The effect of equity market uncertainty on informational efficiency: Cross-sectional evidence

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Abstract

We study the effect of equity market uncertainty (EMUNC) on the informational efficiency of equity prices in the US market. We find that EMUNC negatively affects price efficiency, i.e., as equity market uncertainty increases, equity prices become less efficient. More importantly, this negative impact is heterogeneous in the cross-section of stocks. EMUNC has a stronger negative impact on hard-to-arbitrage stocks. We also find moderate evidence that stocks with a higher historical uncertainty exposure are more sensitive to EMUNC.

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1. Introduction

One of the most fundamental concepts in finance is market efficiency. It refers to the degree to which market prices accurately reflect fundamental information. There are times when market is less efficient, such as when there is a large degree of uncertainty in the market. During such periods, distinguishing information containing reliable signals from noise would be challenging for investors. Uncertainty, therefore, impedes the efficient incorporation of information into prices and reduces informational efficiency.

One recent study, Frijns et al. (2022), links equity market uncertainty with equity price informational efficiency. The authors examine the effects of the US equity market uncertainty (henceforth, EMUNC) on the price efficiency of two ETFs representing large- and small-cap US equities. They document a negative relationship between EMUNC and price efficiency of both ETFs, suggesting that equity market uncertainty leads to an opaque information environment and reduces informational efficiency.

The current study extends Frijns et al. (2022) by exploring the linkage between uncertainty and informational efficiency at a firm level for a large cross-section of US stocks. The cross-sectional nature of our study allows us to explore several key questions. For instance, we examine whether some stocks are more affected by uncertainty than others. We also examine whether the impact of EMUNC on informational efficiency can be attributed to the specific stock characteristics. In practice, understanding these questions is relevant for stock investors when rebalancing their portfolios in order to reduce their investments' overall exposure to economic uncertainty.

We examine two channels as to why different stocks may be affected by EMUNC differently. The first channel is limits-to-arbitrage. Arbitrageurs monitor equity prices and trade when mispricing occurs. In doing so, they can potentially correct mispricing caused by market uncertainty. Therefore, an increase in arbitrage activity will weaken the link between EMUNC and informational efficiency of equity prices. It is important to note that arbitrageurs have finite resources. As such, they focus their efforts on stocks with low arbitrage risks (e.g., Shleifer and Vishny, 1997; Stambaugh et al., 2015; Barroso and Detzel, 2021). Hence, mispricing caused by equity market uncertainty will be more persistent for stocks that are more difficult to arbitrage. Hence, we argue that EMUNC has a larger impact on price efficiency for stocks with higher limits to arbitrage.

Second, some stocks may be affected more by equity market uncertainty than others because they have a higher exposure to EMUNC. For instance, Pastor and Veronesi (2012) examine the impact of policy uncertainty on stock returns. They allow stocks to have different exposures to government policy uncertainty, measured using the firm's beta loading on policy uncertainty. Theoretically, they 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 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 postulate that stocks which have a greater exposure to EMUNC historically will experience a larger decline in price efficiency.

We test the limits-to-arbitrage and the uncertainty exposure channels using a sample of S&P 500 constituent stocks. These stocks account for over 80% of the total market capitalization in the US equities market.[1] We first investigate whether EMUNC has a greater impact on equity price efficiency for stocks that are more difficult to arbitrage. We employ several commonly used proxies for limits-to-arbitrage: market capitalization, analyst coverage, trading volume, stock idiosyncratic volatility, and stock illiquidity. We start by sorting all stocks, at the beginning of each month, into terciles based on one of the above limits-to-arbitrage proxies. We then estimate the effect of EMUNC on price efficiency for the three stock terciles separately and compare the coefficients of EMUNC.

Second, we examine whether stocks with a greater historical EMUNC exposure are more subject to the negative impact of uncertainty. We start by calculating the historical uncertainty beta for each stock. We then sort all stocks into terciles at the start of each month based on their uncertainty betas. Finally, we assess how the EMUNC coefficients differ across these terciles.

There are several key results in our study. First, consistent with Frijns et al. (2022), we find that equity market uncertainty is harmful to the informational efficiency of equity prices.

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

This negative relationship is robust after controlling for both firm- and market-level factors known to affect market efficiency. This finding suggests that uncertainty creates mispricing which leads to informational inefficiency. Second, we find substantial heterogeneity in how equity market uncertainty affects informational efficiency in the cross-section of stocks. Across all our limits-to-arbitrage proxies, EMUNC coefficients are generally more negative and significant for stocks with higher limits-to-arbitrage. This evidence supports the notion that limits-to-arbitrage aggravates the harmful effect of equity market uncertainty. Finally, we provide moderate evidence for the uncertainty exposure channel. Particularly, stocks with a higher historical exposure to EMUNC 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 equity market volatility (EMV) tracker. Second, we test whether the cross-sectional pattern is robust to an alternative price efficiency measure, the excess short-term volatility. Finally, we assess whether our results hold across informational efficiency metrics constructed using various sampling frequencies. These additional tests lend further support to our main finding.

Our study contributes to several strands of literature. First, we contribute to the fast-growing literature on the effect of uncertainty on financial markets. 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 uncertainty on capital markets and corporate finance. [2] Our work documents 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 across stocks.

Second, we add to the market microstructure literature on market efficiency. One key research topic is on the determinants of equity market efficiency. Existing studies show that

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[2] 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).

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 (e.g., Boehmer et al., 2021) can have a significant impact on market efficiency. Our study shows that the tone of newspaper articles significantly impacts the efficient functioning of equity markets.

More broadly, our work 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 cross-sectional return predictability and increases price efficiency. Similarly, using Regulation Short Sales (Reg SHO) 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.

The rest of our study is organized as follows. Section 2 discusses the key variables and the methodology employed. Section 3 describes the data and summary statistics. Section 4 discusses the main results. Robustness checks are reported in section 5. Section 6 concludes.

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.

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. More 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. The series is then normalized to have an average value of 100 for the period 1985-2010, resulting in the final EMUNC index.

We employ the EMUNC index for several reasons. First, we are interested in uncertainty about the US stock market and the EMUNC index is specifically 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). Newspaper articles 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 (e.g., Beschwitz et al., 2020).

2.2. Informational efficiency

We measure price efficiency by the extent to which prices deviate from a random walk. In an efficient market without friction, prices reflect the fundamental value of an asset 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, the martingale property implies that 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 above. Such frictions may come from investor under- or over-reaction to information (e.g., Anderson et al., 2013) or delays in financial markets impounding new information into prices. These frictions are likely to be more important in an opaque information environment. For example, when value-relevant signals are noisy, information signals are harder to observe and thus cannot be impounded into prices instantaneously.

Consequently, equity returns will be serially correlated. A less transparent information environment may also create uncertainty, subsequently affecting investor behavior. In laboratory experiments, Bloomfield et al. (2000) find that when investors are uncertain about the reliability of their information set, prices tend to underreact to reliable information and overreact to unreliable information. Such price under- and over-reactions may also exacerbate the price 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 metrics 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:

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

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 series and name it *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 reflects price efficiency. 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 the size of σ_l^2. The variance ratio exploits this property and measures price inefficiency as its deviation from this linearity. We calculate the variance ratio as follows:

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

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)[3] 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, this metric should equal 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 from a daily to a monthly frequency.

2.3. Cross-sectional variables

We use two criteria to sort sample stocks. The first criterion is the degree of a stock's limits to arbitrage. The second criterion is a stock's past exposure to equity market uncertainty. We discuss both criteria below.

2.3.1. Limits-to-arbitrage measures

We follow the existing literature and consider several commonly used proxies for limits-to-arbitrage. The first proxy is firm size (MV). Large firms receive more media attention, attract more institutional investors, and have higher analyst coverage and better information environments. Thus, we expect firm size to be 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 reduce information uncertainty and accelerate information dissemination (e.g., Hong et al., 2000; Lam and Wei, 2011). Therefore, we expect higher analyst coverage to

[3] Although the choice of sampling frequency for both *AF_efficiency* and *VR_efficiency* metrics are somewhat arbitrary, we show in Section 5.3 that our main results are robust to using other frequency combinations.

reduce 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). 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. In line with 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 stock 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[4] in month m:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i MKT_d + s_i SMB_d + h_i HML_d + \varepsilon_{i,d}, \tag{3}$$

where $R_{i,d} - r_{f,d}$ is the excess daily return of stock i on day d in month m. r_f is the three-month US Treasury bill rate. 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.[5] 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

[4] Using a four-factor model specification does not change our results. They are available upon request.
[5] Data is available from the Kenneth Data Library:
https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

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:

$$ILLIQ_{i,m} = log\left[1 + \frac{1}{D}\sum_{d=1}^{D}\frac{10^6|r_{i,d}|}{\$Volume_{i,d}}\right], \tag{4}$$

where $r_{i,d}$ and $\$Volume_{i,d}$ are the daily stock returns based on the closing price and daily dollar trading volume, respectively. We calculate the ILLIQ for each stock i on each day d and average across D trading days within the 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 the monthly dollar trading volume (DVOL). 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.

2.3.2. Uncertainty beta

We capture a stock's historical exposure to equity market uncertainty using its uncertainty beta. 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 preceding monthly returns for estimation.

$$R_{i,m} - r_{f,m} = \alpha_i + \beta_i^{EMUNC}EMUNC_m + \beta_i^{MKT}MKT_m + s_iSMB_m + h_iHML_m + \varepsilon_{i,m}, \tag{5}$$

where all variables are at a monthly frequency. The monthly Fama-French factors are retrieved from the Kenneth Data Library. We estimate Eq. (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) 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 comparable to ours. Using the beta measure as a proxy for stock-level sensitivity is also a common practice in the asset pricing literature (e.g., Bali et al., 2017).

3. Data and summary statistics

As our proxy for equity market uncertainty, we obtain the daily US equity market uncertainty (EMUNC) index from the policy uncertainty website.[6] To construct a monthly EMUNC index, we average across days within each month. Our sample comprises all S&P 500 constituent stocks as of December 2020 and covers the period January 1, 2010 to December 31, 2020.[7] We remove stocks whose average price in our 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 further remove the first and last 10 minutes of trading to avoid the impact of market opening and closing.

For the control variables, we employ several commonly used stock-level and market-level characteristics known to affect price efficiency. For each stock, we construct a monthly time-

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

[7] Stock tickers can change over time. We carefully investigate each stock and ticker manually to ensure the continuity of our sample.

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 the Amihud's (2002) illiquidity ratio from Eq. (4). Data for monthly price, volume, and the total number of shares outstanding are obtained from Refinitiv Datastream. We include proxies for firm-level information environment such as analyst coverage and institutional ownership. 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. Institutional ownership is the number of shares held by large institutions as a percentage of the total outstanding shares. 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. For the market-level control variables, we use the monthly S&P 500 index returns and the CBOE volatility index (VIX).

Table 1 provides summary statistics for 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).

[Insert Table 1 here]

Our sample covers a wide range of stocks. Share prices display significant cross-sectional variation from a low of $4.06 to a high of $1794.06. Monthly trading volumes range from $2.79 million to $146 billion per month, with an average of $5.2 billion. 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 and the ILLIQ measure. In terms of the firm-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).

4. Empirical results

We first investigate the aggregate effects of equity market uncertainty on equity price efficiency. We then conduct analyses in the cross-section of stocks to examine whether the effects of uncertainty are heterogeneous across stocks. Specifically, we focus on two stock-level characteristics: limits-to-arbitrage and the stocks' historical exposure to equity market uncertainty.

4.1. The aggregate effect of EMUNC

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

$$y_{i,m} = \alpha_i + \gamma_t + \beta EMUNC_m + \sum_{j=1}^{J} \delta_j X_{j,i,m} + \varepsilon_{i,m}, \tag{6}$$

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 the stock and time fixed effects, respectively. $X_{j,i,m}$ is an array of control variables. We consider various control variables. At the stock level, we include 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 dependent variables to control for the persistence in market efficiency characteristics and potential omitted variable bias.

[Insert Table 2 here]

Table 2 reports the regression results. In columns (1) through (4) for each of the two price efficiency metrics, we add additional control variables progressively to examine whether the EMUNC-efficiency relationship depends on model specifications. Turning first to *AF_efficiency*, we observe that an increase in equity market uncertainty is associated with less informationally efficient stock prices. The EMUNC coefficients across all regression specifications are negative and significant. A similar relationship is also observed for *VR_efficiency* where the EMUNC coefficients remain negative and statistically significant. This finding suggests that equity market uncertainty is a market friction that impedes efficient incorporation of information into stock prices. Equity market uncertainty reduces precision of value-relevant signals, which in turn increases stock mispricing and reduces price efficiency.

The control variables show that informational efficiency is negatively correlated with trading volume and stock illiquidity but positively correlated with market capitalization (although for *VR_efficiency* market cap is insignificant). 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 2 supports the view that equity market uncertainty is harmful to the informational efficiency of stock prices.

4.2. Cross-sectional effects

The previous section has documented a negative impact of EMUNC on stock price efficiency. In this section, we further investigate if this effect is heterogeneous across stocks.

4.2.1. Limits-to-arbitrage

The first cross-sectional variable we consider is limits-to-arbitrage. Previously, we argued that when market participants face uncertain information, mispricing tends to be high, leading to a reduction in information efficiency. Thus, we observe a negative relationship between EMUNC and informational efficiency. To study the cross-sectional effects, we argue that arbitrageurs will enter the market when expected profits of arbitrage are high. Arbitrageurs correct stock mispricing and, thus, weaken the negative relationship between EMUNC and informational efficiency. Conversely, EMUNC will have a larger negative impact on informational efficiency for stocks that are more difficult to arbitrage. In other words, limits-to-arbitrage tends to aggravate the harmful effect of uncertainty on price efficiency.

We split the sample into terciles at the start of each month based on one of the limits-to-arbitrage proxies defined in Section 2.3.1. Next, we run Eq. (6) separately for each tercile to estimate the coefficient of EMUNC for stocks with high, medium, and low levels of limits-to-arbitrage, respectively. The EMUNC coefficients across the three terciles will indicate whether the effect of EMUNC on price efficiency is heterogeneous across stocks. Table 3 reports these coefficients.

[Insert Table 3 here]

Panel A reports EMUNC coefficients calculated from terciles with high(H), medium(M), and low(L) values of each respective limits-to-arbitrage proxy. For instance, for market value (MV), we find that the coefficient of EMUNC on *AF_efficiency* decreases from -0.386 for high-MV stocks, which is statistically insignificant, to -0.868 for low-MV stocks, significant at the 5% level. A similar pattern is observed for the *VR_efficiency* metric where the EMUNC coefficients decrease from -0.487 to -1.129. The more negative EMUNC coefficient from high (*H*) to low (*L*) tercile stocks is consistently observed 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 negative impact on more difficult to arbitrage stocks.

We observe an opposite pattern when we consider idiosyncratic volatility (IVOL) or the Amihud's illiquidity (ILLIQ) as a limits-to-arbitrage proxy. In such cases, the coefficient of EMUNC increases from -0.786 (-0.827) for high-IVOL (high-ILLIQ) stocks, significant at the

5% level, to -0.453 (-0.432) for low-IVOL (low-ILLIQ) stocks, which is only marginally significant. A similar increasing 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 3, Panel A, documents consistent patterns across all the five limits-to-arbitrage proxies and for both price efficiency metrics. In particular, limits-to-arbitrage amplifies the negative effect of EMUNC on the informational efficiency of equity prices.

Next, we compare the significance of EMUNC coefficients across the three terciles. Specifically, we estimate the following model:

$$y_{i,m} = \alpha_i + \gamma_t + \beta EMUNC_m + \delta EMUNC_m \cdot M + \varphi EMUNC_m \cdot L + \sum_{j=1}^{J} \delta_j X_{j,i,m} + \varepsilon_{i,m}, \quad (7)$$

Eq. (7) augments Eq. (6) by including two additional interaction terms. M and L are the set of dummy variables that indicate stocks within the medium- and low-tercile group with respect to the corresponding limits-to-arbitrage proxy.[8] Therefore, the coefficients δ and φ capture the marginal impact of EMUNC on informational efficiency across different limits-to-arbitrage stock portfolios. These results are reported in Panel B of Table 3.

Consistent with Table 2, the coefficients of EMUNC (i.e., β in Eq. (7)) are negative across the various limits-to-arbitrage proxies, 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.[9] 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

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[8] In each month, we sort sample stocks by their limits-to-arbitrage proxies measured from the previous month. M (L) equals one for stocks within the medium (low) tercile group.

[9] Note that the impact of EMUNC in Eq. (7) indicates the benchmark effect, i.e., the impact of EMUNC on informational efficiency for stocks in the H tercile.

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 pattern is observed if we consider DVOL as the proxy for limits-to-arbitrage, and if we consider *VR_efficiency* as the informational 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 decreases monotonically for medium-tercile stocks (with a coefficient of -0.917 + 0.281) and low-tercile stocks (with a coefficient of -0.917 + 0.516). A similar pattern is observed if we consider ILLIQ as the proxy for limits-to-arbitrage, and if we consider *VR_efficiency* as the informational efficiency metric. Overall, the statistical evidence in Panel B concurs with our prediction, i.e.,, limits-to-arbitrage amplifies the negative effect of EMUNC on the informational efficiency of equity prices.

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 A4, 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).[10] Such an index not only circumvents the above-mentioned issue but also provides a more comprehensive summary of the true limits-to-

[10] 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 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).

arbitrage of a stock. Results based on this limits-to-arbitrage index are reported in the Appendix Table A5, which are also consistent with the main finding.

4.2.2. Stock uncertainty exposure

The second cross-sectional stock characteristic we consider is the stock's historical exposure to equity market uncertainty. The argument is that 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 2.3.2, we form tercile portfolios each month based on stocks' historical uncertainty exposure. Tercile *L, M*, and *H* comprise stocks with the lowest, medium, and highest $|\beta_i^{EMUNC}|$. We then estimate Eq. (6) for each tercile portfolio and report the coefficients of EMUNC in Table 4.

[Insert Table 4 here]

The results in Panel A of Table 4 show that all the coefficients of EMUNC are negative, which is consistent 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 similar results. This finding suggests that stocks with higher uncertainty exposure tend to be more sensitive to EMUNC.

Panel B of Table 4 reports the statistical significance of the difference in EMUNC 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 relatively weaker for the *AF_efficiency* metric. Nevertheless, Table 4 provides evidence suggesting that stocks with a higher historical exposure to EMUNC also experience a larger reduction in price efficiency when uncertainty rallies.

To illustrate the cross-sectional patterns, we plot the coefficients of EMUNC in Figure 1. It shows that the EMUNC coefficients tend to be larger in magnitudes for stocks with higher limits-to-arbitrage (lower MV, lower ANACOV, lower DVOL, higher IVOL and higher ILLIQ) or greater uncertainty exposure (higher $|\beta_i^{EMUNC}|$).

[Insert Fig 1 here]

5. Additional analyses

So far, we have shown that equity market uncertainty is harmful to the informational efficiency of equity prices. The effect of equity market uncertainty is also heterogeneous in the cross-section of stocks, depending on the stock's 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 conduct the cross-sectional analysis under different sampling frequencies to test whether our main results depend on a particular estimation method.

5.1. Alternative proxies for uncertainty

The first robustness test we consider is whether the cross-sectional pattern holds when other uncertainty proxies 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 that 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 additional uncertainty proxies considered should closely follow these two criteria. Following this logic, we use two alternative proxies for uncertainty: the US newspaper-based economic policy uncertainty (EPU_news) index and the US newspaper-based equity market volatility (EMV) tracker. Both indexes are available 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).[11] As for the EMV tracker, it focuses on the US equity market, just like EMUNC. However, 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 uncertainty (e.g., Bloom et al., 2007; Bloom, 2009). Thus, we assume that newspaper readers interpret the word “volatility/volatile” and “uncertainty/uncertain” synonymously.

[Insert Table 5 here]

Table 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). Similarly, Panel B suggests that greater limits to arbitrage lead to stronger coefficients. In Table 6, we test the robustness of the cross-sectional pattern by stock uncertainty exposure reported in Table 4 with the two additional uncertainty proxies. Overall, Table 6 finds supporting, albeit weak, evidence only when the EPU_news index is considered. On the contrary, we do not observe significant results when using the EMV index. To illustrate these results, we plot the cross-sectional pattern of EPU_news coefficients in Fig 2.

[Insert Table 6 here]

[Insert Fig 2 here]

[11] 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 those for 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.

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 and market participants interpret these two words differently.

5.2. Alternative measure of informational efficiency

Next, we check whether the cross-sectional results reported in Section 4.2 are robust to the alternative informational efficiency measure. We 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 fundamental values, indicating that market is not efficient. Excess short-term volatility captures noise and temporary price deviations from the equilibrium caused by trading frictions, leading to less efficient prices. Short-term volatility has also been viewed in the literature as an inverse indicator of market 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.[12]

To capture excess short-term return volatility, we take the ratio of high- and low-frequency return volatility for a given stock-month, which we label *HL_ratio*. This volatility ratio approach is intuitive and similar in spirit to Bandi and Russell (2006).[13] Similar to the construction of *AF_efficiency* metric, we define high-frequency volatility as the first principal component of mid-quote returns standard deviation measured at three intraday frequencies, $k \in \{30 \text{ sec}, 1 \text{ min}, 2 \text{ min}\}$. We then average across days within a month to obtain a monthly

[12] 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."

[13] We do not use the high-frequency volatility metric directly. This is because in the cross-section of stocks, such a metric can mean different things. For instance, for the most liquid stocks in our sample, a high-frequency volatility measure may reflect intraday flow of information through fast trading rather than noise. Conversely, for the illiquid stocks that are not traded as frequently, a high-frequency volatility measure is a more accurate reflection of temporary price deviations caused by market frictions and noise. A ratio of high- and low-frequency volatility measures helps alleviate this measurement issue in the cross-section.

high-frequency volatility metric. Low-frequency volatility is the standard deviation of daily returns within the same month, which is a proxy for fundamental volatility. A higher *HL_ratio* indicates greater intraday excess volatility relative to fundamental volatility, thus capturing "excess" short-term volatility. For consistency with other informational efficiency metrics, we multiply *HL_ratio* by -1 to convert it into an efficiency measure. We label this *ESV_efficiency*.

[Insert Table 7 here]

Table 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 (ANACOV, DVOL, and IVOL). For the cross-sectional effect of EMUNC by historical uncertainty exposure, we find mixed evidence. The pattern only appears when the uncertainty beta is estimated using the Fama-French four-factor model. Therefore, we are cautious in interpreting the results. Overall, Table 7 provides moderate support to our main findings.

5.3. Different estimation frequencies

Finally, we construct the informational efficiency measures estimated using different sampling frequencies. Since there is no theoretical argument guiding us what the optimal estimation frequency is, we experiment with different 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).

Table 8 replicates the cross-sectional analyses in Table 3 under the two alternative sampling frequencies described above. For both informational efficiency measures (Panels A and B) and under both estimation frequencies, 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.

[Insert Table 8 here]

Similarly, Table 9 provides supporting evidence on the cross-sectional effect by stocks' historical uncertainty exposure. 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 3.[14] We therefore conclude that the cross-sectional effect of uncertainty on equity price efficiency is robust to alternative estimation schemes.

[Insert Table 9 here]

[Insert Fig 3 here]

6. Conclusion

We study the impact 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. This result suggests that uncertainty is a market friction that creates noise and mispricing, which renders equity prices less efficient. Further cross-sectional analyses reveal that the negative impact of EMUNC is stronger for some stocks. We postulate and find supporting evidence for two plausible channels leading to such cross-sectional heterogeneity: limits-to-arbitrage and stock's historical uncertainty exposure. Specifically, we find that stocks with higher limits-to-arbitrage or greater historical uncertainty exposure are more subject to the negative impact of EMUNC. This cross-sectional pattern is observed across various limits-to-arbitrage proxies and informational efficiency measures. We conclude that arbitrage activity plays a beneficial role in financial markets. Stocks that attract more arbitrageurs are less sensitive to EMUNC because arbitrage activity partially mitigates the negative impact of uncertainty.

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[14] The coefficients for Figures 1-3 are reported in the Appendix 1-3.

From a practical perspective, our study sheds light on a potentially useful way to diversify equity portfolios. An equity investor can reduce her investment's overall exposure to uncertainty by strategically adjusting the weight of individual stocks based on the stock characteristics discussed in this study.

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Table 1. Descriptive statistics.

This table reports summary statistics for uncertainty index and the set of stock characteristics. The sample contains the S&P 500 constituent stocks as of December 2020 and the sample period is from January 1, 2010 to December 31, 2020. EMUNC is the US equity market uncertainty index. 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.

	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

Table 2. Baseline panel regression.

This table reports the aggregate effect of equity market uncertainty on informational efficiency. The sample contains the S&P 500 constituent stocks as of December 2020 and the sample period is from January 1, 2010 to December 31, 2020. *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. The EMUNC index is scaled 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 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 persistence of the informational efficiency characteristics). Fixed effects include both stock and year fixed effects. Standard errors are clustered by stock and month. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	AF_efficiency				VR_efficiency			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
EMUNC	-0.728*	-0.709*	-0.706**	-0.658*	-0.836*	-0.826**	-0.805***	-0.716***
	(-1.83)	(-1.66)	(-1.97)	(-1.73)	(-1.95)	(-2.05)	(-2.86)	(-2.58)
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	0.466***	0.475***	0.484***	0.484***	0.416***	0.418***	0.424***	0.422***
	(9.32)	(8.83)	(9.00)	(8.91)	(8.33)	(7.73)	(7.90)	(7.73)
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

Table 3. The cross-sectional effect of EMUNC on informational efficiency by limits-to-arbitrage.

This table reports the effect of equity market uncertainty on informational efficiency for stocks with different levels of limits-to-arbitrage. The sample contains the S&P 500 constituent stocks as of December 2020 and the sample period is from January 1, 2010 to December 31, 2020. *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. The EMUNC index is scaled 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 2. For brevity, 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. Fixed effects include both stock and year fixed effects. Standard errors are clustered by stock and month. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

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

Table 4. The cross-sectional effect of EMUNC on informational efficiency by stocks' historical uncertainty exposure.

This table reports the effect of equity market uncertainty on informational efficiency for stocks with different historical exposure to uncertainty. The sample contains the S&P 500 constituent stocks as of December 2020 and the sample period is from January 1, 2010 to December 31, 2020. *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. EMUNC index is scaled 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 2. For brevity, 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. Fixed effects include both stock and year fixed effects. Standard errors are clustered by stock and month. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

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

Table 5. Robustness tests of Table 3 using alternative proxies for uncertainty.

This table checks the robustness of the cross-sectional effect of EMUNC on informational efficiency reported in Table 3 using two alternative proxies for uncertainty. The sample contains the S&P 500 constituent stocks as of December 2020 and the sample period is from January 1, 2010 to December 31, 2020. *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 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. *EPU_news* index is scaled by 1,000. Regression specification for all results is the same as column (4) in Table 2. For brevity, results for control variables are not reported. In Panel B, we repeat the analyses in Panel A, but replacing the *EPU_news* by the *EMV* index as an alternative proxy for uncertainty, where *EMV* index is the monthly newspaper-based US equity market volatility tracker. *EMV* index is scaled by 1,000. 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 1%, 5%, and 10% levels, respectively.

Panel A: The cross-sectional effect of EPU_news on 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 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

Table 6. Robustness tests of Table 4 using alternative proxies for uncertainty.

This table checks the robustness of the cross-sectional effect of EMUNC on informational efficiency reported in Table 4 using two alternative proxies for uncertainty. The sample contains the S&P 500 constituent stocks as of December 2020 and the sample period is from January 1, 2010 to December 31, 2020. *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 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. *EPU_news* index is scaled by 1,000. Regression specification for all results is the same as column (4) in Table 2. For brevity, results for control variables are not reported. In Panel B, we repeat the analyses in Panel A, but replacing the *EPU_news* by the *EMV* index as an alternative proxy for uncertainty, where *EMV* index is the monthly newspaper-based US equity market volatility tracker. *EMV* index is scaled by 1,000. Fixed effects include both stock and year fixed effects. Standard errors are clustered by stock and month. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: The cross-sectional effect of EPU_news on 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 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

Table 7. Robustness tests using excess short-term volatility (*ESV_efficiency*) as an alternative informational efficiency metric.

This table checks the robustness of the cross-sectional effect of EMUNC on informational efficiency reported in Table 3 & 4 using excess short-term volatility (*ESV_efficiency*) as an additional informational efficiency metric. The sample contains the S&P 500 constituent stocks as of December 2020 and the sample period is from January 1, 2010 to December 31, 2020. The panel regression uses monthly data. *ESV_efficiency* is the ratio of high- and low-frequency realized volatility within a stock-month. *EMUNC* index is scaled by 1,000. Panel A follows Panel B of Table 3 whereas Panel B follows Panel B of Table 4. Regression specification for all results is the same as column (4) in Table 2. For brevity, results for control variables are not reported. Fixed effects include both stock and year fixed effects. Standard errors are clustered by stock and month. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	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

Table 8. Robustness tests of Table 3 under different estimation frequencies.

This table checks the robustness of the cross-sectional effect of EMUNC on informational efficiency reported in Table 3 under different estimation frequencies. The sample contains the S&P 500 constituent stocks as of December 2020 and the sample period is from January 1, 2010 to December 31, 2020. 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 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 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. *EMUNC* index is scaled by 1,000. Regression specification for all results is the same as column (4) in Table 2. For brevity, results for control variables are not reported. 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 1%, 5%, and 10% levels, respectively.

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

Table 9. Robustness tests of Table 4 under different estimation frequencies.

This table checks the robustness of the cross-sectional effect of EMUNC on informational efficiency reported in Table 4 under different estimation frequencies. The sample contains the S&P 500 constituent stocks as of December 2020 and the sample period is from January 1, 2010 to December 31, 2020. 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 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 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. EMUNC index is scaled by 1,000. Regression specification for all results is the same as column (4) in Table 2. For brevity, results for control variables are not reported. Fixed effects include both stock and year fixed effects. Standard errors are clustered by stock and month. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

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

Table A1. EPU_news coefficients across stock terciles.

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 2. For brevity, results for control variables are not reported. The sample contains the S&P 500 constituent stocks as of December 2020 and the sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Standard errors are clustered by stock and month. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	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)

Table A2. EMUNC coefficients across stocks terciles sorted by limits-to-arbitrage under different estimation frequencies.

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 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 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 2. For brevity, results for control variables are not reported. The sample contains the S&P 500 constituent stocks as of December 2020 and the sample period is from January 1, 2010 to December 31, 2020. Fixed effects include both stock and year fixed effects. Standard errors are clustered by stock and month. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

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)

Table A3. EMUNC coefficients across stocks terciles sorted by uncertainty exposure under different estimation frequencies.

This table reports the coefficients of EMUNC across different stock terciles, where stocks are sorted by their historical uncertainty exposure $|\beta^{EMUNC}|$. The sample contains the S&P 500 constituent stocks as of December 2020 and the sample period is from January 1, 2010 to December 31, 2020. 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 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 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 2. For brevity, results for control variables are not reported. Fixed effects include both stock and year fixed effects. Standard errors are clustered by stock and month. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: AF_efficiency metric estimated at different measurement frequencies				
	AF_efficiency(15s,30s,1min)		AF_efficiency(2min,5min,10min)	
	$|\beta^{EMUNC}|$-FF3F	$|\beta^{EMUNC}|$-FF4F	$|\beta^{EMUNC}|$-FF3F	$|\beta^{EMUNC}|$-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)

Table A4. Descriptive statistics across stock terciles.

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.

	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

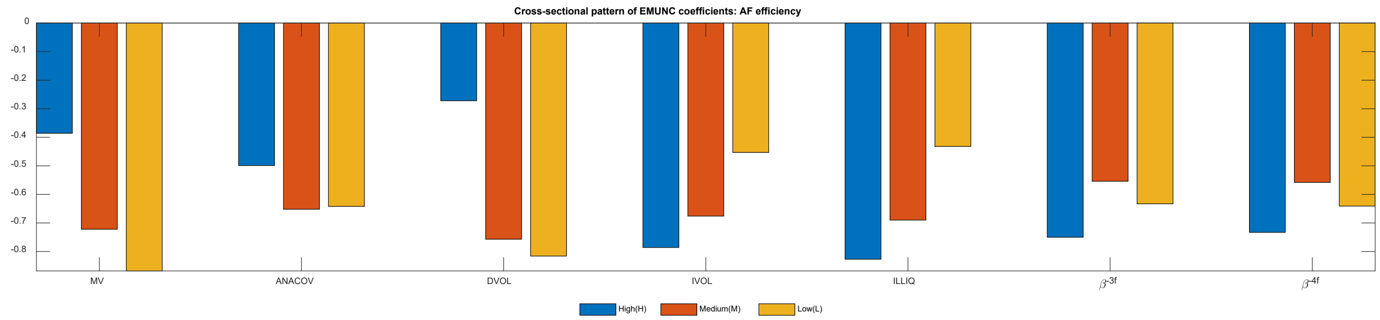
Table A5. The cross-sectional effect of EMUNC on informational efficiency using the limits-to-arbitrage index.

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.

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

Fig 1. The cross-sectional patterns of EMUNC coefficients

This plot shows the cross-sectional patterns of EMUNC coefficients reported in Panel A of Tables 3 & 4. The three coefficients for the high (H), medium (M), and low (L) stock tercile are represented by three bars with different colors.



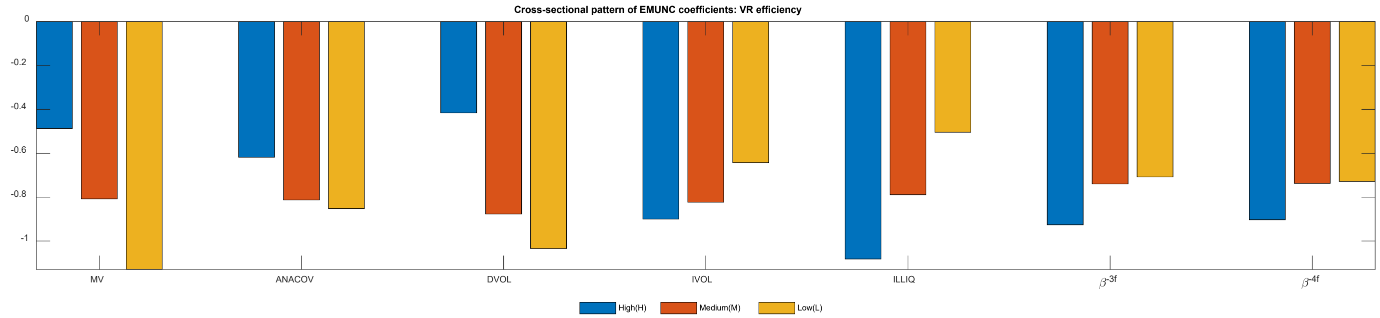
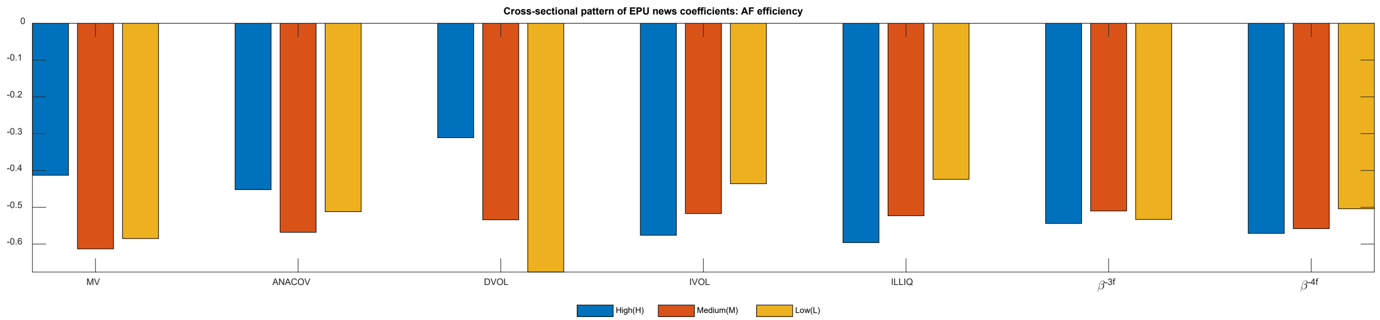


Fig 2. The cross-sectional patterns of *EPU_news* coefficients

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.



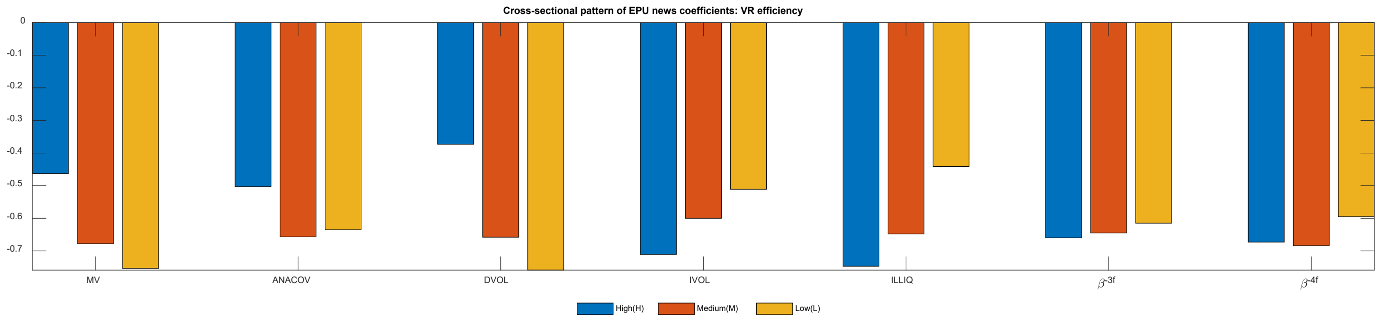


Fig 3. The cross-sectional patterns of EMUNC coefficients under different estimation methods

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.