A Microstructure Perspective on the Effect of Information Uncertainty on Equity Market Quality

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Abstract

As Paulos (2003, para. 1) notes, "uncertainty is the only certainty there is, and knowing how to live with insecurity is the only security." This statement cannot be more pertinent in the context of equity markets. Uncertainty makes it difficult to interpret information and can arguably hinder the efficient functioning of equity markets. The prevalence of uncertainty in equity markets emphasizes the need to thoroughly understand its impact on various aspects of equity markets. A good understanding of the impact of uncertainty is important not only for investors to fine-tune portfolio strategies but also for market regulators to maintain market quality. In that respect, this thesis is devoted to understanding the effect of information uncertainty on equity market quality. The empirical chapters of this thesis focus on the US equity market.

Chapter 3 studies the effect of equity market uncertainty (EMUNC) on the informational efficiency of US equity prices. We consider the US equity market as a whole by focusing on exchange-traded funds (ETFs) and find that EMUNC significantly reduces ETFs' price efficiency. This result indicates that uncertainty reduces the quality of the information environment and makes value-relevant signals noisy, which hinders the process of price discovery.

Chapter 4 focuses on uncertainty about the Federal Open Market Committee (FOMC) announcement. These announcements represent informational shocks in the US equity market. Since investors anticipate these news announcements, they compete for trading profits using their private information about the forthcoming news. Thus, possessing accurate predictions about these news events should matter. Using analyst forecast dispersion to measure uncertainty about the impending FOMC news, we find that uncertainty significantly affects equity market quality during the FOMC announcement. In particular, uncertainty increases pre-announcement information asymmetry and reduces liquidity surrounding announcement times. Despite a reduction in liquidity, uncertainty leads to higher trading volume both before and after the announcement. Finally, we find that informational efficiency during the FOMC announcement deteriorates with higher analyst forecast disagreement. We also show that the effect of uncertainty is independent of and incremental to the effect of the FOMC announcement itself.

Chapter 5 extends the first empirical chapter. In the first chapter, we find that EMUNC reduces the informational efficiency of ETF prices. In this chapter, we explore whether such an effect is cross-sectionally heterogeneous. We hypothesize and test two plausible channels that facilitate this cross-sectional heterogeneity: limits-to-arbitrage and uncertainty exposure channels. Using a sample of S&P 500 constituent stocks, we show that EMUNC has a stronger negative impact on stocks that are harder to arbitrage or have a higher past uncertainty exposure.

Overall, this thesis enhances our understanding of uncertainty and its impact on equity market quality. The findings in empirical chapters are also potentially helpful for investors and market regulators for better investments and policy-making.

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Attestation of Authorship

I, Chris Hengbin Zhang, hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher education.

Signed: Chris H. Zhang

Date: March 2022

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Chapter 1

Introduction

Financial markets provide a valuable service by bringing together buyers and sellers of financial assets with different information. As market participants trade with each other, information from the market is aggregated and incorporated into asset prices. These prices often serve as signals to guide investment and economic activities. Understanding the role of information in the price formation process is at the heart of market microstructure research, which studies “the process by which investors’ latent demands are ultimately translated into prices and volumes” (Madhavan, 2000, p. 205).

Clearly, the quality of information is of utmost importance for the accuracy of asset prices and the efficient functioning of the market. When accurate information is incorporated into asset prices, prices become a reliable indicator of fundamental values. Investors can then use these prices to better allocate their capital. If information becomes less precise, it is more difficult for investors to make accurate judgments about true asset values. Asset prices impound more noise through their subsequent trading, driving them away from fundamental values. Noisy prices can, in turn, adversely affect investment efficiency and the real economy (e.g., Dessaint et al., 2019).

One market friction that decreases the precision of information and creates noise in financial markets is uncertainty. According to Paulos (2003, para. 1), “uncertainty is the only certainty there is, and knowing how to live with insecurity is the only security.” This statement is more pertinent in financial markets. Financial market uncertainty comes from various sources. For instance, equity investors face uncertainty about their future portfolio returns. A lack of clarity in the policy-making process of government authorities makes it difficult for market participants to interpret the implications of market-related policies. Rare events such as natural disasters, wars, terrorist attacks, and political shocks are also known to create heightened market uncertainty due to a lack of preparation. Another instance when precise knowledge about new information should matter most is during periods of informational shocks such as news releases. This is because investors anticipate the arrival of new information and compete with each other for profits using their predictions of the forthcoming information. Uncertainty reduces the quality of the information environment surrounding news announcements and obtaining profits in such an environment becomes more challenging. Given the prevalence and relevance of uncertainty in financial markets, participants in financial markets need to understand its impact on financial market quality.

This thesis is devoted to studying the effect of information uncertainty on equity market quality. Market quality refers to how well the market functions. In market microstructure, financial markets have two crucial functions: liquidity and price discovery (O'Hara, 2003). Liquidity facilitates quick financial transactions with low price pressures, whereas price discovery is the process of prices incorporating information and, thus, achieving informational efficiency. From a practical perspective, market quality may also involve fairness and integrity as regulators and policymakers are most concerned about fair market access and trading.[1] Issues such as insider trading and market manipulation disturb financial market order and impair market fairness. Therefore, such illegal activities may also impair market quality.[2] Although we acknowledge various dimensions of equity market quality, this thesis examines it from a microstructure perspective and focuses on liquidity and informational efficiency.

Understanding the impact of uncertainty on equity market quality is helpful in several aspects. For instance, equity market participants are subject to varying degrees of uncertainty throughout their investments. Knowledge of how uncertainty affects various aspects of financial market quality can help investors fine-tune their investment strategies and the timing of trades to minimize their portfolios' exposure to market uncertainty. Since exchanges and regulatory authorities are most concerned with maintaining the quality and competitive advantage of their respective financial market, studies in this thesis can potentially inform regulators of the importance of incorporating the surveillance of market uncertainty into their overall market regulatory framework.

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1 In the US, for instance, legislations such as the Regulation Alternative Trading Systems (Reg ATS) Fair Access Rule, the Regulation Fair Disclosure (Reg FD), and the Regulation National Market System (Reg NMS) have been made to ensure that financial markets are fair, impartial, and competitive.

2 For details regarding issues such as insider trading and market manipulation, we refer to Putniņš (2012) and Bhattacharya (2014).

Starting with the basics, Chapter 2 provides a primer on the two themes covered in this thesis: uncertainty and financial market quality. This chapter first discusses several types of uncertainty commonly observed in financial markets and then presents measures of uncertainty used in this thesis. Next, we introduce the concept of financial market quality from a microstructure perspective. We then set up the empirical framework to measure these market quality concepts, which we use in the subsequent empirical chapters. Since this thesis is about the effect of uncertainty on equity market quality, this chapter also briefly surveys the existing literature on these topics and identifies the gap.

In Chapter 3, we examine the effect of equity market uncertainty on the informational efficiency of equity prices. Existing studies on related issues are twofold. One stream of literature examines the impact of uncertainty stemming from specific events such as presidential elections (e.g., Li and Born, 2006; Pasquariello and Zafeiridou, 2014; Brogaard et al., 2020), government regulatory changes (e.g., Battalio and Schultz, 2011), or natural disasters (e.g., Rehse et al., 2019). These studies cover only a portion of uncertainty that equity investors face from day to day. Another stream of literature studies uncertainty in a general time-series framework. However, these studies focus primarily on the impact of uncertainty on asset pricing (e.g., Brogaard and Detzel, 2015; Bali et al., 2017; Li, 2017) and corporate finance (e.g., Wang et al., 2014; Gulen and Ion, 2016; Xu, 2020; Guan et al., 2021; Cui et al., 2021). Less research is devoted to studying how uncertainty affects financial market quality. In this respect, Chapter 3 adds to our understanding of the impact of uncertainty on financial market quality beyond insights from well-studied events.

Relating the US newspaper-based equity market uncertainty index to the informational efficiency of US exchange-traded funds (ETFs), Chapter 3 finds that uncertainty reduces the informational efficiency of ETF prices. This result indicates that uncertainty reduces the quality of the equity market information environment and, thus, renders value-relevant signals noisy. Noisy signals impede the efficient incorporation of information into equity prices, making them less informationally efficient.

A critical time when obtaining accurate information should matter most is the announcement of pre-scheduled news. These events represent informational shocks in financial markets. Since investors anticipate the arrival of new information, they compete for profits using their own predictions of the forthcoming information. If there is high uncertainty about the forthcoming information, obtaining profits becomes more challenging because accurately predicting new information is more difficult. Uncertainty reduces the quality of the information environment surrounding news events and raises several important questions relevant to investors. For instance, does an uncertain information environment increase the cost of trading around the news release? If ex-ante uncertainty regarding the news is high, do investors face a higher adverse selection risk for trading prior to its announcement? Existing studies have not fully addressed these questions.

The aim of Chapter 4 is to address the above questions. Instead of looking at general equity market uncertainty, Chapter 4 focuses on uncertainty surrounding the content of the news to be announced. This chapter uses the FOMC announcement as a proxy for informational shocks in the US equity market and dispersion in analysts' forecasts as a proxy for ex-ante uncertainty about the forthcoming Fed Funds Rate. We estimate a battery of market quality metrics using a 15-minute window surrounding the FOMC announcement times. These metrics include market liquidity (spread and its underlying components), trading activity (volume and trade size), and informational efficiency of prices. Next, we link these market quality measures to analyst forecast dispersion (our proxy for uncertainty). Our analysis shows that uncertainty caused by analyst disagreement has a significant impact on trading costs (liquidity deteriorates and information asymmetry increases), volume, and price efficiency surrounding FOMC announcements. Thus, this chapter highlights the role of information environment during periods of informational shocks in financial markets. It also informs equity investors of the potential costs associated with trading at such times.

Chapter 5 is a direct extension of the third chapter. In Chapter 3, we examine the impact of equity market uncertainty using two liquid US ETFs, the S&P 500 SPDR ETF to represent the large and mid-sized firms and the iShares Russell 2000 ETF to represent the small firms. Essentially, we consider the US equity market as a whole. However, relying on ETFs restricts us in answering a more interesting question: Is the harmful effect of equity market uncertainty heterogeneous in the cross-section of stocks. Finance theory suggests at least two reasons why such cross-sectional heterogeneity may exist. One of them is limits-to-arbitrage. If arbitrageurs focus on correcting mispricing in stocks that are easier to arbitrage, equity market uncertainty should have a lower impact on such stocks. This is because mispricing caused by uncertainty is identified and corrected by arbitrageurs. Second, some stocks are more subject to the impact of uncertainty simply because they are more sensitive to it.

To test the above theoretical predictions, Chapter 5 employs a large cross-section of 500 US stocks that comprise the S&P 500 index. These stocks account for over 80% of the US equity market capitalization.[3] We first sort these stocks by limits-to-arbitrage proxies and historical uncertainty exposure measures. Based on limits-to-arbitrage or uncertainty exposure, we then form three stock portfolios. Next, we examine the effect of equity market uncertainty on price efficiency for each portfolio. This procedure allows us to investigate the potential cross-sectional heterogeneity in the impact of uncertainty. Our empirical results show that if a stock is more difficult to arbitrage or has a greater uncertainty exposure, its price efficiency tends to be more sensitive to equity market uncertainty. This finding is consistent with the notion that arbitrageurs partially correct uncertainty-induced mispricing and, thus, mitigate the negative impact of uncertainty.

Overall, this thesis enhances our understanding of the impact of uncertainty on equity market quality. The empirical chapters in this thesis show that uncertainty matters both in general and during the information release of public announcements in financial markets. For equity investors, these results address the importance of uncertainty as a key parameter in the investment process. For instance, Chapter 5 suggests a potential portfolio rebalancing method for equity investors concerned with reducing their portfolios' overall uncertainty exposure. Such a method may involve strategically picking stocks with specific characteristics. Regulators and policymakers are most concerned with keeping the domestic financial market competitive. In this respect, this thesis also informs the regulatory authorities of the importance of incorporating the surveillance of market uncertainty into their overall market regulatory framework. The main findings and the implications of this thesis are summarized in Chapter 6.

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[3] https://www.spglobal.com/spdji/en/indices/equity/sp-500/#overview.

Chapter 2

2. Uncertainty and equity market quality: A primer

2.1. Introduction

This chapter discusses the two themes covered in the thesis: uncertainty and financial market quality. First, we introduce the concept of uncertainty in the finance context and discuss measures of uncertainty used in the subsequent empirical chapters. We then discuss the key aspects of financial market quality from a market microstructure perspective. We also set up the empirical framework that we use in the remainder of this thesis to measure these market quality aspects.

2.2. Uncertainty in financial markets

Uncertainty has always been an important theme in the field of financial economics. The concept of uncertainty in theoretical economic studies dates back to Knight (1921) and Keynes (1936). In general, uncertainty in financial markets arises from market participants' day-to-day business and investment activities. For instance, when a firm decides its optimal level of investment, it has to consider uncertainty caused by factors such as future price instability, changes in labor and other investment costs, or unpredictable future cash flows from invested projects. A formal analysis of optimal firm investment with uncertainty is found in Oi (1961), Hartman (1972), and Abel (1983). Similarly, a security investor explicitly bears the impact of possible undesirable future price movements on her portfolio returns when holding a position. The aforementioned uncertainty may come from multiple sources and vary significantly over time. Below, we review some common scenarios when uncertainty can increase in financial markets.

One instance when uncertainty in financial markets can arise, potentially in a dramatic way, is the occurrence of rare episodic events such as terrorist attacks, natural disasters, or political shocks (e.g., Bloom, 2014; Rehse et al., 2019; Baker et al., 2020). For instance, after the 9/11 terrorist attack, uncertainty and panic spread across the US financial system, leading to a temporary shutdown of major US stock exchanges and the plummeting of stock market performance afterward. The 2008 financial crisis also witnessed heightened global economic uncertainty following the collapse of Lehman Brothers. More recently, events such as the 2016 Brexit referendum and the 2019 Coronavirus pandemic have brought about great uncertainty about many aspects of financial activities both locally and around the globe, including firm operations, investment, household finance decisions, as well as real economic outputs.[4] Although rare in nature, these events may provoke prolonged uncertainty in financial sectors, which in turn imposes a potential threat to the efficient functioning of financial markets.

Another source of financial market uncertainty is a lack of clarity in the policy-making process of government authorities (e.g., Pástor and Veronesi, 2012, 2013; Bloom, 2014; Baker et al., 2016). Since government policies often set the rules that market participants follow, an unusual or ambiguous policy signal can often create economic uncertainty and distort the financial market order. For instance, the 2011 US debt ceiling crisis created heightened political and policy uncertainty that proliferated in the US Treasury and government credit default swap (CDS) markets. Similarly, the US economic uncertainty rallied around the 2012 "fiscal cliff" policy debate due to the pending government actions. The US-China trade war in 2018 and 2019 also brought tension and high uncertainty to the US-China relationship, which took its toll on financial market performance and economic growth.[5]

There is yet a third type of uncertainty that is contingent on a specific future market event. Compared with the other two types of uncertainty discussed above, this uncertainty is unique in two ways. First, unlike unforeseeable rare disasters, market participants anticipate the forthcoming event. In such a case, uncertainty does not come from whether the event will occur. Instead, it originates from a lack of precise prior knowledge about the specific information revealed by an event. Second, this uncertainty tends to be short-lived and cluster around the

[4] See, e.g., https://bit.ly/34yCUvQ and https://rebrand.ly/tqlb5sv.
[5] See, e.g., https://bit.ly/3IcPUVP, https://rebrand.ly/97daae, https://rebrand.ly/thds12r, and https://rebrand.ly/28ee7a.

time of the particular event. Scheduled macroeconomic news or corporate earnings announcements are an example of such events. While market participants are aware of these pre-scheduled events, they do not know ex-ante the exact information to be released during the announcement. It, therefore, creates temporary uncertainty among market participants regarding the impact of the upcoming new information. Following the announcement, information becomes public, and uncertainty is resolved. Theoretical and empirical studies on uncertainty surrounding news releases, among others, include Kim and Verrecchia (1991), Chen and Clements (2007), Fernandez-Perez et al. (2017), Amengual and Xiu (2018), and Gu et al. (2018).

2.2.1. Measures of uncertainty

Measuring uncertainty in financial markets is challenging because uncertainty is governed by an unobservable latent process. The empirical literature has, so far, used multiple indirect proxies to infer the level of uncertainty.

One common measure of uncertainty is the volatility of stock market returns (e.g., Bloom et al., 2007; Bloom, 2009; Chung and Chuwonganant, 2014; Gu et al., 2018; Kurov et al., 2021). These studies implicitly assume that the implied or realized stock market volatility correlates well with the latent process driving uncertainty. Other uncertainty measures based on the cross-sectional dispersion in firm-level variables such as earnings and productivity are also used in the literature (e.g., Jorgensen et al., 2012).

Recently, Baker et al. (2016) developed economic uncertainty indexes based on the US newspaper articles. Specifically, they consider the mainstream newspapers such as USA Today, the Washington Post, and Wall Street Journal. They then develop algorithms to search the digital archives of these newspapers to count the number of newspaper articles that contain specific terms. The economic uncertainty indexes reflect this newspaper article counts. For instance, an index of Economic Policy Uncertainty (EPU) is created by searching and counting newspaper articles containing the following terms: “uncertainty/uncertain”, “economic/economy”, and “congress/legislation/white house/regulation/federal reserve/deficit”. Similarly, an index of Equity Market Uncertainty (EMUNC) is constructed by focusing on newspaper articles that discuss the following terms: “uncertainty/uncertain”, “economic/economy”, and “equity market/equity price/stock market/stock price”. To control for the general increase in the total number of articles over time, Baker et al. (2016) normalize the newspaper article counts by dividing the raw counts of relevant articles by the total number of articles issued in the same newspaper, which leads to the final newspaper-based economic uncertainty index.

Compared to other uncertainty proxies, the above newspaper-based economic uncertainty indexes have several advantages. First, many finance-based uncertainty proxies such as implied or realized stock return volatility are indirect approximations of the underlying uncertainty. On the contrary, newspaper-based economic uncertainty indexes directly reflect mainstream medias’ uncertain perspectives that ultimately affect market participants. Second, the construction of a newspaper-based uncertainty index is independent of the state of the financial market (unlike implied or realized market volatility). Thus, a statistical relationship between this uncertainty index and other market variables is unlikely to be data-driven. Third, the newspaper-based uncertainty indexes are all-encompassing and capture various uncertainty episodes such as rare disasters and policy-driven events. These indexes are also flexible and can be applied to various settings. For instance, the EPU index can be used in a setting where one is particularly interested in the impact of government policy-related economic uncertainty. Since this thesis focuses on the equity market, the EMUNC index is used as a proxy for uncertainty about the equity market in Chapters 3 and 5 of this thesis.

Dispersion in professional opinions is also widely used to measure uncertainty (e.g., Barron and Stuerke, 1998; Zhang, 2006; Barron et al., 2009). This measure is often used to proxy for uncertainty or the quality of information environment surrounding specific events. This is because professionals such as financial analysts often provide forecasts about a scheduled future news release such as earnings announcement or macroeconomic news release. Market participants often use these forecasts to guide their investments. Greater analyst forecast dispersion renders the consensus forecast imprecise, which leads to an uncertain information environment and creates uncertainty among market participants (e.g., traders) with regard to the content of forthcoming news. In Chapter 4 of this thesis, I use dispersion in analyst forecasts to proxy for uncertainty surrounding the Federal Open Market Committee (FOMC) announcement times. Analyst forecast dispersion can be measured as the cross-sectional standard deviation among analyst forecasts scaled by the absolute average forecast:

$$DISP_j = \frac{\sigma_j(Forecast_i)}{|\mu_j|}, \tag{2.1}$$

where $DISP_j$ is analyst forecast dispersion associated with the news release (FOMC announcement in our case) j. $\sigma_j(Forecast_i)$ is the cross-sectional standard deviation of analyst forecasts for the news release j, where $Forecast_i$ is the forecast of analyst i. μ_j is the mean forecast among all analysts associated with that announcement.

2.3. Financial market quality: A microstructure perspective

According to O'Hara (2003), financial markets provide two vital services: liquidity and price discovery. In general, a liquid financial market facilitates timely and smooth financial transactions between buyers and sellers of financial assets. Price discovery is the process of a market impounding relevant information into prices and, thus, achieving informational efficiency. In empirical market microstructure,[6] market quality often refers to a market's ability to provide liquidity and efficient prices. O'Hara and Ye (2011, p. 463) note that "markets with lower transactions costs are viewed as higher quality, as are markets in which prices exhibit greater efficiency." For market quality analysis, this thesis focuses on liquidity and informational efficiency. We provide an overview below.

2.3.1. Market liquidity

According to O'Hara (2004, p. 1), a financial market is liquid when "buyers and sellers can trade into and out of positions quickly and without having large price effects." This definition positions transactions cost as a key aspect of financial market liquidity. In a frictionless market, transaction price should equal the asset's fundamental value. In reality, however, a financial asset (e.g., stock or bond) is bought and sold at two different prices at any point in time, with the purchasing price being higher than the selling price (from an investor's

[6] Market microstructure is an area in finance that studies how the design of trading systems and specific trading roles affect the quality of financial markets. For further readings on the theory and empirics of market microstructure, we refer to O'Hara (1998) and Hasbrouck (2007).

perspective). This positive price difference, called the bid-ask spread, reflects the various market frictions observed in real financial markets, the size of which also reflects the magnitude of these frictions. This spread becomes transaction costs that investors ultimately bear.

Market microstructure studies acknowledge several sources of market frictions. The first source of market frictions reflects pure costs associated with liquidity providers offering an "immediate execution" service to both the demand and supply side of the market (e.g., Demsetz, 1968; Tinic, 1972). In providing this immediacy service, liquidity providers bear the costs of administering these prompt transactions, such as clearing and settlement expenses and record-keeping fees. This type of cost is referred to as order processing cost, which is partially compensated by the bid-ask spread.

The second type of market friction originates from the undesired inventory positions held by liquidity providers (e.g., Garman, 1976; Stoll, 1978; Amihud and Mendelson, 1980; Ho and Stoll, 1981). Liquidity providers, acting as market intermediaries, temporarily exceed (fall short of) their target inventory levels to meet the liquidity demand of a seller (buyer) counterparty. As Madhavan (2000, p. 215) notes, "just as physical market places consolidate buyers and sellers in *space*, the market maker can be seen as an institution to bring buyers and sellers together in *time* through the use of inventory." By holding undesired inventory positions, liquidity providers undertake additional risks from price fluctuations, which they must be compensated for to offer this costly intermediation service. Thus, on top of order processing costs, liquidity providers will also account for fluctuations in their inventory levels. This type of cost is normally referred to as inventory holding cost, which comprises the second component of the bid-ask spread.

The third type of market friction arises due to information asymmetry. Information asymmetry arises if some investors possess more information than others. Thus, the presence of more informed traders creates adverse selection risks in trading. This informational friction is also incorporated into classical market microstructure theory models (e.g., Glosten and Milgrom, 1985; Kyle, 1985; Easley and O'Hara, 1987). When a market maker provides liquidity, she is typically unaware whether her counterparty is more informed, in which case she assigns a subjective probability of dealing with a more informed trader. This probability is implicitly revealed in the quote revision process of the market maker. For instance, when a trader approaches a market maker for a purchase (sale), the market maker may assume that her counterpart possesses more information. As a result, she may adjust her likely stale ask (bid) quote upwards (downwards) before the next trading round. Therefore, part of the bid-ask spread exists to recoup liquidity providers' trading loss when confronting more informed traders. This leads to the third component of the bid-ask spread, the adverse selection costs.

Adverse selection occurs on various occasions. One such occasion is when some traders can process public information faster than others. The proliferation of high-frequency traders (HFTs) in the past decade has led to a long-lasting debate among policymakers and academics. One of the concerns is that HFTs render financial markets an unlevel playing field by leveraging their speed advantage at the expense of other investors. Moreover, some controversial HFT practices, such as stale quote sniping and quote stuffing,[7] are also blamed for the increased volatility and adverse selection risk in financial markets.

Another occasion that increases adverse selection risk in financial markets is when a portion of market participants possess privileged information unavailable to the rest of the market. A corporate director or board member may obtain confidential inside information that affects future stock prices. If she trades on such information ahead of the public, she will profit at the cost of her investors. Insider trading undermines investor confidence and disrupts the proper functioning of financial markets. Although insider trading is deemed illegal in most markets, the occurrence of illegal insider trading cases represents occasional extreme adverse selection risks in financial markets.

One interesting point in time when adverse selection risk can temporarily rise is the arrival of new information. This is because when market participants expect new information, they tend to predict such new information based on the existing information set. Some market participants can, however, make better judgments about the incoming information (either because they simply have privileged inside information or are more sophisticated and thus can better predict the future) and will pose a higher adverse selection risk for others when they trade on this information. One such example is news announcements. A large literature shows that

[7] Quote sniping is a tactic often used by HFTs to intercept other traders' limit orders before they are able to cancel them. Quote staffing involves quickly entering and withdrawing a large quantity of orders with an aim of confusing competitors. For a detail survey on HFTs and their impact on financial markets, we refer to Biais and Foucault (2014) and Menkveld (2016).

informed traders tend to trade with their superior information around news announcements (e.g., Park et al., 2014; Bernile et al., 2016; Brennan et al., 2018; Kurov et al., 2019). Thus, a news release temporarily aggravates the adverse selection risk in financial markets, especially around the release time.

2.3.1.1. Measures of liquidity

The transactions cost aspect of financial market quality, i.e., liquidity, can be measured using several proxies. The most commonly used proxy is the bid-ask spread (BAS), which is the difference between the highest bid price (a price at which a market maker is willing to buy, B_t) and the lowest ask price (a price at which a market maker is willing to sell, A_t) scaled by the bid-ask midpoint (Q_t), i.e., $BAS_t = (A_t - B_t)/Q_t$. A tighter spread indicates higher market liquidity. BAS is also referred to as the quoted spread (QS), which measures the hypothetical transaction costs. Another spread measure that captures the actual transaction costs is called effective spread (ES), which is defined as twice the absolute difference between the transaction price and the bid-ask midpoint scaled by the bid-ask midpoint (Q_t), i.e., $ES_t = 2|P_t - Q_t|/Q_t$. We use both QS and ES in Chapter 4 of this thesis.

Lin et al. (1995) (LSB hereafter) decompose the effective spread into three components: information asymmetry, order flow persistence, and order processing cost. The information asymmetry component reflects the compensation to liquidity providers for trading against better-informed counterparts, thus reflecting the degree of adverse selection in the market due to privately held information. The order flow persistence component measures the degree of order flow autocorrelation (i.e., a buy order following a buy order, or vice versa). The order processing cost is the gross profit for liquidity provision after accounting for the adverse selection cost.

We choose the LSB (1995) spread decomposition model because this model does not rely on a certain degree of order reversals (a buy order following a sell order, or vice versa) in transactions data to generate plausible empirical results.[8] Without relying on any prior

[8] On the contrary, the covariance spread models such as Stoll (1989) and George et al. (1991) and the trade indicator spread models such as Huang and Stoll (1997) implicitly assume a probability of order reversal of at least 0.5 to estimate the underlying spread components reliably. Van Ness et al.

assumptions of data structure, the LSB (1995) model is more suitable for intraday analysis in a market where order persistence is prevalent (e.g., order splitting and stealth trading strategies). Below, we briefly discuss the LSB (1995) model.

Let A_t and B_t be the prevailing ask and bid quotes at trade t and δ be the probability of order persistence. Then the expected gross profit of a liquidity supplier at trade t+1, conditional on a sell order at trade t (i.e., $P_t = B_t$), is:

$$E_t(P_{t+1}) - P_t = \delta B_{t+1} + (1-\delta)A_{t+1} - B_t, \quad (2.2)$$

where $E_t(P_{t+1}) = \delta B_{t+1} + (1-\delta)A_{t+1}$ is the expected future transaction price conditional on a sell order at trade t. Since the quote midpoint (Q_t) at trade t is $(A_t + B_t)/2$, the effective half-spread z_t can be defined as $P_t - Q_t$ so that $z_t > 0$ ($z_t < 0$) for a buy (sell) order. To reflect possible adverse selection cost revealed by trade t, bid and ask quotes are revised as $B_{t+1} = B_t + \lambda z_t$ and $A_{t+1} = A_t + \lambda z_t$, where $0 < \lambda < 1$ is the proportion of the spread due to information asymmetry. Thus, both the bid and ask prices adjust upward (downward) following a buy (sell) order. One can rewrite Eq. (2.2) as:

$$E_t(P_{t+1}) - P_t = [\delta B_{t+1} + (1-\delta)A_{t+1}] - P_t = \lambda z_t + (1-2\delta)(Q_t - B_t) + Q_t - P_t = -(1-\lambda-\theta)z_t, \quad (2.3)$$

where $\theta = 2\delta - 1$ and $(1-\lambda-\theta)z_t$ is the liquidity supplier's expected gross profit when she buys at B_t. The liquidity supplier's expected gross profit for a buy order at trade t (i.e., $P_t = A_t$) is derived in a similar fashion and identical. The parameters λ and θ reflect the quote revision in response to a trade due to asymmetric information and the level of order persistence, respectively. Following Huang and Stoll (1994), these parameters can be estimated using the following equations:

$$\Delta Q_{t+1} = Q_{t+1} - Q_t = \lambda z_t + e_{t+1}, \quad (2.4)$$

$$z_{t+1} = \theta z_t + \eta_{t+1}, \quad (2.5)$$

(2001) compare the performance of several spread decomposition models. They find that the Huang and Stoll (1997) model creates more than 50% of theoretical implausible estimates. The Madhavan et al. (1997) model creates 152 theoretical implausible estimates. In comparison, the LSB (1995) model generates only 4 such invalid observations.

where the disturbance terms e_{t+1} and η_{t+1} are assumed to be uncorrelated. Using Eq. (2.4) and (2.5), knowing that $z_{t+1} = P_{t+1} - Q_{t+1}$, the temporary price effect for trade t due to order processing costs can also be expressed as a fraction of the effective half-spread z_t:

$$\Delta P_{t+1} = P_{t+1} - P_t = (Q_{t+1} - Q_t) + z_{t+1} - z_t = -\gamma z_t + u_{t+1}, \quad (2.6)$$

where $\gamma = 1 - \lambda - \theta$ reflects the order processing cost component of the spread and $u_{t+1} = e_{t+1} + \eta_{t+1}$. The three spread components, namely information asymmetry, order persistence, and order processing costs, are estimated by parameters λ, θ, and γ using Eqs. (2.4)-(2.6), respectively. The LSB (1995) model is used in Chapter 4 to infer changes in different spread components around FOMC announcements.

In addition to the QS and ES, several other liquidity metrics are employed in the literature. For instance, dollar volume is also an indicator of liquidity as more liquid markets tend to attract more traders and, thus, higher trading volume. Volume is used in Chapter 4 and Chapter 5. In addition, according to Amihud (2002), price should be less sensitive to a given volume in a more liquid financial market. Therefore, the price sensitivity to volume can be treated as an inverse indicator of market liquidity. The Amihud (2002) illiquidity measure is generally defined as $\frac{|r|}{\$Volume}$. Depending on the setting, it can be measured at different sampling frequencies. We apply this Amihud illiquidity metric in all three chapters of this thesis.

2.3.2. Informational efficiency

In addition to providing liquidity, financial markets also have a second critical function, which is to effectively aggregate information and accurately reflect it into prices. This is known as informational efficiency.

Generally, asset prices are considered informationally efficient when they impound value-relevant information accurately and in a timely manner. Informational efficiency is achieved through price discovery, a process of "efficient and timely incorporation of the information implicit in investor trading into market prices" (Lehmann, 2002). Therefore, informationally efficient prices have two basic properties. One such property is to reflect market information accurately. That is, asset prices increase when aggregate market information is positive about fundamental values and decrease when the market as a whole is negative about fundamental values. In other words, in an informationally efficient market, prices can be viewed as a barometer of the true underlying asset values.

Another important property of informationally efficient prices is immediacy, which means that any value-relevant information should be reflected in asset prices with minimum time delays. For instance, when new information is released into financial markets (e.g., scheduled macroeconomic news or earnings announcements), an efficient market should digest the new information promptly and impound it into the prevailing prices. With the development of automated trading algorithms monitoring newswires in almost real-time, such new information should be reflected in market prices instantaneously nowadays.

Informational efficiency is a desirable property for many reasons. For instance, when the price of a financial asset accurately reflects its fundamental values, investors can use such a price to guide their investment decisions. Corporate managers can use financial market reactions to a mergers and acquisitions (M&A) announcement to help them decide whether the M&A deal will be potentially profitable (e.g., Luo, 2005; Suk and Wang, 2021). When financial markets promptly reflect available information, it also creates a level playing field for all financial market participants. In contrast, toxic latency arbitrage, often practiced by fast traders such as High-Frequency Traders (HFTs), poses higher trading costs for regular investors and discourages broad market participation.[9] If financial markets can glean information and quickly reflect it into prices, these toxic latency arbitrage opportunities should largely diminish.

Informational efficiency and market liquidity are two different concepts, but they are also closely related. For instance, when a stock market is liquid, traders with better information tend to trade in such a market due to cheaper transaction costs. Thus, their private information will be reflected in asset prices in this market first through their trading. In addition, better liquidity facilitates arbitrage trading, which serves to identify and quickly correct any short-term mispricing that may exist in the market. The presence of both more informed traders and arbitrageurs facilitates efficient and timely incorporation of information into market prices and,

[9] See, e.g., https://www.cnbc.com/2020/01/27/latency-arbitrage-trading-costs-investors-5-billion-a-year-study.html.

thus, leads to higher informational efficiency of prices.

2.3.2.1. Measures of informational efficiency

Informational efficiency measures are designed to capture the ability of market prices to reflect relevant information in an efficient and timely manner. In a perfectly informationally efficient financial market, prices reflect the fundamental values of financial assets and only change when new information about the financial assets arrives. Since new information arrival is random, future price movements should be unpredictable and follow a random walk. In reality, many market frictions exist, which will lead to price deviations from the characteristics expected in a perfectly informationally efficient market. The extent to which prices deviate from such a perfectly informationally efficient benchmark is a rough measure of how inefficient the market is. This is the underlying logic of the informational efficiency measures discussed below.

The first metric, *AutoCorrel*, captures both positive and negative mid-quote return autocorrelations as a form of informational inefficiency. Informationally efficient prices should follow a random walk. Thus, there should be no autocorrelation in prices. Both positive and negative autocorrelation are undesirable properties as they reflect price under- and overreactions (e.g., Bloomfield et al., 2000). *AutoCorrel* can be measured as follows:

$$AutoCorrelation_k = \left|Corr(r_{k,n}, r_{k,n-1})\right|, \tag{2.7}$$

where $r_{k,n}$ is the n^{th} return measured at frequency k. Depending on the setting, k can be days within a month for a low-frequency measure or seconds/minutes within a day for a high-frequency measure.

The second informational efficiency metric is the Variance Ratio of Lo and MacKinlay (1988), i.e., *VarRatio*. When prices follow a random walk, the variance of equity returns is linear with respect to the return measurement frequency. In other words, σ_{kl}^2 is k times larger than σ_l^2. The Variance Ratio test exploits this property and measures informational inefficiency as its deviation from this characteristic. *VarRatio* can be measured as follows:

$$VarRatio = \left|\frac{\sigma_{kl}^2}{k\sigma_l^2} - 1\right|, \tag{2.8}$$

where σ_{kl}^2 and σ_l^2 are the stock return variances measured at frequency kl and l, respectively. Depending on the setting, *VarRatio* can also be measured at different frequencies, such as daily or monthly.

In an informationally efficient market, one cannot use past information to predict the future price. Since information is incorporated into prices through trading, the information contained in past order flow should not affect future prices in an efficient market. Therefore, the slope coefficient from a regression of stock returns on past order imbalance (i.e., *OIBPred*) can be regarded as an inverse measure of informational efficiency. For instance, for a particular trading day *d*, the slope coefficient can be measured using the following equation:

$$r_{d,t} = \alpha_d + \beta_d OIB_{d,t-1} + \mu_{d,t}, \tag{2.9}$$

where $r_{d,t}$ is the midquote return aggregated over the intraday interval *t* (e.g., one-minute interval) on day *d* and $OIB_{d,t-1}$ is the signed order imbalance (difference between buyer- and seller-initiated dollar trading volume) over the lagged interval *t*-1 on the same day. The slope coefficient, *OIBPred*, is defined as $|\beta_d|$.

Finally, prices in an efficient market should not fluctuate too much beyond the variation in the fundamental asset values. High short-term price volatility is deemed harmful to long-term investors who "may not be in a position to access and take advantage of short-term price movements" (SEC, 2010). Therefore, high-frequency intraday returns volatility is also used in the literature to capture short-term volatility as an inverse market quality indicator.

2.4. Related literature

Chapters 3 and 5 of this thesis study the effect of Equity Market-related Economic Uncertainty on the informational efficiency of equity prices. We aim to understand how uncertainty affects the quality of price discovery in the equities market, which is the process of prices incorporating relevant information. Whether uncertainty affects equity prices' informational efficiency is not conclusive based on the extant literature.

Most empirical studies on economic uncertainty focus primarily on its implications on asset prices and the equity premium. For instance, Brogaard and Detzel (2015), Bali et al. (2017), and Nartea (2020) study the asset pricing implications of uncertainty and whether equity investors demand an uncertainty premium. These studies show that uncertainty is priced in the cross-section of stock returns. Stocks with a higher (lower) exposure to uncertainty earn lower (higher) risk-adjusted returns. Similarly, Brogaard et al. (2020) find that global political uncertainty results in lower equity returns. However, a fall in equity returns does not itself imply a fall in equity price efficiency. In fact, the opposite can be true if lower equity prices reflect a reduction in firms' fundamental values when uncertainty leads to a reduction in corporate investments in positive NPV projects.[10] Thus, whether and how uncertainty affects equity price efficiency is not clear.

Other studies linking uncertainty and financial markets exploit specific events such as presidential elections (e.g., Li and Born, 2006; Pasquariello and Zafeiridou, 2014; Brogaard et al., 2020), government regulatory changes (e.g., Battalio and Schultz, 2011), or natural disasters (e.g., Rehse et al., 2019). However, studies with a focus on one specific event have two limitations. First, such events represent only a tiny portion of uncertainty that equity investors face from day to day. In this respect, a general study (as opposed to event studies) is perhaps more interesting from an investor's perspective. Second, whether these events represent the whole picture is not clear. Recent event studies indicate that lessons from specific events can sometimes lead to opposite conclusions. For instance, Pástor and Veronesi (2017) document a co-existence of high economic policy uncertainty and low market volatility during 2016 – 2017, which goes against the well-established positive relationship between market uncertainty and stock market volatility. Thus, Chapters 3 and 5 aim to overcome some of the above limitations.

Chapter 4 of this thesis examines the impact of uncertainty on market quality during FOMC announcement times. These announcements represent informational shocks in financial markets. Uncertainty about the impending new information reduces the quality of the information environment. Information environment should matter most during periods of such

[10] Numerous studies show that uncertainty reduces firm-level investments. For instance, Wang et al. (2014) find that economic policy uncertainty reduces corporate investments in China, whereas Kang et al. (2014) and Gulen and Ion (2016) find the same result for US-listed companies.

informational shocks because traders are most likely to utilize their private information at such times. Although numerous studies have investigated the market impact of news releases (e.g., Lucca and Moench, 2015; Bernile et al., 2016; Kurov et al., 2019), less research has focused on the consequences of uncertainty about the upcoming news during announcement times. This chapter fills this gap in the extant literature.

Chapter 3

3. Equity market uncertainty and ETF price efficiency

3.1. Introduction

In the spirit of the Efficient Market Hypothesis (EMH) of Fama (1970), an equity market is efficient when all available information is fully reflected in prices in a timely manner. Therefore, the level of equity price informational efficiency depends on the quality and quantity of information revealed through investor trading. Since information acquisition is costly from the market participant's perspective, their ability to extract and accurately interpret value-relevant signals relies on the quality of the information environment in the equity market. As such, numerous regulatory efforts have been made to improve equity market quality, such as the 2000 Regulation Fair Disclosure (Reg FD), the 2002 Sarbanes-Oxley (SOX) Act, and the 2006 Regulation National Market System (Reg NMS). The underlying assumption is that impartial corporate disclosures and competition reduce uncertainty and improve the quality of the overall information environment, allowing market participants to access more accurate and reliable information.

One market friction that can render the information environment of equity markets murky is investors' uncertainty about the quality and precision of value-relevant signals.[11] Information signals may be less precise and are harder to interpret in an uncertain information environment, making it more difficult for market participants to assess the value implications of a given piece of information. Uncertainty about the quality and precision of informational signals comes from various sources, such as pending government policy decisions, political

[11] In the address at the Council of Institutional Investors 2018 Fall Conference, the then-US SEC Commissioner Kara M. Stein stated that "uncertainty about the quality and veracity of the information may be contributing to a poor information environment".

events such as presidential elections, and ever-changing international relationships. For example, many commentators and government documents raise concerns that the US debt ceiling debates in 2011 and 2013 have spurred an elevated level of uncertainty in the US Treasury Market.[12] The 2016 US presidential election has since created turmoil and uncertainty in global financial markets due to the unpredictability of future government economic policies. The recent US-China trade tension also injects much uncertainty into the business and economic environment.[13] When there is uncertainty in the information environment of equity markets, valuation can be a daunting task as investors spend more resources and efforts on distinguishing value-relevant signals from noise. This may impair the efficient and timely incorporation of value-relevant information into prices, leading to informational inefficiency.

The relationship between uncertainty and asset prices has been studied extensively. Following the theoretical framework of Pástor and Veronesi (2012, 2013), a large empirical literature shows that political and government policy uncertainty negatively affects the returns of a variety of asset classes (e.g., Brogaard and Detzel, 2015; Kelly et al., 2016; Bali et al., 2017; Brogaard et al., 2020). Whereas the above-mentioned studies focus on the asset pricing implications of uncertainty, the current paper considers its impact on the informational efficiency of prices. Despite the insight from extant studies, the link between uncertainty and informational efficiency remains unclear. First, a decrease in equity returns does not by itself indicate a decrease in equity market informational efficiency. Instead, this may simply reflect a decline in fundamental values during uncertain times if corporations reduce capital investment in positive-NPV projects (Gulen and Ion, 2016; Jens, 2017). Second, there can be a periodic lack of stock market reaction to policy (or political) uncertainty.[14] Pástor and Veronesi (2017), for instance, document the co-existence of high policy uncertainty and low market volatility, i.e., when the policy (or political) signals are less precise, market participants may not respond

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[12] For example, see "Debt Limit: Delays Create Debt Management Challenges and Increase Uncertainty in the Treasury Market" (Government Accountability Office, February 22, 2011) and "US Debt Ceiling: Costs and Consequences" (Council on Foreign Relations, October 4, 2013).
[13] For example, see "Trump victory increases uncertainties for global economy" (Chicago Tribune, November 9, 2016), "Trump economic 'uncertainty' worse than '08 financial crisis levels, index shows" (CNBC, May 19, 2017), "Why "Uncertainty Shocks" Are Part of the Trump-Era Economy" (Stanford Business, September 6, 2018), "US-China Deal Eases, But Doesn't End, Business Uncertainty" (Wall Street Journal, December 13, 2019), and "Trump's China Deal Leaves the Global Economy as Uncertain as Ever" (New York Times, October 16, 2019).
[14] For example, see https://bit.ly/3J0u5cZ, and https://bit.ly/3tSDRI6.

to them. This implies that uncertainty and informational efficiency may not be necessarily related.

This paper fills the gap in the literature by empirically investigating the impact of equity market uncertainty on the informational efficiency of US equity prices. We measure equity market informational efficiency using transaction-level data and use the SPDR S&P 500 Trust, which is the largest and most liquid ETF tracking the S&P 500 stock market index, to proxy for the aggregate US equity market. We define equity market uncertainty as unpredictable future outlooks for the performance of the US equity market as a whole. We use the Baker et al. (2016) Equity Market Uncertainty Index (EMUNC) as a proxy for the overall level of the US equity market uncertainty and test how US equity market informational efficiency responds to equity market uncertainty.

We consider Baker et al.'s (2016) Equity Market Uncertainty Index to be a good proxy for our definition of equity market uncertainty for several reasons. First, EMUNC is constructed using textual analysis of major US newspaper articles. Unlike other uncertainty measures such as realized stock volatility or VIX, EMUNC is not derived directly from market variables. Therefore, any relationship between EMUNC and other market characteristics must be economically motivated rather than data-driven. Second, EMUNC focuses on uncertainty explicitly related to the US equity market and, thus, is a good match to our definition of "equity market uncertainty." Finally, as we are interested in the general level of uncertainty rather than uncertainty from any single source such as government policies, EMUNC suits our purpose better as it is designed to capture uncertainty in a broader way.

We consider two commonly used high-frequency measures of informational efficiency: return autocorrelation and the variance ratio. When equity prices are informationally efficient, they should follow a random walk closely. Both return autocorrelation and the variance ratio capture the extent to which prices deviate from a random walk benchmark. Therefore, they are inverse measures of informational efficiency. A higher value of either return autocorrelation or the variance ratio indicates a deterioration in informational efficiency. We flip the sign of both measures throughout the paper to make them informational efficiency measures.

We begin our empirical analysis by regressing these two informational efficiency metrics on EMUNC. We find that increased equity market uncertainty is associated with a significant increase in both return autocorrelation and the variance ratio. These findings suggest that equity market uncertainty harms the informational efficiency of equity prices. The results are robust to a range of model specifications that control for a battery of market microstructure characteristics also known to affect market efficiency. We still observe significant negative EMUNC coefficients when splitting our sample into three subperiods. This subsample analysis indicates that our main inference is unlikely to be driven by any particular period or market event. In other words, the negative effect of equity market uncertainty on informational efficiency is persistent.

We then perform several robustness tests. First, we consider several alternative measures of equity price informational efficiency. In addition to following a random walk, informationally efficient prices should also exhibit other properties. For example, future returns should not be predictable using past information. Also, the price variation should roughly line up with changes in the underlying fundamental values. We quantify these concepts using the following two empirical metrics: short-term price volatility and short-horizon return predictability using past order flow. Short-term volatility reflects excessive price movements relative to the fundamental value. Return predictability indicates delays in incorporating relevant information into prices, both of which are undesirable under efficient markets. Using these two alternative informational efficiency measures and a range of model specifications, we consistently find that an increase in EMUNC is associated with a significant increase in both short-term return volatility and return predictability. This further indicates that equity price informational efficiency deteriorates with high equity market uncertainty.

Second, we consider another index ETF. The primary analysis uses the SPDR S&P 500 Trust, which represents the large-cap investment universe. We also consider iShares Russell 2000 ETF, which is the most liquid ETF tracking the performance of the Russell 2000 Index (i.e., the smallest 2,000 stocks). Our choice of this alternative ETF is motivated by our expectation that the negative impact of equity market uncertainty on informational efficiency is generic and should also be observed in the small-cap universe. The empirical results support our view. The coefficients and the associated statistical significance are similar to the main findings.

Third, we consider alternative proxies for market uncertainty. The main analyses employ EMUNC as the primary uncertainty proxy. We additionally use the economic policy uncertainty (EPU) index as well as the equity market volatility (EMV) index. Both indexes are constructed similarly to the EMUNC index as all of them are based on newspaper articles. However, each index is also unique with a different focus. For instance, the EPU index focuses on policy-related economic uncertainty, whereas the EMV index focuses on equity market volatility. Results based on these two additional proxies echo the main finding. Overall, these additional tests further support our conclusion that equity market uncertainty negatively affects equity price informational efficiency.

Our study has several practical implications. We show that the tone of equity market-related newspaper articles can significantly affect the quality of equity markets beyond other traditional market factors. This knowledge is relevant to market participants. For instance, for equity market investors, our finding implies that newspaper-based economic uncertainty should be an essential factor to consider when devising an investment strategy. Since market regulators and policymakers are most concerned with the quality and competitiveness of local financial markets, they should add the surveillance of market uncertainty tool into the overall market regulatory framework.

The rest of this chapter is structured as follows. In the next section, we describe EMUNC and provide some economic justifications on how it relates to the informational efficiency of equity prices. Section 3.3 discusses the high-frequency measures of informational efficiency. Section 3.4 discusses the data and sample used in this study and describes their properties. The empirical approach and the main results are presented in section 3.5. Section 3.6 concludes.

3.2. Equity market uncertainty and implications for informational efficiency

In this section, we first provide economic arguments and discuss related literature to support our argument that equity market uncertainty negatively affects equity price informational efficiency. We then discuss our choice of the empirical proxy for this equity market uncertainty.

3.2.1. Economic reasoning

We expect that a higher level of equity market uncertainty will reduce the informational efficiency of equity prices. According to Grossman and Stiglitz (1980), prices reflect private information, albeit imperfectly, obtained by informed agents through costly information acquisition. Therefore, frictionless acquisition and accurate interpretation of such information are catalysts for informationally efficient prices. A high-quality information environment in equity markets plays a critical role in facilitating price efficiency as value-relevant signals are straightforward to distinguish and easy to interpret. In contrast, uncertainty about the relevance or accuracy of information signals reduces the quality of the information environment and adversely impacts market participants' ability to predict the future performance of equity markets.

To be concrete, consider an example where equity market uncertainty is triggered by an ongoing debate among policymakers at the Federal Reserve regarding how to set the future target interest rate. This policy-related uncertainty also leads to uncertainty in the equity market. As FOMC's primary monetary policy tool, the federal funds rate determines the cost of capital for firms. Since firms need to evaluate the value of future investment projects conditional on their cost of capital, uncertainty about the future federal funds rate makes it difficult for corporate managers to make sound investment decisions. This also adds to the difficulty of evaluating firms' fundamental values for market participants. On the one hand, uncertainty about the new federal funds rate may render the previous analyst reports for these firms obsolete. On the other hand, less clear corporate investment plans may indicate that firms miss potential positive-NPV projects, which may also harm firms' fundamental values. Overall, uncertainty about the future target interest rate reduces the quality of firms' information environment. Value-relevant signals about firms' fundamental values become harder to interpret. Investors trade with such noisy information, making the subsequent stock prices less informationally efficient.

Not only does equity market uncertainty affect individual securities in the equity market, but it also leads to a systematic impact that ripples through the overall equity market. In the above example, for instance, the federal funds target interest rate affects the cost of capital raising for almost all firms. Thus, uncertainty about the future target interest rate tends to cause a systematic market impact that cannot be easily diversified. Equity market uncertainty is often associated with systematically important events. Anecdotal accounts suggest that natural disasters, terrorist attacks, wars, and political uncertainty often lead to heightened uncertainty in the overall equity market. As a result, this uncertainty may trigger market-wide movements.[15] Therefore, we expect that the negative impact of equity market uncertainty on informational efficiency is true not only at the individual stock level but also at the market level.

Existing studies support that uncertainty is detrimental to the information environment and makes it more difficult for market participants to interpret value signals in various settings. Some studies examine the behaviour of financial analysts, who are important information intermediaries in financial markets. For example, Zhang (2006a) defines information uncertainty as ambiguity with respect to the implications of new information for fundamental values (e.g., volatility of a firm's fundamental value and poor information) and measures it by dispersion in analyst forecasts. Using a large sample of US firms from 1983 to 2001, Zhang (2006a) finds that analysts underreact to new information and produce higher forecast errors when information uncertainty is high. Their definition of uncertainty is very similar in spirit to ours. Many studies investigate how uncertainty related to future government policies affects the behaviour of financial analysts (e.g., Baloria and Mamo, 2017; Biswas, 2019; Chahine et al., 2021; Chen et al., 2022). Baloria and Mamo (2017) use the US presidential election cycles as a proxy for policy uncertainty, whereas others use Baker et al.'s (2016) economic policy uncertainty index. These studies document a negative relationship between policy uncertainty and analyst forecast accuracy. This finding suggests that uncertainty undermines the value and precision of the information in financial markets and increases the complexity of forecasting tasks. In this study, we build our analysis on the same argument. However, instead of looking only at policy-related uncertainty, which is one source of uncertainty, we investigate uncertainty more broadly but focus on the context of the US equity market.

Other studies also examine other market participants, such as investors and corporations. For example, in the same setting as Zhang (2006a), Zhang (2006b) studies how information

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[15] See, e.g., https://bit.ly/3KuqRPm, https://bit.ly/3sXYHGw, https://bit.ly/3tEbihi, https://bit.ly/3JcZ4Tv, and https://bit.ly/3sWVp6w.

uncertainty affects investor behaviour biases. He investigates price anomalies such as post-analyst revision price drift and price momentum and finds that such anomalies are more significant when information uncertainty is high. The author further argues that this is because investors underreact more to new information when they are uncertain about its implications for firm values. As a result, there is a delay in information flowing into asset prices, leading to return predictability. The implications of this finding are relevant in the context of our study in that if the equity price is informationally efficient, it incorporates information quickly, and returns should therefore be unpredictable. Therefore, we postulate that when the information environment of equity markets is filled with uncertain signals, equity prices are less informationally efficient. Krause et al. (2017) examine the quality and quantity of corporate disclosure in extremely uncertain times. They hypothesize that high economic uncertainty during the global financial crisis makes accurate forecasting more difficult. To meet the disclosure mandate, firms choose to reduce both the precision and horizon of their forecasts to be disclosed while maintaining or increasing the number of such disclosures. In other words, disclosure quality is reduced during uncertain times, and firms mitigate reduced quality by increasing the frequency of such disclosures. Using 123 German firms over the period 2005-2009, the authors find empirical evidence that firm disclosure quality reduces while its frequency increases during uncertain times. Krause et al. (2017) argue that this firm disclosing behaviour dilutes the information density of disclosures.

Overall, extant literature supports our argument that equity market uncertainty negatively impacts the informational efficiency of equity prices. Equity market uncertainty adversely affects the behaviour of equity market participants (e.g., analysts, investors, firms), which in turn harms the overall information environment, making it more difficult to predict fundamental values. The lack of accurate signals delays the incorporation of value-relevant information into equity prices, leading to informational inefficiency.

3.2.2. The empirical proxy

As we define uncertainty in the context of the US equity market, the empirical proxy should satisfy the following two conditions. First, the proxy should be about the US equity market. Second, the proxy should capture market participants' uncertain perceptions about the future performance of the equity market. Recent advances in text search methods in the economic literature have led to several measures of economic uncertainty. Specifically, Baker et al. (2016) build several uncertainty-related indexes in the US by searching keywords from the major US newspaper articles. Out of several such indexes, we consider Baker et al.'s (2016) Equity Market Uncertainty Index (EMUNC) to be the best candidate as this is the only index that focuses specifically on the US equity market.

Baker et al. (2016) create a daily equity market uncertainty index by textually analyzing newspaper articles containing a combination of several keywords. Specifically, they first obtain daily counts, among over 1,000 US newspapers in Access World News' NewsBank, of articles that contain the term "uncertain" or "uncertainty", the term "economy" or "economic", and one or more of the following terms: "equity market", "equity price", "stock market", or "stock price". In other words, all the included newspaper articles must be about the economy, uncertainty, and the US equity market. To control for the increase in newspaper volume over time, the raw daily counts of related newspaper articles are scaled by the total number of articles in that same newspaper. The final equity market uncertainty index is then scaled to have an average value of 100 for the period 1985-2010.

The EMUNC is a good proxy for this study for several reasons. First, the construction of the EMUNC relies on mainstream US newspapers. Therefore, this index reflects the uncertain perspective of the public about the US equity market. Second, anecdotal accounts of how market participants trade indicate that such uncertain perspective reflected in newspapers is likely to affect how traders behave. For example, newspapers are an important source of information for retail investors without access to professional investment advice. Recent advances in algorithm-based trading allow computers to automate the trading process by textually scanning newspaper articles using natural language processing (NLP) techniques and generating trading strategies based on newspaper sentiments.

3.3. Measuring informational efficiency

In this section, we define informational efficiency and discuss how it can be measured using transaction-level data.

In a perfectly informationally efficient financial market, prices move following the arrival of information. Since the arrival of new information is unpredictable, prices should follow random walks. In addition, all relevant information should be reflected in prices at any time. Therefore, one cannot predict future price changes based on past information. However, in reality, many frictions and sources of inefficiency exist in financial markets, which cause prices to deviate from a random walk benchmark. Therefore, the level of informational inefficiency can be inferred by the extent to which asset prices deviate from the theoretical path expected under perfectly efficient markets.

In this paper, we consider the following two high-frequency informational efficiency metrics commonly used in the market microstructure literature: (i) absolute values of midquote return autocorrelations (*AF_efficiency*); and (ii) absolute values of the variance ratio (*VF_efficiency*), both of which are calculated using intraday midquote returns instead of the actual transaction prices to avoid the bid-ask bounce. As both proxies capture deviations from an efficient market benchmark, they are inverse measures of informational efficiency.

The first measure is the absolute autocorrelation of midquote returns (e.g., Hendershott and Jones, 2005; Boehmer and Wu, 2013; Comerton-Forde and Putniņš, 2015). If prices are close to a random walk (i.e., efficient), past returns should not predict future returns. Therefore, there should be little autocorrelation in midquote returns when prices are informationally efficient. Positive or negative midquote returns autocorrelation indicates short-term return predictability, suggesting informationally inefficient prices. Anderson et al. (2013) show that this inefficiency is due to a partial price adjustment to information such as investors' under- and over-reaction. We calculate the absolute values of the first-order midquote return autocorrelation for each day at intraday frequencies k:

$$AutoCorrelation_k = \left|Corr(r_{k,t}, r_{k,t-1})\right|, \tag{3.1}$$

where $r_{k,t}$ is the t^{th} midquote return measured at intraday frequency k in a given day. Similar in spirit to Comerton-Forde and Putniņš (2015), we estimate Eq. (3.1) using three intraday frequencies, $k \in \{1\text{min}, 2\text{min}, 5\text{min}\}$ and combine the autocorrelation metrics calculated at these frequencies by taking their first principal component. This procedure helps alleviate the measurement errors inherent in individual informational efficiency proxies by capturing the common variation of autocorrelation measured at different frequencies. We name this quantity *AutocorFactor*. A higher value of *AutocorFactor* indicates a reduction in informational efficiency. As a final step, we multiply *AutocorFactor* by -1 so that it becomes an informational efficiency measure. We label this informational efficiency measure *AF_efficiency*.

We also compute the variance ratios developed by Lo and MacKinlay (1988) as our second proxy for informational efficiency. If stock price follows random walks, then the variance of the stock returns is linear with respect to the measurement frequency. In other words, σ_{kl}^2 is k times larger than σ_l^2. The variance ratio is calculated as follows:

$$VarianceRatio_{kl} = \left|\frac{\sigma_{kl}^2}{k\sigma_l^2} - 1\right|, \tag{3.2}$$

where σ_{kl}^2 and σ_l^2 are the kl-second and l-second midquote return variances in a given day. We consider three frequency combinations of (l, kl) and combine them by calculating their first principal component to capture the common variations in the three individual variance ratio measures, which we name *VarRatioFactor*. This metric is close to zero if the price is informationally efficient. A higher value of *VarRatioFactor* indicates lower informational efficiency. Similarly, the final measure is the *VarRatioFactor* multiplied by -1, similar to the *AF_efficiency* metric. We label the second informational efficiency metric *VR_efficiency*.

We choose these two specific informational efficiency measures for the following reasons. First, extant literature suggests that these metrics are useful in various settings to capture market efficiency (e.g., Hendershott and Jones, 2005; O'Hara and Ye, 2011; Comerton-Forde and Putniņš, 2015). Second, the empirical relationship between these two informational efficiency metrics and an uncertainty proxy is also predicted by existing studies. For example, Zhang (2006b) finds that when investors are uncertain about the implications of new information for fundamental values, they tend to underreact to new information, leading to price continuation anomalies such as post-analyst forecast revision drift and price momentum. In other words, asset returns are more serially correlated. Zhang (2006b) argues that uncertainty delays the market reaction to new information and leads to news-based return predictability. Therefore, there is a clear empirical prediction that returns will deviate from random walk benchmarks under an uncertain information environment, leading to lower *AF_efficiency* and *VR_efficiency*.

3.4. Data and descriptive statistics

3.4.1. Data and sample selection

In this study, we consider the US equity market as a whole. Our analysis uses the SPDR S&P 500 Trust, which is the largest and most liquid exchange-traded fund (ETF) tracking the S&P 500 stock market index. Our sample period is between May 1, 2001 and December 31, 2019. The start of our sample is chosen to avoid potential confounding effects of the minimum tick size change in the US equity market due to the full implementation of decimalization by April 9, 2001.[16]

Baker et al.'s (2016) EMUNC is available at a daily frequency from the economic policy uncertainty website.[17] We obtain detailed transaction-level data for our sample from Thomson Reuters Tick History maintained by Refinitiv. Transaction-level data consolidates the best bid and ask quotes and the corresponding depths as well as all the transactions from the US exchanges, with all records timestamped to the nearest microsecond. We only include data within the NYSE's normal trading hours between 9:30 a.m. and 4:00 p.m. and further remove the first and last 10 minutes of each trading day to avoid the impact of opening and closing call auctions. We then follow Chordia et al. (2001) to clean and filter negative and outlier bid-ask spreads from the raw transaction data: (a) Quoted bid-ask spread (difference between the ask and bid prices) > $5; (b) Effective Spread (twice the absolute difference between the transaction price and bid-ask midpoint)/Quoted Spread > 4; (c) Quoted Spread/mid-quote Price > 25%. If multiple transactions within a day are observed with the same timestamp, we treat them as a single transaction resulting from one market order interacting with multiple resting limit orders. Therefore, we replace such transactions with a single trade record with volume-weighted

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[16] The changes in tick size have a direct impact on market quality (e.g., Porter and Weaver, 1997; Comerton-Forde et al., 2019; Chung et al., 2020) but is irrelevant to the level of uncertainty in the equity market.
[17] See http://www.policyuncertainty.com/equity_uncert.html.

average price (VWAP) and aggregate volume.

3.4.2. Descriptive statistics

Panel A of Table 3.1 reports descriptive statistics of the main variables used in this study. The key variable, EMUNC, captures the variation of the US equity market uncertainty. EMUNC has an average value of 59.31 over the sample period. It also varies dramatically over time depending on the underlying market condition, from a minimum value of just 4.8 to a maximum value of 1811.33. As is shown in Fig. 3.1, EMUNC spikes around major historical events in the US such as the 9/11 attack, Gulf War II in 2003, 2008 Global Financial Crisis, debt-ceiling debate in 2011 and 2013, the 2016 presidential election, and the recent US-China trade war since 2018. As the most liquid ETF in the world, SPDR has a total trading volume of around \$13.48 billion on an average trading day. The median trading day has a slightly lower value of roughly \$12.18 billion trading volume. The SPDR ETF price ranges between \$68.37 and \$323.05 over the sample period. The two informational efficiency measures (i.e., *AF_efficiency* and *VR_efficiency*) are both right-tailed and have a zero mean and standard deviation of one since they are both principal components. We also include several other market characteristics to form a basket of control variables such as liquidity (Amihud's ILLIQ and market depth, *NBBODepth*) and market volatility (VIX and return volatility, *LFVolatility*).[18] Likewise, all these control variables are also skewed to the right.

Table 3.1, Panel B provides correlations between the set of variables. As expected, the two informational efficiency measures are highly correlated. The correlation between *AF_efficiency* and *VR_efficiency* is 0.695 and significant at the 1% level. In addition, both measures are negatively correlated with Amihud's (2002) illiquidity measure. The correlation between ILLIQ and *AF_efficiency* (*VR_efficiency*) is -0.477(-0.543) and significant at 1% level. These results are consistent with prior studies, suggesting that a decrease in market liquidity is

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[18] Amihud's ILLIQ applies the Amihud (2002) metric using hourly intraday return and volume $ILLIQ_d = log\left[1 + \frac{1}{J}\sum_{h=1}^{H}\frac{10^5|r_{d,h}|}{\$Volume_{d,h}}\right]$. NBBODepth is the daily time-weighted average of quoted dollar depth based on National Best Bid and Offer (NBBO) and is scaled by 10,000. LFVolatility is low-frequency return volatility calculated using daily returns from a one-month rolling window surrounding each day in our sample, which we use to proxy for fundamental volatility.

Table 3.1

Descriptive statistics of the main variables.

	EMUNC	*AF_efficiency*	*VR_efficiency*	*VIX*	*Price*	*$Volume(billions)*	*LFVolatility*	*ILLIQ(x100)*	*NBBODepth ($10,000)*
Panel A: Descriptive statistics									
Mean	59.31	0	0	19.16	159.02	13.48	98.88	0.24	4.55
Std. dev.	93.19	1	1	8.62	60.17	9.50	62.77	0.46	3.41
Min	4.80	-8.12	-7.08	9.14	68.37	0.06	22.16	0.01	0.32
P25	12.71	-0.39	-0.35	13.31	114.46	6.28	61.11	0.06	2.42
Median	29.63	0.22	0.23	16.65	134.84	12.18	81.51	0.09	3.68
P75	64.87	0.68	0.65	22.15	203.32	18.05	117.87	0.18	5.83
Max	1811.33	1.58	1.48	80.86	323.05	76.90	550.45	10.03	26.00
Panel B: Pearson correlation									
EMUNC	1.00								
AF_efficiency	-0.23***	1.00							
VR_efficiency	-0.24***	0.70***	1.00						
VIX	0.43***	-0.11***	-0.12***	1.00					
Price	-0.24***	0.20***	0.26***	-0.54***	1.00				
$Volume	-0.13***	0.46***	0.54***	0.15***	0.34***	1.00			
LFVolatility	0.39***	-0.07***	-0.08***	0.89***	-0.42***	0.19***	1.00		
ILLIQ	0.26***	-0.48***	-0.54***	0.24***	-0.33***	-0.61***	0.19***	1.00	
NBBODepth($10,000)	-0.01	-0.28***	-0.40***	-0.22***	-0.32***	-0.53***	-0.21***	0.28***	1.00

Panel A of this table reports descriptive statistics on the key variables used in this paper. *AF_efficiency* and *VR_efficiency* are the negative values of the first principal components of the absolute values of the midquote returns autocorrelation and variance ratio measured at various intraday frequencies. *EMUNC* is the Baker et al. (2016) equity market uncertainty index. *VIX* is the CBOE option implied volatility index. *Price* and *$Volume* are the daily volume-weighted average price and daily total dollar trading volume, respectively. *LFVolatility* measures daily return standard deviation based on a one-month rolling window, a proxy for fundamental volatility. *ILLIQ* is the Amihud's (2002) illiquidity metric based on hourly intraday return and volume. *NBBODepth* is the daily time-weighted average of quoted dollar depth based on the National Best Bid and Offer (NBBO). In panel B, Pearson correlation coefficients between these variables are provided. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. The sample is comprised of transaction-level data of SPDR S&P 500 ETF Trust (SPY) from May 1, 2001 to December 31, 2019.

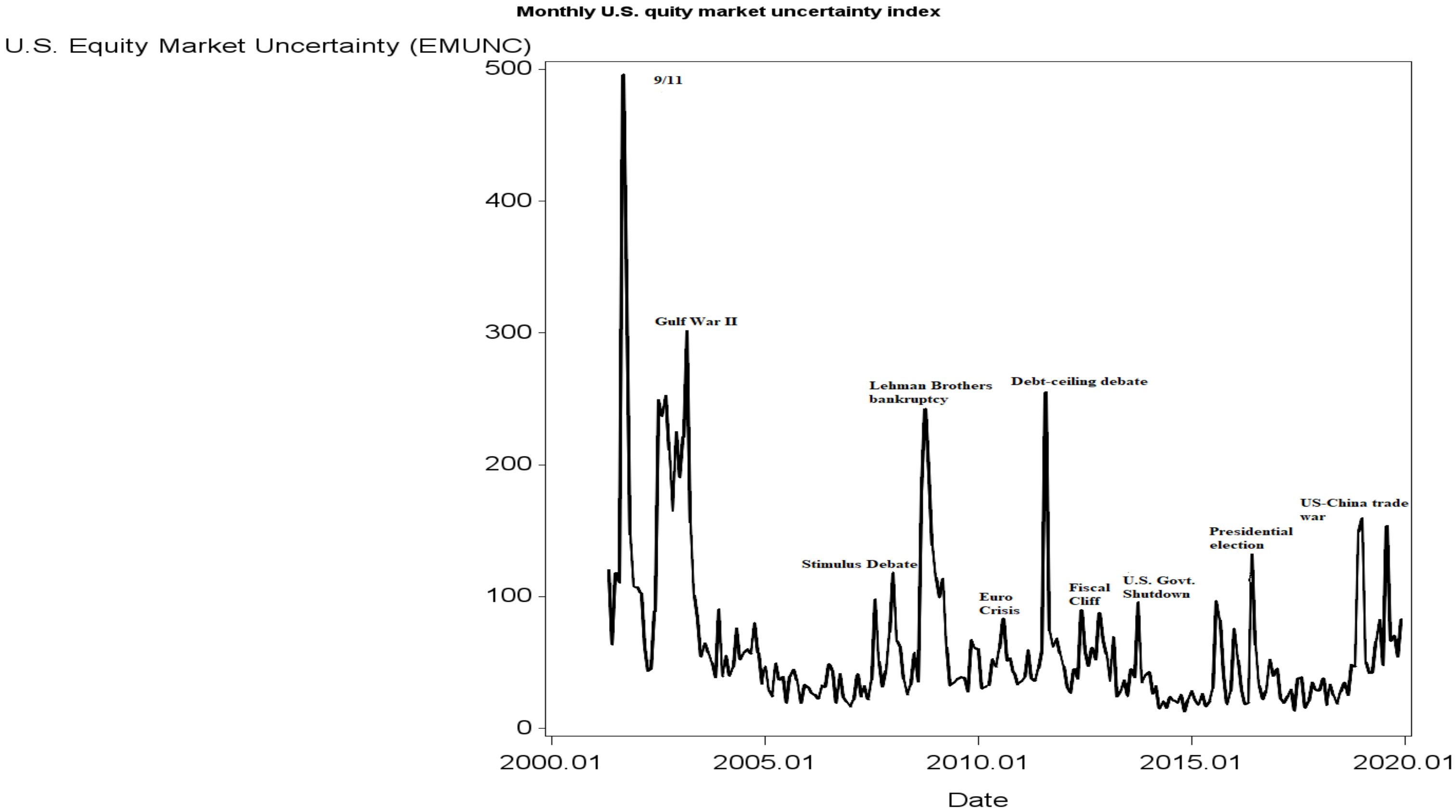

Fig. 3.1. Equity Market Uncertainty Index
This figure plots the monthly variation in the equity market uncertainty index (EMUNC) in the US. The index spans from May 1, 2001 to December 31, 2019 and is provided by Baker et al. (2016).

associated with a decrease in market efficiency (Chordia et al., 2008). Trading volume, a proxy for liquidity, is negatively correlated with ILLIQ and positively correlated with the two informational efficiency metrics but positively correlated with market volatility (VIX and return volatility, *LFVolatility*). Both market volatility measures (VIX and return volatility, *LFVolatility*) are positively correlated with illiquidity but negatively correlated with informational efficiency metrics, suggesting that heightened market volatility is harmful to liquidity and informational efficiency. More importantly, EMUNC is positively correlated with illiquidity but negatively correlated with both informational efficiency measures, with all correlations significant at the 1% level. This provides preliminary evidence that increased equity market uncertainty is associated with a deterioration in liquidity and informational efficiency of equity prices.

3.5. Results

This section discusses the results of our analysis. We first present the baseline results regressing informational efficiency measures on EMUNC. In doing so, we estimate a variety of regression specifications. Next, we consider a battery of robustness tests, including alternative measures of informational efficiency and other investment products.

3.5.1. Equity market uncertainty and informational efficiency

We begin our formal analysis by estimating the following baseline regression:

$$y_d = \alpha_0 + \beta_1 EMUNC_d + \sum_{j=1}^{n} \gamma_j \, Control_{j,d} + \mu_d, \tag{3.3}$$

where y_d is one of the two informational efficiency measures at day d and $EMUNC_d$ is the contemporaneous US equity market uncertainty index. For presentation, we scale the original EMUNC index by dividing it by 1,000. $Control_{j,d}$ are the set of additional control variables in Table 3.1 to control for various market microstructure characteristics also known to affect informational efficiency.

Table 3.2 presents these results. We start with the univariate regression specification. Columns (1) and (9) show that the coefficients on EMUNC are negative and highly significant (at 1% level). The univariate regression results are likely to be subject to the omitted variable bias. Therefore, we add additional control variables progressively to check the robustness of these results. In columns (3) and (11), we include commonly used control variables in the microstructure literature, including price, trading volume, returns volatility, and liquidity characteristics. The significance of EMUNC persists after controlling for these variables, albeit weaker. This finding suggests that equity market uncertainty contains additional information affecting the informational efficiency of equity prices beyond these traditional market factors. To further ensure that the significance of EMUNC is not an artifact of omitting some unknown latent factors that are correlated with both uncertainty and informational efficiency characteristics, we further control for the lagged dependent variable (*AF_efficiency* or *VR_efficiency*) in columns (5) and (13). We find that both the coefficients and the associated *t*-statistics on EMUNC are similar in magnitudes compared to those reported in columns (3) and (11), which further confirms our argument that equity market uncertainty harms the informational efficiency of equity prices.[19]

Prior studies also use alternative proxies for market uncertainty, the most commonly used being return volatility and VIX (e.g., Bloom, 2009). We already control for return volatility (*LFVolatility*) and show that EMUNC is distinct from general market volatility. We are also interested if EMUNC contains additional information not already captured by the VIX. In columns (7) and (15) of Table 3.2, we further control for the VIX. Not surprisingly, we find that a higher value of VIX is associated with a deterioration in informational efficiency. More importantly, EMUNC is still statistically significant at the 1% level after controlling for both return volatility and the VIX. On the other hand, the significance of *LFVolatility*, a measure of daily stock return volatility, is only marginal when the VIX is included. This indicates that even though EMUNC and other alternative uncertainty proxies have some overlapping information content, EMUNC contains unique information that the traditional volatility-based uncertainty measures have not captured. This additional analysis suggests that equity market uncertainty

[19] We also notice that EMUNC is a long memory process with slowly decaying autocorrelations (the first-order autocorrelation is over 0.53). Prior literature suggests that a persistent dependent variable tends to bias the regression coefficient. To account for this characteristic, we follow the regression approach in Kurov and Stan (2018) and use the fitted value instead of the original EMUNC as the explanatory variable. This procedure provides consistent results.

has an incremental impact on equity price informational efficiency beyond market volatility.

The negative impact of equity market uncertainty is also economically meaningful. To elaborate, we use columns (7) and (15) of Table 3.2 as examples. As the two informational efficiency metrics are principal components, their coefficients do not have a natural interpretation. Therefore, we explain the economic effects in terms of standard deviation. After controlling for a battery of market characteristics, a one standard deviation increase in EMUNC is associated with a 6.04% - 7.68% standard deviation decrease in either *AF_efficiency* or *VR_efficiency*.[20] This indicates a 6-7% standard deviation decrease in informational efficiency measures.

Coefficients on other control variables are consistent with our expectations and prior studies. Chordia et al. (2008) show a positive relationship between liquidity and market efficiency. Our results concur with theirs and show that all the significant coefficients on the Amihud's (2002) illiquidity proxy are negative, suggesting that informational efficiency deteriorates with reduced market liquidity. Coefficients on *$Volume* are positive and significant across the board, indicating that higher trading volume is beneficial to informational efficiency. Coefficients on the lagged dependent variables indicate a strong persistence in the informational efficiency measures.

A potential issue with Eq. (3.3) is reverse causality. The endogeneity concern arises when the informational efficiency characteristics of the SPDR S&P500 ETF also affect the tone of newspaper articles and media reports. However, this is less likely to be a concern. First, EMUNC is based on over 1,000 US newspapers ranging from large national newspapers to small local newspapers, which is unlikely to be systemically influenced by the characteristics of a very specific exchange-traded product (SPDR in this case). Second, anecdotal accounts of these newspaper narratives suggest that endogeneity is likely to be a more serious concern in causally relating EMUNC and asset prices or returns than causally relating EMUNC and

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[20] The numbers are calculated as follows: (st.dev_EMUNC)*coefficient/(st.dev_y), where st.dev_EMUNC is the sample standard deviation of the EMUNC index and st.dev_y is the sample standard deviation of one of the informational efficiency metrics. For instance, from Table 3.1 we find that st.dev_EMUNC is 93.187/1000 = 0.093187 and st.dev_y is 1. Column (7) and (15) in Table 3.2 show that the coefficient of EMUNC is -0.824 and -0.648. Therefore, the economic magnitudes in terms of standard deviation is -0.093187*0.824/1 = -7.68% and -0.093187*0.648/1 = -6.04%.

Table 3.2

OLS regression estimates for high-frequency informational efficiency metrics.

	$AF\_efficiency$								$VR\_efficiency$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
EMUNC	-2.421***		-1.190***		-0.970***		-0.824***		-2.593***		-1.146***		-0.756***		-0.648***	
	(-9.21)		(-4.98)		(-4.26)		(-3.77)		(-8.45)		(-4.53)		(-3.24)		(-2.85)	
Lag_EMUNC		-2.398***		-1.191***		-1.012***		-0.889***		-2.610***		-1.220***		-0.923***		-0.835***
		(-8.75)		(-4.99)		(-4.46)		(-4.07)		(-8.85)		(-5.42)		(-4.92)		(-4.56)
Price			-0.196***	-0.190***	-0.154***	-0.149***	-0.293***	-0.292***			-0.206***	-0.200***	-0.136***	-0.132***	-0.240***	-0.235***
			(-4.27)	(-4.16)	(-3.51)	(-3.41)	(-5.18)	(-5.15)			(-4.76)	(-4.65)	(-3.51)	(-3.42)	(-4.69)	(-4.59)
$Volume			0.325***	0.322***	0.254***	0.250***	0.283***	0.280***			0.323***	0.318***	0.204***	0.198***	0.226***	0.220***
			(5.46)	(5.31)	(5.26)	(5.11)	(5.74)	(5.61)			(5.21)	(5.08)	(4.58)	(4.44)	(4.92)	(4.78)
LFVolatility			-0.001***	-0.001***	-0.001***	-0.001**	-0.001*	-0.001**			-0.002***	-0.002***	-0.001***	-0.001***	0.0001	0.0002
			(-3.05)	(-2.91)	(-2.67)	(-2.49)	(-1.87)	(-2.08)			(-4.25)	(-4.05)	(-3.61)	(-3.34)	(0.24)	(0.51)
ILLIQ			-0.561***	-0.566***	-0.481***	-0.484***	-0.443***	-0.443***			-0.620***	-0.623***	-0.484***	-0.484***	-0.457***	-0.457***
			(-3.34)	(-3.35)	(-3.21)	(-3.20)	(-3.00)	(-2.99)			(-3.52)	(-3.52)	(-3.41)	(-3.40)	(-3.25)	(-3.24)
NBBODepth			-0.028***	-0.029***	-0.024***	-0.024***	-0.030***	-0.031***			-0.067***	-0.067***	-0.049***	-0.049***	-0.054***	-0.054***
			(-4.42)	(-4.43)	(-3.82)	(-3.84)	(-4.58)	(-4.63)			(-10.45)	(-10.47)	(-8.87)	(-8.93)	(-9.16)	(-9.26)
Lag_y					0.179***	0.181***	0.171***	0.173***					0.287***	0.288***	0.279***	0.280***
					(8.06)	(8.10)	(7.91)	(7.95)					(11.56)	(11.57)	(11.53)	(11.55)
VIX							-0.020***	-0.020***							-0.015***	-0.015***
							(-4.53)	(-4.59)							(-3.72)	(-3.62)
Adjusted R^2	5.06%	4.89%	29.44%	29.42%	31.59%	31.64%	31.98%	32.05%	5.82%	5.81%	41.13%	41.23%	45.86%	46.05%	46.07%	46.26%
Observations	4,689	4,689	4,689	4,689	4,687	4,687	4,687	4,687	4,690	4,690	4,690	4,690	4,689	4,689	4,689	4,689
S.E.	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West

This table reports OLS regression estimates with a range of model specifications. The dependent variables are the high-frequency measures of informational efficiency. $AF\_efficiency$ and $VR\_efficiency$ are the first principal components of the absolute values of the midquote returns autocorrelation and variance ratio measured at various intraday frequencies. The key independent variable, *EMUNC*, is the Baker et al. (2016) equity market uncertainty index. For presentation, we divide the original *EMUNC* index by 1000. *Price*, and *$Volume* are the natural logs of daily volume-weighted average price and daily total dollar trading volume, respectively. *LFVolatility* measures daily return standard deviation based on a one-month rolling window, a proxy for fundamental volatility. *ILLIQ* is the Amihud's (2002) illiquidity metric based on hourly intraday return and volume. *NBBODepth* is the daily time-weighted average of quoted dollar depth based on the National Best Bid and Offer (NBBO). *Lag_y* controls for the persistence in the corresponding dependent variable. *VIX* is the CBOE option implied volatility index. Standard errors are the Newey–West standard errors with t-statistics reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is comprised of transaction-level data of SPDR S&P 500 ETF Trust (SPY) from May 1, 2001 to December 31, 2019.

informational efficiency. This is because price efficiency is unobservable. Nevertheless, we modify Eq. (3.3) by replacing the contemporaneous equity market uncertainty index $EMUNC_d$ with its lagged value $EMUNC_{d-1}$. Using lagged values of EMUNC removes reverse causality due to the temporal difference between the dependent and independent variables. Past equity market uncertainty cannot be influenced by the current informational efficiency of equity prices.[21] The only possible exception is through persistence in informational efficiency characteristics. We rule out this possibility by adding lagged dependent variable (*Lag_y*) as a control variable to absorb persistence in informational efficiency characteristics.

We report coefficients of lagged EMUNC in even columns in Table 3.2. Overall, they are consistent with our argument and those based on Eq. (3.3). Across all model specifications, equity market uncertainty is associated with a statistically significant deterioration in the next-period informational efficiency of equity prices. The coefficients and the associated *t*-statistics are very similar in magnitudes compared with those reported in odd columns. These findings support our view that the contemporaneous results relating equity market uncertainty to reduced informational efficiency are not driven by newspaper articles expressing more uncertain views when the informational efficiency of the SPDR S&P500 ETF price is low.

To investigate whether this negative impact of equity market uncertainty is driven by any specific event or time period in our sample, we split our sample into three sub-periods: 2001/05/01 – 2007/12/31, 2008/01/01 – 2013/12/31, 2014/01/01 – 2019/12/31. We then run Eq. (3.3) within each individual sub-period. We report these subsample results in Table 3.3, using the full model specification indicated in columns (7) and (8) or (15) and (16) of Table 3.2.

The subperiod analysis shows that the negative impact of equity market uncertainty on informational efficiency is observed across different sample periods. The coefficients of EMUNC are all negative and comparable to those reported in Table 3.2, but their associated statistical significance is generally lower. One of the explanations is that the smaller sample size of each subsample results in a reduction in statistical significance. The coefficients on

[21] The EMUNC is constructed using newspaper articles from a particular calendar day, including those released outside the normal trading hours. This might mechanically lead to some of the information from these articles being reflected in prices only the next trading day. We also address this potential concern by using the second through fifth lags of EMUNC instead of the first lag. These additional results are consistent with those reported in Table 3.2 and are available in the appendix table.

control variables are largely consistent with those reported in Table 3.2. The overall significance in each sub-period, however, is relatively lower due to the reduced sample size. Overall, Table 3.3 suggests that equity market uncertainty has a negative impact on informational efficiency across all subperiods and is a general phenomenon rather than driven by any specific event such as the global financial crisis.

In a recent study, Nagar et al. (2019) use a similar uncertainty index and find evidence of significant lead-lag effects of uncertainty on liquidity measures. They argue that the lead and lag effects are caused by non-synchronous trading as well as delays in the uncertainty index in capturing market news relative to investors. In this regard, we also add five leads and five lags of EMUNC in addition to the contemporaneous index value. This specification enriches the baseline regression in Table 3.2 by allowing for potential lead and lag effects of equity market uncertainty on informational efficiency. Table 3.4 presents these results. Our findings are similar to those reported in Table 4 of Nagar et al. (2019) in that we report significant coefficients on some of the lead and lag terms. When leads and lags of EMUNC are introduced, the contemporaneous EMUNC is typically less significant than those reported in Table 3.2. In other words, the baseline results in Table 3.2 also capture some of the lead and lag effects of equity market uncertainty on informational efficiency, in addition to the contemporaneous impact. Notably, all the significant leads and lags are also negatively associated with informational efficiency metrics, which is consistent with the overall story. The significant negative lags indicate non-synchronous trading that causes some news to be incorporated into prices only later. In contrast, significant negative leads indicate that investors could capture equity market uncertainty faster from other sources than the newspaper articles reflect it.

Overall, our baseline results show that prices tend to deviate from a random walk when there is high uncertainty about the equity market that leads to frictions in the price discovery process, leading to higher return autocorrelation. As a result, prices become less informationally efficient.

Table 3.3

Subperiod analysis.

	$AF\_efficiency$						$VR\_efficiency$					
Subperiod	2001-2007		2008-2013		2014-2019		2001-2007		2008-2013		2014-2019	
EMUNC	-0.504*		-0.693*		-0.728*		-0.584**		-0.759**		-0.425	
	(-1.90)		(-1.94)		(-1.71)		(-2.26)		(-2.40)		(-0.85)	
Lag_EMUNC		-0.571**		-0.760*		-0.961**		-0.688**		-0.733*		-0.716*
		(-2.05)		(-1.76)		(-2.27)		(-2.13)		(-1.91)		(-1.82)
Price	-0.557***	-0.551***	0.043	0.023	0.414	0.443*	-0.785***	-0.777***	0.036	0.011	-0.071	-0.043
	(-3.66)	(-3.63)	(0.22)	(0.12)	(1.56)	(1.67)	(-5.31)	(-5.26)	(0.23)	(0.07)	(-0.26)	(-0.16)
$Volume	0.138***	0.136***	0.192***	0.188***	0.248***	0.241***	0.090***	0.088***	0.065	0.056	0.133**	0.127*
	(5.07)	(4.96)	(2.90)	(2.86)	(3.79)	(3.68)	(3.05)	(2.97)	(1.11)	(0.97)	(1.96)	(1.88)
LFVolatility	-0.002**	-0.002**	0.000	0.000	-0.002*	-0.002**	-0.002**	-0.002**	0.000	0.001	0.000	0.001
	(-2.21)	(-2.34)	(0.01)	(0.20)	(-1.80)	(-2.00)	(-2.14)	(-2.25)	(0.74)	(0.82)	(0.35)	(0.51)
ILLIQ	0.179	0.181	-0.334	-0.322	-0.270	-0.285	0.145	0.147	-0.376**	-0.385**	-0.697	-0.700
	(1.15)	(1.16)	(-1.62)	(-1.56)	(-0.38)	(-0.40)	(1.03)	(1.06)	(-2.50)	(-2.55)	(-0.90)	(-0.91)
NBBODepth	-0.053***	-0.053***	-0.085	-0.085	-0.181	-0.174	-0.079***	-0.078***	-0.094*	-0.095*	0.003	0.007
	(-2.66)	(-2.61)	(-1.38)	(-1.39)	(-1.07)	(-1.03)	(-3.42)	(-3.38)	(-1.92)	(-1.95)	(0.02)	(0.05)
Lag_y	0.437***	0.436***	0.043*	0.041*	0.077***	0.075***	0.341***	0.341***	-0.007	-0.007	0.009	0.008
	(13.50)	(13.37)	(1.70)	(1.65)	(2.80)	(2.75)	(10.69)	(10.70)	(-0.27)	(-0.27)	(0.37)	(0.34)
VIX	0.001	0.001	0.004	0.003	0.006	0.006	0.001	0.001	0.005	0.004	0.006	0.006
	(0.16)	(0.12)	(0.61)	(0.49)	(0.69)	(0.69)	(0.13)	(0.11)	(0.86)	(0.63)	(0.62)	(0.71)
Adjusted R^2	32.17%	32.22%	1.32%	1.42%	3.38%	3.55%	31.39%	31.60%	1.67%	1.51%	0.61%	0.73%
Observations	1,666	1,666	1,511	1,511	1,510	1,510	1,668	1,668	1,511	1,511	1,510	1,510
S.E.	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West

This table reports OLS regression results for three subperiods using the model specification in columns (7) and (8) or (15) and (16) of Table 3.2. $AF\_efficiency$ and $VR\_efficiency$ are the first principal components of the absolute values of the midquote returns autocorrelation and variance ratio measured at various intraday frequencies. The key independent variable, *EMUNC*, is Baker et al.'s (2016) equity market uncertainty index. For presentation, we divide the original *EMUNC* index by 1000. *Price*, and *$Volume* are the natural logs of daily volume-weighted average price and daily total dollar trading volume, respectively. *LFVolatility* measures daily return standard deviation based on a one-month rolling window, a proxy for fundamental volatility. *ILLIQ* is the Amihud's (2002) daily illiquidity metric based on hourly intraday return and volume. *NBBODepth* is the daily time-weighted average of quoted dollar depth based on the National Best Bid and Offer (NBBO). *Lag_y* controls for the persistence in the corresponding dependent variable. *VIX* is the CBOE option implied volatility index. Standard errors are the Newey–West standard errors with t-statistics reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is comprised of transaction-level data of SPDR S&P 500 ETF Trust (SPY) from May 1, 2001 to December 31, 2019. The three subperiods are 2001/05/01 – 2007/12/31, 2008/01/01 – 2013/12/31, 2014/01/01 – 2019/12/31.

Table 3.4
Lead-lag effects of equity market uncertainty (EMUNC).

	$AF\_efficiency$		$VR\_efficiency$	
$EMUNC_{t-5}$	-0.332		-0.426**	
	(-1.57)		(-2.00)	
$EMUNC_{t-4}$	-0.401**		-0.491***	
	(-2.08)		(-2.86)	
$EMUNC_{t-3}$	0.014		-0.138	
	(0.07)		(-0.76)	
$EMUNC_{t-2}$	0.044		0.008	
	(0.22)		(0.04)	
$EMUNC_{t-1}$	-0.408**		-0.461**	
	(-2.02)		(-2.35)	
$EMUNC_{t}$	-0.411*	-0.558**	-0.276	-0.149
	(-1.74)	(-2.35)	(-1.16)	(-0.63)
$EMUNC_{t+1}$		-0.376		-0.438*
		(-1.50)		(-1.88)
$EMUNC_{t+2}$		-0.131		-0.415*
		(-0.46)		(-1.77)
$EMUNC_{t+3}$		-0.291		-0.281
		(-1.14)		(-1.28)
$EMUNC_{t+4}$		-0.167		-0.483**
		(-0.82)		(-2.52)
$EMUNC_{t+5}$		-0.131		-0.047
		(-0.65)		(-0.26)
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	31.98%	31.82%	46.49%	46.53%
Observations	4,687	4,687	4,689	4,689
S.E.	Newey-West	Newey-West	Newey-West	Newey-West

This table reports OLS results regressing the two high-frequency measures of informational efficiency on the Equity Market Uncertainty (EMUNC) index as well as 5 of its lead and lag terms. Standard errors are the Newey–West standard errors with t-statistics reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. For brevity, results for control variables are not reported. The sample is comprised of transaction-level data of SPDR S&P 500 ETF Trust (SPY) from May 1, 2001 to December 31, 2019.

3.5.2. Robustness tests

In this section, we carry out and discuss the results of a battery of additional robustness tests. First, we examine whether our main results hold using alternative measures of informational efficiency. We consider two additional informational efficiency metrics: (i) short-term midquote return volatility (*HFVolatility*); and (ii) short-term midquote return predictability using lagged order flow (*OIBPred*). The first metric is calculated at an intraday frequency. Distinct from the *LFVolatility* that we used in section 3.5.1, which is a proxy for low-frequency fundamental volatility, *HFVolatility* captures excessive short-term price volatility. Excessive short-term price movements might harm long-term fundamental investors who do not necessarily have the capacity to exploit such short-lived opportunities.[22] This metric has also been used in prior studies to measure market quality under similar settings (e.g., O'Hara and Ye, 2011). As there is no theoretical guidance as to which intraday frequency is the best choice, we measure *HFVolatility* using multiple sampling frequencies (i.e., 1min, 2min, 5min) and aggregate them by taking their first principal component. This procedure follows the logic of constructing both *AF_efficiency* and *VR_efficiency* in section 3.3.

The second alternative informational efficiency metric, *OIBPred*, follows Rösch et al. (2017). In an efficient financial market, asset prices should incorporate available information quickly. Therefore, one cannot predict future returns using past information. Rösch et al. (2017) measure short-term return predictability from past order flow by regressing intraday one-minute stock returns on lagged signed order flow and define it as the slope coefficient from the regression:

$$r_{d,t} = \alpha_d + \beta_d OIB_{d,t-1} + \mu_{d,t}, \tag{3.4}$$

where $r_{d,t}$ is the midquote return aggregated over the one-minute interval *t* on day *d* and $OIB_{d,t-1}$ is the signed order imbalance (difference between buyer- and seller-initiated dollar trading volume) over the one-minute interval *t-1* on the same day. We follow Rösch et al. (2017) and define *OIBPred* as the absolute value of the slope coefficient (i.e., $|\beta_d|$). This is also in line with Chordia et al. (2008) that any return predictability from past order flow is an indication of price inefficiency. Again, we flip the sign of both *HFVolatility* and *OIBPred* to transform them into informational efficiency measures.

We repeat the analysis in Table 3.2 using the two alternative informational efficiency measures and report the results in Table 3.5. Consistent with Table 3.2, coefficients on equity market uncertainty (and its lags) are negative and significant across the board. Whereas Table 3.2 suggests that higher equity market uncertainty causes prices to deviate from a random walk benchmark, Table 3.5 further shows that equity market uncertainty leads to excessive short-term price volatility. In the meantime, there is a delay in the incorporation of information

[22] For example, pp 36-37 of the SEC Concept Release No. 34-61358 notes: "…short-term price volatility may harm individual investors if they are persistently unable to react to changing prices as fast as high frequency traders…long-term investors may not be in a position to assess and take advantage of short-term price movements."

implicit in past order flows into the subsequent equity prices. The economic significance is also similar in magnitude to Table 3.2. For example, Table 3.5 columns (7) and (15) reveal that a one standard deviation increase in the equity market uncertainty index is associated with a 6.73% (10.37%) standard deviation decrease in *HFVolatility* (*OIBPred*) metric, indicating a near 10% standard deviation decrease in informational efficiency.

Second, we consider alternative investment products. The SPDR S&P 500 ETF Trust we use tracks the performance of the largest 500 stocks in the US equity market. We also consider an ETF that tracks different segments of the US equity market. We consider iShares Russell 2000 ETF (ticker symbol: IWM). IWM tracks the performance of the Russell 2000 Index, which is a small-cap stock market index covering the 2000 smallest US stocks. Using this alternative index investment product is motivated by our hypothesis that the impact of equity market uncertainty is general and, thus, should not only be observed in the large-cap sector. This additional test verifies this hypothesis and is also a robustness check of the main results.

Table 3.6 repeats the analysis in Tables 3.2 and 3.4 but with IWM instead of SPY as our test sample. In Panel A, we perform the same analyses following Table 3.2 and only report the coefficients on EMUNC to save space. For example, column (8) of Table 3.6 follows the same model specification as column (8) of Table 3.2. Consistent with our expectations, the coefficients on EMUNC (or its lags) are negative and significant across the board. Both the coefficients and the associated *t*-statistics are similar to those reported in Table 3.2, which indicates that the negative impact of equity market uncertainty on informational efficiency is generic and affects both large- and small-cap stocks. Similarly, Panel B shows that the significant leads and lags of EMUNC are also negative. Overall, these results further support our argument that equity market uncertainty has a negative impact on the informational efficiency of equity prices.

Table 3.5

Evidence from alternative measures of informational efficiency.

	HFVolatility								*OIBPred*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
EMUNC	-4.470***		-1.386***		-0.972***		-0.722***		-0.076***		-0.033***		-0.031***		-0.025***	
	(-12.87)		(-7.96)		(-5.67)		(-4.34)		(-9.29)		(-3.85)		(-3.64)		(-3.16)	
Lag_EMUNC		-4.193***		-1.028***		-0.557***		-0.369**		-0.068***		-0.023***		-0.020***		-0.015**
		(-10.66)		(-4.99)		(-2.85)		(-2.06)		(-7.73)		(-3.14)		(-2.82)		(-2.34)
Price			0.516***	0.521***	0.356***	0.356***	0.090**	0.077**			0.006***	0.006***	0.005***	0.005***	-0.0001	-0.0004
			(14.87)	(14.83)	(9.04)	(8.92)	(2.34)	(1.97)			(4.10)	(4.19)	(3.46)	(3.50)	(-0.03)	(-0.17)
$Volume			-0.318***	-0.314***	-0.271***	-0.264***	-0.225***	-0.217***			0.010***	0.010***	0.009***	0.009***	0.010***	0.011***
			(-7.64)	(-7.31)	(-7.19)	(-6.78)	(-6.52)	(-6.15)			(5.01)	(5.01)	(4.86)	(4.85)	(5.05)	(5.08)
LFVolatility			-0.010***	-0.010***	-0.006***	-0.006***	-0.003***	-0.003***			-0.0001***	-0.0001***	-0.0001***	-0.0001***	0.000	0.000
			(-18.43)	(-18.47)	(-9.36)	(-9.48)	(-4.30)	(-4.18)			(-6.06)	(-6.35)	(-5.71)	(-5.99)	(-0.05)	(0.01)
ILLIQ			-0.289**	-0.300**	-0.235**	-0.244**	-0.155*	-0.158*			-0.349	-0.376	-0.307	-0.333	-0.150	-0.159
			(-2.51)	(-2.53)	(-2.31)	(-2.33)	(-1.69)	(-1.69)			(-1.21)	(-1.28)	(-1.07)	(-1.15)	(-0.51)	(-0.53)
NBBODepth			-0.005	-0.005	-0.008***	-0.008**	-0.022***	-0.022***			0.0003**	0.0004**	0.0003**	0.0003**	0.0001	0.0001
			(-1.59)	(-1.45)	(-2.77)	(-2.55)	(-7.04)	(-6.87)			(2.14)	(2.13)	(2.01)	(2.01)	(0.39)	(0.30)
Lag_y					0.395***	0.403***	0.307***	0.311***					0.091**	0.093**	0.074*	0.075*
					(9.31)	(9.38)	(7.74)	(7.81)					(2.08)	(2.02)	(1.76)	(1.71)
VIX							-0.043***	-0.045***							-0.0008***	-0.0009***
							(-8.90)	(-9.23)							(-4.48)	(-4.60)
Adjusted R^2	17.29%	15.00%	72.36%	71.75%	77.12%	76.68%	78.83%	78.57%	9.86%	7.84%	31.04%	30.27%	31.67%	30.96%	32.95%	32.47%
Observations	4,689	4,689	4,689	4,689	4,687	4,687	4,687	4,687	4,690	4,690	4,690	4,690	4,689	4,689	4,689	4,689
S.E.	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West

This table reports OLS regression estimates with a range of model specifications. The dependent variables are the two alternative informational efficiency metrics. *HFVolatility* is the first principal component of high-frequency intraday midquote return volatility measured using a variety of sampling frequencies. *OIBPred* is the absolute value of the slope coefficient from Eq. (3.4) to capture the short-horizon return predictability from past order flow. The key independent variable, *EMUNC*, is the Baker et al. (2016) equity market uncertainty index. *Price*, and *$Volume* are the natural logs of daily volume-weighted average price and daily total dollar trading volume, respectively. *LFVolatility* measures daily return standard deviation based on a one-month rolling window, a proxy for fundamental volatility. *ILLIQ* is the Amihud's (2002) daily illiquidity metric based on hourly intraday return and volume. *NBBODepth* is the daily time-weighted average of quoted dollar depth based on the National Best Bid and Offer (NBBO). *Lag_y* controls for the persistence in the corresponding dependent variable. *VIX* is the CBOE option implied volatility index. Standard errors are the Newey–West standard errors with *t*-statistics reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is comprised of transaction-level data of SPDR S&P 500 ETF Trust (SPY) from May 1, 2001 to December 31, 2019.

Table 3.6

Evidence from the alternative ETF (IWM).

	AF_efficiency								*VR_efficiency*							
Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
EMUNC	-2.059***		-0.992***		-0.619***		-0.680***		-1.537***		-0.804***		-0.605***		-0.664***	
	(-6.84)		(-4.26)		(-3.20)		(-3.40)		(-6.25)		(-3.69)		(-3.14)		(-3.37)	
Lag_EMUNC		-2.160***		-1.152***		-0.770***		-0.817***		-1.666***		-0.989***		-0.733***		-0.778***
		(-7.38)		(-4.79)		(-3.85)		(-4.03)		(-6.02)		(-3.82)		(-3.22)		(-3.36)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	3.66%	3.98%	23.64%	23.86%	34.28%	34.42%	34.31%	34.44%	2.03%	2.36%	11.43%	11.65%	17.96%	18.08%	17.98%	18.09%
Observations	4,690	4,690	4,690	4,690	4,689	4,689	4,689	4,689	4,690	4,690	4,690	4,690	4,689	4,689	4,689	4,689
S.E.	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West

Panel B: Lead-lag effects of EMUNC

	AF_efficiency		*VR_efficiency*	
$EMUNC_{t-5}$	0.159		0.027	
	(0.61)		(0.13)	
$EMUNC_{t-4}$	-0.087		0.016	
	(-0.36)		(0.07)	
$EMUNC_{t-3}$	-0.103		-0.335*	
	(-0.48)		(-1.74)	
$EMUNC_{t-2}$	-0.142		0.018	
	(-0.62)		(0.09)	
$EMUNC_{t-1}$	-0.549**		-0.589**	
	(-2.38)		(-2.29)	
$EMUNC_{t}$	-0.308	-0.300	-0.187	-0.402
	(-1.45)	(-1.29)	(-0.95)	(-1.41)
$EMUNC_{t+1}$		-0.301		0.148
		(-1.14)		(0.54)
$EMUNC_{t+2}$		0.068		0.291
		(0.26)		(1.01)
$EMUNC_{t+3}$		-0.080		-0.444*
		(-0.36)		(-1.70)
$EMUNC_{t+4}$		-0.021		0.309
		(-0.09)		(1.35)
$EMUNC_{t+5}$		-0.510**		-0.049
		(-2.06)		(-0.21)
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	34.45%	34.48%	18.15%	18.11%

This table repeats the analysis in Tables 3.2 and 3.4 for the iShares Russell 2000 index ETF (IWM). Panel A follows Table 3.2, where the column number corresponds to the model specification from the same column in Table 3.2. To conserve space, the control variables are not reported. In Panel B, we report the coefficients for the five leads and five lags of the EMUNC index, as in Table 3.4. Standard errors are the Newey–West standard errors with *t*-statistics reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is comprised of transaction-level data of iShares Russell 2000 ETF (IWM) from May 1, 2001 to December 31, 2019.

Finally, we consider alternative proxies for equity market uncertainty. We use two alternative uncertainty proxies available from the extant literature: Baker et al.'s (2016) Equity Market Volatility (EMV) tracker and the news-based economic policy uncertainty (EPU_news) index. The first alternative proxy, the EMV tracker, is similar to the EMUNC index in several ways. First, both indexes are constructed based on major US newspapers. Second, both indexes are designed to focus on the US equity market. The difference is that instead of counting newspaper articles that mention "uncertain" or "uncertainty", the EMV tracker search for articles containing the keyword "volatile" or "volatility".[23] Since volatility is another commonly used measure of uncertainty in the extant literature (e.g., Bloom et al., 2007; Bloom, 2009), we assume that newspaper readers interpret the word "volatility" and "uncertainty" synonymously.

The second alternative proxy, the EPU_news index, is also constructed using newspaper articles and is very similar to the EMUNC index. The EPU_news index is also distinct from the EMUNC index because it captures uncertainty related to government economic-related policies rather than the equity market. The EPU_news index is widely used in recent finance literature (e.g., Gulen and Ion, 2016; Nagar et al., 2019).

We estimate the impact of both the EMV and EPU_news index. For the EMV index, we aggregate the daily informational efficiency measures to a monthly frequency for the robustness tests. This is because the EMV index is only available at a monthly frequency. Table 3.7 reports the results. The coefficients of both alternative proxies are negative across the board, which supports our main results. However, we notice that the magnitudes and statistical significance of the uncertainty effect are sometimes lower. Two reasons likely cause this. First, the small sample due to time aggregation reduces the coefficient significance. Second, the two alternative uncertainty proxies are not perfect substitutes for equity market uncertainty. For instance, newspaper readers may interpret "uncertainty" and "volatility" differently. Moreover, uncertainty due to government economic policies may not necessarily affect the performance of equity markets (Pástor and Veronesi, 2017). Nevertheless, the significant coefficients from these two alternative market uncertainty proxies provide additional support to our main story.

[23] Data for EMV tracker is available at: https://www.policyuncertainty.com/EMV_monthly.html.

Table 3.7

Evidence from alternative uncertainty proxies.

	AF_efficiency				*VR_efficiency*			
Panel A: the effect of the equity market volatility (EMV) tracker								
EMV	-1.412*	-0.669**	-0.521*	-0.548**	-1.657*	-0.850**	-0.088	-0.096
	(-1.77)	(-2.17)	(-1.94)	(-2.01)	(-1.82)	(-2.33)	(-0.37)	(-0.41)
Price		-0.321***	-0.230***	-0.183**		-0.276***	-0.142**	-0.127
		(-5.23)	(-4.44)	(-2.30)		(-4.20)	(-2.57)	(-1.56)
$Volume		0.068	0.022	0.002		0.165***	0.030	0.023
		(1.34)	(0.53)	(0.04)		(2.64)	(0.63)	(0.45)
LFVolatility		-0.044***	-0.045***	-0.043***		-0.003	-0.008	-0.007
		(-3.00)	(-3.58)	(-3.17)		(-0.20)	(-0.70)	(-0.59)
ILLIQ		-1.534***	-0.965***	-1.002***		-1.428***	-0.673***	-0.685***
		(-12.55)	(-6.03)	(-5.97)		(-8.92)	(-3.55)	(-3.49)
NBBODepth		-0.020**	-0.011	-0.010		-0.056***	-0.027*	-0.027*
		(-2.13)	(-1.55)	(-1.27)		(-3.86)	(-1.93)	(-1.84)
Lag_y			0.383***	0.386***			0.579***	0.580***
			(5.99)	(6.17)			(10.35)	(10.35)
VIX				0.003				0.001
				(0.76)				(0.27)
Adjusted R^2	2.65%	86.74%	88.28%	88.26%	2.69%	86.16%	91.47%	91.43%
Observations	224	224	223	223	224	224	223	223
S.E.	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West
Panel B: the effect of the news-based EPU index								
EPU_news	-0.738***	-0.915***	-0.745***	-0.532**	-0.489*	-0.734***	-0.465**	-0.303*
	(-2.90)	(-3.72)	(-3.12)	(-2.34)	(-1.84)	(-3.52)	(-2.48)	(-1.68)
Price		-0.223***	-0.175***	-0.323***		-0.228***	-0.148***	-0.261***
		(-4.71)	(-3.87)	(-5.51)		(-5.06)	(-3.70)	(-4.98)
$Volume		0.352***	0.273***	0.301***		0.348***	0.217***	0.239***
		(5.61)	(5.47)	(5.97)		(5.34)	(4.76)	(5.13)
LFVolatility		-0.002***	-0.001***	-0.0007*		-0.002***	-0.002***	0.000
		(-3.86)	(-3.49)	(-1.67)		(-5.09)	(-4.49)	(-0.07)
ILLIQ		-0.578***	-0.491***	-0.447***		-0.636***	-0.490***	-0.459***
		(-3.36)	(-3.21)	(-2.98)		(-3.52)	(-3.40)	(-3.22)
NBBODepth		-0.030***	-0.024***	-0.031***		-0.067***	-0.048***	-0.054***
		(-4.35)	(-3.75)	(-4.54)		(-10.10)	(-8.48)	(-8.93)
Lag_y			0.187***	0.178***			0.296***	0.287***
			(8.21)	(8.06)			(11.78)	(11.76)
VIX				-0.022***				-0.017***
				(-4.84)				(-4.08)
Adjusted R^2	0.22%	28.75%	31.15%	31.63%	0.08%	40.41%	45.55%	45.83%
Observations	4,689	4,689	4,687	4,687	4,690	4,690	4,689	4,689
S.E.	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West

This table reports the results of the two alternative uncertainty proxies: the Baker et al.'s (2016) equity market volatility (EMV) tracker and the news-based economic policy uncertainty (EPU_news) index. The EMV index is available at a monthly frequency, whereas the EPU_news index is a daily index. The dependent variables are the high-frequency measures of informational efficiency. AF_efficiency and VR_efficiency are the first principal components of the absolute values of the midquote returns autocorrelation and variance ratio measured at various intraday frequencies. Price, and $Volume are the natural logs of monthly price and total dollar trading volume, respectively. LFVolatility measures daily return standard deviation within a month, which is a proxy for fundamental volatility. ILLIQ is the Amihud's (2002) daily illiquidity metric based on hourly intraday return and volume. *NBBODepth* is the daily time-weighted average of quoted dollar depth based on the National Best Bid and Offer (NBBO). Lag_y controls for the persistence in the corresponding dependent variable. VIX is the CBOE option implied volatility index. All variables are aggregated to a monthly frequency. Standard errors are the Newey–West standard errors with t-statistics reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is comprised of transaction-level data of SPDR S&P 500 ETF Trust (SPY) from May 1, 2001 to December 31, 2019.

3.6. Conclusion

In this study, we empirically analyze the effect of equity market uncertainty on the informational efficiency of equity prices in the US. To capture the overall level of US equity market uncertainty, we employ the Equity Market Uncertainty Index (EMUNC) developed by Baker et al. (2016). This index counts newspaper articles expressing uncertain views about the US equity market. We use S&P 500 index ETF (SPY) to measure the overall US equity market informational efficiency. Relating EMUNC to informational efficiency metrics, we document a significant negative relationship between equity market uncertainty and informational efficiency of equity prices. The significant negative effect is observed both contemporaneously and up to five lags. This result is robust to controlling for a range of market microstructure characteristics and is also consistently found across different subperiods. This indicates that the negative impact of equity market uncertainty on informational efficiency is persistent.

To check the robustness of our results, we run several additional tests. First, we consider several alternative measures of equity price informational efficiency. The results based on these alternative informational efficiency measures are consistent with our main results, suggesting that our results are not driven by any particular empirical metric employed. Second, we consider alternative index ETFs and also find very similar results. The impact of equity market uncertainty is similar in magnitudes for small-cap and large-cap stocks, suggesting that equity market uncertainty has a market-wide influence. Finally, we use other alternative proxies for market uncertainty and also find supporting evidence.

Our results have several implications. They suggest that the sentiment of newspaper articles can significantly influence equity prices. This finding is relevant to market participants. For example, arbitrageurs can exploit potential mispricing opportunities based on media or news sentiments. For equity market investors, our findings imply that newspaper-based economic uncertainty should be an essential factor to consider when devising an investment strategy. Our finding is also helpful for market regulators and policymakers to make more informed rules and policies, thus maintaining the quality and competitiveness of local financial markets.

Appendix A.1. The effect of EMUNC with different lags

Table A.1

The effect of EMUNC on informational efficiency with different lags.

	AF_efficiency				*VR_efficiency*			
Lag2_EMUNC	-0.541**				-0.505***			
	(-2.38)				(-2.76)			
Lag3_EMUNC		-0.344*				-0.631***		
		(-1.90)				(-3.88)		
Lag4_EMUNC			-0.611***				-0.858***	
			(-2.93)				(-5.86)	
Lag5_EMUNC				-0.679***				-0.851***
				(-2.96)				(-4.49)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	31.75%	31.62%	31.80%	31.78%	45.99%	46.12%	46.33%	46.19%
Observations	4,687	4,687	4,687	4,687	4,689	4,689	4,689	4,689
S.E.	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West

This table tests the effect of EMUNC on informational efficiency using the second through fifth lags of EMUNC. Model specification is the same as columns (8) and (16) in Table 3.2. Standard errors are the Newey–West standard errors with t-statistics reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is comprised of transaction-level data of SPDR S&P 500 ETF Trust (SPY) from May 1, 2001 to December 31, 2019.

Chapter 4

4. The effect of an uncertain information environment surrounding FOMC announcements on equity market quality

4.1. Introduction

When it comes to making investment decisions, accessibility to information is vital. Possessing more accurate information allows market participants to better understand the economic fundamentals related to underlying asset values and gives them an advantage in trading. In a market with a high-quality information environment, market participants can obtain more accurate signals before making investment decisions. When the information environment is uncertain, however, information signals become noisy and more difficult to interpret. This creates uncertainty, which may affect the behavior of market participants and the dynamics of asset prices.[24] The importance of the information environment is highlighted by the Securities and Exchange Commission's acting chairman Elad L. Roisman, who, in June 2020, stated that "transparency is a vital tool in assuring that our markets are fair, competitive, and resilient, particularly for retail investors."[25]

Several existing studies have focused on the effect of the information environment. For instance, a transparent information environment is associated with higher firm valuations (e.g., Lang et al., 2003; Lang et al., 2012; Zhang and Toffanin, 2018) and more corporate responsiveness to profitable investment opportunities (e.g., Badertscher et al., 2013). The characteristics of the information environment may affect the investment behavior of certain

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[24] See, for example, https://rebrand.ly/94ou22e and https://bit.ly/3KuqRPm.

[25] https://www.sec.gov/news/public-statement/roisman-opening-remarks-spotlight-transparency-061620.

investors such as institutional investors and corporate insiders. For instance, Frankel and Li (2004) find that a transparent firm-level information environment (measured by analyst following and financial statement informativeness) reduces insider purchases and profitability of insider trades. Maffett (2012) shows that firms with more opaque information environments experience more privately informed institutional trading. An opaque information environment harms market stability and increases liquidity and crash risks (Hutton et al., 2009; Ng, 2011).

Less research has focused on the consequences of an uncertain information environment during periods of informational shocks. During such times, the quality of the information environment should matter most as investors are anticipating the arrival of new information. This is because important news releases, such as macroeconomic news, incentivize market participants to acquire private information and trade accordingly (e.g., McNichols and Trueman, 1994; Bernile et al., 2016; Kurov et al., 2019). When the information environment surrounding informational shocks is uncertain, the incentive for private information acquisition is stronger because possessing more accurate information may lead to trading profits. In such a case, certain traders are more likely to obtain superior information, leading to increased information asymmetry and higher trading costs. Understanding the consequences of an uncertain information environment surrounding informational shocks is relevant not only for investors for their investment decisions, but also for regulators to better understand how financial markets incorporate new information.

In this study, we examine the consequences of an uncertain information environment surrounding US Federal Open Market Committee (FOMC) announcements. We choose the FOMC announcement event for two main reasons. First, these news releases have been shown to cause a systematic impact on financial markets (Bernanke and Kuttner, 2005).[26] Second, existing studies show that FOMC announcements cause stronger market reactions than other macroeconomic news. For instance, using several major US macroeconomic news announcements, Lucca and Moench (2015) document a pre-announcement price drift only for the FOMC announcement. We measure uncertainty in the information environment surrounding the FOMC announcement using analyst forecast dispersion for the FOMC target fed funds

[26] See, e.g., https://voxeu.org/article/predictable-movements-asset-prices-around-fomc-meetings.

rate.[27] We consider analyst forecasts for several reasons. First, financial analysts, as important financial intermediaries, provide forecasts about news prior to their official releases. These forecasts are often used by market participants to guide their investments. Greater analyst forecast dispersion renders the consensus forecast imprecise, leading to an uncertain information environment and creating uncertainty. Second, many analysts provide their forecasts for the upcoming interest rate, more than forecasts for other economic items. This further emphasizes the importance to investors of the information environment surrounding the FOMC announcement.

To examine the impact on market quality, we consider the US equity market as a whole and focus on two exchange-traded funds (ETFs), the SPDR S&P 500 ETF (ticker: SPY) and the iShares Russell 2000 ETF (ticker: IWM), which represent large- and small-cap US equities, respectively. We examine the consequences of an uncertain information environment in terms of changes in a battery of market quality characteristics such as liquidity and informational efficiency (e.g., Comerton-Forde and Putniņš, 2015; Foley and Putniņš, 2016).

We report several notable findings. First, an uncertain information environment (i.e., greater analyst forecast dispersion) leads to an increase in the quoted and effective spread as well as Amihud's (2002) illiquidity surrounding the FOMC announcement. The impact of analyst forecast dispersion is greater for the IWM, i.e., small-cap stocks are more affected by uncertain information environments. This effect is also economically meaningful in terms of the transaction cost. For instance, a one standard deviation increase in analyst forecast dispersion translates to a 0.38 cents increase in per round-trip transaction cost around FOMC announcement times for SPY, given that SPY has an average effective spread of only 1.14 cents. We find similar results for both pre- and post-announcement event windows we examine (although the effects in the pre-announcement event window are weaker). When we investigate the impact of analyst forecast dispersion on spread components, we find that analyst forecast dispersion in the pre-announcement period primarily affects the information asymmetry component, which is in line with the argument that an uncertain information environment creates uncertainty and stimulates private information acquisition prior to the FOMC

[27] Analyst forecast dispersion has been widely used as a proxy for the information environment in the existing literature (e.g., Frankel and Li, 2004; Maffett, 2012; Lang et al., 2012).

announcement (e.g., Kim and Verrecchia, 1991; McNichols and Trueman, 1994). Post-announcement information asymmetry is not related to analyst forecast dispersion. This is because uncertainty is resolved in the post-announcement period. Instead, analyst forecast dispersion increases order processing costs. This finding can be explained by a surge in trading volume in the post-announcement period.

Second, we observe that analyst forecast dispersion is positively related to trading volume surrounding the FOMC announcement. For both ETFs, we find a significant positive impact of analyst forecast dispersion on trading volume and the number of trades. However, analyst forecast dispersion does not affect traders' choice over small or large orders. When splitting the event window into pre- and post-announcement periods, we show that the reaction of trading activity is much stronger in the post-announcement period. A higher trading volume prior to the FOMC announcement can be attributed to both informed and speculative trading motivated by uncertainty, whereas abnormal trading volume after the FOMC announcement can be explained by a combination of informed trading and postponed liquidity trading. A comparison between the two ETFs shows that the impact of analyst forecast dispersion on trading activity is stronger for the large-cap stock ETF, especially during the post-announcement period.

Third, we find that an uncertain information environment is harmful to the price efficiency surrounding the FOMC announcement. We find significant negative coefficients of analyst forecast dispersion on our price efficiency metrics. These findings are consistent for the pre- and post-announcement periods. This suggests that information asymmetry created by an uncertain information environment crowds out uninformed traders, which further reduces the incentives for costly information acquisition. Less aggregate information production thus reduces price informativeness around FOMC announcements (e.g., Admati and Pfleiderer, 1988). Overall, our study shows that an uncertain information environment affects equity market quality during FOMC announcement times. Analyst forecast dispersion increases market illiquidity and leads to less informationally efficient equity prices.

Our study contributes to several strands of literature. First, we contribute to the literature on the effects of macroeconomic news announcements. Extant studies show that macroeconomic news announcements affect various aspects of financial markets, including returns, volatility, and other aspects of market quality.[28] We contribute to the literature by documenting the importance of the information environment surrounding news announcements. We show that uncertainty in the information environment has a significant impact on a set of market quality characteristics surrounding announcement times, and such effects are beyond the impact of the announcement itself.

Second, we add to the literature on the effects of differences of opinion/belief dispersion for financial markets. Recent studies primarily focus on the impact of belief dispersion on stock returns. For example, both Andreou et al. (2018) and Borochin and Zhao (2019) use option-based measures as proxies for heterogeneous beliefs.[29] Both studies document a negative relationship between belief dispersion and future stock returns. Hillert et al. (2018) use the tone of firm-specific newspaper articles to measure journalist disagreement and find that disagreement negatively predicts the next day's market return. We complement these studies by showing that belief dispersion (measure by analyst forecast dispersion in our case) affects equity market quality at times of important news announcements.

Finally, our study is related to the broader literature on the importance of financial analysts as information intermediaries. Lee and So (2017) find that abnormal analyst coverage conveys information about firms' fundamental performance and positively predicts future stock returns. Chen et al. (2017) find that high-quality forecast (higher accuracy and lower forecast dispersion) increases firm-level investment efficiency by reducing both over- and under-investment problems. To et al. (2018) show that higher analyst coverage enhances firms' capital allocation efficiency and leads to higher total factor productivity. Two other recent studies show

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[28] For instance, Bernanke and Kuttner (2005) study how changes in Federal funds rate target affects equity returns. Andersen et al. (2003) and Andersen et al. (2007) study the effect of real-time US macroeconomic news on global stock, bond and foreign exchange markets. Jiang et al. (2011), Evans (2011) and Boudt and Petitjean (2014) study macroeconomic news releases and price jumps. Erenburg and Lasser (2009) and Hautsch et al. (2011) study the effect of macroeconomic news releases on order flow dynamics. Scholtus et al. (2014) study liquidity and volatility around US macroeconomic news releases. Bernile et al. (2016) study informed trading prior to US macroeconomic announcements. Numerous studies have investigated price drifts around macroeconomic announcements (e.g., Lucca and Moench, 2015; Kurov et al., 2019).

[29] Andreou et al. (2018) use dispersion in trading volume across stock options with different moneyness levels to measure investors' heterogeneous expectations. Borochin and Zhao (2019) use the standard deviation of the implied-historical volatility spread, the standard deviation of implied volatility innovations, and the standard deviation of the volatility term structure spread to measure forward-looking belief heterogeneity.

that an exogenous reduction in analyst coverage negatively impacts liquidity and price discovery and increases the profitability of insider trades (e.g., Ellul and Panayides, 2018; Chen et al., 2020). Our study investigates the market impact of analyst forecast dispersion during periods of important information releases and highlights their role, as important information intermediaries, in reflecting the quality of the information environment.

The remainder of this paper is organized as follows. Section 4.2 discusses the theoretical background and related literature. Section 4.3 describes the methodology and the construction of empirical metrics. In section 4.4, we provide a summary of the data used in this study. Section 4.5 reports the main results. We conclude in section 4.6.

4.2. Motivation and related literature

The focus of our paper is to better understand the effect of an uncertain information environment surrounding FOMC announcements on liquidity, trading activity, and price efficiency. In this section, we discuss our theoretical arguments and review the related literature for each of the above aspects.

Theory suggests and empirical studies confirm that informed traders are more active prior to public information releases. McNichols and Trueman (1994) study information acquisition in a model where privately informed traders have short-term investment horizons. In their setting, public announcements stimulate private information acquisition. Short-term informed traders profit by trading on such information prior to the official news release. Bernile et al. (2016) show that E-mini S&P 500 futures' abnormal order imbalances during embargoes of FOMC announcements are in the direction of subsequent policy surprises and predict the market reaction to policy announcements. Their results are consistent with informed trading during FOMC news embargoes due to information leakage. Similarly, both Lucca and Moench (2015) and Kurov et al. (2019) document a price drift before macroeconomic news releases, suggesting that some traders have private information about macroeconomic fundamentals and trade on it prior to the news release.

Given the above evidence, we argue that the degree of information asymmetry depends on the quality of the information environment. This view is supported by extant literature. For instance, using international mutual funds trading data across 63 countries, Maffett (2012) documents more privately informed institutional trading for firms with more opaque information environments.[30] Chen et al. (2015) relate transparent information environments to lower information acquisition costs. They find that a transparent information environment reduces information asymmetry by making information acquisition cheaper. More recently, Cheng et al. (2019) study how the quality of firms' board networks relates to private information leakage and informed short selling. They show that firms with better board networks facilitate information leakage and higher levels of informed trading, but such effects are only observed for firms with less transparent information environments.

In the setting of FOMC announcements, quality of the information environment can be inferred using analyst forecasts. For instance, when analyst forecasts differ from each other regarding the incoming news, the precision of the consensus forecast is reduced. As a result, information becomes imprecise and the quality of the information environment is reduced. Consequently, acquiring private information is costly but more profitable as fewer traders possess equally accurate information. For instance, Diether et al. (2002) show that informed trading is more profitable when analysts disagree with each other. Mele and Sangiorgi (2015) theoretically show that uncertainty-averse investors have stronger incentives to acquire private information in the presence of uncertainty. Stronger incentives to acquire private information imply greater information asymmetry.

Information asymmetry might result in a widening of spreads and greater illiquidity surrounding the FOMC announcement. Kim and Verrecchia (1991) document that information asymmetry prior to news announcements is caused by informed trading as a result of low-quality prior knowledge and information uncertainty. Since news releases resolve ex-ante uncertainty, information asymmetry may no longer respond to analyst forecast dispersion after the FOMC announcement. However, information asymmetry may remain high in the post-announcement period if certain traders are better at processing public information. For instance, Riordan et al. (2013) report an increase in information asymmetry after the arrival of positive and negative news. Brennan et al. (2018) also document informed trading after corporate

[30] The author uses five different proxies for firm-level opacity: analyst following, analyst forecast accuracy, analyst forecast diversity, external auditor's quality, and discretionary earnings smoothing.

announcements.

Despite the widening spreads and greater illiquidity, we predict an increase in trading volume surrounding the FOMC announcement, particularly when the information environment is uncertain. Literature on differences of opinion supports this prediction. Banerjee and Kremer (2010) and Banerjee (2011) combine the standard rational expectations literature with differences of opinion literature and develop dynamic models of trading where traders disagree on how to interpret public information. They find that periods of large but infrequent disagreements are associated with high trading volume. Similarly, Atmaz and Basak (2018) develop a dynamic general equilibrium model where a continuum of investors disagrees with each other. They find that belief dispersion leads to higher trading volume. Higher trading volume can be attributed to informed trading, speculative trading on the news (e.g., Harris and Raviv, 1993; Osambela, 2015; Baker et al., 2016), or liquidity demand of hedgers (Shalen, 1993). On the empirical side, Kandel and Pearson (1995) find that abnormal trading volume surrounding earnings announcements is unrelated to price changes. Instead, they attribute higher trading volume to disagreement among traders regarding how to interpret public signals. Carlin et al. (2014) show that disagreement among Wall Street mortgage dealers about prepayment speeds leads to larger trading volume in the mortgage-backed security market, and such volume increase is induced by uncertainty due to dealers' disagreement. Siganos et al. (2017) use data on positive and negative sentiment from Facebook status updates to construct a daily measure of divergence of sentiment. Using a dataset covering 20 countries, they find that a higher divergence of sentiment is positively related to trading volume and stock price volatility.

Trading volume may be different before and after the FOMC announcement depending on the degree of uncertainty in the information environment. An uncertain information environment creates information asymmetry, which discourages trading by the discretionary liquidity traders (DLTs) prior to the announcement (e.g., Foster and Viswanathan, 1990; Chae, 2005). At the same time, an uncertain environment may attract informed trading. Thus, whether aggregate trading volume increases or decreases before announcements depends on the composition of informed and liquidity traders. Following news announcements, trading volume increases unequivocally. This is because DLTs fulfill their postponed trading needs until after uncertainty is resolved. Informed trading also increases if certain traders have a better capacity to process public information (e.g., Kim and Verrecchia, 1994). Therefore, these theories suggest that the surge in trading volume after the announcements may not be observed in pre-announcement periods.

Finally, we examine the linkage between an uncertain information environment and the informational efficiency of equity prices surrounding FOMC announcement times. We expect a relation between the two since the impact of the information environment on the degree of information asymmetry may further change the incentives to become informed. However, predicting the direction is difficult. On the one hand, information asymmetry discourages market participation and crowds out uninformed traders. With fewer uninformed counterparties to pick off, there is less incentive to obtain private information. Thus, if prior public signals are imprecise, decreased profitability of private information acquisition results in less information production and less informationally efficient prices (e.g., Admati and Pfleiderer, 1988). In such a case, an uncertain ex-ante information environment harms the price efficiency surrounding FOMC announcements. On the other hand, if imprecise ex-ante public signals create high uncertainty among market participants, the incentives to acquire private information might actually increase (e.g., Mele and Sangiorgi, 2015). In such a case, an uncertain information environment may result in more information production and, subsequently, more informative prices. Whether or not an uncertain information environment harms equity price efficiency surrounding news releases remains an empirical question.

4.3. Methodology

4.3.1. Information environment surrounding the FOMC announcement

Financial analysts provide forecasts about major news ahead of its release and contribute directly to the information environment surrounding news announcements. We use dispersion in analyst forecasts to proxy for the degree of uncertainty in the information environment surrounding FOMC announcements. Following Chen et al. (2017) and Hibbert et al. (2020), we calculate forecast dispersion as the cross-sectional standard deviation among analyst forecasts scaled by the absolute average forecast:

$$DISP_t = \frac{\sigma_t(Forecast_i)}{|\mu_t|},^{31} \tag{4.1}$$

where $DISP_t$ is analyst forecast dispersion associated with the FOMC announcement on day t. $\sigma_t(Forecast_i)$ is the cross-sectional standard deviation of analyst forecasts for FOMC announcement t, where $Forecast_i$ is the forecast of analyst i. μ_t is the mean analyst forecast associated with the FOMC announcement on day t.

Additionally, we measure the surprise component of the news. We follow Andersen et al. (2003) and compute the surprise of each announcement as follows:

$$SURP_t = \frac{A_t - E_t}{\sigma(A_t - E_t)}, \tag{4.2}$$

where A_t and E_t are the actual released figure and the ex-ante market expectation calculated as the median forecast for day t's FOMC announcement, respectively. The actual surprise metric is then standardized by σ, which is the sample standard deviation of $A_t - E_t$.

4.3.2. Spreads and trading activity surrounding the FOMC announcement

We use the two spread-based measures, i.e., the quoted and effective spread. We also use the Amihud (2002) illiquidity (ILLIQ) metric. The two spread variables are the quoted and effective spread defined as follows:

$$QS_\tau = (Ask_\tau - Bid_\tau)/m_\tau, \tag{4.3}$$

$$ES_\tau = 2q_\tau(P_\tau - m_\tau)/m_\tau, \tag{4.4}$$

Quoted spread (QS_τ) is the difference between the bid and ask prices and is scaled by

[31] Scaling by the median forecast instead of the mean forecast does not alter our results.

the bid-ask midpoint ($m_\tau = (Ask_\tau + Bid_\tau)/2$) at time τ, and the effective spread (ES_τ) is twice the absolute difference between the transaction price and the bid-ask midpoint and is also scaled by the bid-ask midpoint, where q_τ is a trade direction indicator that equals 1 (-1) for buyer- (seller-) initiated trades.[32] Both spread variables are in basis points relative to the bid-ask midpoint. We then aggregate the intraday spreads into daily measures using time-weighting for QS_τ and volume-weighting for ES_τ, respectively.

The Amihud (2002) $ILLIQ$ metric is defined as the absolute mid-quote return scaled by total dollar volume traded per intraday interval j:

$$ILLIQ_d = log\left[1 + \frac{1}{J}\sum_{j=1}^{J}\frac{10^5|r_{d,j}|}{\$Volume_{d,j}}\right], \tag{4.5}$$

We implement Eq. (4.5) using the 30-second mid-quote return and volume data in day d, where $r_{d,j}$ is the j^{th} 30-second mid-quote return on day d and $\$Volume_{d,j}$ is the traded dollar volume in the j^{th} 30-second intraday interval of day d. Extreme outliers in $ILLIQ_d$ are removed by winsorizing at the 0.5% level on both sides of the distribution.

To capture trading activity, we use the following three variables: dollar volume traded ($\$Volume$), number of trades, and the average trade size (total dollar volume divided by the number of transactions).

4.3.2.1. Inferring the components of the spread

The spreads in the previous section measure the total cost of trading. These costs can be further broken down into several components. The first is information asymmetry cost which represents the compensation to liquidity providers for trading with the informed (Glosten and Milgrom, 1985). The second component reflects costs related to order processing (e.g., fixed settlement fees), while the third component compensates the liquidity provider for maintaining inventory (e.g., digesting persistent order flow). Since the information environment may impact the spread components differently, looking into individual components may further enhance our understanding of the role of the information environment.

[32] Trade direction classification relies on the Lee and Ready (1991) quote rule. All midpoint transactions are discarded.

We follow Lin et al. (1995) (LSB, hereafter) to decompose the spread into its three components: information asymmetry, order processing, and order persistence costs. Compared with other models (e.g., Huang and Stoll, 1997), the LSB model does not rely on the probability of quote reversal to decompose the spread. This is more suitable in a setting where orders are typically highly persistent, and large orders are often split into multiple small quantities to execute gradually. The LSB model has been used in recent empirical studies (e.g., Li et al., 2017; Frijns et al., 2019). Let Q_τ be the quote midpoint at time τ and P_τ be the transaction price. The effective half-spread, z_τ, can be defined as $P_\tau - Q_\tau$ so that $z_\tau > 0$ ($z_\tau < 0$) for a buy (sell) order. The three parameters can then be estimated using the following equations:

$$\Delta Q_{\tau+1} = Q_{\tau+1} - Q_\tau = \lambda z_\tau + e_{\tau+1}, \tag{4.6}$$

$$z_{\tau+1} = \theta z_\tau + \eta_{\tau+1}, \tag{4.7}$$

where λ reflects the information asymmetry and θ reflects the order persistence components, respectively. The disturbance terms $e_{\tau+1}$ and $\eta_{\tau+1}$ are assumed to be uncorrelated. Using Eq. (4.6) and (4.7), and knowing that $z_{\tau+1} = P_{\tau+1} - Q_{\tau+1}$, the temporary price effect for the trade at time τ due to order processing costs can be expressed as a fraction of the effective half-spread, z_τ:

$$\Delta P_{\tau+1} = P_{\tau+1} - P_\tau = (Q_{\tau+1} - Q_\tau) + z_{\tau+1} - z_\tau = -\gamma z_\tau + u_{\tau+1}, \tag{4.8}$$

where $\gamma = 1 - \lambda - \theta$ reflects the order processing cost component of the spread and $u_{\tau+1} = e_{\tau+1} + \eta_{\tau+1}$. The three spread components λ, θ, and γ can then be obtained using the regression models of Eqs. (4.6)-(4.8), respectively. All three components are relative measures as a percentage of the spread.

4.3.3. Price efficiency characteristics surrounding the FOMC announcement

We measure price efficiency by the extent to which prices deviate from a random walk. In a perfectly efficient and frictionless market, prices always reflect the assets' fundamental values and only change when new information arrives. Since new information arrives in a random fashion, price movements should be unpredictable and follow a random walk. Consequently, there should be no return autocorrelation. Furthermore, since prices follow a random walk, the martingale properties imply that the variance of equity returns should grow linearly with the horizon at which returns are observed.

Market inefficiency and frictions, however, lead prices to deviate from a random walk expected in perfectly efficient markets. Such frictions may come from investors' under- and overreaction to information (e.g., Anderson et al., 2013) and delays in impounding new information into prices. These frictions are reasonably more likely in an uncertain information environment. For example, when value-relevant signals are noisy, genuine information can only be partially observed over time and, thus, cannot be impounded into prices instantaneously, leading to serially correlated equity returns. An uncertain information environment may also create uncertainty, which in turn affects investor behavior. In laboratory experiments, Bloomfield et al. (2000) find that when investors are uncertain about the reliability of their information, prices tend to underreact to reliable information and overreact to unreliable information. Such price under- and overreactions may also exacerbate the deviations from a random walk, causing either positive or negative return autocorrelation.

Following Comerton-Forde and Putniņš (2015) and Foley and Putniņš (2016), we consider the following two price efficiency metrics: (i) absolute values of mid-quote return autocorrelations (*AF_efficiency*); and (ii) absolute values of variance ratios (*VR_efficiency*), both of which are calculated using intraday mid-quote prices instead of actual transaction prices to avoid the bid-ask bounce. As both metrics capture deviations from a random walk, they are inverse measures of price efficiency.

The first metric, *AF_efficiency*, captures both positive and negative mid-quote return autocorrelations as a form of price inefficiency. We calculate the absolute values of the first-order mid-quote return autocorrelation for each day at intraday frequencies k:

$$AutoCorrelation_k = \left|Corr(r_{k,n}, r_{k,n-1})\right|, \tag{4.9}$$

where $r_{k,n}$ is the n^{th} mid-quote return measured at intraday frequency k for a given day d. Similar to Comerton-Forde and Putniņš (2015), we estimate Eq. (4.9) using three intraday frequencies, $k \in \{2 \text{ seconds}, 5 \text{ seconds}, 10 \text{ seconds}\}$. We then extract the first principal component of the three daily series and name this metric *AutocorFactor*. This procedure alleviates measurement error issues inherent in individual price efficiency measures by capturing their common variation. We multiply *AutocorFactor* by -1 so that it becomes a price efficiency measure. We label our first informational efficiency metric *AF_efficiency*.

Our second price efficiency metric, *VR_efficiency*, is based on Lo and MacKinlay (1988). If equity prices follow a random walk, the variance of equity returns is linear with respect to the return measurement frequency. In other words, σ_{kl}^2 is k times larger than σ_l^2. The variance ratio test exploits this property and measures price inefficiency as its deviation from this characteristic. We calculate the variance ratio as follows:

$$VarianceRatio_{kl} = \left|\frac{\sigma_{kl}^2}{k\sigma_l^2} - 1\right|, \tag{4.10}$$

where σ_{kl}^2 and σ_l^2 are the kl-second and l-second mid-quote return variances for a given day d. We use three frequency combinations of (l,kl): (5 seconds, 10 seconds), (2 seconds, 10 seconds), (5 seconds, 30 seconds)[33] and calculate the first principal component to capture the common variations in the three individual variance ratio measures, which we name *VarRatioFactor*. If price is informationally efficient, then this metric is close to zero. A higher number indicates lower price efficiency. Again, we multiply *VarRatioFactor* by -1 to turn it into a price efficiency metric. We label our second informational efficiency metric *VR_efficiency*.

4.4. Data and sample description

This study uses two different datasets. The first dataset contains FOMC announcements and analysts' forecasts, and the second dataset records transaction data. Below, we describe the sample, properties of analysts' forecasts, as well as the two ETFs used in our study.

[33] Although these choices are arbitrary, our results do not change qualitatively when we use other frequency combinations.

4.4.1. FOMC announcements and analyst forecasts

The FOMC schedules eight meetings per year to review its current monetary policy and announce the target interest rate for the following six weeks. We collect information for the date and release time of each FOMC meeting from the meeting calendars on the Federal Reserve website. To measure analyst forecast dispersion and announcement surprises, we collect analyst forecast data and actual announced figures from Refinitiv Eikon. Refinitiv surveys major financial institutions prior to each scheduled FOMC meeting to provide market consensus. Our sample is from July 1, 2015 to December 16, 2020. We start from July 2015 as it is the first month when Eikon has uninterrupted survey data so we can meaningfully estimate analyst forecast variables.[34]

Table 4.1 summarizes the FOMC announcements in our sample, along with the associated analyst forecasts. There are in total 43 scheduled FOMC announcements in our sample, all of which are scheduled at 2:00 pm (Eastern Time).[35] Panel B shows that there are, on average, 101 financial analysts providing forecasts for each FOMC announcement. Although analysts' forecasts tend to be accurate in aggregate, we observe some degree of disagreement among them. There are 13 (out of 43) such announcements where analysts disagree with each other regarding the new target Fed Funds rate. The highest degree of analyst forecast dispersion is 0.56 and the average sample forecast dispersion is 0.03.

Table 4.1
US FOMC announcements and analyst forecasts.

Panel A: US FOMC announcements

Sample size	Release time (EST)	Source	Frequency	Obs.
2015/07/01-2020/12/16	14:00	Federal Reserve	Six-weekly	43
Non-announcement days				1334
Sample days				1377

Panel B: Analyst forecast characteristics

Sample size	Dispersion (DISP)	Surprise (SURP)	Analyst coverage	Non-zero dispersion
2015/07/01-2020/12/16	0.030	-0.154	101	13

This table provides summary information about the FOMC announcements and the associated analyst forecasts in our sample from July 1, 2015 to December 16, 2020. Panel A reports the announcement time, announcement frequency, and the total number of announcements. Panel B reports statistics associated with analyst forecasts, including average values of analyst forecast dispersion, analyst coverage, and news surprises, as well as announcements with non-zero dispersion and surprises.

[34] Prior to July 2015, interest rates were near their zero lower bound and no surveys were conducted.
[35] We do not consider unscheduled and cancelled FOMC meetings.

4.4.2. Intraday transaction-level data

We focus on the two most actively traded ETFs on the NYSE Arca: SPDR S&P 500 Trust ETF (ticker: SPY) and iShares Russell 2000 ETF (ticker: IWM). SPY tracks the S&P 500 stock market index, which represents the large-cap US equities. The IWM tracks the Russell 2000 Index, which is a small-cap index. Hence, our two ETFs represent the US equity market. The two ETFs are highly liquid and more actively traded compared to other ETFs, which allows for a more accurate assessment of the market reactions to FOMC announcements.

We obtain intraday transaction-level data for the two ETFs from Refinitiv Tick History in DataScope Select. Transaction-level data consolidates the best bid and ask quotes and the corresponding depth as well as all transactions prices from various US exchanges with a microsecond timestamp. We only include data within the NYSE's normal trading hours between 9:30 a.m. and 4:00 p.m. and remove the first and last 10 minutes of each trading day to avoid the impact of market opening and closing. If multiple transactions are observed with the same timestamp, we treat them as a single transaction resulting from one market order interacting with multiple resting limit orders. We then replace such transactions with a single trade record based on the volume-weighted average price and the aggregate volume. We follow Chordia et al. (2001) to clean the raw transaction data and filter out outliers: (a) Quoted bid-ask spread (difference between the ask and bid prices) > \$5; (b) Effective Spread (twice the absolute difference between the transaction price and bid-ask midpoint)/Quoted Spread > 4; (c) Quoted Spread/mid-quote Price > 25%. Finally, we follow Lee and Ready (1991) and classify trades as buyer- (seller-) initiated if transaction prices are above (below) the midpoint of the prevailing bid and ask quotes. Trades that occur at the bid-ask midpoints are treated as undetermined.

Panel A of Table 4.2 reports descriptive statistics for the SPY. In our sample, SPY has an average quoted (effective) spread of about 0.43 (0.44) basis points. The median quoted (effective) spread is of similar magnitudes, being 0.42 (0.43) basis points. In terms of trading activity, an average trading day has around 152 thousand transactions with a total of 56.76 million shares and a total value of \$14.31 billion. The average trade size is roughly \$0.1 million per trade. The median trading day has fewer transactions with around 117 thousand trades with a total of 46.34 million shares and a total worth \$12.13 billion. The median trade size is also

$0.1 million per transaction and is comparable to its mean value. During the sample period, the price of SPY ranges from the minimum of $182.60 to the maximum of $370.03. The average daily volatility is 93.39 basis points.

Panel B provides summary statistics for the IWM. IWM has much wider spreads, with an average sample quoted (effective) spread of 0.83 (0.79) basis points. The median quoted (effective) spread is 0.76 (0.75) basis points, which is wider than the spread of SPY. As for trading activity, there are, on average, 53 thousand transactions of about 17.97 million shares each day and a total value of $2.45 billion. We find that traders of IWM tend to use smaller orders on average, relative to traders of SPY. The average trade size is less than $0.05 million per trade, which is only half the average trade size of SPY. The price of IWM is roughly half the price of SPY, but its returns are more variable, evident by a larger daily volatility of 119.21 basis points.

Table 4.2

Descriptive statistics of two ETFs.

Variable	Mean	Std	Min	Median	Max
Panel A: SPY					
QSpread (bps)	0.43	0.08	0.31	0.42	1.23
ESpread (bps)	0.44	0.08	0.27	0.43	0.91
Number of trades (thousands)	152.74	127.31	36.40	117.62	1380.74
Volume (millions)	56.76	33.93	13.44	46.34	318.74
$Volume (billions)	14.31	7.84	4.26	12.13	66.61
$Volume per trade (thousands)	103.03	24.70	38.90	100.64	246.91
Price	261.45	43.65	182.60	265.25	370.03
Daily volatility (bps)	93.39	72.57	23.70	73.42	514.96
Panel B: IWM					
QSpread (bps)	0.83	0.50	0.59	0.76	14.81
ESpread (bps)	0.79	0.18	0.51	0.75	2.97
Number of trades (thousands)	53.64	29.01	13.06	44.96	226.49
Volume (millions)	17.97	8.66	3.23	15.81	70.30
$Volume (billions)	2.45	0.99	0.54	2.22	8.28
$Volume per trade (thousands)	48.43	11.51	20.85	48.08	117.38
Price	141.37	19.52	94.55	145.80	193.91
Daily volatility (bps)	119.21	78.32	38.23	103.09	570.15

This table reports descriptive statistics on the two ETFs used in this study. QSpread and ESpread are the quoted and effective spread defined in section 3.2 and are expressed in basis points. Number of trades is the total number of transactions in a trading day. Volume and $Volume are the daily trading volume in the number of shares and in dollars, respectively. $Volume per trade is the average trade size in dollars. For presentation, all statistics related to the trading activity are expressed in either thousands, millions, or billions. Price is the daily volume-weighted average price. Daily volatility is the daily return volatility calculated using a one-month rolling window surrounding each day in the sample. SPY is the ticker name for SPDR S&P 500 Trust ETF, and IWM represents iShares Russell 2000 ETF. The sample is from July 1, 2015 to December 16, 2020.

4.5. Empirical analyses

We first determine the suitable intraday window to calculate the set of market quality metrics for the subsequent analysis. Our formal empirical analysis starts with the investigation of how bid-ask spreads surrounding FOMC announcements are affected by the degree of uncertainty in the information environment. We then decompose the spread into several components to further understand what drives the main result. Next, we study the impact of an uncertain information environment on trading activity surrounding FOMC announcement times. Finally, we empirically test competing theories on how information uncertainty affects the informational efficiency of equity prices.

4.5.1. Event window and market quality metrics

Literature on macroeconomic news announcements documents that financial markets adjust very quickly to new information (e.g., Scholtus et al., 2014; Bernile et al., 2016). Therefore, we need an appropriate intraday event window to capture the short-lived market impact of FOMC announcements. To determine the optimal size of such event windows, we assess the period in which spreads react to the FOMC announcements. In Fig. 4.1, we plot, for both ETFs, the abnormal bid-ask spread (i.e., the difference in bid-ask spreads on days with and without FOMC announcements) using a one-hour window surrounding the FOMC announcement times. For both ETFs, we find a strong market reaction to the FOMC announcements. Spreads start to increase around 5 minutes prior to the FOMC announcement time and peak exactly at 2:00 pm when the announcement is made. The abnormal bid-ask spread is persistent and lasts for around 10 minutes before it reverts back to zero. This observation is consistent with Scholtus et al. (2014) and Frijns et al. (2019) who show that spreads react in the minutes surrounding announcements. Given the short window in which we observe strong spread reactions, we focus our main empirical analyses on an intraday event window from 5 minutes before to 10 minutes after each FOMC announcement.

Table 4.3 reports the summary statistics of various market quality metrics based on the 15-minute event window. As expected, most market quality metrics react strongly to the FOMC announcements. Both quoted and effective spread increase on days with FOMC announcements, suggesting widening spreads surrounding FOMC announcements. Further decomposing the spread into its components reveals a significant increase in the information asymmetry component and a significant decrease in the order processing cost component. This suggests that the increase in spreads surrounding FOMC announcements is at least partially driven by the increase in information asymmetry. Despite the widening spreads, trading volume increases. Both traded volume (in dollar and number of shares) and the number of transactions increase. Equally important, we observe that the informational efficiency of ETF prices also deteriorates as both metrics decrease on days with announcements.

We also investigate the market reaction in the period before and after the FOMC announcement separately. We note similar patterns for the spreads and price efficiency metrics in the two periods. Spreads increase and informational efficiency deteriorates in both periods, which is consistent with the overall pattern. We observe that the underlying spread components react differently before and after FOMC announcements. The information asymmetry component decreases initially and then increases after FOMC announcements, whereas the order processing cost component increases prior to FOMC announcements and decreases afterward. In addition, we find that the increase in trading volume during the 15-minute event window is primarily driven by the increase in trading volume following FOMC announcements. Overall, Table 4.3 indicates that the equity market reacts to the FOMC announcement.

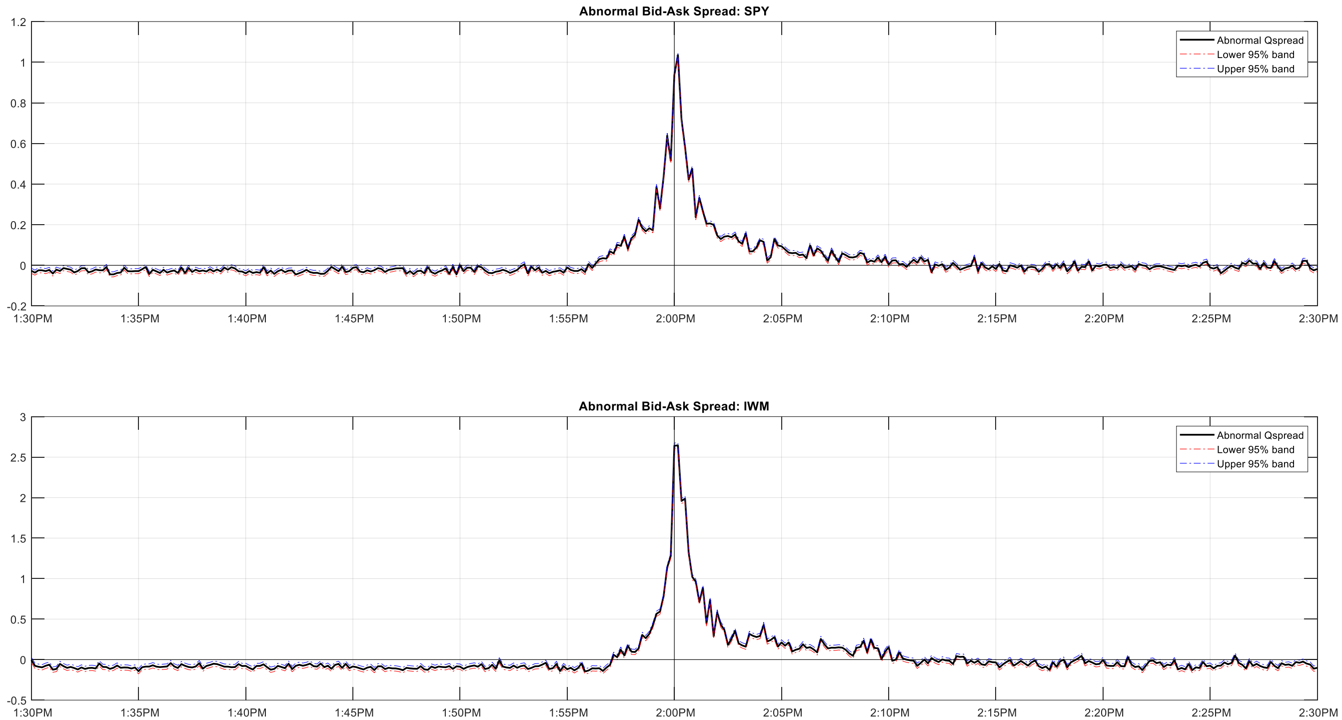

Fig. 4.1. Abnormal bid-ask spread surrounding FOMC announcements
This figure plots the abnormal bid-ask spread (i.e., the difference in bid-ask spreads on days with and without FOMC announcements) of the two ETFs 30 minutes before and after the official FOMC announcement time at 2:00 p.m. (EST), along with the 95% confidence bands. The upper panel presents the abnormal bid-ask spread for SPY, and the lower panel presents the abnormal bid-ask spread for IWM. The plots are sampled at a 10-second frequency and averaged across the sample, which is from July 1, 2015 to December 16, 2020.

Table 4.3

Key market quality metrics surrounding the FOMC announcement.

	Full 15-min window				5 minutes before				10 minutes after			
	NA	A	Mean Diff (A-NA)	*t*-stat	NA	A	Mean Diff (A-NA)	*t*-stat	NA	A	Mean Diff (A-NA)	*t*-stat
Panel A: SPY												
QSpread (bps)	0.434	0.582	0.148***	8.43	0.433	0.575	0.142***	8.41	0.434	0.587	0.153***	8.25
ESpread (bps)	0.441	0.668	0.227***	10.63	0.432	0.581	0.149***	7.28	0.439	0.678	0.239***	10.54
ILLIQ	0.017	0.010	-0.006	-0.64	0.019	0.011	-0.008	-0.64	0.022	0.013	-0.009	-0.61
Information asymmetry cost (λ)	0.203	0.242	0.038***	3.05	0.206	0.175	-0.031**	-2.34	0.203	0.243	0.040***	3.14
Order persistence cost (θ)	0.513	0.520	0.007	0.46	0.494	0.477	-0.017	-0.95	0.510	0.518	0.008	0.50
Order processing cost (γ)	0.284	0.238	-0.046***	-4.24	0.301	0.348	0.047***	3.50	0.287	0.239	-0.048***	-4.25
$Volume (billions)	0.483	1.469	0.986***	16.26	0.138	0.172	0.035**	1.96	0.345	1.297	0.952***	19.77
Volume (millions)	1.907	6.035	4.128***	16.04	0.547	0.695	0.148**	2.03	1.360	5.340	3.981***	19.31
Number of trades (thousands)	5.14	14.07	8.94***	11.17	1.50	1.62	0.12	0.50	3.64	12.46	8.82***	14.75
$Volume per trade (thousands)	104.6	109.9	5.30	0.39	100.3	108.2	7.90	0.57	105.4	109.9	4.43	0.33
AF_efficiency	0.113	-0.800	-0.914***	-6.67	-0.016	-0.386	-0.369**	-2.37	0.082	-0.599	-0.681***	-4.93
VR_efficiency	0.082	-0.343	-0.426***	-3.20	0.033	-0.593	-0.626***	-4.29	0.060	-0.216	-0.276**	-1.99
Panel B: IWM												
QSpread (bps)	0.868	1.196	0.327***	3.54	0.866	1.081	0.215***	2.82	0.870	1.257	0.387***	3.72
ESpread (bps)	0.804	1.119	0.315***	3.14	0.763	0.962	0.198***	3.56	0.805	1.139	0.334***	3.29
ILLIQ	0.148	0.095	-0.053*	-1.85	0.158	0.126	-0.033	-1.17	0.149	0.096	-0.054*	-1.76
Information asymmetry cost (λ)	0.331	0.356	0.025*	1.80	0.341	0.253	-0.088***	-4.48	0.334	0.364	0.030**	2.15
Order persistence cost (θ)	0.459	0.464	0.005	0.29	0.435	0.419	-0.016	-0.85	0.454	0.457	0.003	0.18
Order processing cost (γ)	0.211	0.181	-0.030***	-2.63	0.223	0.328	0.105***	6.88	0.212	0.179	-0.033***	-2.68
$Volume (billions)	0.077	0.201	0.124***	14.83	0.024	0.034	0.010***	3.72	0.053	0.167	0.113***	17.62
Volume (millions)	0.565	1.478	0.914***	13.71	0.172	0.241	0.069***	3.26	0.393	1.237	0.844***	16.34
Number of trades (thousands)	1.72	3.80	2.08***	10.58	0.52	0.63	0.10*	1.79	1.19	3.17	1.98***	13.29
$Volume per trade (thousands)	62.317	53.818	-8.499	-0.10	45.820	52.748	6.929**	2.28	62.362	53.388	-8.974	-0.11
AF_efficiency	0.248	0.030	-0.218*	-1.87	0.061	-0.049	-0.110	-0.76	0.200	0.054	-0.146*	-1.67
VR_efficiency	0.198	-0.054	-0.252**	-2.04	0.124	-0.119	-0.243*	-1.78	0.142	0.028	-0.114	-0.88

This table reports the averages of a battery of market quality metrics on days with and without FOMC announcements, along with their differences (and the associated *t*-statistics). All variables are calculated using three intraday event windows: 5 minutes prior to the FOMC announcement, 10 minutes after the FOMC announcement, and 15 minutes surrounding the FOMC announcement (5 minutes before and 10 minutes after). QSpread and ESpread are the quoted and effective spread expressed in basis points. ILLIQ is the Amihud (2002) illiquidity metric based on 30-second intraday returns and volume data. We also decompose the spread into its three components, i.e., Information asymmetry (λ), Order persistence (θ), and Order processing cost (γ), following Lin et al. (1995) using Eqs. (4.6)-(4.8). All three spread components are expressed in percentage. $Volume and volume are the traded volume in dollars and number of shares, respectively. Number of trades is the total number of transactions in the event window. $Volume per trade is the average trade size in dollars. For presentation, all statistics related to the volume are expressed in either thousands, millions, or billions. AF_efficiency and VR_efficiency are the two high-frequency price efficiency metrics based on Eqs. (4.9) & (4.10). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. SPY is the ticker name for SPDR S&P 500 Trust ETF, and IWM represents iShares Russell 2000 ETF. The sample is from July 1, 2015 to December 16, 2020.

4.5.2. Information environment and spreads surrounding the FOMC announcement

We first analyze the impact of an uncertain information environment surrounding the FOMC announcement on market liquidity. We consider three high-frequency metrics: quoted spread, effective spread, and the Amihud (2002) ILLIQ measure. To formally study the effects, we run the following regression model:

$$LIQ_d = \alpha + \beta_0 \cdot DISP_d + \beta_1 \cdot |SURP|_d + \beta_2 \cdot FOMC_d + \textstyle\sum_i \gamma_i \cdot Controls_{i,d} + \epsilon_d \quad , \tag{4.11}$$

where LIQ_d is one of the three spread measures on day d (i.e., QS_d, ES_d, and $ILLIQ_d$). The key variable of interest is $DISP_d$, which measures the degree of disagreement among financial analysts and captures the degree of uncertainty in the information environment surrounding the FOMC announcement. $|SURP|_d$ accounts for the surprise component of each FOMC announcement. Both $DISP_d$ and $|SURP|_d$ are zero on days without FOMC announcements. We also control for several variables known to affect market quality, such as price (in logs), trading volume (in logs), and return volatility (standard deviation of intraday mid-quote returns). For these variables, we use lagged values to avoid endogeneity issues. We also include lagged dependent variables as an additional control variable. Finally, we isolate the impact of the FOMC announcement itself by further adding an indicator variable that equals one on days with FOMC announcements and zero otherwise. This inclusion allows us to investigate the impact of the information environment that is orthogonal to the FOMC announcement effect.

Table 4.4 reports the regression estimates of the impact of the information environment on spreads surrounding the FOMC announcement. Turning first to the 15-minute event window, we observe strong bid-ask spread and illiquidity reactions to the FOMC announcement for both ETFs, as shown by the significant positive coefficients of the FOMC indicator. Consistent with Table 4.3, this suggests that the FOMC announcement increases the spreads. More importantly, we find that the impact of analyst forecast dispersion is not subsumed by the FOMC announcement effect itself. For both ETFs, the coefficients on DISP are also positive and

Table 4.4

Effects of the information environment on spreads surrounding the FOMC announcement.

Panel A: SPY	Full 15-minute window			5 minutes before			10 minutes after		
	QSpread	**ESpread**	**ILLIQ**	**QSpread**	**ESpread**	**ILLIQ**	**QSpread**	**ESpread**	**ILLIQ**
DISP	0.106***	0.318***	0.041**	0.019	0.148***	0.030*	0.148***	0.336***	0.032**
	(4.66)	(7.08)	(2.03)	(0.66)	(4.39)	(1.73)	(5.87)	(6.46)	(2.12)
|SURP|	-0.019***	-0.007*	0.003*	-0.016***	-0.016***	-0.001***	-0.020***	-0.007*	0.003**
	(-5.80)	(-1.78)	(1.84)	(-3.56)	(-3.16)	(-2.59)	(-6.26)	(-1.69)	(2.34)
FOMC dummy	0.163***	0.234***	0.031**	0.158***	0.161***	0.006	0.167***	0.245***	0.023**
	(8.35)	(10.09)	(2.21)	(5.89)	(5.17)	(1.21)	(8.32)	(10.12)	(1.96)
Lag price	-0.268***	-0.236***	0.018*	-0.276***	-0.283***	0.023**	-0.264***	-0.224***	0.027**
	(-10.84)	(-4.58)	(1.80)	(-12.59)	(-6.07)	(2.46)	(-9.79)	(-4.07)	(2.43)
Lag $Volume	-0.030**	-0.009	-0.032**	-0.029**	0.000	-0.032**	-0.030**	-0.008	-0.023**
	(-2.33)	(-0.61)	(-2.36)	(-2.11)	(-0.00)	(-2.02)	(-2.34)	(-0.48)	(-2.47)
Lag volatility	0.057***	0.027***	0.011***	0.054***	0.028***	0.013***	0.059***	0.026***	0.012***
	(5.22)	(2.89)	(3.35)	(5.24)	(2.85)	(3.33)	(5.04)	(2.86)	(3.47)
Lag y	0.031	0.370***	-0.400	0.035	0.306***	-0.321	0.029	0.383***	-0.217
	(0.41)	(3.11)	(-0.91)	(0.54)	(2.76)	(-0.57)	(0.35)	(3.07)	(-0.50)
Adj-R^2	36.93%	35.35%	8.43%	38.44%	38.31%	6.25%	34.17%	31.77%	2.17%
Obs.	1377	1377	1377	1377	1377	1377	1377	1377	1377
Panel B: IWM									
DISP	2.168***	1.414***	0.107***	1.034***	0.247	0.096	2.735***	1.652***	0.092***
	(20.77)	(30.71)	(3.53)	(10.29)	(1.59)	(1.53)	(25.30)	(24.12)	(3.20)
|SURP|	-0.021	-0.001	-0.00	-0.009	-0.012*	-0.020***	-0.026*	-0.002	0.003
	(-1.54)	(-0.11)	(-0.26)	(-0.71)	(-1.76)	(-4.98)	(-1.89)	(-0.21)	(1.56)
FOMC dummy	0.300***	0.296***	0.096***	0.221***	0.218***	0.011	0.342***	0.309***	0.103***
	(4.36)	(6.73)	(3.05)	(3.36)	(5.63)	(0.58)	(4.72)	(6.61)	(3.02)
Lag price	-0.906**	-0.644***	-0.052**	-0.906**	-0.630***	0.015	-0.907**	-0.633***	-0.046*
	(-2.22)	(-5.83)	(-2.11)	(-2.33)	(-6.99)	(0.55)	(-2.17)	(-5.74)	(-1.70)
Lag $Volume	-0.070	-0.015	-0.142***	-0.085	0.020	-0.079***	-0.063	-0.005	-0.127***
	(-0.77)	(-0.24)	(-4.36)	(-0.89)	(0.52)	(-3.96)	(-0.69)	(-0.07)	(-4.20)
Lag volatility	0.101***	0.041***	0.049***	0.120***	0.046***	0.059***	0.091***	0.037**	0.050***
	(2.83)	(2.71)	(6.71)	(3.03)	(3.10)	(5.86)	(2.66)	(2.55)	(6.38)
Lag y	0.008	0.144*	-0.049	0.012	0.175*	0.020	0.007	0.154*	-0.055
	(0.47)	(1.67)	(-1.03)	(0.57)	(1.75)	(1.00)	(0.41)	(1.90)	(-1.07)
Adj-R^2	1.37%	4.79%	26.60%	1.45%	16.52%	14.97%	1.39%	4.88%	20.16%
Obs.	1377	1375	1375	1377	1371	1371	1377	1375	1375

This table reports regression estimates based on a 15-minute intraday event window surrounding the FOMC announcement. The dependent variables are the different spread measures defined in section 3.2. DISP is the dispersion in analyst forecasts. SURP is the surprise component of the FOMC announcement. FOMC dummy is a binary variable that equals one on days with FOMC announcements and zero otherwise. Lag price and lag $Volume are the volume-weighted average price and total dollar volume traded from the previous trading day, both of which are in logs. Lag volatility is the previous trading day's return volatility. Lag y is the lagged value of the corresponding dependent variable from the previous day. Standard errors are the Newey–West standard errors with *t*-statistics reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample comprises the two most liquid exchange-traded funds (ETFs): SPY in panel A and IMW in panel B from July 1, 2015 to December 16, 2020.

significant for the three liquidity metrics, suggesting that greater disagreement among financial analysts further lowers liquidity surrounding announcement times. Our results for the spread measures are in line with Sadka and Scherbina (2007), who find that stock portfolios with higher analyst disagreement have a larger price impact and effective spread. Comparing coefficients (and their respective t-statistics) of DISP between the two ETFs suggests that the small-cap ETF is more prone to the impact of an uncertain information environment. The impact of news surprises is not consistent across different spread measures and is insignificant for the IWM. In terms of control variables, higher (lagged) trading volume and lower (lagged) return volatility tend to improve liquidity. Price tends to be negatively correlated with spread measures because as price increases, its spread decreases.[36]

Next, we split the 15 minute-window into 5-minute prior to and 10-minute after the FOMC announcement to examine the impact of the information environment that may be different in both periods. Our results indicate that the patterns are consistent in both event windows. Analyst forecast dispersion tends to lower liquidity surrounding FOMC announcements, and such effects are incremental to the FOMC announcement effect. Despite qualitatively similar results, we observe a stronger impact of analyst forecast dispersion on liquidity in the post-announcement window for both ETFs. The difference in magnitudes could be due to different spread components that react differently before and after news releases. For instance, the information asymmetry component may be lower in the post-announcement period as uncertainty gets resolved. At the same time, trading volume may increase following the announcements, leading to higher order processing (i.e., inventory management) costs. This will be explored further in the next section.

4.5.2.1. Impact on different spread components

In this section, we investigate the impact of an uncertain information environment on

[36] The impact of analyst forecast dispersion is also significant in economic terms. For instance, in an unreported table where we replace the effective spreads in bps by effective spreads in dollars, we find that a one standard deviation in analysts' forecasts translates to an increase in transaction cost by 0.38 (0.41) cents for SPY (IWM) per round-trip trade during the FOMC announcement periods. Given that the in-sample average effective spread is only 1.14 (1.13) cents for SPY (IWM), this increase in transaction costs is economically meaningful.

the spread components obtained using the LSB model. More specifically, we replace the dependent variable in Eq. (4.11) with either information asymmetry, order persistence, or order processing costs.

In Table 4.5, we report regression estimates for each of the three spread components separately. In terms of the information asymmetry component, we report significant positive coefficients of DISP for IWM in the 15-minute event window. This is consistent with the argument that analyst disagreement creates uncertainty about the upcoming news, which results in an uncertain information environment. Uncertainty creates incentives to acquire additional information about the forthcoming news, thus, increasing information asymmetry surrounding the FOMC announcement.

Given that uncertainty is resolved upon the news release, this informational impact may be different in the pre- and post-announcement event window. The empirical results from the two separate event windows confirm this prediction. For both ETFs, we find that analyst forecast dispersion significantly increases the level of information asymmetry only for the period prior to the FOMC announcement. This is because uncertainty created by analyst disagreement stimulates private information acquisition about the impending news prior to its public release (see, e.g., Kim and Verrecchia, 1991; McNichols and Trueman, 1994). Analyst forecast dispersion does not affect the level of information asymmetry after the FOMC announcement since uncertainty created by analyst disagreement is resolved once the news is publicly released. Therefore, post-announcement information asymmetry does not respond to analyst forecast dispersion. In other words, the informational impact of analyst forecast dispersion we observe in the 15-minute event window is driven by its pre-announcement effect.

Importantly, we make sure that the above informational impact that we attribute to analyst forecast dispersion is not simply due to the FOMC announcement effect. Similar to Table 4.4, we include a dummy variable that captures the effects of the FOMC announcement. We observe positive and significant coefficients of the FOMC dummy for both ETFs in the 15-minute event window, suggesting that the FOMC announcement increases information asymmetry itself. A more interesting and consistent pattern is that the announcement effect is different in the pre- and post-announcement event window. Specifically, information asymmetry decreases shortly before the FOMC announcement and increases afterward. A decrease in information asymmetry prior to the announcement can be due to postponed trading from discretionary liquidity traders (see, e.g., Foster and Viswanathan, 1990; Chae, 2005) who avoid adverse selection risks associated with the FOMC announcement. Information asymmetry increases after the FOMC announcement because some traders are better at processing public information (e.g., Kim and Verrecchia, 1994; Riordan et al., 2013). We also find that FOMC announcement surprise increases information asymmetry in the period after announcements. News surprise can be interpreted as unexpected information shocks that may lead to some traders gaining a temporary informational advantage for being able to process unexpected information faster than others. We, therefore, note that the overall FOMC announcement effect in the 15-minute event window is driven by its post-announcement effect.

It is worth highlighting that the FOMC announcement effect is different from the impact of the information environment. For instance, although we find that the pre-announcement information asymmetry tends to decrease, an uncertain information environment (measured by analyst forecast dispersion) still increases the level of information asymmetry prior to the FOMC announcement. We also note that the FOMC announcement effect subsumes the effect of the information environment in the post-announcement period.[37] This suggests that the post-announcement degree of information asymmetry is not directly related to the degree of pre-announcement uncertainty in the information environment.

In terms of the other two spread components, we show that analyst forecast dispersion increases the order processing cost component but decreases the order persistence component. These effects are incremental to and different from the FOMC announcement effect. We also find that the pre- and post-announcement effects are different. Prior to the FOMC announcement, analyst forecast dispersion reduces the order processing cost component but increases the order persistence component (although order persistence is insignificant for IWM). An increase in order persistence indicates directional trading that can be attributed to speculation on impending news. In the post-announcement period, analyst forecast dispersion increases the order processing cost component but reduces the order persistence component. The reduction in order persistence can be explained by the presence of discretionary liquidity

[37] In an unreported table where we remove the FOMC announcement dummy, we find positive and significant coefficients of analyst forecast dispersion both before and after the announcement time.

Table 4.5

Effects of the information environment on each % component of the spread surrounding the FOMC announcement.

Panel A: SPY	Full 15-minute window			5 minutes before			10 minutes after		
	Information asymmetry(%)	**Order persistence(%)**	**Order processing(%)**	**Information asymmetry(%)**	**Order persistence(%)**	**Order processing(%)**	**Information asymmetry(%)**	**Order persistence(%)**	**Order processing(%)**
DISP	-0.002	-0.058***	0.067***	0.076***	0.027**	-0.097***	-0.009	-0.061***	0.076***
	(-0.26)	(-5.62)	(6.37)	(7.48)	(1.98)	(-6.26)	(-1.28)	(-5.57)	(6.80)
|SURP|	0.007***	-0.015***	0.013***	0.013***	-0.020***	0.012***	0.010***	-0.016***	0.011***
	(6.32)	(-7.50)	(6.02)	(7.95)	(-8.12)	(4.04)	(8.94)	(-7.75)	(4.91)
FOMC dummy	0.042***	0.018**	-0.059***	-0.029***	-0.006	0.037***	0.043***	0.019**	-0.061***
	(6.80)	(2.00)	(-6.43)	(-3.16)	(-0.52)	(2.59)	(6.95)	(1.99)	(-6.46)
Lag price	0.059***	-0.049***	0.042***	0.042***	-0.070***	0.073***	0.062***	-0.062***	0.047***
	(5.82)	(-3.75)	(3.62)	(3.49)	(-4.10)	(4.97)	(5.92)	(-4.38)	(3.94)
Lag $Volume	0.025***	-0.012**	-0.015**	0.026***	-0.013*	-0.013	0.025***	-0.011*	-0.016**
	(5.44)	(-2.24)	(-2.28)	(4.41)	(-1.73)	(-1.60)	(5.37)	(-1.81)	(-2.36)
Lag volatility	0.004**	-0.002	0.000	0.005*	0.004	-0.007*	0.005**	-0.003	-0.000
	(2.25)	(-1.15)	(0.02)	(1.74)	(1.24)	(-1.90)	(2.38)	(-1.18)	(-0.08)
Lag y	0.779***	0.879***	0.664***	0.735***	0.842***	0.684***	0.774***	0.866***	0.662***
	(27.60)	(33.03)	(10.96)	(21.22)	(24.59)	(9.72)	(26.46)	(29.76)	(10.73)
Adj-R^2	69.47%	72.96%	33.78%	55.69%	58.69%	27.77%	68.44%	68.76%	31.64%
Obs.	1376	1376	1376	1374	1374	1374	1376	1376	1376
Panel B: IWM									
DISP	0.035***	-0.079***	0.049***	0.091***	0.009	-0.097***	0.014	-0.084***	0.075***
	(3.70)	(-9.31)	(5.47)	(6.47)	(0.29)	(-2.94)	(1.23)	(-8.78)	(8.37)
|SURP|	0.013***	-0.017***	0.008***	0.019***	-0.010***	-0.010***	0.013***	-0.022***	0.013***
	(7.31)	(-10.32)	(6.78)	(7.22)	(-3.03)	(-3.32)	(6.61)	(-12.34)	(9.59)
FOMC dummy	0.024***	0.009	-0.034***	-0.092***	-0.016	0.107***	0.030***	0.009	-0.039***
	(3.42)	(1.12)	(-4.86)	(-7.10)	(-0.94)	(5.68)	(3.73)	(1.06)	(-4.92)
Lag price	0.129***	-0.090***	-0.006	0.086***	-0.070***	-0.018	0.139***	-0.093***	-0.014
	(6.64)	(-4.95)	(-0.43)	(3.36)	(-2.76)	(-1.01)	(6.40)	(-4.66)	(-0.98)
Lag $Volume	0.031***	-0.027***	-0.008	0.038***	-0.026***	-0.013	0.030***	-0.025***	-0.010
	(4.53)	(-4.18)	(-1.32)	(4.22)	(-2.88)	(-1.49)	(4.24)	(-3.56)	(-1.43)
Lag volatility	0.018***	-0.002	-0.012***	0.015***	-0.003	-0.012***	0.019***	-0.002	-0.014***
	(5.81)	(-0.98)	(-4.57)	(3.81)	(-1.07)	(-3.81)	(5.77)	(-0.78)	(-4.63)
Lag y	0.754***	0.844***	0.540***	0.807***	0.805***	0.667***	0.754***	0.842***	0.530***
	(21.45)	(29.45)	(10.95)	(18.87)	(19.68)	(10.55)	(19.90)	(25.80)	(10.04)
Adj-R^2	57.38%	58.79%	14.65%	47.79%	41.82%	14.36%	54.36%	53.94%	12.97%
Obs.	1367	1367	1367	1366	1366	1366	1366	1366	1366

This table reports regression estimates based on a 15-minute intraday event window surrounding the FOMC announcement. The dependent variables are the three spread components defined in Section 4.3.2.1 and are expressed in percentage. DISP is the dispersion in analyst forecasts. SURP is the surprise component of the FOMC announcement. FOMC dummy is a binary variable that equals one on days with FOMC announcements and zero otherwise. Lag price and lag $Volume are the volume-weighted average price and total dollar volume traded from the previous trading day, both of which are in logs. Lag volatility is the previous trading day's return volatility. Lag y is the lagged value of the corresponding dependent variable from the previous day. Standard errors are the Newey–West standard errors with *t*-statistics reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample comprises the two most liquid exchange-traded funds (ETFs): SPY in panel A and IMW in panel B from July 1, 2015 to December 16, 2020.

traders who postpone their random liquidity demands until the resolution of uncertainty.

For other variables, we note that FOMC announcement surprise tends to increase information asymmetry and order processing costs but reduces order persistence. Higher prices and greater trading volume tend to increase information asymmetry and reduce the persistence of order flow. Volatility also increases information asymmetry. We also find strong persistence in all three spread components as the coefficients of lag y are all positive and statistically significant.

Overall, our findings suggest that the positive impact of analyst forecast dispersion on spreads prior to the FOMC announcement is primarily driven by its impact on information asymmetry. The post-announcement effect of analyst forecast dispersion on spreads, however, is due to its impact on the order processing cost component.

4.5.3. Information environment and trading surrounding the FOMC announcement

In this section, we examine how an uncertain information environment affects trading activity surrounding the FOMC announcement. We use the following three variables related to trading activity: dollar trading volume, number of transactions, and average trade size (total dollar trading volume divided by the number of transactions).[38] For presentation, dollar trading volume is in logs and both the number of transactions and average trade size are in thousands.

We replace the dependent variables in Eq. (4.11) with the three volume-related variables and report the regression estimates in Table 4.6. Turning first to the regression coefficients of the FOMC dummy, we note that both dollar trading volume and the total number of trades increase significantly on FOMC announcement days, as shown by the significant positive coefficients on the FOMC dummy. Further investigating the pre- and post-announcement windows shows that the reaction of trading volume is much stronger in the post-announcement period. Coefficients on both dollar trading volume and number of trades (as well as the associated t-statistics) are larger. However, we do not find evidence that ETF traders use

[38] We also observe similar results when average trade size is defined as total share volume divided by the number of transactions.

larger/smaller orders during the FOMC announcement.

More importantly, uncertainty in the information environment (i.e., analyst forecast dispersion) has an incremental impact on trading activity that is beyond the effect of the FOMC announcement itself. We report significant positive coefficients on DISP for both dollar volume and the number of trades for both ETFs. The significant positive coefficients are observed in periods both before and after the FOMC announcement times. An increase in trading activity prior to the FOMC announcement can be attributed to more intense informed trading based on privately collected information. Kurov et al. (2019) attribute this increase to information leakage or superior forecasting using proprietary data, consistent with our findings for the information asymmetry in Table 4.5. Increased trading activity prior to the FOMC announcement may also reflect speculative trading in the spirit of Osambela (2015) and Baker et al. (2016). Both information-based and speculative trading increase near announcements in an uncertain information environment. The abnormal trading volume following the FOMC announcement can be explained by an increase in discretionary liquidity traders who fulfill their postponed trading needs after the resolution of uncertainty (Foster and Viswanathan, 1990; Chae, 2005), and informed traders who are better at processing and interpreting public information (Kim and Verrecchia, 1994; Riordan et al., 2013). The positive relation between analyst forecast dispersion and trading volume is also consistent with recent studies on the effects of disagreement on volume (e.g., Carlin et al., 2014; Atmaz and Basak, 2018). However, we find no evidence that information uncertainty changes investors' choice over the size of orders, as most of the coefficients are statistically insignificant.

In terms of the control variables, the impact of the previous day's spread and return volatility on announcement period trading activity (after controlling for persistence in trading activity) tends to be more significant for the small-cap ETF. The previous day's trading activity also affects the volume and the number of transactions. Overall, Table 4.6 provides strong empirical evidence that in an uncertain information environment, trading volume increases surrounding the FOMC announcement.

Table 4.6

Effects of the information environment on trading activity surrounding the FOMC announcement.

Panel A: SPY	Full 15-minute window			5 minutes before			10 minutes after		
	Dollar volume	**Number of transactions**	**Average trade size**	**Dollar volume**	**Number of transactions**	**Average trade size**	**Dollar volume**	**Number of transactions**	**Average trade size**
DISP	1.302***	25.628***	7.387	0.849***	2.230***	-7.909	1.395***	23.398***	9.909*
	(13.51)	(14.16)	(1.39)	(12.14)	(18.03)	(-1.29)	(12.91)	(13.44)	(1.85)
|SURP|	0.043***	-0.514**	4.215***	-0.086***	-0.066***	-4.200**	0.062***	-0.448**	4.920***
	(3.18)	(-2.41)	(2.87)	(-7.72)	(-3.00)	(-2.49)	(4.11)	(-2.22)	(3.08)
FOMC dummy	1.179***	9.176***	2.216	0.440***	0.328***	6.965	1.374***	8.848***	1.025
	(14.23)	(6.86)	(0.63)	(6.78)	(3.26)	(1.53)	(14.87)	(6.92)	(0.29)
Lag price	0.075	1.184	-27.534*	-0.081	0.417*	-29.207*	0.147	0.767	-26.355
	(0.73)	(1.56)	(-1.64)	(-0.69)	(1.77)	(-1.67)	(1.33)	(1.30)	(-1.57)
Lag QSpread	0.315	1.359	-8.892	0.670***	1.027	12.386	0.181	0.332	-17.728
	(1.49)	(0.72)	(-0.50)	(2.61)	(1.48)	(0.61)	(0.79)	(0.25)	(-1.00)
Lag volatility	0.086***	-0.479	-2.796	0.065**	-0.157	-2.777	0.094***	-0.323	-2.646
	(3.21)	(-0.71)	(-1.02)	(2.02)	(-0.73)	(-0.98)	(3.39)	(-0.65)	(-0.96)
Lag y	0.611***	0.033***	0.736***	0.646***	0.010***	0.714***	0.614***	0.023***	0.745***
	(10.62)	(5.26)	(7.61)	(10.16)	(4.85)	(6.89)	(10.00)	(5.12)	(7.39)
Adj-R^2	33.56%	59.76%	5.73%	26.95%	54.20%	5.03%	32.37%	57.93%	5.69%
Obs.	1377	1377	1377	1377	1377	1377	1377	1377	1377
Panel B: IWM									
DISP	0.840***	3.233***	-23.612	1.002***	0.834***	-4.503	0.841***	2.399***	-21.407
	(5.68)	(6.91)	(-0.91)	(10.24)	(15.66)	(-1.43)	(4.68)	(5.59)	(-0.83)
|SURP|	-0.030**	-0.199***	3.221	-0.177***	-0.064***	-2.634***	-0.008	-0.135***	3.586
	(-2.40)	(-4.37)	(0.59)	(-11.90)	(-9.25)	(-3.24)	(-0.55)	(-3.23)	(0.66)
FOMC dummy	1.019***	2.191***	-10.597	0.425***	0.135***	6.561**	1.194***	2.055***	-11.163
	(12.77)	(7.63)	(-0.62)	(4.60)	(3.57)	(2.55)	(13.64)	(7.69)	(-0.65)
Lag price	-0.294***	-0.076	-165.090	-0.250**	0.012	-4.507	-0.266**	-0.087	-165.240
	(-2.60)	(-0.41)	(-1.01)	(-1.98)	(0.23)	(-1.17)	(-2.22)	(-0.57)	(-1.01)
Lag QSpread	0.056***	0.090**	0.568	0.007	0.017	-0.911**	0.066***	0.073**	0.868
	(4.63)	(1.99)	(0.23)	(0.25)	(1.13)	(-2.16)	(4.40)	(2.33)	(0.37)
Lag volatility	0.058***	0.224***	-19.047	0.047***	0.069**	-0.496	0.070***	0.155***	-19.148
	(4.06)	(2.92)	(-1.05)	(2.75)	(2.48)	(-1.09)	(4.63)	(2.84)	(-1.06)
Lag y	0.561***	0.022***	-0.046	0.566***	0.006***	0.878***	0.563***	0.016***	-0.075
	(10.53)	(6.37)	(-0.05)	(9.16)	(5.85)	(12.35)	(10.30)	(5.93)	(-0.09)
Adj-R^2	20.25%	49.33%	0.22%	13.44%	40.08%	28.27%	21.62%	48.31%	0.22%
Obs.	1375	1375	1375	1371	1371	1371	1375	1375	1375

This table reports regression estimates based on a 15-minute intraday event window surrounding the FOMC announcement. The dependent variables are the three volume-related variables: dollar volume traded (in logs), number of transactions, and average trade size. DISP is the dispersion in analyst forecasts. SURP is the surprise component of the FOMC announcement. FOMC dummy is a binary variable that equals one on days with FOMC announcements and zero otherwise. Lag price and lag QSpread are the volume-weighted average price and time-weighted average quoted spread from the previous trading day. Lag volatility is the previous trading day's return volatility. Lag y is the value of the corresponding dependent variable from the previous day. Standard errors are the Newey–West standard errors with *t*-statistics reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample comprises the two most liquid exchange-traded funds (ETFs): SPY in panel A and IMW in panel B from July 1, 2015 to December 16, 2020.

4.5.4. Information environment and price efficiency surrounding the FOMC announcement

Finally, we investigate the impact of the information environment on the informational efficiency of ETF prices surrounding the FOMC announcement. More specifically, we replace the dependent variables in Eq. (4.11) with either of the two price efficiency metrics. These results are reported in Table 4.7.

First, we observe that price efficiency metrics tend to decrease during periods with FOMC announcements. We find that the coefficients of the FOMC dummy are negative and significant, indicating a deterioration in price efficiency characteristics. More importantly, we find that the coefficients of DISP are negative and significant. This suggests that an uncertain information environment surrounding the FOMC announcement is harmful to the informational efficiency of prices. We also observe that price efficiency decreases when analyst forecast dispersion increases in both the pre- and post-announcement periods. Theories suggest that uncertainty can either decrease or increase price efficiency depending on whether it increases or hinders aggregate information production. Our empirical results align with the view that an uncertain information environment increases information asymmetry and reduces aggregate information production, which leads to the deterioration in the informational efficiency of equity prices (Admati and Pfleiderer, 1988).

For the control variables, we find that higher lagged trading volume is associated with higher price efficiency. The relation between price efficiency and the lagged value of quoted spread and price is not consistent between the two price efficiency measures and different event windows. The relation between price efficiency and the news surprise is not consistent across different event windows and between the two ETFs. Overall, Table 4.7 provides empirical evidence that lends support to the view that an uncertain information environment is harmful to the informational efficiency of equity prices surrounding the FOMC announcement.

Table 4.7

Effects of the information environment on price efficiency surrounding the FOMC announcement.

Panel A: SPY	Full 15-minute window		5 minutes before		10 minutes after	
	AF_efficiency	**VR_efficiency**	**AF_efficiency**	**VR_efficiency**	**AF_efficiency**	**VR_efficiency**
DISP	-2.861***	-1.842***	-1.788***	-1.088***	-2.904***	-1.052***
	(-11.32)	(-8.83)	(-9.26)	(-3.20)	(-8.26)	(-5.58)
|SURP|	-0.503***	-0.356***	0.087***	-0.163***	-0.489***	-0.375***
	(-18.74)	(-14.04)	(3.36)	(-5.21)	(-17.88)	(-15.91)
FOMC dummy	-0.753***	-0.315**	-0.317*	-0.566***	-0.521***	-0.186
	(-4.48)	(-1.98)	(-1.95)	(-2.84)	(-3.00)	(-1.26)
Lag QSpread	-0.175	-0.385	0.207	0.674*	-0.258	-0.564*
	(-0.49)	(-1.37)	(0.43)	(1.87)	(-0.64)	(-1.78)
Lag Price	-0.698***	-0.604***	-0.142	-0.080	-0.538***	-0.339**
	(-4.28)	(-3.93)	(-0.71)	(-0.46)	(-3.16)	(-2.14)
Lag $Volume	0.205***	0.141***	-0.006	-0.073	0.127**	0.132**
	(3.81)	(2.58)	(-0.08)	(-1.17)	(2.10)	(2.18)
Lag y	0.077***	0.032	0.043	-0.009	0.028	-0.003
	(2.80)	(1.31)	(1.63)	(-0.32)	(1.13)	(-0.11)
Adj-R^2	7.71%	2.67%	0.48%	1.38%	4.10%	0.89%
Obs.	1377	1377	1377	1377	1377	1377
Panel B: IWM						
DISP	-0.811***	-1.012***	-0.686***	-0.969***	-0.833***	-0.717***
	(-6.75)	(-5.37)	(-3.65)	(-3.19)	(-5.19)	(-3.72)
|SURP|	0.142***	-0.116***	0.177***	-0.140***	0.117***	-0.027
	(8.34)	(-5.46)	(6.28)	(-5.16)	(6.10)	(-1.04)
FOMC dummy	-0.206**	-0.254*	-0.101	-0.186	-0.140	-0.069
	(-1.99)	(-1.88)	(-0.57)	(-1.05)	(-1.18)	(-0.42)
Lag QSpread	-0.037	0.021	-0.058**	0.00	0.008	-0.026
	(-1.42)	(0.43)	(-2.13)	(0.00)	(0.28)	(-1.33)
Lag Price	-0.777***	-0.123	-0.131	-0.414**	0.594***	-0.150
	(-5.79)	(-0.80)	(-0.71)	(-2.55)	(4.04)	(-0.80)
Lag $Volume	0.129**	0.133**	0.027	0.088	-0.088	-0.090
	(1.96)	(2.23)	(0.39)	(1.33)	(-1.26)	(-1.25)
Lag y	0.049**	-0.002	-0.017	-0.001	0.048**	-0.002
	(2.11)	(-0.07)	(-0.73)	(-0.04)	(2.08)	(-0.08)
Adj-R^2	3.63%	0.52%	0.37%	0.59%	1.86%	0.20%
Obs.	1377	1377	1377	1377	1375	1375

This table reports regression estimates based on a 15-minute intraday event window surrounding the FOMC announcement. The dependent variables are the price efficiency metrics defined in section 3.3. DISP is the dispersion in analyst forecasts. SURP is the surprise component of the FOMC announcement. FOMC dummy is a binary variable that equals one on days with FOMC announcements and zero otherwise. Lag price and lag $Volume are the volume-weighted average price and total dollar volume traded from the previous trading day, both of which are in logs. Lag QSpread is the time-weighted average quoted spread from the previous trading day. Lag y is the value of the corresponding dependent variable from the previous day. Standard errors are the Newey–West standard errors with *t*-statistics reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample comprises the two most liquid exchange-traded funds (ETFs): SPY in panel A and IMW in panel B from July 1, 2015 to December 16, 2020.

4.6. Conclusion

We study the effect of an uncertain information environment surrounding the FOMC announcement on equity market quality. We consider two highly liquid ETFs, SPY and IWM, to proxy for large- and small-cap US equities, respectively. We measure the degree of uncertainty in the information environment surrounding the FOMC announcement using analyst forecast dispersion. Using a sample from July 1, 2015 to December 31, 2020, we study the effect of an uncertain information environment surrounding the FOMC announcement on various market quality measures, including liquidity, trading activity, and price efficiency.

We show that an uncertain information environment has a significant impact on equity market quality. An uncertain information environment causes liquidity to worsen surrounding FOMC news releases, and this effect is independent of and incremental to the impact of the announcement itself. We further investigate various bid-ask spread components and find that the increase in the spreads during announcement times is primarily driven by the increase in the information asymmetry costs, suggesting that an uncertain information environment provides incentives for private information acquisition. Despite widening spreads, trading volume increases significantly surrounding the FOMC announcement when there is greater disagreement among financial analysts. An increase in trading volume in the period prior to the FOMC announcement can be attributed to more informed and speculative trading leading up to the FOMC announcement, whereas the abnormal trading volume after the announcement can be attributed to both informed and postponed liquidity trading. Finally, we show that an uncertain information environment surrounding the FOMC announcement is harmful to the informational efficiency of equity prices.

Overall, our study highlights the importance of the information environment during periods of important information releases and particularly the role of financial analysts in contributing to such information environments. A future research direction is to study the effects of monetary policy news on different industry sectors. For instance, one may argue that the financial sector is more subject to monetary policy effects whereas other industries such as defense or energy sectors may be less affected by the Fed policies. Investigating this industry-specific impact of monetary policy news can enrich our understanding of the rule of FOMC in different industries.

Chapter 5

5. The effect of equity market uncertainty on equity price efficiency: Cross-sectional evidence

5.1. Introduction

Market efficiency is a fundamental concept in finance. It reflects the price formation process and, thus, how accurately prices reflect asset fundamentals. A systematic source of market inefficiency is the inability of market participants to make accurate judgments about fundamentals, whose subsequent trading will at least partially be driven by noise. Therefore, asset prices should become less informationally efficient when impounding such noise. This noise-driven inefficiency is especially prevalent during periods of high market uncertainty when reliably distinguishing signals from noise is less straightforward for most investors. One apparent reason is that uncertainty renders the information environment murky and the value-relevant signals elusive.

Recent research connects the concepts of uncertainty and informational efficiency. Chapter 3 of this thesis is among the first to analyze how uncertainty affects equity price efficiency. It examines the effects of the US equity market uncertainty (EMUNC hereafter) on the price efficiency of two ETFs representing large- and small-cap US equities. Chapter 3 documents a negative relation between EMUNC and both ETFs' price efficiency and concludes that equity market uncertainty reduces the quality of the information environment. Uncertainty, therefore, impedes the efficient incorporation of information into prices and reduces informational efficiency.

This chapter extends Chapter 3's work on informational efficiency and uncertainty by utilizing a large cross-section of US stocks. Instead of considering the equity market as a whole, as in Chapter 3, we investigate the effect of EMUNC at the individual stock level. Given the cross-sectional nature of our sample, we can address a more interesting question. For instance, does the impact of EMUNC depend on stock characteristics? And if so, are some stocks affected more by uncertainty than others? Understanding this question is important not only for investors to rebalance their portfolios during periods of high economic uncertainty, but also for regulatory authorities to maintain market stability more effectively.

We examine two channels as to why different stocks can be affected by EMUNC differently. The first channel is the limits-to-arbitrage. Arbitrageurs monitor equity prices and trade when mispricing occurs. By doing so, arbitrageurs can potentially correct mispricing and noise caused by EMUNC, thus offsetting the negative impact of uncertainty. However, arbitrageurs typically have limited capital and due to market frictions that impede arbitrage activities, they dedicate their efforts primarily to stocks with low arbitrage risk (e.g., Shleifer and Vishny, 1997; Pontiff, 2006; Stambaugh et al., 2015; Gu et al., 2018; Barroso and Detzel, 2021). If limits-to-arbitrage are more severe for specific stocks, mispricing and noise caused by equity market uncertainty tend to be more persistent in such stocks. Therefore, it is reasonable to postulate that EMUNC has a larger impact on price efficiency for stocks with higher limits-to-arbitrage.

Second, some stocks may be affected more by uncertainty than others because they have a higher exposure to this uncertainty. For instance, Pástor and Veronesi (2012) theoretically model the impact of policy uncertainty on stock returns and allow stocks to have different exposures to government policy uncertainty.[39] They theoretically show that firms with a greater policy uncertainty exposure have higher expected returns. Nagar et al. (2019) study how economic policy uncertainty affects investor information asymmetry. They empirically show that firms with higher uncertainty exposure (measured by economic policy uncertainty beta) experience a larger increase in investor information asymmetry when uncertainty increases. We, therefore, postulate that stocks with greater exposure to EMUNC will experience a larger decline in price efficiency.

We test the limits-to-arbitrage channel and the uncertainty exposure channel using a sample of S&P 500 constituent stocks, which account for over 80% of the total market

[39] Pástor and Veronesi (2012) define a firm's policy exposure as beta loading on policy.

capitalization in the US equities market.[40] We first test the limits-to-arbitrage channel and investigate whether EMUNC has a larger impact on equity price efficiency for stocks that are more difficult to arbitrage. We use several commonly used proxies for limits-to-arbitrage: market capitalization (MV), analyst coverage (ANACOV), trading volume (DVOL), idiosyncratic volatility (IVOL), and stock illiquidity (ILLIQ). First, we sort all stocks into terciles at the start of each month based on one of the above limits-to-arbitrage proxies. Next, we estimate the effect of EMUNC on price efficiency for the three stock terciles separately and compare the coefficients of EMUNC.

We next test the uncertainty exposure channel and investigate whether stocks with greater EMUNC exposure are more subject to the negative impact of uncertainty. We first calculate the uncertainty beta for each stock. We then sort individual stocks into terciles at the start of each month based on their uncertainty betas. We then investigate how the EMUNC coefficients differ across terciles.

We find several key results. First, consistent with Chapter 3, we find that equity market uncertainty is harmful to the informational efficiency of equity prices. The negative effect of EMUNC is robust to controlling for firm- and market-level factors also known to affect market efficiency. This aggregate effect corroborates the notion that uncertainty creates mispricing and renders equity prices noisy. Second, we find substantial heterogeneity in how uncertainty affects informational efficiency in the cross-section of stocks. Across all the five limits-to-arbitrage proxies, we find that EMUNC coefficients are typically more negative and more significant in higher limits-to-arbitrage terciles. These cross-sectional differences are also statistically significant. Overall, this evidence supports the notion that limits-to-arbitrage aggravates the harmful effect of equity market uncertainty. For the uncertainty exposure channel, we also observe a similar but weaker cross-sectional pattern for the EMUNC coefficients. That is, stocks that have more exposure to EMUNC also suffer a greater reduction in informational efficiency when uncertainty rallies.

We conduct several robustness tests. First, we consider two alternative uncertainty proxies: the news-based economic policy uncertainty (EPU_news) index and the news-based

[40] https://www.spglobal.com/spdji/en/indices/equity/sp-500/#overview.

equity market volatility (EMV) tracker. Second, we check whether the cross-sectional pattern is robust to other price efficiency measures such as excess short-term volatility. Finally, we test whether the cross-sectional patterns are robust when the main informational efficiency metrics are estimated using alternative sampling frequencies. By and large, the additional robustness tests support our main conclusion.

Our study contributes to several strands of literature. First, we contribute to the fast-growing literature on the effect of uncertainty. The development of newspaper-based indices of economic and policy uncertainty since Baker et al. (2016) has resulted in numerous studies on the effect of economic and policy uncertainty on capital markets and corporate finance.[41] Our paper contributes to this line of work, and we document the importance of equity market uncertainty on the informational efficiency of equity prices. We show that uncertainty adversely affects equity price efficiency, and such effects are also heterogeneous in the cross-section of stocks.

Second, we add to the market microstructure literature on market quality. A key research topic in this line of research focuses on the determinants of equity market quality. Existing studies show that factors such as trading activity (e.g., Chordia et al., 2011; Comerton-Forde and Putniņš, 2015; Foley and Putniņš, 2016), market liquidity (e.g., Chordia et al., 2008; Chung and Hrazdil, 2010), funding liquidity and arbitrage efficacy (Rösch et al., 2017), sophisticated investors (e.g., Boehmer and Kelley, 2009; Chen et al., 2020), as well as the proliferation of proprietary trading technologies such as algorithmic and high-frequency trading (e.g., Boehmer et al., 2021) can have a significant impact on the market efficiency characteristics. Our study enriches this line of literature and shows that the tone of newspaper articles has a significant impact on the efficient functioning of equity markets.

More broadly, this paper is also related to the general study on the role of arbitrageurs. Akbas et al. (2016) find that an increase in mutual fund flows to arbitrage strategies reduces

[41] For instance, Gulen and Ion (2016) study how policy uncertainty affects corporate investment activities. Bonaime et al. (2018) study the effect of policy uncertainty on corporate mergers and acquisitions activities. Xu (2020) studies the impact of economic policy uncertainty on cost of capital and corporate innovation. Nagar et al. (2019) study the effect of economic policy uncertainty on liquidity and information asymmetry in the stock market. Other studies focus on the asset-pricing implications of economic/policy uncertainty (e.g., Brogaard and Detzel, 2015; Bali et al., 2017; Brogaard et al., 2020).

cross-sectional return predictability based on well-known market anomalies and increases price efficiency. Similarly, using Regulation SHO[42] as a natural experiment that relaxed short-sale constraints, Chu et al. (2020) find that the 11 documented asset pricing anomalies were weaker for pilot stocks during the pilot period. They report a 72 basis points reduction in monthly returns for anomaly-based long-short portfolios. Rösch (2021) shows that arbitrage in the American Depositary Receipt (ADR) market decreases price pressure and increases liquidity. Our cross-sectional evidence points to the beneficial role of arbitrage activity in alleviating the adverse impact of market uncertainty.

This paper is organized as follows. Section 5.2 discusses the key variables used in this study and the methodology. In section 5.3, we describe the sample, data sources, and provide summary statistics. Section 5.4 presents and discusses the main results. Robustness checks are provided in section 5.5. Section 5.6 concludes the paper.

5.2. Variable definitions and methodology

This section describes the equity market uncertainty index (EMUNC), the informational efficiency measures, and the variables used in the cross-sectional analyses.

5.2.1. Equity market uncertainty

We measure US equity market-related economic uncertainty using the EMUNC index. Baker et al. (2016) construct the EMUNC index using frequency counts of newspaper articles from over 1,000 US newspapers. Specifically, they obtain counts of articles that contain the term "uncertain" or "uncertainty," the term "economic" or "economy," and at least one of the following terms: "equity market," "equity price," "stock market," or "stock price.". To adjust for the growth in newspaper coverage over time, these raw article counts are scaled by the total number of articles in the same newspaper. Finally, Baker et al. (2016) normalize this time series of scaled counts to have an average value of 100 over the period 1985-2010, resulting in the

[42] Regulation SHO is a SEC pilot program designed to relax short sales restrictions for a selected group of US stocks.

final EMUNC index.

This EMUNC index is a good proxy for our study for several reasons. First, we are interested in uncertainty about the US stock market. The EMUNC index is designed to capture uncertain perceptions of the public about the US equity market. Second, studies have documented that newspaper articles affect how traders behave (Fang and Peress, 2009; Birz and Lott, 2011; Ammann et al., 2014). For example, newspapers are an important source of information for retail investors without access to professional investment advice. Recent advances in algorithm-based trading technologies also allow computers to automate the trading process by textually scanning newspaper articles using natural language processing (NLP) techniques and generating trading strategies based on newspaper sentiments.

5.2.2. Informational efficiency

We measure price efficiency by the extent to which prices deviate from a random walk. In an efficient and frictionless market, prices always reflect the fundamental value and only change when new information arrives. Since new information arrives randomly, price movements should be unpredictable and follow a random walk. Consequently, there should be no return autocorrelation. Furthermore, since prices follow a random walk, the martingale property implies that the equity return variance should grow linearly with the horizon at which returns are observed.

However, market inefficiency and frictions can lead to price deviations from the characteristics expected in perfectly efficient markets. Such frictions may come from investor under- or overreaction to information (e.g., Anderson et al., 2013) or delays in impounding new information into prices. These frictions are more likely to be important in an uncertain information environment. For example, when value-relevant signals are noisy, information signals are hard to observe and thus cannot be impounded into prices instantaneously, leading to serially correlated equity returns. An uncertain information environment may also affect investors' behavior. In laboratory experiments, Bloomfield et al. (2000) find that when investors are uncertain about the reliability of their information, prices tend to underreact to reliable information and overreact to unreliable information. Such price under- and overreactions may also exacerbate the deviations from a random walk, causing either positive or negative return autocorrelation.

Following Comerton-Forde and Putniņš (2015) and Foley and Putniņš (2016), we consider the following two price efficiency metrics: (i) absolute values of mid-quote return autocorrelations (*AF_efficiency*); and (ii) absolute values of variance ratios (*VR_efficiency*), both of which are calculated using intraday mid-quote prices to avoid the bid-ask bounce. As both metrics capture deviations from a random walk, they are measures of price inefficiency.

The first metric, *AF_efficiency*, captures both positive and negative mid-quote return autocorrelations as a form of price inefficiency. We calculate the absolute values of the first-order mid-quote return autocorrelation for each day at intraday frequencies k:

$$AutoCorrelation_k = \left|Corr(r_{k,n}, r_{k,n-1})\right|, \tag{5.1}$$

where $r_{k,n}$ is the n^{th} mid-quote return measured at intraday frequency k for a given day d. Similar in spirit to Comerton-Forde and Putniņš (2015), we calculate mid-quote returns autocorrelation using three intraday frequencies, $k \in \{30\text{ sec}, 1\text{ min}, 2\text{ min}\}$. We then extract the first principal component of the three daily series and name this quantity *AutocorFactor*. This procedure alleviates measurement error issues inherent in individual price efficiency measures by capturing their common variation. We multiply *AutocorFactor* by -1 so that it becomes a price efficiency measure. We label our first informational efficiency metric *AF_efficiency*.

Our second price efficiency metric, *VR_efficiency*, is based on Lo and MacKinlay (1988). If equity prices follow a random walk, the variance of equity returns is linear with respect to the return measurement frequency, i.e., σ_{kl}^2 is k times larger than σ_l^2. The variance ratio test exploits this property and measures price inefficiency as its deviation from this linearity. We calculate the variance ratio as follows:

$$VarianceRatio_{kl} = \left|\frac{\sigma_{kl}^2}{k\sigma_l^2} - 1\right|, \tag{5.2}$$

where σ_{kl}^2 and σ_l^2 are the kl-second and l-second mid-quote return variances for a given day d. We use three frequency combinations of (l,kl): (30 seconds, 1 min), (1 min, 5 min), (5 min, 10 min)[43] and calculate the first principal component to capture the common variation in the three individual variance ratio measures, which we name *VarRatioFactor*. If prices are perfectly informationally efficient, then this metric is zero. A higher number indicates lower price efficiency. Again, we multiply *VarRatioFactor* by -1 to turn it into a price efficiency metric. We label our second informational efficiency metric *VR_efficiency*. Both informational efficiency metrics are aggregated to a monthly frequency.

5.2.3. Cross-sectional variables

We use two criteria to sort the cross-section of stocks. The first is based on the degree of limits-to-arbitrage, and the second is the stock's past exposure to equity market uncertainty. We discuss both criteria below.

5.2.3.1. Limits-to-arbitrage measures

We follow the existing literature and consider several common proxies of limits-to-arbitrage. The first proxy for limits-to-arbitrage is firm size. Large firms receive more media attention, attract more institutional investors, and have higher analyst coverage and better information environments. Thus, we expect that firm size is inversely related to arbitrage costs. Firm size is also used to proxy for limits-to-arbitrage in other studies (e.g., Andreou et al., 2018; DeLisle et al., 2021).

Second, we consider analyst coverage (ANACOV) to proxy for limits-to-arbitrage. Financial analysts' reports reduce information uncertainty and accelerate information dissemination (e.g., Hong et al., 2000; Lam and Wei, 2011). Therefore, we expect higher analyst coverage to reduce the uncertainty faced by arbitrageurs, which allows them to allocate limited arbitrage capital more efficiently. Gu et al. (2018) also use analyst coverage to construct a limits-to-arbitrage index.

The third proxy for limits-to-arbitrage is the stock's idiosyncratic volatility (IVOL).

[43] Although the frequency choices for both *AF_efficiency* and *VR_efficiency* metrics are somewhat arbitrary, we show in section 5.5.3 that using other frequency combinations does not significantly change the results.

Pontiff (2006) highlights stocks' idiosyncratic risk as the single largest holding cost that limits arbitrageurs' ability to correct mispricing. Baker and Wurgler (2006) argue that stocks with high volatility are more likely to be mispriced. Supporting this argument, Stambaugh et al. (2015) document a stronger negative IVOL-return relationship among overpriced stocks than the positive IVOL-return relationship among underpriced stocks. They argue that IVOL deters arbitrage activities, and due to arbitrage asymmetry, mispricing in overpriced stocks is more difficult to correct. Similarly, Cao and Han (2016) show an increase (decrease) in stock returns with the stock's idiosyncratic risk for undervalued (overvalued) stocks, which is consistent with the theory that idiosyncratic risk impedes arbitrage efficiency. IVOL has also been used in the context of limits-to-arbitrage in recent studies (e.g., Andreou et al., 2018; Chen and Zheng, 2021; DeLisle et al., 2020; DeLisle et al., 2021).

Following Ang et al. (2006), we calculate the monthly IVOL for stock i as the standard deviation of daily return residuals ($\varepsilon_{i,d}$) from the Fama and French (1993) three-factor model[44] in month m:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i MKT_d + s_i SMB_d + h_i HML_d + \varepsilon_{i,d}, \tag{5.3}$$

where $R_{i,d} - r_{f,d}$ is the excess daily return of stock i on day d in month m. MKT_d, SMB_d, and HML_d are the daily excess market return, the daily size and book-to-market factors of Fama and French (1993), respectively. For a stock to be considered, we require a minimum of 15 non-missing daily return observations in a given month.

Finally, we use two trading cost measures to proxy for arbitrage costs. Lower trading costs and greater liquidity reduce arbitrage frictions and allow arbitrageurs to promptly correct mispricing (e.g., Mashruwala et al., 2006; Gu et al., 2018). The first trading cost measure is the Amihud (2002) illiquidity metric (ILLIQ). ILLIQ is defined as the absolute stock return scaled by total dollar volume traded:

$$ILLIQ_{i,m} = log\left[1 + \frac{1}{D}\sum_{d=1}^{D}\frac{10^6|r_{i,d}|}{\$Volume_{i,d}}\right], \tag{5.4}$$

where $r_{i,d}$ and $\$Volume_{i,d}$ are the daily stock returns based on the closing price and daily

[44] Using a four-factor model specification does not change our results.

dollar trading volume, respectively. We calculate the ILLIQ for each stock i on each day d and average across D trading days within month m. We scale ILLIQ by 10^6 and take the natural logarithm to mitigate the impact of extreme outliers.

The second trading cost measure is monthly dollar trading volume (DVOL). For instance, Mashruwala et al. (2006) argue that the accrual anomaly found in low-price and low-volume stocks is due to higher transaction costs associated with these stocks that impede arbitrage. Thus, low trading volume indicates illiquidity, which deters arbitrage activities and exacerbates mispricing.

5.2.3.2. Uncertainty beta

We capture a stock's historical exposure to equity market uncertainty using its uncertainty beta, which measures the sensitivity of stock returns to uncertainty. Similar to Bali et al. (2017) and Bonaime et al. (2018), we run the following regression using monthly return observations over the previous 60 months for a given stock-month and require at least 24 valid non-missing preceding monthly returns for estimation:

$$R_{i,m} - r_{f,m} = \alpha_i + \beta_i^{EMUNC} EMUNC_m + \beta_i^{MKT} MKT_m + s_i SMB_m + h_i HML_m + \varepsilon_{i,m} \ , \tag{5.5}$$

where all variables are at a monthly frequency. MKT_m, SMB_m, and HML_m are the Fama-French pricing factors from the Kenneth website. $r_{f,m}$ is the three-month US Treasury bill rate. We estimate Eq. (5.5) using the 60 monthly returns of stock i prior to month m and assign β_i^{EMUNC} to the current month m. We then roll the 60-month estimation window forward by one month to update β_i^{EMUNC}, which is then assigned to the subsequent month, $m+1$. This estimation procedure results in a monthly time series of uncertainty beta for each stock. Since both positive and negative betas indicate uncertainty exposure, we use the absolute value of the beta coefficients ($\left|\beta_i^{EMUNC}\right|$). We also augment Eq. (5.5) by the momentum factor to get a four-factor uncertainty beta for robustness. To differentiate, we label them $|\beta^{EMUNC}|$-FF3F and $|\beta^{EMUNC}|$-FF4F, respectively.

Using beta as a proxy for stock-level exposure is common in cross-sectional studies.

For instance, Yang et al. (2019) study how policy uncertainty exposure affects firm market value and Tobin's Q. They measure a stock's exposure to policy uncertainty using a rolling regression approach similar to ours. Nagar et al. (2019) study how economic policy uncertainty affects investor information asymmetry. They also consider potential cross-sectional variation by controlling for stock-level policy uncertainty beta, which is calculated using a model similar to ours. Using the beta measure as a proxy for stock-level sensitivity is also common practice in the asset pricing literature (e.g., Bali et al., 2017).

5.3. Data sources, sample, and summary statistics

In this section, we describe different data sources for equity market uncertainty, informational efficiency, as well as various other control variables used in this study. We then provide summary statistics for the sample stocks.

5.3.1. Data and sample

We obtain the daily US EMUNC index from the economic policy uncertainty website.[45] We average across days within a month to construct a monthly EMUNC index.

Our sample comprises all S&P 500 constituent stocks as of December 2020 and covers the period January 1, 2010 to December 31, 2020.[46] We remove stocks whose average price in the sample is less than $1 or over $2,000. We retrieve intraday data sampled at a one-second frequency from Refinitiv Tick History to construct our informational efficiency metrics. These second-by-second data contain the best bid and ask prices, along with the corresponding quantities, for each second interval. We only include data within the regular trading hours between 9:30 a.m. and 4:00 p.m. and remove the first and last 10 minutes of each trading day to avoid the impact of the market opening and closing.

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[45] https://www.policyuncertainty.com/equity_uncert.html.

[46] We realize that the ticker symbol of a particular stock can change over time and in some cases, a particular ticker symbol previously assigned to a stock can be reused later by a different stock. This adds to the difficulties of correctly identifying a complete time-series of a stock. We carefully investigate each stock and its ticker manually to get a complete history of its ticker symbol(s) throughout our sample. These are used later to retrieve the intraday data.

We also control for several commonly used stock-level and market-level variables known to affect market quality. For each stock, we construct a monthly time-series of market capitalization (stock price multiplied by total shares outstanding), total trading volume (stock price multiplied by total shares traded), market-to-book ratio (market equity divided by the book equity), and Amihud's (2002) illiquidity defined in Section 2.3.1. Data for monthly price, volume, and total shares outstanding are from Refinitiv Datastream. Additionally, we control for firm-level characteristics by adding analyst coverage and institutional ownership as additional control variables. Analyst coverage is the number of financial analysts providing earnings per share (EPS) forecasts for the next financial year and is available from I/B/E/S via Datastream (i.e., Datastream data item: EPS1NE). Institutional ownership is the number of shares held by large institutions as a percentage of total shares outstanding. We retrieve this information from Refinitiv Eikon. The institutional holdings data are based on the quarterly Form 13-F filings. We carry these quarterly values backward for months within each quarter to obtain a monthly time series of institutional ownership. At the market level, we control for monthly S&P 500 index returns and the CBOE volatility index (VIX).

5.3.2. Summary statistics

Table 5.1 provides summary statistics for the set of variables used in this study. During the period January 2010 to December 2020, the US equity market uncertainty index fluctuates significantly from the lowest level of 13.09 to the highest level of over 476. For both *AF_efficiency* and *VR_efficiency* measures, the median value is higher than the mean value, suggesting negative skewness of price efficiency measures. There is also considerable variation in price efficiency across stocks, from -1.309 (-0.857) to 0.350 (0.326).

Our sample covers a wide range of stocks with different characteristics. For instance, the average market capitalization of the sample stocks is around $35.45 billion, varying from $80 million to over $700 billion. The same cross-sectional variation can be observed in the stocks' market-to-book ratio. Share price also displays significant cross-sectional variation from a low of $4.06 to a high of $1794.06. Stocks, on average, have a monthly trading volume of about $5.2 billion, with variations in trading volume from a high of over $146 billion to a low of around \$2.79 million per month. Similarly, ILLIQ, as a measure of stock illiquidity, displays significant cross-sectional variation with a max/min ratio of over 1,000. In terms of the firm-

Table 5.1

Descriptive statistics.

	Mean	Median	Min	Max	Std. dev.
EMUNC	59.16	40.64	13.09	476.33	60.68
AF_efficiency	0.093	0.117	-1.309	0.350	0.151
VR_efficiency	0.082	0.102	-0.857	0.326	0.123
Price (in \$)	83.76	58.82	4.06	1794.06	122.83
Volume (in million \$)	5203.48	2954.57	2.79	146023.92	9347.82
Market cap (in billion \$)	35.45	15.89	0.08	700.02	61.56
ILLIQ (x100)	0.45	0.31	0.005	5.56	0.55
M/B ratio	5.75	3.18	0.68	88.57	8.85
Analyst coverage	18	18	1	46	7.40
Institutional holding	0.754	0.787	0.004	0.973	0.158

This table reports summary statistics for the uncertainty index and the set of stock characteristics. EMUNC is the US equity market uncertainty index from the policy uncertainty website (https://www.policyuncertainty.com/equity_uncert.html). All other statistics are calculated for each variable aggregated at a stock level. *AF_efficiency* is the informational efficiency measure based on the intraday mid-quote returns autocorrelation. *VR_efficiency* is the informational efficiency measure based on the mid-quote returns variance ratio. Price, volume, and market cap are the monthly stock price, total dollar trading volume, and market capitalization, respectively. ILLIQ is the Amihud's (2002) illiquidity metric calculated for each stock-month based on daily return and trading volume. M/B ratio is the stock's market-to-book ratio. Analyst coverage is the number of financial analysts following the stock, and institutional holding is the percentage of outstanding shares held by institutions. The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020.

level information environment, an average stock has about 18 analysts following it and institutional ownership of about 75.4%. Both values also vary cross-sectionally. For instance, some stocks are covered by a single analyst and are barely held by large institutions (i.e., 0.4% institutional holding). On the other hand, other stocks are covered by 46 analysts and almost entirely held by large institutions (i.e., 97.3% institutional holding). Overall, these statistics show that our sample covers a wide range of US stocks.

5.4. Empirical results

This section discusses the main empirical results. We start by investigating the aggregate effects of equity market uncertainty on equity price efficiency. Next, we conduct further analyses in the cross-section of stocks to examine whether the effects of uncertainty are homogeneous across stocks. Specifically, we focus on two stock-level characteristics. The first is limits-to-arbitrage, and the second is stocks' historical exposure to equity market uncertainty.

5.4.1. The aggregate effect of EMUNC

Our first objective is to establish an empirical relation between EMUNC and equity price efficiency. To do so, we estimate the following regression:

$$y_{i,m} = \alpha_i + \gamma_t + \beta EMUNC_m + \sum_{j=1}^{J} \delta_j X_{j,i,m} + \varepsilon_{i,m}, \tag{5.6}$$

where $y_{i,m}$ is one of the two price efficiency metrics for stock i on month m. $EMUNC_m$ is the monthly US equity market uncertainty index. For presentation, *EMUNC* is scaled by 1,000. α_i and γ_t are stock and time fixed effects, respectively. $X_{j,i,m}$ is an array of control variables. We consider different various control variables. At the stock level, we control for characteristics known to affect market efficiency, including trading volume, market-to-book ratio, market capitalization, and stock illiquidity. We also control for the stock-level information environment by using analyst coverage and institutional holding. At the market level, we control for the S&P 500 index returns and the CBOE volatility index (VIX). All models include lagged values of price efficiency to control for persistence in market efficiency characteristics and potential omitted variable bias.

Table 5.2 reports the regression results. From columns (1) through (5) for each price efficiency metric, we add additional control variables progressively to examine whether the EMUNC-efficiency relationship depends on model specifications. Consistent across all regression specifications and between the two price efficiency metrics, we observe that an increase in equity market uncertainty is associated with less informationally efficient stock prices. All the EMUNC coefficients are negative and significant, supporting the argument that equity market uncertainty reduces the quality of the information environment, which impedes the efficient incorporation of information into prices and, thus, reduces informational efficiency. The magnitude of this negative effect tends to be higher for the *VR_efficiency* metric than for the *AF_efficiency* metric.

The control variables show that informational efficiency is negatively correlated with trading volume and stock illiquidity but positively correlated with market capitalization (although market cap is insignificant for *VR_efficiency*). These results indicate that larger stocks tend to have more informationally efficient prices (e.g., Comerton-Forde and Putniņš, 2015) and are consistent with Chordia et al. (2008), who find that market efficiency increases with more liquidity. The market-to-book ratio and institutional holding are not significantly related to price efficiency. Analyst coverage, however, is positively related to price efficiency. Thus, higher analyst coverage can potentially mitigate the negative impact of equity market uncertainty by improving the firm-level information environment (e.g., Harford et al., 2019). The significance of both VIX and the S&P 500 index returns is marginal. Finally, we find strong persistence in price efficiency characteristics over time, evident by the significant coefficients of lagged dependent variables. Overall, Table 5.2 supports the view that equity market uncertainty is harmful to the informational efficiency of stock prices.

5.4.2. Cross-sectional effects

The previous section has established a negative aggregate effect of EMUNC. This section further investigates whether such an effect varies across stocks with different characteristics.

5.4.2.1. Limits-to-arbitrage

The first cross-sectional stock characteristic we consider is limits-to-arbitrage. The negative effect of EMUNC on informational efficiency documented in Section 5.4.1. is likely caused by mispricing when market participants face uncertain information. We argue that arbitrageurs will step in to correct such mispricing when the expected profits are high, which in part counters the negative effect of EMUNC. If some stocks have more frictions that limit arbitrageurs' ability to correct mispricing induced by uncertainty, EMUNC will have a larger impact on these stocks. In other words, limits-to-arbitrage tends to aggravate the harmful effect of uncertainty on price efficiency. To test this prediction, we estimate the effect of uncertainty for stocks with different levels of limits- to-arbitrage. Specifically, at the start of each month, we split the sample into terciles based on one of the limits-to-arbitrage proxies defined in Section 5.2.3.1. Next, we run Eq. (5.6) separately for stocks within each tercile to estimate the coefficient of EMUNC with respect to informational efficiency for stocks with high, medium,

Table 5.2

Baseline panel regression.

	AF_efficiency				VR_efficiency			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
EMUNC	-0.428*	-0.409*	-0.506*	-0.658**	-0.436*	-0.426**	-0.505***	-0.716***
	(-1.83)	(-1.66)	(-1.73)	(-1.97)	(-1.95)	(-2.05)	(-2.58)	(-2.86)
Total $ volume		-0.056***	-0.062***	-0.064***		-0.045***	-0.047***	-0.050***
		(-5.98)	(-6.81)	(-7.35)		(-4.80)	(-5.29)	(-6.05)
Market cap		0.042**	0.043***	0.045***		0.008	0.017*	0.011
		(2.25)	(4.02)	(4.42)		(0.71)	(1.91)	(1.07)
ILLIQ		-0.129*	-0.183**	-0.189***		-0.074	-0.119*	-0.124*
		(-1.79)	(-2.57)	(-2.70)		(-0.85)	(-1.66)	(-1.64)
M/B ratio		4.68E-6	1.13E-5	1.18E-5		1.08E-5	1.61E-5	1.72E-5
		(0.25)	(0.65)	(0.67)		(0.77)	(1.25)	(1.30)
Analyst coverage			0.002***	0.002***			0.002***	0.002***
			(2.67)	(2.59)			(2.71)	(2.59)
Institutional holding			0.003	0.004			-0.017	-0.014
			(0.21)	(0.27)			(-1.12)	(-0.93)
VIX				0.002				0.002
				(1.51)				(1.54)
S&P return				-0.027				-0.213
				(-0.18)				(-1.39)
Lag y	0.665***	0.669***	0.679***	0.679***	0.594***	0.596***	0.614***	0.614***
	(35.09)	(34.38)	(40.14)	(40.10)	(25.68)	(25.24)	(31.52)	(31.35)
Adj-R^2	56.48%	56.99%	58.30%	58.32%	50.27%	50.69%	52.72%	52.78%
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month

This table reports the aggregate effect of equity market uncertainty on informational efficiency. The panel regression uses monthly data. *AF_efficiency* and *VR_efficiency* are the monthly average value of the daily informational efficiency measures. EMUNC is the monthly average value of the daily US equity market uncertainty index from the policy uncertainty website (https://www.policyuncertainty.com/equity_uncert.html). For presentation, the EMUNC index is divided by 1,000. Total $ volume and Market cap are the natural logs of total dollar trading volume and market capitalization of the month, respectively. ILLIQ is the Amihud's (2002) illiquidity measure. M/B is the market value to the book value of equity. Analyst coverage and institutional holding are, respectively, the number of analysts following the stock and the percentage of outstanding shares owned by institutions. VIX is the contemporaneous realization of the CBOE volatility index, and S&P return is the S&P 500 index return. Lag y stands for the lagged value of the dependent variable (i.e., controlling for the persistence of the informational efficiency characteristics). The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Stock-month in the S.E. row indicates that the standard errors are two-way clustered by stock and by month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

and low levels of limits-to-arbitrage, respectively. The changes in the EMUNC coefficients across the three terciles indicate whether the effect of uncertainty on price efficiency is heterogeneous across stocks. Panel A of Table 5.3 reports these coefficients.

The three rows with "*H*", "*M*", and "*L*" in Panel A show EMUNC coefficients calculated from tercile stocks with high, medium, and low values of each respective limits-to-arbitrage proxy. For instance, for market value (MV), we find that the negative coefficient of EMUNC on *AF_efficiency* increases from 0.386 for high-MV stocks, which is statistically insignificant, to 0.868 for low-MV stocks, which is significant at the 5% level. A similar increasing pattern is observed for the *VR_efficiency* metric. The increase in the magnitude of the negative EMUNC coefficient from high (*H*) to low (*L*) tercile stocks is consistently found for market value (MV), analyst coverage (ANACOV), and trading volume (DVOL) and is consistent with the limits-to-arbitrage argument. In other words, equity market uncertainty has a larger impact on more difficult to arbitrage stocks.

We observe a reverse pattern if idiosyncratic volatility (IVOL) or the Amihud illiquidity (ILLIQ) is considered a limits-to-arbitrage proxy, in which case the negative coefficient of EMUNC decreases from 0.786 (0.827) for high-IVOL (high-ILLIQ) stocks, which is significant at 5% level, to 0.453 (0.432) for low-IVOL (low-ILLIQ) stocks, which is only marginally significant. A similar decreasing pattern is observed for the *VR_efficiency* metric. This pattern is expected as stocks with higher levels of either IVOL or ILLIQ are considered more difficult to arbitrage.

In sum, Table 5.3, Panel A, documents consistent patterns across all the five limits-to-arbitrage proxies and for both price efficiency metrics. That is, limits-to-arbitrage amplifies the negative effect of EMUNC on the informational efficiency of equity prices.

Next, we provide further evidence on how limits-to-arbitrage interacts with the EMUNC-efficiency relationship by testing the significance of the observed coefficient differences across tercile stocks reported in Table 5.3, Panel A. More specifically, we estimate the following model:

$$y_{i,m} = \alpha_i + \gamma_t + \beta EMUNC_m + \delta EMUNC_m \cdot M + \varphi EMUNC_m \cdot L + \sum_{j=1}^{J} \delta_j X_{j,i,m} + \varepsilon_{i,m}, \quad (5.7)$$

Table 5.3

The cross-sectional effect of EMUNC on informational efficiency by limits-to-arbitrage.

Panel A: The effect of EMUNC on informational efficiency across tercile stocks sorted by alternative limits-to-arbitrage proxies

	AF_efficiency					VR_efficiency				
	MV	ANACOV	DVOL	IVOL	ILLIQ	MV	ANACOV	DVOL	IVOL	ILLIQ
H	-0.386	-0.499	-0.272	-0.786**	-0.827**	-0.487**	-0.618**	-0.416**	-0.900***	-1.082***
	(-1.46)	(-1.52)	(-1.12)	(-2.01)	(-2.16)	(-2.20)	(-2.26)	(-2.08)	(-2.62)	(-2.73)
M	-0.722*	-0.652*	-0.757*	-0.676**	-0.690*	-0.808**	-0.813**	-0.877***	-0.823***	-0.789**
	(-1.93)	(-1.69)	(-1.93)	(-2.24)	(-1.87)	(-2.45)	(-2.31)	(-2.70)	(-2.74)	(-2.49)
L	-0.868**	-0.642*	-0.816**	-0.453	-0.432*	-1.129***	-0.852**	-1.034**	-0.643***	-0.504**
	(-2.21)	(-1.94)	(-2.13)	(-1.51)	(-1.66)	(-2.78)	(-2.50)	(-2.53)	(-2.60)	(-2.32)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month
Panel B: Statistical tests of the cross-sectional differences										
EMUNC	-0.276	-0.528	-0.393	-0.917**	-0.867**	-0.455**	-0.653**	-0.507**	-1.109***	-1.057***
	(-1.06)	(-1.61)	(-1.49)	(-2.35)	(-2.54)	(-1.96)	(-2.32)	(-2.25)	(-3.32)	(-3.09)
EMUNC*M	-0.450**	-0.070	-0.289*	0.281**	0.178*	-0.386*	-0.140	-0.303*	0.334***	0.261***
	(-2.36)	(-0.82)	(-1.88)	(2.52)	(1.71)	(-1.89)	(-1.19)	(-1.86)	(5.51)	(3.26)
EMUNC*L	-0.629**	-0.182*	-0.470***	0.516***	0.491***	-0.633*	-0.201	-0.510**	0.635***	0.580***
	(-2.27)	(-1.92)	(-2.78)	(2.85)	(4.18)	(-1.94)	(-1.40)	(-2.09)	(5.53)	(3.19)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month

This table reports the effect of equity market uncertainty on informational efficiency for stocks with different levels of limits-to-arbitrage. The panel regression uses monthly data. *AF_efficiency* and *VR_efficiency* are the monthly average value of the daily informational efficiency measures. EMUNC is the monthly average value of the daily US equity market uncertainty index from the policy uncertainty website (https://www.policyuncertainty.com/equity_uncert.html). For presentation, the EMUNC index is divided by 1,000. Panel A reports the coefficients of EMUNC across three tercile stock portfolios sorted by five alternative limits-to-arbitrage proxies. Rows with H, M, and L represent, respectively, portfolios with high, medium, and low values of each corresponding limits-to-arbitrage proxy, which is indicated by the title of each column. Regression specification for all results is the same as column (4) in Table 5.2. To conserve space, results for control variables are not reported. In Panel B, we test whether the coefficients across rows (i.e., tercile stocks) within each column from Panel A are statistically different from each other. The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Stock-month in the S.E. row indicates that the standard errors are two-way clustered by stock and by month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Eq. (5.7) augments Eq. (5.6) by including two additional interaction terms. *M* and *L* are the set of dummy variables that identify stocks within the medium- and low-tercile group with respect to the corresponding limits-to-arbitrage proxy.[47] Therefore, the coefficients δ and φ capture the incremental/decremental impact of EMUNC on informational efficiency across different limits-to-arbitrage stock portfolios. These results are reported in Panel B of Table 5.3.

Consistent with Table 5.2, the coefficients of EMUNC (i.e., β in Eq. (5.7)) are negative across the board, with some of them being statistically insignificant (i.e., MV, ANACOV, and DVOL for *AF_efficiency*). These insignificant EMUNC coefficients can be explained by equity market uncertainty having only a negligible impact on stocks where mispricing due to uncertainty can easily be arbitraged.[48] More importantly, δ and φ are statistically significant in most cases, and their signs are in line with the overall patterns displayed in Panel A. For instance, in terms of MV-sorted stocks, we find that stocks with the highest previous-month MV are affected by EMUNC the least (with an insignificant coefficient of -0.276 with respect to *AF_efficiency*). This negative effect increases monotonically for medium- (with a coefficient of -0.276-0.450) and low-tercile stocks (with a coefficient of -0.276-0.629). A similar increasing pattern is observed for the *VR_efficiency* metric.

In terms of IVOL-sorted stocks, we find that stocks with the highest previous-month IVOL are affected by EMUNC the most (with a coefficient of -0.917 with respect to *AF_efficiency*). This negative effect then decays monotonically for medium-tercile stocks (with a coefficient of -0.917+0.281) and for low-tercile stocks (with a coefficient of -0.917+0.516). A similar decreasing pattern is also observed for the *VR_efficiency* metric.

The cross-sectional pattern from MV (IVOL) also applies to DVOL (ILLIQ). We, however, do not observe strong cross-sectional differences in the impact of EMUNC on informational efficiency for the ANACOV proxy. Overall, the statistical evidence in Panel B concurs with our prediction. That is, limits-to-arbitrage amplifies the negative effect of EMUNC on the informational efficiency of equity prices.

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[47] In each month, we sort all sample stocks in the cross-section by their limits-to-arbitrage proxies measured from the previous month. Tercile groups are formed using an indicator variable (i.e., 0 for low tercile, 1 for medium tercile, and 2 for high tercile). *M* (*L*) equals one for stocks that fall into the medium (low) tercile group.

[48] Note that the impact of EMUNC in Eq. (5.7) indicates the benchmark effect, i.e., the impact of EMUNC on informational efficiency for stocks in the *H* tercile.

One may argue that the five limits-to-arbitrage proxies may be highly correlated with the firm size. That is, the cross-sectional results using tercile groupings of some of the limits-to-arbitrage proxies may simply mirror the results based on size terciles. Indeed, in the Appendix Table A.2, we find very similar cross-tercile patterns for many of the descriptive statistics across the five limits-to-arbitrage proxies. The positive correlation between firm size and limits-to-arbitrage is possible. For instance, it is well-known that large stocks typically have higher liquidity and, thus, tend to be more attractive to arbitrageurs. Empirically, we minimize this concern by controlling for market capitalization and stock illiquidity in the regression model. Alternatively, we construct a limits-to-arbitrage index that encompasses all five individual proxies, similar in spirit to Gu et al. (2018).[49] Such an index not only circumvents the above-mentioned issue but also provides a more comprehensive summary of the true limits-to-arbitrage of a stock. Results based on this limits-to-arbitrage index are reported in the Appendix Table A.3, which are also consistent with the main finding.

5.4.2.2. Stock uncertainty exposure

The second cross-sectional stock characteristic we is the historical stock exposure to equity market uncertainty. Stocks that are historically more exposed to uncertainty should be more prone to its negative effect. Using the uncertainty beta ($|\beta_i^{EMUNC}|$) defined in Section 5.2.3.2., each month we form tercile portfolios by sorting individual stocks based on their historical uncertainty exposure, where tercile L (H) comprises stocks with the lowest (highest) $|\beta_i^{EMUNC}|$. We then estimate Eq. (5.6) separately for each tercile portfolio and report the coefficients of EMUNC for each portfolio in Table 5.4, Panel A.

The results show that all the coefficients of EMUNC are negative, which is consistent

[49] Gu et al. (2018) use six different limits-to-arbitrage variables. They create dummy indicators based on cross-sectionally sorted stocks for each month and assign value of one for stocks "about which high limits of arbitrage are recognized, and zero otherwise". The indicator variables we construct in Section 5.4.2.1 to form tercile groups (H, M, and L tercile groups) are similar to such dummies. We follow the authors and take average values across the five indicator variables in order to construct the limits-to-arbitrage index. Note that MV, ANACOV, and DVOL are inverse measures of limits-to-arbitrage, we thus reverse the respective indicator values (i.e., 2 becomes 0 which indicates low arbitrage costs, whereas 0 becomes 2 which indicates high arbitrage costs) so that a higher value of the final constructed limits-to-arbitrage index indicates greater arbitrage frictions. Finally, we form tercile groups based on this limits-to-arbitrage index (as opposed to each individual proxy).

with those reported in other tables. Comparing the coefficients of EMUNC from the low-beta tercile portfolio to the high-beta tercile portfolio, we find that the negative effect of EMUNC generally increases as $|\beta_i^{EMUNC}|$ increases. For instance, for the *AF_efficiency* (*VR_efficiency*) metric, the EMUNC coefficient changes from -0.633 (-0.708) for the low-beta tercile portfolio to -0.750 (-0.926) for the high-beta tercile portfolio. For robustness, we also estimate $|\beta_i^{EMUNC}|$ using the Fama-French four-factor model and find qualitatively very similar results. This suggests that stocks with higher uncertainty exposure tend to be more sensitive to EMUNC.

Table 5.4, Panel B reports the statistical significance of the difference in the EMUNC

Table 5.4
The cross-sectional effect of EMUNC on informational efficiency by stocks' historical uncertainty exposure.

Panel A: The effect of EMUNC on informational efficiency across tercile stocks sorted by uncertainty betas ($\lvert\beta^{EMUNC}\rvert$)				
	AF_efficiency		VR_efficiency	
	$\lvert\beta^{EMUNC}\rvert$-FF3F	$\lvert\beta^{EMUNC}\rvert$-FF4F	$\lvert\beta^{EMUNC}\rvert$-FF3F	$\lvert\beta^{EMUNC}\rvert$-FF4F
H	-0.750**	-0.733**	-0.926***	-0.903***
	(-2.04)	(-2.03)	(-2.87)	(-2.91)
M	-0.554*	-0.558*	-0.740**	-0.737**
	(-1.69)	(-1.70)	(-2.19)	(-2.18)
L	-0.633**	-0.641**	-0.708**	-0.728**
	(-1.96)	(-1.96)	(-2.22)	(-2.23)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month
Panel B: Statistical tests of the cross-sectional differences				
EMUNC	-0.682*	-0.676*	-0.889***	-0.882***
	(-1.88)	(-1.84)	(-2.78)	(-2.74)
EMUNC*M	0.183*	0.176**	0.232***	0.211**
	(1.88)	(1.96)	(2.85)	(2.56)
EMUNC*L	0.065	0.042	0.160*	0.145*
	(0.61)	(0.41)	(1.80)	(1.75)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month

This table reports the effect of equity market uncertainty on informational efficiency for stocks with different historical exposure to uncertainty. The panel regression uses monthly data. *AF_efficiency* and *VR_efficiency* are the monthly average value of the daily informational efficiency measures. EMUNC is the monthly average value of the daily US equity market uncertainty index from the policy uncertainty website (https://www.policyuncertainty.com/equity_uncert.html). For presentation, the EMUNC index is divided by 1,000. Panel A reports the effects of EMUNC on informational efficiency across three tercile stock portfolios sorted by the stock uncertainty betas $|\beta^{EMUNC}|$. Rows with H, M, and L represent, respectively, portfolios with high, medium, and low historical uncertainty exposures. Regression specification for all results is the same as column (4) in Table 5.2. To conserve space, results for control variables are not reported. In Panel B, we test whether the coefficients across rows (i.e., tercile stocks) within each column from Panel A are statistically different from each other. The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Stock-month in the S.E. row indicates that the standard errors are two-way clustered by stock and by month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

coefficients across beta-sorted tercile portfolios. We find that the coefficients of both interaction terms are positive, which echoes the overall pattern we observe in Panel A. The cross-sectional pattern is strong for the *VR_efficiency* metric but weaker for the *AF_efficiency* metric in comparison. For instance, the difference in the EMUNC coefficients between the high- and low-beta stocks is statistically insignificant for *AF_efficiency*. Nevertheless, Table 5.4 provides some evidence that suggests that stocks with greater historical exposure to EMUNC also experience a greater reduction in price efficiency when uncertainty rallies.

To visualize the cross-sectional patterns, we plot in Fig 5.1 the coefficients of EMUNC. Fig 5.1 shows that the EMUNC coefficients tend to be larger in magnitudes for stocks with higher limits-to-arbitrage or greater uncertainty exposure.

5.5. Additional analyses

So far, we have shown that equity market uncertainty is harmful to the informational efficiency of equity prices. In addition, this effect is heterogeneous in the cross-section, depending on the stock-level limits-to-arbitrage or historical uncertainty exposure. This section provides additional robustness tests of these cross-sectional results. First, we check whether the cross-sectional pattern holds using alternative proxies for uncertainty. Second, we use an additional measure of equity price informational efficiency to check whether the main results depend on the choice of empirical measures. Finally, we redo the cross-sectional analyses under different sampling frequencies to test whether our main results depend on the particular estimation method.

5.5.1. Alternative proxies for uncertainty

The first robustness test we consider is whether the cross-sectional pattern holds when other uncertainty measures are used. In the main analyses, we use Baker et al.'s (2016) EMUNC index. This uncertainty index has two main features. First, it is a newspaper-based proxy and is distinct from other market-based uncertainty measures such as return volatility or the VIX. Second, the EMUNC index focuses on the US equity market. Therefore, the choice of additional uncertainty proxies should closely follow these two criteria. Following this logic, we use two alternative measures of uncertainty: the US newspaper-based economic policy uncertainty (EPU_news) index and the US newspaper-based equity market volatility (EMV) tracker. Both indexes are obtained from the economic policy uncertainty website.

Both EPU_news and EMV indexes are constructed using newspaper articles and, thus, are similar in spirit to the EMUNC index. The EPU_news index is distinct from the EMUNC index because it captures uncertainty related to government economic-related policies rather than the equity market. The EPU_news index is widely used in the finance literature (e.g., Gulen and Ion, 2016; Nagar et al., 2019).[50] Both EMV and the EMUNC index focus on the US equity market. EMV is distinct from EMUNC because it tracks newspaper articles that mention the keywords "volatility/volatile" instead of "uncertainty/uncertain." We choose the EMV index because extant literature often uses volatility as a measure of uncertainty (e.g., Bloom et al., 2007; Bloom, 2009).

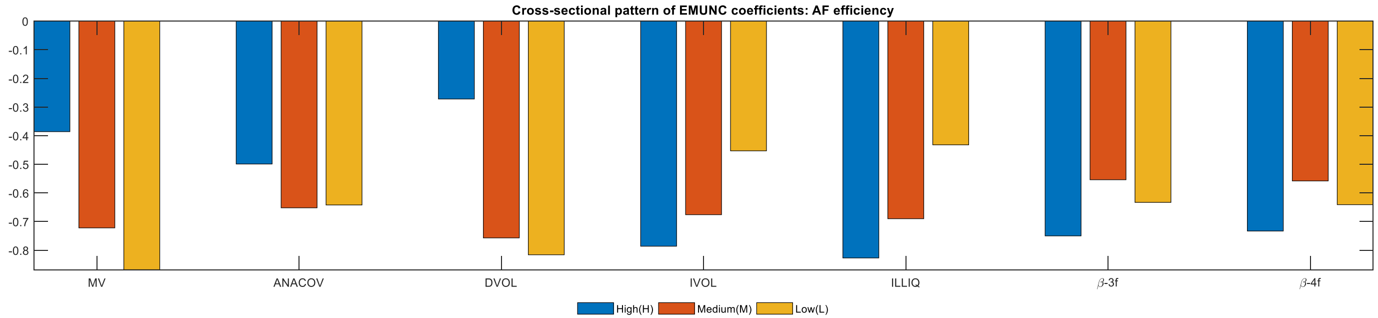
Table 5.5 reports the cross-sectional pattern by limits-to-arbitrage using the two alternative uncertainty proxies. Starting with the EPU_news index, Panel A finds supporting evidence for three of the five limit-to-arbitrage proxies (DVOL, IVOL, and ILLIQ). Panel B also suggests that greater limits to arbitrage lead to stronger coefficients. In Table 5.6, we test the robustness of the cross-sectional pattern by stock uncertainty exposure reported in Table 5.4 with the two additional uncertainty proxies. Overall, Table 5.6 finds supporting but weak evidence only when the EPU_news index is considered. To visualize the results, in Fig 5.2, we also plot the cross-sectional pattern of EPU_news coefficients.

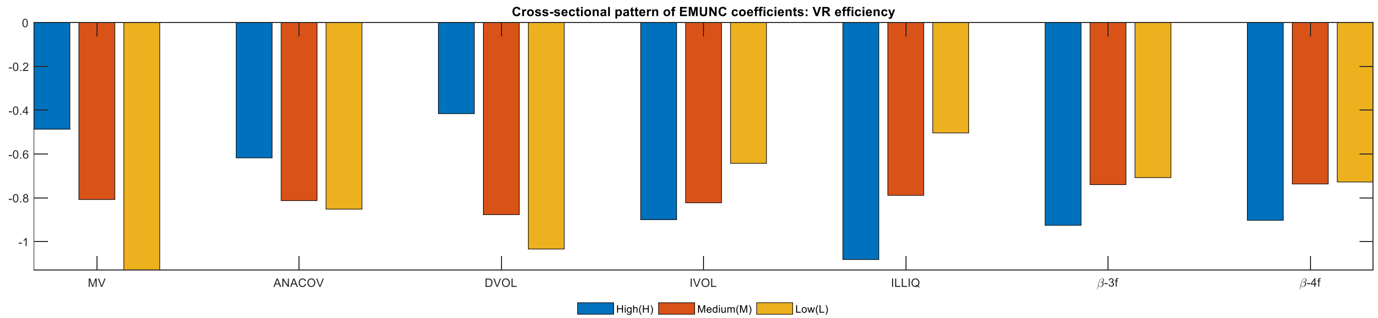
Overall, we use two alternative proxies for uncertainty, the news-based EPU index and the news-based EMV index, to test the robustness of our main results. We show that the EPU_news index survives the robustness tests. We postulate that the insignificant results using the EMV index are likely because the word "volatility" and "uncertainty" are not perfect substitutes for each other from the perspective of market participants.

[50] We also consider the aggregate EPU index, which is the weighted average of three individual components: the news-based EPU index, the tax expirations index, and the economic forecast disagreement about CPI and government spending. In an unreported table, we also find some supporting evidence. However, these results are weaker compared to the EPU_news index. We believe this is because the other two components from the aggregate EPU index is not so relevant for our context, which render the overall results weaker.

Fig 5.1

The cross-sectional patterns of EMUNC coefficients.





This plot shows the cross-sectional patterns of EMUNC coefficients reported in Tables 5.3 & 5.4. The three coefficients for the high (H), medium (M), and low (L) stock tercile are represented by three bars with different colors.

Table 5.5

Robustness tests of Table 5.3 using alternative proxies for uncertainty.

Panel A: The cross-sectional effect of EPU_news on the informational efficiency of equity prices

	AF_efficiency					VR_efficiency				
	MV	ANACOV	DVOL	IVOL	ILLIQ	MV	ANACOV	DVOL	IVOL	ILLIQ
EPU_news	-0.386**	-0.421**	-0.347**	-0.631**	-0.656***	-0.486***	-0.497**	-0.405**	-0.776***	-0.759***
	(-2.17)	(-1.97)	(-2.00)	(-2.57)	(-2.69)	(-2.70)	(-2.51)	(-2.48)	(-3.38)	(-2.98)
EPU_news*M	-0.237*	-0.150	-0.174*	0.109*	0.122*	-0.189	-0.153	-0.199**	0.169***	0.155**
	(-1.81)	(-1.59)	(-1.78)	(1.67)	(1.80)	(-1.29)	(-1.44)	(-2.00)	(3.25)	(1.97)
EPU_news*L	-0.145	-0.126	-0.342**	0.250**	0.296**	-0.154	-0.142	-0.395**	0.374***	0.322**
	(-0.89)	(-1.09)	(-2.39)	(2.39)	(2.39)	(-0.81)	(-1.21)	(-2.39)	(4.40)	(1.99)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month
Panel B: The cross-sectional effect of EMV on the informational efficiency of equity prices										
EMV	0.988	0.527	1.305	-0.522	-0.930	-0.286	-0.267	0.429	-1.922	-1.851
	(0.88)	(0.38)	(0.95)	(-0.40)	(-0.65)	(-0.21)	(-0.20)	(0.30)	(-1.42)	(-1.33)
EMV*M	-0.996	0.751	-0.761	0.755**	1.419***	-0.614	0.327	-0.911	1.199***	1.436***
	(-0.72)	(1.36)	(-1.21)	(1.97)	(3.42)	(-0.43)	(0.54)	(-1.39)	(4.03)	(3.00)
EMV*L	-0.653	-0.551	-1.913**	1.669***	2.593***	-0.064	-0.518	-1.977*	2.418***	2.501**
	(-0.43)	(-0.69)	(-2.21)	(2.70)	(3.46)	(-0.04)	(-0.58)	(-1.81)	(4.60)	(2.51)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month

This table checks the robustness of the cross-sectional effect of EMUNC on informational efficiency reported in Table 5.3 using two alternative proxies for uncertainty. The panel regression uses monthly data. *AF_efficiency* and *VR_efficiency* are the monthly average value of the daily informational efficiency measures. Panel A reports the cross-sectional pattern (comparable to those reported in Table 5.3, Panel B) using *EPU_news* as an alternative proxy for uncertainty, where *EPU_news* is the monthly average value of the daily newspaper-based US economic policy uncertainty index from the policy uncertainty website (https://www.policyuncertainty.com/us_monthly.html). For presentation, the *EPU_news* index is divided by 1,000. Regression specification for all results is the same as column (4) in Table 5.2. To conserve space, results for control variables are not reported. In Panel B, we repeat the analyses in Panel A but replace the *EPU_news* with the *EMV* index as an alternative proxy for uncertainty, where *EMV* index is the monthly newspaper-based US equity market volatility tracker from the policy uncertainty website (https://www.policyuncertainty.com/EMV_monthly.html). For presentation, the *EMV* index is divided by 1,000. The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Stock-month in the S.E. row indicates that the standard errors are two-way clustered by stock and by month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5.6

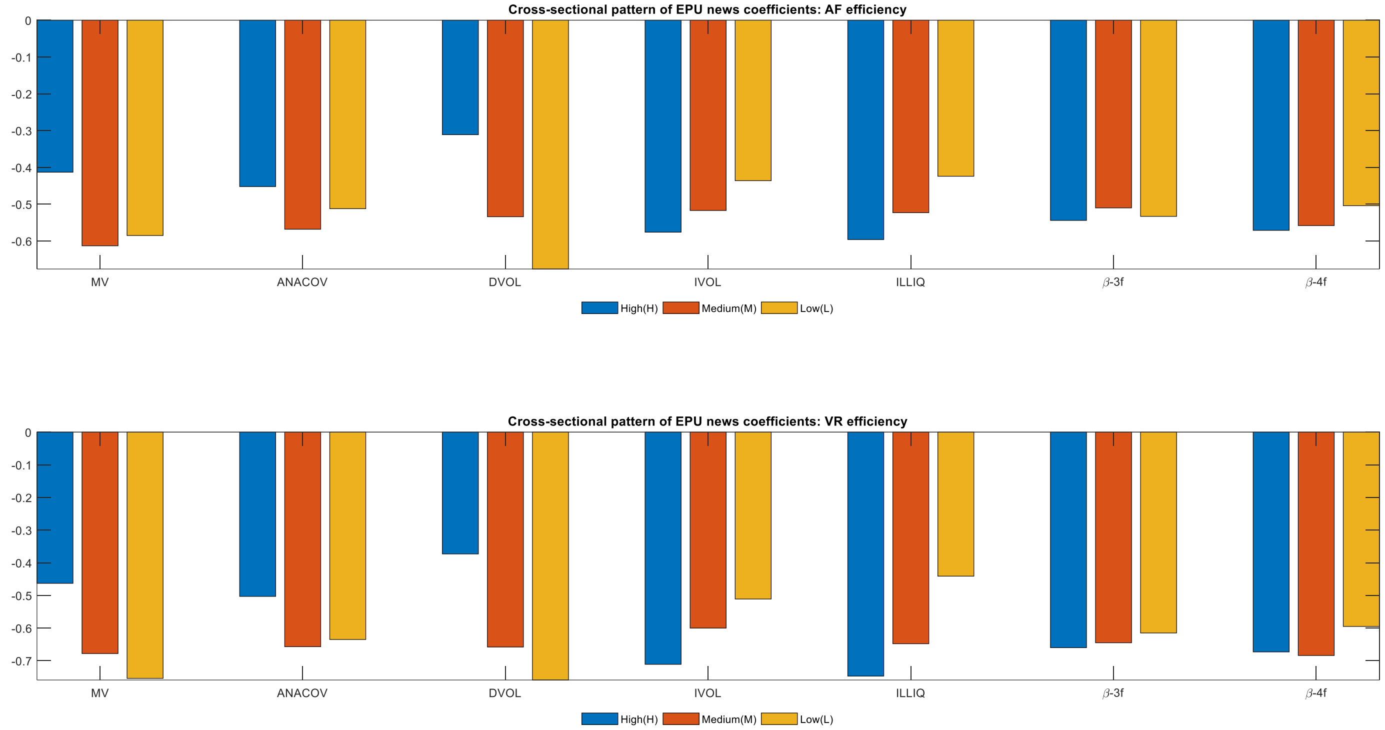
Robustness tests of Table 5.4 using alternative proxies for uncertainty.

Panel A: The cross-sectional effect of EPU_news on the informational efficiency of equity prices				
	AF_efficiency		VR_efficiency	
	$\lvert\beta^{EPU\_news}\rvert$-FF3F	$\lvert\beta^{EPU\_news}\rvert$-FF4F	$\lvert\beta^{EPU\_news}\rvert$-FF3F	$\lvert\beta^{EPU\_news}\rvert$-FF4F
EPU_news	-0.553***	-0.559***	-0.648***	-0.647***
	(-2.63)	(-2.68)	(-3.24)	(-3.28)
EPU_news*M	0.073**	0.069*	0.081**	0.068
	(2.14)	(1.65)	(2.50)	(1.62)
EPU_news*L	0.009	0.030	0.019	0.026
	(0.23)	(0.63)	(0.49)	(0.57)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month
Panel B: The cross-sectional effect of EMV on the informational efficiency of equity prices				
	$\lvert\beta^{EMV}\rvert$-FF3F	$\lvert\beta^{EMV}\rvert$-FF4F	$\lvert\beta^{EMV}\rvert$-FF3F	$\lvert\beta^{EMV}\rvert$-FF4F
EMV	0.655	0.425	-0.370	-0.500
	(0.50)	(0.32)	(-0.28)	(-0.38)
EMV*M	-0.189	0.217	-0.037	0.261
	(-0.83)	(0.98)	(-0.15)	(1.30)
EMV*L	-0.068	0.218	-0.013	0.079
	(-0.28)	(0.87)	(-0.05)	(0.30)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month

This table checks the robustness of the cross-sectional effect of EMUNC on informational efficiency reported in Table 5.4 using two alternative proxies for uncertainty. The panel regression uses monthly data. *AF_efficiency* and *VR_efficiency* are the monthly average value of the daily informational efficiency measures. Panel A reports the cross-sectional pattern (comparable to those reported in Table 5.4, Panel B) using *EPU_news* as an alternative proxy for uncertainty, where *EPU_news* is the monthly average value of the daily newspaper-based US economic policy uncertainty index from the policy uncertainty website (https://www.policyuncertainty.com/us_monthly.html). For presentation, the *EPU_news* index is divided by 1,000. Regression specification for all results is the same as column (4) in Table 5.2. To conserve space, results for control variables are not reported. In Panel B, we repeat the analyses in Panel A but replace the *EPU_news* with the *EMV* index as an alternative proxy for uncertainty, where *EMV* index is the monthly newspaper-based US equity market volatility tracker from the policy uncertainty website (https://www.policyuncertainty.com/EMV_monthly.html). For presentation, the *EMV* index is divided by 1,000. The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Stock-month in the S.E. row indicates that the standard errors are two-way clustered by stock and by month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Fig 5.2

The cross-sectional patterns of EPU_news coefficients.



This plot shows the cross-sectional patterns of EPU_news coefficients reported in Table A1. The three coefficients for the high (H), medium (M), and low (L) stock tercile are represented by three bars with different colors.

5.5.2. Alternative measure of informational efficiency

Next, we check whether the cross-sectional results reported in Section 5.4.2 are robust to alternative informational efficiency measures. We additionally consider excess short-term volatility as a sign of deterioration in equity price informational efficiency. This is similar in spirit to Shiller (1981), who argues that stock price volatility is too high to be explained by changes in fundamentals. This fails the notion of efficient markets. Excess short-term volatility captures noise and temporary price deviations from the equilibrium values caused by trading frictions, leading to less efficient prices.

To capture excess short-term return volatility empirically, we take the ratio of high- and low-frequency return volatility for a given stock-month, which we label *HL_ratio*. Similar to the construction of *AF_efficiency* metric, we define high-frequency volatility as the first principal component of mid-quote return standard deviation measured at three intraday frequencies, $k \in \{30\ \text{sec}, 1\ \text{min}, 2\ \text{min}\}$. We then aggregate this daily high-frequency volatility to a monthly measure. Low-frequency volatility is the standard deviation of daily returns within a given month, which is a proxy for fundamental volatility. Therefore, a higher *HL_ratio* indicates greater high-frequency volatility relative to fundamental volatility, thus capturing "excess" short-term volatility. For consistency with other informational efficiency metrics, we multiply *HL_ratio* by -1 so that it becomes an efficiency measure. We label this quantity *ESV_efficiency*.

Short-term volatility has also been used in the literature as an inverse indicator of price efficiency (e.g., Chordia et al., 2011; O'Hara and Ye, 2011). The regulatory authority also views excess short-term volatility as a negative indicator of market quality.[51]

Table 5.7 reports the cross-sectional results using the *ESV_efficiency* metric. Panel A reports the cross-sectional effect of EMUNC by limits-to-arbitrage. For the five limits-to-arbitrage proxies, we find supporting evidence for three of them. For the cross-sectional effect of EMUNC by historical uncertainty exposure, we find mixed evidence. The pattern only

[51] For instance, pp 36-37 of the SEC Concept Release No. 34-61358 notes: "…short-term price volatility may harm individual investors if they are persistently unable to react to changing prices as fast as high frequency traders…long-term investors may not be in a position to assess and take advantage of short-term price movements."

appears when the uncertainty beta is estimated using the Fama-French four-factor model. Therefore, we are cautious in interpreting the results. Overall, Table 5.7 provides moderate support to our main findings.

Table 5.7
Robustness tests using excess short-term volatility (ESV_efficiency) as an alternative informational efficiency metric.

	ESV_efficiency				
Panel A: The cross-sectional effect of EMUNC on short-term excess volatility by limits-to-arbitrage					
	MV	ANACOV	DVOL	IVOL	ILLIQ
EMUNC	-40.506*	-52.726**	-44.568**	-96.692**	-69.498**
	(-1.67)	(-2.11)	(-1.97)	(-2.45)	(-2.13)
EMUNC*M	7.565	-8.823	-10.744*	17.717	12.030
	(1.07)	(-1.08)	(-1.70)	(0.90)	(0.67)
EMUNC*L	3.935	-16.535***	-38.530*	80.766*	14.559
	(0.29)	(-3.19)	(-1.90)	(1.66)	(0.55)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month

Panel B: The cross-sectional effect of EMUNC on short-term excess volatility by stocks' historical uncertainty exposure		
	$\lvert\beta^{EMUNC}\rvert$-FF3F	$\lvert\beta^{EMUNC}\rvert$-FF4F
EMUNC	-63.819***	-64.750***
	(-2.65)	(-2.64)
EMUNC*M	8.177	9.515*
	(1.53)	(1.85)
EMUNC*L	9.992	11.435**
	(1.61)	(1.96)
Controls	Yes	Yes
Fixed effects	Stock-year	Stock-year
S.E.	Stock-month	Stock-month

This table checks the robustness of the cross-sectional effect of EMUNC on informational efficiency reported in Tables 5.3 & 5.4 using excess short-term volatility (*ESV_efficiency*) as an additional informational efficiency metric. The panel regression uses monthly data. *ESV_efficiency* is the ratio of high- and low-frequency realized volatility within a stock-month. For presentation, the EMUNC index is divided by 1,000. Panel A follows Panel B of Table 5.3, whereas Panel B follows Panel B of Table 5.4. Regression specification for all results is the same as column (4) in Table 5.2. To conserve space, results for control variables are not reported. The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Stock-month in the S.E. row indicates that the standard errors are two-way clustered by stock and by month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5.5.3. Different estimation methods

Finally, we replicate our main results using the same informational efficiency measures estimated using different methods. In the main analyses, we estimate *AF_efficiency* and *VR_efficiency* using somewhat arbitrary sampling frequencies. Since there is no theoretical guidance as to what the optimal estimation frequency is, we experiment with other options. Specifically, we estimate the *AF_efficiency* metric using two alternative frequency combinations: $\{15 \text{ sec}, 30 \text{ sec}, 1 \text{ min}\}$ and $\{2 \text{ min}, 5 \text{ min}, 10 \text{ min}\}$. These two additional frequency combinations straddle the one used in the main analyses. Therefore, we test the robustness of the main results when sampling fast or slow. We do the same for the *VR_efficiency* metric and use the following two additional frequency combinations: (10sec_30sec, 10sec_1min, 30sec_1min) and (1min_5min,5min_10min,2min_10min).[52]

Table 5.8 replicates the cross-sectional analyses in Table 5.3 under the two alternative estimation frequencies described above. For both informational efficiency measures and under both estimation methods, we find very similar cross-sectional patterns that are in line with the main result. The negative impact of EMUNC is larger in magnitudes for stocks with lower MV, ANACOV, and DVOL but smaller in magnitudes for stocks with lower IVOL and ILLIQ. In other words, limits to arbitrage aggravate the harmful effect of uncertainty. Turning to the cross-sectional effect by stocks' historical uncertainty exposure, Table 5.9 also finds supporting evidence. That is, stocks with higher historical uncertainty exposure are more subject to the negative effect of EMUNC. Similarly, these cross-sectional patterns are plotted in Fig 5.3.[53] We, thus, conclude that the cross-sectional effect of uncertainty on equity price efficiency is robust to alternative estimation methods.

[52] A caution is in order. We also find that when sampling too fast (e.g., 1sec, 2sec, 5sec), the pattern we obtain from the main analyses disappear. This is likely because under very high sampling frequencies, the informational efficiency metrics capture more microstructure noise than the latent process governing informational efficiency, more so for less actively traded and illiquid stocks.
[53] The coefficients for Figs 5.1-5.3 are in the Appendix Table A.1.1-A.1.3.

Table 5.8

Robustness tests of Table 5.3 under different estimation frequencies.

Panel A: AF_efficiency metric estimated at different measurement frequencies

	AF_efficiency(15s,30s,1min)					AF_efficiency(2min,5min,10min)				
	MV	ANACOV	DVOL	IVOL	ILLIQ	MV	ANACOV	DVOL	IVOL	ILLIQ
EMUNC	-0.375	-0.602*	-0.467*	-1.069**	-0.853**	-0.137	-0.238	-0.195	-0.499**	-0.610***
	(-1.38)	(-1.71)	(-1.76)	(-2.35)	(-2.31)	(-0.72)	(-1.09)	(-0.68)	(-2.20)	(-2.58)
EMUNC*M	-0.356*	-0.026	-0.300	0.397**	0.093	-0.299**	-0.173**	-0.289*	0.123***	0.283***
	(-1.78)	(-0.25)	(-1.47)	(2.54)	(0.71)	(-2.26)	(-2.02)	(-1.72)	(2.92)	(2.90)
EMUNC*L	-0.472*	-0.078	-0.409**	0.672***	0.363**	-0.494***	-0.234**	-0.490***	0.249***	0.428***
	(-1.64)	(-0.73)	(-2.08)	(3.00)	(2.41)	(-2.64)	(-2.03)	(-3.12)	(4.11)	(3.95)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month

Panel B: VR_efficiency metric estimated at different measurement frequencies

	VR_efficiency(10sec_30sec,10sec_1min,30sec_1min)					VR_efficiency(1min_5min,5min_10min,2min_10min)				
EMUNC	-0.255	-0.411	-0.236	-0.986**	-0.657*	-0.377**	-0.451**	-0.459***	-0.757***	-0.789***
	(-0.84)	(-1.09)	(-0.80)	(-2.25)	(-1.68)	(-2.02)	(-2.31)	(-2.78)	(-3.66)	(-3.66)
EMUNC*M	-0.178	0.002	-0.314*	0.519***	0.129	-0.223*	-0.155*	-0.097	0.173***	0.229***
	(-1.00)	(0.02)	(-1.72)	(5.46)	(1.04)	(-1.67)	(-1.74)	(-1.01)	(4.32)	(3.03)
EMUNC*L	-0.353	-0.039	-0.489**	0.891***	0.345**	-0.401*	-0.188*	-0.263*	0.349***	0.403***
	(-1.24)	(-0.27)	(-2.51)	(6.52)	(2.42)	(-1.77)	(-1.72)	(-1.86)	(5.44)	(3.86)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month	Stock-month

This table checks the robustness of the cross-sectional effect of EMUNC on informational efficiency reported in Table 5.3 under different estimation frequencies. The dependent variables, *AF_efficiency* and *VR_efficiency*, are estimated using different sampling frequencies. Panel A reports the cross-sectional pattern (comparable to those reported in Table 5.3, Panel B) when *AF_efficiency* is estimated using two alternative sets of frequencies, i.e., (15sec, 30sec, 1min) and (2min, 5min, 10min). Panel B reports the cross-sectional pattern (comparable to those reported in Table 5.3, Panel B) when *VR_efficiency* is estimated using two alternative sets of frequencies, i.e., (10sec_30sec, 10sec_1min, 30sec_1min) and (1min_5min, 5min_10min, 2min_10min). EMUNC is the monthly average value of the daily US equity market uncertainty index from the policy uncertainty website (https://www.policyuncertainty.com/equity_uncert.html). For presentation, the EMUNC index is divided by 1,000. Regression specification for all results is the same as column (4) in Table 5.2. To conserve space, results for control variables are not reported. The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Stock-month in the S.E. row indicates that the standard errors are two-way clustered by stock and by month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5.9

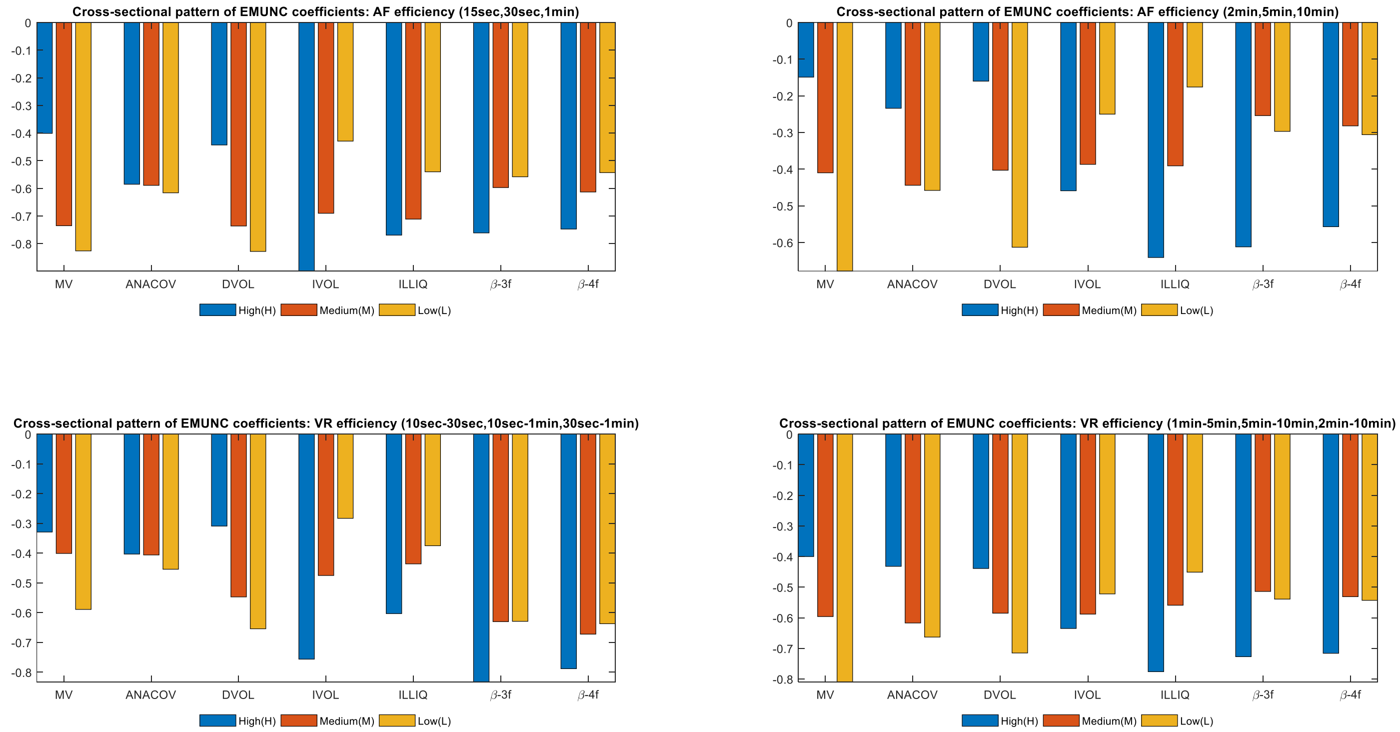
Robustness tests of Table 5.4 under different estimation frequencies.

Panel A: AF_efficiency metric estimated at different measurement frequencies				
	AF_efficiency(15s,30s,1min)		AF_efficiency(2min,5min,10min)	
	$\lvert\beta^{EMUNC}\rvert$-FF3F	$\lvert\beta^{EMUNC}\rvert$-FF4F	$\lvert\beta^{EMUNC}\rvert$-FF3F	$\lvert\beta^{EMUNC}\rvert$-FF4F
EMUNC	-0.744**	-0.768**	-0.481**	-0.436*
	(-2.01)	(-2.11)	(-2.09)	(-1.87)
EMUNC*M	0.062	0.092	0.217**	0.152*
	(1.12)	(1.54)	(2.15)	(1.67)
EMUNC*L	0.104**	0.143**	0.199**	0.117
	(2.01)	(2.52)	(2.03)	(1.17)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month
Panel B: VR_efficiency metric estimated at different measurement frequencies				
	VR_efficiency(10sec_30sec,10sec_1min,30sec_1min)		VR_efficiency(1min_5min,5min_10min,2min_10min)	
EMUNC	-0.771**	-0.778**	-0.699***	-0.681***
	(-1.96)	(-2.02)	(-3.21)	(-3.29)
EMUNC*M	0.087*	0.095*	0.228***	0.189**
	(1.83)	(1.76)	(2.91)	(2.49)
EMUNC*L	0.147***	0.159***	0.179**	0.153*
	(3.04)	(2.93)	(1.99)	(1.80)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Stock-year	Stock-year	Stock-year	Stock-year
S.E.	Stock-month	Stock-month	Stock-month	Stock-month

This table checks the robustness of the cross-sectional effect of EMUNC on informational efficiency reported in Table 5.4 under different estimation frequencies. The dependent variables, *AF_efficiency* and *VR_efficiency*, are estimated using different sampling frequencies. Panel A reports the cross-sectional pattern (comparable to those reported in Table 5.4, Panel B) when *AF_efficiency* is estimated using two alternative sets of frequencies, i.e., (15sec, 30sec, 1min) and (2min, 5min, 10min). Panel B reports the cross-sectional pattern (comparable to those reported in Table 5.4, Panel B) when *VR_efficiency* is estimated using two alternative sets of frequencies, i.e., (10sec_30sec,10sec_1min,30sec_1min) and (1min_5min,5min_10min,2min_10min). EMUNC is the monthly average value of the daily US equity market uncertainty index from the policy uncertainty website (https://www.policyuncertainty.com/equity_uncert.html). For presentation, the EMUNC index is divided by 1,000. Regression specification for all results is the same as column (4) in Table 5.2. To conserve space, results for control variables are not reported. The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Stock-month in the S.E. row indicates that the standard errors are two-way clustered by stock and by month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Fig 5.3

The cross-sectional patterns of EMUNC coefficients under different estimation methods.



This plot shows the cross-sectional patterns of EMUNC coefficients reported in Tables A2 & A3. The three coefficients for the high (H), medium (M), and low (L) stock tercile are represented by three bars with different colors.

5.6. Conclusion

We study the effect of equity market uncertainty (EMUNC) on the informational efficiency of equity prices. Using a sample of S&P 500 constituent stocks, we find a significant negative impact of EMUNC on price efficiency. Consistent with Chapter 3 which finds similar results using two liquid ETFs, this suggests that uncertainty is a market friction that creates noise and mispricing, thus rendering equity prices less efficient. Further cross-sectional analyses reveal that the negative impact of EMUNC is stronger for specific stocks. We postulate and find supporting evidence for two plausible channels that facilitate cross-sectional heterogeneity: limits-to-arbitrage and stock-level uncertainty exposure. Specifically, we find that stocks with higher limits-to-arbitrage or higher historical uncertainty exposure are more subject to the negative effect of EMUNC. This cross-sectional pattern is significant and survives many of the robustness tests. We conclude that arbitrage activity plays a beneficial role in financial markets. Thus, stocks that attract more arbitrageurs are less sensitive to EMUNC because arbitrage activity partially mitigates the negative impact of uncertainty.

There are several interesting directions for future research. For instance, we focus on S&P 500 stocks, which are the top 500 stocks from the entire US equity universe. Further analyses, especially for the small- and micro-cap stocks, are important before our conclusions can be extrapolated to the entire equity universe. In addition, further analyses in different settings, such as different countries/markets and different asset classes, can provide additional insights into the impact of uncertainty on capital markets. For instance, do different market mechanisms play a role in the impact of uncertainty? Is the cross-sectional pattern we document unique to the institutional setting in the US market? Another future research question is to link equity market uncertainty to the behavior of institutional and retail traders. How different types of traders react to uncertainty can be an interesting behavioral finance topic. These questions are left for future research.

Appendix A.1. The uncertainty coefficients for Fig 5.1-5.3

Table A.1.1

EPU_news coefficients across stock terciles.

	MV	ANACOV	DVOL	IVOL	ILLIQ	$\lvert\beta^{EPU\_news}\rvert$-FF3F	$\lvert\beta^{EPU\_news}\rvert$-FF4F
Panel A: AF_efficiency							
H	-0.413**	-0.452**	-0.311*	-0.576**	-0.596**	-0.544**	-0.571**
	(-2.35)	(-2.23)	(-1.83)	(-2.31)	(-2.37)	(-2.37)	(-2.39)
M	-0.613**	-0.568**	-0.534**	-0.517**	-0.523**	-0.510**	-0.558**
	(-2.43)	(-2.36)	(-1.99)	(-2.35)	(-2.07)	(-2.25)	(-2.57)
L	-0.585**	-0.512**	-0.676***	-0.436**	-0.424**	-0.533**	-0.504**
	(-2.22)	(-2.27)	(-2.83)	(-2.11)	(-2.44)	(-2.54)	(-2.40)
Panel B: VR_efficiency							
H	-0.463***	-0.503***	-0.373**	-0.711***	-0.747***	-0.660***	-0.673***
	(-2.64)	(-2.74)	(-2.36)	(-3.43)	(-2.96)	(-3.05)	(-2.96)
M	-0.678***	-0.657***	-0.658***	-0.600***	-0.648***	-0.645***	-0.684***
	(-2.81)	(-2.91)	(-2.58)	(-2.63)	(-3.02)	(-2.85)	(-3.26)
L	-0.754***	-0.635***	-0.759***	-0.511**	-0.441***	-0.615***	-0.595***
	(-2.91)	(-2.85)	(-2.78)	(-2.55)	(-2.59)	(-2.87)	(-2.93)

This table reports the coefficients of EPU_news across different stock terciles, where EPU_news index is used as an alternative proxy for uncertainty. The results for the two informational efficiency metrics, *AF_efficiency* and *VR_efficiency*, are reported in Panel A and Panel B, respectively. Regression specification for all results is the same as column (4) in Table 5.2. To conserve space, results for control variables are not reported. The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Stock-month in the S.E. row indicates that the standard errors are two-way clustered by stock and by month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.1.2

EMUNC coefficients across stocks terciles sorted by limits-to-arbitrage under different estimation frequencies.

Panel A: AF_efficiency metric estimated at different measurement frequencies										
	AF_efficiency(15s,30s,1min)					AF_efficiency(2min,5min,10min)				
	MV	ANACOV	DVOL	IVOL	ILLIQ	MV	ANACOV	DVOL	IVOL	ILLIQ
H	-0.401	-0.585*	-0.443*	-0.899*	-0.769*	-0.149	-0.234	-0.160	-0.459**	-0.641**
	(-1.16)	(-1.66)	(-1.87)	(-1.92)	(-1.81)	(-0.80)	(-1.16)	(-0.91)	(-2.31)	(-2.21)
M	-0.735*	-0.589	-0.736*	-0.690**	-0.711*	-0.410*	-0.444*	-0.403*	-0.387	-0.391*
	(-1.80)	(-1.63)	(-1.73)	(-2.07)	(-1.74)	(-1.66)	(-1.66)	(-1.67)	(-1.60)	(-1.70)
L	-0.826*	-0.616*	-0.828*	-0.429	-0.540*	-0.678**	-0.458*	-0.613**	-0.250	-0.176
	(-1.90)	(-1.86)	(-1.94)	(-1.40)	(-1.93)	(-2.38)	(-1.69)	(-2.13)	(-1.01)	(-0.93)
Panel B: VR_efficiency metric estimated at different measurement frequencies										
	VR_efficiency(10sec_30sec,10sec_1min,30sec_1min)					VR_efficiency(1min_5min,5min_10min,2min_10min)				
H	-0.329	-0.403	-0.309	-0.756	-0.603	-0.400**	-0.432**	-0.439**	-0.635***	-0.776***
	(-0.79)	(-0.98)	(-0.68)	(-1.59)	(-1.32)	(-2.12)	(-2.41)	(-2.38)	(-3.18)	(-3.09)
M	-0.401	-0.406	-0.547	-0.475	-0.436	-0.596***	-0.617***	-0.585***	-0.588***	-0.559***
	(-1.23)	(-1.07)	(-1.17)	(-1.27)	(-1.45)	(-2.69)	(-2.71)	(-2.60)	(-2.85)	(-2.72)
L	-0.589	-0.454	-0.654*	-0.283	-0.375	-0.809***	-0.663***	-0.715**	-0.522**	-0.451**
	(-1.19)	(-1.18)	(-1.82)	(-1.00)	(-0.89)	(-3.20)	(-3.10)	(-2.56)	(-2.33)	(-2.35)

This table reports the coefficients of EMUNC across different stock terciles, where stocks are sorted by the limits-to-arbitrage proxy. The dependent variables, *AF_efficiency* and *VR_efficiency*, are estimated using different sampling frequencies. Panel A reports the EMUNC coefficients (comparable to those reported in Table 5.3, Panel A) when *AF_efficiency* is estimated using two alternative sets of frequencies, i.e., (15sec, 30sec, 1min) and (2min, 5min, 10min). Panel B reports the EMUNC coefficients (comparable to those reported in Table 5.3, Panel A) when *VR_efficiency* is estimated using two alternative sets of frequencies, i.e., (10sec_30sec, 10sec_1min, 30sec_1min) and (1min_5min, 5min_10min, 2min_10min). Regression specification for all results is the same as column (4) in Table 5.2. To conserve space, results for control variables are not reported. The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Stock-month in the S.E. row indicates that the standard errors are two-way clustered by stock and by month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.1.3

EMUNC coefficients across stocks terciles sorted by uncertainty exposure under different estimation frequencies.

Panel A: AF_efficiency metric estimated at different measurement frequencies

	AF_efficiency(15s,30s,1min)		AF_efficiency(2min,5min,10min)	
	$\lvert\beta^{EMUNC}\rvert$-FF3F	$\lvert\beta^{EMUNC}\rvert$-FF4F	$\lvert\beta^{EMUNC}\rvert$-FF3F	$\lvert\beta^{EMUNC}\rvert$-FF4F
H	-0.761*	-0.747*	-0.612***	-0.557**
	(-1.91)	(-1.90)	(-2.64)	(-2.46)
M	-0.597*	-0.613*	-0.254	-0.282
	(-1.66)	(-1.74)	(-0.97)	(-1.21)
L	-0.558	-0.543	-0.297	-0.306
	(-1.50)	(-1.46)	(-1.23)	(-1.29)

Panel B: VR_efficiency metric estimated at different measurement frequencies

	VR_efficiency(10sec_30sec,10sec_1min,30sec_1min)		VR_efficiency(1min_5min,5min_10min,2min_10min)	
H	-0.832**	-0.788*	-0.727***	-0.716***
	(-1.99)	(-1.90)	(-3.39)	(-3.67)
M	-0.630	-0.672*	-0.514**	-0.531**
	(-1.62)	(-1.76)	(-2.14)	(-2.14)
L	-0.629*	-0.637	-0.539**	-0.543**
	(-1.65)	(-1.62)	(-2.43)	(-2.47)

This table reports the coefficients of EMUNC across different stock terciles, where stocks are sorted by their historical uncertainty exposure $\lvert\beta^{EMUNC}\rvert$. The dependent variables, *AF_efficiency* and *VR_efficiency*, are estimated using different sampling frequencies. Panel A reports the EMUNC coefficients (comparable to those reported in Table 5.4, Panel A) when *AF_efficiency* is estimated using two alternative sets of frequencies, i.e., (15sec, 30sec, 1min) and (2min, 5min, 10min). Panel B reports the EMUNC coefficients (comparable to those reported in Table 5.4, Panel A) when *VR_efficiency* is estimated using two alternative sets of frequencies, i.e., (10sec_30sec, 10sec_1min, 30sec_1min) and (1min_5min, 5min_10min, 2min_10min). Regression specification for all results is the same as column (4) in Table 5.2. To conserve space, results for control variables are not reported. The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Stock-month in the S.E. row indicates that the standard errors are two-way clustered by stock and by month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix A.2. Descriptive statistics across stock terciles

Table A.2

Descriptive statistics across stock terciles.

	AF_efficiency	VR_efficiency	Price (in $)	Volume (in million $)	Market cap (in billion $)	ILLIQ (x100)	M/B ratio	Analyst coverage	Institutional holding
MV – H	0.143	0.144	107.50	1.10E+4	84.2	0.004	6.90	23	0.708
MV – M	0.129	0.126	80.23	3.16E+3	16.5	0.011	5.23	18	0.773
MV – L	0.084	0.083	59.08	1.56E+3	6.92	0.480	4.53	14	0.819
ANACOV – H	0.137	0.134	97.96	9.43E+3	62.6	0.007	5.52	27	0.748
ANACOV – M	0.133	0.130	75.98	4.26E+3	30.6	0.012	5.34	18	0.769
ANACOV – L	0.094	0.095	73.51	2.19E+3	15.0	0.130	6.03	10	0.787
DVOL – H	0.140	0.136	107.83	1.16E+4	80.6	0.004	6.07	23	0.721
DVOL – M	0.123	0.120	74.96	2.89E+3	18.3	0.010	6.09	18	0.783
DVOL – L	0.094	0.096	63.81	1.18E+3	8.29	0.483	4.52	13	0.797
IVOL – H	0.089	0.071	73.69	5.61E+3	24.1	0.288	5.39	19	0.784
IVOL – M	0.116	0.117	84.86	4.85E+3	33.8	0.146	5.10	18	0.774
IVOL – L	0.151	0.164	88.07	5.25E+3	49.4	0.061	6.26	18	0.743
ILLIQ – H	0.089	0.088	60.45	1.32E+3	7.82	0.484	4.58	13	0.804
ILLIQ – M	0.125	0.122	76.02	3.03E+3	17.5	0.010	4.83	18	0.781
ILLIQ – L	0.142	0.143	110.04	1.13E+4	81.8	0.003	7.19	23	0.717

This table reports the descriptive statistics of stocks across limits-to-arbitrage terciles. All stock characteristics are those reported in Table 5.1. The limits-to-arbitrage proxies are those defined in Section 5.4.2.1. Rows with H, M, and L represent portfolios with high, medium, and low values of each corresponding limits-to-arbitrage proxy, respectively. The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020.

Appendix A.3. Cross-sectional results using the limits-to-arbitrage index

Table A.3

The cross-sectional effect of EMUNC on informational efficiency using the limits-to-arbitrage index.

Panel A: The effect of EMUNC on informational efficiency across tercile stocks sorted by the limits-to-arbitrage index		
	AF_efficiency	VR_efficiency
H	-0.818**	-1.055***
	(-2.23)	(-2.62)
M	-0.757*	-0.897***
	(-1.93)	(-2.65)
L	-0.376	-0.461**
	(-1.52)	(-2.22)
Controls	Yes	Yes
Fixed effects	Stock-year	Stock-year
S.E.	Stock-month	Stock-month
Panel B: Statistical tests of the cross-sectional differences		
EMUNC	-0.892**	-1.089***
	(-2.44)	(-2.82)
EMUNC*M	0.181***	0.248***
	(2.81)	(3.27)
EMUNC*L	0.498***	0.605**
	(2.78)	(2.29)
Controls	Yes	Yes
Fixed effects	Stock-year	Stock-year
S.E.	Stock-month	Stock-month

This table reports the cross-sectional effect of equity market uncertainty (EMUNC) on informational efficiency across tercile stocks sorted by the limits-to-arbitrage index. A higher index value indicates greater limits to arbitrage. Panel A reports the coefficients of EMUNC for different tercile groups and Panel B tests the statistical differences between these coefficients. The sample contains the S&P 500 constituent stocks as of December 2020. The sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Stock-month in the S.E. row indicates that the standard errors are two-way clustered by stock and by month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Chapter 6

Concluding Remarks

This thesis aims to understand the impact of information uncertainty on equity market quality. Uncertainty makes value-relevant signals hard to interpret and hinders the efficient functioning of financial markets. For equity market investors, uncertainty reduces the quality of the information environment and makes value-relevant signals noisy. Since information is crucial for every investment decision, understanding the impact of uncertainty on market quality is particularly relevant to equity investors' welfare. This knowledge is also helpful for market regulators and policymakers whose most important task is to maintain the quality and competitiveness of a local financial market.

Four chapters comprise this thesis. Starting with Chapter 2, we first provide an overview of uncertainty in financial markets. We show several types of uncertainty commonly observed in financial markets, how existing studies measure such uncertainty, and what uncertainty proxies we choose in our thesis. We then review financial market quality and discuss the key aspects of market quality from a market microstructure perspective. We also set up the empirical framework that we use in the remainder of this thesis to measure these market quality aspects. Finally, we relate this thesis to the existing literature and identify the gaps we aim to fill. Chapters 3-5 are the empirical chapters of this thesis. In the remainder of this chapter, we address each empirical chapter and highlight the findings.

In Chapter 3, we examine the impact of equity market uncertainty on the informational efficiency of equity prices. We use the US newspaper-based equity market uncertainty (EMUNC) index and consider the US equity market as a whole by focusing on ETFs. Using a sample from May 2001 to December 2019, Chapter 3 finds that equity market uncertainty significantly reduces the informational efficiency of ETF prices. We check the robustness of this result using alternative measures of informational efficiency, a different ETF, as well as alternative uncertainty proxies. These additional tests further support the main finding. Previous studies suggest that uncertainty is a significant risk factor that affects equity returns: Uncertainty reduces contemporaneous equity prices but leads to higher future returns as investors demand an uncertainty premium. We show that uncertainty not only drives the dynamics of equity prices but also reduces market efficiency. Our findings suggest that uncertainty reduces the quality of equity markets' information environment, making value-relevant signals less precise and harder to interpret. In this respect, Chapter 3 is also related to studies on how uncertainty hinders information production in stock markets.

Chapter 4 investigates uncertainty regarding information revealed in a pre-scheduled news release. Such events represent informational shocks in financial markets. We choose the FOMC announcement because it is one of the most important news events in the US. We measure uncertainty surrounding FOMC announcements using dispersion in analysts' forecasts and study how it affects various market quality characteristics around announcement times. We find that uncertainty (measured by analyst forecast dispersion) significantly affects equity market quality around the FOMC announcement. In particular, greater analyst forecast dispersion reduces market liquidity. This effect is observed both before and after the announcement. When decomposing the effective spread into its underlying components, we find that analyst dispersion only increases information asymmetry prior to the announcement but not after. This is because uncertainty reduces the quality of the pre-announcement information environment. As a result, investors have stronger incentives to acquire private information leading up to the announcement. Since uncertainty is fully resolved when news is released, post-announcement information asymmetry is not related to analyst forecast dispersion. Instead, we find that the post-announcement effect of analyst forecast dispersion on spreads is due to its impact on the order processing costs.

We also show that, despite lower liquidity, analyst dispersion increases trading volume both before and after the FOMC announcement. An increase in trading volume in the period prior to the FOMC announcement can be attributed to more informed and speculative trading leading up to the FOMC announcement, whereas the abnormal trading volume after the announcement can be attributed to both informed and postponed liquidity trading. Finally, we show that an uncertain information environment surrounding the FOMC announcement is harmful to the price efficiency of equity prices. Overall, Chapter 4 shows that uncertainty significantly impacts equity market quality during periods of informational shocks.

In Chapter 5, we extend the empirical analysis in Chapter 3. Instead of considering the US equity market as a whole, we turn our focus to individual stocks. Our goal is to understand whether some stocks are more sensitive to equity market uncertainty than others. Utilizing a large cross-section of S&P 500 constituent stocks, we find strong cross-sectional heterogeneity in the impact of equity market uncertainty. In particular, equity market uncertainty has a stronger negative impact on stocks that are more difficult to arbitrage and on stocks that are historically more sensitive to uncertainty. Our explanation is that arbitrageurs identify and correct mispricing caused by uncertainty. Since arbitrageurs are risk-averse and have limited capital, they dedicate arbitrage resources primarily to stocks that are easy to arbitrage. Thus, arbitrage trading partially mitigates the negative impact of uncertainty.

Overall, this thesis adds to our understanding of the impact of uncertainty on equity market quality. The empirical chapters have covered several key market quality aspects, including liquidity, trading, and informational efficiency. The findings of this thesis are relevant to equity investors who care about the impact of uncertainty on their investments. For instance, the finding in Chapter 4 warns investors of the potential trading costs during news releases if there is uncertainty about such news. The finding in Chapter 5 provides a potentially helpful portfolio rebalancing strategy for an uncertainty-averse investor aiming to reduce her portfolio's overall uncertainty exposure. For market regulators and policymakers, our thesis highlights the importance of monitoring market uncertainty as part of their overall market regulatory framework. This thesis, for instance, emphasizes the necessity for regulatory authorities to devise effective policy tools so they can alleviate the adverse impact of market uncertainty should a regulatory intervention be required. It also emphasizes the importance of transparency and clarity in the policy-making process of government bodies since our results show that policy-related economic uncertainty also reduces equity market efficiency.

One potential limitation of the current thesis is that no perfect measure of uncertainty exists. Although we believe that our main uncertainty proxy, EMUNC, is the best candidate for uncertainty about the US equity market, it may represent only a portion of total information available to market participants. For instance, sophisticated large institutional investors may have their own proprietary sources of news and information that they can utilize to generate profitable trading strategies. Such internal information may not be reflected in newspapers and does not necessarily correlate with the publicly available information through media-based news outlets (both content and timing related). For instance, in-house financial analysts of large institutions provide independent research and forecasts containing unique information not leaked to the mainstream media. Some sophisticated traders may employ state-of-the-art forecasting models to fine-tune their investment strategies. As such, these type of market participants are less likely to be affected by EMUNC. This bias can be more serious when studying the effect of EMUNC on the behavior of sophisticated traders (e.g., large institutions and informed traders). On the contrary, the current thesis examines the effect of EMUNC in general. We also try to alleviate such a concern by using multiple uncertainty proxies (i.e., the *EPU_news* index and the *EMV* tracker), each of which contains unique information and, thus, complements the information set included in EMUNC.

Studies in this thesis lead to several future research questions. First, this thesis focuses on the US equities market. Due to the differences in institutional backgrounds, market structures, and cultures, extending the analyses to a different market or country is potentially helpful as additional insights may be obtained. Second, it is interesting to investigate other channels that lead to the differential impact of uncertainty. One potential factor to consider is a stock's industry classification. It is reasonable to believe that certain industries, such as the defense and energy sectors, are less exposed to uncertainty. Third, one can extend the analyses in Chapter 4 to different industries. Since the FOMC announcement is related to monetary policies, it is possible that such announcements have a more significant impact on certain sectors such as financial industries. Such a cross-industry study can enhance our understanding of the effect of FOMC announcements. Another potential area to look at is how uncertainty affects the behaviour of different types of traders. For instance, do retail traders behave more irrationally relative to institutional traders? Do retail traders make more trading losses in periods of high uncertainty? These are important behaviour finance research questions. In addition, it may be interesting to compare the performance of traditional financial assets (e.g., stocks and bonds) with alternative investments such as cryptocurrencies and other digital assets. One argument is that such alternative investment vehicles have very different risk-return properties. Thus, investors may use them for hedging or speculative purposes when there is high uncertainty in the stock market.

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