Essays on Behavioural Finance: Effects of Salience and Sleep Deprivation on Asset Pricing

Arbab Khalid Cheema

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Abstract

This thesis comprises three essays; the first two essays are related to an intra-week variation in comovement and its behavioural explanation, and the third essay pertains to the behavioural effect of sleep deprivation on stock returns caused by watching late-night TV shows.

The first essay provides evidence of an intra-week pattern in comovement of stock returns in the U.S., whereby it is significantly higher on Mondays over a 90-year period. The pattern is stronger whether market returns, or individual stocks returns are positive or negative. Hence, the Monday anomaly in returns cannot explain this pattern. Higher (lower) uncertainty over longer (shorter) weekends contributes to increasing (decreasing) Monday's comovement.

The second essay proposes an explanation for higher Monday comovement based on the simultaneous contrast effect, i.e., perception of a stimulus depending on its surrounding environment. Just as a thunder in a quiet night sounds relatively louder, release of macroeconomic news on Mondays, which typically see fewer announcements than other weekdays, leads to a stronger market comovement. These findings are robust after controlling for economic uncertainty, risk aversion, and attention to firm-specific and macroeconomic news.

The third essay provides evidence that the cultural trend of watching late-night TV has become widespread enough to affect financial markets by causing sleep loss. Market returns significantly decline on days following the release of popular late-night TV shows. The effect is stronger in stocks with larger market capitalisation, higher price, higher institutional ownership, and higher B/M ratio. Sleep deprived investors are willing to take less risk and the resulting demand for higher premiums causes current stock prices to decrease. The decline in returns is stronger if market uncertainty is high. These effects are unaccompanied by any change in trading activity of retail or institutional investors.

Thesis Supervisor: Dr. Qingwei Wang

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Chapter 1

Introduction

This thesis focuses on the effect of two psychological phenomena, salience and sleep, on financial markets. First, I look at intra-week patterns of stock return synchronicity in U.S. stock markets and discover that it is higher on Monday. Second, I demonstrate that higher Monday synchronicity can be best explained by the salience of macroeconomic announcements released on Mondays. Third, I find that sleep loss caused by watching late-night TV shows affects stock returns on the following day. This thesis aims to contribute to literature on comovement of stock returns, salience of financial information, and effect of sleep deprivation on equity markets.

At first glance, salience and sleep are distinct processes. Salience is an attentional mechanism by which a stimulus that 'stands out' among others, elicits a stronger response. In simple words, such a stimulus 'catches our eye. The role of sleep disturbance in reducing attention levels and affecting our responses to various stimuli is well known in literature. Sleep is a vital physiological function regulated by the brain's biological clock. Salience also has a physiological dimension in the sense that visual perception plays an important role even in abstract decision making. For example, the colour coding of negative and positive historical price data affects financial decisions. Thus, salience and sleep are not only physiological processes, but they also affect cognitive functions like attention.

1.1 Background

Return synchronicity, the extent to which individual stock returns comove with market and industry portfolio returns, is a well-researched topic in finance literature.[1] Efficient market hypothesis is the cornerstone of modern finance theory. The concept of efficient markets is centred around finding the answer to one question: *Is all available information reflected in current prices?* This question is vital because if stock prices are purely random walks, then all past and present information should provide no predictions about the change that prices will undergo in the future. Apart from information about a specific firm, a piece of information can have implications for the entire market or an entire sector. Thus, comovement becomes an important issue in the investigation of market efficiency because market-wide and/or sector-wide information will cause the prices of multiple stocks to move in the same direction.

Extensive research has been carried out to find the extent to which the movement in stock prices can be explained by market-wide and sector-wide price movement. In econometric terms, the R^2 of the synchronicity regression measures the extent of this comovement. A lower value will indicate that market and sector factors explain only a small part of the price movement. This also implies that the source of unexplained variation is firm-specific information. Therefore, a low R^2 indicates that stock prices are more informative, and hence, markets are more efficient. However, there is no consensus on this explanation in literature.

The debate on comovement still continues, and its relationship with many factors has been investigated. Naturally, some of these factors are directly or indirectly related to the nature of the information environment. Similarly, some factors are related to information-processing because any available information will only get reflected in prices when investors pay attention to it and respond accordingly. Behavioural factors are also important for comovement because they affect information processing.

[1] I use the terms ‘synchronicity’ and ‘comovement’ interchangeably in the thesis.

The aim of this thesis is not to answer whether a low R^2 indicates price informativeness or otherwise. Instead, in the first part, I explore an important question that has received little focus in literature: *Is return synchronicity constant over the entire week, or does it change from one weekday to the other?* In the first part of my thesis, I find it is higher on Monday. Such variation is not surprising given the evidence of intra-week variations in returns, information arrival, processing, level of risk aversion, and uncertainty.

In the second part, I continue to investigate the probable cause of intra-week variation in synchronicity found in the first part. I find that salient macroeconomic announcements on Monday elicit an abnormal response in terms of comovement. This psychological effect best explains the intra-week variation in synchronicity. Historically, salience (and contrast effect) was considered as a physiological phenomenon in which the visual perception is stronger for stimuli which are relatively prominent as compared to other stimuli in the surroundings. Ibn al-Haytham, an 11$^{\text{th}}$ century physicist, described the contrast effect in his book on optics, titled 'Kitāb al-Manāẓir', using the following example: spots of coloured paint appear almost black on a white background; conversely, they appear paler than their true colour on a black background. In recent years, however, salience has received considerable interest in many areas of decision making, like choice of consumer goods and investments. Research has established that salience exists for complex and abstract stimuli besides simple visual inputs. Hence, the concept of salience also applies to complex cognitive mechanisms, such as processing financial information.

Human cultures have long believed that elements of nature like the day-night cycle, lunar cycle, temperature and rainfall affect socio-political behaviour. In modern times, a vast literature exists on the psychological impact of these natural phenomena on our activities, including trading in financial markets. Similarly, sunlight has been associated with hope, optimism, and happiness throughout human history. In recent years, research has established that reduced exposure to sunlight has behavioural effects. Shorter daylight hours in winters have been known to cause mood and sleep disturbances, which in turn affect stock returns (Kamstra *et al.*, 2003). Daylight Saving Time (DST) was introduced to align people's work hours with sunlight hours. However, in a seminal study, Kamstra *et al.* (2000) find that sleep disturbance caused by DST change results in negative stock returns on the following Monday. The body's circadian rhythm regulates sleep and other physiological functions over a 24-hour period. Any disruption in sleep will affect various functions, including cognitive processes required for economic decision making.

In the third part of my thesis, I focus on the effect of sleep deprivation on the stock market. I depart from using fluctuations in sunlight hours or clock time changes, and instead rely on a recent cultural trend that is affecting sleep. Emergence of internet-based streaming services like Netflix or Hulu has brought about a cultural change in TV entertainment. Traditional TV channels usually telecast a single episode in the late-evening or night, but Netflix does it differently. Complete series comprising many hours of viewing time is released simultaneously, usually late in the night at 03:00 AM. Hence, a trend of late-night binge-watching has emerged. Consistent with previous literature on sleep deprivation, I find that market returns are lower on days following the release of the most popular late-night shows.

Table 1.1: Brief Summary of Research Topics

	First Essay	**Second Essay**	**Third Essay**
Research Questions	Is there an intra-week variation in stock return synchronicity?	What explains higher return synchronicity on Monday?	Does sleep deprivation because of late-night TV shows impact stocks returns, trading activity, and liquidity?
Previous Literature	An extensive body of literature on stock return synchronicity exists; however, these studies estimate a firm-year measure of synchronicity by pooling returns within a year. Therefore, intra-week changes in return synchronicity have not been investigated, despite the evidence that stock returns and investor sentiment vary during the week.	There is some evidence that the reaction to macroeconomic announcements is abnormally high on Monday, but both macroeconomic and earnings announcements are more frequently released in the middle of the week. Moreover, uncertainty and risk aversion are higher on Monday after the weekend, during which both market-wide and firm-specific information is usually scarce.	Sleep loss caused by DST change negatively affects aggregate stock returns. The decline in returns is because of anxiety suffered by sleep deprived investors, who prefer safer investments in such circumstances.
My Study	I contribute to literature by testing day-of-the-week return synchronicity by separately regressing each weekday's stock returns with the market and industry returns for the same weekday. I test relationship between the intra-week variations in returns and synchronicity.	I examine the role of macroeconomic and earnings announcements in day-of-the-week return synchronicity. I present a novel explanation based on the simultaneous contrast effect, whereby higher Monday synchronicity can be explained by the salience of a small number of macroeconomic announcements released on Monday. The contrast is notable because Monday is usually a quiet night with only a few announcements; any macroeconomic announcement becomes more salient in this background and an abnormal increase in comovement is observed.	ăăI use a new proxy of sleep deprivation, based on the trend of watching late-night TV shows. I examine the impact on stock returns, volume, and liquidity. I also contribute to the literature on trading activity of retail and institutional investors under conditions of sleep disturbance. I find results consistent with previous literature on the impact of sleep loss on financial markets.
My Findings	I find that return synchronicity is consistently higher on Monday for U.S. stock markets over a long time period. This pattern exists in both up-market and down-market conditions; hence, it is distinct from the infamous Monday anomaly. Moreover, arbitrage constraints also fail to provide an explanation. The intra-week pattern is more (less) prominent after longer (shorter) weekends.	I find that intra-week variation in synchronicity is not a seasonality in the sense that it is high on every Monday. Synchronicity on Monday is abnormally high only occasionally when macroeconomic announcements are released, and not otherwise. Removal of macroeconomic announcement days results in elimination of the intra-week variation. Lower frequency of earnings announcements and heightened uncertainty at the start of the week also contribute to keeping comovement high on Mondays.	I find that market returns are significantly lower on days following late-night TV shows. The results are stronger for stocks with large market cap, high price, high institutional ownership and high B/M ratio. Stock returns decline even further when VIX is high, implying that sleep deprived investors become more risk averse. The decline in stock returns is not accompanied by a drop in liquidity. Similarly, odd lot trading and algorithmic trading are unaffected.

1.2 Motivations & Findings

1.2.1 Day-of-the-week return synchronicity

Despite an extensive literature on stock return synchronicity, an important research gap exists regarding its intra-week variation. Most studies estimate synchronicity regressions using daily or weekly returns data pooled within a year. Thus, intra-week variations in comovement have skipped the attention of these studies. Therefore, in Chapter 3, I estimate separate synchronicity regressions for each weekday from Monday to Friday to compare the R^2 values with each other. My empirical design is motivated by Keloharju *et al.* (2016), who test return seasonalities and find that past same-calendar-month returns can predict current same-calendar-month return. I find that comovement is persistently higher on Monday in U.S. stock markets over a 90-year period.

The question about day-of-the-week synchronicity is interesting for the following reasons: First, it matters for investors with short-term horizons such as day traders. Comovement among asset returns imposes a risk on investors' portfolios, and is a critical input for asset allocation, risk assessment, and hedging (Engle, 2002). Second, information environment is not necessarily constant within a week. The frequency of macroeconomic and firm news is not uniform across the weekdays. Moreover, factors that affect how investors respond to information e.g., investor attention and sentiment, also have intra-week seasonalities (Liu and Peng, 2015; Birru, 2018). Similarly, economic uncertainty and risk aversion also vary across weekdays (Fisher *et al.*, 2021). Therefore, estimation of day-of-the-week return synchronicity provides an opportunity to explore how these time-varying factors are related to any intra-week variation in synchronicity.

The next logical question is obviously what explains higher Monday comovement. When the word "Monday" appears in reference to a seasonal variation, attention is naturally drawn towards the infamous Monday anomaly in returns. *Is Monday synchronicity effect another manifestation of the Monday anomaly?* I find that Monday anomaly is unrelated to higher Monday comovement.

Since information arrival and its processing slow down over the weekend, uncertainty is expected to be high at the start of the week on Monday. Comovement could be higher if investors prefer to learn more about market-wide information, which is more valuable for resolving uncertainty (Kacperczyk *et al.*, 2016), and is also consistent with category-learning behaviour described by Peng and Xiong (2006). I use the length of the weekend to test the relationship between uncertainty over the weekend and Monday synchronicity, and find evidence in support of its role. I find that longer (shorter) weekends lead to relatively higher (lower) comovement at the start of the following week.

1.2.2 Contrast effect of Monday macro announcements

I continue my investigation for a plausible explanation of higher Monday comovement in Chapter 4. Since uncertainty plays a role in keeping Monday comovement higher; I focus on macroeconomic and earnings announcements, as their arrival and processing will resolve uncertainty. Macroeconomic and earnings announcements are expected to have opposite effects on comovement.

Higher Monday synchronicity appears 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 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.*, 2019). Firm-specific events reduce synchronicity by inducing idiosyncratic (firm-specific) shocks to stock prices, as investors are paying attention to individual firms. Conversely, comovement is expected to be higher on days when investors are distracted by numerous macroeconomic announcements. In contrast, I find that a small number of macroeconomic announcements on Mondays drives my results: R^2 on Mondays with macroeconomic announcements is about twice higher than the average R^2 of other weekdays with macroeconomic announcements, even though other weekdays have more frequent macroeconomic announcements. If I exclude the macroeconomic announcement days from the analysis, Monday's synchronicity is no longer the highest during the week. Hence, Monday synchronicity effect is not a seasonal anomaly in the sense that comovement is always high on Monday.

As I have already ruled out Monday anomaly and investor sentiment in Chapter 3, I look for other potential explanations. I find that the most plausible explanation is given by the well-documented salience effect. Salience describes the extent to which a stimulus stands out relative to other stimuli in the environment. Thus, such stimulus may attract attention for being novel, figurative, unexpected, extreme, negative, rare, or physically prominent (Fiske and Taylor, 2017). There is an extensive literature in support of the salience theory in decision making (Bordalo *et al.*, 2012, 2013a,b; Huang *et al.*, 2018; Dertwinkel-Kalt and Köster, 2020).

I 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 few news releases. The "simultaneous contrast" of this announcement makes it more salient, which leads to a stronger reaction in terms of comovement. The simplest example of simultaneous contrast effect comes from visual perception—individuals perceive a neutral grey object to be lighter (darker) when it is simultaneously compared to a dark (light) grey object. Besides its physiological aspect exemplified in visual perception, contrast effect is also a psychological phenomenon affecting financial decision making (Hartzmark and Shue, 2018; Kim and Hoffman, 2018; Bazley *et al.*, 2021).

There is nothing special about the type of macroeconomic announcements released on Mondays. They are released on other weekdays as well, but they do not cause an abnormal reaction in those days. They are salient in the context of their quiet background on Monday, not because they are inherently vivid. Consistent with context-dependent salience, I find that the abnormal reaction in terms of comovement on Monday exists, although the most important and attention-grabbing macroeconomic announcements are released in the middle of the week rather than on Monday.

I revisit the rational explanation based on higher uncertainty over the weekend. However, contrast effect continues to work in both high and low levels of uncertainty. Importantly, the removal of macroeconomic announcement days results in elimination of the intra-week variation in comovement, whether uncertainty is high or low. If uncertainty were to explain the Monday synchronicity effect, comovement should remain higher even after the removal of a few announcement days.

1.2.3 The morning after: late-night shows and the stock market

In Chapter 5, I investigate the effect of sleep deprivation using a new social inclination in TV entertainment. Binge watching late-night shows on Netflix, Hulu and others has become a popular trend. The number of subscribers of these internet-streaming services is constantly increasing. For example, Netflix has 213.5 million subscribers globally and 74 million for U.S. and Canada region (Third Quarter, 2021). Instead of using DST changes to proxy for sleep loss like Kamstra *et al.* (2000) and Mugerman *et al.* (2020), I rely on popular late-night shows as exogenous sources of sleep disturbance.

There are, however, some limitations in my approach: 1) People only voluntarily choose to watch these shows unlike clock change, which affects everyone uniformly; 2) the precise number of viewers of a particular show at a given time is unknown; and 3) it is impossible to find out how many of the viewers are also investors/traders in the stock markets. I restrict my analysis to only the most popular shows to ensure that a sizeable number of investors presumably suffer from sleep loss. I also recognise that a show does not necessarily become popular overnight; it may gain popularity many weeks or months after its initial release. These late-night shows are, however, more frequent than the bi-annual clock time change. The extent of sleep loss is also greater than one-hour disturbance in sleep caused by DST.

I find that market index is significantly down by an average of 0.25% on days following popular late-night shows. The effect is more pronounced in stocks with larger market capitalisation, higher institutional ownership, higher stock price, and higher book-to-market ratio. This cross-sectional pattern is not surprising because traders of institutional investors already have lesser sleep hours than retail investors (Kamstra *et al.*, 2000; Siganos, 2021).

I also investigate trading volume and liquidity to determine whether the decline in returns is due to reduced liquidity caused by distracted and sleep deprived investors staying away from trading. In the other case, the decline in returns could be a consequence of a selling pressure due to noise trading by retail investors. Noise trading can induce informed traders to enter the market and thus trading volume should increase even more (Kyle, 1985). I find that trading volume, turnover, bid-ask spread, and price range do not change significantly. Moreover, there is no significant change in noise trading by retail investors or algorithmic trading by institutional investors. Only the Amihud ratio is less for the large-cap stocks with high institutional ownership. Thus, liquidity, in terms of price impact, improves for these stocks. In summary, the results support neither reduced liquidity due to investor distraction, nor increased noise trading. My findings are consistent with other studies that also find no evidence of any appreciable change in trading volumes accompanying negative stock returns caused by sleep loss (Cai *et al.*, 2018; Dickinson *et al.*, 2020).

My findings differ from Peress and Schmidt (2020), who find that liquidity decreases in small stocks with low institutional ownership when retail investors are distracted by sensational news on TV. TV coverage of sensational news occurs during trading hours. If investors are distracted by such news, they will reduce their trading. In my study, investors are not distracted by TV during trading hours. They sacrificed their sleep in the previous night, which affected their risk-taking behaviour the next morning.

I find that stock returns decline even further if uncertainty, proxied by VIX, is high. Sleep deprived investors demand a higher risk premium; therefore, current prices must fall for the future expected returns to become more attractive. Mckenna *et al.* (2007) find that risk-taking behaviour of sleep deprived individuals will either increase or decrease depending on whether the outcomes are framed as potential losses or gains, respectively. Therefore, sleep deprived investors take less risk due to heightened fear of losses on investments when VIX is higher. Kamstra *et al.* (2000) also conjecture that sleep disturbance because of DST change raises the anxiety among investors and they shun risky investments, leading to a decline in returns. Since buying decisions require a greater cognitive effort than selling decisions, sleep deprived individuals will accept a smaller monetary reward requiring less effort, consistent with the findings of Killgore (2007) and Libedinsky *et al.* (2013). Thus, selling will be more prevalent than buying and stock prices will go down.

1.3 Contributions

In Chapter 3, I contribute to the synchronicity literature by examining its seasonal variations, 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 U.S. stocks. I show that higher synchronicity on Mondays is distinct from the Monday anomaly in returns, and cannot be explained by investor sentiment or arbitrage constraints.

While Chapter 3 presents the Monday synchronicity effect, Chapter 4 presents its novel explanation based on the contrast effect. I 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). Contrast effect is strong enough to keep the comovement higher on Monday despite the low supply of macroeconomic announcements. The salience of 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. A simplistic assumption that higher (lower) supply of macroeconomic (earnings) news causes higher synchronicity is unable to explain my findings. 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 besides the type of news (market-wide and firm-specific).

In Chapter 5, I focus on sleep, which is another physiological function affecting cognitive processes. I contribute to the literature on the impact of sleep deprivation on financial markets using a new proxy for sleep loss as opposed to the commonly used DST change. The fact that market returns are significantly affected on the day following late-night shows, imply that a sizeable cohort of traders are indeed watching these popular shows. I explore the effects of sleep loss in different market segments and for stocks with varying characteristics, unlike other studies on the impact of sleep loss on stock markets (Kamstra *et al.*, 2000; Mugerman *et al.*, 2020). I also contribute to the literature on noise trading and algorithmic trading by relating them to behavioural changes induced by sleep loss.

1.3.1 Implications

Abnormally high comovement on Monday upon release of macroeconomic announcements has potential implications for policies regarding the release of such information by government agencies and other institutions. In particular, my findings warrant policy review by the Institute for Supply Management and the United States Bureau of Economic Analysis, which are responsible for publishing the two macroeconomic announcements that are occasionally announced on Monday, i.e. the Purchasing Managers' Index and the Personal Consumption Expenditures, respectively.

One of the regulatory functions of the Securities & Exchange Commission is to avoid extreme market conditions and plan interventions to protect the markets from crises. Excessively higher comovement can entice investors to exhibit herd behaviour where the majority of the participants follow the market's trend. In turn, herd behaviour increases the risk that investors will suffer losses in unison, which in turn affects the proper functioning of financial markets and may eventually lead to a crash. Moreover, large downturns in one market can spillover to other financial assets and markets around the globe. Therefore, the market regulator must review how information by companies and other entities is publicly released.

Identification of days with high comovement are essential for investors, particularly day traders. If stocks are largely following the market index, trading decisions based on individual trends in stocks may involve taking higher risk. For example, buying a stock when most stocks are in red. Investors have to take into account the market's trend while making a trading decision based on an individual stock's trend. In conditions characterised by high comovement, diversification is less beneficial and may even become counter-productive. Ungeheuer and Weber (2021) find that investors perceive comovement heuristically by counting the number of stocks whose returns are moving in the same direction as the index's return. If they perceive comovement to be high, they diversify less.

Distortion in the perception of macroeconomic announcements evident from my study highlights the fact that finance professionals making frequent investment decisions are as susceptible to contrast effects as households making infrequent decisions, e.g. a housing investment (Simonsohn and Loewenstein, 2006). Since prices in financial markets are a consequence of interactions among multiple participants, one may argue that cognitive biases among a subset of investors should not significantly affect market dynamics in the presence of arbitrageurs. However, my findings show that contrast effects leads to overreaction in terms of comovement that impact equilibrium prices and capital allocation.

My research on the impact of late-night TV shows on the stock market highlights the fact that economic decisions of market participants are affected by cultural trends that are seemingly distinct from the financial world. Since markets represent the aggregate behaviour of the investors, it is unsurprising to see that psychological and physiological changes brought about by extraneous and non-economic events like TV shows lead to changes in economic behaviour. The market must be seen in the light of the overall society rather than distinct from it. The economic impact of due to decline in S&P 500 index returns due to late-night TV shows is around 105 billion dollars annually. Consistent with past literature, my findings inform about the lack of sleep suffered by professional traders employed by institutional investors. Thus, there is a need to improve the work-life balance of these traders to avoid such significant losses. My findings have implications for day traders and arbitrageurs who can devise trading strategies to exploit price fluctuations brought about by non-economic events and news.

Chapter 2

Literature Review

2.1 Return Synchronicity

Synchronicity and price informativeness

Despite extensive literature, the notion that return synchronicity, typically measured by R^2 (or its logarithmic transformation) estimated from an asset pricing model, is a measure of stock price informativeness is subject to open debate in finance. Some studies propose that a high R^2 implies that less firm-specific variation is being impounded into stock prices, while market-wide systematic factors are explaining variation in returns to a greater degree. Therefore, high (low) R^2 indicates low (high) price informativeness, which is associated with capital allocation inefficiency (efficiency) and higher (lower) cost of capital (Roll, 1988; Morck *et al.*, 2000; Durnev *et al.*, 2003, 2004).

In contrast, empirical evidence shows that stocks with low R^2 usually feature small market capitalisation, infrequent trading activity, poor analyst coverage and greater arbitrage constraints, suggesting that a low R^2 is associated with poor informational environment, inconsistent with the argument that prices of such stocks are more informative (Kelly, 2014; Li *et al.*, 2014). Similarly, Dasgupta *et al.* (2010) show that, as transparency increases due to adequate and timely disclosure, there is little surprise about any future event when it actually takes place. Some information about the event is already incorporated into stock prices, therefore, the magnitude of reaction to the event is smaller. Moreover, the disclosures allow investors to learn about the time-invariant firm characteristics and incorporate this information into stock prices. Both these channels cause the firm-specific variation to decrease, and thus, increase the R^2. Hence, more price informative stocks have higher R^2.

Grossman and Stiglitz (1980) argue that markets are only partially informative since information is costly to acquire. Informational inefficiency of the markets incentivises traders to make returns by acquiring private information and arbitraging against mispricing. Informativeness will improve if the prevalence of informed trading increases and the cost of private information decreases. Campbell *et al.* (2001) argue that firm-specific variation arises exogenously and makes the arbitrage more risky because arbitrageurs have to expose themselves to large undiversified positions. This viewpoint is contested by Roll (1988), who shows that firm-specific variation is not associated with public information announcements; hence, firm-specific variation reflects either informed arbitrage or noise trading. Out of these two possibilities, Durnev *et al.* (2003) find support for the former. Durnev *et al.* (2004) provide further support to this argument by finding that more informative stock prices, reflected in low R^2 values, result in more efficient capital investment and better corporate governance. Regardless of the exogenous or endogenous origin of firm-specific variation, there is a trade-off between arbitrage profits and incorporation of information into stock prices. In other words, as arbitrage trading increases in the presence of firm-specific variation, further arbitrage becomes increasingly risky as more information is incorporated into stock prices.

Drawbacks of using R^2

Several studies consider high (low) R^2 as equivalent to low (high) idiosyncratic risk (measured as variance of the residual from a market model).[1] However, Li *et al.* (2014) contest that they are not interchangeable proxies for firm-specific risk. Contrary to the expectation that lower R^2 or higher idiosyncratic risk is correlated with more transparent firm-specific information environments, they

[1] For example, Hutton *et al.* (2009), Bartram *et al.* (2012), Irvine and Pontiff (2009) and Chen *et al.* (2012).

find inconsistent results across both proxies. Campbell *et al.* (2001) and Morck *et al.* (2013) propose that higher idiosyncratic risk or lower R^2 can simultaneously capture both noise and firm-specific return variation. According to Morck *et al.* (2013), higher firm-specific return volatility around corporate events can either encourage or discourage arbitrage, leading to either higher or lower market efficiency, respectively.

While there are several studies interpreting low R^2 as a sign of greater price efficiency with respect to firm-specific information,[2] a contrasting stream of literature suggests the opposite, i.e. lesser price efficiency.[3] Bramante *et al.* (2015) suggest that higher R^2 implies more efficient markets because the delay in the incorporation of information into prices is less for stocks with higher R^2 values. Similarly, Pagano and Schwartz (2003) find that an increase in market quality (and hence, efficiency) due to introduction of a closing call auction results in higher R^2. Alves *et al.* (2010) find that a country's R^2 fluctuates significantly from year to year; thus, it cannot be considered a reliable measure of a country's corporate governance and investor protection regimes, contrary to the suggestion by Morck *et al.* (2000).

Cheng *et al.* (2021) also challenge interpreting low R^2 as an indication of protective investor rights by finding that governance and market capitalization are highly collinear in predicting synchronicity and they cannot be disentangled from each other. Instead, industry structure can serve as a alternative explanation for the differences in average R^2 values across developed and emerging countries. R^2 is lower in inefficient, uncompetitive, and highly concentrated markets with few large firms. Prices of such firms have higher idiosyncratic variances due to dispersed business networks; thus, R^2 is lower. Chan and Chan (2014) find that discounts on seasoned equity offerings (differences between pre-offer day closing prices and offer prices) are less if synchronicity is higher, implying that prices are more informative, in contravention of the hypothesis forwarded by Morck *et al.* (2000).

[2] Examples include Wurgler (2000), Durnev *et al.* (2003), Durnev *et al.* (2004), Piotroski and Roulstone (2004), Jin and Myers (2006), Ferreira and Laux (2007), and Bakke and Whited (2010)

[3] Examples include Xu and Malkiel (2003), Chan and Hameed (2006), Hou *et al.* (2006), Mashruwala *et al.* (2006), Pontiff (2006), Skaife *et al.* (2006), Khandaker and Heaney (2009), Griffin *et al.* (2010), and Kelly (2014).

Gassen *et al.* (2020) highlight another drawback in R^2 by attributing its low values for informationally poor firms to a downward bias in measurement caused by illiquidity characterising such stocks. The effect of firm-specific information flows is masked due to illiquidity; hence, low R^2 appears to reflect more noise in prices. The use of lags and leads of market returns in the regression model, or weekly instead of daily returns can only rectify the measurement bias in the beta but not the R^2.

The premise that idiosyncratic risk reflects firm-specific information is undermined by two theoretical issues. First, information dissemination affects the timing of uncertainty resolution but does not affect its total amount over time or the total amount of stock return volatility (West, 1988; Ross, 1989; Campbell *et al.*, 2001). Hence, idiosyncratic risk cannot be simply considered as equivalent to information dissemination (Hou *et al.*, 2013). Second, return volatility may reflect either the reaction to fundamental information flow or investor sentiment (Hirshleifer, 2001; Barberis and Thaler, 2003). Thus, the theoretical link between R^2 and efficiency is unclear (Hou *et al.*, 2013).

My study on comovement in Chapters 3 and 4 does not attempt to address the debate whether R^2 reflects either high or low price informativeness. Since my investigation is focused on U.S. stocks, any drawbacks in the R^2 measure associated with cross-country differences are irrelevant. Instead, I focus on within-week variation in return synchronicity and explanations for abnormally high Monday synchronicity. Existing literature has proposed several rational and behavioural factors that are related to return synchronicity, including information supply and demand, investor sentiment, limits to arbitrage, internal/external corporate governance, etc. Some of these factors have intra-week patterns, and thus, they may provide an explanation for intra-week patterns in synchronicity.

Information arrival, processing and Monday anomaly

Arrival of firm-specific and macroeconomic information may cause changes in comovement of stock returns. Conceivably, incorporation of firm-specific news, especially earnings announcements, reduces return comovement since uncertainty is resolved and firm-specific information is impounded into stock prices. Macroeconomic announcements affect returns relatively uniformly across business sectors, and increase return comovement because they have a systematic effect across the entire market and investors gain information about aggregate earnings. Variations in information production over business cycles have been found to be related to variations in return synchronicity (Brockman *et al.*, 2010). Many studies show that information dissemination, such as firms public disclosures, facilitates its rapid incorporation into stock prices. For example, Fishman and Hagerty (1989) developed a model in which firm disclosure increases price informativeness regarding future cash flows. Gelb and Zarowin (2002) find that prices are more informative about changes in future earnings if good disclosure policies are adopted.

Information can only be incorporated into stock prices if investors pay attention to it. However, attention is a scarce resource (Kahneman, 1973) and investors can only acquire and process a limited amount of information at any given time. Such limited attention induces investors to learn information about the market first, then the industry, and finally the individual firm-a behaviour termed as category-learning (Peng and Xiong, 2006). According to Sims (2003), when information acquisition becomes excessively cost-prohibitive, investors make rational decisions based on incomplete information and remain inattentive to the complete set of information. Moreover, heightened uncertainty due to market-wide macroeconomic shocks forces investors to allocate relatively more attention to market-wide news than firm-specific information (Peng *et al.*, 2007). Thus, category-learning may induce higher return correlations than fundamental correlations. Since the arrival of news over the weekend is usually scarce, uncertainty and risk aversion at the start of the week will be high. Consistent with this expectation, Fisher *et al.* (2021) find that VIX, the market's 'fear gauge', is indeed higher on Monday. Thus, comovement may be higher at the start of the week as investors focus more on market-wide information under conditions of uncertainty (Kacperczyk *et al.*, 2016).

Peng and Xiong (2006) also provide an explanation for the findings of Morck *et al.* (2000) and Durnev *et al.* (2003) by proposing that low comovement in certain sectors or countries is due to higher efficiency of information processing, which entices the investor to abandon category-learning behaviour. They also attribute the decreasing trend in R^2 in U.S. markets over time to the reduction in investors attention constraints in processing firm-specific information caused by advancement in information technology.

Liu *et al.* (2019) state that macroeconomic announcements crowd out attention of retail investors to earnings announcements. This crowding-out effect may also imply that synchronicity will be high if investors are focused more on market-wide information and less on firm-specific information. However, Chen *et al.* (2018), and Hirshleifer and Sheng (2021) contest this crowding-out effect by providing evidence that despite the distraction caused by macroeconomic announcements, the response to concurrent earnings announcements actually increases because the amount of total attention overall increases. In other words, the size of the pie for attention to firm-specific news increases, although most of the attention is allocated to market-wide information. They find that earnings announcements with concurrent macroeconomic news announcements have stronger immediate market response and weaker post-earnings announcement drift.

Consistent with category-learning behaviour, Veldkamp (2006) suggests that synchronicity also arises because investors, limited by their information processing ability, pay attention to news that has the highest value in terms of its ability to evaluate multiple assets simultaneously at a lower cost. Huang *et al.* (2019) document that preferential allocation of attention to aggregate information leads to higher synchronicity when investors are distracted by exogenous events like jackpot lotteries. Peng *et al.* (2018) also support category-learning behaviour by finding that attention towards firm-specific information is lower if macroeconomic uncertainty is higher. Fund managers resort to stock selection in economic booms by relying on firm-specific information; and resort to market timing in times of recession by analysing aggregate shocks (Kacperczyk *et al.*, 2014).

Some studies have contested the prediction that attention to firm-specific information reduces synchronicity. According to Dasgupta *et al.* (2010) and Hou *et al.* (2013), when information is processed, uncertainty about the future is alleviated, and idiosyncratic volatility in the future is also lesser. Thus, investor attention may increase synchronicity instead. Consistent with this explanation, Lin *et al.* (2014) find that the positive effect of analyst coverage on return synchronicity is stronger when investor attention is high because information generated by the analysts is diffused quickly. Mondria (2010) presents an alternate explanation for the positive relationship between investor attention and comovement by theorising that investors tend to look at a linear combination of assets rather than each asset separately. A good (bad) news about one asset is also attributed as good (bad) for other assets in the portfolio, especially when firm-specific information is in limited supply. Thus, attention to such news leads to higher synchronicity. Drake *et al.* (2017) provide yet another explanation for this positive relationship by finding that attention itself comoves because attention to an event in one firm draws attention to other peer firms as well. The attention spillover to peer firms increases return synchronicity. In this way, attention may affect synchronicity even in the absence of correlated liquidity shocks (Calvo, 2004), wealth effects (Kyle and Xiong, 2001), direct or indirect macroeconomic links (King and Wadhwani, 1990; Kodres and Pritsker, 2002), borrowing constraints (Yuan, 2005) and endogenous information supply (Veldkamp, 2006).

The debate on news arrival and its processing is intertwined with the extensive literature on the day-of-the-week effects in returns, betas, and volatility. Monday anomaly, the finding that Monday returns are significantly lower than those of other weekdays, especially the preceding Fridays, has been difficult to explain with classical market equilibrium models (Lakonishok and Smidt, 1988). French (1980) rules out both calendar-time and trading-time hypotheses as explanations for the negative returns on Monday. Lakonishok and Levi (1982) hypothesise that the Monday effect comes from delays in trading, settlement and clearing over the weekend, while Keim and Stambaugh (1984) report evidence that rejects this hypothesis. Abraham and Ikenberry (1994) attribute the Monday effect to selling pressure by individual investors, particularly following bad news, whereas Kamara (1997) and Chan *et al.* (2004) argue that trading of institutional investors drives Monday anomaly. Short-selling is another proposed explanation for the Monday anomaly as short sellers close short positions on Fridays due to uncertainty, and open new short positions on

Monday (Fields, 1934; Chen and Singal, 2003). The pattern of arrival of firm-specific news during the week is a plausible cause of the Monday effect. Damodaran (1989) conjectures that small firms release negative announcements after trading hours on Friday, causing lower Monday returns. The various explanations put forth to explain the intra-week seasonality in returns may also be linked to a seasonality in comovement.

The arrival pattern of firm-specific news explains a very small proportion of the Monday anomaly. Instead, Admati and Pfleiderer (1989) attribute intra-week seasonalities in returns to similar seasonalities in information processing. Abraham and Ikenberry (1994) and Chang *et al.* (1995) state that processing of macroeconomic news is related to these day-of-the-week effects. Moreover, Chang *et al.* (1995) also find that higher betas on Monday are mainly due to higher contemporaneous correlations of returns. Chang *et al.* (1998) suggest that seasonality in processing macroeconomic news accounts for much of the intra-week seasonality in returns. Thus, similar intra-week seasonality in synchronicity may be expected in the presence of higher correlations caused by abnormal response to macroeconomic news released on Monday. The role of macroeconomic announcements is also important because over 60% of the cumulative annual equity risk premium is earned on macroeconomic announcement days (Savor and Wilson, 2013, 2014). In summary, day-of-the-week effects in synchronicity are expected because of seasonalities in information arrival and its processing, which is contingent on investor attention. Liu and Peng (2015) provide direct evidence for the suggestion by DellaVigna and Pollet (2009) that investor attention is significantly lower on Friday. DellaVigna and Pollet (2009) show that the response to Friday's announcements is higher in the following week starting from Monday. Apart from seasonalities in returns, information processing and limited attention have a role in explaining other anomalies like post-earnings announcement drift, accruals anomaly, and momentum that have been hard to explain under the assumptions of the efficient market hypothesis (Hirshleifer and Teoh, 2003).

Non-fundamental factors of synchronicity

Price informativeness is contingent on the ease of arbitrage by informed investors. Since short-sale constraints are one of the many impediments to informed arbitrage, any change in these constraints will potentially affect comovement (Bris *et al.*, 2007). According to Barberis *et al.* (2005), if price comovement is reflected in firm fundamentals (i.e. firm-specific information), markets need to be essentially frictionless with rational investors facing no constraints on informed arbitrage. However, in the real world, there are limits to arbitrage due to frictions and irrational investors. Hence, comovement may be theorised as arising from non-fundamental factors.

Some studies have found that comovement of stocks increases after inclusion in the market index (Vijh, 1994; Barberis *et al.*, 2005; Greenwood, 2008; Claessens and Yafeh, 2012), which cannot be explained by fundamentals since inclusion or deletion from the index provides no new signals regarding change in fundamentals. Similarly, Green and Hwang (2009) find that after stock splits, comovement with low-priced stocks increases while comovement with high-priced stocks decreases. However, Chen *et al.* (2016) insist that comovement is still associated with fundamentals because stocks undergoing index additions and stock splits display a positive momentum in past returns leading to an increase in their betas. Thus, excess comovement comes from higher betas rather than index addition or stock split. Kumar and Lee (2006) report that trades of noise investors are systematically correlated, and drive the comovement of stocks with high retail concentration. Pindyck and Rotemberg (1993) show that market segmentation can explain comovement. They find stocks held by institutional owners to have higher comovement. They surmise that segmentation among groups of investors occurs due to differences in sentiment about future payoffs of different assets. These differences in sentiment may explain both comovement and segmentation.

Among the non-fundamental factors affecting comovement, investor sentiment deserves a special mention. Chue *et al.* (2019) document that synchronicity increases with increasing positive investor sentiment, while it does not decrease with increasing negative investor sentiment. This asymmetry is due to short-sale constraints in the face of a bullish sentiment which allow overpricing to prevail.

Prices become less informative because the marginal benefit of paying attention to firm-specific news will be less in periods of extreme sentiment. In the cross-section, this relationship is strongest for the most sentiment-prone stocks (Baker and Wurgler, 2006) such as small, young, volatile, non-dividend paying and low-priced stocks. Lee *et al.* (1991) find comovement among discounts of closed-end funds and small stocks that are subject to identical patterns of investor sentiment. Hou *et al.* (2013) question the validity of R^2 as a measure of market efficiency by demonstrating that if stock price volatility is driven by investor sentiment, stocks with low R^2 values will have strong momentum and reversal patterns in their prices which implies that prices are not informative. R^2 may be a reflection of investor sentiment rather than incorporation of firm-specific information into prices.

Birru (2018) find that intra-week variations in mood cause an identical pattern in investor sentiment to emerge. Sentiment decreases on Monday and increases on Friday. Thus, taking short positions on Monday and long positions on Friday on speculative stocks will give higher returns because such stocks perform poorly on Monday and perform better on Friday. Abu Bakar *et al.* (2014) show that the Monday anomaly may come from lower mood on Monday. Hirshleifer *et al.* (2020) find that seasonal patterns in the cross-sectional variation of returns persist in future time periods if the mood is congruent and reverses if the mood is incongruent. Thus, intra-week variation in sentiment/mood is not only related to intra-week seasonality of returns but may also cause similar variations in comovement.

Several studies examine the time trend and cross-country variations in return synchronicity. Campbell *et al.* (2001) find an increasing time trend in idiosyncratic volatility relative to market volatility for U.S. data. In contrast to Morck *et al.* (2000), they do not attribute the decrease in R^2 over time to development and improvement of institutional and legal framework. Wei and Zhang (2006) partially explain the time trend by showing that volatility of fundamentals (return on equity) has concurrently increased over time. Bartram *et al.* (2012) also link idiosyncratic risk to volatility of fundamentals. However, this does not support the information or fundamentals-based explanation for low synchronicity since the positive relationship between return volatility and earnings volatility is mostly driven by newly listed firms having a poor informational environment (Wei and Zhang, 2006). Morck *et al.* (2000) find that R^2s are high in countries with low GDP per capita and low in developed countries. They attribute this high synchronicity to poor protection of property rights of outside investors, particularly against corporate insiders. The lack of legal and institutional protection deters informed arbitrage against noise traders and, hence, firm-specific information is not impounded into stock prices. Jin and Myers (2006) argue that the combination of poor legal protection and lack of transparency results in high R^2 values in markets with poor informational environment.

Information disclosure and transparency

There are many studies that show that public disclosure of information, either through institutional measures or voluntarily by firms, and actions of informed market participants facilitate rapid incorporation of this information into stock prices, making them more asynchronous. Ferreira *et al.* (2011) hypothesise that price informativeness can be a substitute for monitoring by the corporate board, hence, board independence is lower and a less demanding board structure is required. Boubaker *et al.* (2014) argue that controlling shareholders hide firm-specific information for their own opportunistic benefits and thus, increase comovement of stock prices, while Piotroski and Roulstone (2004) find that insider trades decrease synchronicity by incorporating firm-specific information into prices. External monitoring, particularly by institutional investors, increases the transparency of firm-specific information and leads to both low synchronicity and low crash risk (An and Zhang, 2013). Piotroski and Roulstone (2004) and Chan and Hameed (2006) show that analysts increase synchronicity by facilitating the incorporation of industry-level information into prices. Synchronicity is also higher in stocks which are covered by a common set of analysts (Israelsen, 2016), or connected by a common set of brokers providing margin financing (Kahraman and Tookes, 2019). Other monitoring mechanisms like foreign ownership and auditor quality also decrease the comovement of stock prices (Gul *et al.*, 2010; Fang *et al.*, 2019). Morck *et al.* (2000) and Fernandes and Ferreira (2009) show that lower synchronicity is associated with stronger legal protection. Similarly, improvement in information disclosure and financial reporting after adoption of International Financial Reporting Standards (IFRS) results in reduced comovement. Moreover, the effect of IFRS adoption on comovement is moderated by analyst coverage and existing institutional framework (Kim and Shi, 2012). Synchronicity is also reduced by measures that reduce information-processing cost, e.g. presentation of financial data in a standardised, tagged, and machine-readable format (Dong *et al.*, 2016). However, all the aforementioned determinants are likely to remain constant over a week, therefore, they cannot be considered to cause any intra-week seasonality in synchronicity.

2.2 Contrast Effect & Salience

Contrast effect is the relative enhancement or diminution of perception or cognition of a stimulus because of successive or simultaneous exposure to similar stimuli. A stimulus must be salient, i.e. stand out relative to other stimuli in the environment. In other words, salience is context-dependent, as it describes how much a stimulus stands out relative to its surroundings. A stimulus may stand out for being novel, figural, unexpected, extreme, negative, rare, or physically prominent (Fiske and Taylor, 2017). If the exposure to various stimuli occurs over a period of time and one (or few) of them is salient, successive contrast effect is at play. If the exposure to various stimuli occurs all at once, the salient stimulus will result in simultaneous contrast effect.

The idea of contrast originated from optics: colours are perceived as brighter and smaller against a dark background than against a light background (Chevreul, 1855). Simultaneous contrast is considered having both physiological (i.e. the design and functionality of the eye) as well as psychological explanations (Helmholtz, 1962; Hering, 1964). Even though contrast effect in visual perception seems to be a distinct phenomenon from financial decision making, there is evidence of a neurological connection between visual perception and risk preferences (Bordalo *et al.*, 2012). In a visual gambling experiment involving monkeys, neuronal activity increased in a particular area of the brain linked to visual orientation and reward processing when risky choices were made. Salience of a risky option was a better predictor of this increased neuronal activity than the actual value of the option. Thus, it was hypothesised that this neuronal activity biases the attention towards risky choices, making larger payoffs as more salient (Mccoy and Platt, 2005). Bazley *et al.* (2021) find that representation of negative historical price data in red colour, as compared to black, has a significant impact on risk preferences, future expectations and trading decisions. Similarly, Bose *et al.* (2020) conduct several experiments to find that individuals overweight visually salient adjacent prices in the investment decisions.

It is important to relate the concept of salience to attention. 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 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. Salience models by Bordalo *et al.* (2012, 2013a,b, 2020) explain behavioural biases, such as probability weighting, menu effects, reference point effects, and framing.

The retail attention measure based on Google searches for a company's ticker symbol is quantifying top-down retail attention. Individual investors are voluntarily and consciously searching for a company's financial information through Google. Similarly, Bloomberg's institutional attention measure is quantifying the top-down attention of institutional investors. Hence, high levels of top-down attention are not required for a stronger reaction to salient macroeconomic announcements because attention is drawn exogenously, spontaneously, involuntarily, and subconsciously.

Successive contrast effect has been studied in diverse areas, including finance. Hartzmark and

Shue (2018) use it to explain the distortion in prices caused by investors who perceive earnings news as more (less) impressive if yesterday's surprise in earnings was bad (good). They attribute this effect to error in perception of investors and rule out other potential explanations like irrational expectations or information spillovers from previous announcements. Cosemans and Frehen (2021) find that salient past returns are overweighted in forming expectations about future returns. Thus, stocks with salient positive returns become overvalued and then underperform in future periods. Similarly, stocks with salient negative returns become undervalued and then yield high returns in future periods. The effect is stronger in stocks with greater limits to arbitrage and during high-sentiment periods. Ramos *et al.* (2020) find that the predictability of investor attention for trading volume and returns is high when the market reaches 52-week highs or lows, which are salient reference prices. Their results support the category-learning behaviour because investors process market-wide information preferentially over firm-specific information. Salience theory has also been applied for educational choices (Choi *et al.*, 2021), taxation (Chetty *et al.*, 2009), judicial decisions (Bordalo *et al.*, 2015), corporate managerial decisions (Dessaint and Matray, 2017), and consumer choice (Bordalo *et al.*, 2013b).

2.3 Sleep Deprivation

The typical environment for a trader is characterised by long working hours and extreme stress (Kahn and Cooper, 1990; Kahn *et al.*, 1994; Oberlechner and Nimgade, 2005). Sleep is an important coping mechanism for stress and fatigue caused by long working hours (Rodahl, 2003). Sleep is essential for good health and circadian rhythms. Poor sleep quality leads to more illnesses and other health issues (Tanaka *et al.*, 2002). Sleep loss can cause brain damage, as the synapses (i.e. connections between the brain cells) deteriorate physiologically (Bellesi *et al.*, 2017). Moreover, fundamental cognitive processes such as concentration, attention, and memory are also negatively affected by sleep deprivation (Dinges *et al.*, 1997; Smith *et al.*, 2002; Harrison and Horne, 2000; Ellenbogen, 2005; Alhola and Polo-Kantola, 2007; Banks and Dinges, 2007). In particular, sleep deprivation leads to reduced cognitive flexibility in responding to new information in dynamically changing conditions (Whitney *et al.*, 2015; Honn *et al.*, 2019; Whitney *et al.*, 2019).

DST change may affect sleep by only one hour, but this small change can affect sleep pattern for up to two weeks (Valdez *et al.*, 1997); the average duration of the effect is about one week (Harrison, 2013). Only a single episode of mild sleep loss significantly reduces vigilance (Stojanoski *et al.*, 2019; Gibbings *et al.*, 2021). Such small sleep loss due to DST change has been related to an increase in pedestrian accidents (Sullivan and Flannagan, 2002), traffic accidents (Coren, 1996; Robb and Barnes, 2018), workplace injuries (Barnes and Wagner, 2009) and a decrease in mood (Kountouris and Remoundou, 2014).

Sleep deprivation and risk

Sleep loss is also related to risky social behaviours like alcohol, cigarette, and drug use (O'Brien and Mindell, 2005; Schoenborn and Adams, 2008; Vail-Smith *et al.*, 2009; Yen *et al.*, 2010; McKnight-Eily *et al.*, 2011). It is also associated with an increased suicidal tendency (Pasch *et al.*, 2010; Blasco-Fontecilla *et al.*, 2011). Sleep deprived individuals show greater propensity for financial risk-taking behaviour in many studies, such as those that use the Iowa Gambling Task (Killgore *et al.*, 2006, 2007, 2012) or Balloon Analog Risk Task (Killgore *et al.*, 2008). However, there is no conclusive evidence that sleep deprivation always increases the propensity for risk-taking. Horne (2013) states that decision making in conditions of sleep deprivation also involves alterations in risk perception. If sleep deprived individuals are optimistic about success, they take more risk.[4] If they perceive that failure is likely, they become more risk averse.[5] Perceptions about uncertainty and the physical/social context influence how sleep deprivation affects the decision-making process (Anderson and Dickinson, 2010).

[4] For example, Venkatraman *et al.* (2007), Mckenna *et al.* (2007), and Anderson and Platten (2011).
[5] For example, Killgore (2010), Mckenna *et al.* (2007), Chaumet *et al.* (2009), and Harrison and Horne (2000).

Horne (2013) points out that most studies assess the effects of sleep deprivation on very simple monotonous tasks. Only a few aspects of complex executive functions have been investigated in literature, and they have little applicability to the real world. These complex executive functions include dealing with novelty, unexpected change, uncertainty, ignoring incongruous and irrelevant information, following and remembering recent developments, concentrating on key issues, predicting potential outcomes, and innovative planning of responses. Moreover, the effect of sleep deprivation on different components of executive functions is different. For example, Tucker *et al.* (2010) find a differential effect of sleep deprivation on distinct components of cognitive processes—sleep loss resulted in degradation of dissociated non-executive components of cognition, while executive functions were not significantly affected. Libedinsky *et al.* (2013) find that sleep deprived individuals are willing to accept a smaller monetary reward that requires less effort (i.e. increased effort discounting), but their willingness to accept a smaller reward earlier rather than later (i.e. delay discounting) is not affected. Horne (2013) conjectures that the differential effect of sleep deprivation on the two types of discounting is due to changes in risk perception.

Killgore (2007) find that, contrary to other studies, the propensity for risk-taking is less in sleep deprived individuals. He argues these individuals refrain from risky decisions because they want to spend less effort. Hence, these findings are consistent with increased effort discounting observed by Libedinsky *et al.* (2013). Killgore (2015) summarises the literature on the varied effect of sleep loss on risk-taking behaviour, "sleep deprivation increases many aspects of risk-taking, including simple impairments in attention and judgment, greater willingness to accept risk, and a tendency to focus on short-term rather than long-term consequences, but it may also reduce the effort that individuals are willing to devote toward risky behavior.

Nofsinger and Shank (2019) criticize Iowa Gambling Task and Balloon Analog Risk Task for not being financial risk experiments. Moreover, these tools assume a linear utility function with no loss aversion despite the well-documented fact that investors utility functions are non-linear, e.g. prospect theory by Kahneman and Tversky (1979). Nofsinger and Shank (2019) employ the

Dynamic Experiments for Estimating Preferences (DEEP) method, which caters to distortion of probability, the curvature of their function, loss aversion, present bias, and daily discounting rate. They use the Pittsburgh Sleep Quality Index to measure several determinants of sleep effectiveness and examine how sleep affects financial decision making.

Kamstra *et al.* (2000) find that stock market returns are lower on Monday following DST change; this effect has been recently corroborated by Mugerman *et al.* (2020). They argue that sleep loss causes market participants to suffer from greater anxiety. In such circumstances, there will be a preference for safer assets over riskier assets. Thus, stock prices decline. Siganos (2019) find that investors overreact to information about firms targeted for mergers when experiencing sleep disturbances due to DST change. Hagendorff *et al.* (2021) find that investors initially under-react to a firm's earnings surprise after DST, and then reassess the information leading a positive post-earnings announcement drift. However, many studies challenge that asset prices are affected by DST (Pinegar, 2002; Worthington, 2003; Lamb *et al.*, 2004; Jacobsen and Marquering, 2008; Müller *et al.*, 2009; Gregory-Allen *et al.*, 2010). Cai *et al.* (2018) use late-night sports matches to proxy for sleep deprivation, while Siganos (2021) develop a proxy of sleep based on Google search activity of sleepiness terms. Both proxies are negatively related to stock returns. I use late-night TV shows to proxy for exogenous shocks to the circadian rhythm of investors, and find that stock returns are lower on days following such shows. These results confirm that a large segment of investors sacrifice their sleep hours during such nights.

Sleep pattern may also get affected by a change in the day's length and thus, impact financial decision making. When daylight hours are shorter in winters, people suffer from the Seasonal Affective Disorder (SAD), commonly called winter blues. SAD is a depressive disorder characterised by low mood, lack of concentration, irritability, lethargy, sleep disturbance, or oversleeping (Mayo Clinic, 2017; NHS, 2018). Kamstra *et al.* (2003) find a seasonal pattern in returns induced by SAD, as depressed and risk-averse investors avoid risky assets in the fall and resume their risky holdings in the winter. Stock returns in the fall are lower than average, and following the longest night of the year, they are higher than average. Garrett *et al.* (2005) find that increase in risk aversion due to SAD can be fully explained by a conditional CAPM that allows the price of risk to vary with seasonal variation in the day's length. Dickinson *et al.* (2020) find that participants trading in experimental markets during odd hours of the day (relative to local time) due to time differences across the globe cause greater mispricing and price bubbles. They attribute this effect to sleep deprivation suffered by such traders.

Sleep deprivation reduces the neural function of the prefrontal cortex (Horne, 2012). This region of the brain is highly active during decision making, cognitive behaviours and emotion (Euston *et al.*, 2012). There is evidence that activity in the prefrontal cortex increases in individuals who are influenced by realisation utility, leading to a stronger disposition effect (Frydman *et al.*, 2014). This region is also involved in an individual's propensity to buy during market bubbles (De Martino *et al.*, 2013). Decreased activity in the prefrontal cortex due to sleep loss leads to an increase in risk-taking behaviour (Telzer *et al.*, 2013). Sleep loss also decreases attention by reducing the brain's cortical response to incoming stimuli (Boonstra *et al.*, 2007).

Sleep deprivation is also associated with depressive illness (Ford and Kamerow, 1989; Lustberg and Reynolds, 2000; Riemann *et al.*, 2001). There is evidence that depression and mood influence financial decisions (Shu, 2010; Lerner *et al.*, 2015; Hirshleifer *et al.*, 2020). The level of cortisol, a hormone released by the adrenal gland, is elevated due to sleep loss during the previous night (Leproult *et al.*, 1997). Interestingly, cortisol is also associated with financial decision making (Coates and Herbert, 2008; Kandasamy *et al.*, 2014; Nofsinger *et al.*, 2018). Thus, the relationship of sleep deprivation with investor behaviour and trading activity is an area of research that deserves more attention.

Sleep deprivation may affect asset pricing through different mechanisms. The negative effect of sleep loss on mood (Dinges *et al.*, 1997) could lead to a decrease in stock returns, consistent with the observations by Saunders (1993) and Hirshleifer and Shumway (2003) that stock returns are positively correlated with elated investor mood in a sunny weather. Since sleeplessness decreases attention by reducing the brain's response to incoming stimuli (Boonstra *et al.*, 2007), stock returns may be lower because of a reduction in attention-driven buying (Barber and Odean, 2008). Killgore (2007) and Nofsinger and Shank (2019) find that the propensity for risk-taking is less in sleep deprived individuals. Hence, higher levels of risk aversion due to sleep deprivation may lead to lower stock prices, as investors will require higher expected returns.

Sleep deprivation and liquidity

Since sleep loss negatively affects attentiveness, trading activity may be affected on days following late-night shows. Investors may reduce their trading and liquidity may decline. Alternatively, declining stock returns may be a consequence of a selling pressure, and trading activity will be higher in this case. While Google search volume index (SVI) and Bloomberg's abnormal institutional attention (AIA) measure are direct proxies of retail and institutional attention measures respectively (Da *et al.*, 2011; Ben-Raphael *et al.*, 2018), trading volume is considered as an indirect measure of attention (Barber and Odean, 2008; Gervais *et al.*, 2001). According to Miller (1977), high volume can attract attention and make a stock more visible. Thus, a change in the level of attention is closely related to changes in trading activity and liquidity.

Trading activity that is uncorrelated with stock fundamentals (noise trading) is necessary for financial markets to function (Black, 1986). Otherwise, traders private information will be fully reflected in asset prices, which will eliminate any incentive to collect costly information and the market will collapse (Grossman and Stiglitz, 1980). Informed investors generate profits from their informational advantage by utilising the liquidity provided by noise trading. Market makers also get compensated by noise traders for their losses incurred by trading with informed investors.

Empirical analysis of the influence of noise trading on liquidity is challenging due to an endogenous relationship between them. According to Glosten and Milgrom (1985), the ratio of informed trading to uninformed trading is exogenous, and an increase in noise trading reduces adverse selection costs of the market maker because the extent of informed trading does not change. Kyle (1985), however, formulates informed trading to rise endogenously when noise trading is increasing. In other words, informed traders are induced to become active when uninformed trading is higher. Consequently, the effect of informed trading on adverse selection costs is offset by uninformed trading and hence, liquidity is unaffected by the level of noise trading. The Admati-Pfleiderer (1988) framework is similar to that of Kyle's in terms of endogenously increasing informed trading; however, market depth increases despite the increased activity of informed traders. Thus, adverse selection costs of market makers decrease and liquidity increases. In summary, the effect of noise trading on liquidity may have contrasting predictions depending on what adverse selection model is at work.

Lee *et al.* (1993) support the assumptions of Glosten-Milgrom framework by finding that liquidity is less around earnings announcements, implying that market makers increase the bid-ask spreads and decrease the quoted depths because they want to avoid losses from trading with informed investors. Greene and Smart (1999) find support for the Glosten-Milgrom and Kyle frameworks by exploiting a natural experiment to evaluate the effect of an exogenous increase in noise trading caused by an increase in investor attention.[6] Bid-ask spreads decrease and market depths increase as market makers face more uninformed traders against whom they can make profits. Other studies use Google SVI to measure retail investor attention and find that liquidity improves when it is high (Bank *et al.*, 2011; Aouadi *et al.*, 2013; Ding and Hou, 2015). Similarly, Peress and Schmidt (2020) find that liquidity decreases when retail investors get distracted by TV coverage of sensational news that is unrelated to the economy.

The prediction of inventory risk models (Ho and Stoll, 1981; Grossman and Miller, 1988) about the impact of noise trading on liquidity is the complete opposite of adverse selection models. Market makers will face inventory imbalance due to noise trading, and they will either widen the bid-ask spreads or alternatively, increase their bid and ask quotes without widening the spreads. As a result, liquidity will decrease due to noise trading. Thus, the outcome of noise trading on liquidity also depends on whether the decrease in adverse selection cost or the increase in inventory risk is the dominating effect.

[6] In a competition, a few investment professionals select some stocks they expect to perform well over the next six months. These recommendations appear in the *Wall Street Journal*s Dartboard Column, and stimulate uninformed trading in these stocks.

Retail investors are attracted to volatile stocks because such stocks have attention-grabbing features (Barber and Odean, 2008), or lottery-like features preferred by such traders (Kumar, 2009). This argument is, however, countered by evidence that volatile stocks have less liquidity (Benston and Hagerman, 1974; Chordia *et al.*, 2000; Hameed *et al.*, 2010). Thus, it is unclear whether noise traders contribute to increasing the liquidity of volatile stocks, or whether they stay away from volatile stocks due to low liquidity.

On one hand, some studies suggest retail investors contribute to noise for a multitude of reasons: their trading activity is weakly correlated with firm fundamentals (Peress and Schmidt, 2021); their trades increase return volatility (Foucault *et al.*, 2011); their performance, on average, is poor (Barber and Odean, 2013); and their trades are systematically correlated (Kumar and Lee, 2006; Barber *et al.*, 2009). On the other hand, Kelley and Tetlock (2013) show that buy-sell imbalances from retail trades predict the cross-section of returns, and the lack of return reversal up to horizons of one year makes the *Noise Trader Hypothesis* (De Long *et al.*, 1990) doubtful. Retail investors use market orders to act upon firm cash flow news, and use limit orders to provide liquidity. Overall, they improve market efficiency. Kaniel *et al.* (2008) find that retail buying (selling) behaviour following increase (decrease) in stock price in the previous month is not highly correlated across various stocks. Thus, any noise generated by retail sentiment is diversifiable and not systematic.

Stressing the role of retail investors does not imply that institutional investors are immune to distraction events. Kempf *et al.* (2017) find that institutional investors get distracted by exogenous shocks unrelated to their portfolios. Firms exploit these investors in such distracting circumstances by increasing accrual-based and real earnings management (Garel *et al.*, 2021). Kamstra *et al.* (2017) find that risk aversion of fund managers changes in winter due to SAD, and this affects their asset allocation decisions. Similarly, analysts are more pessimistic, less precise, and more asymmetric in their boldness in the fall due to SAD (Lo and Wu, 2018). Hirshleifer *et al.* (2019) find that analysts suffer from decision fatigue as they continue to publish forecasts for multiple firms throughout the day, and increasingly resort to heuristic decision-making in their forecasts later in the day. Thus, it is reasonable to assume that investment professionals can get distracted by events unrelated to the market.

My findings do not support distraction of either retail investors like Peress and Schmidt (2020), or institutional investors like Kempf *et al.* (2017). Contrary to the expectation that distracted investors will trade less, I find that liquidity in terms of price impact increases for large-cap stocks and stocks with high institutional ownership. Trading volume, bid-ask spread, and price range are unaffected by sleep deprivation. Absence of any decline in trading activity implies that reduced investor attention is not the cause of price decline on days following late-night shows.

While the quasi-natural experimental settings used by Greene and Smart (1999) and Foucault *et al.* (2011) involve exogenous but medium to long-term changes in noise trading, I use short-term shocks to investors sleep. Thus, I do not expect a reduction in inventory costs of market makers that occurs when the intensity of noise trading declines for a long time period. In my study, any change in liquidity derives from the adverse selection channel. Foucault *et al.* (2011) find that noise trading permanently declines and reduction in inventory cost more than offsets any increase in adverse selection costs, resulting in improved liquidity. Greene and Smart (1999) find that the increase in noise trading lasts for ten days to several weeks; the increase in inventory risk and the decrease in adverse selection costs nearly offset each other; and thus, there is little change in liquidity.

Odd lot trades are small-sized transactions of less than 100 shares and account for about a quarter of all trades on U.S. stock exchanges (O'Hara *et al.*, 2014). Before the widespread adoption of algorithmic trading and high frequency trading (HFT), odd lot trades were typically used only by retail investors because of capital constraints (Ritter, 1988; Dyl and Maberly, 1992). In recent years, algorithmic traders and HFTs have been playing the dominant role in odd lot trading (Johnson and Roseman, 2017). Odd lots as little as one share (exploratory trading) are also used to explore market conditions and to gauge the responses of other traders (Clark-Joseph, 2014; Davis *et al.*, 2017).

According to O'Hara *et al.* (2014) and Kupfer and Schmidt (2021), the use of odd lots by retail investors is still important despite their extensive use by algorithmic traders and HFTs. HFTs use odd lot trades to splice their large orders into small ones (smaller than the regular lot size) to minimise price impact and execution costs (Bertsimas and Lo, 1998). Johnson and Roseman (2017) find that odd lot trading is more informative if non-HFTs are more active market participants. O'Hara *et al.* (2014) point out that exclusion of odd lot trading data is problematic for behavioural finance research involving retail trading behaviour and sentiment. Kupfer and Schmidt (2021) find that odd lot trading intensifies for large-priced stocks if retail investor attention is high. Thus, any change in retail attention due to sleep loss may cause a change in the intensity of odd lot trading. I find that it does not change on days following late-night shows for large-priced stocks; hence, trading activity of retail investors is not affected by sleep deprivation.

In the Glostern-Milgrom framework, presence of HFTs should theoretically result in reduced information asymmetry versus informed investors because public information flow can be quickly parsed, and quotes can be updated rapidly (Menkveld, 2016). Thus, bid-ask spread should become tighter; adverse selection costs should reduce; quote updates should be more frequent between trades; price discovery should be greater; and the probability of trade execution should increase. Harris (2013) and Conrad *et al.* (2015) both find empirical evidence of reduced transaction costs. In particular, bid-ask spread has been found to be lower due to HFT (Friederich and Payne, 2011; Aitken *et al.*, 2012). There is empirical support for the improvement in liquidity because of algorithmic traders (Hendershott *et al.*, 2011) and HFTs (Hasbrouck and Saar, 2013). Similarly, Ait-Sahalia and Saglam (2013) and Goettler *et al.* (2009) formulate models in which high frequency informed market makers improve liquidity. Brogaard (2011) find that HFTs are liquidity suppliers in conditions of both high and low volatility. There is also evidence of improvement in price discovery (Brogaard *et al.*, 2014; Chaboud *et al.*, 2014).

Even though most of theoretical and empirical literature is in favour of the beneficial effects of algorithmic trading and HFT on liquidity and transaction costs (Virgilio, 2019), some studies contest that slow traders get penalised by HFTs and their transaction costs increase (Ding *et al.*, 2014; Hoffmann, 2014). HFTs can rapidly switch from being liquidity suppliers to being front-runners when large orders are placed by informed institutional investors (Van Kervel and Menkveld, 2019). In contrast, they can time their own informed trades when noise trading is high (Collin-Dufresne and Fos, 2015). Thus, any change in the intensity of noise trading due to sleep deprivation will expectedly change the intensity of algorithmic trading. Since there is no significant change in retail trading on days following late-night shows, as expected, I find that algorithmic trading also does not change on such days.

Chapter 3

Day-of-the-week Return Synchronicity

3.1 Introduction

In this chapter, I test whether return synchronicity differs among different weekdays. Most of the studies estimate a firm-year measure of synchronicity by pooling returns within a year. Therefore, intra-week changes in return synchronicity have received far less attention. These questions are 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. Comovement among asset returns imposes a risk on investors portfolios, and is important for asset allocation, risk assessment, and hedging (Engle, 2002). The study of comovement can help to reveal the links between the real economy and financial markets since aggregate shocks affect comovement. Answers to these questions can also enrich our 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 and firm news changes during the week which may induce variations in synchronicity (Brockman *et al.*, 2010). Behavioural factors that affect investors response to information, e.g., investor attention and sentiment, also have intra-week variations (Liu and Peng, 2015; Birru, 2018).

Economic uncertainty and risk aversion are important factors that affect comovement. Attention is preferentially and endogenously allocated to more valuable aggregate signals (macroeconomic information) over relatively less valuable idiosyncratic signals (firm-level information) in times of recession and economic uncertainty when aggregate volatility and price of risk are high; consequently, assets comove more in such circumstances (Kacperczyk *et al.*, 2016). Learning about aggregate shocks is the most efficient way of risk reduction; hence, more risk averse investors allocate more attention to aggregate shocks. Kacperczyk *et al.* (2014) find that fund mangers switch between stock selection and market timing depending on whether the market is experiencing an upturn or downturn, respectively. Such a change in trading strategy affects comovement because stock selection requires paying attention to firm-specific information, while market timing is reliant on attention to aggregate signals. Fisher *et al.* (2021) find that both economic uncertainty and market volatility are higher on Monday as compared to other weekdays.[1] This finding is unsurprising since Monday is the first trading day after the weekend during which little information is released publicly. Thus, intra-week variations in uncertainty and risk aversion are expected to cause similar variations in comovement.

I measure Monday synchronicity by the R^2 from regressions of Monday stock returns on contemporaneous (i.e. Monday) and lagged (i.e. previous Friday) market and industry returns. I run identical regressions separately for other weekdays as well. I find that Monday's R^2 is about 12% higher than the average R^2 for other weekdays over the 1953-2017 period. Importantly, this pattern is persistent over the past 60 years. In addition to the R^2, regression coefficients for Monday regressions are also significantly higher for Monday. The differences in coefficients between Monday and other weekdays have very little predictive power to explain the differences in R^2. Similarly, the unexplained part of the variation in stock returns from these regressions has no consistent pattern across the week. Therefore, idiosyncratic volatility lends no explanation for higher Monday synchronicity.

[1] In Table 2: Descriptive Statistics, both Economic Policy Uncertainty (EPU) index and Implied Volatility Index (VIX) are higher for Monday and decrease almost monotonically across the week.

Since higher Monday synchronicity resembles a seasonal anomaly, naturally, the foremost question is whether it is a manifestation of the infamous Monday anomaly in stock returns. *Are they two sides of the same coin?* The pattern of negative Monday returns, which constitutes the Monday anomaly, implies that correlation may be asymmetrically high in such a downside market (Jiang *et al.*, 2018). Thus, Monday comovement could be higher because of this asymmetry. However, I find that Monday synchronicity is higher in both upside and downside market conditions. The same is true if individual stock returns are either positive or negative. Thus, I provide proof that Monday synchronicity is unrelated to the Monday anomaly.

Monday differs from other weekdays since it is the first trading day of the week. Scarcity of publicly available information over the weekend leads to uncertainty and higher risk aversion. In such conditions, investors tend to value the market-wide information more than firm-specific information (Kacperczyk *et al.*, 2016). Such preference is consistent with category-learning behaviour (Peng and Xiong, 2006). Consequently, return comovement is expected to be high if aggregate information is driving the market. I find the R^2 differences between Monday and other weekdays to be relatively smaller in the 1927-1952 period, when the weekends were shorter because Saturday was also a trading day. I also test the sample of longer three-day weekends (Friday holiday or Monday holiday) and find that R^2 for the first trading day of the week is higher than normal weeks. Thus, higher uncertainty, risk aversion, and the resulting focus on market-wide news at the start of the week does play a role in explaining the higher synchronicity on Monday. I further explore this plausible explanation in the next chapter by analysing the role of macroeconomic and earnings announcements on day-of-the-week synchronicity.

The rest of this chapter is organised as follows. Section 3.2 documents the data and methodology. Section 3.3 reports the empirical findings and various robustness tests. Finally, Section 3.4 concludes.

3.2 Data & Methodology

The sample period extends from January 1927 to December 2017. Daily total stock returns, daily volume, and daily total returns of value-weighted CRSP Index are obtained from the CRSP daily stock files beginning 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.[2] 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. Daily returns are winsorized at 1st and 99th percentiles. 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.

3.2.1 Day-of-the-week synchronicity regressions

I 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:

$$r_{i,d,y} = \alpha_{i,d,y} + \beta_1 r_{Mkt,d,y} + \beta_2 r_{Mkt,d-1,y} + \beta_3 r_{Ind,d,y} + \beta_4 r_{Ind,d-1,y} + \epsilon_{i,d,y} \tag{3.1}$$

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. I include the lagged returns of the CRSP index and industry to accommodate for non-synchronous trading. As an example, I regress Monday's stock returns on contemporaneous (i.e., Monday's) and lagged (i.e., previous Friday's) CRSP index returns and industry returns. A firm needs to have at least 30 values for a weekday in a given year to be included in the sample for that year.

The R^2 estimated from Equation 3.1, $R^2_{i,d,y}$, is the measure of weekday d synchronicity for the

[2] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

firm i in the calendar year y. To compare Monday R^2 with those of other weekdays, I 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, I compute synchronicity using the logarithmic transformation of R^2, i.e., $ln\left(\frac{R^2}{1-R^2}\right)$.

3.3 Results

In this section, I first provide the main empirical evidence for Monday synchronicity effect in various specifications for robustness. Then, I disentangle this effect from the Monday anomaly, investor sentiment, and arbitrage constraints. Lastly, I show the role of shorter and longer weekends.

3.3.1 Monday synchronicity

The sample period for the baseline results is from 1953 to 2017. The sample for the 1927-1952 period is analysed separately because Saturday is also a trading day in this period. Tables 3.1 and 3.2 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 3.1. Table 3.1 shows that Monday R^2 is about 21.8%, whereas the overall average of R^2 for all other weekdays is about 19.5%. 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 R^2 differences among weekdays other than Monday, however, are relatively small and statistically insignificant. 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 industry return and its lag are also higher for Monday.

The t-tests in Table 3.2 show that Monday R^2 and regression coefficients are significantly higher than those of other weekdays, except the insignificant differences between Monday and Wednesday's market betas, and between 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 and industry indices on Monday. Note that high synchronicity can also originate from low values of idiosyncratic volatility. Therefore, I conduct similar t-tests for *RMSE* of these regressions. The results are rather mixed as 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, idiosyncratic volatility cannot explain higher Monday synchronicity.

A t-test for differences in R^2 cannot reveal whether Monday's values are consistently higher over the entire sample period. Therefore, I plot each year's Monday R^2 and the average R^2 of other weekdays in Figure 3.1. It shows the former is higher than the latter for most of the years, indicating that synchronicity on Monday remains persistently higher than on other weekdays. Apart from the intra-week difference in synchronicity, the figure shows a general downtrend in comovement from the 1950s up to 1990s, which then reverses in later years. Parsley and Popper (2020) find an identical pattern of the time trend in their study. They attribute the reversal to instability in macroeconomic policies and various financial crises during this period.

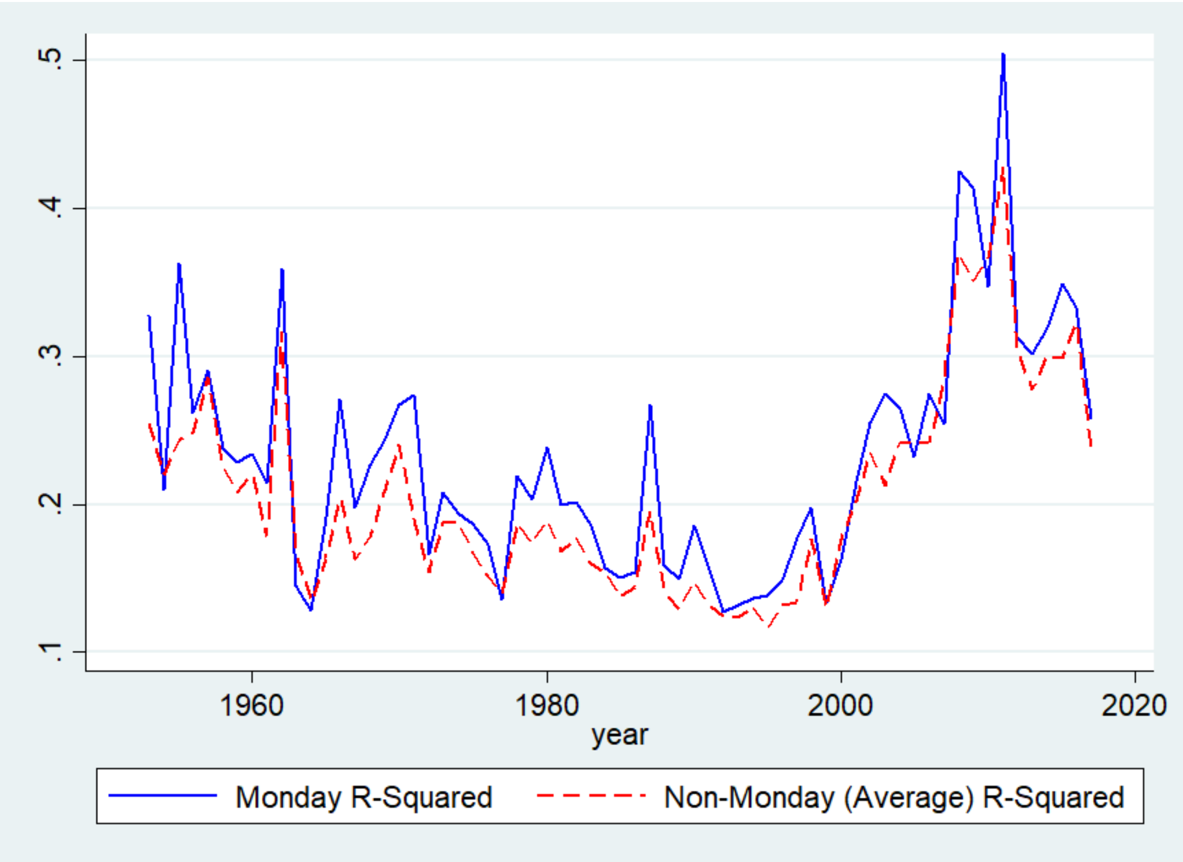


Figure 3.1: Monday R^2 vs. Non-Monday R^2

Table 3.1: 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 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 3.2: 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.

	Difference	t-statistic		Difference	t-statistic
Monday and Tuesday			Monday and Thursday		
$\Delta R^2_{i,d,y}$	0.0209***	(42.86)	$\Delta R^2_{i,d,y}$	0.0205***	(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		
$\Delta R^2_{i,d,y}$	0.0229***	(46.98)	$\Delta R^2_{i,d,y}$	0.0267***	(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)

I test the extent to which higher comovement on Monday 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 3.3 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).

Table 3.3: 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 3.1 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	$\Delta R^2_{Mon-Tue}$	$\Delta R^2_{Mon-Tue}$	$\Delta R^2_{Mon-Wed}$	$\Delta R^2_{Mon-Wed}$	$\Delta R^2_{Mon-Thu}$	$\Delta R^2_{Mon-Thu}$	$\Delta R^2_{Mon-Fri}$	$\Delta R^2_{Mon-Fri}$
$\Delta\beta^{Mon-Tue}_{Mkt}$	0.004***	0.025***						
	(37.833)	(123.566)						
$\Delta\beta^{Mon-Tue}_{Ind}$		0.018***						
		(119.257)						
$\Delta\beta^{Mon-Wed}_{Mkt}$			0.004***	0.024***				
			(36.701)	(121.107)				
$\Delta\beta^{Mon-Wed}_{Ind}$				0.017***				
				(117.044)				
$\Delta\beta^{Mon-Thu}_{Mkt}$					0.000***	0.005***		
					(10.595)	(75.450)		
$\Delta\beta^{Mon-Thu}_{Ind}$						0.014***		
						(77.119)		
$\Delta\beta^{Mon-Fri}_{Mkt}$							0.004***	0.024***
							(38.157)	(121.388)
$\Delta\beta^{Mon-Fri}_{Ind}$								0.017***
								(116.900)
Constant	0.021***	0.020***	0.023***	0.022***	0.020***	0.020***	0.027***	0.026***
	(83.860)	(82.152)	(91.503)	(92.535)	(81.225)	(80.118)	(104.983)	(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

3.3.2 Robustness tests for synchronicity regressions

I test whether Monday R^2 is higher in different specifications of the synchronicity regressions. First, I run the regressions in Equation 3.1 without the lagged market and industry returns. Second, I repeat these regressions with returns that are not winsorized. In both cases, Monday R^2 remains higher, as shown in Table 3.4. For further robustness checks, I run pooled OLS and fixed effects regressions in Table 3.5. Following Chue *et al.* (2019), I also use alternate models like the Carhart's 4-factor Model (Carhart, 1997) and the Market Model in Table 3.6. These regressions are identical to the baseline regressions, i.e., firm-level, one-year rolling window regressions for each weekday. The four factors are market (RMRF), size (SMB), value (HML), and momentum (UMD). The Market Model contains only the market factor.

$$R_{i,d,y} = \alpha_{i,d,y} + \beta_1 RMRF_{d,y} + \beta_2 SMB_{d,y} + \beta_3 HML_{d,y} + \beta_4 UMD_{d,y} + \epsilon_{i,d,y} \tag{3.2}$$

$$R_{i,d,y} = \alpha_{i,d,y} + \beta_1 RMRF_{d,y} + \epsilon_{i,d,y} \tag{3.3}$$

Monday R^2 remains consistently higher in these specifications. Thus, the Monday synchronicity effect is dependent neither on the choice of the factor model, nor on the regression specification.

Table 3.4: Synchronicity Regressions: No Lags & Non-Winsorized Returns

The sample period extends from 1953 to 2017. The R values (in percentage) are obtained by regressing stock returns on CRSP Value-weighted Index returns and Fama-French 48 Industry returns for each weekday d from Monday to Friday for each stock i in each calendar year y. Average values of the $R^2_{i,d,y}$ (%age) are reported in columns 1 and 2.

	No Lags	Non-Winsorized Returns
Monday	17.379	17.900
Tuesday	15.372	15.401
Wednesday	15.306	15.486
Thursday	15.453	15.451
Friday	14.798	14.865
Total	15.660	15.819

Table 3.5: Pooled Synchronicity Regressions

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

	Monday	Tuesday	Wednesday	Thursday	Friday
$\beta_{Mkt,d,y}$	0.412***	0.370***	0.426***	0.403***	0.386***
	(90.282)	(84.696)	(96.029)	(91.143)	(88.858)
$\beta_{Mkt,d-1,y}$	0.067***	0.048***	0.026***	0.033***	0.031***
	(26.735)	(21.154)	(11.864)	(14.044)	(13.865)
$\beta_{Ind,d,y}$	0.387***	0.370***	0.361***	0.365***	0.348***
	(81.473)	(78.196)	(75.613)	(77.152)	(75.988)
$\beta_{Ind,d-1,y}$	0.064***	0.057***	0.057***	0.056***	0.043***
	(34.426)	(32.758)	(32.619)	(32.809)	(26.499)
Constant	-0.001***	-0.001***	0.001***	0.000***	0.001***
	(-13.959)	(-10.149)	(7.133)	(5.137)	(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

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

Table 3.6: 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 $R^2_{i,d,y}$ (%age) are reported in columns 1 and 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

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, I separate the daily returns into two sub-samples, one with negative market returns and the other with positive market returns. Specifically, the daily observations are divided into two parts, depending on whether the excess market return (or individual stock return) is positive or negative on a given day. I 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 (as opposed to one year in the baseline regressions) is applied to ensure that each regression has a sufficient sample size. Thus, I obtain a downside R^2 (R^2_D) and an upside R^2 (R^2_U) for each weekday and each firm in each 3-year period. I report the t-tests for differences between Monday and other weekdays in terms of R^2_D (i.e. ΔR^2_D) and R^2_U (i.e. ΔR^2_U) in Table 3.7. In Panel A, down days and up days are defined by negative or positive excess market returns; whereas, in Panel B, they are defined by negative or positive individual stock returns. These tests show that R^2 always remains significantly higher on Monday, whether the market or individual stock is up or down.

I also test whether differences in R^2 between Monday and other weekdays are different between down days and up days. The difference-in-difference $\Delta(R^2_D - R^2_U)$ is significantly positive except for the Monday-Friday difference in Panel A. This implies that even though Monday's synchronicity is higher regardless of up or down-market conditions, it generally exceeds that of other weekdays when the market or individual stock is down. In However, regarding Monday-Friday comparison, the difference in synchronicity is higher on up days rather than down days. While the magnitudes of the difference-in-difference are sizeable (1.9% in Panel A & 2.1% in Panel B) for the Monday-Tuesday comparisons, they are less for Monday-Wednesday comparisons (0.4% in Panel A & 1.7% in Panel B). In Monday-Thursday or Monday-Friday comparisons, the magnitudes are even smaller in both Panels, and even negative in one case. Therefore, the asymmetry in comovement on down days only partially contributes to Monday's higher comovement. Existence of the Monday synchronicity effect beyond 1990s (see Figure 3.1) further proves that Monday anomaly cannot be a viable explanation because Dubois and Louvet (1996) find that it has largely disappeared since then.

Table 3.7: 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. In **Panel A**, the down (up) days are defined as those on which the excess market return is smaller (larger) than zero. In **Panel B**, the down (up) days are defined as those on which the individual stock return is smaller (larger) than zero. R^2_D denotes the Downside R^2, R^2_U denotes the Upside R^2, and $R^2_D - R^2_U$ 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.

Panel A: Downside & Upside Excess Market Returns

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

Panel B: Downside & Upside Individual Stock Returns

	Difference	t-statistic		Difference	t-statistic
Monday and Tuesday			Monday and Thursday		
ΔR^2_D	0.0327***	(48.61)	ΔR^2_D	0.0216***	(30.83)
ΔR^2_U	0.0102***	(18.03)	ΔR^2_U	0.0119***	(21.37)
$\Delta(R^2_D - R^2_U)$	0.0206***	(35.46)	$\Delta(R^2_D - R^2_U)$	0.00862***	(14.46)
Monday and Wednesday			Monday and Friday		
ΔR^2_D	0.0303***	(43.96)	ΔR^2_D	0.0264***	(38.67)
ΔR^2_U	0.0120***	(21.82)	ΔR^2_U	0.0171***	(31.67)
$\Delta(R^2_D - R^2_U)$	0.0165***	(27.84)	$\Delta(R^2_D - R^2_U)$	0.00738***	(12.45)

3.3.4 Monday synchronicity and investor sentiment

Periods of extremely bullish or bearish investor sentiment can affect return synchronicity by making stock prices less informative as rational investors get discouraged from making trading decisions based on firm-specific information. Chue *et al.* (2019) find an asymmetrical relationship between investor sentiment and synchronicity where a bullish sentiment leads to higher synchronicity, while a bearish sentiment has no affect. They argue that short-sale constraints force arbitrageurs to sit on the sidelines in a bullish sentiment period, allowing overpricing to persist.

There are several studies that document lower mood on Monday to Thursday which then elevates on Friday.[3] Birru (2018) argues that intra-week variations in mood lead to similar patterns in investor sentiment, which in turn affect long-short anomaly returns over the week. Therefore, it may be worthwhile to explore the relationship of intra-week return synchronicity with investor sentiment. Figure 3.1 shows that the Monday synchronicity effect is quite persistent over a long sample period and a large number of stocks. R^2 on Monday has remained higher most of the time whether the market has experienced bearish or bullish sentiment. Moreover, the results in Table 3.7 further prove that R^2 on Monday remains higher whether the market or individual stock is bearish or bullish. Hence, investor sentiment does not play a role in the intra-week seasonality of return synchronicity.

3.3.5 Limits to arbitrage

The presence of arbitrage constraints allows 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 amplify return volatility. In contrast, high levels of firm-specific variation in developed markets is an evidence of more arbitrage activity arising endogenously due to lower costs of information acquisition, better access to capital, and more secure property rights (Morck *et al.*, 2000; Wurgler, 2000). Moreover, short-selling constraints may also contribute to opaqueness because negative information cannot be timely incorporated into stock prices. Bris *et al.* (2007) finds that cross-sectional variation in returns is less in markets with tighter short-selling constraints. In other words, comovement may be higher because of

[3] Examples include Rossi and Rossi (1977), McFarlane *et al.* (1988), Golder and Macy (2011).

constraints-induced opaqueness.

I test whether short-sale constraints play a role in causing higher synchronicity on Mondays by using the Pilot Program (SEC, 2004), initiated under Regulation SHO (SEC, 2015), by the Securities and Exchange Commission (SEC). The exogenous removal of the uptick rule, which prohibits placement of short-sale orders on upticks for a randomly selected subset of stocks from the Russell 3000 Index, provides a natural experimental setting where treatment stocks became easier to arbitrage than control stocks (Diether *et al.*, 2009; Chu *et al.*, 2020). I estimate diff-in-diff regressions using a treatment dummy and a time dummy on the differences in R^2 between Monday and other weekdays:

$$\begin{aligned}\Delta R^2_{i,d,y} &= \alpha + \delta_1 TIME_y + \delta_2 SHO_i + \delta_3 TIME * SHO_{i,y} + \gamma_1 \beta_{i,y} + \gamma_2 \beta^2_{i,y} + \gamma_3 TURNOVER_{i,y} \\ &\quad + \gamma_4 IVOL_{i,y} + \gamma_5 IVOL^2_{i,y} + \gamma_6 ln(MKT.CAP)_{i,y-1} + \gamma_7 BK/MKT_{i,y-1} + \gamma_8 LEV_{i,y-1} \\ &\quad + \gamma_9 ROA_{i,y-1} + \epsilon \end{aligned} \tag{3.4}$$

In Table 3.8, 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. I provide the definitions of firm fundamentals in Table 3.9.

Table 3.8: Diff-in-Diff Regressions

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, $\Delta R^2_{i,d,y}$, is the difference between R-squared of Monday and that of other weekdays. $TIME$ is the treatment period dummy, while SHO is the treatment dummy. $TIME * SHO$ is the interaction term (DiD coefficient). DiD regressions are run both with and without covariates. The covariates 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. $ln(MKT.CAP)_{i,y-1}$ is the log of market capitalisation 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.

	Monday-Tuesday		Monday-Wednesday		Monday-Thursday		Monday-Friday	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Without Covariates	With Covariates	Without Covariates	With Covariates	Without Covariates	With Covariates	Without Covariates	With Covariates
$TIME$	-5.702***	-6.635***	-0.824***	-1.718***	-3.300***	-4.416***	-0.073	-1.297***
	(-20.331)	(-21.581)	(-2.882)	(-5.527)	(-10.951)	(-13.250)	(-0.253)	(-4.085)
SHO	0.162	0.120	-0.093	-0.041	0.126	0.089	0.156	0.126
	(1.167)	(0.798)	(-0.638)	(-0.267)	(0.895)	(0.594)	(1.147)	(0.851)
$TIME * SHO$	-0.262	-0.234	-0.302	-0.308	0.477	0.354	-0.252	-0.229
	(-0.535)	(-0.452)	(-0.605)	(-0.586)	(0.926)	(0.649)	(-0.522)	(-0.445)
$\beta_{i,t}$		4.286***		4.020***		4.450***		3.222***
		(13.267)		(12.023)		(13.679)		(10.355)
$\beta^2_{i,t}$		-1.628***		-1.660***		-1.494***		-0.392***
		(-11.180)		(-11.192)		(-10.128)		(-2.821)
$TURNOVER_{i,t}$		0.924		2.542***		4.976***		3.660***
		(1.418)		(3.588)		(5.661)		(4.969)
$IVOL_{i,t}$		-39.032*		-13.826		-119.831***		-58.405***
		(-1.922)		(-0.687)		(-6.117)		(-3.028)
$IVOL^2_{i,t}$		-751.887***		-563.228**		538.269**		-373.880
		(-2.595)		(-2.024)		(2.032)		(-1.397)
$ln(MKT.CAP)_{i,t-1}$		-0.165***		0.026		-0.266***		-0.408***
		(-3.651)		(0.566)		(-5.780)		(-8.968)
$BK/MKT_{i,t-1}$		-0.131		0.200*		0.125		-0.177
		(-1.469)		(1.668)		(0.923)		(-1.107)
$LEV_{i,t-1}$		0.008**		-0.003		0.008**		0.009***
		(2.244)		(-1.014)		(2.115)		(2.676)
$ROA_{i,t-1}$		-0.010***		-0.002		-0.002		-0.007*
		(-2.875)		(-0.473)		(-0.718)		(-1.719)
Constant	2.724***	5.310***	3.005***	1.292	2.651***	7.488***	2.607***	9.450***
	(34.435)	(5.379)	(37.425)	(1.275)	(32.266)	(7.420)	(32.752)	(9.572)
Observations	55,844	45,722	55,528	45,190	55,821	45,702	55,836	45,717
$AdjR^2$	0.0133	0.0225	0.0003	0.0058	0.0039	0.0118	-0.0000	0.0106
Mean treated t_0	2.8860	5.4306	2.9114	1.2510	2.7768	7.5775	2.7635	9.5759
Mean control t_0	2.7238	5.3104	3.0046	1.2923	2.6507	7.4885	2.6074	9.4499
Diff t_0	0.1622	0.1202	-0.0931	-0.0413	0.1261	0.0891	0.1561	0.1260
Mean treated t_1	-3.0785	-1.4380	1.7858	-0.7757	-0.0467	3.5156	2.4383	8.0505
Mean control t_1	-2.9786	-1.3242	2.1807	-0.4262	-0.6497	3.0722	2.5345	8.1530
Diff t_1	-0.0999	-0.1137	-0.3949	-0.3495	0.6030	0.4434	-0.0962	-0.1025

Table 3.9: Firm Fundamentals

Variable Name	Description
Firm Size	$ln(MKT.CAP)_{i,y}$ is the natural log of market capitalisation 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: $R_{i,y} - R_{f,y} = \alpha_y + \beta\left(R_{Mkt,y} - R_{f,y}\right) + \epsilon_y$
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: $R_{i,y} - R_{f,y} = \alpha_y + \beta_1\left(R_{Mkt,y} - R_{f,y}\right) + \beta_2 SMB_y + \beta_3 HML_y + \epsilon_y$
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.

3.3.6 Shorter & longer weekends

Saturday used to be a trading day, at least up to 1952. Thereafter, a trading week in U.S. equity markets comprised the usual five days from Monday to Friday. Thus, the CRSP data for the 1927-1952 period provides an experimental setting for testing whether a shorter one-day weekend affects Monday synchronicity. The average R^2 values reported in Table 3.10 show that comovement is indeed higher on Monday, but the relative difference is less than the difference in the 1953-2017 period. Monday R^2 is only around 6% higher than the average R^2 of other weekdays. Moreover, the t-test between Monday and Tuesday is insignificant. Overall, the results for this period are weaker than the baseline results. The shorter weekend leads to weakening of the Monday synchronicity effect, presumably because uncertainty on Mondays is not too high. The pause in information arrival and its processing is shorter and, therefore, the level of uncertainty at the start of the week is relatively less, as compared to the case of a two-day weekend.

Table 3.10: 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		

I also test for the effect of a longer weekend by focusing on weeks which are either preceded by a Friday holiday (in the previous week), or those that commence on Tuesday because of a holiday on Monday. In both cases, I expect that uncertainty and scarcity of information will increase because of a longer pause in processing of information and lesser frequency of its arrival. Therefore, I expect higher synchronicity on the first trading days of such weeks.

In the 1953-2017 sample, I find 124 weeks preceded by a Friday holiday. Similarly, there are 252 weeks with a Monday holiday in the 1953-2017 period. Pooled synchronicity regressions are run separately for such weeks, and the 'normal weeks i.e., weeks preceded by the usual two-day weekend. Results in Table 3.11 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 following 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. These results are consistent with those for the shorter weekend. The longer (shorter) the weekend, the higher (lower) the synchronicity at the start of the week. Investors have an incentive to pay more (less) attention to aggregate information under conditions of high (low) uncertainty and risk aversion (Kacperczyk *et al.*, 2016). Consistent with category-learning behaviour (Peng and Xiong, 2006), such investor preferences affect synchronicity.

Table 3.11: 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.

Panel A: Pooled OLS Regressions

	(1) Normal Week	(2) Friday Holiday	(3) 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) Normal Week	(2) Friday Holiday	(3) 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

3.4 Conclusion

In this chapter, I provide the first empirical evidence of an intra-week pattern in stock return synchronicity for U.S. equity markets over a 90-year period. I find that stock return synchronicity is persistently higher on Mondays as compared to other weekdays in robust specifications. This anomaly is present in both up-market and down-market conditions; hence, it is distinct from the infamous Monday anomaly. Even if up days and down days are identified by positive and negative individual stock returns, synchronicity on Monday remains higher in either case. Even though higher downside correlation of stock returns on Mondays plays a role in keeping comovement higher, it cannot quantitatively account for the entire effect. Persistence of this intra-week pattern over a long sample period demonstrates that it is present in both bullish and bearish sentiment periods; hence, it is unrelated to investor sentiment. Moreover, the effect cannot be explained by arbitrage constraints.

The intra-week pattern in synchronicity is more prominent after longer weekends, and less prominent after shorter weekends (1927-1952 period). Synchronicity is generally higher at the start of the week but its difference from subsequent weekdays is higher after a 3-day weekend (due to a Friday or Monday holiday), and lower in those years when U.S. markets had a 1-day weekend (i.e., only Sunday holiday). Therefore, scarcity of public announcements and lack of information processing during the weekends contribute to increasing the comovement on Mondays, as investors prefer to allocate more attention to the more valuable market-wide information in the face of higher economic uncertainty and risk aversion. The increasing (decreasing) length of the weekend aggravates (mitigates) the extent of economic uncertainty and risk aversion at the start of the week. In turn, this causes the difference in comovement between the first weekday and subsequent weekdays to become higher (lower).

The relationship between Monday synchronicity and uncertainty at the start of the week is further explored in the next chapter. Since uncertainty is expected to get resolved with the arrival of new information, I analyse the effect of important news like earnings and macroeconomic announcements on day-of-the-week synchronicity. I also test whether VIX, which is a proxy of uncertainty, can explain the Monday synchronicity effect. Moreover, I also evaluate the role of investor attention.

Chapter 4

Contrast Effect of Monday Macro Announcements

4.1 Introduction

If synchronicity on Monday is higher and unrelated to the Monday anomaly or investor sentiment, what else can explain it? Is synchronicity high on all or most Mondays like a seasonality? If there is no explanation, have I stumbled upon a new anomaly? In this chapter, I explore the role of macroeconomic and earnings announcements in explaining the Monday synchronicity effect. As macroeconomic announcements have a market-wide effect, their release should expectedly increase synchronicity (Brockman *et al.*, 2010), as investor prioritise the allocation of their limited attention towards such news (Peng and Xiong, 2006; Veldkamp, 2006). Whereas, incorporation of firm-specific information in earnings announcements leads to lower synchronicity (Morck *et al.*, 2000; Durnev *et al.*, 2003, 2004).

The role of announcements is also important in the light of my evidence that the length of the weekend affects Monday synchronicity, during which the arrival and processing of information is slower. Uncertainty is expected to be high because both macroeconomic and earnings announcements are rarely released during weekends. Consistent with this argument, both economic uncertainty and risk aversion are higher on Monday (Fisher *et al.*, 2021). In the risk preference model of Ai and Bansal (2018), macroeconomic announcement premiums are primarily determined by economic uncertainty and risk aversion.

Higher Monday synchronicity is puzzling and rather counter-intuitive because the number of macroeconomic announcements is the lowest on Mondays as compared to other weekdays. As macroeconomic announcements are released more frequently in the middle of the week, comovement should be intuitively higher on such weekdays when more aggregate information is available to investors (Brockman *et al.*, 2010). Investors with limited information processing capacity allocate more attention to macroeconomic news (Peng and Xiong, 2006; Veldkamp, 2006), which crowds out their attention to firm-specific news, such as earnings announcements (Liu *et al.*, 2019). Thus, firm-specific events reduce synchronicity by inducing idiosyncratic shocks to stock prices, while the effect should be opposite if macroeconomic announcements are forcing investors to pay attention to market-wide information. Surprisingly, a small number of macroeconomic announcements on Mondays drives my results: R^2 on Mondays with macroeconomic announcements are about twice higher than the average R^2 of other weekdays with macroeconomic announcements, even though other weekdays have more macroeconomic announcements. If I exclude the macroeconomic announcement days from the analysis, Monday's synchronicity is no longer the highest during the week. Therefore, this effect is not a seasonal anomaly since it is not present on every Monday.

After examining several rational and behavioural explanations, the effect is 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) theorise that lotteries with salient payoffs are preferred 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 applied to consumer goods (Bordalo *et al.*, 2013b), salient earnings news (Huang *et al.*, 2018), and financial assets such as stocks with extreme payoffs (Bordalo *et al.*, 2013a) or positively skewed returns (Dertwinkel-Kalt and Köster, 2020). Experimental studies also show 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).

I argue that higher Monday comovement is due to 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, leading 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 of large firms stock prices to proxy the arrival of macroeconomic news. This prevents them from discovering that a small number of salient macroeconomic news drives high Monday synchronicity.

Higher uncertainty at the beginning of the week may rationally explain the effect, since investors may want to learn more about aggregate shocks. In the previous chapter, I report that Monday comovement is related to the length of the weekend. However, this rational channel cannot completely explain the Monday synchronicity effect because of two reasons: 1) the contrast effect for Monday macroeconomic announcements operates in both high and low levels of uncertainty; and 2) removal of macroeconomic announcement days results in elimination of the Monday synchronicity effect even when uncertainty is high. Thus, the contrast effect does not require conditions of heightened uncertainty to work. 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 focus on whatever market-wide information is available, regardless of any announcement. Contrary to my findings, the uncertainty-based explanation implies that comovement should be high on every Monday like a seasonal anomaly.

The contrast effect on Monday is not dependent on the type of macroeconomic announcement. Purchasing managers' index (PMI) and personal consumption expenditures (PCE) are the two types of macroeconomic announcements that are released on Mondays; however, they are also announced on other weekdays, thus, they are not exclusively concentrated on Mondays. Notably, the most important and attention-grabbing macroeconomic news, namely Federal Open Market Committee decision (FOMC) and non-farm payroll (NFPAY), are rarely ever announced on Monday.[1] Yet, the contrast effect does not manifest in the middle of the week when such announcements are released. Thus, increased investor attention to macroeconomic news is not a necessary requirement for the contrast effect. Consistent with theoretical predictions by Bordalo *et al.* (2021), macroeconomic announcements on Monday spontaneously draw bottom-up attention because of their salience, regardless of how much top-down attention is being consciously allocated by investors.

The rest of this chapter is organised as follows. Section 4.2 documents the data. Section 4.3 reports the empirical findings and various robustness tests. Finally, Section 4.4 concludes.

4.2 Data

Macroeconomic & earnings announcement dates

I obtain earnings announcement dates from Bloomberg terminal between 1998 and 2017 for baseline analysis. This data always includes the time of news release, classified as before/during/after market

[1] 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 (Pasquariello and Vega, 2007). Average stock market returns and Sharpe ratios in the U.S. 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 for other macroeconomic announcements. Brusa *et al.* (2020) find that the returns in international stock markets on days near the FOMC announcement are very high and similar announcements made by other central banks have a weaker effect, even for the domestic 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). I select these announcements on the basis of previous literature and the R-Index[2] assigned by the Bloomberg terminal. I also obtain daily VIX data for the 1998-2017 period from WRDS.

Earnings announcement dates prior to 1998 (1984-1997) are obtained from I/B/E/S and COMPUSTAT. The sample is restricted 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, I 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, I 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, I 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, I also drop the returns data for the respective firm-date observation so that such days are not erroneously categorised as non-announcement days.

I also obtain macroeconomic announcement dates prior to 1998 (1971-1997). However, release dates are obtained only for six announcements (i.e. excluding PCE, TRBAL, and CCI) from the websites of the U.S. Federal Reserve (FOMC), Bureau of Labor Statistics (NFPAY, CPI, and PPI), Bureau of Economic Analysis (GDP), and Institute of Supply Management (PMI).[3]

[2] 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.

[3] Dates 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`. I am grateful to the Bureau of Economic Analysis for providing historical release dates of advance

Investor attention data

To measure individual investor attention, I 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. Similarly, SVIs are also obtained for Russell 3000 Index firms using ticker symbols as search terms. 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 AAPL is more likely to reveal a demand for the financial information of the Apple Company.

Firm-specific 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. Bloomberg records the number of times news articles on a particular stock are read by its terminal users and the number of times users actively search for news about a specific stock. Searching for news requires users to actively type the firm’s stock ticker symbol followed by the function CN (Company News). In contrast, users may read an article without initially realising it refers to a specific firm. To place more emphasis on deliberate news search for a specific firm, Bloomberg assigns a score of ten when users actively search for news, and one when users read a news article. These numbers are then aggregated into hourly counts. Using the hourly counts, Bloomberg then creates a numerical attention score each hour by comparing the average hourly count during the previous 8 hours to all hourly counts over the previous month for the same stock. They assign a score of 0 if the rolling average is in the lowest 80% of the hourly counts over the previous 30 days. Similarly, Bloomberg assigns a score of 1, 2, 3 or 4 if the average is between 80% and 90%, 90% and 94%, 94% and 96%, or greater than 96% of the previous 30

estimates of quarterly GDP and the dates maintained by the Federal Reserve Bank of St. Louis. I also thank the Institute of Supply Management for providing historical release dates of PMI.

days hourly counts, respectively. Finally, Bloomberg aggregates up to a daily frequency by taking a maximum of all hourly scores throughout the calendar day. Bloomberg provides these latter transformed scores, but does not provide the raw hourly counts or scores.

4.3 Results

4.3.1 The relation between news and contrast effect

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

To examine whether high Monday synchronicity stems from more macroeconomic announcements on Mondays, I report the frequencies of macroeconomic announcement dates in Panel A and Panel B of Figure 4.1. Mondays have the lowest frequency, while Fridays have the highest. This is in sharp contrast with the intra-week 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. Only a handful of macroeconomic announcements were released on Sundays and Saturdays.

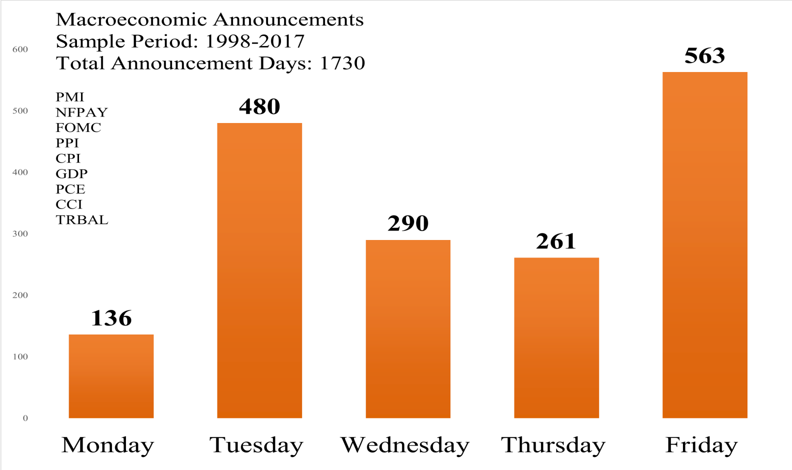
PMI is released on the first business day of each month. It will be released on a Monday if a calendar month starts with a Saturday and/or Sunday. Therefore, as shown in Panel B of Figure 4.1, the frequency of PMI for Monday release is higher as compared to other weekdays. PCE is released on the last business day of each month. It will be released on a Friday if a calendar month ends on a Saturday and/or Sunday. Therefore, the frequency of PCE for Friday release is higher as compared to other weekdays. One might think that the stronger reaction to PMI on Mondays is a rational response to the first macroeconomic announcement in a month. However, this conjecture is jeopardized by the stronger reaction to a Monday release of PCE, the last announcement in a month. NFPAY is concentrated on Fridays as a matter of policy by the Bureau of Labor Statistics. It is almost always released on the first Friday of a month. Similarly, the Federal Reserve has a policy to almost always hold FOMC meetings on Tuesdays and Wednesdays. The Confidence Board always releases CCI on the last Tuesday of every month. PPI and CPI are usually released by during the second full week of the month by the Bureau of Labor Statistics. However, they are never released on Mondays of such weeks. The Bureau of Economic Analysis also avoids Monday to release the TRBAL that is usually announced early in the month, and the advanced estimate of quarterly GDP that is usually announced around the end of the month in which the relevant quarter ends. In summary, the various institutions responsible for releasing these macroeconomic announcements generally avoid Mondays. Thus, it can be presumed that they are aware of heightened uncertainty at the start of the week.

My sample of macroeconomic news does not include a very important announcement, namely Initial Jobless Claims (IJC). IJC is usually released every week on Thursday, whereas all other announcements in the 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 R^2 in the baseline results in Table 3.1 should have been higher for the 1998-2017 period, as the announcement is made every Thursday. Since, I do not find this to be the case, exclusion of IJC does not invalidate my results.

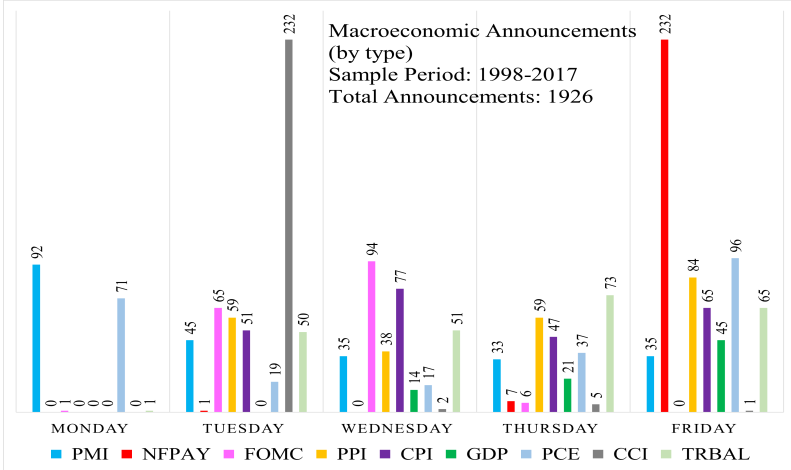
Firm-specific news such as earnings announcements, once incorporated into stock prices, reduces return comovement. As some earnings announcements were released in aftermarket hours or on non-trading days like weekends, the dates of these earnings announcements need to be adjusted to the next trading day. The frequencies of actual and adjusted earnings announcements across weekdays are reported in Panel C and Panel D of Figure 4.1, 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. Most announcements were made in the middle of the week. 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.

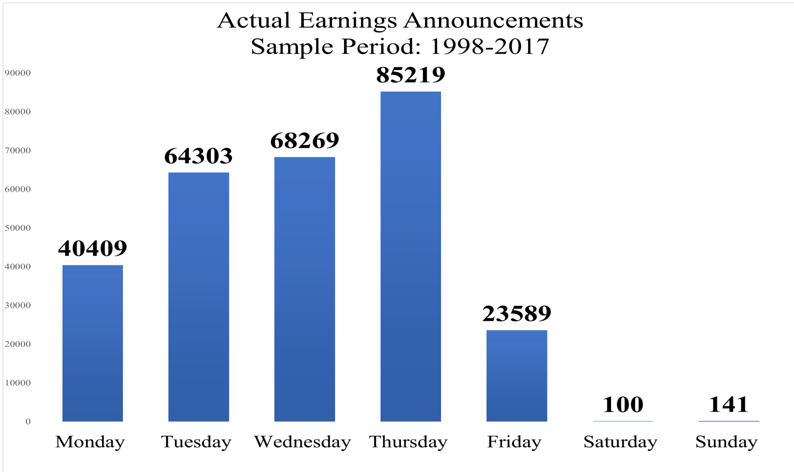
The t-tests for differences in idiosyncratic volatility (*RMSE*) in Table 3.2 (Chapter 3) provide further evidence that firm-specific news (including but not limited to earnings announcements) alone cannot explain the Monday synchronicity effect. Lower (higher) idiosyncratic volatility implies that firm-specific information impounded into stock prices to a lesser (greater) degree (Roll, 1988). However, Monday's *RMSE* values are significantly lower than only Wednesday's values. The differences are insignificant with respect to Tuesdays and Thursdays; and significantly higher with respect to Fridays. In other words, idiosyncratic volatility is not consistently lower for Monday. Therefore, the lower frequency of firm-specific news on Monday is insufficient in explaining higher comovement.



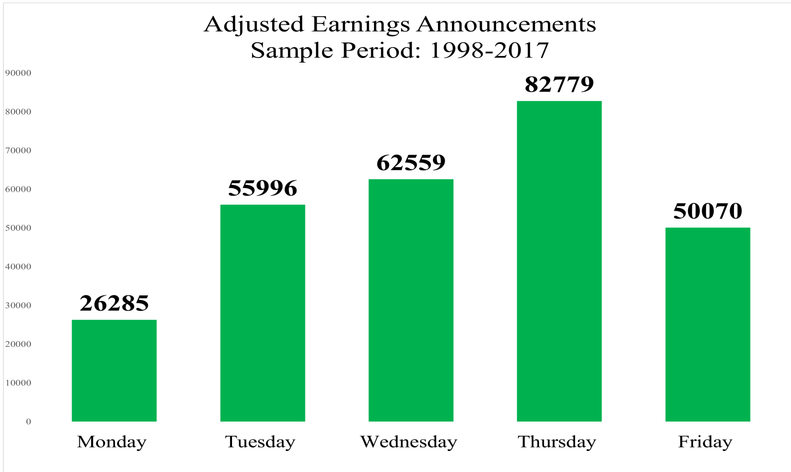
Panel A: All Macroeconomic Announcements



Panel B: Macroeconomic Announcements by Type



Panel C: Actual Earnings Announcements



Panel D: Adjusted Earnings Announcements

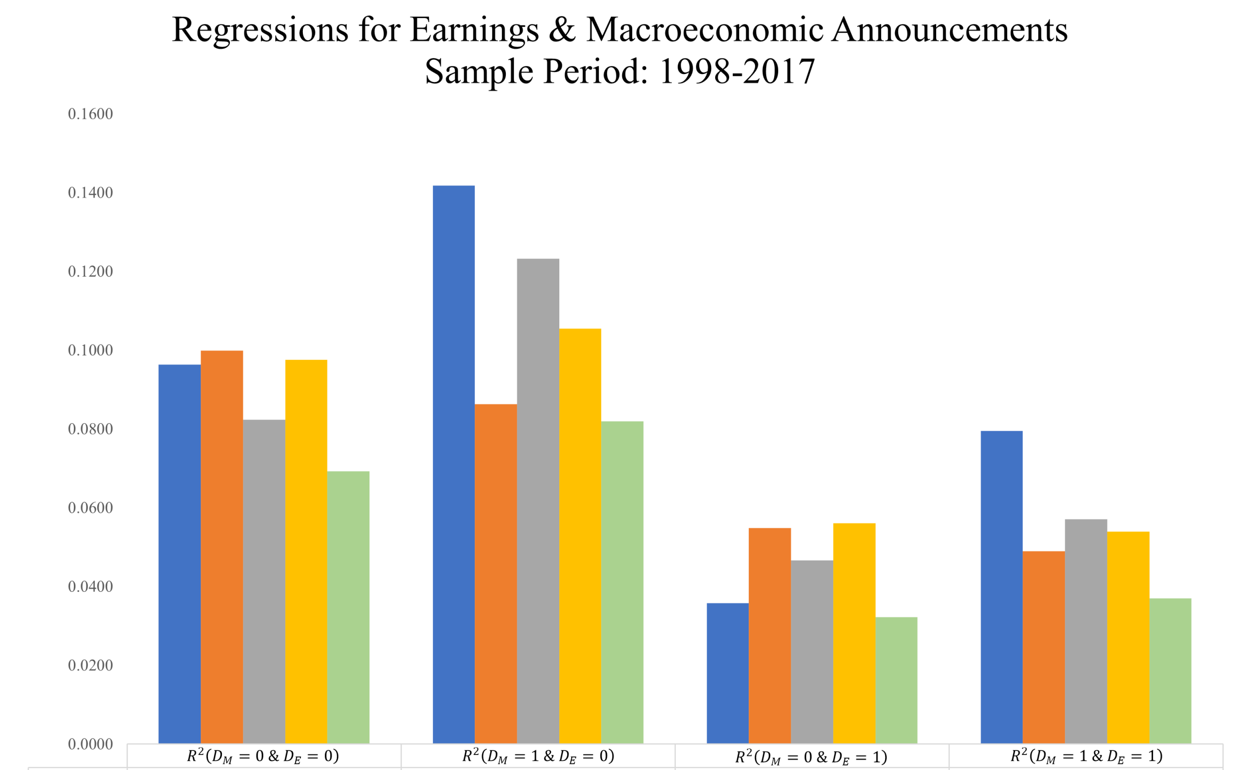
Figure 4.1: News Announcements by Weekday

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.

I analyse 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 for D_E but with respect to earnings announcements for the relevant firm-day observations. Under each combination of dummy variables and for each weekday, I run firm fixed effects regressions to control for unobserved and time-invariant firm heterogeneity. Figure 4.2 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. 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 clear from the fact that Monday R^2 is approximately 15% (39%) higher than Wednesday R^2 in the second (fourth) case. Moreover, the effect is more prominent when macroeconomic announcements are not accompanied by earnings announcements (second case vs. fourth case).

These comparisons show that high Monday synchronicity mainly occurs when macroeconomic announcements are released on Monday. Otherwise, Monday synchronicity is not necessarily higher than other weekdays. The disappearance of the Monday synchronicity effect after exclusion of macroeconomic announcements suggests that a small number of these announcements are driving the intra-week pattern in comovement.

As indicated in Panel D of Figure 4.1, earnings announcements after adjustments were the least frequent on Monday. Most announcements were made in the middle of the week. This low frequency of Monday earnings announcements contributes to the high Monday synchronicity. As shown in Figure 4.2, synchronicity is indeed lower on earnings announcement dates (third case and fourth case). However, this reduction occurs less frequently on Mondays as compared to other weekdays. Similar to the baseline results, synchronicity remains the lowest for Fridays across both announcement and non-announcement days.



	$R^2(D_M = 0 \,\&\, D_E = 0)$	$R^2(D_M = 1 \,\&\, D_E = 0)$	$R^2(D_M = 0 \,\&\, D_E = 1)$	$R^2(D_M = 1 \,\&\, D_E = 1)$
Monday	0.0963	0.1418	0.0358	0.0795
Tuesday	0.0999	0.0863	0.0549	0.0490
Wednesday	0.0823	0.1232	0.0466	0.0571
Thursday	0.0976	0.1055	0.0561	0.0539
Friday	0.0693	0.0819	0.0322	0.0370

Figure 4.2: 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 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.

Longer sample period

I 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 B1 of Appendix B, show that the Monday synchronicity effect is blurred but not eliminated by these missing announcements. Specifically, the absence of release dates for

PCE results in Monday comovement remaining higher despite the removal of announcement days, as 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. This pattern is again consistent with the contrast effect because a small amount of missing data of Monday announcements results in higher Monday comovement despite removal of other announcement dates.

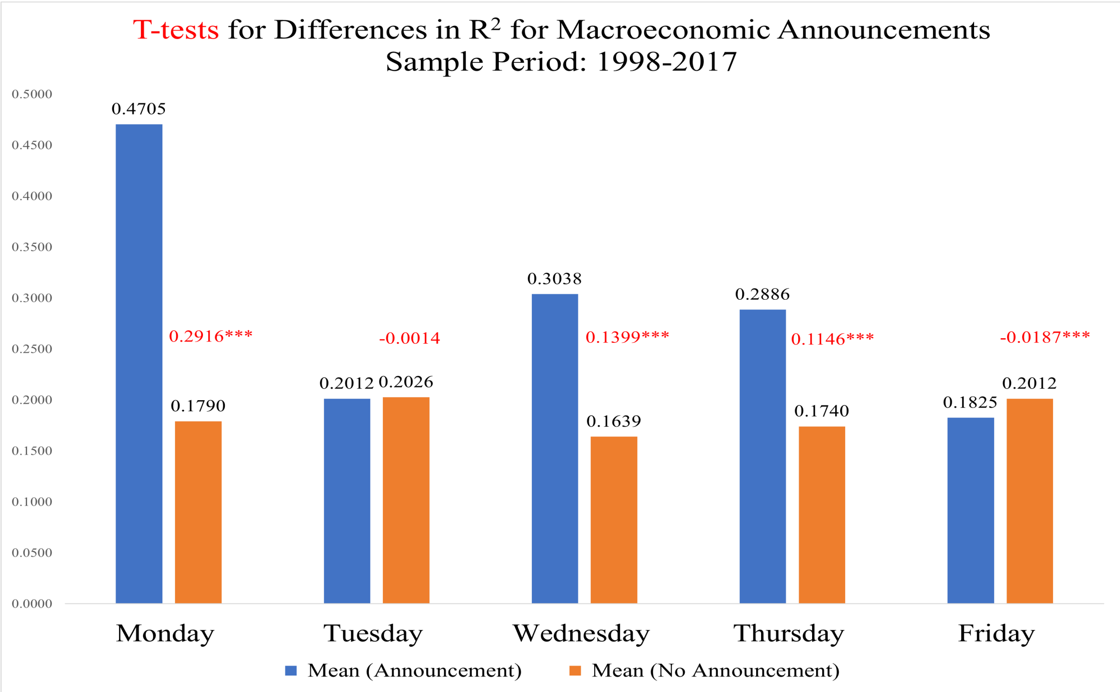
4.3.2 Robustness tests for the contrast effect

I conduct several robustness tests for the contrast effect. First, I analyse macroeconomic and earnings announcements separately. Second, I test the role of high spillover of firm-specific information in the earnings season when many firms are announcing their earnings reports. Third, I use rolling window regressions while removing the announcement days instead of splitting the sample into announcement and non-announcement days. Fourth, I weight the R^2 values from split-sample regressions (announcement and non-announcement days) with the frequency of macroeconomic announcements to reconcile these results with the baseline result in the previous chapter.

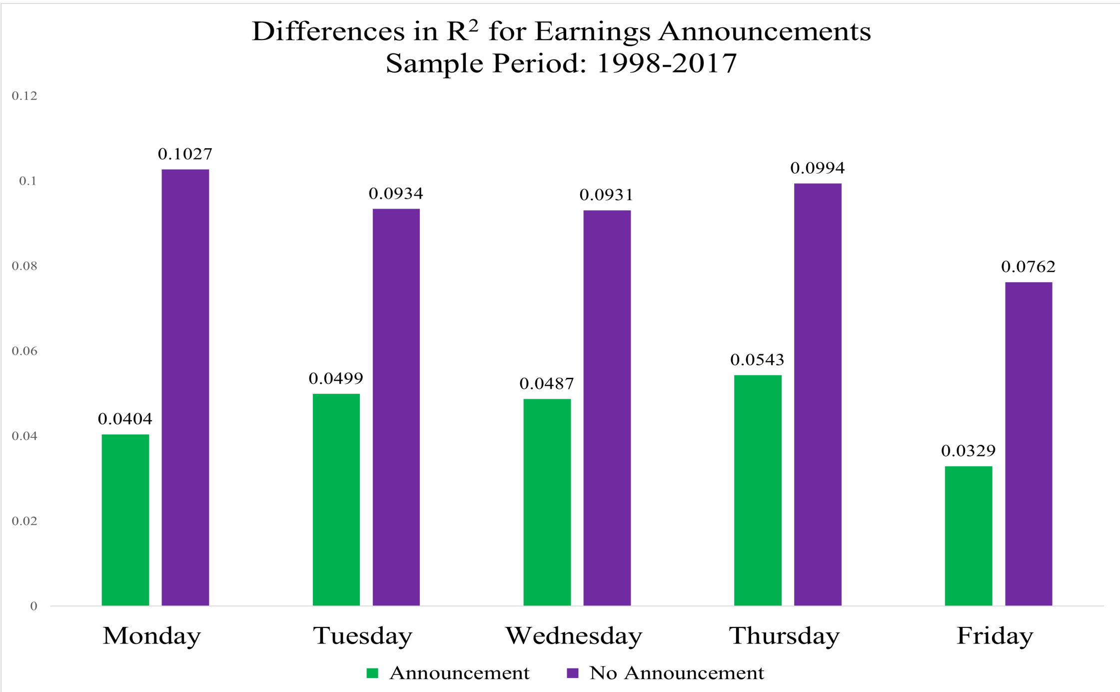
Separate analysis of macroeconomic and earnings announcements

I analyse the role of macroeconomic announcements separately (from earnings announcements) by dividing the sample into two sub-samples, one for the announcement days and the other for non-announcement days. I run synchronicity regressions separately for each firm and weekday in each sub-sample. For example, I estimate separate firm-wise regressions for Monday announcement days and Monday non-announcement days. As shown in Panel A of Figure 4.3, the difference between announcement and non-announcement R^2 averages is the largest for Monday at 29.16%, while differences for other weekdays are less. The average R^2 with macroeconomic announcements on Mondays is about three times the average for non-announcement Mondays. The differences for Tuesday and Friday are negative, inconsistent with the expectation that a macroeconomic announcement will lead to higher comovement. This inconsistent pattern indicates that processing of macroeconomic news is not uniform throughout the week. If announcement R^2 values are compared across the week (i.e., blue bars), Monday's average is significantly higher than averages of other weekdays. Monday is the highest at 47.05%, followed by 30.38% for Wednesday and lower for other weekdays. However, such is not the case if non-announcement R^2 values are compared (i.e., orange bars). The average for Monday is lower than that of Tuesday and Friday. The sharp increase in comovement from non-announcement days to announcement days for Mondays is a clear demonstration of the contrast effect.

Similarly, I analyse the earnings announcements separately from macroeconomic announcements. Since a firm can have a maximum of 80 quarterly earnings announcements during my sample period (1998-2017), it can have only 16 announcements on average for each of the five weekdays. Thus, running regressions separately for each firm is not feasible. Therefore, I run pooled regressions for earnings announcements instead of running firm-level regressions. 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, such as weekends. The results in Panel B of Figure 4.3 show that R^2 is only higher on Monday for non-announcement days, but not for the announcement days. Thus, the low frequency of earnings announcements on Monday complements the contrast effect of macroeconomic announcements by making the background quieter. 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.



Panel A: R^2 for Macroeconomic Announcements



Panel B: R^2 for Earnings Announcements

Figure 4.3: Synchronicity Regressions for News Announcements

The sample period extends from 1998 to 2017. 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 coloured 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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

R^2 values in Panel A of Figure 4.3 cannot be directly compared to those in Panel B because I use firm-level regressions in the former and pooled regressions in the latter. Thus, I use pooled regressions for macroeconomic announcements to allow for such comparison. The results reported in Table 4.1 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 higher than R^2 values for announcement days on other weekdays, as predicted by the contrast effect. It is also higher than R^2 values for earnings announcements reported in Panel B of Figure 4.3.

Table 4.1: 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

Information spillover during earnings season

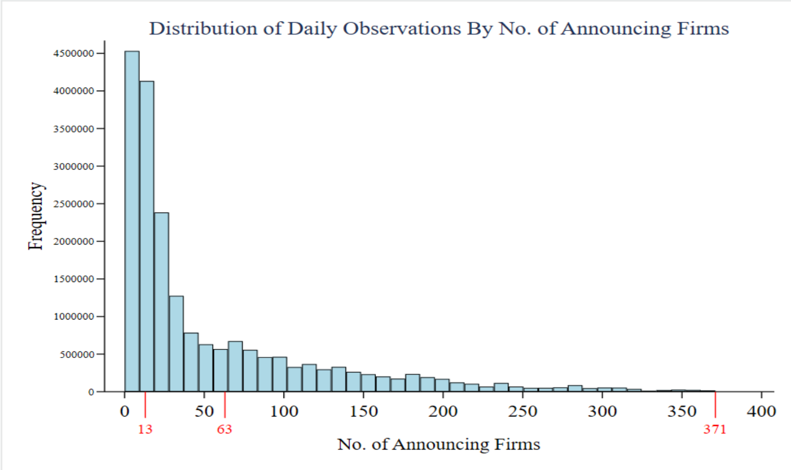
The role of earnings announcements is complementary to the contrast effect of Monday macroeconomic announcements. Since the contrast will be more if the background is quieter, fewer earnings announcements on Monday make the macroeconomic announcement more salient. Therefore, the number of firms releasing their earnings news will influence the contrast effect. If many firms are releasing their earnings news on the same day, the R^2 of non-announcing firms can be affected by the strong spillover of information from the announcing peer firms. This effect will be quite strong during the earnings season because many firms will announce their earnings news. The contrast effect will be absent or weaker on such dates because the background has more clutter.

I 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 4.4, the maximum value of this count is 371, while the 30th percentile is 13 and the 70th percentile is 63. The histogram shows that earnings announcements are concentrated around a few days in the entire year. Most firms announce their earnings in these few days, and very few announcements are made on other days. I divide the daily observations into three sub-samples using the 30th and 70th percentile values as breakpoints. Sub-sample 1 is significantly larger than the other two because most dates of the year 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 few dates on which a large number (64 or more) of firms are announcing their earnings. Hence, sub-sample 3 can be a proxy for the earnings season. I run regressions identical to the ones in Panel B of Figure 4.3 for each sub-sample.

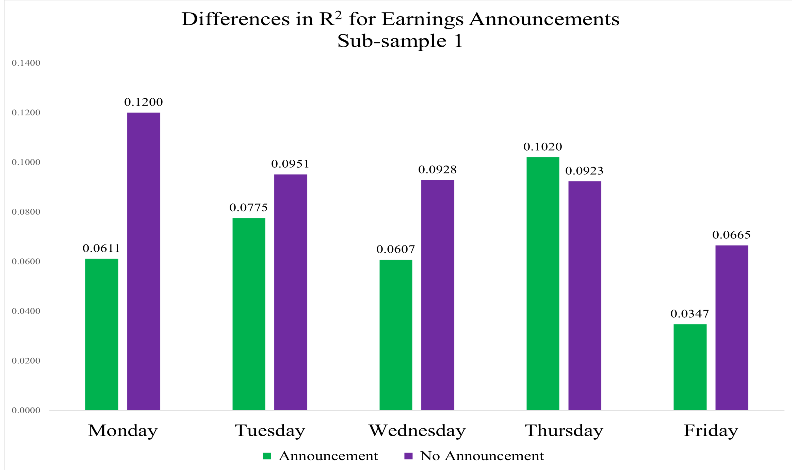
The following example illustrates how a daily observation of a given firm is allocated to different bins. Assume that 12 firms released their earnings on a specific date, but Microsoft Inc. (MSFT) did not announce its earnings. Therefore, its daily return for this date will fall under the non-announcing firm-date observations in sub-sample 1. Assume that on the next day, 40 firms announced their earnings, but MSFT still did not announce its earnings. In this case, the daily return of MSFT will fall under the non-announcing firm-date observations in sub-sample 2.

The results in Figure 4.4 show that 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 the spillover effect is stronger with increasing concentration of earnings announcements, which results in lower comovement across the entire market. Monday R^2 is significantly higher at 12.00% (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 for non-announcing firm-days in sub-sample 2 (Panel C), but it is not the highest in any other case. 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 there is little spillover.

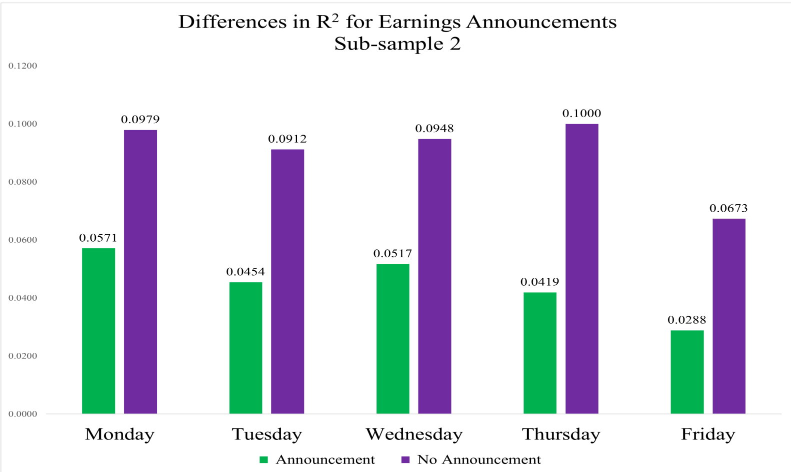
My results are further supported by Chan and Marsh (2021) who find that influential S&P 500 firms, which are market movers, rarely announce their earnings on Monday. Therefore, there is very little spillover effect on Mondays. They also find that macroeconomic announcements lose their importance for the return-beta relationship if they are overlapped by leading announcements of influential firms. Hence, macroeconomic announcements on Mondays are rarely overlapped by earnings announcements of S&P 500 firms, and the contrast effect will be stronger.



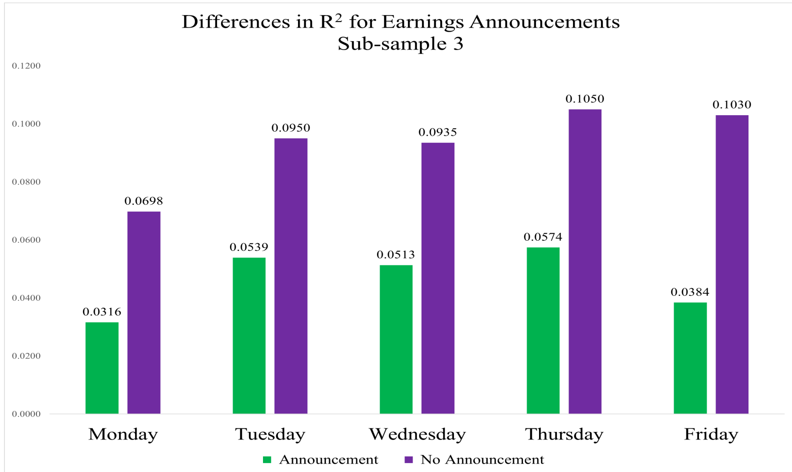
Panel A: Distribution of Daily Observations



Panel B: Sub-sample 1



Panel C: Sub-sample 2



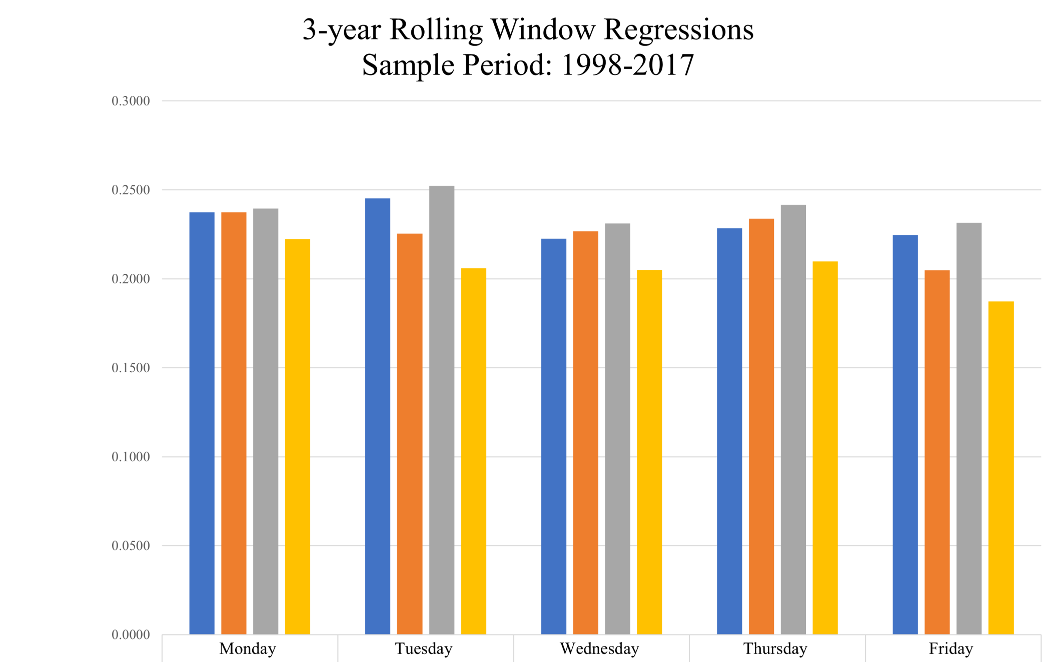
Panel D: Sub-sample 3

Figure 4.4: 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.

Rolling window regressions

As an additional robustness test, I 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 4.5 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).



	Monday	Tuesday	Wednesday	Thursday	Friday
No Macro	0.2374	0.2452	0.2226	0.2284	0.2247
No Earn	0.2374	0.2254	0.2267	0.2338	0.2049
No Macro/Earn	0.2395	0.2523	0.2312	0.2415	0.2315
All Days	0.2224	0.2060	0.2050	0.2098	0.1873

Figure 4.5: 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 the aforementioned results, I 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 3.1 (Chapter 3) seemingly depict that comovement is higher on Mondays akin to a seasonal anomaly. However, the analysis of news announcements reveals that comovement is only higher when macroeconomic announcements are released on Monday. Otherwise, comovement on Monday is not significantly different from comovement on other days. To reconcile both results, I employ a frequency-weighed R^2. Specifically, I calculate weighted averages of the mean values of R^2, reported in Panel A of Figure 4.3, 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 announcement 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 corresponding R^2 mean values and then adding them up:

$$R^2_{Wtd.\ Avg.} = R^2_{Ann.} \times Weight_{Ann.} + R^2_{NoAnn.} \times Weight_{NoAnn.} \tag{4.1}$$

Table 4.2 reports the results. 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, I demonstrate that a simple weighting scheme based on the frequency of macroeconomic announcements can produce a pattern of R^2 values close to my baseline results.

Table 4.2: 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 3.1) for comparison with weighted averages of R^2 in Panel A.

Panel A: Firm-Level Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Weekday	Ann.	Non-Ann.	Total Days	$W_{Ann.}$	$W_{NoAnn.}$	$Avg.R^2_{Ann.}$	$Avg.R^2_{NoAnn.}$	$Wtd.AvgR^2$	$\%\Delta R^2$
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 3.1)

	Sample Period 1998–2017		Sample Period 1953–2017	
	(1)	(2)	(3)	(4)
Weekday	$Avg.R^2$	$\%\Delta R^2$	$Avg.R^2$	$\%\Delta R^2$
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%

Taken together, 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 my 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, Monday macroeconomic news are few and far between, making them stand out more against the quieter information background.

Significantly higher values of regression coefficients on Monday, reported in Table 3.2 (Chapter 3), 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 are 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 behaviour in contributing to abnormally high synchronicity because of 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.

4.3.3 Contrast effect & uncertainty

I revisit the role of uncertainty over longer weekends to analyse how the contrast effect is moderated. I use the sample of weeks preceded by a Friday holiday, and weeks with a Monday holiday, identical to those used in Table 3.11 (Chapter 3). Two regressions are run for each weekday over the sample period 1998-2017: one for announcement days, and the other for non-announcement days. The results in Table 4.3 depict that the contrast effect is present even for weeks that 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 increases for such Tuesdays (columns 5 and 6), but it is not as striking 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 I have used elsewhere.

Results in Table B1 of Appendix B show that VIX is consistently higher on the first trading day of the week (whether Monday or Tuesday). Thus, confirming that heightened uncertainty because of a longer weekend contributes to higher comovement at the start of the week. In summary, while uncertainty over (long) weekends plays a role in higher Monday synchronicity, the role of the contrast effect remains significant.

I further explore the role of uncertainty by running synchronicity regressions under increasing levels of VIX. I divide the daily observations into three sub-samples (low, medium and high) using the 30^{th} and 70^{th} percentile values of VIX as breakpoints. As shown in Panel A of Table 4.4, R^2 values consistently increase for all weekdays as the level of VIX increases. Thus, comovement increases as uncertainty in the market becomes higher. 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 under low levels of VIX. This indicates that uncertainty plays a role in keeping the comovement higher on Monday. However, the regressions for announcement and non-announcement days in Panel B of Table 4.4 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 seem to amplify the contrast effect, but it is not a necessary requirement since it works even when VIX is low. However, when VIX is within medium range, there is no evidence of the contrast effect. Overall, how VIX interacts with the contrast effect is unclear. A greater in-depth inspection of this issue is indeed an avenue of future research.

Table 4.3: Macroeconomic Announcements & 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. In **Panel A** and **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: Pooled OLS Regressions for Macroeconomic Announcements

	(1)	(2)	(3)	(4)	(5)	(6)
	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 B: Pooled Fixed Effects Regressions for Macroeconomic Announcements

	(1)	(2)	(3)	(4)	(5)	(6)
	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 4.4: 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: $VIX_{\leqslant 30}$ includes firm-date observations on which the value of VIX is less than or equal to its 30th percentile; $VIX_{>30\,\&\,\leqslant 70}$ 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)	(2)	(3)
	$VIX_{\leqslant 30}$	$VIX_{>30\,\&\,\leqslant 70}$	$VIX_{>70}$
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)	(2)	(3)	(4)	(5)	(6)
	$VIX_{\leqslant 30}$		$VIX_{>30\,\&\,\leqslant 70}$		$VIX_{>70}$	
	Ann.	No Ann.	Ann.	No Ann.	Ann.	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

4.3.4 Investor attention

Even though, I focus on the effect of news announcements (information supply) on Monday return synchronicity, 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 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 there is a commonality in investor attention to firm-specific information, which in turn drives up excess return comovement.

Attention to macroeconomic announcements

I test whether investor attention leads to high Monday synchronicity. I first consider attention to macroeconomic news. Table B2 of Appendix B reports the averages of the standardised Google SVIs for each of the nine macroeconomic news, separately for announcement and non-announcement days. Standardisation is necessitated by the unequal scales of the data over time, as well as across the different types of news. The raw values of SVIs for each year are subtracted by the annual mean and then divided by the annual standard deviation. Negative values simply imply that the raw values are below the mean. As expected, the attention to macroeconomic news is generally higher on announcement days. Among the different types of announcements, FOMC is the most attention-grabbing one, followed by NFPAY-an observation consistent with several studies.[4]

In Figure 4.6, I compare the standardised 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 attention.[5] 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 comparatively more attention.

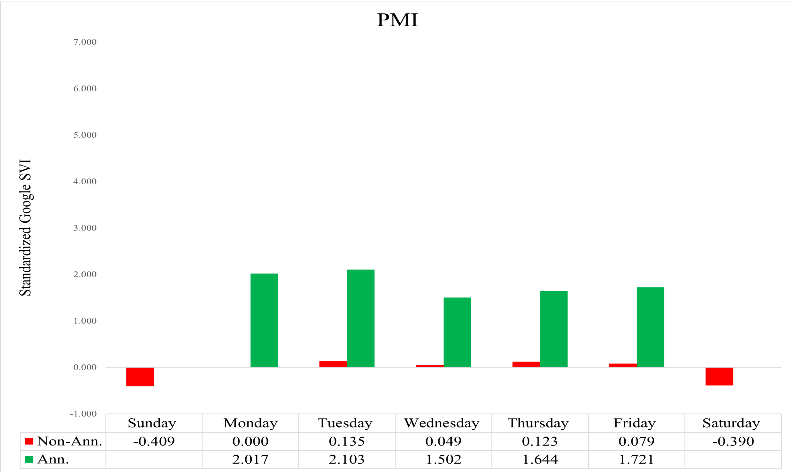
If announcements of FOMC and NFPAY, which generally do not occur on Mondays, attract more attention than other news, why is synchronicity not higher for days other than Monday? I argue that PCE and PMI are more salient on Monday, despite being less vivid than FOMC and NFPAY in terms of capturing attention. 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

[4] See Carnes and Slifer (1991); Andersen and Bollerslev (1998); Pasquariello and Vega (2007); Savor and Wilson (2013); Lucca and Moench (2015); Brusa *et al.* (2020).

[5] In the period 1998-2017, all Monday announcements, except two (one each for FOMC and TRBAL), are 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.

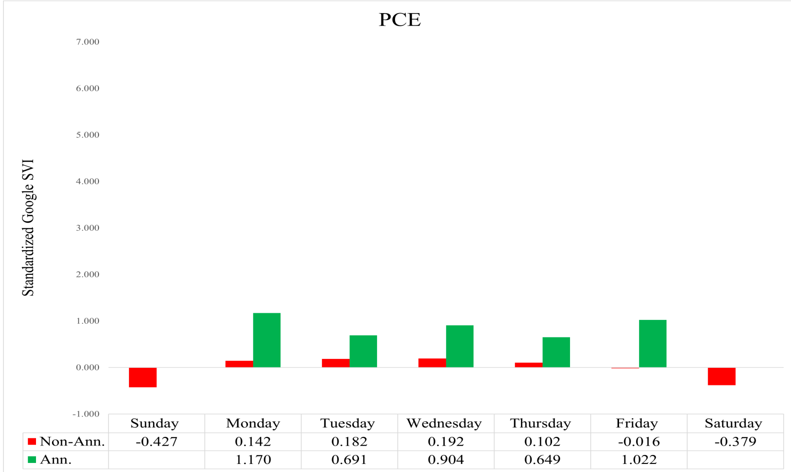
may capture more attention because it is inherently more vivid than other stimuli, regardless of the surroundings; but any stimulus may become more salient because of its positioning in relation to other stimuli. Thus, the salience of PMI and PCE announcements on Mondays is not necessarily because of 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.

A strong contrast effect does not necessarily imply higher attention. The contrast effect refers to the higher (or lower) perception of a stimulus in the presence of other stimuli in the surroundings. The more salient a stimulus, the stronger is the contrast effect. Salience does not require individuals to actively increase their attention towards that stimulus; instead, such stimulus draws attention towards itself. Hence, it is not required of individual and institutional investors to actively search on Google or Bloomberg terminals to make such information salient. Hartzmark and Shue (2018) find evidence of contrast effect even for large firms with salient earnings announcements, as opposed to the literature on limited attention which 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).



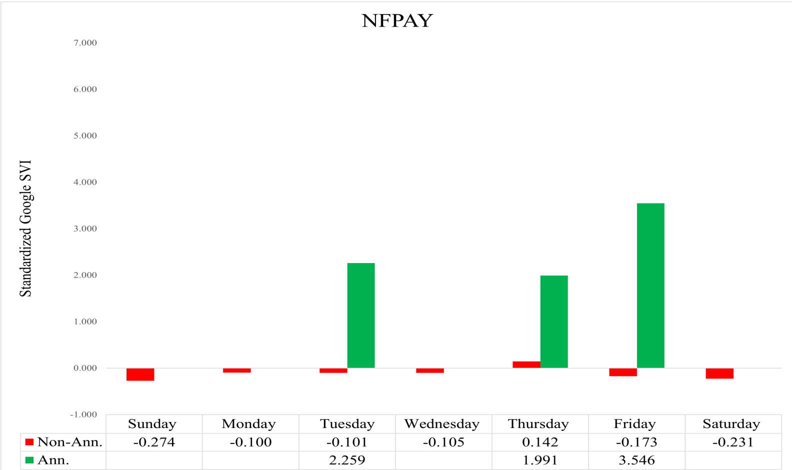
	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Non-Ann.	-0.409	0.000	0.135	0.049	0.123	0.079	-0.390
Ann.		2.017	2.103	1.502	1.644	1.721	

Panel A: Google SVI for PMI



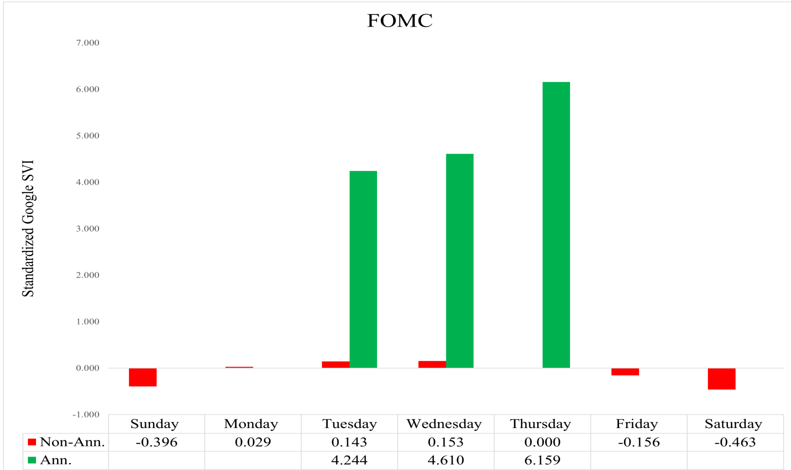
	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Non-Ann.	-0.427	0.142	0.182	0.192	0.102	-0.016	-0.379
Ann.		1.170	0.691	0.904	0.649	1.022	

Panel B: Google SVI for PCE



	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Non-Ann.	-0.274	-0.100	-0.101	-0.105	0.142	-0.173	-0.231
Ann.			2.259		1.991	3.546	

Panel C: Google SVI for NFPAY



	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Non-Ann.	-0.396	0.029	0.143	0.153	0.000	-0.156	-0.463
Ann.			4.244	4.610	6.159		

Panel D: Google SVI for FOMC

Figure 4.6: 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.

Attention to firm-specific information

I also analyse the role of investor attention towards firm-specific news, which is expected to reduce synchronicity by facilitating rapid incorporation of information into stock prices. Comovement is indeed less if investors actively seek firm-specific information (Kong *et al.*, 2019). However, attention itself can cause comovement, as hypothesised by Mondria (2010). Figure 4.7 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.

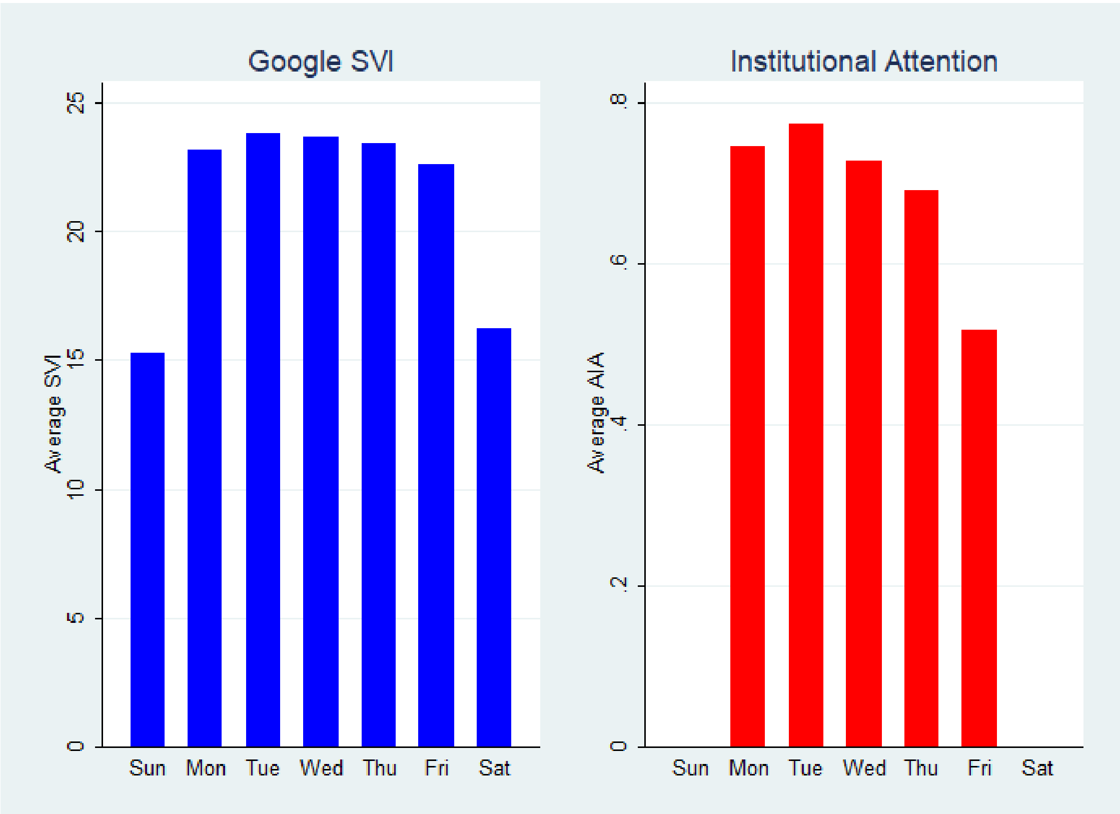


Figure 4.7: Firm-Specific Investor Attention

Google SVI is the measure of retail attention to firm-specific news. The bar chart on the left dispalys 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.

I test day-of-the-week synchronicity under abnormally high levels of retail and institutional attention. AIA is a categorical variable assigning a score based on how high (or low) is the level of institutional attention on a given day, relative to its previous 30-day moving average. I construct a dummy variable D_{AIA} where the value is 1 for a firm on a given day if the AIA score is 4 (i.e. institutional attention is more than 96% higher than its 30-day moving average), and 0 otherwise. Thus, the dummy identifies days with extremely high institutional attention for a firm. Since the Google SVI is a continuous variable, I construct a categorical variable analogous to the AIA, assigning scores from 0 to 4 based on retail attention relative to its 30-day moving average. Similarly, I transform it into a dummy variable D_{ADSVI} where the value is 1 if the score is 4, and 0 otherwise. I divide the sample into two sub-samples using D_{ADSVI}, and run pooled synchronicity regressions for all weekdays combined, as well as each weekday separately. I repeat the procedure for D_{AIA}.

R^2 values of these regressions are reported in Table 4.5. When all weekdays are considered together in Panel A, R^2 is expectedly lower when retail or institutional attention is extremely high because investors are focused on firm-specific information and thus, comovement is lower. When each weekday is analysed separately in Panel B, the same pattern exists. However, when R^2 values are compared across the week, Monday R^2 is always higher whether attention (retail or institutional) is extremely high or not. Thus, the Monday synchronicity effect cannot be explained by firm-specific investor attention, even when it is extremely high. Macroeconomic announcements on Monday remain salient even when investors are allocating much of their top-down attention to firm-specific information.

Table 4.5: Synchronicity Regressions for Firm-specific Investor Attention

The sample period extends from 2004 to 2017. D_{ADSVI} is a dummy variable indicating days with abnormally high daily SVI for a firm. D_{AIA} is a dummy variable indicating days with abnormally high institutional attention. In Panel A, two pooled fixed effects regressions are run, one for those days when D_{ADSVI} (or D_{AIA}) is equal to 0 and the other for those days when D_{ADSVI} (or D_{AIA}) is equal to 1. In Panel B, the regressions are run separately for each weekday in the same manner as in Panel A. R^2 values of the pooled regressions are reported.

Panel A: All Weekdays

	(1)	(2)	(3)	(4)
	$D_{ADSVI} = 0$	$D_{ADSVI} = 1$	$D_{AIA} = 0$	$D_{AIA} = 1$
	0.2815	0.2493	0.2502	0.1963

Panel B: Separate Weekdays

	(1)	(2)	(3)	(4)
	$D_{ADSVI} = 0$	$D_{ADSVI} = 1$	$D_{AIA} = 0$	$D_{AIA} = 1$
Monday	0.3120	0.3119	0.2631	0.2305
Tuesday	0.2886	0.2525	0.2553	0.2135
Wednesday	0.2863	0.2570	0.2588	0.2104
Thursday	0.2897	0.2438	0.2583	0.1744
Friday	0.2292	0.2048	0.2214	0.1738

4.4 Conclusion

In this chapter, I conclude that the higher Monday synchronicity found in Chapter 3 can be best explained by the well-documented contrast effect (Hartzmark and Shue, 2018). Abnormally high Monday return synchronicity is striking since fewer macroeconomic announcements are released on Monday, while one would expect more macroeconomic news to drive up return comovement. Fewer earnings announcements on Monday and increased uncertainty after weekends do contribute to higher Monday return synchronicity. However, I show neither of them can fully explain the Monday synchronicity anomaly. Instead, it is primarily driven by a small number of macroeconomic news arriving on Monday. I rule out that Monday synchronicity effect is a seasonal anomaly recurring on a weekly basis.

Similar to a thunder sounding louder during quiet nights compared to noisier nights, the few macroeconomic and firm announcements constitute a quiet background on Mondays. When the occasional macroeconomic announcement is released, it becomes more salient and drives up return comovement. Higher economic uncertainty and risk aversion over the weekend also contribute to keeping the comovement higher on Monday by forcing investors to prioritise learning about aggregate shocks to the economy over firm-specific information. Salience does not depend on the vividness of macroeconomic announcements. NFPAY and FOMC are the two most important announcements for market participants, but they are not salient because they are released on days when there are many other announcements for investors to look at. Even PMI and PCE, which comprise almost all Monday announcements, are not salient when they are released on days other than Monday.

Both salience of Monday macroeconomic announcements and the category-learning behaviour (Peng and Xiong, 2006) result in a preferential allocation of attention to market-wide news. However, bottom-up attention exogenously rises for market-wide news in the case of salience, while investors voluntarily and endogenously allocate top-down attention to market-wide news in category-learning. Hence, these processes are distinct from each other. Further research is required to determine whether salience of announcements has a moderating role in the crowding-out effect (Liu *et al.*, 2019) or complementary effect (Hirshleifer and Sheng, 2021) of macroeconomic news on attention to firm-specific news.

This study, to the best of my knowledge, is the first to document the Monday synchronicity anomaly. It contributes to both the literature on return synchronicity and on calendar effects in financial markets. I also extend the application of salience theory to macroeconomic announcements. While I focus 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. My findings have important implications not only for day traders but also for financial regulators and stock exchanges concerned with financial stability seeking to moderate extreme levels of volatility and comovement.

Chapter 5

The Morning After: Late-night Shows and the Stock Market

5.1 Introduction

In the previous chapter, I emphasise on the role of salience as an attentional mechanism. In economic decision making, salience manifests not only psychologically, but also physiologically. For example, visual perception also plays a role in influencing investors choices. In this chapter, I study the effect of sleep deprivation on cognitive processes, which in turn affect financial market outcomes. Sleep is an important physiological function and its disruption negatively affects cognitive processes involved in decision making, such as concentration, attention, and memory (Dinges *et al.*, 1997; Smith *et al.*, 2002; Harrison and Horne, 2000; Ellenbogen, 2005; Alhola and Polo-Kantola, 2007; Banks and Dinges, 2007).

The concept of market efficiency entails unlimited information processing capacity and instantaneous adjustment in asset prices by market participants. However, human cognitive processes are bounded by attentional constraints (Kahneman, 1973). Moreover, various physiological processes influence a person's cognitive functions. The body's internal clock regulates many biological processes over a 24-hour cycle, including sleep. Thus, any disruption in the circadian rhythm causing sleeplessness will also affect other psychological and physiological processes.

My study is not the first to explore this question. DST change has been used to study the impact of sleep loss on stock returns (Kamstra *et al.*, 2000; Mugerman *et al.*, 2020). However, many studies contest that stock returns could be significantly affected by a one-hour change in sleep because of DST change (Pinegar, 2002; Worthington, 2003; Lamb *et al.*, 2004; Jacobsen and Marquering, 2008; Müller *et al.*, 2009; Gregory-Allen *et al.*, 2010). Even though DST changes represent an exogenous shock to sleep for all market participants, they take place only twice a year.

Late-night shows have become prevalent since the advent of internet-based TV services like Netflix and Hulu. These services usually make their shows available to their subscribers late in the night around 3:00 AM. Moreover, they frequently release an entire season of the show instead of releasing a single episode. Therefore, it can be expected that people would stay up late in the night to watch these episodes as and when they become available. The number of Netflix subscribers by the end of 2011 was about 23.5 million worldwide. By the third quarter of 2021, this figure has reached 213.5 million globally and 74 million for U.S. and Canada region.[1] Similarly, Hulu's subscribers in the U.S. have increased to 43 million in 2021 from 1 million in 2011. It is pertinent to note that a single Netflix subscription can be used on multiple devices. Therefore, the number of viewers is considerably more than the number of subscriptions. Thus, a popular show released late at night may attract a sizeable number of traders who may decide to forgo their sleep and binge-watch multiple episodes. Naturally, sleep deprivation during the night will affect their behaviour during the next day. Trading days following the release of these late-night shows provide a framework to study the impact of sleep deprivation on financial markets.

According to a media report, when Netflix released all fifteen episodes of a new season of *Arrested Development* in 2013, approximately 10% of the viewers watched the entire season

[1] Netflix Third-Quarter 2021 financial results; available at: https://s22.q4cdn.com/959853165/files/doc_financials/2021/q3/Q3'21-Website-Financials.xlsx

within 24 hours of release (Wallenstein, 2013). Matrix (2014) states that binge viewing, mostly on Netflix, is becoming culturally permissible for viewers of all ages, and the terms ‘binge viewing’, ‘marathon viewing’ and ‘Netflix’ are becoming synonymous in popular press. Mudhar (2013) writes “Entertainment is fast becoming an all-you-can-eat buffet. Call it the Netflix effect.” Exelmans and Van den Bulck (2017) find that frequent binge viewers have a poorer sleep quality, increased fatigue and more symptoms of insomnia, not found in regular television viewers. According to one poll (2018), 52% of TV watchers across all age groups have stayed up all night to watch a show, whereas in the 18-29 age group 76% of the TV watchers have resorted to this habit. In recent years, TV viewers have developed a preference to see the entire season all at once. In a survey (2019), 44% of U.S. viewers across all age groups prefer to see an entire season with an additional 21% demanding to see at least a few episodes of the season. Only 15% of the viewers prefer to watch a single episode at a time. In the 18-29 and 30-44 age groups 58% and 53% of the viewers want to see the entire season in a single setting. Even in the 45-54 age group, this proportion is 45%. The preference for traditional single weekly episode now remains in sizeable proportion only in the much older age groups. In summary, the practice of binge-watching late in the night has become quite widespread. Hence, it is reasonable to assume that this emerging cultural trend may significantly impact financial markets.

Both DST and late-night shows have the advantage of being exogenous shocks to sleep, unrelated to financial markets and the state of the economy. DST affects all individuals in a geographical region uniformly, however, watching late-night TV shows is indeed a voluntary act. Moreover, the precise number of individuals choosing to watch a show at a given time is unknown. One cannot know whether the individuals watching the shows are also traders in financial markets. Despite these obvious limitations, my study is motivated by the fact that the popular late-night shows potentially draw a sizeable proportion of traders to sacrifice their sleep. Therefore, I restrict my analysis to only the most popular shows. Even after imposing this restriction, it is important to recognise that a show may become popular after many weeks or even months of its initial release. However, the extent of sleep loss due to a late-night show is considerably more than a one-hour clock time change. People will have to stay awake till 03:00 AM and then start watching the show. Similarly, the frequency of these shows is much higher than the bi-annual clock time change.

I find that market returns are significantly down on days following popular late-night shows, consistent with the findings of Kamstra *et al.* (2000). On average, the market index drops by about 0.25% on the day following these shows. Annually, the decrease in market returns is around 2.5% cumulatively, based on an average of 10 popular shows being released every year. The effect is more pronounced in stocks with larger market capitalisation, higher institutional ownership, higher stock price, and higher book-to-market ratio. Perhaps sleep deprivation due to late-night shows should affect individual investors more than professional traders of institutional investors. However, sleep hours of such professionals have been found to be lower than others (Kamstra *et al.*, 2000; Siganos, 2021). It is plausible that their sleep hours will deteriorate even further if they are watching late-night shows. Thus, the effect is stronger for stocks which are the habitat of institutional investors. The fact that there is a market-wide effect on returns, predominantly in large-cap stocks with high institutional ownership, implies that sleep deprivation is affecting the behaviour of institutional investors that currently hold most of the U.S. firms ownership.

The decrease in stock returns might be driven by lack of trading activity by sleep deprived investors. In other words, negative returns may be accompanied by decreased trading activity and liquidity on such days. Alternatively, negative returns could also be a consequence of a selling pressure due to increased noise trading by retail investors. In such circumstances, informed traders, particularly those employing trading algorithms, may endogenously increase their trading activity once they detect higher levels of noise trading (Kyle, 1985). By focusing on exogenously driven sleep deprivation, I study the unadulterated effect of exogenous changes in noise trading on liquidity. Identification of such an environment is necessary because there is no clear evidence whether retail investors cause liquidity to increase, or whether they are attracted by liquidity. For instance, Grullon *et al.* (2004) find that both liquidity and ownership by individuals increase for firms that attract attention of investors through advertising activities. Abudy (2020), however, find that retail investors trade more when liquidity is high.

I find that there is no significant change in noise trading by retail investors or algorithmic trading by institutional investors. Apart from a decrease in the Amihud illiquidity ratio, trading volume, turnover, bid-ask spread and price range do not change significantly. The decrease in Amihud ratio indicates that the price impact of trades is less and liquidity improves in terms of depth and resilience (Amihud, 2002). My findings are consistent with other studies that also find no evidence of any appreciable change in trading volumes accompanying negative stock returns caused by sleep loss (Cai *et al.*, 2018; Dickinson *et al.*, 2020).

My findings differ from Peress and Schmidt (2020), who find that liquidity decreases in small stocks with low institutional ownership when retail investors are distracted by sensational news on TV. If sleep deprivation leads to investor distraction and reduced attention, liquidity should have decreased in such stocks. However, I find that Amihud ratio improves for larger stocks with high institutional ownership, while there is no change in liquidity for the smaller stocks with low institutional ownership. Intuitively, TV coverage of sensational news during market hours will distract retail investors and they will stay away from trading and, hence, liquidity will decline. In my study, investor distraction would manifest only if investors continue to binge-watch the late-night shows into the morning when trading starts. The fact that liquidity does not decline implies that investors resume trading in the morning, albeit suffering from sleep deprivation.

The presence of higher risk aversion and uncertainty will depress stock returns because investors will demand a higher risk premium. The contemporaneous price must then decrease to make future expected returns high enough to entice the risk-averse investors. I find that sleep deprived investors are more risk-averse on days following late-night shows. Thus, stock returns are lower due to a demand for higher risk premiums. High levels of VIX on such days lead to a stronger (and negative) impact on returns, since risk aversion is already high and sleep loss further inhibits the propensity for risk-taking. This finding is consistent with the study by Mckenna *et al.* (2007) who find that sleep deprived individuals have a lesser (higher) propensity for risk-taking if the outcome is framed in terms of a potential loss (gain). The fear of losses on investments will be greater when VIX is higher; under such circumstances, sleep deprived investors will take lesser risk than usual and stock prices will decline. Similarly, Kamstra *et al.* (2000) argue that stock returns are negative after DST change because of greater anxiety caused by sleep disturbance. Chaumet *et al.* (2009) also find that risk-taking propensity is lower in sleep deprived individuals in stressful conditions, like being placed in isolation. In summary, market returns decline because sleep deprived investors become more risk-averse to potential losses. This behaviour is further aggravated when uncertainty (characterised by high levels of VIX) is high.

Detrimental effects of sleep loss on cognitive processes will make it more difficult for investors to process macroeconomic, sector, and firm fundamentals, as well as technical charting patterns, to buy a stock. In other words, buying decisions require a greater cognitive effort than selling decisions. Killgore (2007) and Libedinsky *et al.* (2013) find that sleep deprived individuals are willing to accept a smaller monetary reward that requires less effort (i.e. higher effort discounting). Stock returns will then decline if sellers outnumber the buyers. Furthermore, Horne (2013) relates higher effort discounting to a change in risk perception, which is consistent with my finding that higher risk aversion leads to more negative returns. Risk-averse investors suffering from sleep disturbance will prefer to make heuristic selling decisions rather than making more mentally challenging and complex buying decisions.

I contribute to the literature on the impact of sleep deprivation on financial markets using a new proxy for sleep loss as opposed to the commonly used DST change. The fact that market returns are significantly affected on the day following late-night shows, imply that a sizeable cohort of traders are indeed watching these popular shows. I explore the effects of sleep loss in different market segments and for stocks with varying characteristics, unlike other studies on the impact of sleep loss on stock markets (Kamstra *et al.*, 2000; Mugerman *et al.*, 2020). I also contribute to the literature on noise trading and algorithmic trading by relating them to behavioural changes induced by sleep loss.

The rest of this chapter is organised as follows. Section 5.2 documents the data. Section 5.3 presents the methodology. Section 5.4 reports the empirical findings and various robustness tests.

Finally, Section 5.5 concludes.

5.2 Data

Late-night TV shows

I manually collect the dates and times of the release of seasons/episodes of TV shows from the Futon Critic website.[2] These shows have been telecasted between the period January 2012 to December 2020.[3] All times are represented as Eastern Standard Time for the U.S. I define late-night TV shows as those that are released between 12:00 AM and 5:00 AM. A show that is seen by only a few individuals cannot be considered as a sufficiently strong exogenous shock to sleep for a sizeable cohort of investors. Thus, the sample is restricted to all those shows that have been listed as the most watched or most popular shows by Netflix/Hulu or third-party rating websites like "Rotten Tomatoes and "IMDb.[4] Out of 1225 shows in total, 129 are categorised as the most popular. Moreover, this restriction is also necessitated by the ever-increasing frequency of late-night show releases. For example, the number of release dates (with one or more shows) in 2018, 2019 and 2020 is 213, 259 and 295, respectively. Thus, only a few non-event days will be left if all these shows are included in the sample. I also restrict the sample to exclude shows in languages other than English, and shows released only outside the U.S. geographical region.

Stock returns, firm fundamentals & macroeconomic data

I collect daily returns data for the following portfolios from January 1, 2012 to December 31, 2020 from WRDS: CRSP value-weighted index, CRSP equal-weighted index, S&P500 index, decile portfolios sorted by market capitalisation, decile portfolios sorted by CAPM beta, and decile

[2] http://www.thefutoncritic.com
[3] Data on release dates prior to 2012 is incomplete and the number of shows in any year is less than 10.
[4] https://www.rottentomatoes.com
https://www.imdb.com/?ref_=nv_home

portfolios sorted by standard deviation of returns. In addition, I obtain daily returns data for decile portfolios sorted by B/M ratio from Kenneth French's website.[5] I also collect institutional ownership data from Capital IQ to construct decile portfolios sorted by institutional ownership.

Daily returns data is also collected for individual stocks covered by CRSP, with share code 10 or 11 to exclude ADRs, REITs, closed-end funds, primes, and scores. I also exclude penny stocks (i.e. price below $1). Firm fundamentals data is obtained from COMPUSTAT, while analyst coverage data is obtained from I/B/E/S. I also obtain daily data of VIX from WRDS, Aruoba-Diebold-Scotti (ADS) business conditions index,[6] EPU index, Daily News Pressure (DNP) measure, and Twitter Economic Uncertainty (TEU) index.

Studies have shown that macroeconomic and earnings announcements significantly affect asset pricing (Savor and Wilson, 2014; Chan and Marsh, 2021). I obtain macroeconomic announcement dates from Bloomberg terminal, which include the same nine macroeconomic announcements used in Chapter 4: 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). I select these news on the basis of previous literature and the R-Index assigned by the Bloomberg terminal.

Earnings announcement dates are obtained from I/B/E/S and COMPUSTAT. The sample is restricted 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, I 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, I 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.

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[6] https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads

Sleepiness index

I construct the sleepiness index developed by Siganos (2021), which is based on Google SVIs for 28 different terms related to sleepiness. The search terms are listed in Section C2 of Appendix C. I use Python to obtain the data with the online algorithm, 'pytrendsdaily.[7] I collect daily data from January 2012 to December 2020 for each term separately. The daily data for each term is scaled by its monthly value and then averaged across all terms to construct the index.

SEC MIDAS data

I obtain the SEC's Market Information Data Analytics System (MIDAS) data to construct proxies for odd lot trading and algorithmic trading. The dataset provides daily metrics for individual securities partitioned by exchange. Following Weller (2018) and Kupfer and Schmidt (2021), I restrict the sample to the following exchanges: BATS-Y, BATS-Z, CHX, Direct Edge-A, Direct Edge-X, NASDAQ, NASDAQ BX, NASDAQ PHLX, and NYSE ARCA. NYSE and NYSE MKT (Amex) are excluded because they use a level-book method for the direct feed that does not allow proper identification of all odd lot trades. All other exchanges use an order-based method that is more granular and permits a correct trade identification (SEC, 2014).

5.3 Methodology

Late-night TV shows & stock returns

The event dummy has a value of 1 for dates on which one or more late-night shows are released, and 0 otherwise. Since late-night shows are released after midnight, date of release and date of the return observation in the morning are identical. I regress the event dummy on market portfolio returns (CRSP and S&P500 indices); as well as portfolios sorted by market capitalisation, institutional

[7] https://pypi.org/project/pytrendsdaily/

ownership, price, B/M ratio, CAPM beta, and standard deviation of returns. All returns are winsorized at 1st and 99th percentiles. Various proxies for macroeconomic uncertainty, VIX, ADS, EPU, and TEU indices, are added as controls. The ADS index is composed of seasonally adjusted economic indicators (weekly initial jobless claims, monthly payroll employment, monthly industrial production, monthly real personal income minus transfer payments, monthly real manufacturing and trade sales, and quarterly real GDP). Average value of the index is zero. Progressively larger positive values indicate progressively better-than-average conditions and vice versa (Aruoba *et al.*, 2009). EPU index measures policy uncertainty based on newspaper coverage (Baker *et al.*, 2016). TEU index represents the total number of daily English-language tweets in U.S. geographical region containing both ‘Uncertainty terms and ‘Economy terms, weighted by the number of retweets of each message (Baker *et al.*, 2021). A dummy for macroeconomic announcements is also used. Seasonal effects are controlled by day-of-the-week, month, and year dummies. $R_{p,t}$ is the return of the portfolio p on the day t, while D_t represents the event dummy:

$$R_{p,t} = \alpha + \beta_1 D_t + \sum_{j=1}^{J} \gamma_j Macro\ Controls_{j,t} + day_t + month_t + year_t + \epsilon \tag{5.1}$$

I also run panel regressions for individual stock returns along with firm characteristics and earnings announcement dummy as control variables, besides the ones used for portfolio regressions. All firm controls are defined in Table C1 of Appendix C. $R_{i,t}$ is the return of the firm i on the day t:

$$R_{i,t} = \alpha + \beta_1 D_t + \sum_{j=1}^{J} \gamma_j Macro\ Controls_{j,t} + \sum_{k=1}^{K} \delta_k Firm\ Controls_{k,i,t} + day_t + month_t + year_t + \epsilon \tag{5.2}$$

Late-night TV shows & liquidity

To analyse the effect of late-night shows on trading activity, I construct several liquidity variables for each firm at a daily frequency. I calculate equal-weighted daily cross sectional averages across all firms in the sample for each liquidity variable. Thus, market-wide averages of each liquidity variable are obtained. Similarly, averages are calculated for each quintile portfolio sorted by market capitalisation and institutional ownership. All liquidity variables are winsorized at 1st and 99th percentiles. Liquidity variables are computed as follows:[8]

1. ln(Adj. Dollar Volume) = $ln(Absolute\ Adj.\ Price \times Adj.\ Volume)$

2. ln(Turnover) = $ln\left(\frac{Volume}{Previous\ day's\ Shares\ Outstanding}\right)$

3. Bid–Ask Spread = $2 \times \frac{(Ask - Bid)}{(Ask + Bid)}$

4. ln(Amihud Illiquidity) = $ln\left(\frac{Absolute\ Return}{Dollar\ Volume}\right)$

5. ln(Price Range) = $ln\left(\frac{Ask\ or\ High\ Price}{Bid\ or\ Low\ Price}\right)$

Serial correlation in daily observations is controlled by de-trending the liquidity measures. Specifically, the 30-day moving average (day $t-1$ to day $t-31$) is subtracted from the value of measure for day t. Cross-sectional averages of the de-trended liquidity variables for the entire sample, as well as across each size and institutional ownership quintile, are regressed on the event dummy. I repeat these regressions after adding control variables. Following Peress and Schmidt (2020), I use the DNP measure as one of the control variables to account for any distraction caused by sensational news coverage. DNP is defined as the median number of minutes that major U.S. news broadcasters (ABC, CBS, NBC, and CNN) devote to the first three news segments (Eisensee and Strömberg, 2007). $X_{p,t}$ is the de-trended liquidity measure of the portfolio p (cross-sectional average) at day t:

$$X_{p,t} = \alpha + \beta_1 D_t + \sum_{j=1}^{J} \gamma_j Macro\ Controls_{j,t} + day_t + month_t + year_t + \epsilon \qquad (5.3)$$

Similar to the analysis for stock returns, regression analysis is also performed at the firm level. $X_{i,t}$ is the de-trended liquidity measure of the firm i at day t:

$$X_{i,t} = \alpha + \beta_1 D_t + \sum_{j=1}^{J} \gamma_j Macro\ Controls_{j,t} + \sum_{k=1}^{K} \delta_k Firm\ Controls_{k,i,t} + day_t + month_t + year_t + \epsilon \qquad (5.4)$$

[8] The variables are re-scaled for regression analysis.

Since a late-night show is an exogenous event unrelated to the stock market or a particular firm, the event window is identical for all firms in the sample. Campbell *et al.* (1997) proposes to use event study at the portfolio level to allow for cross-sectional correlation caused by the identical event window for all firms (i.e., event clustering). However, late-night shows have been released frequently in later years, restricting the availability of a 'clean estimation window for the event study. A regression approach using a dummy variable for event dates allows to avoid this problem. Moreover, it also allows for the use of control variables.

The regression approach for event analysis using dummy variables has been described by Schipper and Thompson (1983, 1985). A pooled regression where the weights are implied by the inverse of the estimated covariance matrix will be equivalent to a portfolio which has minimum estimated residual variance. Therefore, it is possible to interpret the coefficient estimates from a pooled GLS (Generalised Least Squares) regression as estimates from a portfolio which has minimum estimated residual variance. Since the data has more firms (around 5700) than the number of daily observations (around 2300), I use the fixed effects approach rather than GLS in pooled regressions.

Karafiath (1988) proposes to combine the dummy variable approach with Zellner's (1962) SUR (Seemingly Unrelated Regression). However, Bernard (1987) criticises GLS and SUR for not being an adequate remedy for cross-sectional correlation. Thus, I use Driscoll-Kraay standard errors (1998) in fixed effects regressions to control for cross-sectional dependence in the panel data.

5.4 Results

5.4.1 Late-night TV shows

Frequency distribution of late-night TV shows by year and day-of-the-week is presented in Table 5.1. Besides all late-night shows in column 1, the frequency distribution of popular shows is in column 3. In Panel A, the number of late-night shows has consistently increased every year. Panel B reveals that late-night shows are most frequently released on late Thursday night (i.e. early hours of Friday). Thus, Friday may be the day most affected by sleep deprivation. Since multiple shows can be released on the same night, there are duplicate values in terms of dates. After controlling for these duplicates, the frequency distribution in terms of release dates is shown in columns 2 and 4. Out of 98 release dates for popular shows, 13 fall on non-trading days, i.e. Saturdays and Sundays. This leaves 85 event days over 8 years from 2013 to 2020. Therefore, the average number of event days in a year is around 10. The list of these 85 shows is presented in Table C3 of Appendix C.

Table 5.1: Summary Statistics of Late-Night TV Shows

The sample period exists from January 2012 to December 2020. “Late-night" shows are defined as those that released between 12:00 AM to 05:00 AM. “Popular" shows are defined as those that have appeared in the lists of most-watched or most popular shows published by Netflix/Hulu, Rotten Tomatoes and/or IMDb. Panel A shows the break-up by year, while Panel B shows the break-up by weekday. Columns (1) and (3) show the number of shows released. Columns (2) and (4) show the number of release dates.

Panel A: Late-Night Shows by Year

	Late-night Shows		Popular Shows	
	(1)	(2)	(3)	(4)
Year	No. of Shows	Release Dates	No. of Shows	Release Dates
2012	11	11		
2013	39	24	4	4
2014	68	54	4	4
2015	118	77	21	20
2016	227	115	14	8
2017	359	130	32	15
2018	623	213	45	16
2019	793	259	54	21
2020	834	295	36	10
Total	3072	1178	210	98

Panel B: Late-Night Shows by Weekday

	Late-night Shows		Popular Shows	
	(1)	(2)	(3)	(4)
Weekday	No. of Shows	Release Dates	No. of Shows	Release Dates
Mon	138	111	2	2
Tue	262	162	19	16
Wed	310	166	39	29
Thu	332	177	19	10
Fri	1656	328	110	28
Sat	196	109	15	8
Sun	178	125	6	5
Total	3072	1178	210	98

5.4.2 Impact on stock returns

In Table 5.2, the event dummy is regressed with the S&P500 index, CRSP value-weighted index and CRSP equal-weighted index, respectively. Day-of-the-week, month, and year dummies are included in all regressions to control for seasonal effects. The standard errors are clustered in a month, as suggested by Petersen (2009). Coefficient for the event dummy is negatively significant in various specifications, consistent with the expectation that market returns are lower due to sleep deprivation (Kamstra *et al.*, 2000) caused by watching late-night shows. For S&P500 index, the returns drop by around 0.25% on event days. Considering that the average number of popular late-night shows in a year is 10, the cumulative decrease in market returns in a year is approximately 2.5%.

Magnitudes of the coefficient are the highest S&P500 index, relatively less for CRSP value-weighted index, and the lowest for CRSP equal-weighted index. The S&P500 index is composed of the 500 leading publicly traded companies in the U.S., weighted by their market capitalisation. Thus, higher magnitudes of the coefficient imply that large-cap stocks are affected more by late-night shows, as compared to small-cap stocks. Since the CRSP indices consist of all stocks regardless of the market capitalisation, magnitudes of the coefficient are lower. Equal weighting of the CRSP index dilutes the effect of large-cap stocks and, hence, the coefficient has the smallest values.

The baseline regressions in column 1 for each index only include the event dummy and the seasonal dummies. I conduct several robustness checks by using additional regressors. In column 2, VIX, ADS index and EPU index are added as controls. Coefficients for VIX and EPU index are significant but have opposite signs, negative for VIX while being positive for EPU index. As higher policy uncertainty leads to a greater frequency of large equity market moves triggered by policy-related news (Baker *et al.*, 2016), the positive sign is consistent with the fact that U.S. equity market has mostly experienced upward moves over the 2012-2020 period. Since VIX is the ‘fear gauge of the market reflecting the level of investors risk aversion, it has a negative relationship with market returns (Whaley, 2000). Coefficient for the ADS index is insignificant. Similarly, the dummy for macroeconomic announcement added in column 3 is also insignificant. While ADS index is based on information content of the macroeconomic indicators, the dummy captures the timing of macroeconomic announcements. The EPU index is replaced by the TEU index in column 4. However, its insignificant coefficient implies that, as compared to newspaper coverage of economic policy uncertainty, uncertainty expressed by individuals on Twitter has no meaningful impact on market returns.

In column 5, I test whether Google searches for sleepiness terms can capture the effect of sleep deprivation on market returns. Moreover, I test for the interaction between the sleepiness index and the late-night shows. Contrary to the findings of Siganos (2021), the sleepiness index is insignificant; hence, it fails to capture any effect of sleep deprivation on the market. Since the interaction term is also insignificant, increased Google search activity for sleep-related terms on the event day does not result in any additional effect on market returns, other than the effect already captured by the event dummy. The popular late-night shows turn out to be better at capturing the effects of sleep loss.

I de-trend the market returns by subtracting the daily observations by their 30-day moving average (day $t-1$ to day $t-31$), and repeat the baseline regressions. The results, reported in Table C2 (see Appendix C), are almost identical to those in Table 5.2. Coefficient of the event dummy remains significantly negative in various specifications with magnitudes similar to the baseline results. Thus, the effect of late-night shows is independent of any prevailing time trend in returns.

Table 5.2: Market Returns

Release dates of popular late-night shows are designated as the event dates. S&P500, CRSP value-weighted and CRSP equal-weighted indices are regressed with the event dummy D_t. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. $ln(VIX)_t$ is the natural log of VIX on day t. ADS_t is the Aruoba-Diebold-Scotti business conditions index on day t. $ln(EPU)_t$ is the natural log of Economic Policy Uncertainty index on day t. $ln(TEU\text{-}WGT)$ is the natural log of Twitter Economic Uncertainty index on day t. $Sleepiness_{t-1}$ is the Sleepiness index on day $t-1$. D_{Macro} is the dummy variable for macroeconomic announcement date. Day-of-the-week, month and year dummies are also added as controls. Regression coefficients are reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

	S&P500 Index					CRSP Value-weighted Index					CRSP Equal-weighted Index				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
D_t	-0.246**	-0.256***	-0.256***	-0.272***	-0.250**	-0.226**	-0.236**	-0.236**	-0.252***	-0.229**	-0.140*	-0.146*	-0.146*	-0.162**	-0.137*
	(-2.896)	(-3.157)	(-3.133)	(-3.386)	(-3.004)	(-2.703)	(-2.902)	(-2.886)	(-3.136)	(-2.769)	(-2.010)	(-2.071)	(-2.068)	(-2.318)	(-1.962)
$ln(VIX)_t$		-1.056***	-1.055***	-0.966***	-1.063***		-1.057***	-1.056***	-0.964***	-1.064***		-0.913***	-0.913***	-0.825***	-0.920***
		(-7.849)	(-7.838)	(-6.248)	(-8.108)		(-7.782)	(-7.776)	(-6.214)	(-8.055)		(-6.864)	(-6.869)	(-5.477)	(-7.144)
ADS_t		-0.013	-0.013	-0.016	-0.013		-0.015	-0.015	-0.018	-0.015		-0.016	-0.016	-0.018	-0.016
		(-1.209)	(-1.212)	(-1.233)	(-1.225)		(-1.425)	(-1.430)	(-1.438)	(-1.443)		(-1.423)	(-1.427)	(-1.466)	(-1.437)
$ln(EPU)_t$		0.213***	0.213***		0.213***		0.217***	0.216***		0.217***		0.215***	0.215***		0.216***
		(7.265)	(7.298)		(7.173)		(7.050)	(7.076)		(6.954)		(5.980)	(5.988)		(5.965)
D_{Macro}			-0.022					-0.017					-0.004		
			(-0.453)					(-0.359)					(-0.095)		
$ln(TEU\text{-}WGT)_t$				0.037					0.036					0.042*	
				(1.434)					(1.488)					(1.925)	
$Sleepiness_{t-1}$					-0.001					-0.001					-0.001
					(-0.816)					(-0.829)					(-0.556)
$D_t \times Sleepiness_{t-1}$					-0.005					-0.006					-0.007
					(-0.786)					(-0.855)					(-1.221)
Constant	0.008	1.939***	1.942***	2.609***	1.942***	0.018	1.933***	1.935***	2.617***	1.935***	0.057	1.568***	1.568***	2.234***	1.568***
	(0.196)	(4.107)	(4.109)	(5.673)	(4.167)	(0.483)	(4.000)	(4.000)	(5.619)	(4.062)	(1.661)	(3.126)	(3.124)	(4.824)	(3.179)
Time Dummies:															
Day-of-the-week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,265	2,265	2,265	2,265	2,264	2,265	2,265	2,265	2,265	2,264	2,265	2,265	2,265	2,265	2,264
R^2	0.0082	0.0684	0.0685	0.0564	0.0696	0.0086	0.0676	0.0677	0.0554	0.0688	0.0125	0.0628	0.0628	0.0498	0.0639

Comparison with DST change

I compare the late-night shows with DST changes, the most commonly used proxy for sleep loss. Clock time changes in the U.S. on the second Sunday of March and first Sunday of November. Coincidentally, not a single popular show is released near these dates (i.e. the week following the DST change). Hence, it is impossible to analyse an interaction between the event dummy and DST change. Nevertheless, I construct a dummy variable for the Monday following DST change and add it to the set of regressors. Results in Table 5.3 show that the coefficient for DST change is insignificant. The late-night show is a better proxy for capturing the effect of sleep deprivation despite the limitation that only a subset of investors might watch such shows. My methodology imposes a stricter test for the event dummy because the returns on days following late-night shows are tested against all other days while incorporating many control variables. Kamstra *et al.* (2000) test the weekend returns (calculated from Friday's closing price to Monday's opening price) following the DST change against all other weekend returns.

Table 5.3: Comparison with Daylight Savings Time Change

Release dates of popular late-night shows are designated as the event dates. S&P500, CRSP value-weighted and CRSP equal-weighted indices are regressed with the event dummy D_t and the dummy for DST change D_{DST}. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. D_{DST} has a value of 1 for the Monday following the DST change and 0 for all other days. $ln(VIX)_t$ is the natural log of VIX on day t. ADS_t is the Aruoba-Diebold-Scotti business conditions index on day t. $ln(EPU)_t$ is the natural log of Economic Policy Uncertainty index on day t. Day-of-the-week, month and year dummies are also added as controls. Regression coefficients are reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

	(1) S&P500 Index	(2) CRSP Value-weighted	(3) CRSP Equal-weighted
D_t	-0.256***	-0.236**	-0.146*
	(-3.168)	(-2.909)	(-2.073)
D_{DST}	0.274	0.236	0.270
	(0.897)	(0.731)	(0.860)
$ln(VIX)_t$	-1.056***	-1.057***	-0.913***
	(-7.880)	(-7.810)	(-6.876)
ADS_t	-0.013	-0.015	-0.016
	(-1.227)	(-1.443)	(-1.441)
$ln(EPU)_t$	0.213***	0.216***	0.215***
	(7.305)	(7.086)	(5.987)
Constant	1.933***	1.928***	1.562***
	(4.084)	(3.977)	(3.109)
Time Dummies:			
Day-of-the-week	Yes	Yes	Yes
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	2,265	2,265	2,265
R^2	0.0691	0.0681	0.0636

Impact on characteristics-sorted portfolios

I run similar regressions on decile portfolios sorted by various firm characteristics in Table 5.4. I start with decile portfolios sorted by market capitalisation in Panel A. Portfolios are numbered in ascending order of the decile rank. Coefficient of the event dummy is insignificant for the first four smallest sorts (deciles 1 to 4); only significant at 10% for the next two sorts (deciles 5 and 6); and highly significant at 5% for the remaining larger sorts (deciles 7 to 10). Magnitude of the coefficient increases monotonically from the smallest to the largest size decile. These results confirm that the returns of larger firms decrease relatively more than smaller firms.

Results of regressions for decile portfolios sorted by institutional ownership are reported in Panel B of Table 5.4. Coefficient of the event dummy in the smallest three institutional ownership deciles is insignificant, while it is significant at 10% for the fourth decile. Results are overall stronger in terms of statistical significance and magnitude for the larger deciles. This pattern is consistent with the fact that institutional ownership is higher for large-cap stocks for which I find stronger results in Panel A. Stronger impact of sleep deprivation on stocks with large market capitalisation and high institutional ownership is consistent with the conjecture of Kamstra *et al.* (2000) that the average sleeping hours of fund managers have decreased over the years. Siganos (2021) conducted a case study on a fund manager in UK whose trading intensity was lower when the duration of his sleep in the previous night was less. The effect of sleep loss on institutional investors is also plausible in the light of evidence that they also suffer from attentional constraints like individuals, and can get distracted by various information events (Fang *et al.*, 2014; Kempf *et al.*, 2017; Schmidt, 2019; Abramova *et al.*, 2020; Garel *et al.*, 2021).

Regressions for deciles sorted by the natural log of price are reported in Panel C. The results in terms of statistical significance and magnitude of the coefficient are stronger for larger deciles. Thus, the effect is stronger for large-priced stocks as compared to small-priced stocks. This pattern is consistent with the results in Panels A and B, since large-cap stocks with high institutional ownership usually have larger prices.

The pattern for decile portfolios sorted on B/M ratio in Panel D is similar to that observed for market capitalisation and institutional ownership. Coefficient of the event dummy is insignificant for the first three deciles; significant at 10% for the next three deciles; and then significant at 5% for remaining larger deciles except for decile 10. Magnitudes of the coefficient generally increase from decile 1 to decile 9. Thus, value stocks (i.e. those with low B/M ratios) are affected less by sleep deprivation.

Panel E of Table 5.4 reports the results for decile portfolios sorted on CAPM beta. The coefficient is only insignificant for the smallest (decile 1) and the largest (decile 10) sorts. The coefficients are significant and negative for all other deciles, with the magnitude being highest for decile 2 and then progressively decreasing up to decile 10. Since the CAPM beta is a measure of systematic risk, my results show that returns of defensive stocks are affected more by sleep deprivation as compared to risky stocks.

Results for decile portfolios sorted on standard deviation of returns are reported in Panel F of Table 5.4. The coefficient is insignificant for deciles 1, 2 and 10. Values of t-statistic consistently increase from decile 1 to decile 8. Deciles 3 and 4 are significant at 10%, deciles 5 and 6 are significant at 5%, and deciles 7, 8, and 9 are significant at 1%. Magnitudes of the coefficients increase from decile 1 to decile 6, but then are lower for the remaining deciles. In fact, the magnitude is the smallest for decile 10. This pattern indicates that returns of extremely volatile and extremely non-volatile stocks are less affected by late-night shows as compared to stocks with moderate levels of volatility.

I also run regressions for the 2×3 double-sorted portfolios on market capitalisation and B/M ratio by Kenneth French. The portfolios are the intersections of 2 portfolios formed on size (ME1 & ME2) and 3 portfolios formed on B/M ratio (BM1, BM2 & BM3). Size breakpoint is the median NYSE market equity, while the B/M ratio breakpoints are the 30th and 70th NYSE percentiles. Results in Panel G of Table 5.4 show that the coefficient of the event dummy has a greater negative value as both size and B/M ratio increase. The coefficient is insignificant for the 'ME1 BM1 portfolio comprising the smallest size and B/M ratio sort. Magnitudes are higher for 'ME1 BM2 and ‘ME1 BM3 portfolios. The coefficient is statistically significant and stronger for the remaining three portfolios ‘ME2 BM1, ‘ME2 BM2 and ‘ME3 BM3, as they consist of larger firms. The coefficient is the strongest for ‘ME3 BM3 portfolio, which is the largest in terms of both size and B/M ratio.

Table 5.4: Characteristic-sorted Portfolios

Release dates of popular late-night shows are designated as the event dates. In Panels A to F, returns of each decile portfolio sorted on market capitalisation, institutional ownership, ln(Price), B/M ratio, CAPM beta, and standard deviation of returns are regressed with the event dummy D_t. Portfolios are numbered from (1) to (10) in ascending order of the decile rank. In Panel G, returns of six double-sorted portfolios on market capitalisation and B/M ratio are regressed with the event dummy D_t. ME1 and ME2 represent the two sorts on market capitalisation, while BM1, BM2 and BM3 represent the three sorts on B/M ratio. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. The control variables (not shown) are as follows: $ln(VIX)_t$ is the natural log of VIX on day t; ADS_t is the Aruoba-Diebold-Scotti business conditions index on day t; $ln(EPU)_t$ is the natural log of Economic Policy Uncertainty index on day t. Day-of-the-week, month and year dummies are also added as controls. Only the regression coefficient for the event dummy is reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

Panel A: Market Capitalisation Deciles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_t	-0.001	0.033	-0.126	-0.137	-0.150*	-0.164*	-0.203**	-0.221**	-0.230**	-0.248**
	(-0.017)	(0.472)	(-1.690)	(-1.628)	(-1.905)	(-1.956)	(-2.458)	(-2.567)	(-2.815)	(-2.965)

Panel B: Institutional Ownership Deciles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_t	-0.002	-0.076	-0.146	-0.159*	-0.222**	-0.240**	-0.234**	-0.240**	-0.238**	-0.216*
	(-0.028)	(-1.052)	(-1.699)	(-1.870)	(-2.422)	(-2.909)	(-2.656)	(-2.558)	(-2.425)	(-2.053)

Panel C: ln(Price) Deciles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_t	-0.002	-0.035	-0.129	-0.163*	-0.187*	-0.214**	-0.262**	-0.237**	-0.229**	-0.214**
	(-0.013)	(-0.331)	(-1.431)	(-2.023)	(-2.124)	(-2.624)	(-2.922)	(-2.537)	(-2.780)	(-2.292)

Panel D: B/M Ratio Deciles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_t	-0.098	-0.153	-0.174	-0.172*	-0.169*	-0.165*	-0.192**	-0.181**	-0.204**	-0.149
	(-0.838)	(-1.655)	(-1.628)	(-2.116)	(-1.883)	(-1.873)	(-2.302)	(-2.353)	(-2.328)	(-1.419)

Panel E: CAPM Beta Deciles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_t	-0.199	-0.273**	-0.232**	-0.222**	-0.229**	-0.195**	-0.177**	-0.139**	-0.110**	-0.063
	(-1.216)	(-2.392)	(-2.440)	(-2.548)	(-2.800)	(-2.586)	(-2.912)	(-2.629)	(-2.392)	(-1.501)

Panel F: Standard Deviation Deciles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_t	-0.123	-0.136	-0.215*	-0.210*	-0.227**	-0.250**	-0.216***	-0.223***	-0.147***	-0.023
	(-1.027)	(-1.122)	(-2.137)	(-2.143)	(-2.670)	(-3.060)	(-3.147)	(-4.107)	(-3.203)	(-0.524)

Panel G: 2×3 Double-sorted Portfolios on Market Capitalisation and B/M Ratio

	(1)	(2)	(3)	(4)	(5)	(6)
	ME1 BM1	ME1 BM2	ME1 BM3	ME2 BM1	ME2 BM2	ME2 BM3
D_t	-0.179	-0.216**	-0.254**	-0.251**	-0.253***	-0.341**
	(-1.654)	(-2.391)	(-2.586)	(-2.415)	(-3.779)	(-3.001)

Role of VIX

I analyse the moderating role of VIX, a common proxy of market-level uncertainty and risk aversion, to test whether sleep deprived investors are more risk-averse and cause the contemporaneous returns to decrease as expectations of future returns increase. I interact the VIX with the event dummy in regressions on the three market indices. The results are reported in Table 5.5. In the presence of the interaction, coefficient for the event dummy represents the effect of the event conditional on the absence of uncertainty (i.e. $ln(VIX) = 0$). It is positive and insignificant for S&P500 and CRSP value-weighted indices, while positive and significant at 10% for the CRSP equal-weighted index. The interaction term is negative and insignificant for S&P500 and CRSP value-weighted indices, while negative and significant at 10% for the CRSP equal-weighted index. Since the t-values of the interaction term and coefficient of the event dummy are not too small, I explore the marginal effects of the event dummy on market returns at multiple levels of $ln(VIX)$. The slope for the event dummy turns negative when $ln(VIX)$ is 2.75, and continues to become steeper (more negative) as VIX increases. Statistical significance of the slope is also the highest when $ln(VIX)$ is around 2.75 to 3.00. Since the median and mean of $ln(VIX)$ is 2.69 and 2.76 respectively, the negative effect on market returns is significant at this level of VIX, similar to the baseline results without the interaction term. The slope is positive but insignificant when $ln(VIX)$ is below the average. Hence, VIX moderates the effect of sleep deprivation—higher uncertainty leads to a stronger negative effect of late-night shows on market returns. If uncertainty is already high and investors are more risk-averse, market returns will deteriorate relatively more on days following late-night shows, as sleep deprivation aggravates the risk-averse behaviour of investors.

Mckenna *et al.* (2007) find that the effect of sleep loss on the propensity for risk-taking is dependent on the framing of the outcomes. Sleep deprived investors will indulge in lesser (greater) risk-taking behaviour if the potential outcome is a loss (gain). Similarly, Horne (2013) argue that this differential effect of sleep loss depends on optimism for potential success or pessimism for potential failure. Consistent with this explanation, sleep deprived investors are willing to take less risk when the fear gauge, i.e., VIX is higher. In such circumstances, the outcome becomes framed in terms of losses rather than gains. Hence, sleep-deprived risk-averse investors sell their positions to exit the market, leading to negative returns.

Table 5.5: Interaction with VIX

Release dates of popular late-night shows are designated as the event dates. S&P500, CRSP value-weighted and CRSP equal-weighted indices are the dependent variables. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. $ln(VIX)_t$ is the natural log of VIX on day t, while $D_t \times ln(VIX)_t$ is the interaction between the event dummy and natural log of VIX. The control variables (not shown) are as follows: ADS_t is the Aruoba-Diebold-Scotti business conditions index on day t; $ln(EPU)_t$ is the natural log of Economic Policy Uncertainty index on day t; and time dummies for day-of-the-week, month and year. Panel A shows the regression coefficients along with t-statistics in the parentheses. Panel B shows the marginal effects of D_t at multiple levels of $ln(VIX)_t$. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

Panel A: Regression

	(1) S&P500	(2) CRSP Value-weighted	(3) CRSP Equal-weighted
D_t	1.911	2.072	2.443*
	(1.638)	(1.592)	(1.829)
$ln(VIX)_t$	-1.026***	-1.025***	-0.878***
	(-7.880)	(-7.788)	(-6.767)
$D_t \times ln(VIX)_t$	-0.801	-0.853	-0.956*
	(-1.776)	(-1.706)	(-1.906)

Panel B: Marginal Effects of D_t

	(1) S&P500	(2) CRSP Value-weighted	(3) CRSP Equal-weighted
$ln(VIX) = 2.00$	0.310	0.367	0.530
	(1.142)	(1.192)	(1.567)
$ln(VIX) = 2.25$	0.110	0.154	0.291
	(0.667)	(0.817)	(1.338)
$ln(VIX) = 2.50$	-0.090	-0.059	0.052
	(-1.179)	(-0.691)	(0.485)
$ln(VIX) = 2.75$	-0.291**	-0.272**	-0.187*
	(-2.892)	(-2.664)	(-2.176)
$ln(VIX) = 3.00$	-0.491**	-0.485**	-0.426**
	(-2.462)	(-2.294)	(-2.292)
$ln(VIX) = 3.25$	-0.691**	-0.699*	-0.665*
	(-2.244)	(-2.103)	(-2.178)
$ln(VIX) = 3.50$	-0.891*	-0.912*	-0.904*
	(-2.129)	(-2.003)	(-2.112)
$ln(VIX) = 3.75$	-1.091*	-1.125*	-1.143*
	(-2.058)	(-1.943)	(-2.070)
$ln(VIX) = 4.00$	-1.291*	-1.338*	-1.382*
	(-2.011)	(-1.903)	(-2.043)
$ln(VIX) = 4.25$	-1.491*	-1.551*	-1.621*
	(-1.977)	(-1.874)	(-2.023)
$ln(VIX) = 4.50$	-1.691*	-1.764*	-1.860*
	(-1.952)	(-1.853)	(-2.008)

Reversal of returns

A behavioural response due to lack of sleep is unrelated to fundamentals. Hence, it may be expected that stock returns will reverse over the days following the event as investors rectify the initial mispricing. In Table 5.6, I use five dummy variables representing five days following the late-night show. However, none of the coefficients for these dummies are significant, and they have very small magnitudes. Thus, there is no evidence that a significant reversal of market returns takes place in days following the event.

Table 5.6: Reversal of Returns

Release dates of popular late-night shows are designated as the event dates. S&P500, CRSP value-weighted and CRSP equal-weighted indices are regressed with the event dummy D_t. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. $ln(VIX)_t$ is the natural log of VIX on day t. ADS_t is the Aruoba-Diebold-Scotti business conditions index on day t. $ln(EPU)_t$ is the natural log of Economic Policy Uncertainty index on day t. Day-of-the-week, month and year dummies are also added as controls. Regression coefficients are reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
	S&P500	CRSP Value-weighted	CRSP Equal-weighted
D_{t+1}	0.059	0.037	-0.079
	(0.718)	(0.544)	(-1.464)
D_{t+2}	-0.012	-0.006	-0.010
	(-0.118)	(-0.055)	(-0.093)
D_{t+3}	-0.042	-0.041	-0.003
	(-0.406)	(-0.411)	(-0.029)
D_{t+4}	0.013	-0.003	0.002
	(0.110)	(-0.026)	(0.016)
D_{t+5}	0.001	0.003	0.011
	(0.010)	(0.048)	(0.139)
$ln(VIX)_t$	-1.060***	-1.061***	-0.919***
	(-8.225)	(-8.143)	(-7.179)
ADS_t	-0.013	-0.015	-0.016
	(-1.253)	(-1.465)	(-1.446)
$ln(EPU)_t$	0.215***	0.219***	0.217***
	(7.210)	(7.011)	(5.988)
Constant	1.937***	1.931***	1.559***
	(4.129)	(4.027)	(3.152)
Time Dummies:			
Day-of-the-week	Yes	Yes	Yes
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	2,261	2,261	2,261
R^2	0.0663	0.0659	0.0625

Impact of COVID-19 pandemic

The COVID-19 pandemic has had widespread effects on all aspects of life including economic activity and financial markets. The COVID-19 crisis and the subsequent lockdown is an unexpected and exogenous shock to global markets that originated out of public health concerns. U.S. stock markets were adversely affected by the pandemic (Xu, 2021); even though the S&P500 index peaked on February 19, 2020, it declined by almost 30% a month later. In four trading days of March 2020 (9, 12, 16 and 23), the Dow Jones Industrial Average (DJIA) declined by about 26% (Mazur *et al.*, 2021). Baker *et al.* (2020) suggest that government restrictions on business activities and social distancing in a service-oriented economy caused a much stronger reaction of U.S. stock markets to COVID-19 as compared to previous pandemics in 1918-19, 1957-58 and 1968.

The pandemic and subsequent lockdowns have had a mixed impact on the business models of streaming TV services like Netflix. While there has been an increase in viewership by quarantined consumers at home, disruption in film and TV productions has halted the addition of fresh content (Rahman and Arif, 2021). According to Ofcom (2020), individuals increased their daily consumption time for streaming services by more than an hour during the pandemic. Raza *et al.* (2021) find that increased binge-watching during the pandemic has aggravated psychological and mental health problems like stress, loneliness, insomnia, depression and anxiety.

The decline in market returns is expected to become aggravated by an increase in binge-watching during the pandemic, *ceteris paribus*. However, during the lockdown, investors working from home may have changed their sleeping patterns to compensate for sleep deprivation after a night of binge-watching. For instance, they can sleep in the evening or early hours of the night before starting to binge on late-night TV. Therefore, the effect of sleep deprivation may get dampened instead. Consistent with this conjecture, I find that the decline in market returns becomes insignificant during the pandemic. I define the pre-COVID period from January 2012 to February 2020. The month of March in 2020 is excluded since the market experienced a severe crash and lockdown measures had only started to come into force. Thus, the COVID period commences from April

2020 and lasts up to December 2020, the end of the sample period. A dummy variable is created having a value of 1 for the COVID period, and 0 for the pre-COVID period. I interact this dummy with the event dummy in Table 5.7.

The results show that the impact of sleep deprivation caused by late-night shows during the COVID-period, represented by the interaction term, is insignificant. The significantly positive coefficient for the COVID dummy implies a strongly bullish market that was recovering after the crash in March 2020. The results are robust to placebo tests in which the pre-COVID and COVID periods are shifted forwards and backwards by one month, and the month of March 2020 is included in the sample. I also get similar results if separate regressions are run for COVID and pre-COVID periods. The analysis of COVID-19 crisis is limited by the sample period ending in December 2020, when the pandemic had not abated as yet.

Table 5.7: Impact of COVID-19

Release dates of popular late-night shows are designated as the event dates. S&P500, CRSP value-weighted and CRSP equal-weighted indices are the dependent variables. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. D_{COVID} is the dummy variable with values 1 for the COVID period, and 0 otherwise. $D_t \times D_{COVID}$ is the interaction between the event dummy and COVID duumy. $ln(VIX)_t$ is the natural log of VIX on day t. ADS_t is the Aruoba-Diebold-Scotti business conditions index on day t. $ln(EPU)_t$ is the natural log of Economic Policy Uncertainty index on day t. Day-of-the-week, month and year dummies are also added as controls. Regression coefficients are reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

	(1) S&P500 Index	(2) CRSP Value-weighted	(3) CRSP Equal-weighted
D_t	-0.217**	-0.188**	-0.070
	(-2.983)	(-2.684)	(-0.977)
D_{COVID}	1.068***	1.127***	1.225***
	(7.419)	(7.133)	(7.289)
$D_t \times D_{COVID}$	-0.425	-0.544	-0.947
	(-0.682)	(-0.803)	(-1.511)
$ln(VIX)_t$	-1.227***	-1.236***	-1.115***
	(-13.925)	(-12.819)	(-9.983)
ADS_t	-0.014	-0.015	-0.014
	(-1.316)	(-1.426)	(-1.183)
$ln(EPU)_t$	0.141***	0.140***	0.130***
	(4.202)	(4.127)	(3.940)
Constant	2.904***	2.952***	2.713***
	(8.323)	(7.785)	(6.296)
Time Dummies:			
Day-of-the-week	Yes	Yes	Yes
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	2,243	2,243	2,243
R^2	0.0844	0.0866	0.0895

Panel Regressions

I analyse the impact of late-night shows at firm-level by running fixed effects panel regressions in Table 5.8. I control for cross-sectional dependence in the error terms caused by the commonality of events for all firms. Stock returns in excess of the risk-free return are regressed with the event dummy and control variables. All firm control variables are defined in Table C1 of Appendix C. In the baseline specification in column (1), coefficient of the event dummy is negative and significant at 10%. Thus, the negative effect of late-night shows can be seen at the firm-level as well.

I control for the Fama-French five factors (2015) in columns (2), (3), and (4). They include RMRF, SMB, HML RMW, and CMA. RMRF is the market premium over the risk-free rate. SMB is the average return on nine small capitalisation portfolios minus the average return on nine large capitalisation portfolios. HML is the average return on two value portfolios minus the average return on the two growth portfolios. RMW is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios. CMA is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios.

The 'market' factor (RMRF) is added in column (2); 'size' (SMB) and 'value' (HML) factors are added in column (3); and 'operating profitability' (RMW) and 'investment' (CMA) factors are added in column (4). Since the results in Tables 5.2 and 5.4 show that the market portfolio and characteristic-sorted portfolios are significantly affected by the event, addition of Fama-French factors causes the coefficient of the event dummy to become insignificant. In column (5), coefficient of the event dummy is negatively significant when firm controls are added to the regression. This result implies that firm controls cannot account for the effect of the event, unlike the Fama-French factors.

Table 5.8: Panel Regressions on Stock Returns

Release dates of popular late-night shows are designated as the event dates. The dependent variable is stock return of the firm i on day t, in excess of risk-free return. Fixed Effects panel regressions with Driscoll-Kraay standard errors are used. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. $ln(VIX)_t$ is the natural log of VIX on day t. ADS_t is the Aruoba-Diebold-Scotti business conditions index on day t. $ln(EPU)_t$ is the natural log of Economic Policy Uncertainty index on day t. D_{Macro} is the dummy variable for macroeconomic announcement date. Day-of-the-week, month and year dummies are also added as controls. $RMRF_t$, SMB_t, HML_t, RMW_t and CMA_t are the market, size, value, operating profitability and investment factors respectively (Fama and French, 2015). Firm control variables are defined in the Appendix. Regression coefficients are reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)
D_t	-0.189*	0.054	0.014	0.012	-0.260**
	(-1.743)	(1.118)	(0.793)	(0.675)	(-2.011)
$ln(VIX)_t$	-1.168***	-0.047	-0.064**	-0.049*	-1.246***
	(-6.630)	(-0.704)	(-2.362)	(-1.902)	(-6.081)
ADS_t	-0.023	-0.001	-0.004	-0.004	-0.024
	(-1.622)	(-0.150)	(-1.320)	(-1.109)	(-1.488)
$ln(EPU)_t$	0.252***	0.028	0.022***	0.021***	0.312***
	(4.559)	(1.172)	(2.710)	(2.590)	(4.622)
D_{Macro}	-0.006	0.024	0.001	-0.004	-0.047
	(-0.110)	(1.083)	(0.138)	(-0.497)	(-0.741)
$RMRF_t$		0.900***	0.817***	0.811***	
		(20.644)	(23.856)	(24.522)	
SMB_t			0.712***	0.690***	
			(55.164)	(51.415)	
HML_t			0.068***	0.093***	
			(5.300)	(5.772)	
RMW_t				-0.145***	
				(-10.163)	
CMA_t				-0.027	
				(-1.363)	
D_{Earn}					0.243***
					(6.056)
$Std.Dev_{i,y}$					-1.494
					(-1.477)
$Div.Yld_{i,y}$					-0.012***
					(-2.756)
$ln(Mkt.Cap)_{i,y-1}$					-0.101***
					(-8.430)
$B/M_{i,y-1}$					0.105
					(1.399)
$Lev_{i,y-1}$					0.000
					(1.635)
$NITA_{i,y-1}$					-0.000
					(-1.248)
$ln(Age)_{i,y-1}$					0.046
					(1.390)
$ln(Cover)_{i,y-1}$					-0.004
					(-0.199)
$Inst.Own_{i,y-1}$					-0.000
					(-1.345)
Constant	2.063***	0.001	0.097	0.061	4.380***
	(3.970)	(0.003)	(1.314)	(0.842)	(6.023)
Observations	7,848,147	7,848,147	7,848,147	7,848,147	3,887,127
R^2	0.009	0.125	0.148	0.149	0.014
No. of Firms	5,747	5,747	5,747	5,747	2,691

5.4.3 Impact on liquidity

In this section, I analyse the impact of sleep deprivation caused by late-night shows on market liquidity. Sleep deprived investors may stay away from trading, and therefore, the negative impact on stock returns may be driven by a reduction in liquidity. Conversely, there could be a selling pressure with high trading volume pushing down stock returns. I start with regressing the event dummy on the market-wide cross-sectional averages of de-trended liquidity variables. The results in Table 5.9 are mostly insignificant. Only the Amihud illiquidity ratio significantly decreases on event days, once control variables are taken into account. Thus, there is an improvement in liquidity in terms of the price impact of trades on event days. Despite statistical insignificance regarding other liquidity variables, signs of the coefficients are at least consistent with an improvement in liquidity. The volume-based measures, dollar volume and turnover, have a positive sign, while the transaction cost measures, bid-ask spread and price range, have a negative sign. The slight increase in liquidity is contrary to the expectation that sleep deprived investors stay away from trading and cause liquidity to deteriorate.

I investigate the effect on liquidity in each size and institutional ownership quintile as well. The event dummy is regressed on the cross-sectional average of each quintile. The results in Table 5.10 are consistent with the market-wide analysis. For brevity, I report only the coefficients for the event dummy. Regressions in columns (2), (4), (6), (8) and (10) include VIX, EPU and ADS index as additional control variables. Amihud illiquidity ratio is significantly decreasing for all size and institutional ownership quintiles except the smallest ones. Since the impact on returns is also more pronounced in stocks with larger size and higher institutional ownership, liquidity is also higher for such stocks. Similar to Table 5.9, results for other liquidity variables are mostly insignificant. Notably, signs of the coefficient for bid-ask spread and price range become negative for the larger (i.e. third, fourth and fifth) size and institutional ownership quintiles.

I repeat the analysis at the firm-level using fixed effects panel regressions with Driscoll-Kraay standard errors to account for cross-sectional dependence. Results in Table 5.11 mirror the findings of the portfolio-level analysis of the full sample, and each size and institutional ownership quintile in Tables 5.9 and 5.10, respectively. Coefficient of the event dummy is significantly negative only for the Amihud illiquidity ratio, while it is insignificant for other liquidity variables.

In summary, liquidity is mostly unaffected by sleep deprivation. Stock returns and Amihud illiquidity ratios of large-cap stocks with higher institutional ownership are affected more than small-cap stocks with low institutional ownership. However, these effects are not accompanied by any significant increase in trading activity, evident from insignificant results for dollar volume and turnover. Any increase in noise trading can be detected by informed investors, particularly those who use algorithmic trading (Collin-Dufresne and Fos, 2015; Dong *et al.*, 2019). Thus, there will be a multiplier effect on trading volume—an increase (decrease) in noise trading will cause an increase (decrease) in informed trading. On the other hand, the effect on liquidity in terms of price impact (e.g. Amihud illiquidity ratio) will be dampened because any reduction in market makers adverse selection costs is being offset by informed trading. Peress and Schmidt (2020) find that in the post-2007 period, a decrease in noise trading by distracted retail investors led to relatively stronger effect on trading activity and a relatively weaker effect on price impact as compared to earlier periods. They attribute this change to widespread use of algorithmic trading in recent years.

My results paint an opposite picture because I find that Amihud ratio significantly decreases, while trading activity does not change significantly. Thus, the effect of late-night shows on returns cannot be attributed to an increase in noise trading. The fact that noise traders are usually active in small-sized firms with low institutional ownership further rules out noise trading as a plausible explanation. In an experimental study by Dickinson *et al.* (2020), sleepy and tired traders do not exhibit greater share turnover in a low cash environment. Turnover is only higher when more cash is infused into the experimental market that tends to produce larger bubbles. Similarly, mood changes induced by sports games affect stock returns without any change in trading volume (Edmans *et al.*, 2007). Cai *et al.* (2018) also find that negative stock returns due to sleep loss and/or distraction during sports games are not caused by a reduction in trading volumes.

Table 5.9: Market-wide Impact on Liquidity

Release dates of popular late-night shows are designated as the event dates. The event dummy D_t is regressed on market-wide cross-sectional averages of de-trended liquidity variables. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. $ln(VIX)_t$ is the natural log of VIX on day t. ADS_t is the Aruoba-Diebold-Scotti business conditions index on day t. $ln(EPU)_t$ is the natural log of Economic Policy Uncertainty index on day t. D_{Macro} is the dummy variable for macroeconomic announcement date. D_P is the dummy variable for the DNP measure, having a value of 1 if the measure is greater than or equal to its 90th percentile, and 0 otherwise. Day-of-the-week, month and year dummies are also added as controls. Regression coefficients are reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

	ln(Adj. $ Vol.)		ln(Turnover)		Bid–Ask		ln(Amihud)		ln(Price Range)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_t	9.923	29.303	10.399	26.091	-0.931	-2.109	-18.106	-59.391**	-0.906	-2.144
	(0.546)	(1.423)	(0.564)	(1.264)	(-0.157)	(-0.382)	(-0.711)	(-2.184)	(-0.152)	(-0.388)
$ln(VIX)_t$		10.667		93.861***		80.417***		294.803***		80.485***
		(0.537)		(4.717)		(15.126)		(11.249)		(15.117)
ADS_t		-10.086		-11.481		1.293		-0.870		1.281
		(-0.735)		(-0.834)		(0.352)		(-0.048)		(0.348)
$ln(EPU)_t$		33.150***		31.294***		3.148		-7.689		3.137
		(4.172)		(3.928)		(1.479)		(-0.733)		(1.472)
D_{Macro}		6.178		5.215		6.185***		14.962		6.193***
		(0.704)		(0.592)		(2.631)		(1.291)		(2.630)
D_P		-2.089		-1.473		2.281		22.388*		2.268
		(-0.208)		(-0.146)		(0.848)		(1.688)		(0.842)
Constant	21.988	-176.609**	10.208	-418.708***	0.915	-246.555***	19.592	-820.325***	0.881	-246.742***
	(1.320)	(-2.480)	(0.604)	(-5.864)	(0.168)	(-12.925)	(0.840)	(-8.724)	(0.161)	(-12.916)
Time Dummies:										
Day-of-the-week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,265	1,754	2,265	1,754	2,265	1,754	2,265	1,754	2,265	1,754
R^2	0.0978	0.1115	0.0891	0.1125	0.0391	0.1598	0.0457	0.1258	0.0392	0.1596

Table 5.10: Impact on Liquidity in Size & Institutional Ownership Quintiles

Release dates of popular late-night shows are designated as the event dates. The event dummy D_t is regressed on cross-sectional averages of de-trended liquidity variables in each size and institutional ownership quintile. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. Day-of-the-week, month and year dummies are added as controls in all regressions. In columns (2), (4), (6), (8) and (10), $ln(VIX)_t$, ADS_t, $ln(EPU)_t$, D_{Macro} and D_P are added as additional control variables. $ln(VIX)_t$ is the natural log of VIX on day t. ADS_t is the Aruoba-Diebold-Scotti business conditions index on day t. $ln(EPU)_t$ is the natural log of Economic Policy Uncertainty index on day t. D_{Macro} is the dummy variable for macroeconomic announcement date. D_P is the dummy variable for the DNP measure, having a value of 1 if the measure is greater than or equal to its 90th percentile, and 0 otherwise. Only the regression coefficient of the event dummy is reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

Panel A: Size Quintiles

		ln(Adj. $ Vol.)		ln(Turnover)		Bid–Ask		ln(Amihud)		ln(Price Range)	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintile 1	D_t	14.361	25.674	13.667	21.871	2.963	2.228	6.879	-4.391	3.143	2.072
		(0.804)	(1.322)	(0.819)	(1.174)	(0.481)	(0.380)	(0.376)	(-0.245)	(0.505)	(0.350)
Quintile 2	D_t	20.418	44.352*	23.000	41.146*	1.230	0.473	-14.279	-55.690**	1.188	0.469
		(0.944)	(1.788)	(1.067)	(1.672)	(0.187)	(0.074)	(-0.614)	(-2.251)	(0.180)	(0.073)
Quintile 3	D_t	12.596	36.103	13.508	32.340	-3.277	-4.441	-21.815	-75.746**	-3.280	-4.448
		(0.593)	(1.471)	(0.628)	(1.314)	(-0.468)	(-0.646)	(-0.730)	(-2.311)	(-0.468)	(-0.647)
Quintile 4	D_t	5.434	23.250	5.252	19.850	-2.200	-4.138	-25.778	-69.094*	-2.204	-4.145
		(0.272)	(1.025)	(0.255)	(0.864)	(-0.330)	(-0.663)	(-0.769)	(-1.858)	(-0.330)	(-0.663)
Quintile 5	D_t	1.837	20.146	1.505	18.505	-2.597	-3.896	-29.216	-79.142*	-2.596	-3.896
		(0.097)	(0.955)	(0.076)	(0.866)	(-0.437)	(-0.715)	(-0.804)	(-1.928)	(-0.437)	(-0.715)

Panel B: Institutional Ownership Quintiles

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintile 1	D_t	15.419	33.663*	15.227	30.516	1.969	1.144	-2.358	-21.783	2.105	1.051
		(0.873)	(1.728)	(0.905)	(1.619)	(0.322)	(0.194)	(-0.127)	(-1.181)	(0.342)	(0.177)
Quintile 2	D_t	16.987	36.033	19.176	33.269	1.127	0.943	-7.392	-42.458*	1.117	0.943
		(0.851)	(1.576)	(0.965)	(1.473)	(0.178)	(0.159)	(-0.317)	(-1.704)	(0.176)	(0.159)
Quintile 3	D_t	6.879	32.705	8.107	29.761	-3.061	-3.768	-22.179	-76.006**	-3.064	-3.769
		(0.340)	(1.419)	(0.390)	(1.281)	(-0.483)	(-0.637)	(-0.723)	(-2.238)	(-0.483)	(-0.637)
Quintile 4	D_t	2.866	25.018	3.823	22.544	-2.670	-4.103	-24.373	-76.823**	-2.672	-4.104
		(0.145)	(1.119)	(0.188)	(1.002)	(-0.421)	(-0.694)	(-0.712)	(-2.008)	(-0.421)	(-0.694)
Quintile 5	D_t	2.959	21.945	3.270	18.695	-3.209	-5.065	-33.256	-81.723**	-3.210	-5.067
		(0.151)	(0.994)	(0.162)	(0.836)	(-0.479)	(-0.811)	(-0.962)	(-2.107)	(-0.478)	(-0.811)

Table 5.11: Panel Regressions on Liquidity

Release dates of popular late-night shows are designated as the event dates. The event dummy D_t is regressed on de-trended liquidity variables. Fixed Effects panel regressions with Driscoll-Kraay standard errors are used. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. $ln(VIX)_t$ is the natural log of VIX on day t. ADS_t is the Aruoba-Diebold-Scotti business conditions index on day t. $ln(EPU)_t$ is the natural log of Economic Policy Uncertainty index on day t. D_{Macro} is the dummy variable for macroeconomic announcement date. D_P is the dummy variable for the DNP measure, having a value of 1 if the measure is greater than or equal to its 90th percentile, and 0 otherwise. Firm control variables are defined in the Appendix. Day-of-the-week, month and year dummies are also added as controls. Regression coefficients are reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

	ln(Adj. $ Vol.)		ln(Turnover)		Bid–Ask		ln(Amihud)		ln(Price Range)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_t	10.386	25.750	13.005	25.144	-0.089	-0.250	-13.928	-60.609**	-0.090	-0.250
	(0.452)	(0.976)	(0.571)	(0.957)	(-0.169)	(-0.665)	(-0.548)	(-2.056)	(-0.170)	(-0.664)
$ln(VIX)_t$	0.623	67.883*	89.856***	156.159***	9.860***	8.978***	304.889***	312.949***	9.865***	8.980***
	(0.022)	(1.776)	(2.648)	(3.932)	(3.357)	(5.489)	(6.125)	(7.952)	(3.349)	(5.485)
ADS_t	4.051*	-29.168	2.610	-26.493	0.258	0.718	1.109	42.105	0.261	0.719
	(1.898)	(-1.178)	(0.900)	(-1.023)	(0.649)	(0.838)	(0.215)	(1.378)	(0.655)	(0.837)
$ln(EPU)_t$	21.839**	39.951***	11.332	37.945***	-1.242**	0.463	-47.044***	-4.130	-1.246**	0.463
	(1.974)	(3.079)	(0.983)	(2.953)	(-2.330)	(1.039)	(-3.441)	(-0.312)	(-2.333)	(1.039)
D_{Macro}	18.008*	-1.110	17.518*	-1.158	0.730*	0.666**	10.148	23.115	0.730*	0.666**
	(1.792)	(-0.096)	(1.725)	(-0.100)	(1.951)	(2.494)	(0.910)	(1.567)	(1.947)	(2.493)
D_P		-11.036		-11.251		0.102		13.015		0.102
		(-0.818)		(-0.817)		(0.216)		(0.674)		(0.216)
D_{Earn}		989.139***		988.072***		40.566***		237.734***		40.622***
		(74.895)		(74.232)		(48.182)		(15.490)		(48.120)
$\beta^{SW}_{i,y}$		-2.729		-3.924		0.040		9.254		0.044
		(-0.157)		(-0.229)		(0.105)		(0.479)		(0.113)
$R100_{i,y}$		37.474***		-1.086		-0.406**		-47.125***		-0.406**
		(5.880)		(-0.223)		(-2.467)		(-5.560)		(-2.466)
$R100YR_{i,y}$		48.806***		5.546		-0.242		-57.253***		-0.241
		(9.547)		(1.389)		(-1.528)		(-8.016)		(-1.517)
$Std.Dev_{i,y}$		-226.883		296.783*		-17.768**		346.126*		-18.447**
		(-1.334)		(1.917)		(-2.435)		(1.746)		(-2.520)
$Div.Yld_{i,y}$		0.206		1.785		0.025		-0.582		0.025
		(0.116)		(1.004)		(0.513)		(-0.252)		(0.520)
$ln(Mkt.Cap)_{i,y-1}$		5.968*		8.175**		0.097		-0.401		0.097
		(1.785)		(2.487)		(0.828)		(-0.088)		(0.825)
$Lev_{i,y-1}$		-0.013		-0.030		-0.000		-0.017		-0.000
		(-0.189)		(-0.463)		(-0.057)		(-0.174)		(-0.048)
$NITA_{i,y-1}$		0.016		0.044		0.003		0.042		0.003
		(0.266)		(0.787)		(1.220)		(0.620)		(1.222)
$ln(Age)_{i,y-1}$		-7.584		-6.173		0.119		4.471		0.117
		(-0.599)		(-0.511)		(0.359)		(0.332)		(0.353)
$ln(Cover)_{i,y-1}$		-0.396		1.385		0.017		2.380		0.018
		(-0.059)		(0.209)		(0.093)		(0.238)		(0.095)
$Inst.Own_{i,y-1}$		-0.424***		-0.421***		-0.000		0.322***		-0.000
		(-4.371)		(-4.508)		(-0.128)		(2.734)		(-0.126)
Constant	-94.212	0.000	-307.500***	0.000	-22.040***	0.000	-602.850***	-835.252***	-22.042***	0.000
	(-1.097)	(.)	(-3.105)	(.)	(-2.760)	(.)	(-3.778)	(-4.713)	(-2.753)	(.)
Observations	7,786,112	2,759,323	7,785,492	2,759,323	7,787,429	2,759,323	7,553,755	2,697,771	7,787,429	2,759,323
R^2	0.007	0.061	0.007	0.063	0.012	0.100	0.005	0.007	0.012	0.100
No. of Firms	5,809	2,389	5,805	2,389	5,809	2,389	5,803	2,389	5,809	2,389

5.4.4 Impact on odd lot trading

Even though the results for liquidity variables do not support noise trading by retail investors as a plausible explanation, it is impossible to directly observe whether retail or institutional trading activity has changed on event days because the daily trading volume data lacks such details. According to Kupfer and Schmidt (2021), odd lot trading may provide a clue whether retail investors are more attentive towards a specific stock and, hence, trade more. If retail investors are trading in a stock with a high price, the odd lot ratio is expected to be high because they cannot easily trade in regular lots due to their wealth constraints. Institutional investors do not face such constraints and hence, the odd lot ratio will be lower as the order volume in regular lots will be higher. In case of low-priced stocks, retail investors do not need to trade in odd lots, hence, the odd lot ratio will be lower if they are trading more. In case institutional investors are more active in such small-priced stocks, the ratio will further decrease because of large volumes in regular lots.

I compute the natural log of odd lot ratio, denoted as $ln(Odd)$, by dividing the number of odd lot trades by the number of total trades for each firm-day observation. Similar to the analysis on liquidity, regressions are run at both the portfolio and firm levels. At the portfolio level, the dependent variable is the equal-weighted cross-sectional average of the odd lot ratios for all firms in the sample on a given day. The event dummy D_t is the independent variable and time dummies are added as controls:

$$ln(Odd)_t = \alpha + \beta_1 D_t + day_t + month_t + year_t + \epsilon \tag{5.5}$$

At the firm level, I run fixed effects panel regressions with firm controls and error terms adjusted for cross-sectional dependence. I include the firm controls used by Kupfer and Schmidt (2021). Since I expect the odd lot trading to be sensitive to stock price, an interaction term between the event dummy D_t and natural log of price $ln(Price)$ is added to the panel regression:

$$
\begin{aligned}
ln(Odd)_{i,t} &= \alpha + \beta_1 D_t + \beta_2 ln(Price)_{i,t} + \beta_3 D_t \times ln(Price)_{i,t} + \sum_{k=1}^{K} \delta_k Firm\ Controls_{k,i,t} \\
&+ day_t + month_t + year_t + \epsilon \qquad (5.6)
\end{aligned}
$$

Results of the portfolio-level regression and firm-level panel regressions are reported in Table 5.12. Coefficient of the event dummy is insignificant in all specifications, implying that odd lot trading is unaffected by sleep deprivation after late-night shows. This result is consistent with the results on liquidity, which is also mostly unaffected by the event. The natural log of price is significantly positive in panel regressions, consistent with the expectation that odd lot trading by retail investors is generally higher in large-priced stocks because of wealth constraints. However, this may also be caused by algorithmic traders or HFTs. In column (3), the interaction between the event dummy and log of price is insignificant. Thus, the intensity of odd lot trading is not sensitive to stock price on event days.

Results in Panel C of Table 5.4 show that the returns of large-priced stocks are affected more by sleep deprivation. The Amihud illiquidity ratio is also lower in large-cap stocks with high institutional ownership. I further explore the role of price in odd lot trading by running panel regressions in each decile of $ln(Price)$. The results in Table 5.13 show that odd lot ratio decreases significantly only for the three smallest price deciles.

If retail trading in large-priced stocks were to increase on event days, the odd lot ratio should be higher because such investors cannot trade in regular lots. However, the results are completely opposite. There is an increase in retail trading in small-priced stocks; hence, the odd lot ratio is decreasing because investors can easily use regular lots for such stocks. However, liquidity and returns of such stocks are not significantly affected on event days. It can be argued that increased noise trading by retail investors in small-priced stocks does not affect liquidity because an endogenous increase in informed trading counter-balances any reduction in adverse selection costs (Kyle, 1985). It is well documented that such stocks are the habitat of retail noise traders. In summary, the slight increase in liquidity of large stocks and the stronger effect on their returns cannot be attributed to increased noise trading by retail investors. Insignificant results for large-priced stocks also show that odd lot trading by algorithmic traders and HFTs does not increase on event days.

Table 5.12: Impact on Odd Lot Trading

Release dates of popular late-night shows are designated as the event dates. In column (1), the event dummy D_t is regressed on the market-wide equal-weighted cross-sectional average of the natural log of the odd lot ratio $ln(Odd)$. In columns (2) and (3), Fixed Effects panel regressions with Driscoll-Kraay standard errors are used. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. $ln(Price)_{i,t}$ is the natural log of unadjusted price of the firm i on day t, while $D_t \times ln(Price)_{i,t}$ is the interaction between the event dummy and natural log of unadjusted price. Firm control variables are defined in the Appendix. Day-of-the-week, month and year dummies are also added as controls. Regression coefficients are reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

	(1) Market-wide	(2) FE Panel	(3) FE Panel
D_t	-0.008	-0.009	-0.032
	(-1.393)	(-1.207)	(-1.554)
$ln(Price)_{i,t}$		0.185***	0.185***
		(64.647)	(64.036)
$D_t \times ln(Price)_{i,t}$			0.008
			(1.386)
$Return_{i,t}$		-0.194***	-0.194***
		(-12.628)	(-12.608)
$\|Return\|_{i,t}$		0.351***	0.351***
		(15.682)	(15.698)
$Price.Range_{i,t}$		-1.757***	-1.756***
		(-6.515)	(-6.505)
$Spread_{i,t}$		1.744***	1.743***
		(7.629)	(7.616)
$ln(Vol)_{i,t}$		-0.219***	-0.219***
		(-82.917)	(-82.946)
$\sum^{63} Return_{i,t-5}$		-0.065***	-0.065***
		(-11.686)	(-11.676)
$Std.Dev^{63}_{i,t-5}$		0.881***	0.881***
		(12.254)	(12.254)
$ln(Cancels)_{i,t}$		0.054***	0.054***
		(28.345)	(28.362)
$ln(Mkt.Cap)_{i,t}$		0.056***	0.056***
		(13.563)	(13.565)
Constant	3.048***	3.553***	3.554***
	(513.700)	(63.577)	(63.631)
Time Dummies:			
Day-of-the-week	Yes	Yes	Yes
Month	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	2,264	3,821,719	3,821,719
R-squared	0.960	0.462	0.462
No. of Firms		2,857	2,857

Table 5.13: Impact on Odd Lot Trading in Price Deciles

Release dates of popular late-night shows are designated as the event dates. Fixed Effects panel regressions with Driscoll-Kraay standard errors are used for each decile sorted on ln(Price). Deciles are numbered from (1) to (10) in ascending order of the rank. The dependent variable is natural log of odd lot ratio of the firm i on day t. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. $ln(Price)_{i,t}$ is the natural log of unadjusted price of the firm i on day t. Firm control variables are defined in the Appendix. Day-of-the-week, month and year dummies are also added as controls. Regression coefficients are reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_t	-0.025**	-0.024**	-0.015*	-0.010	-0.009	-0.008	-0.005	-0.002	-0.002	-0.001
	(-2.202)	(-1.986)	(-1.650)	(-1.060)	(-1.098)	(-1.242)	(-0.798)	(-0.277)	(-0.426)	(-0.186)
$ln(Price)_{i,t}$	0.199***	0.156***	0.110***	0.048***	0.135***	0.164***	0.189***	0.204***	0.191***	0.186***
	(26.989)	(15.896)	(11.326)	(3.702)	(10.770)	(14.019)	(16.866)	(16.214)	(20.192)	(33.268)
$Return_{i,t}$	-0.226***	-0.203***	-0.164***	-0.140***	-0.130***	-0.116***	-0.124***	-0.162***	-0.157***	-0.189***
	(-8.752)	(-8.553)	(-7.622)	(-5.113)	(-5.228)	(-4.698)	(-5.223)	(-6.712)	(-7.017)	(-7.761)
$\|Return\|_{i,t}$	0.379***	0.381***	0.271***	0.286***	0.260***	0.129***	0.090**	0.157***	0.170***	0.177***
	(10.537)	(10.584)	(8.229)	(8.200)	(7.249)	(3.505)	(2.312)	(4.047)	(4.693)	(4.363)
$Price.Range_{i,t}$	-3.791***	-3.715***	-1.244**	1.832***	1.181**	1.858***	2.623**	4.968***	8.623***	15.355***
	(-10.768)	(-6.430)	(-2.435)	(3.294)	(2.320)	(3.703)	(2.559)	(4.719)	(5.844)	(10.469)
$Spread_{i,t}$	3.572***	3.535***	1.367***	-1.257**	-0.783*	-1.338***	-1.997**	-4.043***	-7.294***	-13.185***
	(11.890)	(6.718)	(2.953)	(-2.528)	(-1.732)	(-2.975)	(-2.078)	(-4.079)	(-5.210)	(-9.629)
$ln(Vol)_{i,t}$	-0.229***	-0.239***	-0.238***	-0.239***	-0.226***	-0.211***	-0.204***	-0.201***	-0.192***	-0.179***
	(-91.823)	(-92.658)	(-84.935)	(-81.753)	(-73.436)	(-60.440)	(-61.831)	(-57.624)	(-54.248)	(-50.267)
$\sum^{63} Return_{i,t-5}$	-0.065***	-0.097***	-0.096***	-0.076***	-0.081***	-0.050***	-0.048***	-0.054***	-0.034***	-0.028***
	(-11.112)	(-17.004)	(-12.714)	(-10.679)	(-11.130)	(-6.413)	(-6.333)	(-6.421)	(-4.621)	(-3.830)
$Std.Dev^{63}_{i,t-5}$	1.079***	1.206***	0.838***	0.864***	0.494***	0.432***	0.723***	0.409**	0.177	0.072
	(13.840)	(13.930)	(7.500)	(6.534)	(4.788)	(3.053)	(5.606)	(2.507)	(1.387)	(0.536)
$ln(Cancels)_{i,t}$	0.026***	0.045***	0.045***	0.033***	0.046***	0.037***	0.029***	0.032***	0.027***	0.027***
	(8.251)	(15.698)	(14.461)	(12.771)	(20.964)	(14.176)	(11.511)	(12.315)	(9.182)	(8.490)
$\ln(Mkt.Cap)_{i,t}$	0.067***	0.131***	0.148***	0.137***	0.058***	0.010	-0.011	-0.009	0.014*	0.022***
	(12.521)	(17.207)	(16.016)	(14.046)	(7.041)	(1.239)	(-1.484)	(-1.146)	(1.947)	(4.811)
Constant	3.461***	2.360***	2.190***	2.658***	3.840***	4.652***	5.033***	4.922***	4.425***	4.205***
	(39.672)	(19.559)	(15.425)	(16.808)	(28.457)	(35.970)	(40.438)	(36.192)	(35.605)	(47.945)
Time Dummies:										
Day-of-the-week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	248,380	324,572	350,880	358,962	380,169	405,942	428,020	433,826	428,495	458,242
R^2	0.277	0.290	0.336	0.350	0.379	0.430	0.505	0.560	0.589	0.608
No. of Firms	681	949	1,153	1,266	1,335	1,314	1,202	1,047	844	567

5.4.5 Impact on algorithmic trading

The results for odd lot trading also suggest that algorithmic trading does not alter significantly on event days. Algorithmic traders time their informed trades to occur when they expect noise trading to be high, such as when the market's trading volume is abnormally high (Collin-Dufresne and Fos, 2015). Peress and Schmidt (2020) suggest that technological developments in computer hardware and software have allowed algorithmic traders to detect noise trading and exploit it by front-running their orders. I find neither trading volume to be abnormally high, nor noise trading to be more intense on event days. Any increase in retail trading activity is only evident in small-priced stocks, which are not the usual target of sophisticated algorithmic traders and HFTs. Weller (2018) suggests that high-priced stocks have a finer price grid due to the sub-penny rule (SEC Rule 612) which imposes a minimum tick size of one cent for securities covered by Regulation NMS.[9] This restriction encourages algorithmic trading for liquidity provision or liquidity uptake in high-priced stocks. Thus, I do not expect algorithmic trading to be abnormally high in any market segment.

Following Weller (2018), I construct four proxies for algorithmic trading from the SEC MIDAS data for each firm at daily frequency: $ln(Odd.Vol)_{i,t}$ is the natural log of the odd lot volume ratio, calculated by dividing the odd lot volume with the total volume traded; $ln(T/O)_{i,t}$ is the natural log of the trade-to-order volume ratio, calculated by dividing the total volume traded with the total volume across all orders placed; $ln(C/T)_{i,t}$ is the natural log of the cancel-to-trade ratio, calculated by dividing the number of cancellations with the count of total trades; and $ln(\overline{Trade.Size})_{i,t}$ is the natural log of the average trade size, calculated by dividing the total volume traded with the count of total trades. I run fixed effects panel regressions identical to those in Equation 5.6 for each of the four variables for algorithmic trading. As before, I account for cross-sectional dependence by using Driscoll-Kraay standard errors.

[9] Market participants are prohibited from displaying, ranking, or accepting quotations in NMS stocks that are priced in an increment of less than \$0.01, unless the price of the quotation is less than \$1.00. If the price of the quotation is less than \$1.00, the minimum increment is \$0.0001.

Higher values of odd lot volume and cancel-to-trade ratio, and lower values of trade-to-order ratio and average trade size should indicate higher algorithmic trading activity. Results in Table 5.14 confirm that there is almost no change in the intensity of algorithmic trading on event days. The coefficient for event dummy is negatively significant only in one regression in which the dependent variable is the trade-to-order ratio, and the interaction term between the event dummy and log of price is included. The results are insignificant in all other cases.

I also run panel regressions for each dependent variable in each decile rank sorted by log of price. For brevity, I report only the coefficients of the event dummy for these regressions in Table 5.15. I find that odd lot volume significantly decreases (hence, less algorithmic trading) only in the smallest price decile. The coefficient is insignificant in all other cases. Therefore, I conclude that negative market returns on days following late-night shows cannot be attributed to any change in algorithmic trading.

Table 5.14: Impact on Algorithmic Trading

Release dates of popular late-night shows are designated as the event dates. The event dummy D_t is regressed on four proxies of algorithmic trading. Fixed Effects panel regressions with Driscoll-Kraay standard errors are used. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. $ln(Price)_{i,t}$ is the natural log of unadjusted price of the firm i on day t, while $D_t \times ln(Price)_{i,t}$ is the interaction between the event dummy and natural log of unadjusted price. Firm control variables are defined in the Appendix. Day-of-the-week, month and year dummies are also added as controls. Regression coefficients are reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

	$ln(Odd.Vol)_{i,t}$		$ln(T/O)_{i,t}$		$ln(C/T)_{i,t}$		$ln(\overline{Trade.Size})_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_t	-0.001	-0.017	0.005	-0.027**	0.001	-0.007	0.004	-0.007
	(-0.123)	(-0.581)	(0.572)	(-2.285)	(0.150)	(-0.699)	(0.759)	(-0.844)
$ln(Price)_{i,t}$	0.434***	0.434***	0.303***	0.302***	-0.129***	-0.129***	-0.146***	-0.146***
	(78.998)	(79.136)	(69.599)	(69.017)	(-37.396)	(-37.352)	(-52.174)	(-51.941)
$D_t \times ln(Price)_{i,t}$		0.005		0.010***		0.003		0.004*
		(0.627)		(3.225)		(1.056)		(1.685)
$Return_{i,t}$	-0.305***	-0.305***	-0.078***	-0.078***	0.198***	0.198***	0.148***	0.148***
	(-10.777)	(-10.783)	(-4.166)	(-4.149)	(11.044)	(11.053)	(8.777)	(8.789)
$\lvert Return\rvert_{i,t}$	0.609***	0.609***	-0.282***	-0.282***	-0.207***	-0.206***	-0.184***	-0.184***
	(14.437)	(14.442)	(-8.298)	(-8.286)	(-9.185)	(-9.187)	(-10.316)	(-10.315)
$Price.Range_{i,t}$	3.819***	3.819***	6.641***	6.642***	-3.498***	-3.498***	-1.307***	-1.306***
	(6.577)	(6.579)	(16.057)	(16.076)	(-10.109)	(-10.109)	(-5.238)	(-5.238)
$Spread_{i,t}$	-2.541***	-2.542***	-5.225***	-5.226***	2.552***	2.552***	0.919***	0.918***
	(-5.256)	(-5.258)	(-14.534)	(-14.558)	(8.543)	(8.542)	(4.350)	(4.349)
$ln(Vol)_{i,t}$	-0.339***	-0.339***	0.719***	0.719***	-0.595***	-0.595***	0.230***	0.230***
	(-71.985)	(-71.999)	(178.248)	(178.182)	(-152.837)	(-152.853)	(119.259)	(119.290)
$\sum Return_{i,t-5}$	-0.149***	-0.149***	-0.055***	-0.055***	0.106***	0.106***	0.092***	0.092***
	(-14.512)	(-14.508)	(-13.866)	(-13.844)	(23.703)	(23.708)	(23.604)	(23.614)
$Std.Dev_{i,t-5}$	1.261***	1.261***	-0.693***	-0.694***	-0.675***	-0.676***	-0.538***	-0.538***
	(10.889)	(10.884)	(-8.220)	(-8.227)	(-10.652)	(-10.654)	(-9.690)	(-9.700)
$ln(Cancels)_{i,t}$	0.147***	0.147***	-0.639***	-0.639***	0.679***	0.679***	-0.101***	-0.100***
	(33.329)	(33.357)	(-149.667)	(-149.818)	(156.328)	(156.310)	(-54.118)	(-54.133)
$ln(Mkt.Cap)_{i,t}$	0.034***	0.034***	-0.118***	-0.118***	-0.103***	-0.103***	-0.097***	-0.097***
	(7.023)	(7.016)	(-29.297)	(-29.359)	(-26.886)	(-26.883)	(-42.824)	(-42.850)
Constant	0.808***	0.809***	0.130**	0.131**	6.236***	6.236***	-1.525***	-1.525***
	(11.175)	(11.163)	(2.070)	(2.106)	(93.941)	(93.960)	(-41.096)	(-41.130)
Time Dummies:								
Day-of-the-week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,574,238	3,574,238	3,867,553	3,867,553	3,867,553	3,867,553	3,867,553	3,867,553
R^2	0.190	0.190	0.571	0.571	0.656	0.656	0.440	0.440
No. of Firms	2,853	2,853	2,859	2,859	2,859	2,859	2,859	2,859

Table 5.15: Impact on Algorithmic Trading in Price Deciles

Release dates of popular late-night shows are designated as the event dates. Fixed Effects panel regressions with Driscoll-Kraay standard errors are used for each decile sorted on ln(Price). Deciles are numbered from (1) to (10) in ascending order of the rank. In each Panel from A to D, one of the four proxies of algorithmic trading is the dependent variable. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. The control variables (not shown) are the same as in Table 5.14. Only the regression coefficient for the event dummy is reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

Panel A: Odd Lot Volume Ratio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_t	-0.036**	-0.014	-0.021	-0.004	-0.009	-0.007	0.011	0.013	0.011	0.008
	(-2.039)	(-0.863)	(-1.314)	(-0.293)	(-0.701)	(-0.610)	(0.898)	(1.255)	(0.973)	(0.777)

Panel B: Trade-to-Order Volume Ratio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_t	0.001	0.010	0.006	0.002	0.002	0.008	0.006	0.002	0.002	0.001
	(0.065)	(1.096)	(0.694)	(0.170)	(0.232)	(0.764)	(0.524)	(0.209)	(0.175)	(0.116)

Panel C: Cancel-to-Trade Ratio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_t	0.008	0.002	-0.001	0.004	0.004	0.003	0.000	-0.005	-0.002	-0.001
	(1.044)	(0.298)	(-0.108)	(0.514)	(0.444)	(0.286)	(0.018)	(-0.611)	(-0.249)	(-0.128)

Panel D: Average Trade Size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_t	0.007	0.010	0.005	0.006	0.005	0.008	0.002	-0.000	0.002	0.001
	(1.018)	(1.514)	(0.860)	(0.939)	(0.791)	(1.576)	(0.382)	(-0.065)	(0.553)	(0.136)

5.5 Conclusion

In a seminal study, Kamstra *et al.* (2000) find that market returns decline when sleep is disturbed by DST change. I use a new proxy for sleep deprivation based on the growing trend of binge watching late-night TV shows and find similar results. Market returns significantly drop on days following popular late-night shows. The effect is stronger in stocks with larger market capitalisation, higher price, higher institutional ownership, and higher B/M ratio. This cross-sectional pattern shows that sleep disturbance affects institutional traders more than retail traders.

Due to the fear of potential losses, the propensity for risk-taking decreases in sleep deprived investors. The demand for a higher risk premium in the future has a negative effect on current market returns. High levels of VIX aggravate their risk-averse behaviour, leading to a stronger decline in returns. Kamstra *et al.* (2000) merely conjecture that sleep deprived investors are anxious and, hence, they are more risk-averse. I contribute to literature by clearly showing evidence in support of the risk-aversion channel causing negative returns. My findings confirm that risk-taking propensity of sleep deprived individuals declines if they fear a negative outcome (Mckenna *et al.*, 2007). Since sleep deprivation results in mental lethargy, investors are less willing to spend effort in making decisions that require more mental effort. As a result, investors may make fewer buying decisions that require more effort as compared to selling decisions, leading to a decline in stock prices.

The negative returns are not accompanied by any significant change in trading volume, turnover, bid-ask spread, or price range. Only the Amihud ratio improves for large-cap stocks with high institutional ownership. Thus, there is no evidence that noise trading increases on such days. The lack of change in trading activity rules out the possibilities that stock returns are decreasing either due to increased noise trading, or because of a decline in trades by distracted investors. Similarly, there is no appreciable change in the intensity of odd lot trading by retail or algorithmic traders.

Chapter 6

Conclusion

6.1 Conclusions

The vast literature on comovement is still lacking in the analysis of its seasonal variations. Extensive research has been carried out to find seasonal patterns in many asset pricing dynamics, like stock returns, investor sentiment, mood, investor attention, etc. However, little work has been done for comovement. I contribute to literature by investigating the intra-week pattern in comovement, and finding that it is higher on Mondays for U.S. stock markets over a long time period. I examine several plausible explanations like Monday anomaly, investor sentiment, arbitrage constraints, uncertainty and risk aversion, investor attention to market-wide news, and retail/institutional attention to firm-specific news. I rule out these explanations in favour of simultaneous contrast effect of macroeconomic announcements on Monday to explain this intra-week pattern. I also rule out the possibility that higher Monday synchronicity is a seasonal anomaly, recurring every week.

I show that intra-week variation in comovement results from an interplay between macroeconomic and earnings announcements. Since both macroeconomic and earnings announcements are infrequently released on Mondays, the information environment is like a quiet night. Hence, the occasional macroeconomic announcement becomes more salient because there is little else out there. It acts as a thunder in a quiet night. There is an abnormal reaction in terms of comovement.

The effect is so strong that it seems as if Monday synchronicity effect is a seasonal anomaly; however, I find that majority of the Mondays have no macroeconomic announcements, and comovement is not higher than other weekdays on these occasions. Only a small number of announcements on Monday are responsible for the effect.

Besides a psychological explanation, salience also has a physiological dimension because of the anatomical design of the human eye, which plays a role in visual contrast (Helmholtz, 1962; Hering, 1964). Similarly, sleep is essentially a physiological process that has psychological effects if it is disrupted. In Chapter 5, I find that sleep loss caused by watching late-night TV has a significant impact on stock returns. My study highlights the fact that financial markets are influenced by continuously evolving societal practices. I contribute to literature by developing a new proxy for sleep loss based on the recent cultural fad of watching late-night TV shows released by internet streaming services like Netflix.

Consistent with previous studies on the effects of sleep loss on equity markets, I find that market returns are negative on days following popular late-night shows. Unlike previous literature, I examine the effect of sleep loss in various cross-sections. I find that stocks with larger market capitalisation, higher price, higher institutional ownership, and higher B/M ratio are affected more. Market returns decline further if the investors fear gauge, i.e. VIX, is high. Hence, sleep deprivation makes investors more risk-averse and stock returns decline. Since volume and liquidity do not drop on such days, it implies that sleep deprived investors are not distracted, and do not curtail their trades. Liquidity improves in terms of the Amihud ratio for large-cap stocks with high institutional ownership. Moreover, both the intensity of noise trading by retail investors and algorithmic trading by institutional investors, remains unchanged. Thus, I contribute to literature by examining retail and institutional trading under exogenous behavioural shock caused by sleep loss.

6.2 Discussion

Almost all macroeconomic announcements on Monday consist of either PMI or PCE. One may think that the type of announcement is responsible for an abnormal increase in comovement. Maybe PMI or PCE are the most important announcements for the market and cause stock prices to comove more. However, I find two caveats to this argument. First, PMI and PCE are not only announced on Mondays; they are announced on other weekdays as well, but there is no abnormal reaction in terms of comovement. Second, NFPAY and FOMC are the most widely followed and influential macroeconomic announcements, but there is no abnormal increase in comovement when they are announced. I argue that NFPAY and FOMC do not become salient because they are usually announced in the middle of the week, along with many other announcements for investors to follow. In summary, I rule out that the sharp increase in Monday's comovement is dependent on the type of announcement.

Salience is an attentional mechanism, but I find that investor attention measures fail to capture the contrast effect. According to the category-learning behaviour (Peng and Xiong, 2006), investors rationally allocate more of their limited attention to market-wide information. Salience of macroeconomic announcements also results in a preferential allocation of attention to these market-wide news. The two phenomena are, however, different because top-down attention is being allocated endogenously and voluntarily in the former case, while bottom-up attention is exogenously increasing in the latter case. Therefore, investor attention measures cannot explain the Monday synchronicity effect because they can only proxy for top-down attention, but cannot capture the bottom-up attention that is drawn by the salient stimulus.

Some factors play a complementary role in increasing Monday's comovement. Uncertainty is higher at the start of the week because of limited information arrival and processing. Economic uncertainty and risk aversion measures are higher on Mondays. This problem is aggravated if weekends are longer than the usual two days. Investors have to rely on more valuable market-wide information in such circumstances, and hence, stock prices comove more. Higher downside correlation of stock returns on Mondays also contributes to a small degree. These factors, unlike the contrast effect, cannot explain why comovement on non-announcement Mondays in not higher than other weekdays.

One may presume that only retail investors are likely to watch late-night TV shows and suffer from sleep loss. My results, however, depict that professional traders are also influenced by the cultural trend of binge-watching late night TV. The decline in market indices implies that institutional investors, who own most of the equity in U.S. stock markets, are indeed affected more. The decline in returns is more prominent in those stocks that are the usual habitat of institutional investors. These results are not surprising since investment professionals are known to have lesser sleep hours than retail investors. Hence, they are more vulnerable to sleep disturbance if they choose to further sacrifice their sleep by watching late-night shows.

Sleep deprivation can negatively affect stock returns in different ways. Stock prices can decline if sleep deprived investors are distracted and stay away from trading. On the other hand, they may propagate a selling pressure by increasing their trading activity. However, I exclude both these possibilities by finding that trading volume does not change on days following late-night shows. In fact, the decline in returns can be best explained by a change in risk-taking behaviour caused by sleep loss. Empirical evidence on the effect of sleep loss on risk-taking behaviour is mixed, with some studies finding an increase while others documenting a decrease. However, the direction of this relationship is contingent on whether the outcomes are framed as potential losses or gains. Consistent with this argument, I find that sleep deprived investors become more risk-averse when they face potential losses on their equity investments. If the fear of loss is already high (i.e., high levels of VIX), risk aversion of sleep deprived investors increases further, leading to a stronger decline in stock prices.

Negative stock returns may also be a consequence of mental fatigue caused by sleep deprivation. There is evidence in literature that sleep deprived investors accept a smaller reward that requires little effort. This increased effort discounting may favour relatively simple selling decisions over buying decisions that require a greater cognitive effort. The buy/sell imbalance will then lead to a decline in stock returns. However, the preference for making little effort and accepting a smaller reward is brought about by a change in risk perception. Hence, it is consistent with the risk aversion channel.

6.3 Research Limitations

I examine the role of nine macroeconomic announcements and earnings announcements in explaining the intra-week pattern in synchronicity. However, several macroeconomic, industry, and firm-specific news other than these announcements have not been analysed, even though they are vital components of the information environment potentially affecting comovement.

Diversification and hedging strategies are reliant on dependence of stock returns with each other. However, portfolio selection and risk management are affected by asymmetries in stock returns. While I use a model-dependent measure for analysing the intra-week pattern of comovement, model-free entropy measures have not been investigated, which can incorporate asymmetries in the joint distribution of individual stock returns and market returns (Hong *et al.*, 2007; Jiang *et al.*, 2018).

Even though I develop a new proxy for sleep loss based on release dates of late-night TV shows, there are some limitations. First, the act of watching TV is voluntary, unlike the uniform and unavoidable effect of DST change. Second, there are no statistics regarding the number of viewers of a particular show at a given time. Third, not all viewers are market participants, and their proportion out of total viewership is unknown. Fourth, a show does not necessarily become popular overnight; it may gain popularity many weeks or months after its initial release.

6.4 Areas for Further Research

While high levels of VIX seems to amplify the contrast effect, it works even when VIX is low. However, when VIX is within medium range, there is no evidence of the contrast effect. The moderating role of VIX on contrast effect is unclear. Hence, this issue warrants an in-depth analysis in future research.

My application of the contrast effect to macroeconomic announcements also motivates further research into answering whether salience of such news has implications for attention to firm-specific news. There is conflicting evidence that macroeconomic news either crowds out attention to firm-specific news (Liu *et al.*, 2019), or helps in processing firm-specific news (Hirshleifer and Sheng, 2021). Since a salient macroeconomic news on Monday results in an abnormal response in terms of comovement, the reaction of earnings announcements on Monday may be different from other weekdays as well.

The empirical design of running separate synchronicity regressions for each weekday can be extended to test other seasonal patterns in comovement, like variations across calendar months or quarters. Such investigation will be interesting because quarterly earnings announcements of most firms are concentrated around a few dates in the year. In Chapter 5, I show that the contrast effect of Monday macroeconomic announcements is attenuated/absent on these dates. Thus, it is reasonable to assume that comovement fluctuates across different months/quarters of a year. These fluctuations can also be tested against various calendar anomalies to establish causal relationships.

The analysis of sleep deprivation following late-night shows can be extended to studying how sleep deprived investors react to information like earnings announcements, mergers and acquisitions, etc. Moreover, the impact of sleep loss on cognitive processes may have implications for stock return comovement.

In summary, the three essays make several contributions to literature on behavioural finance. This thesis shows that human behaviour is not only affected at higher cognitive levels, but also at a basic biological level. While salience and sleep have behavioural effects on financial markets, they are closely related to human physiology. For advancement in behavioural finance, the way forward should be to investigate various biological factors that modulate human behaviour.

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Appendix A

List of Abbreviations

ABC: ABC News

ADRs: American depository receipts

ADS: Aruoba-Diebold-Scotti index

AIA: Abnormal institutional attention

B/M: Book-to-market ratio

CAPM: Capital Asset Pricing Model

CBS: CBS News

CCI: Consumer confidence index

CNN: Cable News Network Inc.

CPI: Consumer price index

CRSP: Centre for Research in Security Prices

DNP: Daily news pressure measure

DST: Daylight saving time

EPU: Economic policy uncertainty

FOMC: Federal Open Market Committee decision

GDP: Gross domestic product

GLS: Generalised Least Squares

HFT: High frequency trading/trader

I/B/E/S: Institutional Brokers' Estimate System

IFRS: International Financial Reporting Standards

IJC: Initial jobless claims

IVOL: Idiosyncratic volatility

MIDAS: Market Information Data Analytics System

NBC: NBC News

NFPAY: Non-farm payroll

OLS: Ordinary Least Squares

PCE: Personal consumption expenditure

PMI: Purchasing managers' index

REITs: Real estate investment trusts

RMSE: Root mean squared error

ROA: Return on assets

SAD: Seasonal affective disorder

SEC: Securities and Exchange Commission

SVI: Search volume index

TEU: Twitter uncertainty index

TRBAL: Trade balance figure

VIX: Volatility implied index

WRDS: Wharton Research Data Services

Appendix B

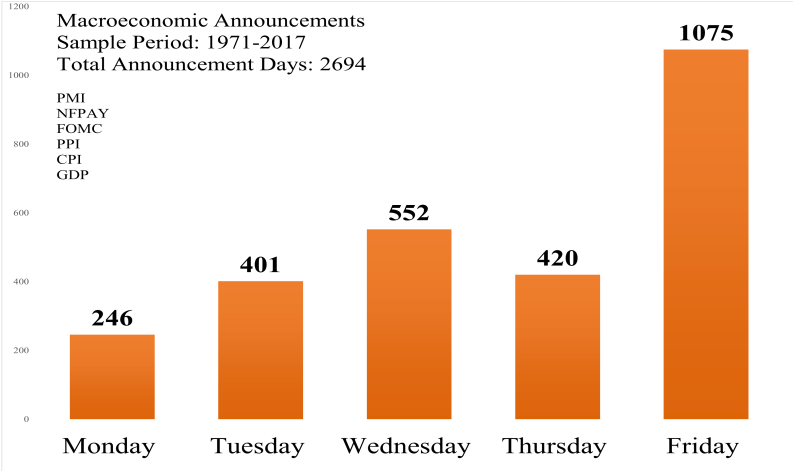
B1 Longer sample period for macroeconomic and earnings announcements

Panel A and Panel B of Figure B1 show that, for six types of announcements from 1971 to 2017, Monday continues to be the day with fewest macroeconomic announcements. Release dates for CCI, TRBAL, and PCE are unavailable. 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 B1, the pattern of frequencies of earnings announcements in the longer sample period (1984-2017) is similar to the 1998-2017 sample.

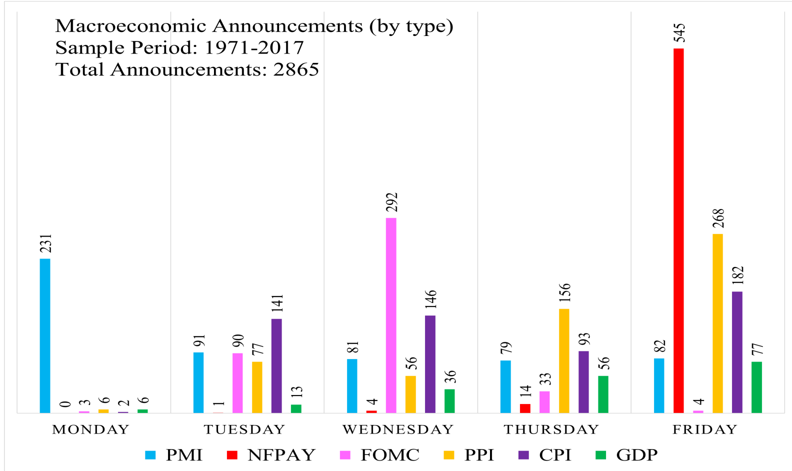
The regressions in Figure B2 involve the interactions between macroeconomic and earnings announcements, identical to those reported in Figure 4.2. The main difference between the two results is in the first case when both D_M and D_E are 0. R^2 values of Monday are higher than other weekdays, whereas, in the 1998-2017 sample, values of Tuesday and Thursday are higher than Monday. It seems as if the removal of macroeconomic announcements has 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, I cannot control for them. Hence, some announcement days are erroneously being categorized as non-announcement days due to this limitation in the data.

I run regressions using the longer sample period, identical to those reported in Figure 4.3. The average R^2 is still the highest for non-announcement Mondays in Panel A of Figure B3, even though its value is very close to that of non-announcement Fridays. In contrast, when I control for these missing announcements in the 1998-2017 period (Panel A of Figure 4.3), the average R^2 for non-announcement Mondays is no longer higher than other weekdays. Among the missing announcements, PCE is the culprit because it has been released 71 times on Monday in the 1998-2017 period, while there is only a single Monday announcement for TRBAL and none for CCI. It is plausible that there a few Mondays in the 1971-1997 period where PCE was announced but the data is missing. Hence, the small number of Monday macroeconomic announcements is mainly responsible for higher Monday synchronicity; missing out only a few of them on Monday results in a considerable difference in the results, as shown by the two sample periods I have investigated.

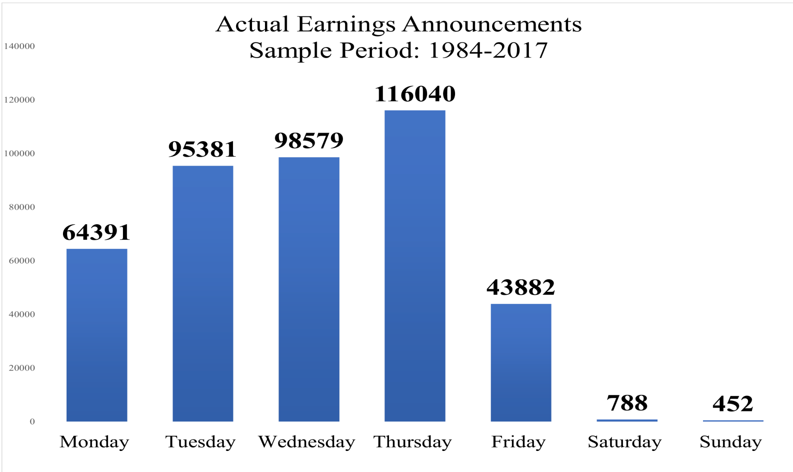
I also use the longer sample period for 3-year rolling regressions. The results, reported in Figure B4, indicate that despite removing macroeconomic announcements ("No Macro"), earnings announcements ("No Earn"), or both ("No Macro/Earn"), Monday's average R^2 remains higher. The reason for the difference in the results of Figure 4.5 and Figure B4 is the same as stated for the difference observed in Panel A of Figure 4.3 and Panel A of Figure B3. When I 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.



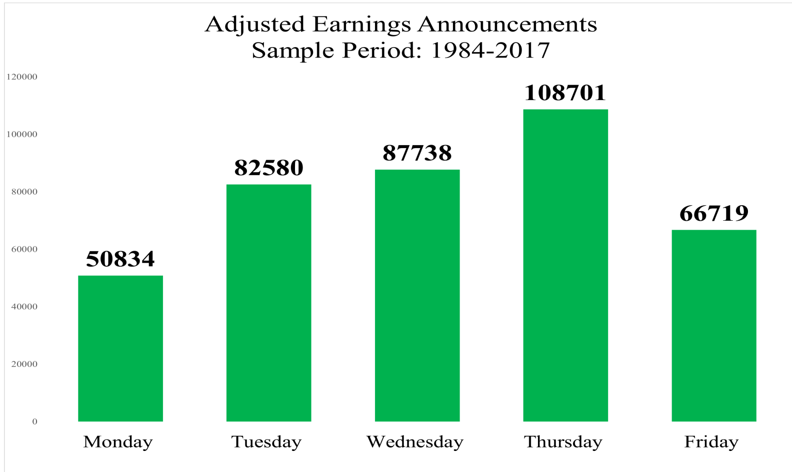
Panel A: All Macroeconomic Announcements



Panel B: Macroeconomic Announcements by Type



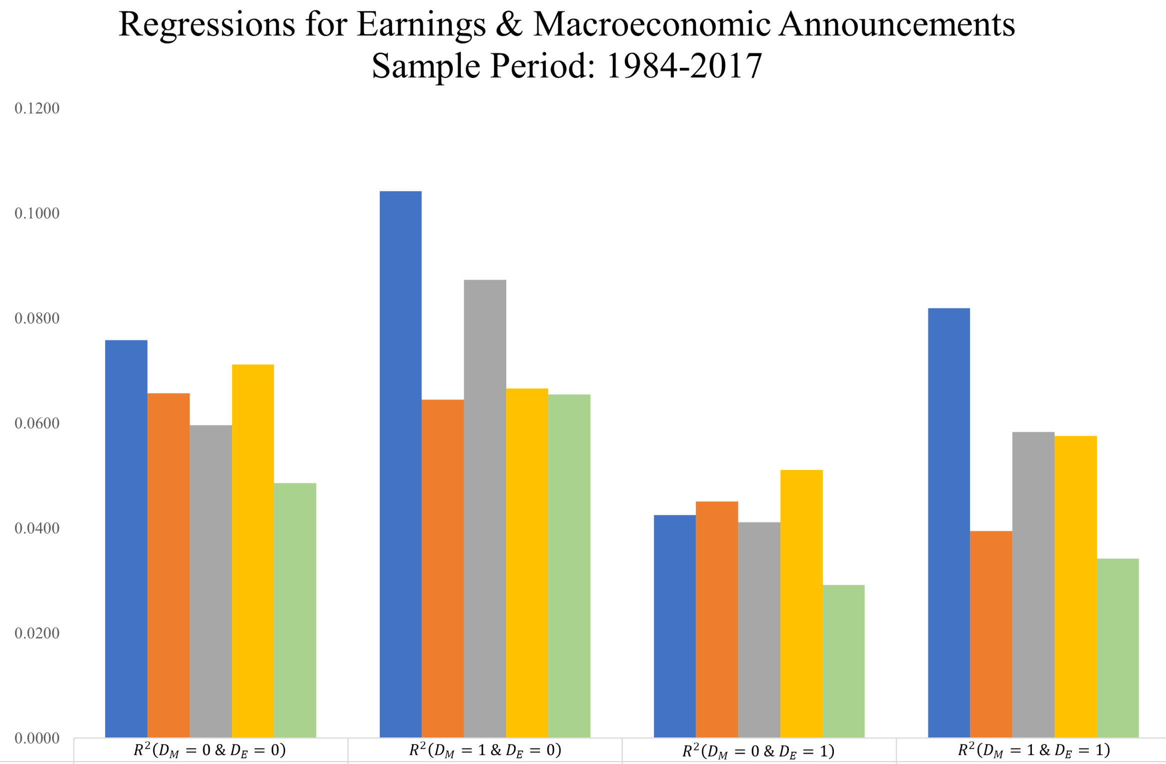
Panel C: Actual Earnings Announcements



Panel D: Adjusted Earnings Announcements

Figure B1: News Announcements by Weekday: Longer Sample Period

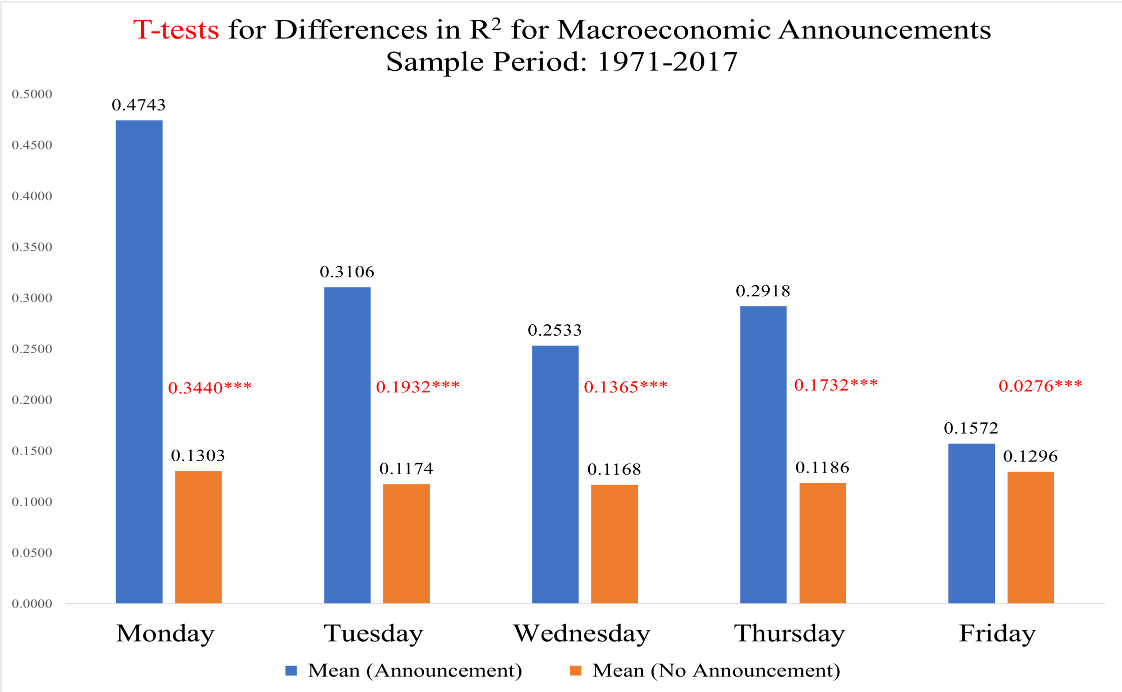
Panel A and **Panel B** show the cumulative and individual distributions of six macroeconomic announcements from 1971 to 2017. PMI: Purchasing Managers Index released by the Institute of Supply Management (usually on the first business day of each month). NFPAY: Non-Farm Payroll released by the Bureau 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. **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.



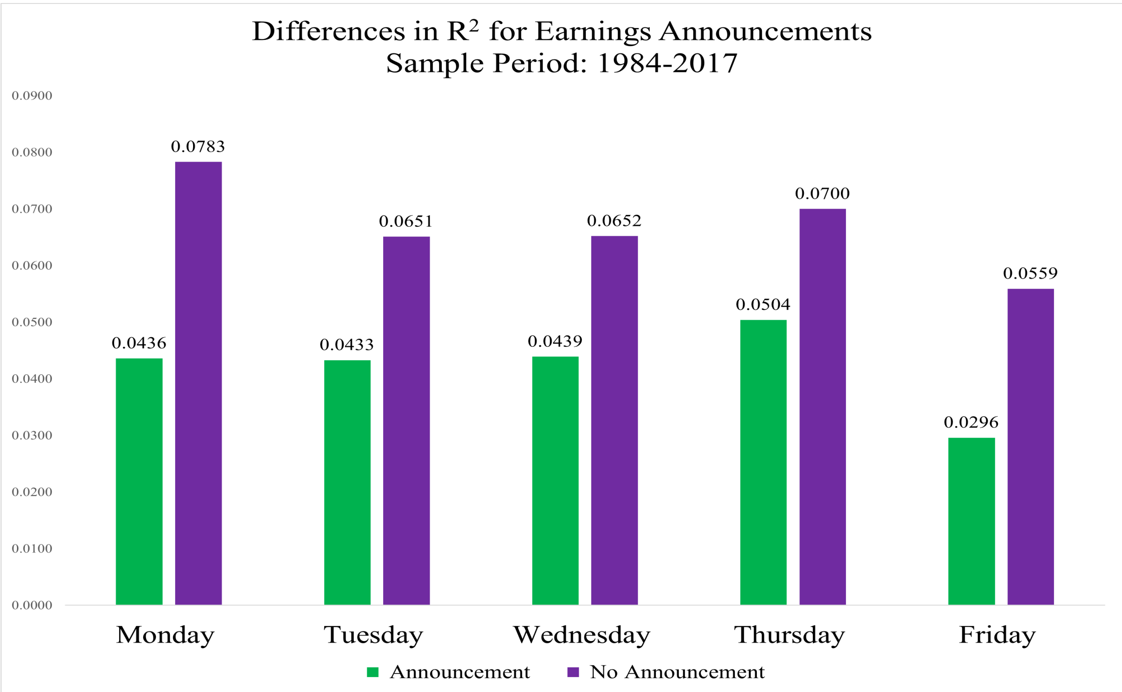
	$R^2(D_M = 0 \& D_E = 0)$	$R^2(D_M = 1 \& D_E = 0)$	$R^2(D_M = 0 \& D_E = 1)$	$R^2(D_M = 1 \& D_E = 1)$
Monday	0.0758	0.1042	0.0425	0.0819
Tuesday	0.0657	0.0645	0.0451	0.0395
Wednesday	0.0596	0.0873	0.0411	0.0583
Thursday	0.0712	0.0666	0.0511	0.0576
Friday	0.0486	0.0655	0.0292	0.0342

Figure B2: 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.



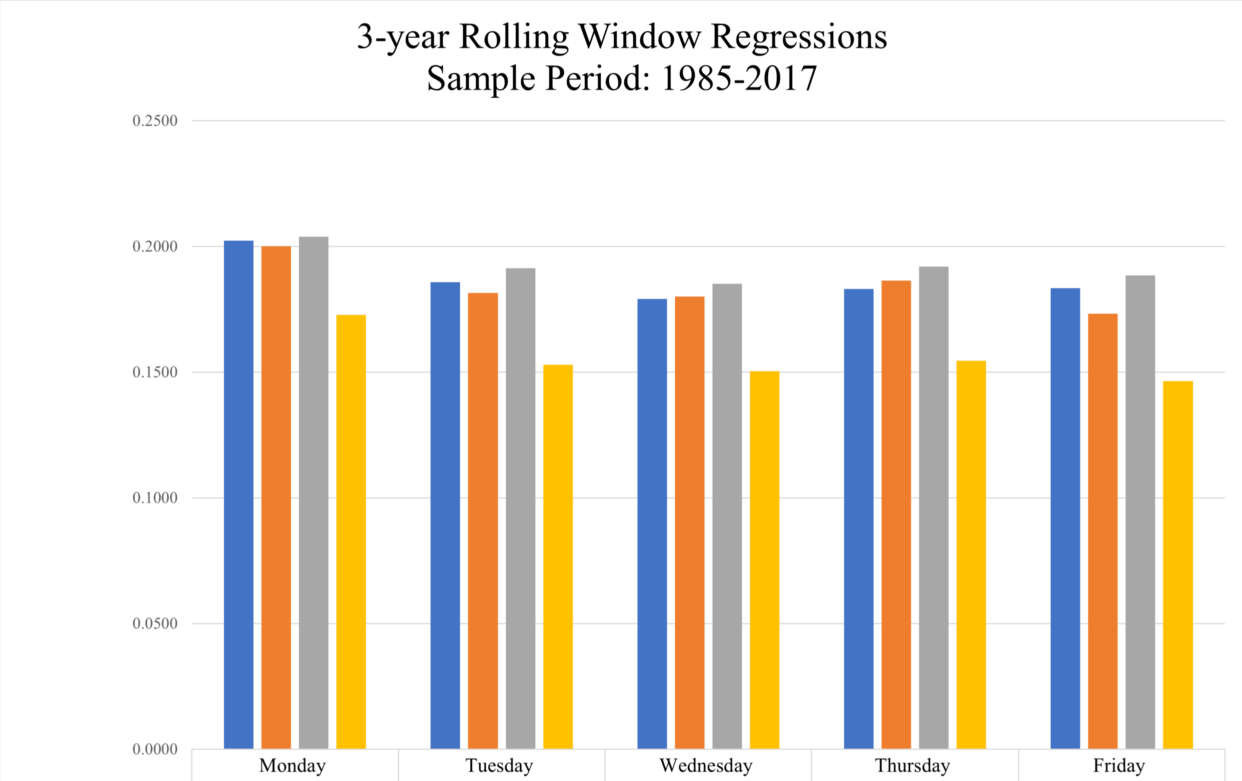
Panel A: R^2 for Macroeconomic Announcements



Panel B: R^2 for Earnings Announcements

Figure B3: 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.



	Monday	Tuesday	Wednesday	Thursday	Friday
No Macro	0.2022	0.1857	0.1791	0.1830	0.1834
No Earn	0.2001	0.1815	0.1800	0.1864	0.1732
No Macro/Earn	0.2038	0.1913	0.1851	0.1919	0.1884
All Days	0.1728	0.1529	0.1503	0.1545	0.1464

Figure B4: 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 labelled "No Macro", earnings announcement days are removed in the row labelled "No Earn", while both macroeconomic and earnings announcement days are removed in the row labelled "No Macro/Earn", while all days are included in the row labelled "All Days".

B2 VIX over long weekends

Table B1: 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

B3 Retail investor attention to macroeconomic announcements

I 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 B2.

Table B2: 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

Weekday	Non-Ann.	Ann.	Total
Sunday	-0.409		-0.409
Monday	0.000	2.017	0.175
Tuesday	0.135	2.103	0.219
Wednesday	0.049	1.502	0.101
Thursday	0.123	1.644	0.171
Friday	0.079	1.721	0.135
Saturday	-0.390		-0.390
Total	-0.063	1.858	0.000

FOMC

Weekday	Non-Ann.	Ann.	Total
Sunday	-0.396		-0.396
Monday	0.029		0.029
Tuesday	0.143	4.244	0.317
Wednesday	0.153	4.610	0.629
Thursday	0.000	6.159	0.042
Friday	-0.156		-0.156
Saturday	-0.463		-0.463
Total	-0.104	4.579	0.000

CCI

Weekday	Non-Ann.	Ann.	Total
Sunday	-0.437		-0.437
Monday	0.023		0.023
Tuesday	0.040	1.984	0.471
Wednesday	0.163	0.011	0.163
Thursday	0.030	1.313	0.037
Friday	0.210		0.210
Saturday	-0.466		-0.466
Total	-0.066	1.944	0.000

PCE

Weekday	Non-Ann.	Ann.	Total
Sunday	-0.427		-0.427
Monday	0.142	1.170	0.211
Tuesday	0.182	0.691	0.191
Wednesday	0.192	0.904	0.205
Thursday	0.102	0.649	0.123
Friday	-0.016	1.022	0.075
Saturday	-0.379		-0.379
Total	-0.033	0.967	0.000

PPI

Weekday	Non-Ann.	Ann.	Total
Sunday	-0.480		-0.480
Monday	0.156		0.156
Tuesday	0.247	1.243	0.327
Wednesday	0.190	1.705	0.257
Thursday	0.189	1.587	0.261
Friday	-0.010	1.286	0.059
Saturday	-0.579		-0.579
Total	-0.048	1.419	0.000

TRBAL

Weekday	Non-Ann.	Ann.	Total
Sunday	-0.244		-0.244
Monday	0.160	0.409	0.161
Tuesday	0.159	1.256	0.212
Wednesday	0.217	0.809	0.246
Thursday	0.122	1.165	0.193
Friday	-0.107	0.725	-0.054
Saturday	-0.513		-0.513
Total	-0.033	0.983	0.000

NFPAY

Weekday	Non-Ann.	Ann.	Total
Sunday	-0.274		-0.274
Monday	-0.100		-0.100
Tuesday	-0.101	2.259	-0.098
Wednesday	-0.105		-0.105
Thursday	0.142	1.991	0.152
Friday	-0.173	3.546	0.656
Saturday	-0.231		-0.231
Total	-0.119	3.501	0.000

CPI

Weekday	Non-Ann.	Ann.	Total
Sunday	-1.072		-1.072
Monday	0.324		0.324
Tuesday	0.528	1.625	0.568
Wednesday	0.489	1.999	0.613
Thursday	0.467	1.573	0.521
Friday	0.118	1.301	0.191
Saturday	-1.143		-1.143
Total	-0.056	1.661	0.000

GDP

Weekday	Non-Ann.	Ann.	Total
Sunday	-0.500		-0.500
Monday	0.257		0.257
Tuesday	0.332		0.332
Wednesday	0.349	2.172	0.374
Thursday	0.358	2.021	0.388
Friday	-0.078	1.156	-0.022
Saturday	-0.829		-0.829
Total	-0.017	1.538	0.000

Appendix C

C1 Late-night TV Shows

Table C1: Firm Control Variables

This table reports definitions of all firm control variables used in all regressions of Chapter 5.

Variable Name	Description
Earnings Announcement	D_{Earn} is a dummy variable indicating the earnings announcement date of the firm.
Return Volatility	$Std.Dev_{i,y}$ is the standard deviation of daily returns of the firm i in the year y.
	$Std.Dev_{i,t-5}$ is the standard deviation of returns for the firm i over 63 past trading days, further lagged by 5 days from day t.
Firm Size	$ln(Mkt.Cap)_{i,y}$ is the natural log of market capitalization of the firm i calculated at the end of the year y.
B/M Ratio	$B/M_{i,y}$ is the book-to-market ratio for the firm i at the end of the year y.
Leverage	$Lev_{i,y}$ is the leverage computed as long-term debt divided by total assets of the firm i in the year y.
Net Income to Total Assets	$NITA_{i,y}$ is the net income divided by total assets of the firm i in the year y.
Firm Age	$ln(Age)_{i,y}$ is the log of the firm i's age in calendar year y.
Analyst Coverage	$ln(Cover)_{i,y}$ is the natural log of 1 + No. of Analysts covering the firm i in calendar year y.
Institutional Ownership	$Inst.Own_{i,y}$ is the percentage institutional ownership of the firm i at the end of year y.

Continued on next page

Table C1 – continued from previous page

Variable Name	Description
Scholes-Williams Beta	$\beta^{SW}_{i,y}$ is computed annually for each cap-based equal-weighted decile portfolio, and assigned to all firms in that portfolio. The formula is: $\beta^{SW} = \frac{\beta_{-1} + \beta_0 + \beta_{+1}}{1 + 2\rho}$ Where β_{-1} is OLS beta with the return on the market index lagged one period; β_0 is OLS beta with the contemporaneous return of the market index; β_{+1} is OLS beta with the return on the market index leading one period; and ρ is the first order autocorrelation coefficient of the market return (Scholes and Williams, 1977).
Cumulative Return	$R100_{i,y}$ is the cumulative return of the firm i during the last 100 trading days of the year y.
	$R100YR_{i,y}$ is the cumulative return of the firm i between the first recorded trade day and 100 trading days before year-end.
	$\sum Return_{i,t-5}$ is the cumulative return of the firm i for 63 past trading days, further lagged by 5 days from day t.
Stock Return	$Return_{i,t}$ is the stock return of the firm i on day t.
Absolute Return	$\lvert Return\rvert_{i,t}$ is the absolute stock return of the firm i on day t.
Price Range	$Price.Range_{i,t}$ is the price range of the firm i on day t, calculated by dividing the difference between daily high price and daily low price with the daily high price.
Bid-Ask Spread	$Spread_{i,t}$ is the bid-ask spread of the firm i on day t, calculated by dividing the difference between daily bid and ask with the average of both.
Volume	$ln(Vol)_{i,t}$ is the natural log of the volume of the firm i on day t.
Order Cancellations	$ln(Cancels)_{i,t}$ is the natural log of the number of order cancellations of the firm i on day t.

Table C2: De-trended Market Returns

Release dates of popular late-night shows are designated as the event dates. S&P500, CRSP value-weighted and CRSP equal-weighted indices are de-trended by their 30-day moving averages, and regressed with the event dummy D_t. D_t has a value of 1 for a trading day if a late-night show is released in the previous night, and 0 otherwise. $ln(VIX)_t$ is the natural log of VIX on day t. ADS_t is the ADS business conditions index on day t. $ln(EPU)_t$ is the natural log of Economic Policy Uncertainty (EPU) index on day t. $ln(TEU\text{-}WGT)$ is the natural log of Twitter Economic Uncertainty index on day t. $Sleepiness_{t-1}$ is the Sleepiness index on day $t-1$. D_{Macro} is the dummy variable for macroeconomic announcement date. Regression coefficients are reported along with t-statistics being shown in the parentheses. Statistical significance is shown at the 1%, 5%, and 10% level, indicated by ***, **, and *, respectively.

	S&P500 Index					CRSP Value-weighted Index					CRSP Equal-weighted Index				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
D_t	-0.249**	-0.253***	-0.253***	-0.269***	-0.245**	-0.234**	-0.236**	-0.237**	-0.253***	-0.228**	-0.154**	-0.153*	-0.153*	-0.169**	-0.143*
	(-3.087)	(-3.215)	(-3.191)	(-3.453)	(-3.027)	(-2.913)	(-2.960)	(-2.945)	(-3.195)	(-2.799)	(-2.245)	(-2.132)	(-2.131)	(-2.370)	(-2.009)
$ln(VIX)_t$		-0.886***	-0.885***	-0.796***	-0.893***		-0.869***	-0.869***	-0.777***	-0.876***		-0.724***	-0.724***	-0.636***	-0.731***
		(-6.886)	(-6.869)	(-5.298)	(-7.112)		(-6.743)	(-6.732)	(-5.206)	(-6.978)		(-5.702)	(-5.703)	(-4.374)	(-5.936)
ADS_t		-0.024**	-0.024**	-0.026**	-0.024**		-0.028**	-0.028**	-0.031**	-0.028**		-0.032***	-0.032***	-0.034***	-0.032***
		(-2.494)	(-2.507)	(-2.310)	(-2.522)		(-2.945)	(-2.957)	(-2.737)	(-2.977)		(-3.289)	(-3.288)	(-3.156)	(-3.321)
$ln(EPU)_t$		0.222***	0.222***		0.222***		0.221***	0.221***		0.221***		0.210***	0.210***		0.210***
		(6.641)	(6.675)		(6.592)		(6.544)	(6.573)		(6.487)		(5.999)	(6.015)		(6.003)
D_{Macro}			-0.021					-0.015					0.001		
			(-0.419)					(-0.308)					(0.024)		
$ln(TEU\text{-}WGT)_t$				0.043					0.039					0.037	
				(1.375)					(1.323)					(1.572)	
$Sleepiness_{t-1}$					-0.001					-0.001					-0.001
					(-0.798)					(-0.808)					(-0.531)
$D_t \times Sleepiness_{t-1}$					-0.006					-0.006					-0.007
					(-0.860)					(-0.931)					(-1.319)
Constant	-0.067	1.333**	1.336**	2.021***	1.335**	-0.060	1.296**	1.298**	1.989***	1.298**	-0.021	0.978*	0.977*	1.635***	0.978*
	(-1.475)	(2.922)	(2.929)	(4.531)	(2.964)	(-1.440)	(2.813)	(2.818)	(4.458)	(2.855)	(-0.506)	(2.093)	(2.095)	(3.782)	(2.129)
Time Dummies:															
Day-of-the-week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,265	2,265	2,265	2,265	2,264	2,265	2,265	2,265	2,265	2,264	2,265	2,265	2,265	2,265	2,264
R^2	0.0065	0.0522	0.0523	0.0395	0.0533	0.0065	0.0508	0.0509	0.0384	0.0520	0.0073	0.0466	0.0466	0.0343	0.0475

Table C3: List of Late-night Shows

This table is a list of popular late-night shows. Shows released on Saturdays and Sundays are excluded.

Show	Date	Time	Network	Genre	Show	Date	Time	Network	Genre
House of Cards	February 01, 2013	12:01:00 AM	NETFLIX	Film/Drama	The Handmaid's Tale	June 14, 2017	3:01:00 AM	HULU	Film/Drama
Orange is the New Black	July 11, 2013	3:01:00 AM	NETFLIX	Film/Drama	Longmire	November 17, 2017	3:01:00 AM	NETFLIX	Film/Drama
House of Cards	February 14, 2014	3:01:00 AM	NETFLIX	Film/Drama	Money Heist	December 20, 2017	3:01:00 AM	NETFLIX	Film/Drama
Orange is the New Black	June 06, 2014	3:01:00 AM	NETFLIX	Film/Drama	Peaky Blinders (UK)	December 21, 2017	3:01:00 AM	NETFLIX	Film/Drama
Peaky Blinders (UK)	September 30, 2014	3:01:00 AM	NETFLIX	Film/Drama	Black Mirror	December 29, 2017	3:01:00 AM	NETFLIX	Film/Drama
Peaky Blinders (UK)	November 14, 2014	3:01:00 AM	NETFLIX	Film/Drama	Jessica Jones	March 08, 2018	3:01:00 AM	NETFLIX	Film/Drama
House of Cards	February 27, 2015	3:01:00 AM	NETFLIX	Film/Drama	A Series of Unfortunate Events	March 30, 2018	3:01:00 AM	NETFLIX	Film/Drama
Community	March 17, 2015	3:01:00 AM	YAHOO	Comedy	The Handmaid's Tale	April 25, 2018	3:01:00 AM	HULU	Film/Drama
Community	March 24, 2015	3:01:00 AM	YAHOO	Comedy	The Handmaid's Tale	May 02, 2018	3:01:00 AM	HULU	Film/Drama
Community	March 31, 2015	3:01:00 AM	YAHOO	Comedy	The Handmaid's Tale	May 09, 2018	3:01:00 AM	HULU	Film/Drama
Community	April 07, 2015	3:01:00 AM	YAHOO	Comedy	The Handmaid's Tale	May 16, 2018	3:01:00 AM	HULU	Film/Drama
Daredevil	April 10, 2015	3:01:00 AM	NETFLIX	Film/Drama	The Handmaid's Tale	June 06, 2018	3:01:00 AM	HULU	Film/Drama
Community	April 14, 2015	3:01:00 AM	YAHOO	Comedy	Marcella (UK)	June 08, 2018	3:01:00 AM	NETFLIX	Film/Drama
Community	April 21, 2015	3:01:00 AM	YAHOO	Comedy	The Handmaid's Tale	June 20, 2018	3:01:00 AM	HULU	Film/Drama
Community	April 28, 2015	3:01:00 AM	YAHOO	Comedy	The Handmaid's Tale	July 11, 2018	3:01:00 AM	HULU	Film/Drama
Community	May 05, 2015	3:01:00 AM	YAHOO	Comedy	Chilling Adventures of Sabrina	October 26, 2018	3:01:00 AM	NETFLIX	Film/Drama
Community	May 12, 2015	3:01:00 AM	YAHOO	Comedy	The Last Kingdom	November 19, 2018	3:01:00 AM	NETFLIX	Film/Drama
Community	May 19, 2015	3:01:00 AM	YAHOO	Comedy	A Series of Unfortunate Events	January 01, 2019	3:01:00 AM	NETFLIX	Film/Drama
Community	May 26, 2015	3:01:00 AM	YAHOO	Comedy	The Order	March 07, 2019	3:01:00 AM	NETFLIX	Film/Drama
Community	June 02, 2015	3:01:00 AM	YAHOO	Comedy	Lucifer	May 08, 2019	3:01:00 AM	NETFLIX	Film/Drama
Sense8	June 05, 2015	3:01:00 AM	NETFLIX	Film/Drama	Black Mirror	June 05, 2019	3:01:00 AM	NETFLIX	Film/Drama
Orange is the New Black	June 12, 2015	3:01:00 AM	NETFLIX	Film/Drama	The Handmaid's Tale	June 12, 2019	3:01:00 AM	HULU	Film/Drama
New Girl	August 17, 2015	1:00:00 AM	TBS	Comedy	The Handmaid's Tale	June 19, 2019	3:01:00 AM	HULU	Film/Drama
Longmire	September 10, 2015	3:01:00 AM	NETFLIX	Film/Drama	The Handmaid's Tale	June 26, 2019	3:01:00 AM	HULU	Film/Drama
Jessica Jones	November 20, 2015	3:01:00 AM	NETFLIX	Film/Drama	The Handmaid's Tale	July 03, 2019	3:01:00 AM	HULU	Film/Drama
F is for Family	December 18, 2015	3:01:00 AM	NETFLIX	Comedy	Stranger Things	July 04, 2019	3:01:00 AM	NETFLIX	Film/Drama
House of Cards	March 04, 2016	3:01:00 AM	NETFLIX	Film/Drama	The Handmaid's Tale	July 10, 2019	3:01:00 AM	HULU	Film/Drama
Daredevil	March 18, 2016	3:01:00 AM	NETFLIX	Film/Drama	This is Us	July 24, 2019	1:37:00 AM	NBC	Film/Drama
Peaky Blinders (UK)	May 31, 2016	3:01:00 AM	NETFLIX	Film/Drama	The Handmaid's Tale	July 31, 2019	3:01:00 AM	HULU	Film/Drama
Orange is the New Black	June 17, 2016	3:01:00 AM	NETFLIX	Film/Drama	The Handmaid's Tale	August 07, 2019	3:01:00 AM	HULU	Film/Drama
Marcella (UK)	July 01, 2016	3:01:00 AM	NETFLIX	Film/Drama	The Handmaid's Tale	August 14, 2019	3:01:00 AM	HULU	Film/Drama
Longmire	September 23, 2016	3:01:00 AM	NETFLIX	Film/Drama	13 Reasons Why	August 23, 2019	3:01:00 AM	NETFLIX	Film/Drama
Luke Cage	September 30, 2016	3:01:00 AM	NETFLIX	Film/Drama	The Great British Baking Show (UK)	September 27, 2019	3:01:00 AM	NETFLIX	Reality
The Crown	November 04, 2016	3:01:00 AM	NETFLIX	Film/Drama	Insatiable	October 11, 2019	3:01:00 AM	NETFLIX	Film/Drama
Iron Fist	March 17, 2017	3:01:00 AM	NETFLIX	Film/Drama	The Great British Baking Show (UK)	October 25, 2019	3:01:00 AM	NETFLIX	Reality
The Handmaid's Tale	April 26, 2017	3:01:00 AM	HULU	Film/Drama	Chilling Adventures of Sabrina	January 24, 2020	3:01:00 AM	NETFLIX	Film/Drama
The Handmaid's Tale	May 03, 2017	3:01:00 AM	HULU	Film/Drama	Narcos: Mexico	February 13, 2020	3:01:00 AM	NETFLIX	Film/Drama
The Handmaid's Tale	May 10, 2017	3:01:00 AM	HULU	Film/Drama	Rick and Morty	April 01, 2020	12:31:00 AM	ADULT SWIM	Comedy
The Handmaid's Tale	May 17, 2017	3:01:00 AM	HULU	Film/Drama	Love, Victor	June 17, 2020	3:01:00 AM	HULU	Comedy
The Handmaid's Tale	May 24, 2017	3:01:00 AM	HULU	Film/Drama	Doom Patrol	June 25, 2020	3:01:00 AM	HBO MAX	Film/Drama
F is for Family	May 30, 2017	3:01:00 AM	NETFLIX	Comedy	Doom Patrol	July 09, 2020	3:01:00 AM	HBO MAX	Film/Drama
The Handmaid's Tale	May 31, 2017	3:01:00 AM	HULU	Film/Drama	Doom Patrol	July 30, 2020	3:01:00 AM	HBO MAX	Film/Drama
The Handmaid's Tale	June 07, 2017	3:01:00 AM	HULU	Film/Drama					

C2 Search Terms for Sleepiness Index

The search terms to construct the sleepiness index are as follows:

1. insomnia
2. insomniac
3. jet lag
4. jet lag calculator
5. jet lag cure
6. jet lag pills
7. jet lag tips
8. lack of sleep
9. lack of sleep headache
10. list of sleep disorders
11. sleep apnea
12. sleep apnea causes
13. sleep apnea devices
14. sleep apnea machine
15. sleep apnea mask
16. sleep apnea mouth guard
17. sleep apnea surgery
18. sleep apnea test
19. sleep apnea treatment
20. sleep deprivation
21. sleep deprivation causes
22. sleep deprivation death
23. sleep deprivation effects
24. sleep disorders
25. sleeping pills
26. sleeping pills and alcohol
27. sleeping pills for dogs
28. sleeping pills names

Appendix D

Ethics Approval

Secondary Data Ethics Application - XSD2021019 Approved

CARBS Research Office-Ethics <CARBS-ResearchEthics@cardiff.ac.uk>
Thu 01/07/2021 18:27
To: Arbab Cheema <CheemaAK@cardiff.ac.uk>

Ethics Approval Reference: **XSD2021019**
Project Title: Thunder in a Quiet Night: Macro News and Monday Synchronicity
Impact of Sleep Deprivation due to Late-Night TV Shows on Trading Behavior

Dear Arbab,

I would like to confirm that your project has been confirmed and logged in the Research Office. Should there be a material change in the methods or circumstances of your project, you would in the first instance need to get in touch with us for re-consideration and further advice on the validity of the approval.

Best wishes,
Ye

Ye Weihua
Research Services Officer
Research Office, Cardiff Business School

Cardiff University
Aberconway Building |Colum Road |Cardiff | CF10 3EU
Tel: +44 (0)29 225 10983
Email: YeW5@cardiff.ac.uk

The University welcomes correspondence in Welsh or English. Corresponding in Welsh will not lead to any delay.

Ye Weihua
Swyddog Gwasanaethau Ymchwil
Swyddfa Ymchwil, Ysgol Busnes Caerdydd
Prifysgol Caerdydd
Adeilad Aberconwy |Rhodfa Colum |Caerdydd |CF10 3EU
Ffôn : +44 (0)29 225 10983
E-bost: YeW5@caerdydd.ac.uk

Mae'r Brifysgol yn croesawu gohebiaeth yn Gymraeg neu'n Saesneg. Ni fydd gohebu yn Gymraeg yn creu unrhyw oedi.