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Macroeconomic News and Price Synchronicity*

Arbab K. Cheema*, Arman Eshraghi[†] and Qingwei Wang[‡]

Abstract

Stock price synchronicity is a critical consideration for asset allocation, risk assessment, and hedging decision. We present novel evidence that individual stock returns comove more persistently on certain days of the week. Specifically, we show that release of macroeconomic news on Mondays, which typically see fewer announcements, leads to such stronger comovement, and that this is distinct from the Monday effect typically discussed in the literature. This synchronicity is more pronounced among large, old and low volatility firms, in both up- and down-market conditions. We argue this effect is partly due to ‘simultaneous contrast’, i.e., perception of stimulus depending on its surrounding environment. Monday announcements have a larger impact just as thunder in a quiet night sounds louder. Our findings are robust after controlling for day-of-the-week effects, economic uncertainty, risk aversion, investor sentiment, short-selling constraints and proxies for attention to news.

Keywords: Monday anomaly; synchronicity; news announcement; salience; contrast effect

JEL Classification: G12, G14

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Abstract

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1 Introduction

Return synchronicity, the extent to which individual stock returns comove with market and industry portfolio returns, has received substantial attention in finance literature.¹ Synchronicity is a critical consideration for asset allocation, risk assessment, and hedging decisions (Engle, 2002). Since Roll (1988), many studies argue that high return synchronicity reflects low price informativeness, which is associated with capital allocation inefficiency and high cost of capital (Durnev *et al.*, 2004; Wurgler, 2000).² Substantial efforts have been devoted to understanding what drives the synchronicity over time (Campbell *et al.*, 2001; Kallberg and Pasquariello, 2008; Chelley-Steeley *et al.*, 2013), and across individual firms and countries (Morck *et al.*, 2000; Jin and Myers, 2006; Veldkamp, 2006; Bekaert *et al.*, 2009; Rua and Nunes, 2009).

Most of prior literature estimates a firm-year measure of synchronicity by pooling returns within a year. Therefore, intra-week changes in return synchronicity have received far less attention. The question of synchronicity is important for short-term investors, such as day traders, who need to consider the short-run level of systematic risk and benefits of cross-sectional diversification. Even investors with longer investment horizons need to be cautious in trading on days with high synchronicity, as price is less informative about firm-specific fundamentals. We also need a richer understanding of how time-varying factors affect synchronicity. Indeed, there are plausible reasons to expect a within-week variation in return synchronicity. For example, the announcement frequency of macroeconomic news and firm-specific news changes during the week which may induce variations in synchronicity (Brockman *et al.*, 2010). Moreover, behavioral factors that affect investors' response to information, e.g., investor attention and sentiment, also have intra-week variations (Liu and Peng, 2015; Birru, 2018). Other factors, such as economic uncertainty and risk

¹ We use the terms 'synchronicity' and 'comovement' interchangeably in the paper.

² Some studies contest the hypothesis that high synchronicity implies less price informativeness. For example, Dasgupta *et al.* (2010) show that for firms with adequate and timely disclosures, there is no surprise about future events when they occur because information is impounded into stock prices beforehand. Firm-specific variation decreases (i.e. R^2 increases) for such stocks. Other examples are the studies by Kelly (2014) and Li *et al.* (2014).

aversion, also vary across weekdays (Fisher *et al.*, 2022).

We examine the intra-week synchronicity of US stocks between 1953 and 2017, an interval spanning more than six decades. Our findings show, *inter alia*, that Monday synchronicity as measured by the R^2 from regressions of Monday stock returns on contemporaneous and lagged market and industry returns is about 12% higher than the average R^2 of similar regressions for other weekdays. Furthermore, this effect has persisted over the past 60 years (see Figure 1) in both up-market and down-market conditions. The economic significance of higher comovement on Monday may seem small at first glance. However, since the increase in Monday comovement is primarily caused by salient macroeconomic news, the effect is magnified when the sample is split between announcement and non-announcement days.

These findings appear puzzling at first glance, since the number of macroeconomic announcements is the lowest on Mondays compared to other weekdays. Intuitively, more macroeconomic news should translate into higher synchronicity (Brockman *et al.*, 2010) because such news affects financial markets at the aggregate level. Investors tend to allocate more attention to macroeconomic news because their capacity to absorb and process information is limited (Peng and Xiong, 2006; Veldkamp, 2006). When these investors focus on macroeconomic news, their attention to firm-specific news, such as earnings announcements, is crowded out (Liu *et al.*, 2023).³ Since firm-specific events reduce synchronicity by inducing idiosyncratic (firm-specific) shocks to stock prices, comovement is expected to be higher on days when investors are distracted by numerous macroeconomic announcements. In contrast, we find that the very small

³ Liu *et al.* (2023) find different effects of macroeconomic news on the attention of retail and institutional investors to earnings news. Institutional investor attention to earnings news increases (enhancement), while retail investor attention decreases (crowding-out). Hirshleifer and Sheng (2022) also find support for the enhancement hypothesis, thereby arguing for the complementary effect of macroeconomic news on the attention to earnings news. They argue that this finding is consistent with the transmission of information channel that macroeconomic news improves rational interpretations of firm-level earnings news. It is also in line with the investor attention channel, as investors focus more on stock analysis than on other activities during announcement days. We discuss the implications of the complementary/substitution effect of macroeconomic news on earnings news on day-of-the-week comovement in the Results Section.

number of macroeconomic announcements on Mondays drives our results: R^2 on Mondays with macroeconomic announcements are about twice higher than the average R^2 of other weekdays, even though other weekdays tend to have more macroeconomic announcements. If we exclude the macroeconomic announcement days from the analysis, Monday's synchronicity is no longer the highest during the week.

Why is Monday synchronicity particularly high? On the one hand, higher uncertainty and risk aversion after a weekend may offer a rational explanation. On the other hand, higher comovement on Mondays may be a manifestation of the infamous Monday anomaly for which several behavioral explanations have been proposed in literature e.g., investor sentiment (Birru, 2018). The supply and demand of information may also offer both rational and behavioral explanations. For instance, higher investor attention or preferential allocation of such attention to market-wide information on Mondays are potential behavioral explanations. In contrast, higher comovement may be explained rationally by a higher supply of macroeconomic information relative to firm-specific information. Another possibility is that the most important macroeconomic announcements are released on Monday; thus, higher comovement is a rational consequence of this pattern. In contrast, macroeconomic announcements on Monday are not necessarily the most important ones but are more salient than others, inducing a behavioral response. We examine all these possibilities and find that the effect is indeed best explained by the well-documented salience effect.

Salience describes the extent to which a stimulus stands out relative to other stimuli in the environment; thus, it is context-dependent. A stimulus may stand out for being novel, figurative, unexpected, extreme, negative, rare, or physically prominent (Fiske and Taylor, 2017). Bordalo *et al.* (2012) theorize that lotteries with salient payoffs are preferably chosen over other lotteries because they attract more attention. They describe salience as an important attentional mechanism, enabling humans to allocate their scarce cognitive resources on a relevant subset of the total information set. Context-dependent preference for salience has been argued to apply to consumer goods (Bordalo *et al.*, 2013b) and salient earnings news (Huang *et al.*, 2018). Moreover, salience

preference has been found for financial assets such as stocks with extreme payoffs (Bordalo *et al.*, 2013a) or positively skewed returns (Dertwinkel-Kalt and Köster, 2019), and mutual funds with high idiosyncratic volatility and extreme returns (Clifford *et al.*, 2021). Experimental studies also demonstrate that an increase in the salience of capital gains, by merely displaying them on the trading screens, increases the disposition effect (Frydman and Rangel, 2014; Frydman and Wang, 2020).

We argue that abnormally high Monday return comovement stems from the higher salience of macroeconomic announcements. Mondays are relatively quiet in the sense that fewer macroeconomic and earnings announcements are released. Akin to thunder in a quiet night that sounds relatively louder, an occasional macroeconomic announcement on a quiet Monday lies in sharp contrast to its background which consists of a small number of other news releases. The “simultaneous contrast” of this announcement makes it more salient, which in turn leads to a stronger reaction in terms of comovement. This is also consistent with Chang *et al.* (1995, 1998) who find that the response to macroeconomic announcements is abnormally stronger on Mondays. However, they do not examine macroeconomic or firm-specific news directly, but rely on movements in large firms’ stock prices to proxy the arrival of macroeconomic news. This prevents them from observing that a small volume of macroeconomic news drives the high levels of Monday synchronicity.

The simultaneous contrast effect is well researched in psychology and cognitive science. For example, individuals commonly perceive a neutral gray object to be lighter (darker) when it is simultaneously compared to a dark (light) gray object.⁴ There is an emerging literature that examines the contrast effect in financial judgment and decision making. For instance, Hartzmark and Shue (2018) find that stock price gets distorted by investors who perceive earnings news as

⁴ Simultaneous contrast is considered to have both physiological (i.e. the design and functionality of the eye) as well as psychological explanations (Helmholtz, 1962; Hering, 1964).

more (less) impressive if yesterday's surprise in earnings was bad (good).⁵ Kim and Hoffman (2020) provide experimental evidence that the contrast effect distorts individuals' risk attitudes in investment and financing decisions. There is also a neurological connection between visual perception and risk preference (Bordalo *et al.*, 2012). Kliger and Gilad (2012) found that individuals presented with financial data on screens with red background assigned higher (lower) subjective probabilities to losses (gains), as compared to individuals exposed to green colour. Representation of negative historical price data in red color, as compared to black, has a significant impact on risk preferences, future expectations and trading decisions (Bazley *et al.*, 2021).

Weber's law, which is a specific case of the more general Weber-Fechner law (Fechner 1860), suggests that our sensory perception is not simply based on the absolute magnitude of the stimulus, but rather on the relative change in stimulus intensity. The abnormal response to salient macroeconomic news on Mondays is consistent with this phenomenon. Since the law states that the smallest detectable difference is proportional to the intensity of the original stimulus, macroeconomic news on Mondays will be highly noticeable because the original stimulus consists of a few announcements. On other weekdays, investors are being exposed to various stimuli, therefore, a macroeconomic news needs to be proportionally much more salient to become noticeable.

The salient macroeconomic news on Monday represents a dramatic change in the otherwise quiet information environment. The abnormal reaction in terms of comovement is consistent with the "frog in the pan" (FIP) hypothesis proposed by Da *et al.* (2014) since investors pay more attention to these news which are more discrete as compared to other weekdays when investors receive a series of continuously arriving information to which they are less attentive. Huang *et al.* (2022) further develop the FIP hypothesis by finding that heightened attention to discrete information about a firm

⁵ This is a case of successive contrast effect because the perception of the stimulus (i.e. earnings surprise) today is being affected by exposure to a similar stimulus yesterday. However, we look at how synchronicity is affected by the simultaneous contrast among the announcements on the same day. Following the literature, lag terms have been included in the synchronicity regressions to control for non-synchronous trading, but the values of their coefficients are too small to have a meaningful effect on R^2 values.

improves inter-firm news transmission leading to higher co-momentum among economically linked firms. Since the discrete information in our context is macroeconomic news on Monday, higher comovement due to the market-wide economic effect of such news is consistent with the study of Huang *et al.* (2022).

We also consider an alternative explanation based on the day-of-the-week effect in economic uncertainty and risk aversion. Prior literature shows that both of them are the highest on Mondays (Fisher *et al.*, 2022), possibly because Monday follows the weekend during which few news announcements are made. This prompts rational investors to learn more about aggregate shocks than idiosyncratic shocks (Kacperczyk *et al.*, 2016), leading to high return comovement. We do find that longer (shorter) weekends amplify (attenuate) the Monday synchronicity effect; however, the contrast effect still plays a prominent role. Importantly, we find the contrast effect for Monday macroeconomic announcements in both high and low levels of VIX. Thus, the contrast effect does not necessarily require conditions of heightened uncertainty to work. Although higher uncertainty at the start of the week contributes to higher comovement on Monday, removal of macroeconomic announcement days results in elimination of the Monday synchronicity effect even when the values of VIX are high. If the Monday synchronicity effect is a consequence of higher economic uncertainty and risk aversion, comovement should remain higher despite removal of macroeconomic announcement days because investors will be focusing on whatever market-wide information is available, regardless of any announcement.

Fridays are also interesting in this context and serve to illustrate our argument about Mondays. The frequency of earnings announcements on Fridays is only slightly higher than that of Mondays. In contrast, the frequency of macroeconomic announcements on Fridays is the highest among all weekdays. However, this pattern does not yield higher comovement because numerous macroeconomic announcements are not salient since they compete in grabbing the attention of investors despite the relatively lower prevalence of firm-specific information. In fact, multiple macroeconomic announcements cause the information environment to become noisier; thus

inhibiting the potential for a given announcement to become salient. Moreover, investors have lower attention on Fridays as they are distracted by the upcoming weekend and pay less attention to all types of financial news (DellaVigna and Pollet, 2009; Louis and Sun, 2010; Michaely *et al.*, 2016).

We further examine other potential explanations for our findings. First, abnormally high synchronicity on Monday naturally raises the question of its connection with the well-known Monday anomaly—the abnormally lower returns on Monday as compared to other weekdays. Are they two sides of the same coin? This is plausible, for example, when noise trading induces both day-of-the-week effects in mean returns and in betas (see Chang *et al.* (1995, 1998), as well as more detailed discussions on the effect of investor sentiment below).⁶ Such an argument has a cross-sectional prediction: since noise trading has a disproportionately stronger effect on sentiment-prone stocks (Baker and Wurgler, 2006, 2007), we would expect both anomalies to be more pronounced among these stocks. In line with this prediction, Birru (2018) shows that Monday anomaly is indeed stronger among these stocks. In contrast, we find Monday synchronicity is significantly higher among stocks with larger firm size, greater firm age, and smaller idiosyncratic volatility.

Alternatively, low Monday returns might be linked with the high synchronicity anomaly since comovement is higher when market returns are negative (Jiang *et al.*, 2018). We find that synchronicity remains higher on Monday in both up-market and down-market conditions. The Monday synchronicity effect continues to exist in periods after 1990, even though the Monday effect in aggregate market returns has disappeared since then (Dubois and Louvet, 1996). Therefore, we conclude that higher Monday synchronicity is not only distinct from the Monday return anomaly, but it also affects the exact opposite of Monday anomaly’s target firms.

⁶ Foucault *et al.* (2011) find that individuals behave like noise traders, and Abraham and Ikenberry (1994) show that such behavior causes the Monday effect; however, Ülkü and Rogers (2018) contest this hypothesis by showing that institutional trading causes negative Monday returns. Wang and Duxbury (2021) show that institutional investor sentiment may distort the risk-return tradeoff.

To emphasize, Mondays have the least frequency of macroeconomic news releases, which is consistent with higher Monday comovement. The removal of earnings announcement days, however, still results in a higher comovement on Monday, although to a lesser degree. This suggests that the scarcity of earnings makes the background quieter, and hence, the macroeconomic announcement becomes more salient. We also find that when attention to macroeconomic news is measured by Google Search Volume Index (SVI), the most attention-grabbing macroeconomic news is not announced on Monday. We also examine the effect of investor attention on firm-specific news on synchronicity. If investors are paying attention to firm-specific information, comovement will be lower. In contrast, the reverse might be true if the common component of firm-specific attention dominates the effect (Chen *et al.*, 2022). We find, however, that neither retail investor attention nor institutional investor attention to firm-specific news on Monday is the highest or lowest compared to other weekdays. Thus, attention to firm-specific news does not seem to explain our results.

We further consider other behavioral explanations, including investor sentiment and limits to arbitrage. Market-wide investor sentiment predicts lower future returns for stocks that are prone to sentiment and difficult to arbitrage.⁷ Birru (2018) shows that sentiment-prone stocks perform relatively poorly on Mondays, consistent with the conjecture of low sentiment on Mondays. Similarly, sentiment also affects how stock prices comove with aggregate market factors and this relationship is consistent with the notion that assets are mispriced during extreme sentiment periods (Chue *et al.*, 2019).⁸ If Monday sentiment drives synchronicity since stock prices comove more with aggregate market factors during low sentiment periods (Chue *et al.*, 2019), we expect that high Monday synchronicity should be more pronounced for sentiment-prone stocks. However, our finding that Monday synchronicity is significantly higher among large, old, and less volatile

⁷ See Baker and Wurgler (2006, 2007), Lemmon and Portniaguina (2006), Baker *et al.* (2012) and Huang *et al.* (2015).

⁸ Since low sentiment can drive the market down, synchronicity can be higher because asset prices comove more in a down-market (Jiang *et al.*, 2018). In contrast, Chue *et al.* (2019) argues that synchronicity increases for the sentiment-prone stocks when sentiment increases during high sentiment periods, but not so when sentiment declines during the low sentiment periods since short-sale constraints are only binding during high sentiment periods.

stocks contradicts this expectation. Arbitrage constraints are closely related to the sentiment-based explanation because limits to arbitrage, such as short-sale constraints, make it more difficult to correct mispricing (De Long *et al.*, 1989, 1990). Using the Regulation SHO experiment conducted by the SEC (Securities & Exchange Commission), we show that the exogenous removal of the uptick rule (which is a short-selling constraint) for the treatment group of stocks did not reduce Monday synchronicity compared to the control group.

Finally, one might argue that abnormal reaction to macroeconomic announcements on Mondays may simply be a result of the most important types of macroeconomic news being announced on Mondays. However, this straightforward intuition is not compliant with the observation that important types of macroeconomic news (Federal Open Market Committee decision [FOMC] and non-farm payroll [NFPAY]) are always announced in the middle of the week. The announcements on Mondays draw a greater reaction by virtue of their salience despite their lower (relative) importance and attention-grabbing potential.

Our paper makes several contributions to the literature. *Firstly*, we contribute to the synchronicity literature by examining its temporal variations. We focus on intra-week seasonality similar to the test of return seasonality by Keloharju *et al.* (2016), and provide the first evidence of a day-of-the-week effect in synchronicity that is persistent in a large sample and over a long period for US stocks. We show that higher synchronicity on Mondays cannot be fully explained by factors that are usually known to affect synchronicity, and propose a novel explanation for our findings.

Secondly, we contribute to the literature on information supply and demand by focusing on day-of-the-week variations in news announcements (macroeconomic and firm-specific) and investor attention (retail and institutional).⁹ The contrast effect is strong enough to keep the comovement higher on Monday despite the low supply of macroeconomic announcements. The salience of

⁹ Information arrival resolves uncertainty and triggers systematic price movements (Beaver, 1968; Kalay and Loewenstein, 1985). Moreover, earnings announcements and macroeconomic announcements have implications for risk premia and performance of CAPM (Patton and Verardo, 2012; Savor and Wilson, 2013, 2014, 2016).

similar announcements released on other weekdays is less because investors are exposed to a larger number of announcements for them to perceive. The low supply of earnings announcements on Mondays does offer a partial explanation for the results. In summary, our findings cannot be explained by making a simplistic assumption that a higher supply of macroeconomic news causes higher synchronicity while a lower supply of earnings news causes lower synchronicity. Since there are intra-week variations in the supply (announcements) and demand (investor attention) of information, its incorporation into stock prices depends on these variations in addition to the type of news (market-wide and firm-specific). Our behavioral explanation for time-varying return synchronicity is distinct from the rational explanation based on endogenous information signals generated by economic activities (Veldkamp, 2006; Brockman *et al.*, 2010). To our knowledge, this is the first empirical evidence of the simultaneous contrast effect in behavioral finance.

Thirdly, this study also contributes to the literature on the Monday anomaly. Studies by Cross (1973), French (1980), Gibbons and Hess (1981), Lakonishok and Levi (1982), Keim and Stambaugh (1984), Abraham and Ikenberry (1994), Cho *et al.* (2007), Alt *et al.* (2011), and Birru (2018) are some examples. We show that the relatively high Monday synchronicity is distinct from the Monday return anomaly. Synchronicity on Monday remains higher in both up-market and down-market conditions. The higher synchronicity on Monday is not driven by more frequent market downturns, which may occur due to the prevalence of negative Monday returns. Interestingly, we also show that the Monday synchronicity anomaly exists even in those periods when the Monday anomaly disappears. We also find that stocks featuring high Monday synchronicity have different characteristics compared to stocks featuring high Monday anomaly.

2 Data & Methodology

The sample period for the baseline results extends from January 1953 to December 2017. However, we also use data for the 1927-1952 period during which Saturday was also a trading day. Daily

total stock returns, daily volume, and daily total returns of value-weighted CRSP Index are obtained from the CRSP daily stock files commencing from January 1, 1927, and ending on December 31, 2017. Daily returns for 48 Industry Portfolios and Fama-French Three Factors are obtained from Kenneth French's website. In line with previous studies, American Depository Receipts (ADRs), Real Estate Investment Trusts (REITs), closed-end funds, primes, and scores are excluded from the sample by restricting the CRSP data to share type code 10 and 11. Data on firm fundamentals to construct book-to-market ratio, leverage, return on equity, firm age, and industry size is obtained from Fundamental Annual and Quarterly files of COMPUSTAT. Analyst coverage data is obtained from I/B/E/S database. The definitions of firm fundamentals and industry variables are provided in Table A10 (see Appendix).

We obtain earnings announcement dates from Bloomberg terminal between 1998 and 2017. This data always includes the time of news release, classified as before/during/after market hours. Dates for macroeconomic news are collected from the Bloomberg terminal between 1998 and 2017, which include nine macroeconomic announcements: purchasing managers' index (PMI), non-farm payroll (NFPAY), Federal Open Market Committee decision (FOMC), producer price index (PPI), consumer price index (CPI), the advanced estimate of quarter-on-quarter GDP growth (GDP), personal consumption expenditure (PCE), trade balance figure (TRBAL), and consumer confidence index (CCI). Our selection of macroeconomic news is based on previous literature and the R-Index¹⁰ assigned by the Bloomberg terminal.

To measure individual investor attention, we obtain Google SVIs for macroeconomic news at a daily frequency from January 2004 to December 2017. The SVIs for macroeconomic announcements are collected by using the 'search by topic' facility provided by Google Trends. Following Da *et al.* (2011), SVIs are also obtained for Russell 3000 Index firms using ticker symbols as search terms.¹¹

¹⁰ R-Index (Relative Index) is defined in the Bloomberg terminal as "the number of alerts that are set for the corresponding economic event relative to all alerts set for all events in the selected country/alert type".

¹¹ The use of ticker symbols as search terms helps reduce noise in the SVI. For instance, if the search term "Apple" is used, it may reflect the search interest in the 'apple' fruit or 'Apple iPhone'. Searching by entering the ticker symbol

Institutional attention is measured using Abnormal Institutional Attention (AIA) data obtained from Bloomberg. AIA is based on news reading and searching activity on Bloomberg's terminals, which are usually available to and affordable only for institutional investors. AIA measures attention as a score, ranked from 0 to 4, based on the percentile in which institutional attention lies relative to its past distribution.

We follow Piotroski and Roulstone (2004) to estimate the following firm-year regression for every weekday to obtain the measure of day-of-the-week synchronicity:

$$r_{i,d,y} = \alpha_{d,y} + \beta_1 r_{Mkt,d,y} + \beta_2 r_{Mkt,d-1,y} + \beta_3 r_{Ind,d,y} + \beta_4 r_{Ind,d-1,y} + \epsilon_{i,d,y} \quad (1)$$

where $r_{i,d,y}$ is the stock return of the firm i for the weekday d in the year y ; $r_{Mkt,d,y}$ is the CRSP index return and $r_{Ind,d,y}$ is the Fama-French 48 industry return. We include the lagged returns of the CRSP index and industry to accommodate for non-synchronous trading. As an example, we regress Monday's stock returns on contemporaneous and lagged (i.e., previous Friday's) Monday's CRSP index returns and industry returns.

The R^2 estimated from Equation (1), $R^2_{i,d,y}$, is the measure of weekday d synchronicity for the firm i in the calendar year y . To compare Monday R^2 with those of other weekdays, we calculate relative synchronicity by taking the difference in R^2 , $\Delta R^2_{i,d,y}$, between Monday R^2 and those of other weekdays (Tuesday to Friday); hence, creating Monday-Tuesday, Monday-Wednesday, Monday-Thursday, and Monday-Friday differences. Alternatively, we compute the synchronicity using the logarithmic transformation of R^2 , i.e., $\ln\left(\frac{R^2}{1-R^2}\right)$.

"AAPL" is more likely to reveal a demand for the financial information of the Apple Company.

3 Empirical Results

In this section, we test whether day-of-the week synchronicity differs across weekdays. Then we examine potential explanations, such as the contrast effect, information demand, Monday anomaly, investor sentiment, and arbitrage constraints to explain higher Monday comovement.

3.1 Monday synchronicity

Tables 1 and 2 report the summary statistics and t-tests of regression outputs, including measures of synchronicity, regression coefficients, and the root mean squared errors (*RMSE*) from Equation (1). Table 1 shows that Monday R^2 is about 21.8%, whereas the overall average of R^2 for all other weekdays is about 19.5%. Notably, average R^2 values for Tuesday to Friday lie close to each other. Therefore, the average Monday's R^2 is around 12% higher than the average R^2 of other weekdays. Similarly, synchronicity, defined as $\ln\left(\frac{R^2}{1-R^2}\right)$, is also higher on Monday than other weekdays. The regression coefficient for the market index is the highest for Wednesday on average, with Monday's coefficient being the second highest, whereas the coefficient for the lagged term of the market index is the highest for Monday. The coefficients for the industry returns and its lag are also higher for Monday. For robustness checks, we run pooled regressions (Table A1 of Appendix), use alternate models like the Carhart's 4-factor Model and the Market Model (Table A2 of Appendix), and find that Monday R^2 remains higher. Thus, the Monday synchronicity effect depends neither on the choice of the factor model, nor on the regression specification.

INSERT TABLE 1 HERE

The t-tests in Table 2 show that Monday R^2 and regression coefficients are significantly higher than those of other weekdays, except the insignificant differences in Monday and Wednesday's market betas and in Monday and Tuesday's lagged industry coefficients. These findings suggest that the

higher synchronicity on Monday seems to stem from the higher correlation of stock returns with the market index and industry index on Monday. However, we show below that the differences in these coefficients can only explain a small fraction of the differences in R^2 between Monday and other weekdays. Note that high synchronicity can also originate from low values of idiosyncratic volatility. Therefore, we conduct similar t-tests for $RMSE$ of these regressions. The results are rather mixed. Monday's $RMSE$ is significantly lower than that of Wednesday but significantly higher than that of Friday; and the difference is insignificant when compared to Tuesday or Thursday. Thus, it is hard to explain higher Monday synchronicity via idiosyncratic volatility. We also run t-tests for differences in R^2 among weekdays other than Monday, for example, between Tuesday and Wednesday. These unreported results show that such differences are relatively small and statistically insignificant.

Higher values of regression coefficients on Monday are consistent with the higher Monday betas found by Chang *et al.* (1995, 1998). They attribute this pattern to an asymmetric response to macroeconomic news on Monday, especially on down-market days (Monday returns tend to be lower than other days). Moreover, this asymmetric response is due to herding by speculators and individual investors with short investment horizons (Lakonishok and Maberly, 1990; Froot *et al.*, 1992). The role of herd behavior in contributing to abnormally high synchronicity due to a macroeconomic announcement on Monday is consistent with the contrast effect. When investors have nothing else to perceive other than the macroeconomic announcement, they may herd on this salient piece of information.

INSERT TABLE 2 HERE

We test the extent to which higher comovement on Mondays is due to higher correlation of stock returns with the market and industry indices by regressing $\Delta R^2_{i,d,y}$ with corresponding differences in market and industry coefficients. For example, Monday-Tuesday ΔR^2 is regressed with Monday-Tuesday differences between market coefficient $\Delta\beta_{Mkt}$ and industry coefficient $\Delta\beta_{Ind}$. Table 3 shows that while the $\Delta\beta_{Mkt}$ and $\Delta\beta_{Ind}$ are indeed statistically significant regressors, the

low R^2 values imply that they only explain a very small portion of the variation in ΔR^2 . The R^2 values are around 0.5% when $\Delta\beta_{Mkt}$ is used (columns 2, 4, 6 and 8) and around 5% when both $\Delta\beta_{Mkt}$ and $\Delta\beta_{Ind}$ are used (columns 1, 3, 5 and 7).

INSERT TABLE 3 HERE

We additionally examine the persistence of the Monday synchronicity effect over the sample period. Figure 1 plots the Monday R^2 and the average R^2 of other weekdays. It shows the former is higher than the latter for most of this time, indicating that synchronicity on Monday remains persistently higher than other weekdays over time.

INSERT FIGURE 1 HERE

3.2 The relation between news and contrast effect

In this section, we consider both macroeconomic and firm-specific news announcements, and discuss how the contrast effect helps to explain the puzzling high Monday synchronicity.

Prior evidence shows that macroeconomic announcements affect the entire market and drive up return synchronicity (Brockman *et al.*, 2010). To examine whether high Monday synchronicity stems from more macroeconomic announcements on Mondays, we report the frequencies of macroeconomic announcements dates¹² in Panel A and Panel B of Figure 2. Mondays have the lowest frequency, while Fridays have the highest. This is in sharp contrast with the within-week

¹² Initial Jobless Claims (IJC) is a very important macroeconomic indicator usually released every week on Thursday, whereas all other announcements in our sample are released on a monthly or a quarterly basis. Therefore, the analysis of day-of-the-week synchronicity will be problematic because the dummy for macroeconomic announcements on Thursday will almost always have a value of 1 due to IJC. If IJC had a role in increasing synchronicity, Thursday's synchronicity in the baseline results in Table 1 should have been higher for the 1998-2017 period because this announcement is made almost every week on Thursday. However, we do not find this to be the case. Hence, the exclusion of IJC does not affect our results.

pattern in synchronicity that is higher on Mondays and lower on Fridays. These results suggest that the intensity of macroeconomic news alone cannot explain the Monday synchronicity effect. A close inspection reveals that NFPAY is most concentrated on Fridays, FOMC is concentrated in the middle of the week (Tuesdays and Wednesdays), PMI occurs most frequently on Mondays, and CCI is almost always announced on Tuesdays. Almost all announcements on Mondays are either for PMI or PCE.

Firm-specific news such as earnings announcements, once incorporated into stock prices, reduces return comovement. As some earnings announcements were released in aftermarket hours or on non-trading days like weekends, the dates of these earnings announcements need to be adjusted to the next trading day. The frequencies of actual and adjusted earnings announcements across weekdays are reported in Panel C and Panel D of Figure 2, respectively. Before adjustments, Thursday has the largest number of actual earnings announcements, while Friday has the smallest. After adjustments, Monday has the smallest number of announcements. The fewer adjusted Monday announcements suggest relatively less firm-specific information is available on Mondays; thus, synchronicity is expected to be higher. Note, however, that comovement on Thursday is not the lowest despite having the largest number of earnings announcements. Therefore, earnings announcements alone do not fully explain the intra-week variations in comovement.¹³

INSERT FIGURE 2 HERE

We analyze the effect of macroeconomic and earnings announcements on day-of-the-week synchronicity separately as well under the interaction between them. First, we divide the sample into two sub-samples; one for days on which one or more macroeconomic announcements are released, and the other for days without macroeconomic announcements. We run synchronicity

¹³ Although we focus on earnings announcement, the intra-week variation in idiosyncratic volatility (*RMSE*) in Table 2 shows that firm-specific news (including but not limited to earnings announcements) alone cannot explain the abnormally high synchronicity on Monday.

regressions separately for each firm and weekday in each sub-sample. For example, we estimate separate firm-wise regressions for Monday announcement days and Monday non-announcement days. The t-tests between the R^2 values in Panel A of Figure 3 show that the average R^2 with macroeconomic announcements on Mondays is about three times the average for non-announcement Mondays. The average change in R^2 from announcement days to non-announcement days is also significantly positive for Wednesday and Thursday, but with a lesser magnitude than that for Monday. Meanwhile, it is negative for Tuesday and Friday. The differences between announcement and non-announcement R^2 averages for other weekdays are notably smaller. These results indicate that the processing of macroeconomic news is not uniform across the week. If the R^2 values are compared across non-announcement days, the average for Monday is lower than that of Tuesday and Friday. This is in sharp contrast to the comparison among announcement days, where the average for Monday is the highest at 47.05%, followed by 30.38% for Wednesday and lower for other weekdays.

Second, we test whether higher synchronicity on Monday is driven by an asymmetric response to earnings announcements. Since a firm can have a maximum of 80 quarterly earnings announcements during our sample period (1998-2017), it can have only 16 announcements on average for each of the five weekdays. Therefore, we run pooled regressions for earnings announcements instead of the firm-level regressions that we employ for macroeconomic announcements. Two regressions are run for each weekday, one pooling the non-announcement days and the other pooling the announcement days. Moreover, the dummy for earnings announcement is adjusted to the next trading day if it is released after market hours or on non-trading days like weekends.

Panel B of Figure 3 shows that synchronicity decreases when earnings are announced and firm-specific information is impounded into stock prices. R^2 values range from 3.29% (Friday) to 5.43% (Thursday) for announcement days, and from 7.62% (Friday) to 10.27% (Monday) for days without announcements. Synchronicity remains higher on Monday for non-announcement days, but not for the announcement days.

Third, we analyze day-of-the-week synchronicity under interactions between macroeconomic and earnings announcements. The daily returns data is divided into four sub-samples based on the values of macroeconomic and earnings announcement dummy variables, denoted D_M and D_E respectively. For D_M , the value is 0 for days without any macroeconomic announcements, and 1 for days on which one or more macroeconomic announcements are released. The same applies to D_E but with respect to the relevant firm-day observations. We run firm fixed-effects regressions, which allow us to control for unobserved and time-invariant firm heterogeneity, for each weekday separately under each combination. Panel C of Figure 3 represents the R^2 values from these regressions. In the first case when both D_M and D_E are 0, R^2 values of Tuesday and Thursday are higher than Monday. In the second case when $D_M = 1$ and $D_E = 0$, Monday R^2 is significantly higher than other weekdays. The third case is the opposite of the second case (i.e., $D_M = 0$ and $D_E = 1$); and R^2 on Monday is only higher than that of Friday while being lower than those of other weekdays. In the fourth case when both D_M and D_E are 1, Monday R^2 is again higher than other weekdays. In summary, whenever $D_M = 1$, whether $D_E = 0$ or $D_E = 1$, Monday's R^2 is higher. In other words, higher synchronicity on Monday is driven by the asymmetric response to macroeconomic announcements. The strength of this asymmetric response is evident from the fact that Monday R^2 is approximately 15% (39%) higher than Wednesday R^2 in the second (fourth) case.

As indicated in Panel D of Figure 2, earnings announcements after adjustments were the least frequent on Monday, while most of them were made in the middle of the week. The role of earnings announcements in comovement and contrast effect of macroeconomic announcements is important from two aspects. First, they reduce comovement because more firm-specific information is incorporated into stock prices. Thus, the lower the frequency of earnings announcements, the higher the comovement, keeping all else equal. Second, the lower frequency helps in lowering the information clutter so that the macroeconomic announcement becomes more salient. In other words, fewer earnings announcements result in a quiet night in which the macroeconomic announcement becomes the thunder. Panel C of Figure 3 shows that the contrast effect is more prominent when

macroeconomic announcements on Monday are not accompanied by earnings announcements (second case vs. fourth case). We argue that Mondays present the most ideal conditions for the contrast effect to manifest. In summary, if a macroeconomic announcement is released on Monday, there is an abnormal response in terms of comovement. The response is stronger if the macroeconomic announcement is not accompanied by earnings announcements. However, Monday's comovement is similar to that of other days if there is no macroeconomic announcement.

INSERT FIGURE 3 HERE

The distribution of earnings announcements shown in Panel D of Figure 2 ignores an important aspect of how quarterly earnings are released by firms. A quarterly announcement is usually released a few weeks after a fiscal quarter ends. Firms may differ from each other in terms of when their fiscal year starts. However, any fiscal quarter of a firm is aligned with a calendar year's quarter i.e., January-March, April-June, July-September, or October-December. Hence, most firms release their earnings on a few dates following a quarter, termed as the "earnings season".¹⁴ A large number of earnings announcements are released on these few dates, while only a handful of announcements are released during the rest of the year.

Note that in Panels B and C of Figure 3, firm-date observations are pooled into separate bins without considering the number of firms announcing (or not announcing) their earnings on a given weekday. Hence, the frequency of earnings announcements is not being controlled despite the evidence presented in Panel D of Figure 2. Since the contrast will be starker if the background is quieter, fewer earnings announcements on Monday make the macroeconomic announcement more salient. Therefore, controlling for the number of firms releasing their earnings is important.

If numerous firms are releasing their earnings news on the same day, the information environment

¹⁴ Under SEC rules, firms have to file quarterly and annual reports within 35 and 60 days, respectively.

will have a lot of clutter. It will no longer be a quiet night to make the macroeconomic announcement more salient. Hence, the contrast may be absent or weaker on such dates because the background will have more clutter. In addition, there will be a spillover effect on peer firms if influential, industry-leading, blue chip firms are announcing their earnings. Chan and Marsh (2021), indeed, find that macroeconomic announcements lose their importance for the return-beta relationship if they are overlapped by leading announcements of influential S&P 500 firms. However, they also find that these influential firms, which are market movers, rarely announce their earnings on Monday. Thus, their study supports our conjecture that Monday is an ideal day for macroeconomic announcements to become more salient.

We control for the earnings season by counting the number of announcing firms for each date in the sample. As shown in Panel A of Figure 4, the maximum value of this count is 371, while the 30th percentile is 13 and the 70th percentile is 63. The histogram shows that on most of the dates in the sample, only a few firms announce their earnings. There are a few dates on which a large number of firms announce their earnings. We divide the sample into three sub-samples using the 30th and 70th percentile values as breakpoints. Sub-sample 1 is significantly larger than the other two because the majority of the dates have few (13 or less) earnings announcements; hence, most of the daily observations belong to this sub-sample. Sub-sample 3 is the smallest because there are only a few dates on which a large number (64 or more) of firms are announcing their earnings. In other words, sub-sample 3 proxies the earnings season. We run regressions identical to the ones in Panel B of Figure 3 for each sub-sample.¹⁵

The results in Figure 4 show that the R^2 values generally get lower from sub-sample 1 to sub-sample 3. The progressively lower R^2 values in sub-samples 2 and 3 are consistent with the expectation that increasing concentration of earnings announcements on a given day results in lower comovement

¹⁵ Take Microsoft Inc. (MSFT) as an example: assume that only 12 other firms released their earnings on a specific date but MSFT did not, then its daily return for this date would fall under the non-announcing firm-date observations in sub-sample 1. If another 40 firms announced their earnings the next day but MSFT still did not, the daily return of MSFT would then fall under the non-announcing firm-date observations in sub-sample 2.

across the entire market. Monday R^2 is significantly higher at 12.02% (followed by 9.51% for Tuesday) as compared to other weekdays for non-announcing firm-days in sub-sample 1 (Panel B). Monday R^2 is also slightly higher than Tuesday and Wednesday for non-announcing firm-days in sub-sample 2 (Panel C), but it is not the highest. In sub-sample 3 (Panel D), Monday R^2 is significantly lower for both the announcing firm-days and non-announcing firm-days. The contrast effect of Monday macroeconomic announcements will be weaker/absent on dates when a large number of firms will be releasing their earnings, but such dates (sub-samples 2 and 3) are few and far between. On most dates (sub-sample 1), there are only a few earnings announcements, and the contrast effect continues to hold because the information environment has less clutter.

The scarcity of earnings announcements on Mondays implies that the contrast effect of macroeconomic announcements remains unaffected whether the attention to such news crowds out or complements the attention to earnings news (Hirshleifer and Sheng, 2022; Liu *et al.*, 2023). The average comovement is significantly higher on such Mondays, regardless of the strength of response to earnings news for a small number of announcing firms.

INSERT FIGURE 4 HERE

Disappearance of the Monday synchronicity effect after exclusion of macroeconomic announcements suggests that a small number of macroeconomic announcements are driving the intra-week pattern in comovement. We also consider a period prior to 1998 (1971-1997) in which the release dates for some macroeconomic announcements (PCE, CCI and TRBAL) were not available. These results, discussed in section 6.4 of the Appendix, show that the Monday synchronicity effect is blurred but not eliminated by these missing announcements. Specifically, the absence of data on release dates for PCE results in Monday comovement remaining higher despite the removal of announcement days because some Monday announcements are erroneously being categorised as non-announcement days. The missing dates keep the Monday synchronicity higher, suggesting the strong influence of a small number of macroeconomic announcements on

Monday, consistent with our explanation.

In addition to using announcement dummies for split-sample regressions in Figure 3, we remove the macroeconomic and earnings announcement days and run 3-year rolling regressions. The results in Figure A1 (see Appendix) are consistent with the Monday synchronicity effect. Monday R^2 is not higher when macroeconomic announcement days are removed from the analysis.

The baseline results in Table 1 seemingly depict that comovement is higher on Mondays akin to a seasonal anomaly. Is synchronicity higher on every Monday? The answer is no since the analysis of news announcements in Figure 3 reveals that Monday's comovement is only higher when macroeconomic announcements are released; otherwise, it is similar to comovement of other weekdays. Moreover, only a few Mondays are announcement days. Thus, synchronicity is only higher on a few announcement Mondays. Our analysis in Figure 3 is limited by the fact that we do not control for the frequency of macroeconomic announcements. Hence, we reconcile these dissimilar findings by weighting the R^2 values in Panel A of Figure 3 by the frequency of macroeconomic announcements. We find the weighted averaged values across the weekdays have a similar pattern to that of the R^2 values in the baseline results (see Table A4 in Appendix).

The results up to this stage show that macroeconomic announcements on Mondays, while less frequent, seem to drive up synchronicity. This is further facilitated by the lower frequency of earnings announcements on Mondays, which otherwise reduces synchronicity. Such a phenomenon is best explained, in our view, by the contrast effect, which refers to the perception of intensified difference stemming from successive or simultaneous exposure to stimuli. Just as a thunder that sounds louder in a quiet night than in a noisy background, macroeconomic announcements on Monday are few and far between, making them stand out more against the quieter information background.¹⁶

¹⁶ We follow the variance decomposition by Brogaard *et al.* (2022) separately for each weekday to decompose stock return variance into several components that include noise, firm-specific private and public information, and market-wide information. In line with our contrast effect explanation, we find the share of variance arising from

3.3 Alternative explanations

In this section, we examine alternative explanations for our findings, including 1) information demand, 2) time-varying uncertainty and risk aversion, 3) Monday anomaly, 4) investor sentiment, and 5) limits to arbitrage. We discuss other factors that affect return synchronicity at the end of this section.

3.3.1 Information demand

Although we focus on the effect of news announcements (information supply) on Monday return synchronicity so far, incorporation of information depends not only on the supply of macroeconomic and firm-specific news, but also on the level of attention that investors pay to such news (information demand). It is well documented that attention is a scarce resource (Kahneman, 1973). Investors with limited attention tend to allocate more attention to macroeconomic news when they are more valuable (Peng and Xiong, 2006; Veldkamp, 2006), causing high return comovement. Besides, Drake *et al.* (2017) show that commonality in investor attention to firm-specific information may also drive up excess return comovement.

Salience is essentially an attentional mechanism in which attention is preferentially allocated to the prominent stimulus (Bordalo *et al.*, 2012). Bordalo *et al.* (2021) mention two broad categories of attention: top-down (voluntary or endogenous), and bottom-up (involuntary or exogenous). Top-down attention is a higher-level cognitive process carried out consciously and motivated by some goals/tasks of the decision maker. The process involves focusing on the most task-relevant stimuli while ignoring other stimuli with lower perceived relevance. In other words, attention is allocated to the most important stimuli. Top-down attention is formalised by models of rational

market-wide information to be significantly higher for Mondays as compared to other weekdays, while the shares of both private and public firm-specific information are lower for Mondays. These patterns are consistent over time and are robust for both equal-weighted and variance-weighted averages of variance component shares. These results are reported in Section 6.7 of the Appendix.

inattention in economic decision-making (Sims, 2003; Woodford, 2012, 2020; Khaw *et al.*, 2020). However, attention is not exclusively driven by conscious goals; it may be automatically drawn to stimuli that are salient in a given context. Salience is the property of a stimulus that draws bottom-up attention (Bordalo *et al.*, 2021). Rational economic choice is distorted when individuals are distracted from their goals by rising bottom-up attention of salient stimuli.

The retail attention measure based on Google searches for a company's ticker symbol or a macroeconomic announcement only quantifies top-down retail attention. Individual investors are voluntarily and consciously searching for financial information through Google. Similarly, Bloomberg's institutional attention measure is quantifying the top-down attention of institutional investors. These proxies of investor attention cannot fully account for the bottom-up attention raised by salient stimuli. Hence, a stronger reaction to a salient macroeconomic announcement does not necessarily imply that top-down attention (e.g., measured by Google SVI) to such news is higher. In this case, attention is drawn towards the salient stimulus exogenously, spontaneously, involuntarily, and subconsciously. Individuals do not need to actively increase their attention (by searching in Google or Bloomberg terminals) towards that stimulus; instead, such stimulus draws attention towards itself.

We first consider attention to macroeconomic news. Table A7 (see Appendix) reports the averages of the standardized Google SVIs for each of the nine macroeconomic news, separately for announcement and non-announcement days. Standardization is necessitated by the unequal scales of the data over time, as well as across the different types of news.¹⁷ As expected, the attention to macroeconomic news is generally higher on announcement days. Among different types of announcements, investors pay the most attention to FOMC, and then to NFPAY. Several studies in the literature highlight the importance of these two announcements.¹⁸

¹⁷ The raw values of SVIs each year are subtracted by its mean for the same year and then divided by the standard deviation for the same year. Negative values simply imply that the raw values are below the mean.

¹⁸ According to Carnes and Slifer (1991) and Andersen and Bollerslev (1998), NFPAY is the "king of kings" among announcements. Moreover, daily bond yield changes and order flow are most sensitive to NFPAY announcements

In Figure 5, we compare the standardized Google SVIs of PMI and PCE, which constitute almost all announcements on Monday, with those of FOMC and NFPAY, which are generally not released on Monday but draw more top-down attention.¹⁹ When PMI is announced on Monday, the average SVI is 2.017, while if it is announced on Tuesday, the average value is slightly higher at 2.103. The values are lower for other days. For the PCE announcement, the average value for Monday is 1.170, which is the highest among the weekdays. If the increase in attention to both PMI and PCE is considered jointly, announcements on Monday draw a comparatively higher top-down attention.

Our findings are consistent with the inability of attention proxies to measure bottom-up attention. Despite the fact that investors are paying more top-down attention to announcements of FOMC and NFPAY, which are generally not released on Mondays, synchronicity does not increase as much as compared to announcements getting released on Mondays. We also argue that PCE and PMI are more salient on Monday despite being less vivid than FOMC and NFPAY in terms of capturing attention. Fiske and Taylor (2017) differentiate between vividness and salience using the following example: A plane crash is inherently more vivid than a normal flight but its salience will be less in the context of wartime carnage as compared to peacetime. A stimulus may capture more attention because it is inherently more vivid than other stimuli, regardless of the surroundings; but any stimulus may become more salient because of its positioning in relation to other stimuli. Thus, we argue that the salience of PMI and PCE announcements on Mondays is not necessarily due to their vividness; it is rather a consequence of their contrast to the environment. The lower frequency of earnings announcements on Mondays in general and the concentration of earnings announcements on a small number of dates in the earnings season helps in keeping Monday's background quieter for the contrast effect to manifest.

(Pasquariello and Vega, 2007). Average stock market returns and Sharpe ratios in the USA are twenty to forty times higher on days with FOMC announcements relative to non-announcement days (Savor and Wilson, 2013; Lucca and Moench, 2015), an effect that is much larger than other macroeconomic announcements. Pre-announcement risk premia of FOMC and NFPAY are quantitatively larger than those of PMI and GDP (Hu *et al.*, 2021).

¹⁹ In the period 1998-2017, all Monday announcements, except two (one each for FOMC and TRBAL), are either for PMI or PCE. Since the data for SVI does not exist for the single Monday FOMC announcement (because it was before 2004), that leaves just one value for TRBAL and the rest for PMI and PCE.

Hartzmark and Shue (2018) find evidence of contrast effect even for large firms with salient earnings announcements. Such firms are generally more vivid because of their size, but an earnings surprise of one large firm that lies in sharp contrast to earnings surprises of other large firms in the previous day still draws more bottom-up attention. On the other hand, the extensive literature on limited attention is primarily related to under-reaction to news about small firms (Peng, 2005), news obscured in footnotes (Aboody, 1996), news released after trading hours (Francis *et al.*, 1992), or news released on Fridays (DellaVigna and Pollet, 2009).

INSERT FIGURE 5 HERE

We then turn to investor attention towards firm-specific news, which is expected to reduce synchronicity by facilitating rapid incorporation of information into stock prices. Comovement is indeed alleviated if investors actively seek firm-specific information (Kong *et al.*, 2019). However, attention itself can cause comovement, as hypothesized by Mondria (2010). Figure 6 shows that the average retail attention for individual firms, measured by Google SVI, is slightly lower on Mondays than on Tuesdays and Wednesdays; while institutional attention on Monday is the second-highest after Tuesday. As Monday is usually the first trading day of the week, retail attention unsurprisingly surges from low values over the weekend. No data for the weekends is available for institutional attention. Taken together, these results do not provide a clear explanation for the abnormally high Monday synchronicity.

INSERT FIGURE 6 HERE

3.3.2 Uncertainty over the weekend

Since macroeconomic announcements and earnings announcements are rarely released during weekends, uncertainty about the economy and individual firms is expected to be high at the start of

the week on Mondays. Therefore, investors can learn little about the economy-wide or firm-specific information over this period. Higher economic uncertainty and risk aversion on Mondays induce investors to learn more about aggregate shocks as compared to idiosyncratic shocks, since they are more valuable in risk reduction (Kacperczyk *et al.*, 2016). Comovement will be high if investors engage in category-learning behavior (Peng and Xiong, 2006; Veldkamp, 2006) and prioritize their attention to these aggregate shocks. Indeed, Fisher *et al.* (2022) find that risk aversion and economic uncertainty (proxied by VIX and Economic Policy Uncertainty measure) are higher on Mondays. Monday synchronicity effect may result from preferential allocation of attention to macroeconomic information over firm-specific information at the start of the week. Bansal and Shaliastovich (2011) and Kacperczyk *et al.* (2016) show that under conditions of higher economic uncertainty and risk aversion, investors endogenously pay more attention to learn about the economy and firm fundamentals.

We test for the effect of uncertainty over the weekend by focusing on weeks which are either preceded by a Friday holiday (in the previous week), or those that commence on Tuesday due to a holiday on Monday. In both cases, the weekend becomes longer and it is expected that uncertainty and scarcity of information will be higher. Therefore, we expect higher synchronicity on the first trading day of such weeks. The period from 1927 to 1952 provides a natural setting to test the effect of a shorter weekend because Saturday also used to be a trading day and only Sunday was a holiday. As uncertainty will be relatively less as trading resumes on Monday after only a one-day break, we expect the Monday synchronicity effect to be weaker.

In our sample, we find 124 weeks preceded by a Friday holiday over the full sample period 1953-2017; 37 of them lie in the 1998-2017 period. Similarly, there are 252 weeks with a Monday holiday in the 1953-2017 period; 96 of them lie in the 1998-2017 period. Pooled synchronicity regressions in Panel A and Panel B of Table 4 show that comovement is high on the first trading day of the week. R^2 value is comparatively higher than normal weeks (column 1) for Mondays preceded by a Friday holiday (column 2), and Tuesdays that follow a Monday holiday (column 3). In fact,

R^2 values are comparatively higher for second trading days (Tuesday in column 2, and Wednesday in column 3) for these weeks as well. As reported in Table A6 (see Appendix), we also find that VIX is consistently higher on the first trading day of the week (whether Monday or Tuesday). Thus, heightened uncertainty due to longer weekend does contribute to higher comovement at the start of the week.

When we control for macroeconomic announcements in Panel C and Panel D of Table 4, the contrast effect is present even for those weeks which are preceded by a Friday holiday. R^2 value jumps from 4.76% (6.18% in FE regression) for non-announcement days to 14.40% (18.90% in FE regression) for announcement days on Mondays that follow Friday holidays. More importantly, this abnormal increase on Mondays is not present for Tuesdays that follow Monday holidays. R^2 does increase for such Tuesdays (columns 5 and 6), but not as sharply as for Mondays in normal weeks and weeks preceded by Friday holidays. For weeks preceded by Friday holidays, R^2 value on Monday announcement days is only slightly higher than that of Wednesday announcement days (in fact, lower in FE regressions). The sharp increase in R^2 on Wednesdays from non-announcement days to announcement days may arise from the small sample size of longer weekends. Moreover, this pattern is neither robust nor stronger than the pattern for Mondays in different specifications that we have used elsewhere.

We also run baseline synchronicity regressions identical to those in Table 1 for the 1927-1952 period. In this case, we have six regressions instead of five because of an additional trading day, i.e. Saturday. Results in Table 5 show that average R^2 value for Monday is higher but it is only around 6% higher than the average R^2 of other weekdays. Moreover, the t-test between R^2 values of Monday and Tuesday is insignificant. We cannot test the contrast effect because data for macroeconomic announcements is not available for this period. Nevertheless, Monday synchronicity is weaker in line with the expectation that there is less uncertainty over a shorter weekend. Taken together, while uncertainty over long (short) weekends does amplify (attenuate) Monday synchronicity, the role of the contrast effect remains significant.

INSERT TABLE 4 HERE

INSERT TABLE 5 HERE

We further explore the role of uncertainty by running synchronicity regressions under increasing levels of VIX. We divide the daily observations into three sub-samples (low, medium and high) using the 30th and 70th percentile values of VIX as breakpoints. In Panel A of Table 6, R^2 values consistently increase for all weekdays as the level of VIX increases. Thus, comovement increases as uncertainty in the market increases. Monday's R^2 value is higher than other weekdays under medium and high levels of VIX, while it is lower than Tuesday and Wednesday in the case of low levels of VIX. This indicates that uncertainty does play a role in keeping the comovement higher on Monday. However, the regressions for announcement and non-announcement days in Panel B of Table 6 show the contrast effect of Monday macroeconomic announcements to manifest in both low and high levels of VIX. Monday's R^2 jumps from 5.88% to 11.39% when VIX is low; similarly, it jumps from 9.34% to 14.60% when VIX is high. However, there is only a very small increase in Monday's R^2 under medium levels of VIX. In addition, Monday's R^2 is not the highest on announcement days. Thus, high levels of VIX seems to amplify the contrast effect, but it is not a necessary requirement since the contrast effect is present even when VIX is low. When VIX is within medium range, however, there is no evidence of the contrast effect. Overall, how VIX interacts with the contrast effect is unclear. We leave a more in-depth inspection of this issue to future research.

INSERT TABLE 6 HERE

3.3.3 Monday synchronicity and Monday anomaly

The Monday anomaly in stock returns refers to lower returns on Monday. Thus, it is conceivable to have more negative returns on Monday as compared to other weekdays. Since returns comove

asymmetrically more on such down days (Jiang *et al.*, 2018), high Monday synchronicity may arise from the Monday anomaly. To test this possibility, we separate the daily returns into two sub-samples, one with negative market returns and the other with positive market returns. We then rerun firm-wise synchronicity regressions for down days and up days, once again separately for each weekday. A rolling window of three calendar years is applied to ensure that each regression has a sufficient sample size. Thus, we obtain a downside R^2 (R_D^2) and an upside R^2 (R_U^2) for each weekday and each firm in each 3-year period. The t-tests for differences between Monday and other weekdays in terms of R_D^2 (i.e. ΔR_D^2) and R_U^2 (i.e. ΔR_U^2) in Table 7 show that R^2 always remains significantly higher on Monday, whether the market is up or down.

We also test whether differences in R^2 between Monday and other weekdays are different between down days and up days. The difference-in-difference $\Delta(R_D^2 - R_U^2)$ is significantly positive except for the Monday-Friday difference. This implies that even though Monday's synchronicity is higher regardless of up or down-market conditions, it exceeds that of Tuesday, Wednesday and Thursday when the market is down. However, with respect to Monday-Friday comparison, the difference in synchronicity is higher on up days rather than down days. Moreover, while the magnitude of the difference-in-difference is sizable (1.9%) for the Monday-Tuesday comparison, it is only around 0.4% for Monday-Wednesday or Monday-Thursday comparison. Therefore, the asymmetry in comovement on down days only partially contributes to Monday's higher comovement.

INSERT TABLE 7 HERE

3.3.4 Firm characteristics and investor sentiment

A number of firm characteristics have been found to be associated with synchronicity in the literature. Some of them, such as firm size and idiosyncratic volatility (firm risk), are also associated with the extent to which firm returns are affected by investor sentiment (Baker and Wurgler, 2006). To understand whether firm fundamentals and investor sentiment drive the differences in R^2 between

Monday and other weekdays, we estimate a baseline regression as follows:

$$\begin{aligned}\Delta R_{i,d,y}^2 = & \alpha + \gamma_1 \beta_{i,y} + \gamma_2 \text{TURNOVER}_{i,y} + \gamma_3 \text{IVOL}_{i,y} + \gamma_4 \ln(\text{MKT.CAP})_{i,y-1} \\ & + \gamma_5 \text{BK/MKT}_{i,y-1} + \gamma_6 \text{LEV}_{i,y-1} + \gamma_7 \text{ROA}_{i,y-1} + \epsilon\end{aligned}\quad (2)$$

Results in Table 8 show that the R^2 differences are higher for stocks with large market capitalization, high CAPM β , higher turnover, and low idiosyncratic volatility. The coefficients for turnover and CAPM β consistently get higher as the week progresses, and their relationship with the R^2 difference is strongest for the Monday-Friday comparison. The coefficients for book-to-market ratio, leverage, and ROA are insignificant. These results are robust when we account for unobservable time-invariant firm heterogeneity using firm fixed-effects regressions.

We conduct several additional robustness checks for our baseline results. First, we replace the dependent variable $\Delta R_{i,d,y}^2$ with the difference in synchronicity, i.e., the logarithmic transformation of R^2 . The results in Table A11 (see Appendix) are similar to the baseline results, except for firm size. Coefficients for market capitalization are now insignificant.

Second, when an individual firm's R^2 is large, it is possible that $\Delta R_{i,d,y}^2$ is large in absolute value too. To account for this, we rescale $\Delta R_{i,d,y}^2$ by the weekly average of R^2 (from Monday to Friday) for each firm-year observation:

$$\text{Scaled} \Delta R_{i,d,y}^2 = \frac{\Delta R_{i,d,y}^2}{\sum_{d=1}^5 R_{i,d,y}^2 / 5}$$

The results for the scaled differences in Table A11 (see Appendix) are overall consistent with, albeit weaker than, the baseline regression results. CAPM β and turnover are significant at the 1% level for Monday-Thursday and Monday-Friday scaled difference, while turnover is also significant at the 10% level for Monday-Wednesday scaled difference. The IVOL is consistently significant for all scaled differences at the 1% level.

Third, we control for analyst coverage in our regressions. Table A12 in the appendix shows

that analyst coverage is positively significant in all regressions except for the Monday-Friday difference. The coefficients for market capitalization are now insignificant. Since analyst coverage is usually higher for larger firms, the addition of analyst coverage in the regression makes firm size insignificant. Fourth, we substitute ROA by its standard deviation to proxy for earnings volatility. Table A12 shows that the standard deviation of ROA remains insignificant like ROA itself. Finally, when we add firm age, industry size, and the number of firms in the industry to our regressions, we find that the intra-week pattern in synchronicity is more prominent in firms belonging to industries which are small and more concentrated (see Table A13 in Appendix). In the fixed-effects specification, firm age is positively associated with R^2 differences.

Since any shift in investor sentiment has a stronger effect on the returns of more sentiment-prone and arbitrage-constrained stocks (Baker and Wurgler, 2006), if sentiment drives the higher Monday comovement, we expect it to be more pronounced among small firms, young firms, and firms with high idiosyncratic volatility. Moreover, small-sized stocks exhibit higher comovement due to correlated retail trading during extreme sentiment periods (Kumar *et al.*, 2013). The results above show, however, that this is not the case. Instead, large, old, and less volatile firms have higher return comovement on Mondays than other weekdays. This implies that sentiment is unlikely to explain this anomaly. Since investor sentiment is also an explanation for the Monday anomaly (Birru, 2018), these panel regressions suggest further that the Monday anomaly is distinct from the higher Monday synchronicity illustrated here.

INSERT TABLE 8 HERE

3.3.5 Limits to arbitrage

The presence of arbitrage constraints makes it possible for mispricing to persist and market-wide volatility to increase (De Long *et al.*, 1989, 1990). Increased market volatility pushes the R^2

to higher values across the entire market. For example, short-sale constraints force pessimistic investors to sit out of the market during high sentiment periods and can amplify return volatility. We test whether short-sale constraints play a role in causing higher synchronicity on Mondays by using the Regulation SHO experiment. The exogenous removal of the uptick rule for a subset of stocks by the SEC provides a natural experimental setting where treatment stocks became easier to arbitrage than control stocks (Chu *et al.*, 2020). Table 9 reports the results of diff-in-diff regressions using a treatment dummy and a time dummy on the R^2 differences. The interaction term $TIME * SHO$ is insignificant for all R^2 differences, implying that easing arbitrage constraints for treatment stocks by removing the uptick rule did not significantly reduce the R^2 differences. In other words, Monday synchronicity did not decrease for the treatment stocks when arbitrage was made easier.

INSERT TABLE 9 HERE

3.3.6 Other explanations

Synchronicity is related to some other factors as well. For example, synchronicity is lower for firms with better corporate governance, implying that their prices are more informative (Durnev *et al.*, 2004). Similarly, enforcement of insider trading laws (Fernandes and Ferreira, 2009), foreign ownership and auditor quality (Gul *et al.*, 2010; Fang *et al.*, 2019), IFRS adoption (Kim and Shi, 2012), external monitoring by institutional investors (An and Zhang, 2013), and controlling shareholders (Boubaker *et al.*, 2014) are also related to synchronicity by affecting price informativeness and transparency. Hence, price informativeness is a substitute for the monitoring role of the corporate board, therefore, board independence of such firms is lower and a less demanding board structure is required (Ferreira *et al.*, 2011). Synchronicity is also reduced by measures that reduce information-processing cost, e.g. presentation of financial data in a standardized, tagged, and machine-readable format (Dong *et al.*, 2016). Analyst coverage

increases synchronicity by facilitating the incorporation of industry-level information into stock prices (Piotroski and Roulstone, 2004; Chan and Hameed, 2006). Synchronicity is also higher in stocks which are either covered by a common set of analysts (Israelsen, 2016), or connected by a common set of brokers providing margin financing (Kahraman and Tookes, 2019). Comovement increases for stocks that are added to market indices (Barberis *et al.*, 2005; Claessens and Yafeh, 2012). However, these factors are unlikely to change systematically across different weekdays, and therefore, they cannot explain the high Monday synchronicity that we document in this paper.

4 Conclusion

Our main finding is that US stock return synchronicity has been persistently higher on Mondays than other weekdays over the past 60 years. This effect exists in both up-market and down-market conditions, and is more prominent among large, old and less volatile firms. Importantly, it is robust to several alternative explanations. This effect is striking since fewer macroeconomic announcements are released on Mondays, while one would expect the opposite, i.e., more macroeconomic news driving up the return comovement. We show that fewer earnings announcements on Mondays and increased post-weekend uncertainty do contribute to higher Monday synchronicity. Our study, however, finds neither of these can fully explain the Monday synchronicity anomaly. Instead, the anomaly is primarily driven by a small number of macroeconomic news being released on Mondays.

We explain the Monday synchronicity anomaly by the well-documented contrast effect (Hartzmark and Shue, 2018). We argue that, similar to a thunder sounding louder during quiet nights, the few macroeconomic and firm-specific announcements on Mondays constitute a quiet background. When the occasional macroeconomic announcement is released, it becomes more salient and increases return comovement. Higher economic uncertainty and risk aversion over the weekend also contribute in keeping the comovement higher on Mondays by forcing investors to prioritize

learning about aggregate shocks to the economy over firm-specific information.

The persistence of high Monday synchronicity across different market conditions suggests that investor sentiment is unlikely to explain the effect we observe. Such a conclusion is also supported by the cross-sectional evidence that Monday synchronicity anomaly is more pronounced among stocks less prone to shifts in investor sentiment (e.g., large stocks). We find little evidence for other explanations such as the Monday return anomaly, the role of investor attention and limits to arbitrage, among others.

This paper, to the best of our knowledge, is the first study documenting the Monday synchronicity anomaly. It contributes to the literature on both return synchronicity and calendar effects in financial markets. While our focus is on within-week variation in return synchronicity, future work can explore other calendar variations, e.g., differences in return synchronicity across different months or quarters. This paper also provides the first empirical evidence for the simultaneous contrast effect in behavioral finance. Our findings have important implications not only for day traders, but also for financial regulators seeking to stabilize extreme levels of volatility and comovement, and stock exchanges concerned with financial stability.

5 Tables and Figures

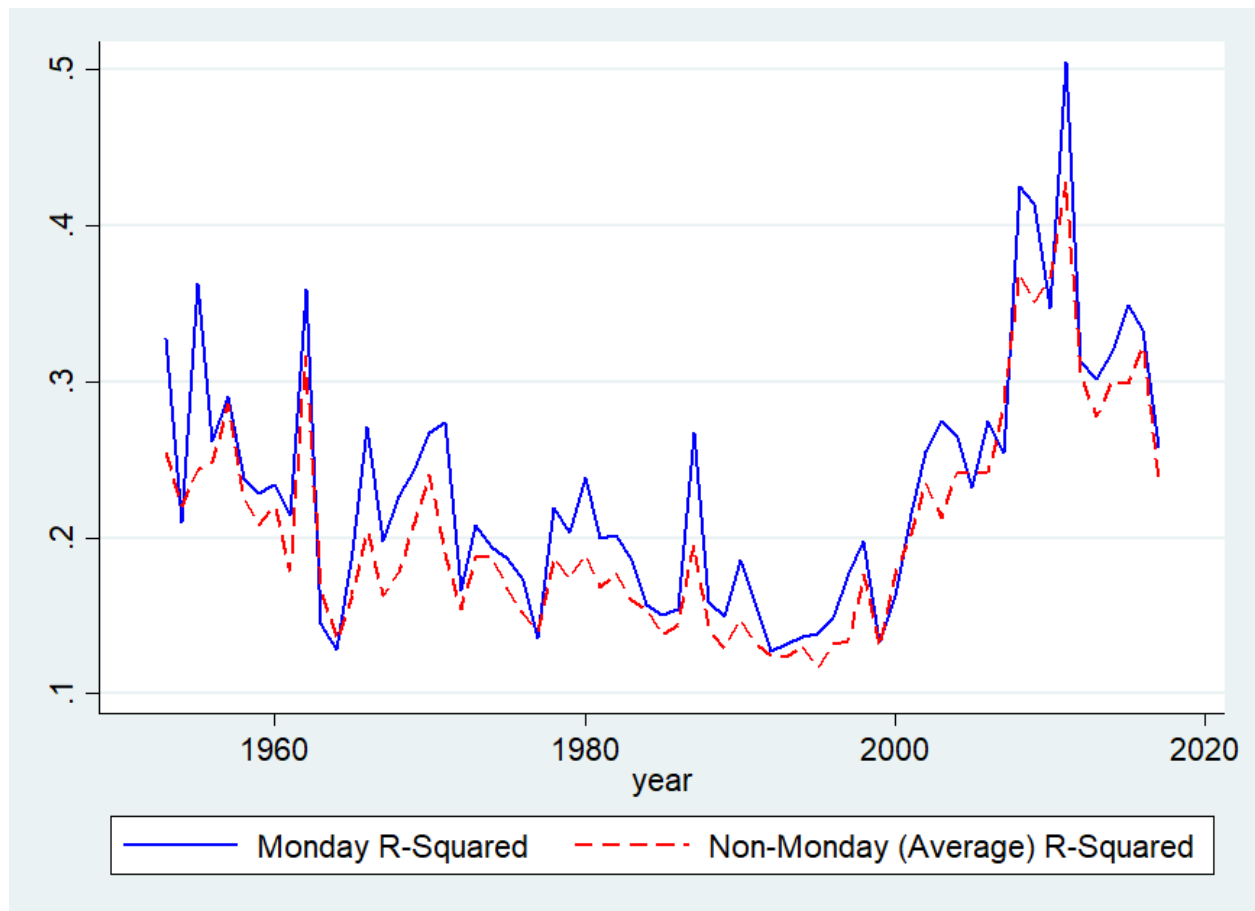
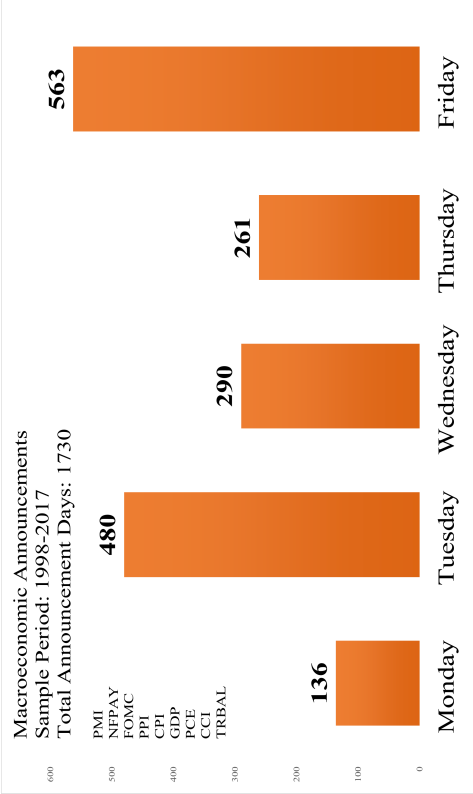
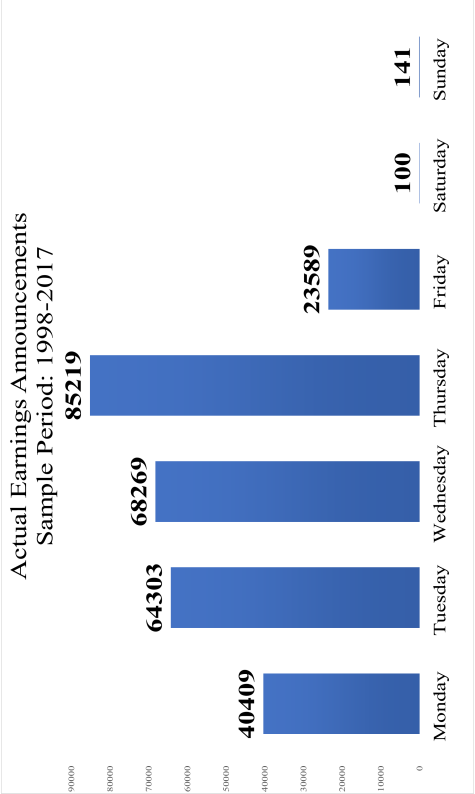


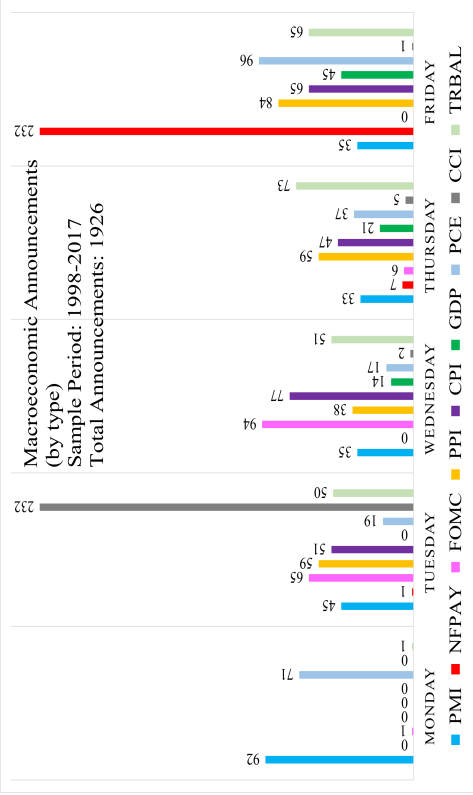
Figure 1: Monday R^2 vs. Non-Monday R^2



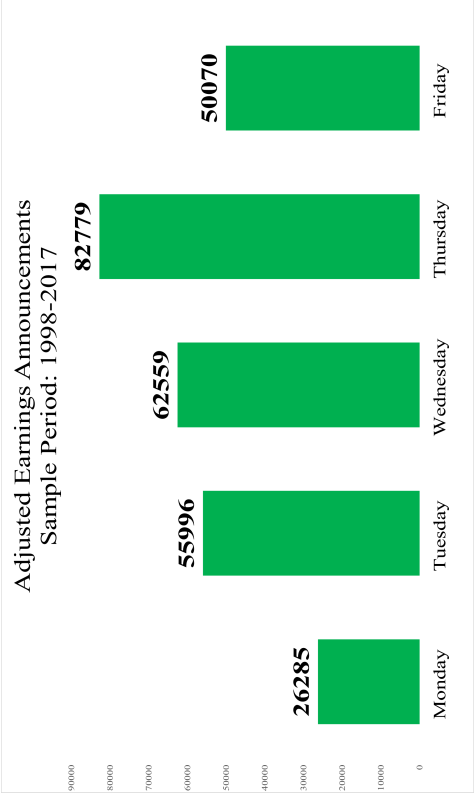
Panel A: All Macroeconomic Announcements



Panel C: Actual Earnings Announcements



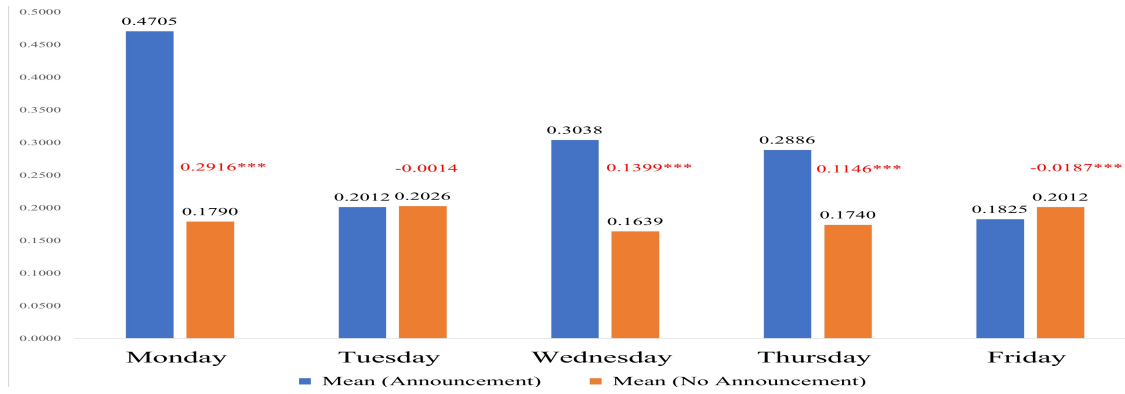
Panel B: Macroeconomic Announcements by Type



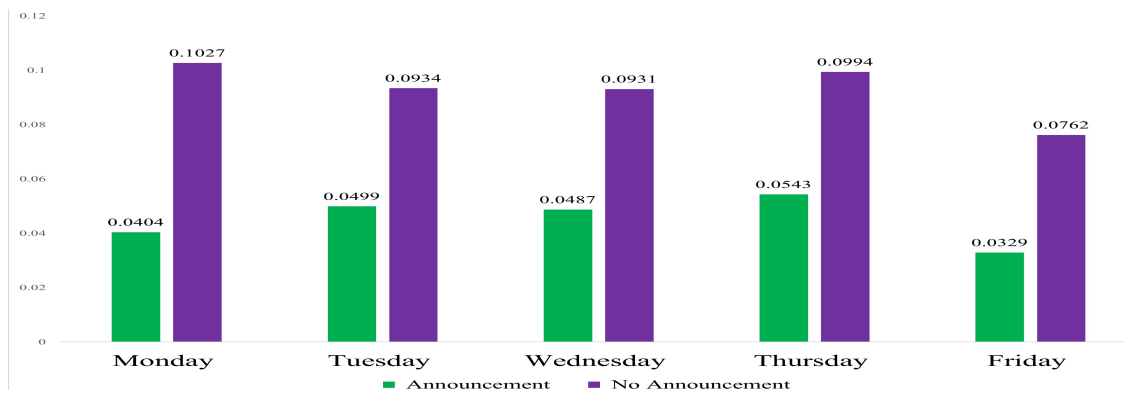
Panel D: Adjusted Earnings Announcements

Figure 2: News Announcements by Weekday

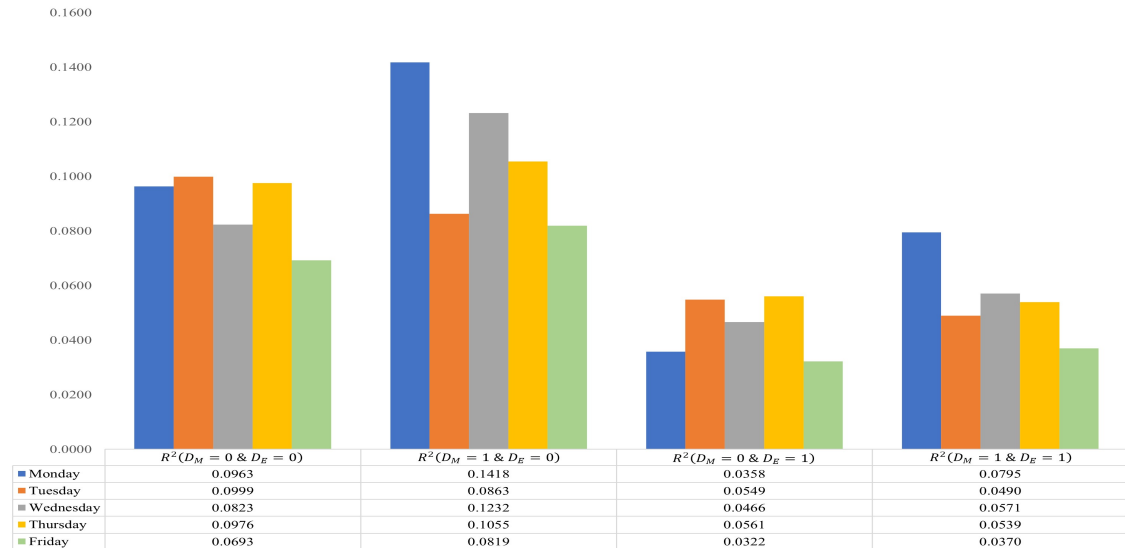
Panel A and Panel B show the cumulative and individual distributions of nine macroeconomic announcements from 1998 to 2017. PMI: Purchasing Managers Index released by the Institute of Supply Management (usually on the first business day of each month). NFPAY: Non-Farm Payroll released by the Bureau of Labor Statistics (usually on the first Friday of each month). FOMC: Federal Open Market Committee decisions released by the Federal Reserve. PPI: Producer Price Index released by the Bureau of Labor Statistics. CPI: Consumer Price Index released by the Bureau of Labor Statistics. GDP: The advanced estimate of Quarter-on-Quarter GDP growth released by the Bureau of Economic Analysis. PCE: Personal Consumption Expenditure released by Bureau of Economic Analysis at around the end of each month. TRBAL: Trade Balance figure released by the Bureau of Census. CCI: Consumers Confidence Index released by 'The Conference Board'. Panel C and Panel D show the distribution of earnings announcements from 1998 to 2017 by their actual day of release, and the distribution after adjusting for aftermarket hours release or release on a non-trading day respectively.



Panel A: R^2 for Macroeconomic Announcements



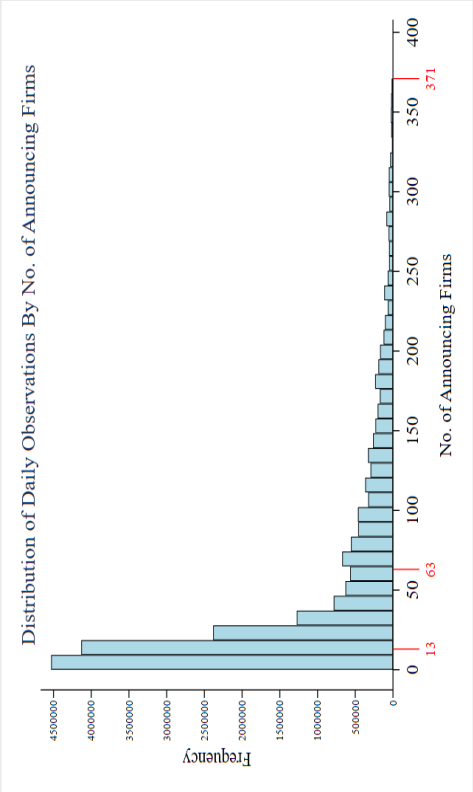
Panel B: R^2 for Earnings Announcements



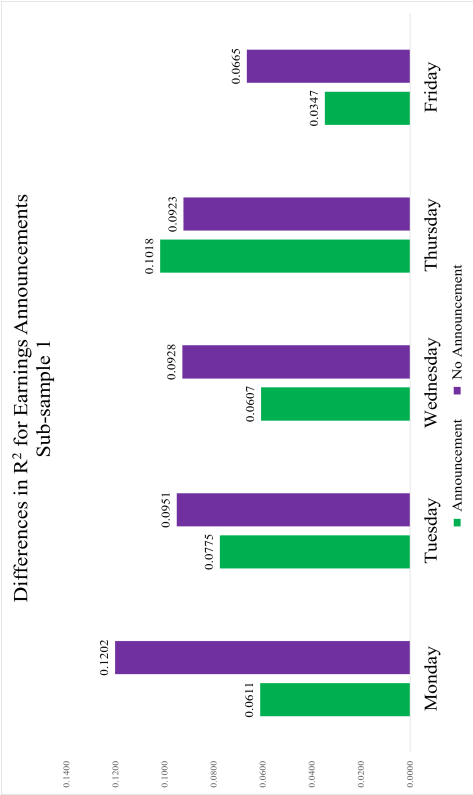
Panel C: R^2 for Earnings & Macroeconomic Announcements

Figure 3: Synchronicity Regressions for News Announcements

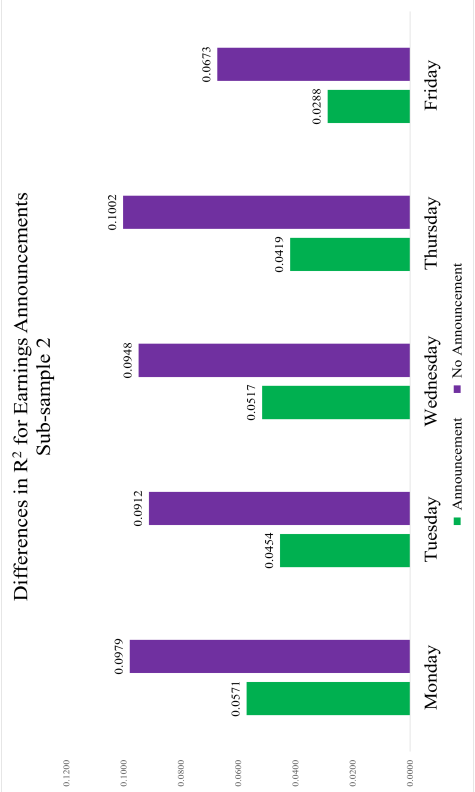
In **Panel A**, two synchronicity regressions are run for each firm and for each weekday, one for those days on which macroeconomic announcements are released and the other for non-announcement days. Year dummies are included in these regressions. R^2 values from both regressions are compared by t-tests (displayed in red colored text). In **Panel B**, two pooled Fixed Effects (both firm and year) regressions are run for each weekday, one for those days on which earnings announcements are released and the other for non-announcement days. R^2 values of the pooled regressions are reported. In **Panel C**, D_M and D_E are dummy variables for macroeconomic and earnings announcements respectively, and have values of 0 for non-announcement day and 1 for announcement day. Four fixed-effects panel regressions are run separately for each weekday from Monday to Friday for the four combinations of the dummy variables D_M and D_E .



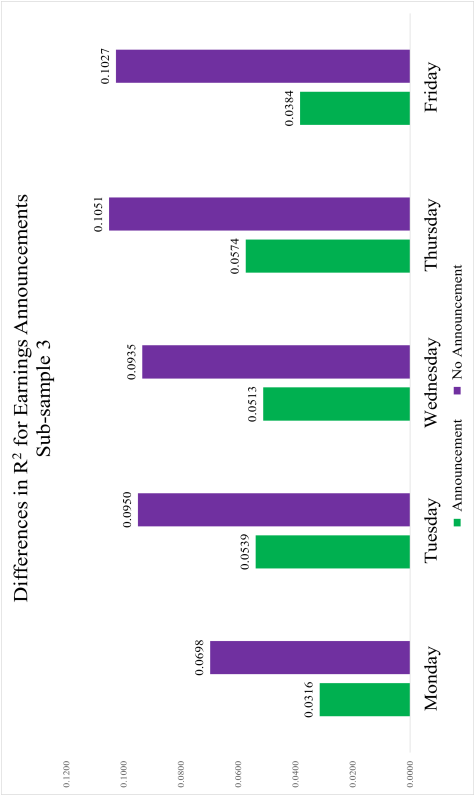
Panel A: Distribution of Daily Observations



Panel B: Sub-sample 1



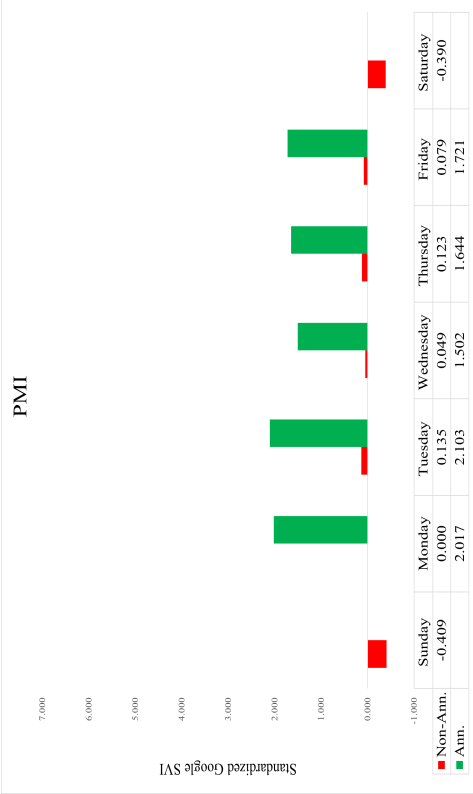
Panel C: Sub-sample 2



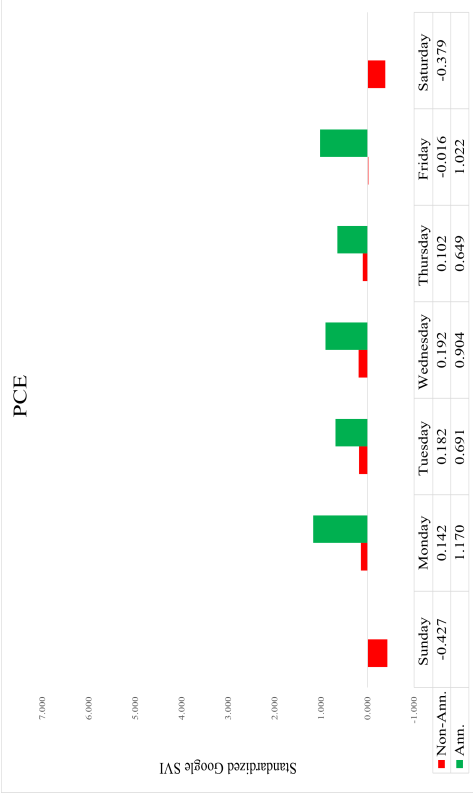
Panel D: Sub-sample 3

Figure 4: Regressions for Earnings Announcements: Controlling for Earnings Season

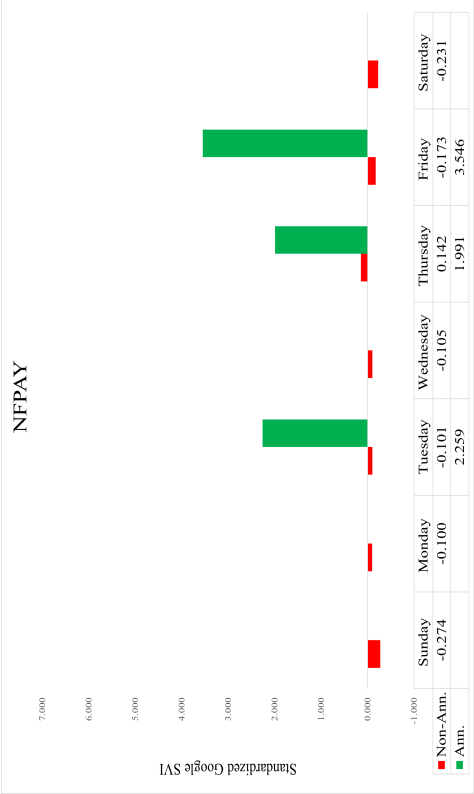
Panel A shows the distribution of the daily firm-day observations with respect to the number of firms announcing their earnings for each date in the sample period 1998-2017. 13 and 63 are respectively the 30th and 70th percentiles of the number of announcing firms, while the maximum value is 371. These values are as breakpoints to divide the sample into three sub-samples: "Sub-sample 1" in **Panel B** includes dates on which 13 or less firms announce their earnings; "Sub-sample 2" in **Panel C** includes dates on which more than 13 firms and a maximum of 63 firms announce their earnings; and "Sub-sample 3" in **Panel D** includes dates on which more than 63 firms announce their earnings. Two pooled fixed effects (both firm and year) regressions are run for each weekday, one for those days on which earnings announcements are released and the other for non-announcement days.



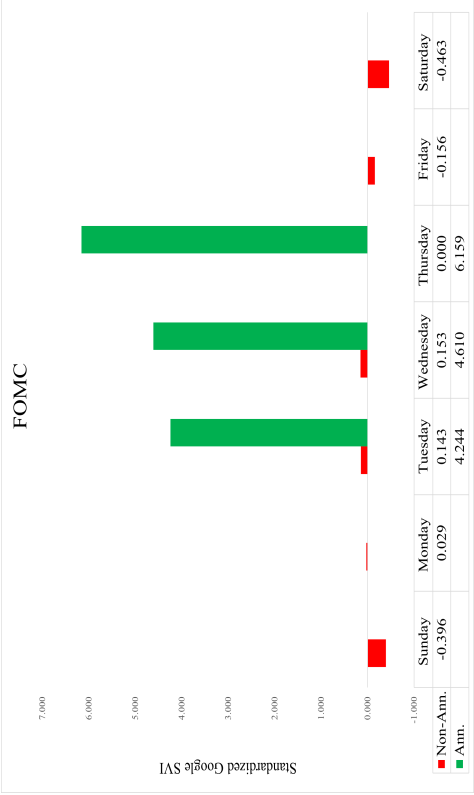
Panel A: Google SVI for PMI



Panel B: Google SVI for PCE



Panel C: Google SVI for NFPAY



Panel D: Google SVI for FOMC

Figure 5: Retail Investor Attention to Macroeconomic Announcements

The sample period extends from 2004 to 2017. For each type of macroeconomic announcement, the averages of the the standardized SVI are reported separately for announcement days ("Ann.") and non-announcement days ("Non-Ann."). The SVIs are standardized by subtracting each value in a given year with its annual mean and dividing it by its annual standard deviation. The scale of the graphs in all panels is identical.

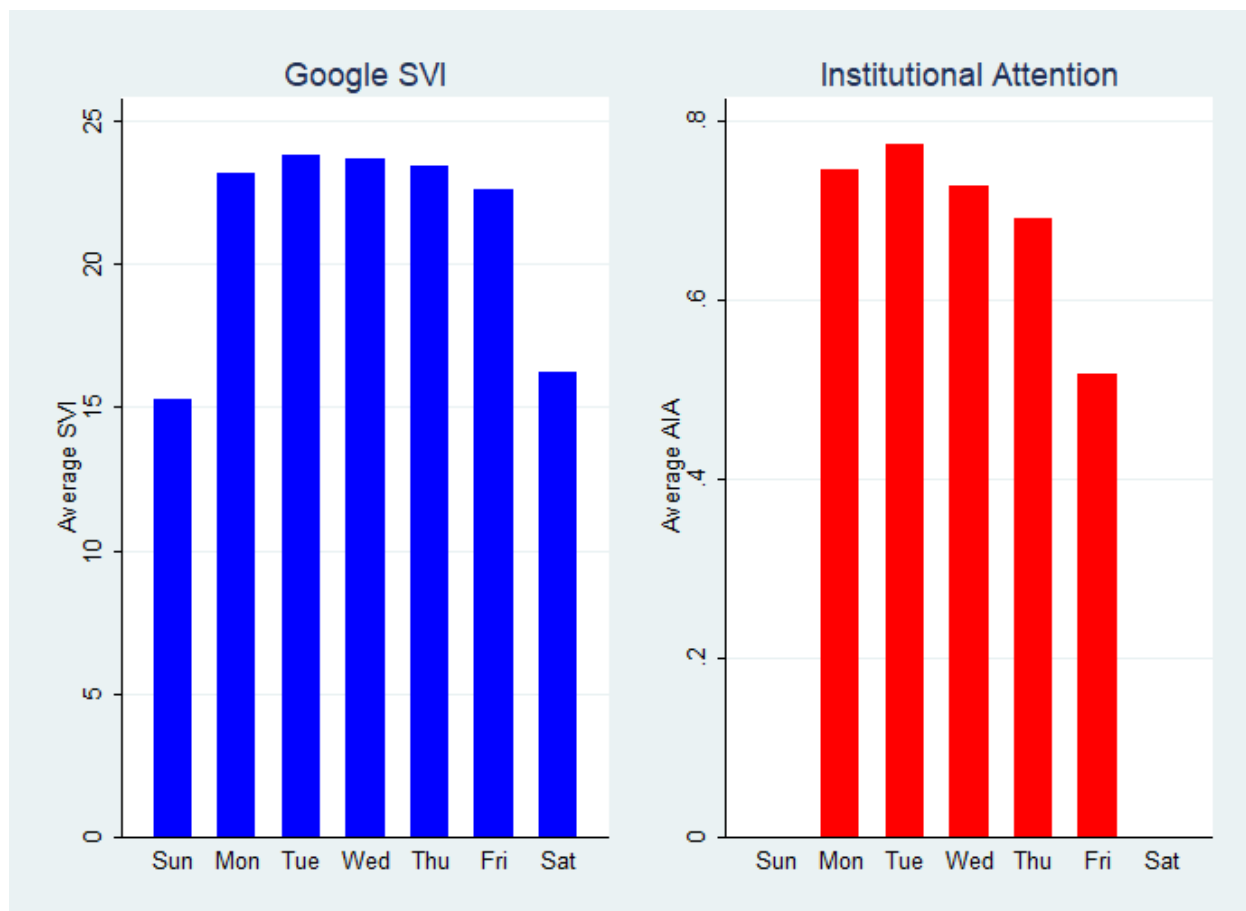


Figure 6: Investor Attention

Google SVI is the measure of retail attention to firm-specific news. The bar chart on the left displays the average value of daily Google SVI for Russell 3000 firms for each weekday for the period 2004 to 2017. Institutional attention is proxied by Bloomberg's Abnormal Institutional Attention (AIA) measure. The bar chart on the right displays the average value of AIA across Russell 3000 firms for each weekday for the period 2010 to 2017.

Table 1: Summary Statistics of Regression Parameters

The sample period extends from 1953 to 2017. The $R^2_{i,d,y}$ values (in percentage) are obtained by regressing stock returns on CRSP Value-weighted Index returns (and its lag) and Fama-French 48 Industry returns (and its lag) for each weekday d from Monday to Friday for each stock i in each calendar year y . $SYNCH_{i,d,y}$ is the logarithmic transformation of $R^2_{i,d,y}$ i.e. $\ln\left(\frac{R^2}{1-R^2}\right)$. $\beta_{Mkt,d,y}$ and $\beta_{Mkt,d-1,y}$ represent the coefficients for the Index and its lag while $\beta_{Ind,d,y}$ and $\beta_{Ind,d-1,y}$ represent the coefficients for the Industry returns and its lag.

	Mean	Std. Dev.	Min	Median	Max	No. of Obs.
Monday						
$R^2_{i,d,y}$	21.770	18.036	0.040	16.107	99.903	257977
$SYNCH_{i,d,y}$	-1.610	1.202	-7.823	-1.650	6.934	257977
$\beta_{Mkt,d,y}$	0.408	1.337	-39.442	0.338	30.366	257977
$\beta_{Mkt,d-1,y}$	0.077	1.284	-24.129	0.056	18.787	257977
$\beta_{Ind,d,y}$	0.371	1.081	-29.658	0.348	27.241	257977
$\beta_{Ind,d-1,y}$	0.058	1.004	-30.615	0.042	33.751	257977
$RMSE$	0.02840	0.01731	0.00034	0.02416	0.13145	257977
Tuesday						
$R^2_{i,d,y}$	19.675	17.115	0.024	14.138	99.973	259803
$SYNCH_{i,d,y}$	-1.759	1.192	-8.343	-1.804	8.219	259803
$\beta_{Mkt,d,y}$	0.386	1.287	-63.972	0.320	21.076	259803
$\beta_{Mkt,d-1,y}$	0.042	1.212	-52.080	0.036	25.548	259803
$\beta_{Ind,d,y}$	0.344	1.041	-14.064	0.313	57.149	259803
$\beta_{Ind,d-1,y}$	0.061	0.949	-13.360	0.046	28.586	259803
$RMSE$	0.02841	0.01723	0.00028	0.02419	0.13232	259803
Wednesday						
$R^2_{i,d,y}$	19.480	16.943	0.035	13.962	99.999	257765
$SYNCH_{i,d,y}$	-1.773	1.187	-7.960	-1.818	11.592	257765
$\beta_{Mkt,d,y}$	0.415	1.346	-216.372	0.342	17.859	257765
$\beta_{Mkt,d-1,y}$	0.050	1.209	-18.940	0.035	61.757	257765
$\beta_{Ind,d,y}$	0.341	1.026	-18.341	0.311	74.701	257765
$\beta_{Ind,d-1,y}$	0.048	0.949	-17.235	0.038	69.413	257765
$RMSE$	0.02855	0.01725	0.00008	0.02438	0.13773	257765
Thursday						
$R^2_{i,d,y}$	19.717	17.019	0.013	14.265	99.949	259327
$SYNCH_{i,d,y}$	-1.753	1.186	-8.969	-1.793	7.589	259327
$\beta_{Mkt,d,y}$	0.393	1.294	-25.307	0.327	89.518	259327
$\beta_{Mkt,d-1,y}$	0.054	1.239	-156.595	0.038	16.538	259327
$\beta_{Ind,d,y}$	0.342	1.048	-69.062	0.310	25.284	259327
$\beta_{Ind,d-1,y}$	0.043	0.918	-17.014	0.036	35.897	259327
$RMSE$	0.02846	0.01711	0.00024	0.02435	0.13743	259327
Friday						
$R^2_{i,d,y}$	19.099	16.389	0.014	13.908	99.916	259020
$SYNCH_{i,d,y}$	-1.790	1.164	-8.865	-1.823	7.079	259020
$\beta_{Mkt,d,y}$	0.390	1.301	-27.650	0.331	22.409	259020
$\beta_{Mkt,d-1,y}$	0.035	1.187	-20.466	0.022	25.833	259020
$\beta_{Ind,d,y}$	0.338	1.065	-31.961	0.308	30.786	259020
$\beta_{Ind,d-1,y}$	0.050	0.927	-18.217	0.040	24.225	259020
$RMSE$	0.02811	0.01709	0.00039	0.02395	0.14080	259020
Total						
$R^2_{i,d,y}$	19.947	17.133	0.013	14.447	99.999	1293892
$SYNCH_{i,d,y}$	-1.737	1.188	-8.969	-1.779	11.592	1293892
$\beta_{Mkt,d,y}$	0.399	1.313	-216.372	0.332	89.518	1293892
$\beta_{Mkt,d-1,y}$	0.052	1.227	-156.595	0.037	61.757	1293892
$\beta_{Ind,d,y}$	0.347	1.052	-69.062	0.318	74.701	1293892
$\beta_{Ind,d-1,y}$	0.052	0.950	-30.615	0.040	69.413	1293892
$RMSE$	0.02838	0.01720	0.00008	0.02420	0.14080	1293892

Table 2: Two-Sample t-tests for Differences

The sample period extends from 1953 to 2017. The $R^2_{i,d,y}$, regression coefficients $\beta_{Mkt,d,y}$, $\beta_{Mkt,d-1,y}$, $\beta_{Ind,d,y}$, $\beta_{Ind,d-1,y}$ and squared errors $RMSE$ for Monday are compared to those of other days using the t-test. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Monday and Tuesday			Monday and Thursday		
	Difference	t-statistic		Difference	t-statistic
$\Delta R^2_{i,d,y}$	2.094***	(42.86)	$\Delta R^2_{i,d,y}$	2.052***	(42.09)
$\Delta \beta_{Mkt,d,y}$	0.0223***	(6.12)	$\Delta \beta_{Mkt,d,y}$	0.0148***	(4.06)
$\Delta \beta_{Mkt,d-1,y}$	0.0351***	(10.12)	$\Delta \beta_{Mkt,d-1,y}$	0.0227***	(6.47)
$\Delta \beta_{Ind,d,y}$	0.0273***	(9.27)	$\Delta \beta_{Ind,d,y}$	0.0294***	(9.92)
$\Delta \beta_{Ind,d-1,y}$	-0.00364	(-1.34)	$\Delta \beta_{Ind,d-1,y}$	0.0149***	(5.57)
$\Delta RMSE$	-0.0000147	(-0.31)	$\Delta RMSE$	-0.0000669	(-1.40)
Monday and Wednesday			Monday and Friday		
$\Delta R^2_{i,d,y}$	2.289***	(46.98)	$\Delta R^2_{i,d,y}$	2.671***	(55.73)
$\Delta \beta_{Mkt,d,y}$	-0.00712	(-1.90)	$\Delta \beta_{Mkt,d,y}$	0.0182***	(4.96)
$\Delta \beta_{Mkt,d-1,y}$	0.0267***	(7.69)	$\Delta \beta_{Mkt,d-1,y}$	0.0415***	(12.05)
$\Delta \beta_{Ind,d,y}$	0.0302***	(10.30)	$\Delta \beta_{Ind,d,y}$	0.0330***	(11.06)
$\Delta \beta_{Ind,d-1,y}$	0.0101***	(3.71)	$\Delta \beta_{Ind,d-1,y}$	0.00756**	(2.81)
$\Delta RMSE$	-0.000150**	(-3.12)	$\Delta RMSE$	0.000290***	(6.07)

Table 3: Regressions between R^2 Differences & Coefficient Differences

The sample period extends from 1953 to 2017. The dependent variables are differences between R^2 values from the synchronicity regressions in Table 1 i.e., ΔR^2 which is R^2 of Monday minus R^2 of other days. Similarly, the independent variables are differences between the market coefficients $\Delta\beta_{Mkt}$ and industry coefficients $\Delta\beta_{Ind}$ of the synchronicity regressions. The t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1) $\Delta R^2_{Mon-Tue}$	(2) $\Delta R^2_{Mon-Tue}$	(3) $\Delta R^2_{Mon-Wed}$	(4) $\Delta R^2_{Mon-Wed}$	(5) $\Delta R^2_{Mon-Thu}$	(6) $\Delta R^2_{Mon-Thu}$	(7) $\Delta R^2_{Mon-Fri}$	(8) $\Delta R^2_{Mon-Fri}$
$\Delta\beta_{Mkt}^{Mon-Tue}$	0.004*** (37.833)	0.025*** (123.566)						
$\Delta\beta_{Ind}^{Mon-Tue}$		0.018*** (119.257)						
$\Delta\beta_{Mkt}^{Mon-Wed}$			0.004*** (36.701)	0.024*** (121.107)				
$\Delta\beta_{Ind}^{Mon-Wed}$				0.017*** (117.044)				
$\Delta\beta_{Mkt}^{Mon-Thu}$					0.000*** (10.595)	0.005*** (75.450)		
$\Delta\beta_{Ind}^{Mon-Thu}$						0.014*** (77.119)		
$\Delta\beta_{Mkt}^{Mon-Fri}$							0.004*** (38.157)	0.024*** (121.388)
$\Delta\beta_{Ind}^{Mon-Fri}$								0.017*** (116.900)
Constant	0.021*** (83.860)	0.020*** (82.152)	0.023*** (91.503)	0.022*** (92.535)	0.020*** (81.225)	0.020*** (80.118)	0.027*** (104.983)	0.026*** (103.809)
Observations	257,778	257,778	255,664	255,664	257,555	257,555	257,635	257,635
R-squared	0.0055	0.0575	0.0052	0.0558	0.0004	0.0230	0.0056	0.0557

Table 4: Pooled Synchronicity Regressions for Long Weekends

The R^2 values are obtained by regressing stock returns on CRSP Value-weighted Index returns and Fama-French 48 Industry returns for each weekday from Monday to Friday. Firms with at least 30 observations for a given weekday in a given year are included in the sample. “Normal Week” is defined as a week which is preceded by trading on previous week’s Friday and has usual trading on Monday. “Friday Holiday” is defined as a week preceded by a trading holiday on previous week’s Friday. “Monday Holiday” is defined as a week in which there is a trading holiday on Monday. **Panel A** shows the results from pooled OLS regressions while **Panel B** shows the results from pooled Fixed Effects regressions for the sample period 1953-2017. In **Panel C** and **Panel D**, two regressions are run for each weekday over the sample period 1998-2017; one for announcement days, and the other for non-announcement days.

Panel A: Pooled OLS Regressions						
	(1)		(2)		(3)	
	Normal Week		Friday Holiday		Monday Holiday	
Monday	0.0595		0.0621			
Tuesday	0.0440		0.0542		0.0650	
Wednesday	0.0475		0.0390		0.0566	
Thursday	0.0517		0.0364		0.0378	
Friday	0.0414		0.0322		0.0446	
Panel B: Pooled Fixed Effects Regressions						
	(1)		(2)		(3)	
	Normal Week		Friday Holiday		Monday Holiday	
Monday	0.0603		0.0702			
Tuesday	0.0446		0.0624		0.0702	
Wednesday	0.0477		0.0441		0.0595	
Thursday	0.0522		0.0437		0.0409	
Friday	0.0419		0.0398		0.0468	
Panel C: Pooled OLS Regressions for Macroeconomic Announcements						
	(1)		(2)		(3)	
	Normal Week		Friday Holiday		Monday Holiday	
	News	No News	News	No News	News	No News
Monday	0.1200	0.0837	0.1440	0.0476		
Tuesday	0.0687	0.0845	0.0589	0.0845	0.1180	0.1010
Wednesday	0.1030	0.0697	0.1430	0.0387	0.1190	0.0849
Thursday	0.0930	0.0872	0.0316	0.0700	0.0593	0.0606
Friday	0.0700	0.0593	0.0280	0.0632	0.0957	0.0499
Panel D: Pooled Fixed Effects Regressions for Macroeconomic Announcements						
	(1)		(2)		(3)	
	Normal Week		Friday Holiday		Monday Holiday	
	News	No News	News	No News	News	No News
Monday	0.1250	0.0847	0.1890	0.0618		
Tuesday	0.0699	0.0853	0.0768	0.1040	0.1330	0.1090
Wednesday	0.1050	0.0702	0.1920	0.0440	0.1350	0.0886
Thursday	0.0951	0.0878	0.0548	0.0837	0.0729	0.0660
Friday	0.0709	0.0611	0.0404	0.0890	0.1030	0.0581

Table 5: Synchronicity Regressions: 1927-1952 Period

The sample period extends from 1927 to 1952. The $R^2_{i,d,y}$ values (in percentage) are obtained by regressing stock returns on CRSP Value-weighted Index returns (and its lag) and Fama-French 48 Industry returns (and its lag) for each weekday d from Monday to Saturday for each stock i in each calendar year y . The $R^2_{i,d,y}$ for Monday are compared to those of other days using the t-test. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Average R^2	Difference	t-statistic
Monday	34.386		
Tuesday	34.183	0.203	(0.92)
Wednesday	33.036	1.350***	(6.15)
Thursday	32.630	1.760***	(8.05)
Friday	32.246	2.140***	(9.75)
Saturday	29.726	4.660***	(21.29)
Total	32.729		

Table 6: Synchronicity Regressions under High/Medium/Low VIX

The 30th and 70th percentiles of VIX are used as breakpoints to divide the sample into three sub-samples: $VIX_{\leq 30}$ includes firm-date observations on which the value of VIX is less than or equal to its 30th percentile; $VIX_{>30 \text{ \& } \leq 70}$ includes firm-date observations on which the value of VIX is greater than its 30th percentile and less than or equal to its 70th percentile; and $VIX_{>70}$ includes firm-date observations on which the value of VIX is greater than its 70th percentile. In **Panel A**, pooled fixed effects regressions are run separately for each weekday over the sample period 1990-2017. In **Panel B**, two regressions are run for each weekday over the sample period 1998-2017; one for announcement days, and the other for non-announcement days

Panel A: All Days

	(1) $VIX_{\leq 30}$	(2) $VIX_{>30 \text{ \& } \leq 70}$	(3) $VIX_{>70}$
Monday	0.0199	0.0389	0.0927
Tuesday	0.0223	0.0364	0.0782
Wednesday	0.0220	0.0348	0.0807
Thursday	0.0178	0.0344	0.0926
Friday	0.0170	0.0318	0.0666

Panel B: Macroeconomic Announcement & Non-Announcement Days

	(1) $VIX_{\leq 30}$	(2) No Ann.	(3) Ann.	(4) No Ann.	(5) Ann.	(6) No Ann.
Monday	0.1139	0.0588	0.0749	0.0725	0.1460	0.0934
Tuesday	0.0753	0.0754	0.0789	0.0641	0.0743	0.1010
Wednesday	0.0765	0.0697	0.0898	0.0566	0.1278	0.0776
Thursday	0.0861	0.0545	0.0541	0.0683	0.1107	0.0989
Friday	0.0632	0.0472	0.0576	0.0579	0.0785	0.0673

Table 7: Two-sample t-tests for Downside & Upside R^2

The sample period extends from 1955 to 2017. For each firm, synchronicity regressions were run for each 3-year period separately for down days and up days, where down (up) days are defined as those on which the excess market return is smaller (larger) than zero. R_D^2 denotes the Downside R^2 , R_U^2 denotes the Upside R^2 , and $R_D^2 - R_U^2$ denotes their differences. The samples for Monday are compared to those of other days using the t-test. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Difference	t-statistic		Difference	t-statistic
Monday and Tuesday			Monday and Thursday		
ΔR_D^2	0.0309***	(46.12)	ΔR_D^2	0.0199***	(29.00)
ΔR_U^2	0.0110***	(16.65)	ΔR_U^2	0.0149***	(22.71)
$\Delta(R_D^2 - R_U^2)$	0.0194***	(37.17)	$\Delta(R_D^2 - R_U^2)$	0.00361***	(6.75)
Monday and Wednesday			Monday and Friday		
ΔR_D^2	0.0227***	(33.19)	ΔR_D^2	0.0202***	(29.77)
ΔR_U^2	0.0177***	(27.17)	ΔR_U^2	0.0233***	(36.47)
$\Delta(R_D^2 - R_U^2)$	0.00365***	(6.78)	$\Delta(R_D^2 - R_U^2)$	-0.00366***	(-6.83)

Table 8: Panel Regressions: Baseline Specification

The sample period extends from 1955 to 2017. The R^2 values are obtained by regressing stock returns on CRSP Value-weighted Index returns (and its lagged term) and Fama-French 48 Industry returns (and its lagged term) for each weekday from Monday to Friday for each stock in each calendar year. The dependent variable, $\Delta R_{i,d,y}^2$, is the difference between R-squared of Monday and that of other weekdays. $\beta_{i,y}$ is the coefficient of the firm i in calendar year y , obtained from a CAPM regression. $TURNOVER_{i,y}$ is the average monthly turnover of the firm i in calendar year y . $IVOL_{i,y}$ is the root mean squared error obtained from rolling Fama-French Three Factor regression, for the firm i in calendar year y . $\ln(MKT.CAP)_{i,y-1}$ is the log of market capitalization for the firm i at the end of calendar year $y-1$. $BK/MKT_{i,y-1}$ is the book-to-market ratio for the firm i at the end of calendar year $y-1$. $LEV_{i,y-1}$ is the leverage ratio (debt/equity) of the firm i in calendar year $y-1$. $ROA_{i,y-1}$ is the return on assets of the firm i in calendar year $y-1$. The t-statistics based on cluster-robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables	Monday-Tuesday		Monday-Wednesday		Monday-Thursday		Monday-Friday	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Fixed Effects	OLS	Fixed Effects	OLS	Fixed Effects	OLS	Fixed Effects
$\beta_{i,y}$	0.761*** (11.361)	0.649*** (8.241)	0.831*** (12.375)	0.735*** (9.160)	1.073*** (15.965)	0.889*** (11.125)	1.997*** (30.382)	1.799*** (22.481)
$TURNOVER_{i,y}$	0.270 (1.171)	-0.202 (-0.745)	1.732*** (7.576)	0.744*** (2.800)	1.997*** (7.802)	1.106*** (3.987)	2.111*** (8.330)	1.309*** (4.598)
$IVOL_{i,y}$	-26.328*** (-11.057)	-34.453*** (-9.882)	-29.958*** (-12.700)	-39.479*** (-11.528)	-18.890*** (-7.861)	-32.017*** (-9.107)	-26.513*** (-11.096)	-37.362*** (-10.760)
$\ln(MKT.CAP)_{i,y-1}$	0.157*** (6.400)	0.112** (2.337)	0.275*** (11.260)	0.119** (2.529)	0.233*** (9.263)	0.154*** (3.163)	0.103*** (4.131)	0.127*** (2.672)
$BK/MKT_{i,y-1}$	0.019 (0.450)	0.025 (0.436)	0.054 (0.850)	0.017 (0.372)	0.134** (2.300)	0.190*** (2.577)	-0.086 (-1.319)	-0.054 (-0.927)
$LEV_{i,y-1}$	0.005*** (3.046)	0.001 (0.561)	-0.001 (-0.495)	0.001 (0.444)	0.002 (1.292)	0.005* (1.907)	0.002 (1.185)	0.003 (1.016)
$ROA_{i,y-1}$	-0.000 (-0.071)	-0.000 (-0.273)	0.001 (1.116)	0.000 (0.449)	0.002** (2.451)	0.000 (0.065)	0.003*** (3.780)	0.002 (1.576)
Constant	-8.970*** (-10.242)	-7.988*** (-7.211)	-5.275*** (-6.528)	-2.100** (-2.069)	-4.335*** (-5.192)	-2.426** (-2.270)	-2.197*** (-2.734)	-1.560 (-1.558)
Observations	180,424	180,424	177,858	177,858	180,274	180,274	180,331	180,331
R^2	0.0545	0.0552	0.0483	0.0453	0.0485	0.0456	0.0900	0.0846
F	108.0	99.25	102.5	87.97	110.2	93.39	172.5	142.2
$AdjR^2$	0.0542		0.0479		0.0482		0.0896	
Number of Firms	16,617	16,617	16,616	16,616	16,611	16,611	16,615	16,615
Firm Fixed Effects		Yes		Yes		Yes		Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Diff-in-Diff Regressions

The sample period extends from 1955 to 2007. The R^2 values are obtained by regressing stock returns on CRSP Value-weighted Index returns (and its lagged term) and Fama-French 48 Industry returns (and its lagged term) for each weekday from Monday to Friday for each stock in each calendar year. The dependent variable, $\Delta R_{i,d,y}^2$, is the difference between R-squared of Monday and that of other weekdays. $TIME$ is the treatment period dummy, while SHO is the interaction term (DID coefficient). DID regressions are run both with and without covariates. The covariates (not shown here) are as follows. $\beta_{i,y}$ is the coefficient of the firm i in calendar year y , obtained from a CAPM regression. $TURNOVER_{i,y}$ is the average monthly turnover of the firm i in calendar year y . $IVOL_{i,y}$ is the root mean squared error obtained from rolling Fama-French Three Factor regression, for the firm i in calendar year y . $ln(MKT.CAP)_{t,y-1}$ is the log of market capitalization for the firm i at the end of calendar year $y - 1$. $BK/MKT_{i,y-1}$ is the book-to-market ratio for the firm i at the end of calendar year $y - 1$. $LEV_{i,y-1}$ is the leverage ratio (debt/equity) of the firm i in calendar year $y - 1$. $ROA_{i,y-1}$ is the return on assets of the firm i in calendar year $y - 1$. The t-statistics based on cluster-robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The means of the dependent variables for both the treatment and control groups, before and during treatment period, are also shown.

Variables	Monday-Tuesday		Monday-Wednesday		Monday-Thursday		Monday-Friday	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Without	With	Without	With	Without	With	Without	With
	Covariates	Covariates	Covariates	Covariates	Covariates	Covariates	Covariates	Covariates
<i>TIME</i>	-5.702*** (-20.331)	-6.517*** (-21.285)	-0.824*** (-2.882)	-1.595*** (-5.156)	-3.300*** (-10.951)	-4.277*** (-12.887)	-0.073 (-0.253)	-1.273*** (-4.021)
<i>SHO</i>	0.162 (1.167)	0.099 (0.642)	-0.093 (-0.638)	-0.064 (-0.406)	0.126 (0.895)	0.065 (0.423)	0.156 (1.147)	0.122 (0.821)
<i>TIME * SHO</i>	-0.262 (-0.535)	-0.226 (-0.437)	-0.302 (-0.605)	-0.298 (-0.567)	0.477 (0.926)	0.374 (0.683)	-0.252 (-0.522)	-0.229 (-0.445)
Constant	2.724*** (34.435)	6.380*** (6.796)	3.005*** (37.425)	2.154** (2.289)	2.651*** (32.266)	7.020*** (7.460)	2.607*** (32.752)	9.936*** (10.707)
Observations	55,844	45,722	55,528	45,190	55,821	45,702	55,836	45,717
Adj R^2	0.0133	0.0196	0.0003	0.0029	0.0039	0.0096	-0.0000	0.0104
Mean treated t_0	2.8860	6.4790	2.9114	2.0906	2.7768	7.0842	2.7635	10.0575
Mean control t_0	2.7238	6.3797	3.0046	2.1544	2.6507	7.0195	2.6074	9.9357
Diff t_0	0.1622	0.0992	-0.0931	-0.0638	0.1261	0.0647	0.1561	0.1218
Mean treated t_1	-3.0785	-0.2642	1.7858	0.1975	-0.0467	3.1816	2.4383	8.5554
Mean control t_1	-2.9786	-0.1370	2.1807	0.5596	-0.6497	2.7428	2.5345	8.6624
Diff t_1	-0.0999	-0.1272	-0.3949	-0.3620	0.6030	0.4387	-0.0962	-0.1069

References

- Aboody, D. 1996. Recognition versus disclosure in the oil and gas industry. *Journal of Accounting Research* 34, pp. 21–32. doi:10.2307/2491423.
- Abraham, A. and Ikenberry, D. L. 1994. The individual investor and the weekend effect. *Journal of Financial and Quantitative Analysis* 29(2), pp. 263–277. doi:10.2307/2331225.
- Alt, R., Fortin, I. and Weinberger, S. 2011. The Monday effect revisited: An alternative testing approach. *Journal of Empirical Finance* 18(3), pp. 447–460. doi:10.1016/j.jempfin.2011.04.002.
- An, H. and Zhang, T. 2013. Stock price synchronicity, crash risk, and institutional investors. *Journal of Corporate Finance* 21, pp. 1–15. doi:10.1016/j.jcorpfin.2013.01.001.
- Andersen, T. G. and Bollerslev, T. 1998. Deutsche Mark–Dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies. *The Journal of Finance* 53(1), pp. 219–265. doi:10.1111/0022-1082.85732.
- Baker, M. and Wurgler, J. 2006. Investor sentiment and the cross-section of stock returns. *The Journal of Finance* 61(4), pp. 1645–1680. doi:10.1111/j.1540-6261.2006.00885.x.
- Baker, M. and Wurgler, J. 2007. Investor sentiment in the stock market. *Journal of Economic Perspectives* 21(2), pp. 129–152. doi:10.1257/jep.21.2.129.
- Baker, M., Wurgler, J. and Yuan, Y. 2012. Global, local, and contagious investor sentiment. *Journal of Financial Economics* 104(2), pp. 272–287. doi:10.1016/j.jfineco.2011.11.002.
- Bansal, R. and Shaliastovich, I. 2011. Learning and asset-price jumps. *The Review of Financial Studies* 24(8), pp. 2738–2780. doi:10.1093/rfs/hhr023.
- Barberis, N., Shleifer, A. and Wurgler, J. 2005. Comovement. *Journal of Financial Economics* 75(2), pp. 283–317. doi:10.1016/j.jfineco.2004.04.003.
- Bazley, W. J., Cronqvist, H. and Mormann, M. M. 2021. Visual finance: The pervasive effects of red on investor behavior. *Management Science* 67(9), pp. 5616–5641. doi:10.1287/mnsc.2020.3747.

- Beaver, W. H. 1968. The information content of annual earnings announcements. *Journal of Accounting Research* 6, pp. 67–92. doi:10.2307/2490070.
- Bekaert, G., Hodrick, R. J. and Zhang, X. 2009. International stock return comovements. *The Journal of Finance* 64(6), pp. 2591–2626. doi:10.1111/j.1540-6261.2009.01512.x.
- Birru, J. 2018. Day of the week and the cross-section of returns. *Journal of Financial Economics* 130(1), pp. 182–214. doi:10.1016/j.jfineco.2018.06.008.
- Bordalo, P., Gennaioli, N. and Shleifer, A. 2012. Salience theory of choice under risk. *The Quarterly Journal of Economics* 127(3), pp. 1243–1285. doi:10.1093/qje/qjs018.
- Bordalo, P., Gennaioli, N. and Shleifer, A. 2013a. Salience and asset prices. *American Economic Review* 103(3), pp. 623–28. doi:10.1257/aer.103.3.623.
- Bordalo, P., Gennaioli, N. and Shleifer, A. 2013b. Salience and consumer choice. *Journal of Political Economy* 121(5), pp. 803–843. doi:10.1086/673885.
- Bordalo, P., Gennaioli, N. and Shleifer, A. 2021. Salience. *NBER Working Paper No. 29274*. doi:10.3386/w29274.
- Boubaker, S., Mansali, H. and Rjiba, H. 2014. Large controlling shareholders and stock price synchronicity. *Journal of Banking & Finance* 40, pp. 80–96. doi:10.1016/j.jbankfin.2013.11.022.
- Brockman, P., Liebenberg, I. and Schutte, M. 2010. Comovement, information production, and the business cycle. *Journal of Financial Economics* 97(1), pp. 107–129. doi:10.1016/j.jfineco.2010.03.008.
- Brogaard, J., Nguyen, T. H., Putnins, T. J. and Wu, E. 2022. What moves stock prices? The roles of news, noise, and information. *The Review of Financial Studies* 35(9), pp. 4341–4386. doi:10.1093/rfs/hhab137.
- Campbell, J. Y., Lettau, M., Malkiel, B. G. and Xu, Y. 2001. Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *The Journal of Finance* 56(1), pp. 1–43. doi:10.1111/0022-1082.00318.

- Carhart, M. M. 1997. On persistence in mutual fund performance. *The Journal of Finance* 52(1), pp. 57–82. doi:10.1111/j.1540-6261.1997.tb03808.x.
- Carnes, W. S. and Slifer, S. D. 1991. *The atlas of economic indicators: A visual guide to market forces and the Federal Reserve*. New York: HarperCollins Publishers.
- Chan, K. and Hameed, A. 2006. Stock price synchronicity and analyst coverage in emerging markets. *Journal of Financial Economics* 80(1), pp. 115–147. doi:10.1016/j.jfineco.2005.03.010.
- Chan, K. F. and Marsh, T. 2021. Asset pricing on earnings announcement days. *Journal of Financial Economics* doi:10.1016/j.jfineco.2021.06.022.
- Chang, E. C., Pinegar, J. M. and Ravichandram, R. 1995. European day-of-the-week effects, beta asymmetries and international herding. *European Financial Management* 1(2), pp. 173–200.
- Chang, E. C., Pinegar, J. M. and Ravichandran, R. 1998. US day-of-the-week effects and asymmetric responses to macroeconomic news. *Journal of Banking & Finance* 22(5), pp. 513–534. doi:10.1016/S0378-4266(98)00023-5.
- Chelley-Steeley, P., Lambertides, N. and Savva, C. S. 2013. Illiquidity shocks and the comovement between stocks: New evidence using smooth transition. *Journal of Empirical Finance* 23, pp. 1–15. doi:10.1016/j.jempfin.2013.04.001.
- Chen, J., Tang, G., Yao, J. and Zhou, G. 2022. Investor attention and stock returns. *Journal of Financial and Quantitative Analysis* 57(2), pp. 455–484. doi:10.1017/S0022109021000090.
- Cho, Y.-H., Linton, O. and Whang, Y.-J. 2007. Are there Monday effects in stock returns: A stochastic dominance approach. *Journal of Empirical Finance* 14(5), pp. 736–755. doi:10.1016/j.jempfin.2007.02.001.
- Chu, Y., Hirshleifer, D. and Ma, L. 2020. The causal effect of limits to arbitrage on asset pricing anomalies. *The Journal of Finance* 75(5), pp. 2631–2672. doi:10.1111/jofi.12947.
- Chue, T. K., Gul, F. A. and Mian, G. M. 2019. Aggregate investor sentiment and stock return synchronicity. *Journal of Banking & Finance* 108, p. 105628. doi:10.1016/j.jbankfin.2019.105628.

- Claessens, S. and Yafeh, Y. 2012. Comovement of newly added stocks with national market indices: Evidence from around the world. *Review of Finance* 17(1), pp. 203–227. doi:10.1093/rof/rfs001.
- Clifford, C. P., Fulkerson, J. A., Jame, R. and Jordan, B. D. 2021. Salience and mutual fund investor demand for idiosyncratic volatility. *Management Science* 67(8), pp. 5234–5254. doi:10.1287/mnsc.2020.3716.
- Cross, F. 1973. The behavior of stock prices on Fridays and Mondays. *Financial Analysts Journal* 29(6), pp. 67–69. doi:10.2469/faj.v29.n6.67.
- Da, Z., Engelberg, J. and Gao, P. 2011. In search of attention. *The Journal of Finance* 66(5), pp. 1461–1499. doi:10.1111/j.1540-6261.2011.01679.x.
- Da, Z., Gurun, U. G. and Warachka, M. 2014. Frog in the pan: Continuous information and momentum. *The Review of Financial Studies* 27(7), pp. 2171–2218. doi:10.1093/rfs/hhu003.
- Dasgupta, S., Gan, J. and Gao, N. 2010. Transparency, price informativeness, and stock return synchronicity: Theory and evidence. *Journal of Financial and Quantitative Analysis* 45(5), pp. 1189–1220. doi:10.2307/27919561.
- De Long, J. B., Shleifer, A., Summers, L. H. and Waldmann, R. J. 1989. The size and incidence of the losses from noise trading. *The Journal of Finance* 44(3), pp. 681–696. doi:10.1111/j.1540-6261.1989.tb04385.x.
- De Long, J. B., Shleifer, A., Summers, L. H. and Waldmann, R. J. 1990. Noise trader risk in financial markets. *Journal of Political Economy* 98(4), pp. 703–738. doi:10.1086/261703.
- DellaVigna, S. and Pollet, J. M. 2009. Investor inattention and Friday earnings announcements. *The Journal of Finance* 64(2), pp. 709–749. doi:10.1111/j.1540-6261.2009.01447.x.
- Dertwinkel-Kalt, M. and Köster, M. 2019. Salience and skewness preferences. *Journal of the European Economic Association* 18(5), pp. 2057–2107. doi:10.1093/jeea/jvz035.
- Dong, Y., Li, O. Z., Lin, Y. and Ni, C. 2016. Does information-processing cost affect firm-specific information acquisition? evidence from XBRL adoption. *Journal of Financial and Quantitative Analysis* 51(2), pp. 435–462. doi:10.1017/S0022109016000235.

- Drake, M. S., Jennings, J., Roulstone, D. T. and Thornock, J. R. 2017. The comovement of investor attention. *Management Science* 63(9), pp. 2847–2867. doi:10.1287/mnsc.2016.2477.
- Dubois, M. and Louvet, P. 1996. The day-of-the-week effect: The international evidence. *Journal of Banking and Finance* 20(9), pp. 1463–1484. doi:10.1016/0378-4266(95)00054-2.
- Durnev, A., Morck, R. and Yeung, B. 2004. Value-enhancing capital budgeting and firm-specific stock return variation. *The Journal of Finance* 59(1), pp. 65–105. doi:10.1111/j.1540-6261.2004.00627.x.
- Engle, R. 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics* 20(3), pp. 339–350. doi:10.1198/073500102288618487.
- Fang, Y., Hasan, I., Leung, W. S. and Wang, Q. 2019. Foreign ownership, bank information environments, and the international mobility of corporate governance. *Journal of International Business Studies* 50(9), pp. 1566–1593. doi:10.1057/s41267-019-00240-w.
- Fechner, G. T. 1966 [First published 1860]. *Elements of psychophysics [Elemente der Psychophysik]*, vol. 1. Translated by Helmut E. Adler. Edited by David H. Howes, Edwin G. Boring. New York: Holt, Rinehart and Winston, Inc.
- Fernandes, N. and Ferreira, M. A. 2009. Insider trading laws and stock price informativeness. *The Review of Financial Studies* 22(5), pp. 1845–1887. doi:10.1093/rfs/hhn066.
- Ferreira, D., Ferreira, M. A. and Raposo, C. C. 2011. Board structure and price informativeness. *Journal of Financial Economics* 99(3), pp. 523–545. doi:10.1016/j.jfineco.2010.10.007.
- Fisher, A., Martineau, C. and Sheng, J. 2022. Macroeconomic attention and announcement risk premia. *The Review of Financial Studies* 35(11), pp. 5057–5093. doi:10.1093/rfs/hhac011.
- Fiske, S. T. and Taylor, S. E. 2017. *Social Cognition: From Brains to Culture*. London: Sage Publications Ltd, Third ed.
- Foucault, T., Sraer, D. and Thesmar, D. J. 2011. Individual investors and volatility. *The Journal of Finance* 66(4), pp. 1369–1406. doi:10.1111/j.1540-6261.2011.01668.x.

- Francis, J., Pagach, D. and Stephan, J. 1992. The stock market response to earnings announcements released during trading versus nontrading periods. *Journal of Accounting Research* 30(2), pp. 165–184. doi:10.2307/2491122.
- French, K. R. 1980. Stock returns and the weekend effect. *Journal of Financial Economics* 8(1), pp. 55–69. doi:10.1016/0304-405X(80)90021-5.
- Froot, K. A., Scharfstein, D. S. and Stein, J. C. 1992. Herd on the street: Informational inefficiencies in a market with short-term speculation. *The Journal of Finance* 47(4), pp. 1461–1484. doi:10.2307/2328947.
- Frydman, C. and Rangel, A. 2014. Debiasing the disposition effect by reducing the saliency of information about a stock's purchase price. *Journal of Economic Behavior and Organization* 107(Pt B), pp. 541–552. doi:10.1016/j.jebo.2014.01.017.
- Frydman, C. and Wang, B. 2020. The impact of salience on investor behavior: Evidence from a natural experiment. *The Journal of Finance* 75(1), pp. 229–276. doi:10.1111/jofi.12851.
- Gibbons, M. R. and Hess, P. 1981. Day of the week effects and asset returns. *The Journal of Business* 54(4), pp. 579–596. doi:10.1086/296147.
- Gul, F. A., Kim, J.-B. and Qiu, A. A. 2010. Ownership concentration, foreign shareholding, audit quality, and stock price synchronicity: Evidence from China. *Journal of Financial Economics* 95(3), pp. 425–442. doi:10.1016/j.jfineco.2009.11.005.
- Hartzmark, S. M. and Shue, K. 2018. A tough act to follow: Contrast effects in financial markets. *The Journal of Finance* 73(4), pp. 1567–1613. doi:10.1111/jofi.12685.
- Helmholtz, H. v. 1962. *Helmholtz's treatise on physiological optics*, vol. 3. New York: Dover Publications.
- Hering, E. 1964. *Outlines of a theory of the light sense*. Cambridge: Harvard University Press.
- Hirshleifer, D. and Sheng, J. 2022. Macro news and micro news: Complements or substitutes? *Journal of Financial Economics* 145(3), pp. 1006–1024. doi:10.1016/j.jfineco.2021.09.012.

- Hu, G. X., Pan, J., Wang, J., and Zhu, H. 2021. Premium for heightened uncertainty: Explaining pre-announcement market returns. *Journal of Financial Economics* 145(3), pp. 909–936. doi:10.1016/j.jfineco.2021.09.015.
- Huang, D., Jiang, F., Tu, J. and Zhou, G. 2015. Investor sentiment aligned: A powerful predictor of stock returns. *The Review of Financial Studies* 28(3), pp. 791–837. doi:10.1093/rfs/hhu080.
- Huang, S., Lee, C. M., Song, Y. and Xiang, H. 2022. A frog in every pan: Information discreteness and the lead-lag returns puzzle. *Journal of Financial Economics* 145(2, Part A), pp. 83–102. doi:10.1016/j.jfineco.2021.10.011.
- Huang, X., Nekrasov, A. and Teoh, S. H. 2018. Headline salience, managerial opportunism, and over- and underreactions to earnings. *The Accounting Review* 93(6), pp. 231–255. doi:10.2308/accr-52010.
- Israelsen, R. D. 2016. Does common analyst coverage explain excess comovement? *Journal of Financial and Quantitative Analysis* 51(4), pp. 1193–1229. doi:10.1017/S002210901600051X.
- Jiang, L., Wu, K. and Zhou, G. 2018. Asymmetry in stock comovements: An entropy approach. *Journal of Financial and Quantitative Analysis* 53(4), pp. 1479–1507. doi:10.1017/S0022109018000340.
- Jin, L. and Myers, S. C. 2006. R^2 around the world: New theory and new tests. *Journal of Financial Economics* 79(2), pp. 257–292. doi:10.1016/j.jfineco.2004.11.003.
- Kacperczyk, M., Van Nieuwerburgh, S. and Veldkamp, L. 2016. A rational theory of mutual funds' attention allocation. *Econometrica* 84(2), pp. 571–626. doi:10.3982/ECTA11412.
- Kahneman, D. 1973. *Attention and effort*. Prentice-Hall Series in Experimental Psychology. Englewood Cliffs: Prentice-Hall.
- Kahraman, B. and Tookes, H. 2019. Margin trading and comovement during crises. *Review of Finance* 24(4), pp. 813–846. doi:10.1093/rof/rfz019.

- Kalay, A. and Loewenstein, U. 1985. Predictable events and excess returns: The case of dividend announcements. *Journal of Financial Economics* 14(3), pp. 423–449. doi:10.1016/0304-405X(85)90007-8.
- Kallberg, J. and Pasquariello, P. 2008. Time-series and cross-sectional excess comovement in stock indexes. *Journal of Empirical Finance* 3(15), pp. 481–502. doi:10.1016/j.jempfin.2007.06.002.
- Keim, D. B. and Stambaugh, R. F. 1984. A further investigation of the weekend effect in stock returns. *The Journal of Finance* 39(3), pp. 819–835. doi:10.2307/2327945.
- Kelly, P. J. 2014. Information efficiency and firm-specific return variation. *Quarterly Journal of Finance* 4(4), p. 1450018. doi:10.1142/S2010139214500189.
- Keloharju, M., Linnainmaa, J. T. and Nyberg, P. 2016. Return seasonalities. *The Journal of Finance* 71(4), pp. 1557–1590. doi:10.1111/jofi.12398.
- Khaw, M. W., Li, Z. and Woodford, M. 2020. Cognitive imprecision and small-stakes risk aversion. *The Review of Economic Studies* 88(4), pp. 1979–2013. doi:10.1093/restud/rdaa044.
- Kim, J.-B. and Shi, H. 2012. IFRS reporting, firm-specific information flows, and institutional environments: International evidence. *Review of Accounting Studies* 17(3), pp. 474–517. doi:10.1007/s11142-012-9190-y.
- Kim, J. H. and Hoffman, E. 2020. Contrast effects in investment and financing decisions. *Working Paper*. doi:10.2139/ssrn.3256087.
- Kliger, D. and Gilad, D. 2012. Red light, green light: Color priming in financial decisions. *The Journal of Socio-Economics* 41(5), pp. 738–745. doi:10.1016/j.socec.2012.07.003.
- Kong, D., Lin, C. and Liu, S. 2019. Does information acquisition alleviate market anomalies? Categorization bias in stock splits. *Review of Finance* 23(1), pp. 245–277. doi:10.1093/rof/rfx028.
- Kumar, A., Page, J. K. and Spalt, O. G. 2013. Investor sentiment and return comovements: Evidence from stock splits and headquarters changes. *Review of Finance* 17(3), pp. 921–953. doi:10.1093/rof/rfs010.

- Lakonishok, J. and Levi, M. 1982. Weekend effects on stock returns: A note. *The Journal of Finance* 37(3), pp. 883–889. doi:10.2307/2327716.
- Lakonishok, J. and Maberly, E. 1990. The weekend effect: Trading patterns of individual and institutional investors. *The Journal of Finance* 45(1), pp. 231–243. doi:10.2307/2328818.
- Lemmon, M. and Portniaguina, E. 2006. Consumer confidence and asset prices: Some empirical evidence. *The Review of Financial Studies* 19(4), pp. 1499–1529. doi:10.1093/rfs/hhj038.
- Li, B., Rajgopal, S. and Venkatachalam, M. 2014. R^2 and idiosyncratic risk are not interchangeable. *The Accounting Review* 89(6), pp. 2261–2295. doi:10.2308/accr-50826.
- Liu, H. and Peng, L. 2015. Investor attention: Seasonal patterns and endogenous allocations. *Proceedings of the FMA Annual Meeting*. Orlando; USA, 14-17 October, 2015.
- Liu, H., Peng, L. and Tang, Y. 2023. Retail attention, institutional attention. *Journal of Financial and Quantitative Analysis* 58(3), pp. 1005–1038. doi:10.1017/S0022109022000734.
- Louis, H. and Sun, A. 2010. Investor inattention and the market reaction to merger announcements. *Management Science* 56(10), pp. 1781–1793. doi:www.jstor.org/stable/40864739.
- Lucca, D. O. and Moench, E. 2015. The pre-FOMC announcement drift. *The Journal of Finance* 70(1), pp. 329–371. doi:10.1111/jofi.12196.
- Michaely, R., Rubin, A. and Vadrashko, A. 2016. Are Friday announcements special? Overcoming selection bias. *Journal of Financial Economics* 122(1), pp. 65–85. doi:10.1016/j.jfineco.2016.05.006.
- Mondria, J. 2010. Portfolio choice, attention allocation, and price comovement. *Journal of Economic Theory* 145(5), pp. 1837–1864. doi:10.1016/j.jet.2010.03.001.
- Morck, R., Yeung, B. and Yu, W. 2000. The information content of stock markets: Why do emerging markets have synchronous stock price movements? *Journal of Financial Economics* 58(1-2), pp. 215–260. doi:10.1016/S0304-405X(00)00071-4.
- Pasquariello, P. and Vega, C. 2007. Informed and strategic order flow in the bond markets. *The Review of Financial Studies* 20(6), pp. 1975–2019. doi:10.1093/rfs/hhm034.

- Patton, A. J. and Verardo, M. 2012. Does beta move with news? Firm-specific information flows and learning about profitability. *The Review of Financial Studies* 25(9), pp. 2789–2839. doi:10.1093/rfs/hhs073.
- Peng, L. 2005. Learning with information capacity constraints. *Journal of Financial and Quantitative Analysis* 40(2), pp. 307–329. doi:10.1017/S0022109000002325.
- Peng, L. and Xiong, W. 2006. Investor attention, overconfidence and category learning. *Journal of Financial Economics* 80(3), pp. 563–602. doi:10.1016/j.jfineco.2005.05.003.
- Piotroski, J. D. and Roulstone, B. T. 2004. The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. *The Accounting Review* 79(4), pp. 1119–1151. doi:10.2308/accr.2004.79.4.1119.
- Roll, R. 1988. R^2 . *The Journal of Finance* 43(3), pp. 541–566. doi:10.2307/2328183.
- Rua, A. and Nunes, L. C. 2009. International comovement of stock market returns: A wavelet analysis. *Journal of Empirical Finance* 16(4), pp. 632–639. doi:10.1016/j.jempfin.2009.02.002.
- Savor, P. and Wilson, M. 2013. How much do investors care about macroeconomic risk? Evidence from scheduled economic announcements. *Journal of Financial and Quantitative Analysis* 48(2), pp. 343–375. doi:10.1017/S002210901300015X.
- Savor, P. and Wilson, M. 2014. Asset pricing: A tale of two days. *Journal of Financial Economics* 113(2), pp. 171–201. doi:10.1016/j.jfineco.2014.04.005.
- Savor, P. and Wilson, M. 2016. Earnings announcements and systematic risk. *The Journal of Finance* 71(1), pp. 83–138. doi:10.1111/jofi.12361.
- Sims, C. A. 2003. Implications of rational inattention. *Journal of Monetary Economics* 50(3), pp. 665–690. doi:10.1016/S0304-3932(03)00029-1.
- Veldkamp, L. L. 2006. Information markets and the comovement of asset prices. *Review of Economic Studies* 73(3), pp. 823–845. doi:10.1111/j.1467-937X.2006.00397.x.

- Wang, W. and Duxbury, D. 2021. Institutional investor sentiment and the mean-variance relationship: Global evidence. *Journal of Economic Behavior & Organization* 191, pp. 415–441. doi:10.1016/j.jebo.2021.08.029.
- Woodford, M. 2012. Prospect theory as efficient perceptual distortion. *American Economic Review* 102(3), pp. 41–46. doi:10.1257/aer.102.3.41.
- Woodford, M. 2020. Modeling imprecision in perception, valuation, and choice. *Annual Review of Economics* 12(1), pp. 579–601. doi:10.1146/annurev-economics-102819-040518.
- Wurgler, J. 2000. Financial markets and the allocation of capital. *Journal of Financial Economics* 58(1-2), pp. 187–214. doi:10.1016/S0304-405X(00)00070-2.
- Ülkü, N. and Rogers, M. 2018. Who drives the Monday effect? *Journal of Economic Behavior & Organization* 148, pp. 46–65. doi:10.1016/j.jebo.2018.02.009.

6 Online Appendix

6.1 Pooled regressions for baseline results

Monday R^2 remains consistently higher in pooled OLS and Fixed Effects regressions reported in Table A1.

Table A1: Pooled Regressions for Baseline Results

The sample period extends from 1953 to 2017. The R^2 values are obtained by regressing stock returns on CRSP Value-weighted Index returns (and its lag) and Fama-French 48 Industry returns (and its lag) for each weekday d from Monday to Friday. **Panel A** shows the from pooled Fixed Effects regressions while **Panel B** shows the results from pooled OLS regressions. $\beta_{Mkt,d,y}$ and $\beta_{Mkt,d-1,y}$ represent the coefficients for the Index and its lag while $\beta_{Ind,d,y}$ and $\beta_{Ind,d-1,y}$ represent the coefficients for the Industry returns and its lag. Firms with least 30 values for a given weekday in a given year are included in the sample. The t-statistics are in parenthesis. *, **, and *** indicate 10%, 5%, and 1% significance respectively.

Panel A: Pooled Fixed Effects Regressions					
	(1) Monday	(2) Tuesday	(3) Wednesday	(4) Thursday	(5) Friday
$\beta_{Mkt,d,y}$	0.412*** (90.282)	0.370*** (84.696)	0.426*** (96.029)	0.403*** (91.143)	0.386*** (88.858)
$\beta_{Mkt,d-1,y}$	0.067*** (26.735)	0.048*** (21.154)	0.026*** (11.864)	0.033*** (14.044)	0.031*** (13.865)
$\beta_{Ind,d,y}$	0.387*** (81.473)	0.370*** (78.196)	0.361*** (75.613)	0.365*** (77.152)	0.348*** (75.988)
$\beta_{Ind,d-1,y}$	0.064*** (34.426)	0.057*** (32.758)	0.057*** (32.619)	0.056*** (32.809)	0.043*** (26.499)
Constant	-0.001*** (-13.959)	-0.001*** (-10.149)	0.001*** (7.133)	0.000*** (5.137)	0.001*** (8.790)
R^2	0.0616	0.0477	0.0488	0.0511	0.0423
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Panel B: Pooled OLS Regressions					
$\beta_{Mkt,d,y}$	0.413*** (90.492)	0.365*** (83.973)	0.425*** (96.257)	0.403*** (91.544)	0.383*** (88.279)
$\beta_{Mkt,d-1,y}$	0.062*** (24.905)	0.047*** (20.691)	0.026*** (11.936)	0.033*** (14.003)	0.033*** (14.629)
$\beta_{Ind,d,y}$	0.388*** (82.003)	0.372*** (78.831)	0.363*** (76.011)	0.366*** (77.454)	0.348*** (76.192)
$\beta_{Ind,d-1,y}$	0.066*** (36.038)	0.059*** (33.739)	0.057*** (33.143)	0.057*** (33.681)	0.044*** (27.006)
Constant	-0.001*** (-66.842)	-0.000*** (-29.817)	0.000*** (17.145)	0.000*** (47.448)	0.001*** (86.122)
R^2	0.0608	0.0472	0.0485	0.0507	0.0418

6.2 Alternative factor models

Following Chue *et al.* (2019), we use the four-factor model by Carhart (1997) for firm-level, one-year rolling window regressions for each weekday:

$$R_{i,d,y} = \alpha_{i,d,y} + \beta_1 MKT_{d,y} + \beta_2 SMB_{d,y} + \beta_3 HML_{d,y} + \beta_4 UMD_{d,y} + \epsilon_{i,d,y} \quad (A1)$$

$$R_{i,d,y} = \alpha_{i,d,y} + \beta_1 MKT_{d,y} + \epsilon_{i,d,y} \quad (A2)$$

The four factors are market (MKT), size (SMB), value (HML), and momentum (UMD). We also run regressions for the Market Model containing only the market factor. Table A2 indicates that Monday R^2 remains higher if either of these factor models are used.

Table A2: Synchronicity Regressions: Carhart 4-factor Model & Market Model

The sample period extends from 1953 to 2017. For the Carhart's 4-factor Model, the $R^2_{i,d,y}$ values are obtained by regressing stock returns on market (MKT), size (SMB), value (HML), and momentum (UMD) factors for each weekday d from Monday to Friday for each stock i in each calendar year y . For the Market Model, the $R^2_{i,d,y}$ values are obtained by regressing stock returns on CRSP Value-weighted Index returns for each weekday d from Monday to Friday for each stock i in each calendar year y . Average values of the $R^2_{i,d,y}$ (%) are reported in columns 1 and 2.

	(1)	(2)
	Carhart 4-factor Model	Market Model
Monday	21.852	12.776
Tuesday	19.259	10.803
Wednesday	19.009	10.745
Thursday	19.136	10.940
Friday	18.725	10.353
Total	19.595	11.122

6.3 Robustness tests for Monday synchronicity effect

The R^2 values in Panel A of Figure 3 cannot be directly compared to those in Panel B because we use firm-level regressions in the former and pooled regressions in the latter. Thus, we use pooled regressions for macroeconomic announcements to allow such comparison. The results reported in Table A3 indicate that the Monday synchronicity effect is robust. The R^2 value for Monday macroeconomic announcement days (12.40% for OLS and 12.80% for FE regression) is not only higher than other weekdays, but also higher than the R^2 values for earnings announcements reported

in Panel B of Figure 3.

Table A3: Pooled Synchronicity Regressions for Macroeconomic Announcements

The sample period extends from 1998 to 2017. Two synchronicity regressions are run for each weekday, one for those days on which macroeconomic announcements are released and the other for non-announcement days. Both pooled OLS and Fixed Effects specifications are used. R^2 values of the pooled regressions are reported.

Pooled OLS			Pooled Fixed Effects		
	Ann. Days	Non-Ann. Days		Ann. Days	Non-Ann. Days
Monday	0.1240	0.0834	Monday	0.1280	0.0846
Tuesday	0.0725	0.0868	Tuesday	0.0738	0.0878
Wednesday	0.1060	0.0708	Wednesday	0.1080	0.0711
Thursday	0.0888	0.0849	Thursday	0.0907	0.0853
Friday	0.0708	0.0587	Friday	0.0715	0.0603

Rolling window regressions

As an additional robustness test, we consider the following four scenarios: 1) remove all macroeconomic announcement days and run firm-wise synchronicity regressions using a 3-year rolling window to allow for a sufficient number of values in each regression; 2) removing only earnings announcement days; 3) removing both types of announcement days; and 4) keeping all days. The results in Figure A1 indicate that the Monday synchronicity effect vanishes when macroeconomic announcement days are excluded (“No Macro”), and Tuesday’s average R^2 becomes the highest. When only earnings announcements are excluded (“No Earn”), Monday’s average R^2 remains relatively higher. When both types of announcements are excluded (“No Macro/Earn”), Monday synchronicity effect vanishes again. Monday synchronicity effect is again visible like the baseline results when all days are included (“All Days”).

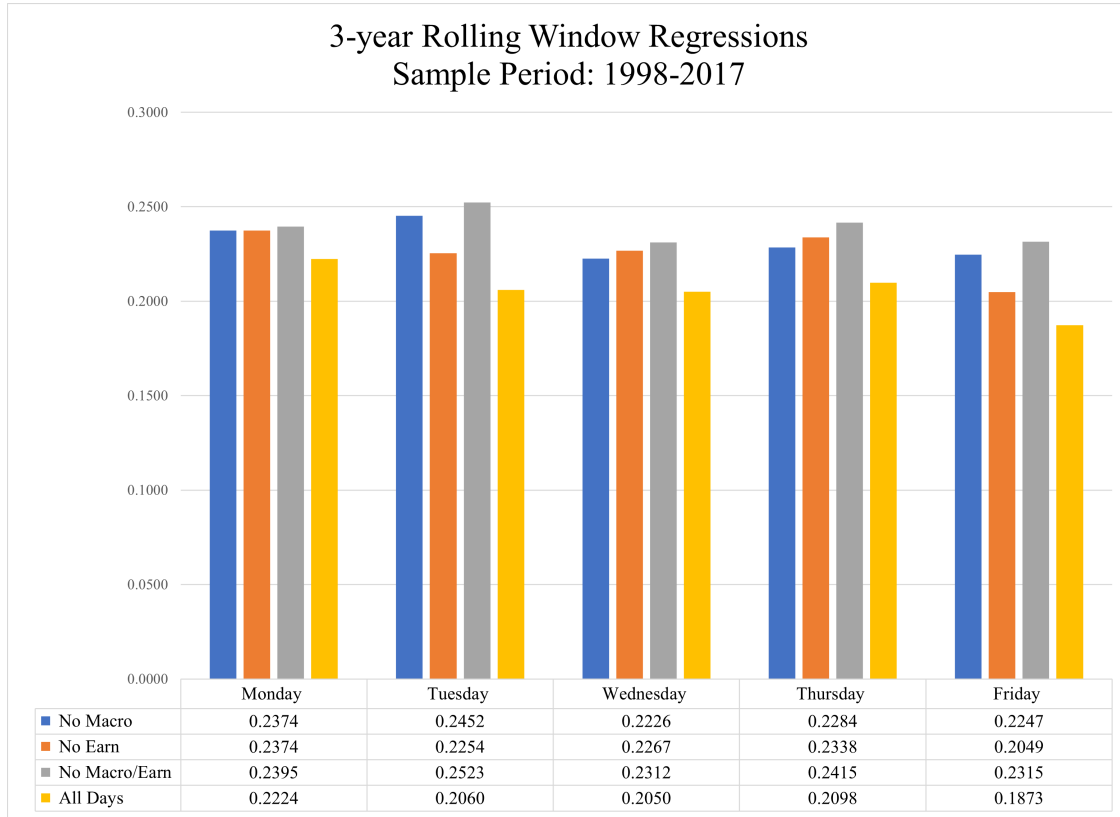


Figure A1: Rolling Window Regressions by Weekday

All regressions are run for each firm and each weekday using a 3-year rolling window. The sample period extends from 1998 to 2017 and includes nine macroeconomic announcements (PMI, NFPAY, FOMC, PPI, CPI, GDP, PCE, CCI and TRBAL). Average R^2 values from these regressions are reported. Macroeconomic announcement days are removed in the row labeled “No Macro”, earnings announcement days are removed in the row labeled “No Earn”, while both macroeconomic and earnings announcement days are removed in the row labeled “No Macro/Earn”, while all days are included in the row labeled “All Days”.

Weighted average R^2

In Panel A of Figure 3, we do not consider how frequently macroeconomic announcements are released on a given weekday. A day is simply designated as the announcement day if a macroeconomic news is released. This ignores the fact only a few Mondays are announcement days, as compared to other weekdays. The baseline results in Table 1 seemingly depict that comovement is higher on Mondays akin to a seasonal anomaly. However, the analysis of news announcements reveal that comovement is only higher when macroeconomic announcements are released on Monday and the market reacts strongly due to the salience of these announcements. To reconcile both of these results, we employ a frequency-weighted R^2 . Specifically, we calculate weighted averages of the mean values of R^2 , reported in Panel A of Figure 3, using the relative

frequency of macroeconomic announcements. The weights are calculated by dividing the number of announcement days with the total days in the sample. For instance, the weight for Monday announcements is 136/945, where there are 136 Mondays on which macroeconomic announcements were released and the total number of Mondays is 945. The weight for non-announcement Mondays is then 1-(136/945). The weighted average is then calculated by first multiplying the weights by the corresponding R^2 mean values and then adding them up:

$$R^2_{Wtd. Avg.} = R^2_{Ann.} \times Weight_{Ann.} + R^2_{NoAnn.} \times Weight_{NoAnn.} \quad (A3)$$

Table A4 reports the results. The weighted average R^2 values calculated in Panel A are compared to the baseline firm-year regression R^2 values in Panel B. It shows that the percentage differences between Monday and other weekdays for the weighted average R^2 values (column 9 in Panel A) are close to percentage differences for the baseline regression R^2 values (columns 2 and 4 in Panel B). Thus, we demonstrate that a simple weighting scheme based on the frequency of macroeconomic announcements can produce a pattern of R^2 values close to our baseline results.

Table A4: Weighted Average R^2 based on Macroeconomic Announcements

The sample period extends from 1998 to 2017. In Panel A, the average values of R^2 , denoted as $Avg.R^2_{Ann.}$ and $Avg.R^2_{NoAnn.}$, are obtained from firm-level synchronicity regressions, run separately for announcement and non-announcement days for each weekday. The weights ($W_{Ann.}$ and $W_{NoAnn.}$) are based on the frequency of announcement and non-announcement days, relative to all days. The weighted average is calculated by first multiplying the weights with the respective average R^2 values, and then adding them together. $Wtd.Avg.R^2 = W_{Ann.} * Avg.R^2_{Ann.} + W_{NoAnn.} * Avg.R^2_{NoAnn.}$. $\% \Delta R^2$ is the percentage change in R^2 of non-Monday days relative to Monday. Panel B includes the averages of R^2 obtained from the firm-year synchronicity regressions (as in Table 1) for comparison with weighted averages of R^2 in Panel A.

Panel A: Firm-Level Regressions

Weekday	(1) Ann.	(2) Non-Ann.	(3) Total Days	(4) $W_{Ann.}$	(5) $W_{NoAnn.}$	(6) $Avg.R^2_{Ann.}$	(7) $Avg.R^2_{NoAnn.}$	(8) $Wtd.Avg.R^2$	(9) $\% \Delta R^2$
Monday	135	810	945	14.29%	85.71%	0.4705	0.1790	0.2206	
Tuesday	480	551	1031	46.56%	53.44%	0.2012	0.2026	0.2019	-8.47%
Wednesday	290	745	1035	28.02%	71.98%	0.3038	0.1639	0.2031	-7.95%
Thursday	261	753	1014	25.74%	74.26%	0.2886	0.1740	0.2035	-7.77%
Friday	554	453	1007	55.01%	44.99%	0.1825	0.2012	0.1909	-13.47%

Panel B: Comparison with Average R^2 of Firm-Year Regressions (from Table 1)

	Sample Period 1998–2017		Sample Period 1953–2017	
	(1) $Avg.R^2$	(2) $\% \Delta R^2$	(3) $Avg.R^2$	(4) $\% \Delta R^2$
Weekday				
Monday	0.2774		0.2177	
Tuesday	0.2609	-5.95%	0.1968	-9.62%
Wednesday	0.2572	-7.29%	0.1948	-10.52%
Thursday	0.2631	-5.17%	0.1972	-9.43%
Friday	0.2463	-11.24%	0.1910	-12.27%

6.4 Longer sample period for macroeconomic and earnings announcements

We obtain earnings announcement dates from I/B/E/S and COMPUSTAT between 1984 and 1997 in addition to the data from Bloomberg Terminal (1998-2017). For I/B/E/S and COMPUSTAT, we restrict the sample to only those announcements that are reported in both databases within six calendar days of each other. To ensure the accuracy of earnings announcement dates, we follow DellaVigna and Pollet (2009) and select the earlier of the two dates as the actual date of the announcement. In case the dates in I/B/E/S and COMPUSTAT coincide, we impute the previous trading date as the announcement date if such date occurs before January 1, 1990. If the dates occur after January 1, 1990, we impute the same date as the announcement date. The timestamp from I/B/E/S is used to determine whether announcements were made before/during/after market hours. Since the accuracy of announcement dates is dubious if they are reported in only one of the databases, we also drop the returns data for the respective firm-date observation so that such days are not erroneously categorized as non-announcement days.

For the period from 1971 to 1997, we obtain release dates for six announcements (i.e. excluding PCE, TRBAL, and CCI) from the websites of the US Federal Reserve (FOMC), Bureau of Labor Statistics (NFPAY, CPI, and PPI), Bureau of Economic Analysis (GDP), and Institute of Supply Management (PMI).²⁰ Only a handful of macroeconomic announcements were released on Sundays and Saturdays.

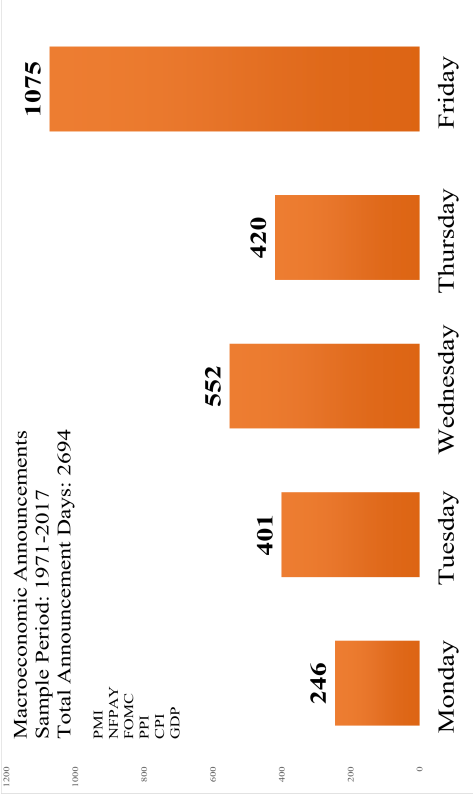
Panel A and Panel B of Figure A2 show that, for six types of announcements from 1971 to 2017, Monday continues to be the day with fewest macroeconomic announcements. Similar to the 1998-2017 sample, NFPAY is most concentrated on Fridays, FOMC is concentrated in the middle of the week (Tuesdays and Wednesdays), PMI occurs most frequently on Mondays, and CCI is almost always announced on Tuesdays. As shown in Panel C and Panel D of Figure A2, the

²⁰Dates of FOMC are obtained from the historical archive on the Federal Reserve website https://www.federalreserve.gov/monetarypolicy/fomc_historical.htm. Dates of NFPAY, CPI, and PPI are obtained from the news release archive on the Bureau of Labor Statistics website https://www.bls.gov/bls/archived_sched.htm. We are grateful to the Bureau of Economic Analysis for providing us with historical release dates of advance estimates of quarterly GDP and the dates maintained by the Federal Reserve Bank of St. Louis. We also thank the Institute of Supply Management for providing us with historical release dates of PMI.

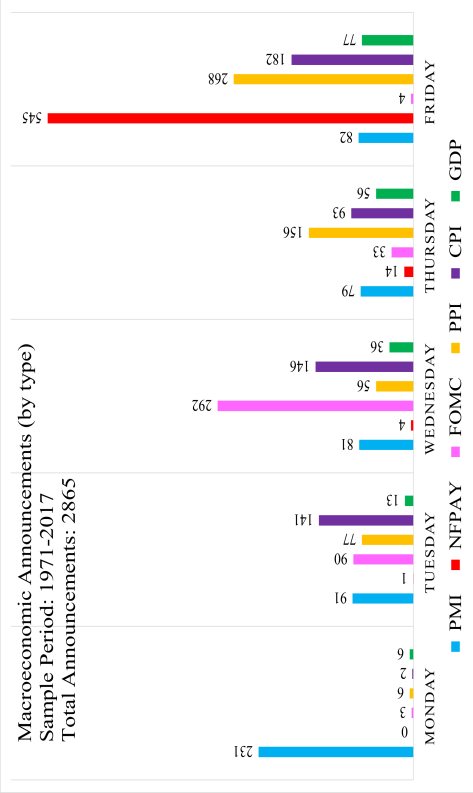
pattern of frequencies of earnings announcements in this longer sample period is also identical to 1998-2017 sample.

We run regressions using the longer sample period, identical to those reported in Figure 3. The average R^2 is still the highest for non-announcement Mondays in Panel A of Figure A4, even though its value is very close to that of non-announcement Fridays. It seems as if the removal of macroeconomic announcements have not completely eliminated the Monday synchronicity effect. This is because the dates for three macroeconomic announcements (CCI, TRBAL, & PCE) are not available from 1971 to 1997 and thus, they are not controlled for the 1971-2017 period. Hence, some announcement days are erroneously being categorized as non-announcement days due to this limitation in the data. Once we control for these missing announcements in the 1998-2017 period (Panel A of Figure 3), the average R^2 for non-announcement Mondays is no longer higher than other weekdays. More specifically, PCE is the culprit because it has been released 71 times on Monday while there is only a single Monday announcement for TRBAL and none for CCI in the 1998-2017 period. The small number of Monday macroeconomic announcements is mainly responsible for higher Monday synchronicity; missing out only a few of these announcements on Monday results in a considerable difference in the results, as shown by the two sample periods we have investigated.

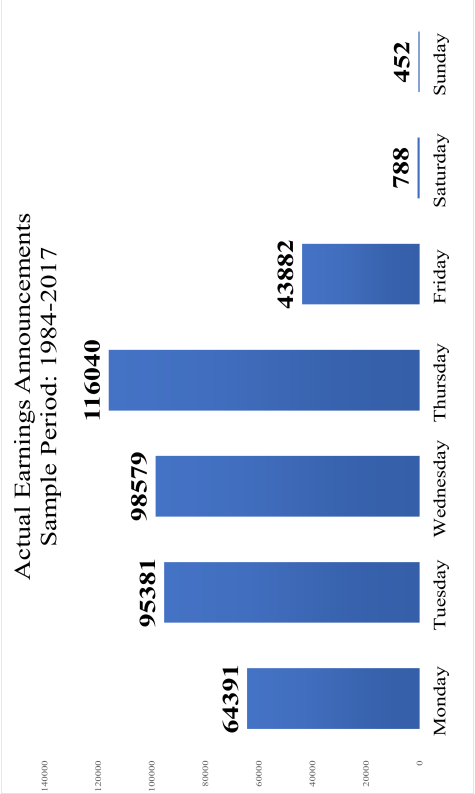
We also use the longer sample period for 3-year rolling regressions. The results, reported in Figure A5, indicate that despite removing macroeconomic announcements (“No Macro”), earnings announcements (“No Earn”), or both (“No Macro/Earn”), Monday’s average R^2 remains higher. The reason for the difference in the results of Figure A1 and Figure A5 is the same as stated for the difference observed in Panel A of Figure 3 and Panel A of Figure A4. When we control for additional macroeconomic announcements (particularly the PCE) in the 1998-2017 period, Monday’s R^2 is no longer higher than those of other weekdays. In other words, although Monday announcement days account for only around 9% of all announcement days, they play a central role in Monday’s higher comovement. We also replicate analysis in Table A4 for the longer sample period, and obtain similar results (see Table A5).



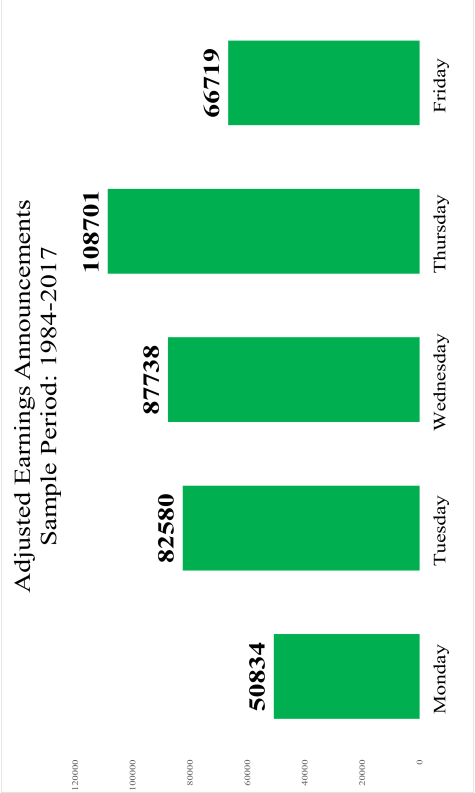
Panel A: All Macroeconomic Announcements



Panel B: Macroeconomic Announcements by Type



Panel C: Actual Earnings Announcements



Panel D: Adjusted Earnings Announcements

Figure A2: News Announcements by Weekday: Longer Sample Period

Panel A and Panel B show the cumulative and individual distributions of six macroeconomic announcements from 1971 to 2017. NFPAY: Non-Farm Payroll released by the Bureau of Labor Statistics (usually on the first Friday of each month). FOMC: Federal Open Market Committee decisions released by the Federal Reserve. PPI: Producer Price Index released by the Bureau of Labor Statistics. CPI: Consumer Price Index released by the Bureau of Labor Statistics. GDP: The advanced estimate of Quarter-on-Quarter GDP growth released by the Bureau of Economic Analysis. Panel C and Panel D show the distribution of earnings announcements from 1984 to 2017 by their actual day of release, and the distribution after adjusting for aftermarket hours release or release on a non-trading day respectively.

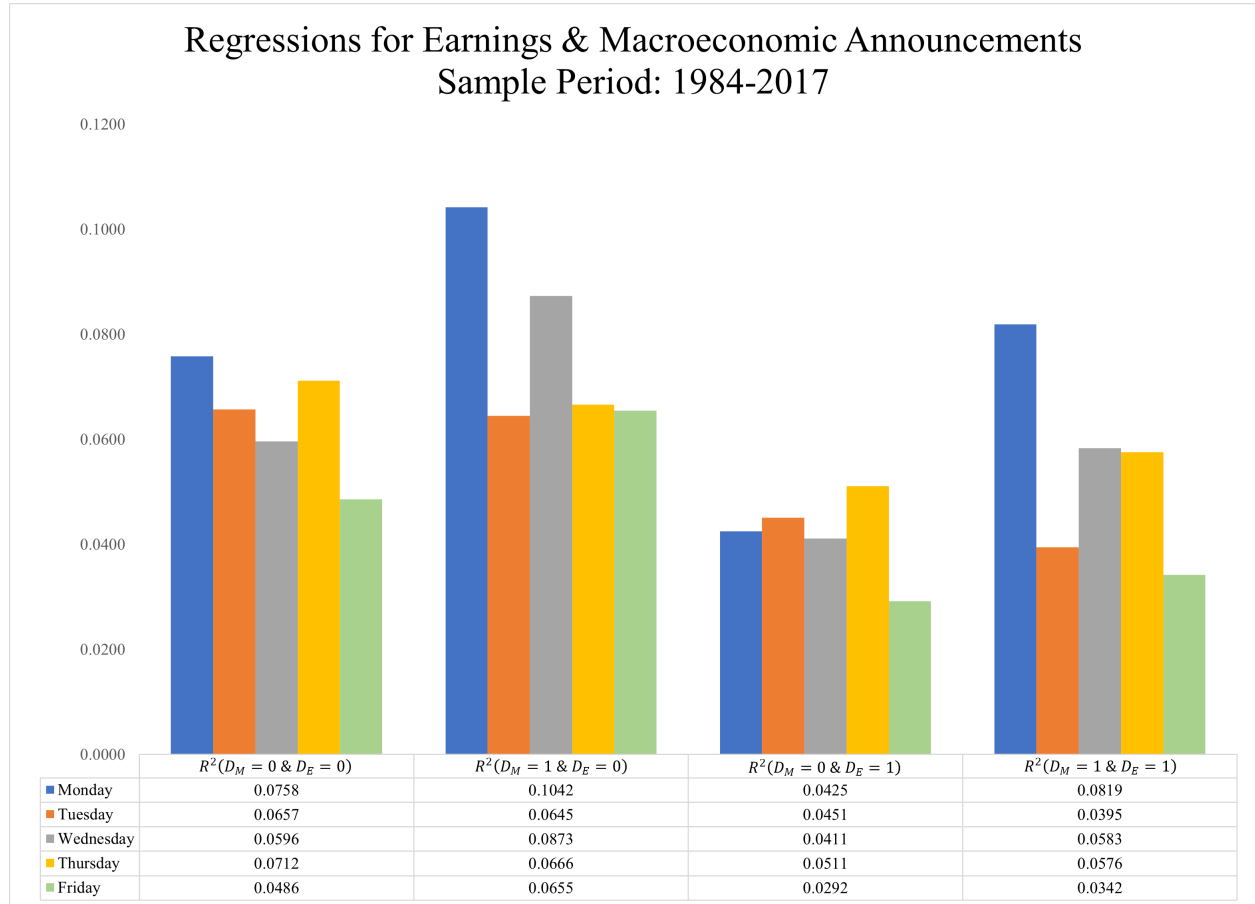
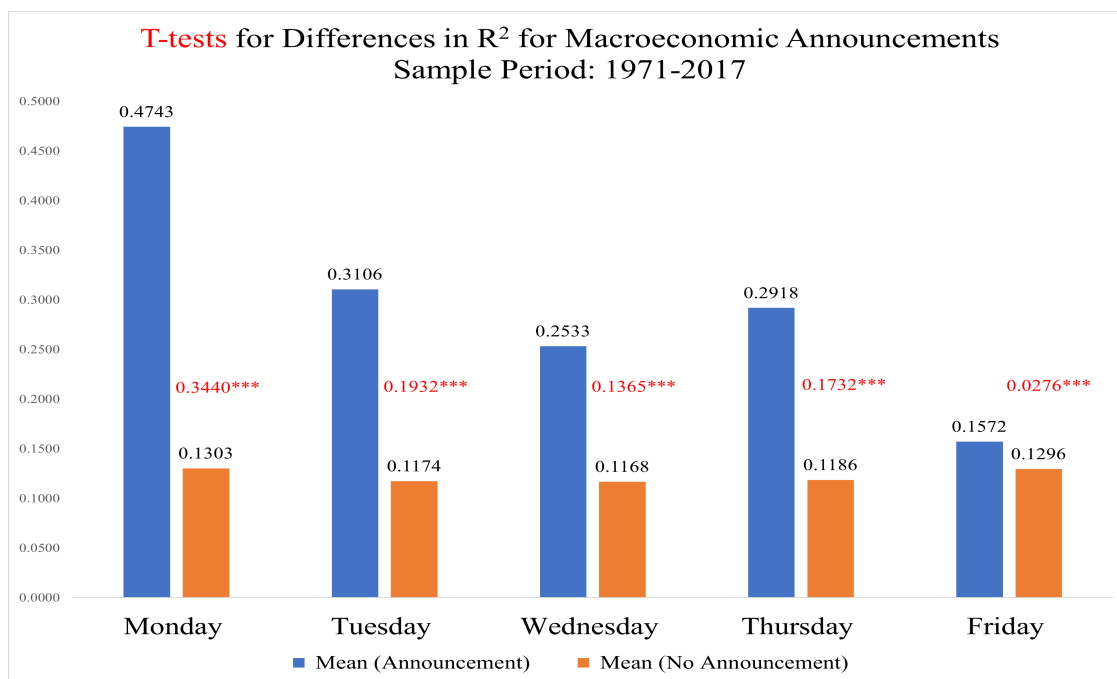
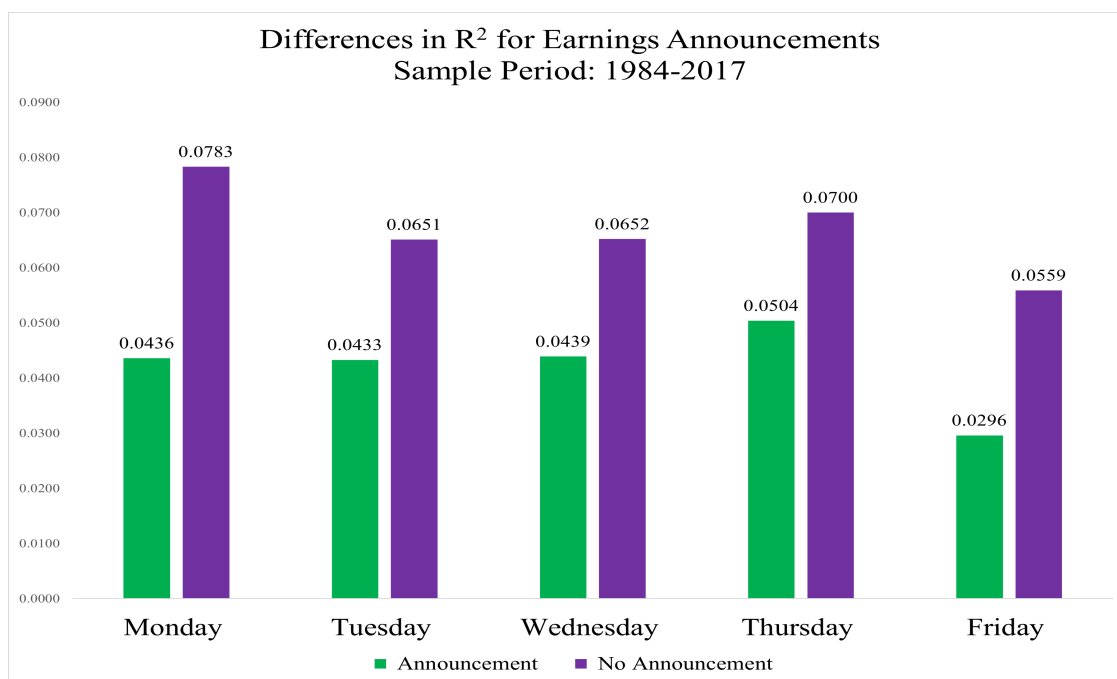


Figure A3: Regressions for Earnings & Macroeconomic Announcements

D_M and D_E are dummy variables for macroeconomic and earnings announcements respectively, and have values of 0 for non-announcement day & 1 for announcement day. Four fixed-effects panel regressions are run separately for each weekday from Monday to Friday for the four combinations of the dummy variables D_M and D_E .



Panel A: R^2 for Macroeconomic Announcements



Panel B: R^2 for Earnings Announcements

Figure A4: Synchronicity Regressions for News Announcements: Longer Sample Period

In **Panel A**, two synchronicity regressions are run for each firm and for each weekday, one for those days on which macroeconomic announcements are released and the other for non-announcement days. Year dummies are included in these regressions. R^2 values from both regressions are compared by t-tests (displayed in red colored text). The sample period extends from 1971 to 2017. In **Panel B**, two pooled Fixed Effects (both firm and year) regressions are run for each weekday, one for those days on which earnings announcements are released and the other for non-announcement days. R^2 values of the pooled regressions are reported. The sample period extends from 1984 to 2017. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

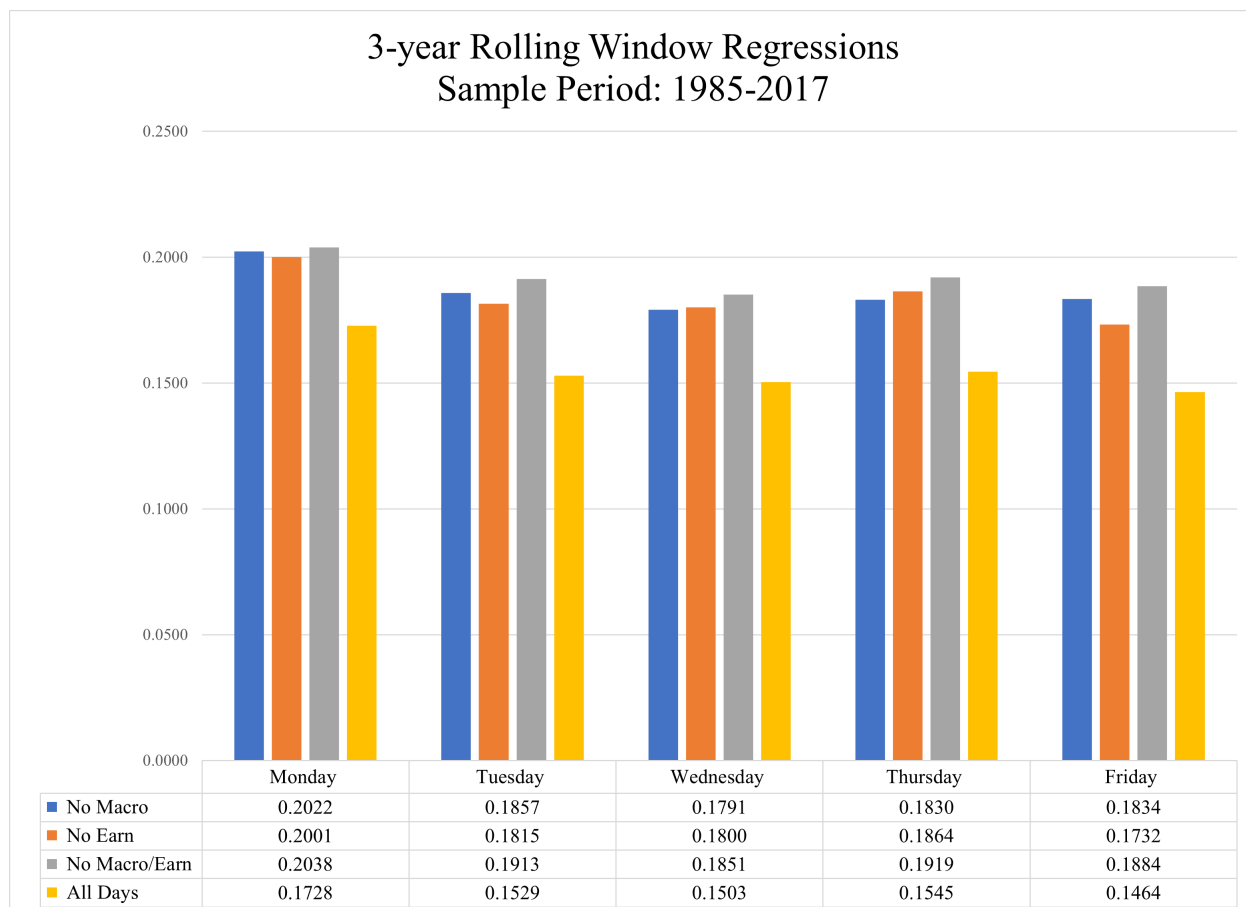


Figure A5: Rolling Window Regressions by Weekday: Longer Sample Period

All regressions are run for each firm and each weekday using a 3-year rolling window. The sample period extends from 1985 to 2017 and includes six macroeconomic announcements (PMI, NFPAY, FOMC, PPI, CPI, and GDP). Average R^2 values from these regressions are reported. Macroeconomic announcement days are removed in the row labeled “No Macro”, earnings announcement days are removed in the row labeled “No Earn”, while both macroeconomic and earnings announcement days are removed in the row labeled “No Macro/Earn”, while all days are included in the row labeled “All Days”.

Table A5: Weighted Average R^2 based on Macroeconomic Announcements: Longer Sample Period

The sample period extends from 1971 to 2017. In Panel A, the average values of R^2 , denoted as $Avg.R^2_{Ann.}$ and $Avg.R^2_{NoAnn.}$, are obtained from firm-level synchronicity regressions, run separately for announcement and non-announcement days for each weekday. The weights ($W_{Ann.}$ and $W_{NoAnn.}$) are based on the frequency of announcement and non-announcement days, relative to all days. The weighted average is calculated by first multiplying the weights with the respective average R^2 values, and then adding them together. $Wtd.Avg.R^2 = W_{Ann.} * Avg.R^2_{Ann.} + W_{NoAnn.} * Avg.R^2_{NoAnn.}$. $\% \Delta R^2$ is the percentage change in R^2 of non-Monday days relative to Monday. Panel B includes the averages of R^2 obtained from the firm-year synchronicity regressions (as in Table 1) for comparison with weighted averages of R^2 in Panel A.

Panel A: Firm-Level Regressions

Weekday	(1) Ann.	(2) Non-Ann.	(3) Total Days	(4) $W_{Ann.}$	(5) $W_{NoAnn.}$	(6) $Avg.R^2_{Ann.}$	(7) $Avg.R^2_{NoAnn.}$	(8) $Wtd.Avg.R^2$	(9) $\% \Delta R^2$
Monday	225	2024	2249	10.00%	90.00%	0.4743	0.1303	0.1647	
Tuesday	397	2028	2,425	16.37%	83.63%	0.3106	0.1174	0.1490	-9.52%
Wednesday	547	1884	2,431	22.50%	77.50%	0.2533	0.1168	0.1475	-10.44%
Thursday	416	1965	2,381	17.47%	82.53%	0.2918	0.1186	0.1489	-9.63%
Friday	1054	1316	2,370	44.47%	55.53%	0.1572	0.1296	0.1419	-13.87%

Panel B: Comparison with Average R^2 of Firm-Year Regressions (from Table 1)

	Sample Period 1971–2017		Sample Period 1953–2017	
	(1) $Avg.R^2$	(2) $\% \Delta R^2$	(3) $Avg.R^2$	(4) $\% \Delta R^2$
Weekday				
Monday	0.2157		0.2177	
Tuesday	0.1951	-9.57%	0.1968	-9.62%
Wednesday	0.1930	-10.54%	0.1948	-10.52%
Thursday	0.1959	-9.18%	0.1972	-9.43%
Friday	0.1906	-11.63%	0.1910	-12.27%

6.5 VIX over long weekends

Table A6: Daily Averages of VIX

The daily averages of the closing value of *VIX* are reported for the period 1998-2017. “Normal Week” is defined as a week which is preceded by trading on previous week’s Friday and has usual trading on Monday. “Friday Holiday” is defined as a week preceded by a trading holiday on previous week’s Friday. “Monday Holiday” is defined as a week in which there is a trading holiday on Monday.

	(1) Normal Week	(2) Friday Holiday	(3) Monday Holiday
Monday	20.660	20.013	
Tuesday	20.475	19.552	20.264
Wednesday	20.425	19.721	20.022
Thursday	20.348	19.982	19.938
Friday	20.281	19.671	19.989

6.6 Retail investor attention to macroeconomic announcements

We compute standardized Google SVIs for five other macroeconomic announcements (CCI, CPI, PPI, GDP and TRBAL), in addition to PMI, PCE, NFPAY and FOMC. The averages are calculated separately for announcement days and non-announcement days for each weekday. The results for all nine types of macroeconomic announcements are shown in Table A7.

Table A7: Standardized Retail Attention to Macroeconomic Announcements

The sample period extends from 2004 to 2017. For each type of macroeconomic announcement, the averages of the the standardized SVI are reported separately for announcement days and non-announcement days. The SVIs are standardized by subtracting each value in a given year with its annual mean and dividing it by its annual standard deviation.

PMI				FOMC				CCI			
Weekday	Non-Ann.	Ann.	Total	Weekday	Non-Ann.	Ann.	Total	Weekday	Non-Ann.	Ann.	Total
Sunday	-0.409		-0.409	Sunday	-0.396		-0.396	Sunday	-0.437		-0.437
Monday	0.000	2.017	0.175	Monday	0.029		0.029	Monday	0.023		0.023
Tuesday	0.135	2.103	0.219	Tuesday	0.143	4.244	0.317	Tuesday	0.040	1.984	0.471
Wednesday	0.049	1.502	0.101	Wednesday	0.153	4.610	0.629	Wednesday	0.163	0.011	0.163
Thursday	0.123	1.644	0.171	Thursday	0.000	6.159	0.042	Thursday	0.030	1.313	0.037
Friday	0.079	1.721	0.135	Friday	-0.156		-0.156	Friday	0.210		0.210
Saturday	-0.390		-0.390	Saturday	-0.463		-0.463	Saturday	-0.466		-0.466
Total	-0.063	1.858	0.000	Total	-0.104	4.579	0.000	Total	-0.066	1.944	0.000

PCE				PPI				TRBAL			
Weekday	Non-Ann.	Ann.	Total	Weekday	Non-Ann.	Ann.	Total	Weekday	Non-Ann.	Ann.	Total
Sunday	-0.427		-0.427	Sunday	-0.480		-0.480	Sunday	-0.244		-0.244
Monday	0.142	1.170	0.211	Monday	0.156		0.156	Monday	0.160	0.409	0.161
Tuesday	0.182	0.691	0.191	Tuesday	0.247	1.243	0.327	Tuesday	0.159	1.256	0.212
Wednesday	0.192	0.904	0.205	Wednesday	0.190	1.705	0.257	Wednesday	0.217	0.809	0.246
Thursday	0.102	0.649	0.123	Thursday	0.189	1.587	0.261	Thursday	0.122	1.165	0.193
Friday	-0.016	1.022	0.075	Friday	-0.010	1.286	0.059	Friday	-0.107	0.725	-0.054
Saturday	-0.379		-0.379	Saturday	-0.579		-0.579	Saturday	-0.513		-0.513
Total	-0.033	0.967	0.000	Total	-0.048	1.419	0.000	Total	-0.033	0.983	0.000

NFPAY				CPI				GDP			
Weekday	Non-Ann.	Ann.	Total	Weekday	Non-Ann.	Ann.	Total	Weekday	Non-Ann.	Ann.	Total
Sunday	-0.274		-0.274	Sunday	-1.072		-1.072	Sunday	-0.500		-0.500
Monday	-0.100		-0.100	Monday	0.324		0.324	Monday	0.257		0.257
Tuesday	-0.101	2.259	-0.098	Tuesday	0.528	1.625	0.568	Tuesday	0.332		0.332
Wednesday	-0.105		-0.105	Wednesday	0.489	1.999	0.613	Wednesday	0.349	2.172	0.374
Thursday	0.142	1.991	0.152	Thursday	0.467	1.573	0.521	Thursday	0.358	2.021	0.388
Friday	-0.173	3.546	0.656	Friday	0.118	1.301	0.191	Friday	-0.078	1.156	-0.022
Saturday	-0.231		-0.231	Saturday	-1.143		-1.143	Saturday	-0.829		-0.829
Total	-0.119	3.501	0.000	Total	-0.056	1.661	0.000	Total	-0.017	1.538	0.000

6.7 Structural VAR variance decomposition

We follow the variance decomposition model by Brogaard *et al.* (2022) to distinguish the role of market-wide information, firm-specific public information, firm-specific private information and noise to test which of these components drive the higher comovement observed on Mondays. Specifically, we use the cumulative impulse response functions (IRFs) from the following structural VAR model to estimate the three components of efficient price—market-wide information, private firm-specific information and public firm-specific information:

$$\begin{aligned} r_{m,t} &= \sum_{l=1}^5 a_{1,l} r_{m,t-l} + \sum_{l=1}^5 a_{2,l} x_{t-l} + \sum_{l=1}^5 a_{3,l} r_{t-l} + \varepsilon_{r_m,t} \\ x_t &= \sum_{l=1}^5 b_{1,l} r_{m,t-l} + \sum_{l=1}^5 b_{2,l} x_{t-l} + \sum_{l=1}^5 b_{3,l} r_{t-l} + \varepsilon_{x,t} \\ r_t &= \sum_{l=1}^5 c_{1,l} r_{m,t-l} + \sum_{l=1}^5 c_{2,l} x_{t-l} + \sum_{l=1}^5 c_{3,l} r_{t-l} + \varepsilon_{r,t} \end{aligned} \quad (A4)$$

where $r_{m,t}$ is the market return, x_t is the signed dollar volume of trading in the given stock, and r_t is the stock return. The innovations in efficient price w_t can be decomposed into three information components:

$$w_t = \theta_{r_m} \varepsilon_{r_m,t} + \theta_x \varepsilon_{x,t} + \theta_r \varepsilon_{r,t} \quad (A5)$$

where θ_{r_m} , θ_x and θ_r are the cumulative IRFs, while $\varepsilon_{r_m,t}$, $\varepsilon_{x,t}$ and $\varepsilon_{r,t}$ are the residuals from the structural VAR model. Thus, stock returns can be represented as the sum of the constant discount rate μ , three information components ($\theta_{r_m} \varepsilon_{r_m,t}$, $\theta_x \varepsilon_{x,t}$, $\theta_r \varepsilon_{r,t}$), and noise Δs_t :

$$r_t = \mu + \theta_{r_m} \varepsilon_{r_m,t} + \theta_x \varepsilon_{x,t} + \theta_r \varepsilon_{r,t} + \Delta s_t \quad (A6)$$

The change in the pricing error (noise return) can then be estimated by rearranging the above equation: $\Delta s_t = r_t - \mu - \theta_{r_m} \varepsilon_{r_m,t} - \theta_x \varepsilon_{x,t} - \theta_r \varepsilon_{r,t}$. The four variance components are then computed

by taking the variances of the information components and noise return²¹:

$$\begin{aligned}
MktInfo &= \theta_{r_m}^2 \varepsilon_{r_m,t}^2 \\
PrivateInfo &= \theta_x^2 \varepsilon_{x,t}^2 \\
PublicInfo &= \theta_r^2 \varepsilon_{r,t}^2 \\
Noise &= \sigma_s^2
\end{aligned} \tag{A7}$$

Since the errors in the structural model are contemporaneously uncorrelated by design, the covariance terms are all zero. Hence, the variance of the innovations in the efficient price is simply the sum of the variances of the three information components: $\sigma_w^2 = \theta_{r_m}^2 \varepsilon_{r_m,t}^2 + \theta_x^2 \varepsilon_{x,t}^2 + \theta_r^2 \varepsilon_{r,t}^2$. The variance components are normalized so that the sum of component shares amounts to 100%:

$$\begin{aligned}
MktInfoShare &= \theta_{r_m}^2 \varepsilon_{r_m,t}^2 / (\sigma_w^2 + \sigma_s^2) \\
PrivateInfoShare &= \theta_x^2 \varepsilon_{x,t}^2 / (\sigma_w^2 + \sigma_s^2) \\
PublicInfoShare &= \theta_r^2 \varepsilon_{r,t}^2 / (\sigma_w^2 + \sigma_s^2) \\
NoiseShare &= \sigma_s^2 / (\sigma_w^2 + \sigma_s^2)
\end{aligned} \tag{A8}$$

We run the VAR model for each firm and each weekday in each 5-year period for the 1953-2017 period. Duplicate stock-day observations and observations with missing return, volume, or price are removed. Stock-periods with fewer than 100 valid daily observations are removed to ensure the VAR has a sufficient number of observations. In Table A8, we report the average variance components using both variance-weighting and equal-weighting methods. In Table A9, we report the variance-weighted averages for 1953-1997 and 1998-2017 periods and t-tests for differences between them.

The results in Table A8 show that the share of market-wide component on Mondays is 8.32% which is more than four times the average for other weekdays at 2.03%. Moreover, the shares of private and public firm-specific information components is lower for Mondays. The pattern of higher share of market-wide component and lower shares of firm-specific components for Mondays

²¹ Since the discount rate is a constant and does not contribute to the variance, it is not required for calculating the variance of Δs_t

is consistent with our explanation that stock prices are driven relatively more by the market-wide effect of macroeconomic announcements. The share of noise is not significantly different on Monday. The results are robust to both equal-weighted means and variance-weighted means. The share of market-wide component remains higher for Monday across the two sub-samples analysed in Table A9.

Table A8: Stock-return Variance Components by Weekday

The table reports the mean variance shares (expressed as percentages of variance) for the period from 1953 to 2017. Stock-return variance is decomposed into market-wide information (MktInfo Share), private firm-specific information (PrivateInfo Share), public firm-specific information (PublicInfo Share), and noise (Noise Share) following Brogaard *et al.* (2022). The VAR model is run separately for each weekday for each firm in each 5-year rolling window. The variance-component shares are calculated separately for each stock in each 5-year period, and then averaged across stocks using the variance-weighted means (**Panel A**) and equal-weighted means (**Panel B**). The 99% confidence intervals are in square brackets.

Panel A: Variance-Weighted Averages				
	MktInfo Share(%) [99% CI]	PrivateInfo Share(%) [99% CI]	PublicInfo Share(%) [99% CI]	Noise Share(%) [99% CI]
Monday	8.323 [7.800–8.846]	8.884 [8.350–9.418]	31.475 [30.751–32.199]	51.318 [49.046–53.591]
Tuesday	1.072 [1.039–1.106]	12.245 [11.148–13.341]	35.132 [34.288–35.976]	51.551 [49.417–53.685]
Wednesday	2.008 [1.926–2.089]	13.356 [10.525–16.186]	35.019 [34.125–35.913]	49.618 [45.523–53.712]
Thursday	2.620 [2.533–2.708]	12.086 [10.551–13.621]	34.849 [34.134–35.565]	50.445 [47.681–53.208]
Friday	2.409 [2.339–2.479]	12.332 [11.522–13.143]	34.580 [33.900–35.260]	50.679 [48.864–52.494]
Panel B: Equal-Weighted Averages				
Monday	12.545 [12.337–12.754]	5.847 [5.697–5.998]	34.301 [33.990–34.612]	47.306 [47.090–47.523]
Tuesday	1.401 [1.370–1.432]	7.231 [7.057–7.405]	42.038 [41.776–42.301]	49.330 [49.116–49.544]
Wednesday	2.613 [2.551–2.676]	7.445 [7.269–7.622]	42.796 [42.530–43.061]	47.146 [46.934–47.358]
Thursday	3.423 [3.3479–3.498]	7.348 [7.172–7.523]	42.827 [42.560–43.094]	46.403 [46.191–46.614]
Friday	3.324 [3.251–3.398]	7.505 [7.327–7.683]	41.658 [41.393–41.923]	47.512 [47.298–47.727]

Table A9: Sub-sample Analysis for Stock-return Variance Components by Weekday

The table reports the mean variance shares (expressed as percentages of variance) for the 1953-1997 and 1998-2017 periods. Stock-return variance is decomposed into market-wide information (MktInfo Share), private firm-specific information (PrivateInfo Share), public firm-specific information (PublicInfo Share), and noise (Noise Share) following Brogaard *et al.* (2022). The VAR model is run separately for each weekday for each firm in each 5-year rolling window. The variance-component shares are calculated separately for each stock in each 5-year period, and then averaged across stocks using the variance-weighted means. The differences in means for the post-1998 period minus the pre-1998 period are also reported. The differences are statistically significant at * $p < .10$, ** $p < .05$, and *** $p < .01$. Values of the t-tests are in parentheses.

		MktInfo Share(%)	PrivateInfo Share(%)	PublicInfo Share(%)	Noise Share(%)
Monday	1953-1997	9.806	11.379	25.180	53.635
	1998-2017	6.521	5.853	39.122	48.504
	Difference (Post-Pre 1998)	-3.285***	-5.526***	13.94***	-5.131**
		(-7.675)	(-12.587)	(24.815)	(-2.755)
Tuesday	1953-1997	0.800	15.659	31.846	51.695
	1998-2017	1.395	8.195	39.030	51.380
	Difference (Post-Pre 1998)	0.594***	-7.464***	7.185***	-0.315
		(23.589)	(-9.004)	(10.571)	(-0.189)
Wednesday	1953-1997	1.649	16.495	30.945	50.911
	1998-2017	2.430	9.657	39.820	48.093
	Difference (Post-Pre 1998)	0.781***	-6.838***	8.875***	-2.819
		(12.988)	(-3.399)	(12.157)	(-0.958)
Thursday	1953-1997	2.016	15.345	30.948	51.691
	1998-2017	3.345	8.174	39.532	48.949
	Difference (Post-Pre 1998)	1.330***	-7.171***	8.584***	-2.742
		(20.173)	(-6.181)	(15.448)	(-1.279)
Friday	1953-1997	1.980	15.981	30.672	51.367
	1998-2017	2.941	7.808	39.424	49.827
	Difference (Post-Pre 1998)	0.960***	-8.173***	8.752***	-1.539
		(17.861)	(-12.820)	(16.612)	(-1.067)

6.8 Firm characteristics and investor sentiment

Table A10: Firm Fundamentals and Industry Variables

Variable Name	Description
Firm Size	$\ln(MKT.CAP)_{i,y}$ is the natural log of market capitalization of stock i calculated at the end of calendar year y .
CAPM Beta	$\beta_{i,y}$ is obtained from rolling CAPM regression for the firm i in calendar year y using excess stock returns and excess market returns: $R_{i,y} - R_{f,y} = \alpha_y + \beta (R_{Mkt,y} - R_{f,y}) + \epsilon_y$
Idiosyncratic Volatility	$IVOL_{i,y}$ is the root mean squared errors obtained from rolling Fama-French Three Factor regression for the firm i in calendar year y : $R_{i,y} - R_{f,y} = \alpha_y + \beta_1 (R_{Mkt,y} - R_{f,y}) + \beta_2 SMB_y + \beta_3 HML_y + \epsilon_y$
Turnover	$TURNOVER_{i,y}$ is the average monthly turnover of firm i for calendar year y .
BM Ratio	$BK/MKT_{i,y}$ is the book-to-market ratio for the firm i at the end of calendar year y .
Leverage	$LEV_{i,y}$ is the debt to equity ratio for the firm i at the end of calendar year y .
ROA	$ROA_{i,y}$ is the return on assets ratio for the firm i at the end of calendar year y .
Volatility of ROA	$SD(ROA)_{i,y}$ is the 5-year rolling standard deviation of return on assets of the firm i in calendar year y .
Analyst Coverage	$LOGCOVER_{i,y}$ is the natural log of 1 + No. of Analysts covering the firm i in calendar year y .
Industry Size	$\ln(IND.ASSETS)_{i,y}$ is the log of total assets of all firms in the Industry for the firm i at the end of calendar year y .
Firm Count per Industry	$\ln(IND.COUNT)_{i,y}$ is the log of the number of firms in the Industry for the firm i at the end of calendar year y .
Firm Age	$\ln(AGE)_{i,y}$ is the log of the firm i 's age in calendar year y .

Table A11: Fixed Effects Regressions: Differences in Synchronicity & Scaled Differences

The sample period extends from 1955 to 2017. The R^2 values are obtained by regressing stock returns on CRSP Value-weighted Index returns (and its lagged term) and Fama-French 48 Industry returns (and its lagged term) for each weekday from Monday to Friday for each stock in each calendar year. $\Delta SYNCH_{i,d,y}$ is the difference between the logarithmic transformation of R-squared $\left[\ln \left(\frac{R^2}{1-R^2} \right) \right]$ of Monday and that of other weekdays. $Scaled\Delta R^2_{i,d,y}$ is the difference between the R-squared of Monday and that of other weekdays, scaled by the average of R-squared across the week from Monday to Friday i.e. $\frac{\Delta R^2_{i,d,y}}{\sum_{d=1}^5 R^2_{i,d,y}/5}$. $\beta_{i,y}$ is the coefficient of the firm i in calendar year y , obtained from a CAPM regression. $TURNOVER_{i,y}$ is the average monthly turnover of the firm i in calendar year y . $IVOL_{i,y}$ is the root mean squared error obtained from rolling Fama-French Three Factor regression, for the firm i in calendar year y . $\ln(MKT.CAP)_{i,y-1}$ is the log of market capitalization for the firm i at the end of calendar year $y-1$. $BK/MKT_{i,y-1}$ is the book-to-market ratio for the firm i at the end of calendar year $y-1$. $LEV_{i,y-1}$ is the leverage ratio (debt/equity) of the firm i in calendar year $y-1$. $ROA_{i,y-1}$ is the return on assets of the firm i in calendar year $y-1$. The t-statistics based on cluster-robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables	Monday-Tuesday		Monday-Wednesday		Monday-Thursday		Monday-Friday	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\beta_{i,y}$	$\Delta SYNCH_{i,d,y}$	$Scaled\Delta R^2_{i,d,y}$	$\Delta SYNCH_{i,d,y}$	$Scaled\Delta R^2_{i,d,y}$	$\Delta SYNCH_{i,d,y}$	$Scaled\Delta R^2_{i,d,y}$	$\Delta SYNCH_{i,d,y}$	$Scaled\Delta R^2_{i,d,y}$
$TURNOVER_{i,y}$	0.017** (2.558)	0.006 (1.327)	0.014** (2.188)	0.003 (0.698)	0.036*** (5.527)	0.018*** (3.857)	0.085*** (13.008)	0.045*** (9.474)
$IVOL_{i,y}$	0.006 (0.260)	-0.006 (-0.336)	0.056*** (2.563)	0.029* (1.708)	0.086*** (3.828)	0.052*** (3.149)	0.108*** (4.733)	0.061*** (3.599)
$\ln(MKT.CAP)_{i,y-1}$	-1.762*** (-5.022)	-0.926*** (-3.432)	-1.872*** (-5.443)	-1.090*** (-4.175)	-1.570*** (-4.449)	-0.989*** (-3.639)	-2.035*** (-5.904)	-1.112*** (-4.205)
$BK/MKT_{i,y-1}$	-0.000 (-0.043)	-0.004 (-1.253)	0.000 (0.083)	-0.005* (-1.716)	0.004 (0.981)	-0.000 (-0.115)	-0.001 (-0.206)	-0.004 (-1.406)
$LEV_{i,y-1}$	-0.000 (-0.035)	0.000 (0.094)	-0.000 (-0.005)	-0.002 (-0.611)	0.015** (2.482)	0.014*** (2.586)	-0.006 (-0.845)	-0.004 (-0.855)
$ROA_{i,y-1}$	-0.000 (-0.417)	-0.000 (-0.207)	-0.000 (-0.551)	-0.000 (-0.260)	0.000 (0.714)	0.000 (1.026)	0.000 (0.735)	0.000 (0.899)
Constant	-0.000 (-0.452)	0.000 (0.155)	0.000 (0.499)	0.000 (1.198)	-0.000 (-0.194)	-0.000 (-0.094)	0.000 (1.284)	0.000* (1.715)
	-0.316*** (-3.811)	-0.180*** (-2.885)	0.049 (0.606)	0.110* (1.856)	0.019 (0.229)	0.064 (1.081)	0.062 (0.764)	0.109* (1.894)
Observations	180,416	180,424	177,851	177,858	180,266	180,274	180,322	180,331
R^2	0.0300	0.0250	0.0259	0.0228	0.0280	0.0247	0.0401	0.0276
F	71.17	60.58	60.31	53.11	69.58	61.89	102.2	76.70
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A12: Panel Regressions: Addition of Analyst Coverage and ROA Volatility

The R^2 values are obtained by regressing stock returns on CRSP Value-weighted Index returns (and its lagged term) and Fama-French 48 Industry returns (and its lagged term) for each weekday from Monday to Friday for each stock in each calendar year. The dependent variable, $\Delta R^2_{i,t,y}$, is the difference between R-squared of Monday and that of other weekdays. $\beta_{i,y}$ is the coefficient of the firm i in calendar year y , obtained from a CAPM regression. $TURNOVER_{i,y}$ is the average monthly turnover of the firm i in calendar year y . $IVOL_{i,y}$ is the root mean squared error obtained from rolling Fama-French Three Factor regression, for the firm i in calendar year y . $\ln(MKT.CAP)_{i,y-1}$ is the log of market capitalization for the firm i at the end of calendar year $y-1$. $BK/MKT_{i,y-1}$ is the book-to-market ratio for the firm i at the end of calendar year $y-1$. $LEV_{i,y-1}$ is the leverage ratio (debt/equity) of the firm i in calendar year $y-1$. $ROA_{i,y-1}$ is the return on assets of the firm i in calendar year $y-1$. $LOGCOVER_{i,y-1}$ is the natural log of 1 + No. of Analysts covering the firm i in calendar year $y-1$. $SD(ROA)_{i,y-1}$ is the 5-year rolling standard deviation of return on assets of the firm i in calendar year $y-1$. The t-statistics (based on cluster-robust standard errors) are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables	Monday-Tuesday (1)	(2)	Monday-Wednesday (3)	(4)	Monday-Thursday (5)	(6)	Monday-Friday (7)	(8)
$\beta_{i,y}$	0.415*** (3.678)	0.622*** (7.679)	0.952*** (8.400)	0.754*** (9.103)	0.700*** (5.982)	0.886*** (10.738)	1.863*** (15.881)	1.831*** (22.142)
$TURNOVER_{i,y}$	-0.208 (-0.595)	-0.171 (-0.620)	0.791** (2.268)	0.719*** (2.674)	1.677*** (4.402)	1.097*** (3.887)	1.607*** (4.223)	1.266*** (4.380)
$IVOL_{i,y}$	-64.605*** (-10.976)	-34.608*** (-9.525)	-76.611*** (-13.252)	-40.041*** (-11.191)	-58.498*** (-9.560)	-30.600*** (-8.375)	-63.222*** (-10.510)	-37.469*** (-10.367)
$\ln(MKT.CAP)_{i,y-1}$	-0.143* (-1.747)	0.109** (2.226)	-0.109 (-1.359)	0.114** (2.345)	0.062 (0.734)	0.173*** (3.455)	0.007 (0.082)	0.146*** (2.977)
$BK/MKT_{i,y-1}$	0.053 (0.371)	0.020 (0.378)	0.110 (0.547)	0.020 (0.463)	0.070 (0.304)	0.205*** (2.734)	-0.162 (-1.011)	-0.011 (-0.180)
$LEV_{i,y-1}$	0.004 (0.989)	0.001 (0.335)	0.001 (0.214)	-0.001 (-0.224)	0.006 (1.419)	0.004 (1.388)	0.004 (1.028)	0.001 (0.293)
$ROA_{i,y-1}$	-0.002 (-0.948)		-0.000 (-0.228)		0.001 (0.325)		0.003 (1.529)	
$LOGCOVER_{i,y-1}$	1.293*** (4.531)		1.597*** (5.591)		0.653** (2.169)		0.131 (0.450)	
$SD(ROA)_{i,y-1}$		-0.000 (-0.444)		-0.000 (-0.786)		0.000 (0.423)		0.000 (0.186)
Constant	-0.195 (-0.130)	-7.824*** (-6.985)	-1.123 (-0.771)	-2.060** (-1.985)	-2.596* (-1.653)	-2.735** (-2.506)	-0.300 (-0.195)	-1.893* (-1.848)
Observations	106,990	173,063	106,974	170,569	106,934	172,968	106,979	172,995
R^2	0.0786	0.0562	0.0620	0.0462	0.0552	0.0465	0.1154	0.0867
F	139.9	97.42	107.3	86.39	106.5	92.60	202.0	141.4
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A13: Panel Regressions: Addition of Industry Variables and Firm Age

The sample period extends from 1955 to 2017. The R^2 values are obtained by regressing stock returns on CRSP Value-weighted Index returns (and its lagged term) and Fama-French 48 Industry returns (and its lagged term) for each weekday from Monday to Friday for each stock in each calendar year. The dependent variable, $\Delta R^2_{i,t,y}$, is the difference between R-squared of Monday and that of other weekdays. $\beta_{i,y}$ is the coefficient of the firm i in calendar year y , obtained from a CAPM regression. $TURNOVER_{i,y}$ is the average monthly turnover of the firm i in calendar year y . $IVOL_{i,y}$ is the root mean squared error obtained from rolling Fama-French Three Factor regression, for the firm i in calendar year y . $\ln(MKT.CAP)_{i,y-1}$ is the log of market capitalization for the firm i at the end of calendar year $y-1$. $BK/MKT_{i,y-1}$ is the book-to-market ratio for the firm i at the end of calendar year $y-1$. $LEV_{i,y-1}$ is the leverage ratio (debt/equity) of the firm i in calendar year $y-1$. $ROA_{i,y-1}$ is the return on assets of the firm i in calendar year $y-1$. $\ln(AGE)_{i,y-1}$ is the log of firm's age in calendar year $y-1$. $\ln(IND.ASSETS)_{i,y-1}$ is the log of total assets of all firms in the industry for the firm i at the end of calendar year $y-1$. $\ln(IND.COUNT)_{i,y-1}$ is the log of the number of firms in the industry for the firm i in calendar year $y-1$. The t-statistics (based on cluster-robust standard errors) are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables	Monday-Tuesday			Monday-Wednesday			Monday-Thursday			Monday-Friday		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\beta_{i,y}$	0.731*** (10.806)	0.663*** (8.353)	0.779*** (11.520)	0.759*** (9.368)	1.012*** (14.895)	0.906*** (11.249)	1.956*** (29.301)	1.818*** (22.516)	1.956*** (29.301)	1.956*** (29.301)	1.956*** (29.301)	1.956*** (29.301)
$TURNOVER_{i,y}$	0.162 (0.698)	-0.203 (-0.748)	1.552*** (6.851)	0.729*** (2.734)	1.795*** (7.116)	1.110*** (3.988)	1.935*** (7.780)	1.291*** (4.528)	1.935*** (7.780)	1.935*** (7.780)	1.935*** (7.780)	1.935*** (7.780)
$IVOL_{i,y}$	-29.390*** (-12.007)	-34.598*** (-9.813)	-33.945*** (-13.989)	-40.591*** (-11.703)	-22.788*** (-9.276)	-31.343*** (-8.826)	-29.879*** (-12.209)	-36.806*** (-10.460)	-29.879*** (-12.209)	-29.879*** (-12.209)	-29.879*** (-12.209)	-29.879*** (-12.209)
$\ln(MKT.CAP)_{i,y-1}$	0.166*** (6.690)	0.130*** (2.702)	0.304*** (12.336)	0.108*** (2.263)	0.267*** (10.441)	0.180*** (3.656)	0.141*** (5.516)	0.142*** (2.918)	0.141*** (5.516)	0.141*** (5.516)	0.141*** (5.516)	0.141*** (5.516)
$BK/MKT_{i,y-1}$	0.030 (0.731)	0.022 (0.373)	0.076 (1.083)	0.004 (0.101)	0.162*** (3.070)	0.183*** (2.439)	-0.054 (-0.968)	-0.057 (-0.975)	-0.054 (-0.968)	-0.054 (-0.968)	-0.054 (-0.968)	-0.057 (-0.975)
$LEV_{i,y-1}$	0.005*** (2.885)	0.001 (0.419)	-0.001 (-0.392)	0.000 (0.117)	0.002 (1.410)	0.005* (1.687)	0.003* (1.657)	0.002 (0.723)	0.003* (1.657)	0.003* (1.657)	0.003* (1.657)	0.002 (0.723)
$ROA_{i,y-1}$	-0.000 (-0.445)	-0.000 (-0.408)	0.001 (0.941)	0.000 (0.339)	0.002** (2.344)	-0.000 (-0.013)	0.003*** (3.901)	0.002 (1.542)	0.003*** (3.901)	0.003*** (3.901)	0.003*** (3.901)	0.002 (1.542)
$\ln(IND.ASSETS)_{i,y-1}$	-0.160*** (-6.489)	-0.476*** (-3.307)	-0.196*** (-7.925)	0.096 (0.664)	-0.211*** (-8.399)	-0.711*** (-4.616)	-0.125*** (-5.167)	-0.394*** (-2.708)	-0.125*** (-5.167)	-0.125*** (-5.167)	-0.125*** (-5.167)	-0.394*** (-2.708)
$\ln(IND.COUNT)_{i,y-1}$	0.088** (2.091)	0.217*** (2.614)	0.170*** (4.009)	0.222*** (2.638)	0.192*** (4.477)	0.297*** (3.408)	0.177*** (4.193)	0.211** (2.512)	0.177*** (4.193)	0.177*** (4.193)	0.177*** (4.193)	0.211** (2.512)
$\ln(AGE)_{i,y-1}$	-0.022 (-0.517)	0.244** (2.101)	-0.129*** (-3.015)	0.122 (1.028)	-0.136*** (-3.208)	0.373*** (3.114)	-0.213*** (-5.059)	0.239*** (2.114)	-0.213*** (-5.059)	-0.213*** (-5.059)	-0.213*** (-5.059)	0.239*** (2.114)
Constant	-8.029*** (-8.965)	-5.387*** (-3.377)	-4.349*** (-5.227)	-3.745** (-2.458)	-3.426*** (-3.984)	1.570 (0.946)	-1.792** (-2.191)	0.429 (0.289)	-1.792** (-2.191)	-1.792** (-2.191)	-1.792** (-2.191)	0.429 (0.289)
Observations	178,740	178,740	176,185	176,185	178,606	178,606	178,647	178,647	178,647	178,647	178,647	178,647
R^2	0.0550	0.0556	0.0489	0.0456	0.0493	0.0461	0.0907	0.0852	0.0907	0.0907	0.0907	0.0852
F	103.5	95.27	98.31	84.14	106.2	90.12	165.3	136.4	165.3	165.3	165.3	136.4
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes