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Information Consumption and Asset Pricing

AZI BEN-REPHAEL, BRUCE I. CARLIN, ZHI DA, and RYAN D. ISRAELSEN*

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 capital asset pricing model performs better. The positive effect of the Federal Reserve Open Market Committee announcements on the risk premia of individual stocks appears to be modulated by EIC. Our findings are most consistent with a risk-based explanation.

HOW INFORMATION BECOMES INCORPORATED INTO asset prices is one of the most fundamental questions in finance. It has long been accepted that risk premia should accrue on days when information gets processed, resolves uncertainty, and generates systematic price movements (e.g., Beaver (1968), Kalay and Loewenstein (1985)). Yet despite the long-standing importance of this idea, there has been renewed interest in these risk premia and the performance of the capital asset pricing model (CAPM) during scheduled information

*Azi Ben-Rephael is with the Rutgers Business School. Bruce Carlin is with the Jones Graduate School of Business at Rice University. Zhi Da is with the Mendoza College of Business at University of Notre Dame. Ryan Israelsen is with the Broad College of Business at Michigan State University. We are grateful to Jules van Binsbergen; Ian Dew-Becker; Karl Diether; Joey Engelberg; Craig Holden; Deborah Lucas; Stefan Nagel (the Editor); Jeff Pontiff; Pavel Savor; Duane Seppi; Avanidhar Subrahmanyam; Mungo Wilson; two anonymous referees; and seminar participants at Aalto University, Brigham Young University, Case Western Reserve University, The Chinese University of Hong Kong, DePaul University, Fordham University, IDC Herzliya, INSEAD, University of Illinois at Chicago, Indiana University, University of Kentucky, Peking University, University of New South Wales, University of Melbourne, Monash University, Rutgers University, University of Texas at Dallas, NBER Asset Pricing 2017 Fall Meeting, the 2018 Jackson Hole Finance Conference, the 2018 Western Finance Association Meeting, the 2018 European Finance Association Meeting, and the Securities Exchange Commission for helpful comments. The authors have no relevant or material financial interests related to the research in this paper. Instructions for obtaining the data used in the paper are provided in the Internet Appendix, which may be found in the online version of this article.

Correspondence: Zhi Da, Mendoza College of Business, University of Notre Dame, Notre Dame, IN 46556; e-mail: zda@nd.edu.

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events such as firm earnings announcements and macroeconomic announcements (Patton and Verardo (2012), Savor and Wilson (2013, 2014, 2016)).[1]

According to Savor and Wilson (2016), a risk-based explanation for an announcement premium relies on the premise that information from issuing firms conveys cash flow news about related firms and the general economy. Under this view, Bayesian investors learn from the news and solve a signal extraction problem to determine how much of the announcing firm's cash flow information is systematic in nature. If information spillover occurs and a risk premium accrues to related firms, it should be less 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. Extending the intuition in Savor and Wilson (2016), we conjecture that the risk premium earned during cross-learning should be monotonically increasing in its precision. We propose novel measures of this type of information processing to 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 firms' news releases and other aggregate news events, even when the subject firms do not release news themselves (abnormal institutional attention [AIA], see Ben-Rephael, Da, and Israelsen (2017)).[2] Such information consumption is likely to be a good proxy for cross-learning during announcements. To examine how this affects prices, we construct an ex ante measure called expected information consumption (EIC). If the information consumption of a firm spiked frequently in the past following the release of news by peer firms or following a macroeconomic announcement, then EIC should be positive when similar events are scheduled to occur in the future.

We find that positive EIC is associated with a return premium in panel regressions similar to those in Engelberg, McLean, and Pontiff (2018) in which we control for scheduled events and weight each firm by its lagged daily gross return. Asparouhova, Bessembinder, and Kalcheva (2010, 2013) recommend this weighted least squares (WLS) approach 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 bps, compared to 4.60 bps for firm-days unaffected by the spillover. The resulting annualized Sharpe ratio is 1.02 for positive EIC firm-days and 0.68 for firm-days unaffected by the spillover.

Using EIC allows us to identify events that are more likely to have important systematic implications. In contrast to previous studies that document

[1] See also Ai and Bansal (2018) and Andrei, Cujean, and Wilson (2018) for recent theoretical analysis.

[2] The AIA measure proposed by Ben-Rephael, Da, and Israelsen (2017) arises contemporaneously with returns. Our EIC measures allow us to associate the excess returns that we observe with return premia that accrue to investors and avoid the reverse causality and endogeneity concerns associated with AIA.

higher stock returns on scheduled information days (e.g., Frazzini and Lamont (2007), Barber et al. (2013), Hartzmark and Solomon (2013)), EIC allows us to characterize return premia for related firms. In addition, prior work explores information spillovers based on the release of information, rather than its consumption (e.g., Hong, Torous, and Valkanov (2007), Cohen and Frazzini (2008), Menzly and Ozabas (2010)). In contrast to these studies, our results show a predictable return premium that does not depend on the sign of the information that is released.

To shed more light on this finding, we compare our results based on EIC to results based on other peer-firm definitions such as SIC-based industry classifications (Fama and French (1997)), text-based industry classifications (Hoberg and Philips (2010) and (2016)), comentioning in the news (Schwenkler and Zheng (2019)), correlated trading volume (Lo and Wang (2006), Cremers and Mei (2007)), and customer-supplier links (Cohen and Frazzini (2008)). Even after controlling for these other definitions, EIC appears to be priced. In addition, while positive EIC firms are sometimes also identified as peers according to other definitions, EIC firms are associated with a higher premium than would obtain using the other definitions alone.

EIC is also associated with a premium when macroeconomic events arise. On macroeconomic announcement days, EIC stocks earn a 6.61 bps higher return than other stocks. On the Federal Reserve Open Market Committee (FOMC) announcement days, the difference increases to 13.70 bps. While a significant market risk premium is associated with macroeconomic announcements (e.g., Savor and Wilson (2013)), we show that stocks vary considerably in their reaction to an announcement. The EIC measure identifies stocks that are most prone: stocks from more cyclical industries (energy, information technology, and customer discretionary) and from larger companies, companies with higher betas, and companies with more leverage. Not surprisingly, these are the companies that are more sensitive to aggregate announcements and therefore are associated with a higher premium.

We next 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 show that our results are stronger among subgroups in which we expect information spillover to be stronger.

We also confirm the finding of Savor and Wilson (2014) that the CAPM works for those days with important macroeconomic announcements, although we find that this result is conditional on information consumption. Overall, the estimated market risk premium on days with FOMC announcements is about 11 bps. However, the estimated CAPM risk premium is 44 bps for stocks with a positive EIC and statistically insignificant for stocks with zero EIC.

While our evidence consistently supports a risk-based explanation, we examine alternative explanations for our findings. One possible explanation is price pressure, whereby the higher average return associated with EIC may simply reflect transitory price pressure that eventually reverts instead of commanding a permanent risk premium. We test this conjecture using a calendar-time trading portfolio approach, which avoids clustering events. If price pressure explains our results, any initial pressure should predict future reversals. We find no reversals 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 cannot completely exclude this explanation because we cannot rule out reversals over 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 whereby underpricing gets corrected but 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 explanation, we use the mispricing score (*MISP*) of Stambaugh, Yu, and Yuan (2012). We do not find evidence in the data to support this explanation. In particular, the EIC coefficient is very similar across mispriced stocks and correctly priced stocks based on the MISP measure.

We note 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 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 (2019)). Nevertheless, our findings 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 I, we describe our raw measures of information consumption and supply, and we outline the construction of our ex ante expected measures of information consumption. In Section II, we analyze how our EIC measures relate to return premia, we provide additional evidence consistent with a risk-based interpretation, and we discuss alternative explanations. Section III concludes. The Appendix provides more details on variable construction.

I. Information Consumption Measures

A. Raw Measures of Ex Post Information Consumption and Events

Bloomberg provides 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 the 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.[3] Following Da, Engelberg, and Gao (2011), we begin with the sample of all stocks that appear in the Russell 3000 index during our sample period. We then require that the stocks in our sample satisfy the following conditions: (i) have nonmissing values for news-searching and news-reading activity on Bloomberg terminals and the Google search engine; (ii) have a share code of 10 or 11 in the CRSP database; (iii) have a stock price greater than or equal to $5 at the end of the previous month; and (iv) have nonmissing book-to-market information. After applying these conditions, we obtain a sample that comprises 3,188 stocks and 4,046,190 day-stock observations.

A.1. Abnormal Institutional Attention (AIA)

Our main information consumption measure captures 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, placing 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. Bloomberg aggregates these numbers into hourly counts and creates an attention score by comparing the average hourly count during the previous eight 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 less than 80%, between 80% and 90%, between 90% and 94%, between 94% and 96%, or greater than 96% of the hourly counts over previous 30 days, respectively. They then aggregate these scores up to a daily frequency by taking a maximum of all hourly scores throughout the day. Using this daily measure, we follow Ben-Rephael, Da, and Israelsen (2017) and set the dummy variable *AIA* to one if Bloomberg's daily maximum is 3 or 4 and zero otherwise. The dummy variable allows for easier interpretation of the differential impact of high versus low institutional attention shocks on economic outcomes. We confirm that alternative definitions of AIA do not alter our conclusions. Ben-Rephael, Da, and Israelsen (2017) provide evidence that AIA facilitates the incorporation of information into prices.

A.2. Abnormal Google Search Volume Index (DADSVI)

Our second measure of information consumption captures 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 (*ADSVI*) by taking the natural log of the ratio of the DSVI to the average of DSVI over the previous month. To facilitate comparison with a stock's AIA, we create a dummy variable version

[3] Bloomberg's historical attention measures begin on February 17, 2010. Historical data are missing for the periods December 6, 2010 to January 7, 2011 and August 17, 2011 to November 2, 2011.

of ADSVI: for each day, we assign a score of 0, 1, 2, 3, or 4 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 zero otherwise. Measures related to retail information consumption are included as controls; we find that these controls have no systematic implications whatsoever.

A.3. Information Events

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

Our sample contains 163,865 scheduled events over the 2010 to 2017 period.[4] Bloomberg classifies each event into one of nine categories. The most common category—accounting for 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 "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," which account 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 construct the dummy variables *SEDAY* and *NESEDAY* to capture scheduled event days and nonearnings scheduled event days (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,[5] namely, announcements related to nonfarm payroll (*NFP*), the producer price index (*PPI*), Federal Open Market Committee rate decisions (*FOMC*), the "advance" forecast of U.S. Gross Domestic Product (*GDP*), and the Institute for Supply Management Manufacturing Index (*ISM*). Announcement dates and times all come 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 construct the dummy variable *MACRO* by setting it equal to one on days when at least one of the five announcement dummies is equal to one and zero otherwise.

[4] We obtain these scheduled events from Bloomberg's Corporate Events Calendar Function (EVTS). These events are all known in advance.

[5] For macro announcements, attention is 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 United States. Users can choose to be alerted to different types of announcement events.

Table I
Summary Statistics

This table reports summary statistics for our abnormal institutional attention (*AIA*) measure and other selected variables over the period February 2010 to 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, nonmissing AIA and book-to-market, and a price of at least \$5. These filters yield a sample of 4,046,091 day-stock observations across 3,188 unique stocks. All variables are defined in Table A.I. *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.I 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

Finally, we obtain news coverage for our sample stocks from RavenPack. We define *NDAY* as a dummy variable 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* to zero on earnings announcement days. We similarly construct the dummy variable *USNDAY* to indicate 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 denote by *FF48_NDAY* and *FF48_EDAY*, respectively. Similarly, we create the variables *AGG_NDAY* and *AGG_EDAY* to capture the value-weighted averages of *NDAY* and *EDAY* using all firms in the sample on a given day.

A.4. Summary Statistics

According to Table I, 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%.

Regarding scheduled firm events, firms have an average of four earnings announcement days per year, or 1.5% of all trading days. Other nonearnings scheduled events occur more frequently, about 2.4% of all trading days.

Focusing on all nonearnings 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 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) bps.

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

The results indicate that in periods with more firm-level news, institutional investors are more likely to consume information about a stock, especially when the events are prescheduled. However, the results 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. In addition, when there is more news about large firms in the market, institutional information consumption about 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 about 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 after we control for firm characteristics and absolute returns (specifications (9) and (10)). Note that we do not expect macro announcements to affect all firms in a similar manner. Below, we explore the impact of macro announcements on the affected stocks.

To summarize, AIA can be triggered not only by firm-specific events, but also by information events related to other firms and the macroeconomy. These observations motivate us to construct EIC measures, based on how investors responded to various events in the past.

B. Expected Information Consumption

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 given threshold, and zero otherwise. Full details on the construction of each measure

Table II

Determinants of Institutional Information Consumption

This table reports results from Logit panel regressions of the abnormal institutional attention (*AIA*) measure from Bloomberg on various measures of scheduled and unscheduled information events and additional control variables. All variables are defined in Table A.I. Specification (1) includes three firm information events: an unscheduled news day dummy (*USNDAY*), a nonearnings scheduled event dummy (*NESEDAY*), and an earnings announcement day dummy (*EDAY*). In specifications (2) to (4), we also include the value-weighted average 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) to (8), we explore macroeconomic announcement days. Macroeconomic announcement dates are from Bloomberg. Specifications (5) and (7) include a dummy variable indicating whether there was at least one of five major macroeconomic news announcements that day (*MACRO*). Specifications (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*), advance estimate for GDP (*GDP*), and the ISM manufacturing index (*ISM*). In specifications (9) and (10), we 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 denoted by *, **, and ***, respectively. *Pseudo* R^2 is the logistic model's Max-rescaled R^2.

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)

(*Continued*)

Table II—*Continued*

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
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^2	0.095	0.095	0.096	0.096	0.005	0.006	YES	0.096	0.236	0.236

Table III

Institutional Investor Expected Information Consumption Measures and Subsamples

This table reports statistics for the four institutional expected information consumption (EIC) measures 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 institutional EIC equal to one. *% of EIC* = 1 *Obs* is the percentage of these observations to total observations in the 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 (1)	*EIC_FOMC* (2)	*EIC_MACRO* (3)	*EIC_ALL* (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	<0.0001	<0.0001	<0.0001	<0.0001
Sample Range	Apr11 to Dec17	Apr10 to Dec17	Mar10 to Dec17	Feb10 to Dec17

are in the Appendix. Summary statistics for the EIC measures are reported in Table III.

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 that firm A's *EIC* is equal to one on firm B's next scheduled event day. This EIC measure is 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, and thus the earnings announcement is systematic in nature. Their model also predicts a risk premium on the affected firms on that day, but the literature to date has not tested this prediction directly. Our *EIC_PEER* measure fills this void.

Column (1) of Table III 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 one on the next FOMC announcement. While previous literature focuses on the market risk premium around FOMC announcements, in this analysis, we consider 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 use a third measure (*EIC_MACRO*) to study the effects of information spillover on macro announcement days using all five macro events defined in Table II.

Columns (2) and (3) of Table III report the number of observations and percentage of $AIA = 1$ observations conditioning on *EIC_FOMC* and *EIC_MACRO* equal to one or zero. 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 EIC (*EIC_ALL*), which aggregates *EIC_PEER*, *EIC_FOMC*, and *EIC_MACRO*. Column (4) of Table III reports the number of observations and percentage of $AIA = 1$ cases conditioning on $EIC\_ALL = 1$ or 0. 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, our various EIC measures speak directly to 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 et al. (2013)), firm-level dividend announcements (Hartzmark and Solomon (2013)), and macro announcements (Savor and Wilson (2013), 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.[6] Second, and more important, this allows us to directly examine information spillover. While existing literature focuses on the return premium for the announcing firm, we study the return premium on other firms 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), 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 information that is released.

[6] In contrast, when we use *ERIC* as the dependent variable (as in Table II), we find that it does not respond to industry or aggregate firm information, or to macroeconomic events.

C. Characteristics of EIC = 1 Stocks

In Table IV, we explore the characteristics of *EIC* = 1 stocks. Similar to Table II, we run logit panel regressions where *EIC_PEER*, *EIC_FOMC*, and *EIC_MACRO* are the dependent variables. Panel A of Table IV 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* measures based on various alternative peer measures. As expected, specifications (1) to (3) indicate that both industry and market scheduled events explain predicted spikes in *EIC_PEER*. Note, however, that when we compare 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.

In specifications (4) to (10), we explore the additional contributions from the scheduled events of alternatively defined peer firms. Specifications (4) to (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 global industry classification standard (GICS2) sectors, and Hoberg and Phillips' (2010, 2016) textual-based similarity score (TINC3). Hoberg and Phillips' measure seems to contribute the most, with a coefficient of 0.235. Next, because prior literature finds that trading volume has systematic implications (e.g., Lo and Wang (2006), Cremers and Mei (2007)). Thus, in specification (7), we replace AIA with abnormal trading volume and construct a similar expected abnormal volume measure (*EAVOL*), where *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 specification (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 that share supplier-customer links (Cohen and Frazzini (2008)). We find that 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*) appear to be more important. This result reinforces our conclusion that *EIC_PEER* captures the 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 sector dummy variables. We use "*Customer Staples*" as our base (excluded) sector. We find that affected stocks tend to come from more cyclical industries (energy, information technology, and customer discretionary). We also find that they tend to be bigger and associated with higher betas and leverage as well. It is perhaps

Table IV

Determinants of *EIC_PEER*, *EIC_MACRO*, and *EIC_FOMC*

This table reports results from Logit panel regressions of the institutional expected information consumption (EIC) measures defined in the Appendix on various measures of scheduled information events and other control variables. All variables are defined in Table A.I. Panel A examines the *EIC_PEER* measure. Specifications (1) to (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) to (10), we explore additional *SEDAY*-based measures using alternative peer firm definitions. In specifications (4) to (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 defined 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) and (2)) and *EIC_FOMC* (specifications (3) and (4)) measures. We include 10 (of the 11) GICS2 sector dummy variables, where the omitted "*Customer Staples*" sector 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 denoted by *, **, and ***, respectively. *Pseudo* R^2 is the logistic model's Max-rescaled R^2.

Panel A. *EIC_PEER*

	BASE			ALTERNATIVEPEERS						
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)

(*Continued*)

Table IV—*Continued*

Panel A. *EIC_PEER*										
	BASE			ALTERNATIVEPEERS						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
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^2	0.184	0.193	0.193	0.193	0.193	0.194	0.236	0.194	0.193	0.237

(*Continued*)

Table IV—*Continued*

Panel 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^2	0.199	0.211	0.201	0.203

not surprising that these stocks are most affected by the information contained in macroeconomic announcements. Importantly, our EIC measures (*EIC_FOMC* and *EIC*_MACRO) uniquely allow us to identify such information spillovers.

II. EIC and Asset Prices

A. Return Premia

We now test whether firm-days with EIC are associated with a return premium. To do so, in Table V 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*, 10 lags of returns, squared returns, news dummies, and trading volume. Day fixed effects are also included and standard errors are clustered by firm and date. Finally, to correct for 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 for each observation. For consistency, we apply the same weighting scheme throughout the remaining analyses.

First, in many of the specifications in Table V, a significant return premium appears to be associated with earnings announcements (*EDAY*), consistent with the results in Engelberg, McLean, and Pontiff (2018) and with the presence of an earnings announcement premium (Frazzini and Lamont (2007), Barber et al. (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 (nonearnings) firm scheduled events carry a return premium that is economically significant. This finding is novel as these firm scheduled events have not been systematically studied previously. 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) to (7) we find a robust premium associated with *EIC_PEER* that ranges between 2.1 and 2.3 bps. 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* is estimated with errors and such errors can lead to attenuation bias. More importantly, the model in Savor and Wilson (2016) predicts the highest premium for announcing firms because these firms have greatest 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 to that of scheduled announcements.

Table V
Expected Information Consumption and the Return Premium

This table reports results from panel regressions of daily returns on measures of institutional expected information consumption (EIC), controlling for scheduled firm information events, expected retail information consumption (*ERIC*), alternative *SEDAY*-based peer measures (see Table IV), and other firm characteristics. All variables are defined in Table A.I. Specifically, we analyze each of the four institutional EIC measures described in Table III and the Appendix. Specifications (1) to (7) explore *EIC_PEER*, Specifications (8) and (9) ((10) and (11)) explore *EIC_FOMC* (*EIC_FOMC)* and specifications (12) to (14) explore *EIC_ALL*. *NESEDAY* is a dummy indicating nonearnings firm scheduled event days. *EDAY* is a dummy indicating firm earnings announcement days. *ERIC* is the EIC of retail investors constructed using *DADSVI* using the same methodology defined in the Appendix. *EAVOL* is constructed similarly based on abnormal trading volume. Following Table IV, in specifications (1) to (7) (*EIC_PEER)* we control for the other alternative peer measures based on *CO-NEWS*, *SUP-CUS*, *FF48_SEDAY*, *GICS2_3CLS*, and *HPTINC3_3CLS* (see Table A.I 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 10 lags of returns, squared returns, news dummies, 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 denoted by *, **, and ***, respectively.

	EIC_PEER							EIC_FOMC		EIC_MACRO		EIC_ALL		
Variable	(1)	(2)	(3)	(4)	FF48 SEDAY (5)	GICS2 3CLS (6)	HPTINC3 3CLS (7)	(8)	(9)	(10)	(11)	(12)	(13)	FF48 SEDAY (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

Extending the intuition in Savor and Wilson (2016), we predict a positive risk premium for firms that experience information spillovers. We further predict that EIC firms are associated with higher risk premia than other peer firms. By self-revealing preferences, EIC firms are more connected to the announcing firm. In addition, EIC captures active information consumption, which improves the precision of cross-learning and results in a higher risk premium. Specifications (3) to (7) confirm these predictions. In particular, we find that the coefficient on *EAVOL* is virtually zero. Even for *FF48_SEDAY*, a one-standard-deviation increase in this measure is associated with 0.47 bps higher returns.

In specifications (8) to (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) bps. Consistent with Table IV, Panel B, the EIC measures identify firms that are most affected by macroeconomic information that earn a higher premium. Finally, in specifications (12) to (14), we look at *EIC_ALL*, which combines all three measures. The estimated premium ranges between 3.6 and 3.8 bps.

B. Calendar-Time Trading Strategies and Economic Magnitudes

In Table VI, 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.

Panel A of Table VI explores calendar-time portfolios based on firm scheduled events. Our analysis differentiates four types of firms: *Announcing Firms*, *EIC Firms*, *Other Peer Firms*, and *Unrelated Firms* (Benchmark). Consequently, in Panel A, we construct the four corresponding nonoverlapping portfolios on each event day. The first portfolio includes *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 *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, which includes all other firms (specification (4)). Detailed information on the construction of the four portfolios appears in the caption of Table VI.

Consistent with the results in Table V, we find that the average daily excess return (over the risk-free rate) associated with these portfolios monotonically decreases from 10.28 bps (the announcing firms) to 4.6 bps (the benchmark). The risk-adjusted returns also decrease accordingly. In particular, the *EIC_PEER* portfolio has a Fama-French five-factor (Daniel et al. (1997, DGTW)) risk-adjusted return of 2.0 (1.7) bps. The portfolio annualized Sharpe ratio is 1.02, representing an almost 50% increase from that of the benchmark

Table VI

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 nonoverlapping 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 scheduled 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 two; we replace the portfolio return with the return of the third portfolio (*Other Peer Firms*). In Panel B, we explore both the FOMC and macroeconomic announcements. To be included in the EIC = 1 portfolios on any given FOMC (macro) announcement day, we require a firm to have only *EIC_FOMC* = 1 (*EIC_MACRO* = 1) events. The benchmark portfolio on these days, includes all other stocks with *EIC_FOMC* = 0 (*EIC_MACRO* = 0). For each calendar-time portfolio, we report the average excess return (*ExPortRet*) together with Fama-French three- and five- factor model risk-adjusted returns, as well as DGTW characteristic-adjusted returns (*ExPortRet - FF3*, *ExPortRet – FF5*, and *ExPortRet - DGTW*, respectively). All returns are in basis points. We also report the 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 denoted by *, **, and ***, respectively.

Panel 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

(*Continued*)

Table VI—*Continued*

Panel 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

portfolio. The return 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 and 8.9 bps, the risk-adjusted returns of the $EIC = 0$ portfolios are around zero.

C. Support for a Risk-Based Explanation

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

In Panel A of Table VII, 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.

Table VII

Additional Evidence from Firm Beta, the CAPM, and Subsample Analysis

This table explores the relation between our institutional expected information consumption (EIC) measures (described in Table III and the Appendix), the CAPM *Beta* in Panel A, the performance of the CAPM in Panel B, and across various subsamples in Panel C. All variables are defined in Table A.I. 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 EIC 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 returns (*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 these three measures. $EIC = 0$ ($EIC = 1$) includes sample observations where $EIC = 0$ ($EIC = 1$). *Diff 1-0* is the difference between the coefficient estimates of the two samples. Given that the number of $EIC = 1$ observations can be very low 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 Newey-West adjustment with 10 lags. In Panel C, we repeat the main analysis conducted in Tables V and Table VII, Panel 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 V (*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 examine the difference between the first quarter (Q1) and the other quarters combined (Q2 to 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 of 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* for the full panel regression. Columns (3) and (4) only report the CAPM slope of the $EIC\_ALL = 1$ subsample (see Beta column in specification (4) of Table VII, Panel B). Finally, to correct for possible microstructure bias, we follow Asparouhova, Bessembinder, and Kalcheva (2010, 2013) and employ a WLS correction, where we use lagged gross return as the weight. In Panel B, the correction is implemented in the cross-sectional regression step. In all panels statistical significance at the 10%, 5%, and 1% level is denoted by *, **, and ***, respectively.

Panel 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)

(*Continued*)

Table VII—*Continued*

Panel A. Expected Information Consumption and Firm Beta							
	EIC_ALL						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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

(*Continued*)

Table VII—*Continued*

Panel 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)

Panel 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 to Q4	Q1	Q2 to 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)

We estimate a time-varying factor loading CAPM beta model using variations of the 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 bps), *MKTRF* is the market return minus the risk-free rate (in bps), 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 most of the spillover observations start in April 2011 (column (1) of Table III), we run our beta tests from April 2011. The results are reported in Panel A of Table VII.

The first five specifications in Table VII, Panel 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 EIC. 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, 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 CAPM. 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 conduct our tests. Each day, we run a cross-sectional regression of excess stock returns on CAPM betas. Panel B of Table VII 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 8.17 to 43.85 bps, 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 bps 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 bps. A risk premium of around 10 bps for *EIC* = 1 is consistent with the sample statistics reported in Table I and the additional increase in risk premium documented in Table V. 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 an increase in not just the quantity of risk, but also the compensation per unit of risk. Our calendar-time portfolios (see Table VI) are consistent with this view, where the Sharpe ratio for *EIC* = 1 stocks is around 50% higher than that for *EIC* = 0 stocks.

Figure 1, Panel A, illustrates the CAPM results graphically. Each day, within the *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, Panel 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. A positive relation between the average excess return and the CAPM beta of a stock obtains when institutional investors are expected to consume information. Among *EIC_ALL* = 0 stocks, the relation is slightly negative.

Specification (2) in Table VII, Panel B, focuses on the interesting case of FOMC announcements. Savor and Wilson (2014) find that the CAPM performs well on those days. We find that their results are modulated by EIC. On FOMC announcement days, the CAPM only works well among the subset of stocks for which institutional investors are expected to consume information. For those stocks, the CAPM regression generates a significant risk premium estimate of 43.85 bps. For the remaining stocks, the risk premium estimate is still small and insignificant.

Figure 1, Panel 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 to *EIC_ALL* as well, as reported in specifications (3) and (4).

Finally, in Panel C of Table VII 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

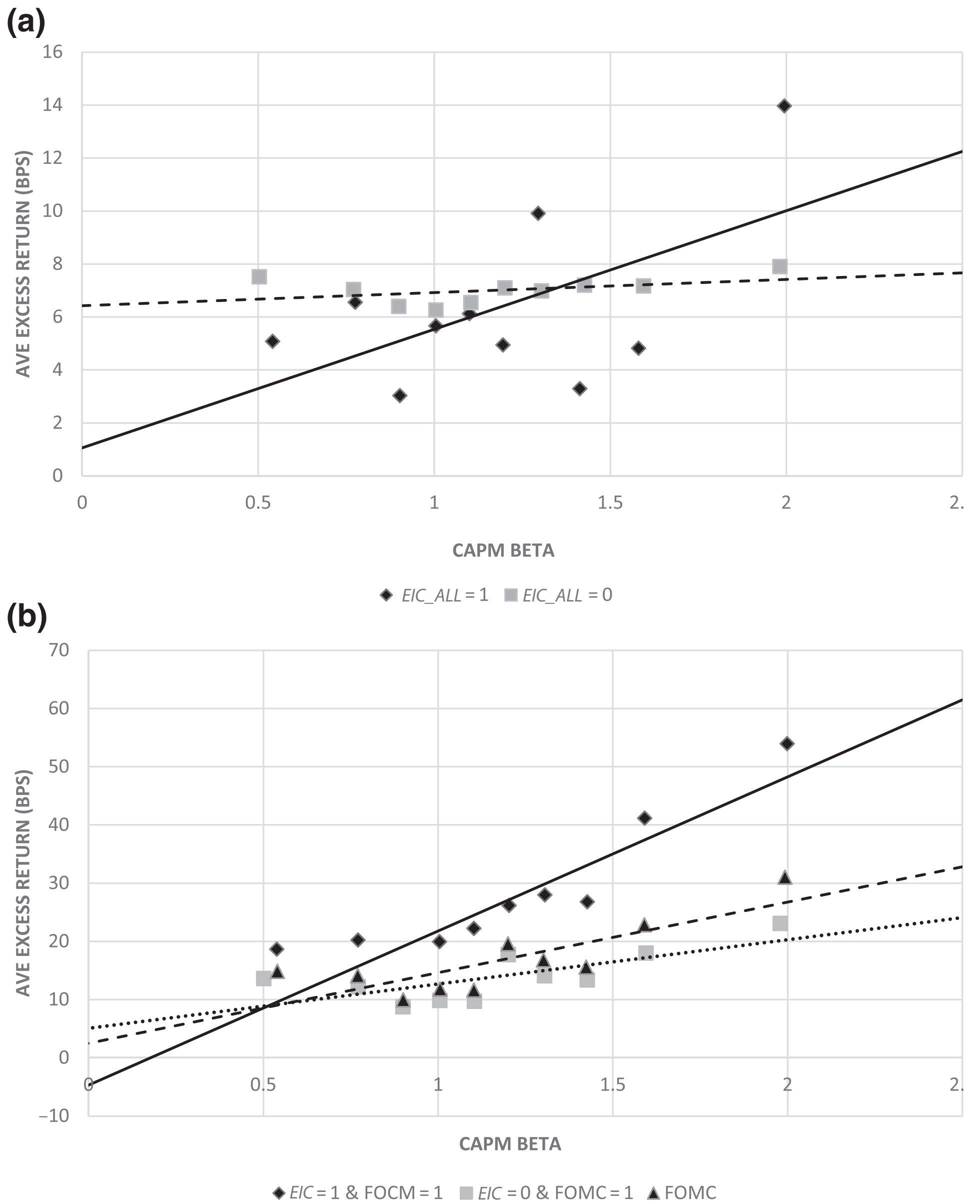

Figure 1. CAPM in various subsamples. Each day, we partition stocks in our sample into 10 decile portfolios based on their CAPM betas, where for each day and stock, betas are estimated using the previous 252 trading days. Then, for each decile, we create two subsamples based on whether their *EIC_ALL* is equal to one or zero 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 *EIC* = 1 stocks over FOMC announcement dates (*EIC* = 1 & FOMC = 1, solid line), *EIC* = 0 stocks over FOMC announcement dates (*EIC* = 0 & FOMC = 1, dotted line), and stocks over FOMC announcement dates (FOMC, dashed line).

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 VII repeats the analyses in Tables V and VII, Panel 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 $EIC = 1$, and their CAPM slopes are steeper. This also appears to be the case for the 10-K quarter and for firms that report in the first half of earnings cycles.

D. Alternative Explanation

Taken together, our evidence is 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 VIII reports the results.

We first examine the role of price pressure. The higher average return associated with EIC could be transitory and subsequently revert. Panel A of Table VIII 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 five-factor model, and the DGTW characteristic-based adjustment.

Regardless of the risk adjustment method used, large p-values are associated with the cumulative abnormal portfolio returns. While the return point estimates range from -2 to 6 bps, their standard errors are much wider, which casts doubts on reliable inference from this analysis. Nevertheless, the short-term abnormal returns show no indication of an immediate reversal. The longer-term analysis does generate negative point estimates around days 40 to 60, but they are not statistically different from zero, nor are they 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 the possibility 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 a potential mispricing explanation, whereby the higher average return associated with EIC reflects a correction to mispricing rather than a risk premium. Panel B of Table VIII extends the analysis conducted

Table VIII

Alternative Explanations

This table examines two alternative explanations: price pressure (Panel A) and mispricing (Panel B). Panel A extends Table VI'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 five-factor model (FF-Factor-Adjustment) and DGTW characteristic-based risk adjustment (DGTW Characteristic Adjustment). For each horizon (Days in Panel 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 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 return distribution of the portfolio before calculating the daily averages. Standard errors are adjusted for heteroskedasticity and serial correlation using Newey-West correction with 10 lags. In Panel B, we extend the analysis conducted in specification (13) of Table V using the mispricing measure (*MISP*) of Stambaugh, Yu, and Yuan (2012), which is available on Stambaugh'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 lagged three-month average *MISP* scores into four quartiles. The mispriced stocks (Mispriced) are stocks with *MISP* values in the top and bottom quartiles (quartiles 1 and 4). Nonmispriced stocks (Nonmispriced) 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 denoted by *, **, and ***, respectively.

Panel 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 B. Mispricing

	BASE		Mispriced	Nonmispriced
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)

(*Continued*)

Table VIII—*Continued*

Panel B. Mispricing

	BASE		Mispriced	Nonmispriced
Variable	(1)	(2)	(3)	(4)
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

in Table V using the mispricing measure (*MISP*) of Stambaugh, Yu, and Yuan (2012). We match our sample with the *MISP* measure and rank 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). Nonmispriced stocks (Nonmispriced) are stocks with *MISP* values in the middle quartiles (quartiles 2 and 3). We find that the returns of the two groups of stocks are almost identical with an associated return premium of 3.63 and 3.64 bps, respectively. To the extent that *MISP* captures relative mispricing across stocks and the mispricing is corrected upon EIC, this evidence suggests that mispricing is unlikely to account for our results.

In sum, we find measures of EIC 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, our results based on ex ante measures, average returns, betas, and the CAPM performance together provide strong support for a risk-based interpretation.

III. 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-searching and news-reading activities, we construct novel measures of EIC on individual firms during such spillovers, when scheduled peer firm or macroeconomic announcements occur.

We confirm that EIC is associated with a higher average return, that the CAPM performs well for individual stocks on days when information consumption is expected to be high, and that EIC appears to modulate the effect of

FOMC announcements on asset prices (Savor and Wilson (2014)). Taken together, this evidence supports a risk-based interpretation of the return premia.

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Appendix: EIC Construction

In this Appendix, we provide more details on the construction of our EIC measures. Table A.I 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' EIC 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 focus on two cases. The first is systematic information spillovers during earnings cycles from other firms' scheduled earnings announcements. The second is systematic information spillovers from other firms' nonearnings scheduled events. The basic idea behind our method is intuitive and simple: if firm A's AIA often spiked during firm B's past earnings announcements (firm B's previous nonearnings scheduled events), we can predict that its AIA will likely be equal to one on firm B's next earnings announcement (nonearnings 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 announcement 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 next construct an earnings spillover dummy variable that receives a value of one for firm i when the max score on a given day is greater than or equal to 3/4 and the median score is greater than 1/4 (i.e., a minimum response to an earnings event out of four 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 noise and increase the possibility that investors learn from peer firm earnings

Table A.I
Variable Definitions

Variable	Definition
Information Supply Variables	
NDAY	A dummy variable that is equal to one on news days for firm i and zero otherwise, *excluding* earnings announcement days. News days are those on which an article about the firm appears on the Dow Jones Newswire. News data come from RavenPack.
USNDAY	A dummy variable that is equal to one on news days for firm i and zero otherwise, *excluding* earnings announcement days and nonearnings firm scheduled events. News days are those on which an article about the firm appears on the Dow Jones Newswire News data come from RavenPack. Firm scheduled events are based on a list of scheduled firm events available to Bloomberg terminal users.
EDAY	A dummy variable that is equal to one on earnings announcement days for firm i and zero otherwise. Earnings announcement data come from I/B/E/S.
SEDAY	A dummy variable that is equal to one on days with a scheduled firm event 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 nine 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 that is equal to one on days with nonearnings scheduled firm events. Specifically, we remove the Earnings Release and Earnings Call categories from Bloomberg's nine 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 come 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 come 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 come 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 equal to one on days when firm i's $SEDAY = 0$ and one of firms i's three closest peers have $SEDAY = 1$. The dummy is set to zero otherwise. Peers are defined based on the same Fama-French 48 industry. Closest peers are defined based on the smallest absolute differences in market cap of firm i and other firms in the same industry.

(*Continued*)

Table A.I—*Continued*

Variable	Definition
GICS2_3CLS	A dummy variable equal to one on days when firm *i*'s *SEDAY* = 0 and one of firms *i*'s three closest peers have *SEDAY* = 1. The dummy is set to zero otherwise. Peers are defined based on the same GICS2 sector. Closest 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 equal to one on days when firm *i*'s *SEDAY* = 0 and one of firms *i*'s three closest peers have *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. Closest peers are the three firms with the highest similarity scores.
CO-NEWS	We use RavenPack data to construct a peer measure based on firm co-mentioning in the same news article. In particular, firms *i* and *j* are considered to be linked via news if both firms are mentioned together in at least two news articles in the past four quarters. To remove outliers, we exclude the top 1%. We then construct a value-weighted average of *SEDAY* for all firms that are co-linked to firm *i*. The measure is set to zero on days when 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' (suppliers') top customers. The data include annual information on sales of suppliers to their customers. We only include observations with "companies" as the customer type ("*CTYPE*") and remove unidentified customer names. The data are 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 when firm *i*'s *SEDAY* = 1. The value weights based on market capitalization are from CRSP. Due to data coverage, the supplier-customer link data include 640,267 observations. We augment missing values with zeros in the same way that we construct *DADSVI*.
NFP	A dummy variable equal to one on days with an announcement of U.S. nonfarm payroll statistics by the Department of Labor, and zero otherwise. Announcement dates come from Bloomberg.
PPI	A dummy variable equal to one on days with an announcement of U.S. Producer Price Index numbers by the Bureau of Labor Statistics, and zero otherwise. Announcement dates come from Bloomberg.
FOMC	A dummy variable equal to one on days with Federal Open Market Committee rate decision annulments, and zero otherwise. Announcement dates come from Bloomberg.
GDP	A dummy variable equal 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 come from Bloomberg.
ISM	A dummy variable equal to one on days with an announcement of the Institute for Supply Management Manufacturing statistics by the Bureau of Labor Statistics, and zero otherwise. Announcement dates come from Bloomberg.
MACRO	A dummy variable equal to one if at least one of *NFP*, *PPI*, *FOMC*, *GDP*, and *ISM* is equal to one, and zero otherwise.

(*Continued*)

Table A.I—*Continued*

Variable	Definition
Information Demand Variables	
AIA	Bloomberg records the number of times the news articles on a particular stock are read by its terminal users and the number of times the users actively search for news for a specific stock. Bloomberg then assigns a value of one for each article read and 10 for each news search. These numbers are then aggregated into an hourly count. Using the hourly count, Bloomberg creates a numerical attention score each hour by comparing past eight-hour average count to all hourly counts over the previous month for the same stock. They assign a value of zero 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 one if Bloomberg's score is 3 or 4, and zero 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 scores (0, 1, 2, 3, or 4) 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 a score of zero. *DADSVI* is equal to one on day t if the score is 3 or 4, and zero otherwise. The data coverage for 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, that 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 EIC of information released by peer firms' scheduled events based on the response of firm i's AIA to previously scheduled events of firm j (see the Appendix for more information regarding measure construction).
EIC_FOMC	A predicted measure of firm i's institutional investor EIC 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 measure construction).
EIC_MACRO	A predicted measure of firm i's institutional investor EIC 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 measure construction).
EIC_ALL	A predicted measure of firm i's institutional investor EIC based on aggregating the *EIC_PEER, EIC_FOMC*, and *EIC_MACRO* measures.
ERIC	We construct measures of the 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.

(*Continued*)

Table A.I—*Continued*

Variable	Definition
EAVOL	We construct measures of the 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 score (0, 1, 2, 3, or 4) 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 a score of zero. *AVOL* is equal to one on day *t* if the score is 3 or 4, and zero 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	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 market capitalization, rebalanced each 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 each June.
Beta	The firm's CAPM beta, calculated for each day based on the previous 252 trading days.
Leverage	Firm leverage, 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.

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 earnings announcement day.

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

For FOMC announcement days, if a given stock's AIA is equal to one at least 50% of the previous four FOMC announcement days,[7] we set *EIC_FOMC* to one on the current FOMC announcement day and to zero otherwise. During the first few months of our sample, we allow for up to four announcements to minimize loss of observations. For macro announcement days, since there are macroeconomic announcements almost every day, we limit attention to the five categories that draw the most attention from institutional investors on Bloomberg terminals (see Table II): Nonfarm Payroll (NFP), Producer Price Index (PPI), FOMC, the advance estimate for GDP (GDP), and the ISM manufacturing index (ISM). The macro announcement dates are from Bloomberg. For each category, for a given stock, if $AIA = 1$ at least 50% of the previous year, we set the category dummy variable to one on the announcement day, and to zero otherwise.[8] The *EIC_MACRO* variable is then the max across five categories.

Finally, we construct an overall spillover measure based on the EIC measures constructed (*EIC_ALL*). The overall measure is based on the aggregation of *EIC_PEER*, *EIC_FOMC*, and *EIC_MACRO*. Summary statistics for all of these measures are provided in Table III together with additional discussions in Section I.C of the paper.

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[7] The FOMC holds eight regularly scheduled meetings per year and additional meetings as needed.

[8] As in the case of nonearnings firm scheduled events, since the number of macro announcements is generally is not fixed, we look at a period of up to a year.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.