect of outliers, we winsorize the top and bottom 0.25% of the daily returns distribution of the formed portfolio, before calculating the daily averages. The standard errors adjusted for heteroskedasticity and serial correlation using Newey-West correction with 10 lags. In Panel B, we extend the analysis conducted in Specification 13 or Table 5 using the mispricing measure (MISP) of Stambaugh, Yu and Yuan's (2012), which is available on Yuan's webpage. We match our sample with the MISP measure, which results in 3,417,057 day-stock observations. We then rank the stocks based on their MISP scores into four quartiles. The mispriced stocks *(Mispriced*) are stocks with MISP values in the top and bottom quartiles (quartiles 1 and 4). Non-mispriced stocks (*Non-Mispriced*) are stocks with MISP values in the middle quartiles (quartiles 2 and 3). Standard errors (in parentheses) are estimated using Newey-West adjustment with 10 lags. Statistical significance at the 10%, 5%, and 1% level is indicated with *, **, and ***, respectively.

Panel 8.A – Long-Term Reversal

	FF5-Factor Adjustment			DGTW-Characteristic-Adjustment		
Days	Cum. Ret	StdErr.	P-value	Cum. Ret	StdErr.	P-value
1	1.050	1.048	0.316	0.594	0.775	0.444
2	1.816	1.788	0.310	1.495	1.329	0.261
3	1.999	2.405	0.406	1.243	1.825	0.496
4	0.904	2.954	0.760	0.353	2.250	0.875
5	1.776	3.576	0.620	1.463	2.682	0.585
10	3.097	6.292	0.623	3.534	4.644	0.447
15	6.305	8.969	0.482	5.408	6.431	0.401
20	5.328	11.650	0.648	2.802	8.240	0.734
30	5.151	17.180	0.764	2.980	11.964	0.803
40	-2.128	22.466	0.925	-2.762	15.574	0.859
60	-1.398	33.363	0.967	3.245	22.917	0.887
90	3.078	49.618	0.951	5.642	33.723	0.867

Panel 8.B – Mispricing

	EIC_ALL			
	BASE		Mispriced	Non-Mispriced
Variable	(1)	(2)	(3)	(4)
EIC	3.625 ***	3.671 ***	3.630 ***	3.644 ***
	(1.017)	(1.002)	(1.132)	(1.154)
NESEDAY	5.943 ***	5.958 ***	5.510 ***	6.400 ***
	(1.167)	(1.164)	(1.432)	(1.345)
EDAY	16.155 ***	16.160 ***	8.061 ***	24.305 ***
	(3.426)	(3.425)	(4.716)	(4.476)
ERIC	0.567	0.561	1.276 *	-0.087
	(0.507)	(0.507)	(0.718)	(0.608)
MISP		-0.026	-0.028	-0.045
		(0.037)	(0.038)	(0.041)
Other Controls?	YES	YES	YES	YES
Day FE?	YES	YES	YES	YES

Table A. Variable Definitions

Variable	Definition
Information Supply Variables	
NDAY	A dummy variable equal to one on news days for firm *i* and zero otherwise. News days are those on which an article about the firm appears on the Dow Jones Newswire, *excluding* earnings announcement days. News data are from RavenPack.
USNDAY	A dummy variable equal to one on news days for firm *i* and zero otherwise. News days are those on which an article about the firm appears on the Dow Jones Newswire, *excluding* earnings announcement days and non-earnings firm scheduled events. News data are from RavenPack. Firm scheduled events are based on a list of scheduled firm events available to Bloomberg terminal users.
EDAY	A dummy variable equal to one on earnings announcement days for firm *i* and zero otherwise. Earnings announcement data are from I/B/E/S.
SEDAY	A dummy variable equal to one on days with a scheduled firm events based on a list of scheduled firm events available to Bloomberg terminal users. Specifically, for each stock, Bloomberg provides an event calendar (Bloomberg command "EVTS") for various events. Bloomberg classifies each event into one of 9 categories. "TV/Conference/Presentation", "Earnings Release", "Earnings Call", "Shareholder Meeting", "Corporate Access", "Mergers and Acquisitions", "Sales Result", "Analyst Marketing", and "Earnings Guidance".
NESEDAY	A dummy variable equal to one on days with non-earnings scheduled firm events. Specifically, we remove the "Earnings Release", "Earnings Call" categories from Bloomberg's 9 categories.
FF48_NDAY	The value-weighted average of *NDAY* for all other firms in the same Fama French 48 industry as firm *i*. Fama French 48 industry definitions are from Ken French's website. Value weights based on market capitalization are from CRSP.
FF48_EDAY	The value-weighted average of *EDAY* for all other firms in the same Fama French 48 industry as firm *i*. Fama French 48 industry definitions are from Ken French's website. Value weights based on market capitalization are from CRSP.
FF48_SEDAY	The value-weighted average of *SEDAY* for all other firms in the same Fama French 48 industry as firm *i*. Fama French 48 industry definitions are from Ken French's website. Value weights based on market capitalization are from CRSP.
AGG_NDAY	The value-weighted average of *NDAY* for all other firms in the sample on day *t*. Value weights based on market capitalization are from CRSP.
AGG_EDAY	The value-weighted average of *EDAY* for all other firms in the sample on day *t*. Value weights based on market capitalization are from CRSP.

AGG_SEDAY	The value-weighted average of *SEDAY* for all other firms in the sample on day *t*. Value weights based on market capitalization are from CRSP.
FF48_3CLS	A dummy variable equals to one on days where firm i's *SEDAY*=0 and one of firms i's three closets peers have an *SEDAY*=1. The dummy is set to zero otherwise. Peers are defined based on the same Fama French 48 industry. Closet peers are defined based on the smallest absolute differences in market cap of firm i and other firms in the same industry.
GICS2_3CLS	A dummy variable equals to one on days where firm i's *SEDAY*=0 and one of firms i's three closets peers have an *SEDAY*=1. The dummy is set to zero otherwise. Peers are defined based on the same GICS2 sector (see e.g., Lee, Ma and Wang, 2015). Closet peers are defined based on the smallest absolute differences in market cap of firm i and other firms in the same sector.
HP-TINC3_3 CLS	A dummy variable equals to one on days where firm i's *SEDAY*=0 and one of firms i's three closets peers have an *SEDAY*=1. The dummy is set to zero otherwise. Peers are defined based on Hoberg and Phillips' (2010, 2016) Text-based Network Industry Classifications (TNIC). The classification is based on firm pairwise similarity scores from text analysis of firm 10K product descriptions. Closets peers are the three firms with the highest similarity scores.
CO-NEWS	We use RavenPack data to construct a peer measure based on firms co-mentioning in the same news article. In particular, firm i and j are considered to be linked via news, if both firms are mentioned together in at least 2 news articles in the past 4 quarters. To remove outliers, we exclude the top 1%. We then construct a value-weighted average of *SEDAY* for all firms that are co-lined to firm *i*. The measure is set to zero on days where firm i's *SEDAY*=1. The value weights based on market capitalization are from CRSP.
SUP-CUS	We use Compustat Capital IQ - Compustat Segments – Customer data to construct a peer measure based on firms (the suppliers) top customers. The data includes annual information of sales of suppliers to their customers. We only include observations with "companies" as the customer type ("*CTYPE*") and remove unidentified customer names. The data is n linked to CRSP by name matching. We then construct a value-weighted average of *SEDAY* for all firms that are defined as firm *i's* customers. The measure is set to zero on days where firm i's *SEDAY*=1. The value weights based on market capitalization are from CRSP. Due to data coverage, the supplier-customer links data includes 640,267 observations. We augment missing values with zeros the same way that we handle *DADSVI*.
NFP	A dummy variable equals to one on days with an announcement of the U.S. nonfarm payroll statistics by the Department of Labor, and zero otherwise. Announcement dates are from Bloomberg.
PPI	A dummy variable equals to one on days with an announcement of the U.S. Producer Price Index numbers by the Bureau of Labor Statistics, and zero otherwise. Announcement dates are from Bloomberg.
FOMC	A dummy variable equals to one on days with an announcement of the Federal Open Market Committee rate decision, and zero otherwise. Announcement dates are from Bloomberg.

GDP	A dummy variable equals to one on days with an announcement of the "advance" estimate of quarterly U.S. Gross Domestic Product by the Bureau of Economic Analysis, and zero otherwise. Announcement dates are from Bloomberg.
ISM	A dummy variable equals to one on days with an announcement of the Institute for Supply Management Manufacturing statistics by Bureau of Labor Statistics, and zero otherwise. Announcement dates are from Bloomberg.
MACRO	A dummy variable equals to one if at least one of *NFP*, *PPI*, *FOMC*, *GDP*, and *ISM* is equal to one, and zero otherwise.

Information Demand Variables

AIA	Bloomberg records the number of times news articles on a particular stock are read by its terminal users and the number of times users actively search for news for a specific stock. Bloomberg then assigns a value of 1 for each article read and 10 for each news search. These numbers are then aggregated into an hourly count. Using the hourly count, Bloomberg then creates a numerical attention score each hour by comparing past 8-hour average count to all hourly counts over the previous month for the same stock. They assign a value of 0 if the rolling average is in the lowest 80% of the hourly counts over the previous 30 days. Similarly, Bloomberg assigns a score of 1, 2, 3 or 4 if the average is between 80% and 90%, 90% and 94%, 94% and 96%, or greater than 96% of the previous 30 days' hourly counts, respectively. Finally, Bloomberg aggregates up to the daily frequency by taking a maximum of all hourly scores throughout the day. These are the data provided to us by Bloomberg. Since we are interested in abnormal attention, our *AIA* measure is a dummy variable that receives a value of 1 if Bloomberg's score is 3 or 4, and 0 otherwise. This captures the right tail of the measure's distribution.
DADSVI	We follow Bloomberg's methodology and assign Google's daily search volume index (*DSVI*) on day *t* one of the potential 0, 1, 2, 3, or 4 scores using the firm's past 30 trading day *DSVI* values. For example, if *DSVI* on day *t* is in the lowest 80% of past *DSVI* values, it receives the score 0. *DADSVI* is equal to one on day *t* if the score is 3 or 4, and 0 otherwise. The data coverage of DADSVI is smaller than AIA. When search volume activity is too low, Google does not provide DSVI data. To avoid creating any bias in the sample by dropping firms with no *DADSVI* information, we follow the approach of Pontiff and Woodgate (2008). That is, we define a dummy variable, which is equal to one whenever *DADSVI* exists and zero otherwise. Next, we replace the missing *DADSVI* observations with zero values. Finally, in the regressions we include both the dummy and the augmented *DADSVI* variable.

Expected Institutional Information Consumption Variables

EIC_PEER	A predicted measure of firm i's institutional investor expected information consumption of information released by peer-firms' scheduled events based on the response of firm i's AIA to firms J previous scheduled events (see the Appendix for more information regarding the measure construction).
EIC_FOMC	A predicted measure of firm i's institutional investor expected information consumption of information released on FOMC announcement days. The measure is calculated based on firm i's AIA response to previous FOMC announcement days (see the Appendix for more information regarding the measure construction).
EIC_MACRO	A predicted measure of firm i's institutional investor expected information consumption of information released on MACRO announcement days. The measure is calculated based on firm i's AIA response to previous MACRO announcement days (see the Appendix for more information regarding the measure construction).
EIC_ALL	A predicted measure of firm i's institutional investor expected information consumption based on an aggregation of the *EIC_PEER, EIC_FOMC* and *EIC_MACRO* measures.
ERIC	We construct measures of expected abnormal increase in retail information consumption the same way we construct our *EIC* measures. Specifically, we replace *AIA* with *DADSVI* and repeat our measure construction procedures.
EAVOL	We construct measures of expected abnormal increase in volume the same way we construct our *EIC* measures. Specifically, we replace *AIA* with abnormal volume (*AVOL)* and repeat our measure construction procedures. To construct *AVOL* We follow Bloomberg's methodology and assign the daily share volume (VOL) on day *t* one of the potential 0, 1, 2, 3, or 4 scores using the firm's past 30 trading day *VOL* values. For example, if *VOL* on day *t* is in the lowest 80% of past *VOL* values, it receives the score 0. *AVOL* is equal to one on day *t* if the score is 3 or 4, and 0 otherwise.

Other Variables

RET	CRSP's daily stock return, reported in basis points (i.e., times 10,000) for ease of presentation.
AbsRet	Absolute value of *RET*.
Ret^2	*Ret* squared.
DolVol	The daily dollar trading volume in millions of dollars.
InstOwn	The percentage of shares held by institutional investors obtained from the Thomson Reuters CDA/Spectrum institutional holdings' (S34) database.
SizeInM	Stock's market capitalization, rebalanced every June, in millions of dollars.

LnSize	The natural logarithm of the stock's size in millions of dollars.
LnBM	The natural logarithm of the firm's book-to-market ratio (*BM*) rebalanced every June following Fama-French (1992).
Beta	The firm's CAPM beta, calculated for each day based on the previous 252 trading days.
Leverage	Firm leverage is calculated as the ratio between long-term debt (DLTT) and total assets (AT) using Compustat data.
RF	The risk free rate of return from Ken French's website, reported in basis points.
ERET	The stock's daily return *(Ret)* in excess of the risk free rate (*RF*), reported in basis points.
MKTRF	The market return in excess of the risk free rate, reported in basis points, from Ken French's website.