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Overnight Learning, Price Discovery, and Macroeconomic Announcements

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JEL Classification: G12, G14

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1 Introduction

Efficient price discovery matters the most for ensuring the informativeness of asset prices and for a well-functioning capital market (Fama, 1970). The existing literature predominantly emphasizes the central role of trading for facilitating the price discovery process in the stock market.[1] The key benefit of market trading is that equilibrium prices are formed through trading which aggregates public and private information across investors. In specific, investors are assumed to observe and learn from the market prices along with other informative signals when trading the assets, which helps incorporate information sources across investors that feed into the market equilibrium of asset prices (Grossman and Stiglitz (1980); Kyle (1985); Biais et al. (1999); and more recently, Goldstein and Yang (2015), Easley et al. (2016), and Xiong and Yang (2023)). Therefore, across a broad class of models and empirical works on price discovery, there is a prevailing assumption that investors continuously learn from prices during trading.[2]

Our paper isolates and evaluates the importance of the "learning from alternative sources other than the asset prices" channel for shifting the process of price discovery in the stock market. To achieve this, we frame our study by focusing on China's stock market and exploit its important and unique institutional features. Macroeconomic announcements in China are often unscheduled and arrive to the market with significant timing variations.[3] Many of these macroeconomic announcements fall within non-trading hours, during which investors do not have immediate access to trading.[4] In the absence of the real-time market

[1] Boehmer and Wu (2012) and Beber and Pagano (2013) show that trading frictions such as constrained short sales prevent efficient price discovery. Barclay and Hendershott (2003, 2008) highlight that price discovery should always benefit from trading during and outside the trading sessions and during the pre-opening period. That is, though prices are more efficient during the day, an after-hours trade contains more information. Brogaard et al. (2014, 2019) identify the contributions of high-frequency traders for installing efficient price discovery.

[2] For example, to rationalize the role of trading for aggregating information, the framework of rational expectations equilibrium (REE) models with costly information acquisition is derived from a critical assumption that investors *immediately* act upon prices and informative signals through trading. In addition, the empirical evidence on price discovery is established based on the specification that trading of assets reacts to important news within minutes upon data releases (e.g., Hu et al. (2017)).

[3] First, unlike the U.S. market, macro announcements in China that regularly release economic and financial statistics can fall outside regular trading hours. Second, most macro announcements in China do not follow a fixed and pre-scheduled timetable, and the day and time of data release vary substantially across announcements. For example, the National Bureau of Statistics of China publishes PMI data as early as 9:00 a.m. and as late as 8:00 p.m. China's central bank, the People's Bank of China (PBOC) may release China's monetary and financial statistics such as monetary aggregates and total social financing data after market close, before market open, or during the weekends (Guo et al., 2023).

[4] Brokerage firms and the stock exchanges in China do not accept, execute, or clear orders when markets

prices as signals, investors could still make an effort to learn from non-price sources during these information-sensitive hours – after seeing an important macroeconomic announcement but before trading is possible. Thus, China's market setting gives us the leverage to explore the impacts of "learning without trading" on price discovery through cross-event studies for causal inference. This contrasts sharply with developed markets, where the effects of learning from real-time prices and trading are often intertwined with alternative sources as investors trade, often in high volume, immediately following the release of macroeconomic news by utilizing either the equity or the almost around-the-clock derivatives markets. Our explorations of the price discovery process using the Chinese setting is of significant general interest, especially for emerging markets where financial market developments are still in progress.[5]

We provide several pieces of important empirical evidence along with theoretical rationalizations in this paper. We first show significant variations in the timing of Chinese macroeconomic announcements. In our sample of 20 indicators, which includes the 15 most tracked Chinese macroeconomic indicators by Bloomberg and 5 monetary policy announcements by the People's Banks of China (PBOC) from 2009 to 2020, a total of 854 announcements were made outside trading hours, making up 45% of all our sampled events. The variations in the releasing time arise from differences between macroeconomic indicators as well as changes within indicators, as a result of the lack of a fixed announcement release schedule. The release time of M2 announcements by the PBOC, for example, ranges from as early as 8:00 a.m. to as late as 8:00 p.m. Most importantly, the variations in the timing of these macroeconomic releases are not related to their information content (Guo et al., 2023). There is no correlation between announcement timing and the surprise component of macroeconomic announcements, nor does timing affect post-announcement market returns.

Exploiting such timing variations, we document quicker and more efficient price discovery if macro announcements are released overnight. Following Boguth et al. (2023), we rely on the R-squared (R_t^2) of an unbiased regression model that regresses the total announcement

are closed. In addition, China's derivatives markets are still considered underdeveloped, meaning that these markets are closed while the stock markets are closed. For example, the trading hours of stock exchanges in China and the hours for trading stock index futures in China are completely overlapped.

[5] An incomplete list of emerging market countries that do not have a 24-hour domestic derivative market includes Argentina, Brazil, Chile, Colombia, Egypt, India, Indonesia, Mexico, Nigeria, Philippines, Russia, South Africa, Thailand, Turkey among many others. In addition, we see the statistical agencies in Brazil, India, South Africa, Turkey and others routinely release their GDP and CPI data outside the regular trading hours of their domestic stock exchanges.

day returns on the cumulative announcement returns to capture the price informativeness up to the time stamp t. For announcements made during non-trading hours, R_t^2 jumps immediately by 31% at the market opening time (9:30 a.m.), a substantially larger jump than that following announcements made during trading hours. Clearly, announcements made during non-trading hours generate significant improvements of the price discovery even when trading is absent. We further demonstrate that the speed and efficiency of price discovery are directly related to *distance-to-trading*, the calendar time elapsed between the release time of a macro announcement and the market opening time. In a regression setup, we estimate that a one-day increase in distance-to-trading leads to a 3.8% increase in price informativeness at the market opening time, with a significant t-value of 3.90.

In a simple model, we examine the asset pricing implications of an environment when an important macro news announcement is made outside trading hours. Our model entertains the possibility that investors learn from the non-price sources overnight after announcements are released. The equilibrium price of a risky asset at the market opening is more informative of the payoff fundamentals if an overnight announcement exhibits a longer distance-to-trading, which gives investors more time to process the related information through learning. Our model features three important timestamps, i.e., the market-close of a trading day, the market-opening of the next trading day, and the time of asset payoff realization, in the spirit of a three-period model of Vayanos and Wang (2012). Investors differ by their information positions and the liquidity needs are the source of trading at the market opening. Two types of liquidity-supplying investors of differed information positions jointly accommodate the trading needs of the liquidity-demanding investors. Taking the fact that investors react to overnight news with delays and it takes time to filter out noises and process relevant information for trading (Dugast, 2018; Dugast and Foucault, 2018), our model demonstrates that as greater distance-to-trading of an announcement turns more under-informed investors to be better informed upon market opening, increased learning among investors enhances the equilibrium price informativeness at the market opening. Therefore, our model predicts that overnight learning helps reduce the information asymmetry across investor types at market opening.

We further show in the data that one of the important non-price sources for learning about macro announcements among retail investors, who are relatively less informed, is the social media news. We provide our measure of investors' learning and document that the intensity of investors' overnight learning increases with the distance-to-trading. In the spirit of Da et al. (2011), Ben-rephael et al. (2021) and Fisher et al. (2022), we construct measures of retail investors' learning efforts counting the number of posts, fans, and the interaction intensity related to the released macroeconomic news on China's largest social media platform, Weibo Inc. We confirm that a longer duration of distance-to-trading is associated with higher degree of overnight learning intensity. Importantly, we further document that more intense overnight learning among investors leads to faster post-announcement price discovery once the market reopens. Specifically, at the first minute when investors can trade on the news, a one standard deviation increase in overnight posts (75 posts), fans following these posts (147 million), and retweets, comments, and likes following these posts (204 retweets, comments, and likes) are associated with 4.81%, 4.98%, and 6.55% faster price discovery.

In addition to faster price discovery, we present further empirical evidence supporting our theoretical predictions that overnight learning significantly reduces information asymmetry among investors. Using two measures of information asymmetry just before market opening – bid-ask spreads and investor opinion divergence during the market opening call auction – we find that an increase in distance-to-trading significantly reduces both. A one-day increase in distance-to-trading leads to an average reduction of 0.010% in bid-ask spreads and a 0.004% decrease in investor opinion divergence, representing 2.5% and 1.8% reductions relative to their mean levels. Moreover, while overnight learning enhances price discovery at market opening for all stocks, the effect is more pronounced for those with lower stock prices or low institutional ownership – stocks characterized by higher levels of information asymmetry and thus more likely to benefit from overnight learning.

Our analysis further reveals that the improvement in information asymmetry due to overnight learning substantially benefits retail investors in the Chinese stock market. First, we observe that retail investor trading activity increases significantly for macroeconomic announcements with longer distance-to-trading. Specifically, a one-day increase in distance-to-trading leads to a 0.250% and 0.158% increase in the trading volume for small- and medium-size trades, categories typically dominated by retail investors. Additionally, while retail investors generally exhibit a misalignment between their trading directions and announcement-day returns, we find that this misalignment is substantially corrected when they have more time to process the news before trading. Lastly, we find that the return reversals between overnight and daytime periods, as documented by Lou et al. (2019) and Akbas et al. (2022), are significantly mitigated when macroeconomic announcements are associated with greater overnight learning. These results are consistent with the investor clientele-based interpretations of Lou et al. (2019), suggesting that overnight learning leads to a higher proportion of informed retail investors trading at market open.

Finally, we emphasize that our paper is the first that examines the causal impacts of investors' learning from the "non-price sources", e.g., the social media, on price discovery. Our paper therefore is not about showing that market reacts more to macro news released outside of the regular trading hours, which apparently complements the evidence related to firm-level earnings announcements (Michaely et al., 2013, 2016). Rather, we uncover and disentangle the mechanism behind these facts, which highlights that gains on price discovery are direct results of investors making efforts to learn from news during overnight hours. The distance-to-trading of announcements thus nicely proxies for the degree of investor learning overnight. Importantly, while Barber and Odean (2008) and more recently Cookson et al. (2023) find that social media sentiment may result in overreaction of trading and asset prices, our results provide a complementary view that retail investors still extract accurate information from social media posts that are directly related to the relevant macro announcements. This overnight learning channel then helps close the information gaps among investors and reinstall the price efficiency at the market opening.

Related Literature. Our paper is related to several strands of literature. First, the existing literature stresses the critical importance of market trading that facilitates information aggregation and price discovery. Biais et al. (1999) identify the benefits of having pre-opening sessions in the stock market for faster price discovery. Barclay and Hendershott (2003) find that the largest fraction of price discovery is achieved through day trading, though price discovery can be quicker and more efficient during the pre-opening sessions. Barclay and Hendershott (2008) document that it is important to have high trading volume in the pre-trading sessions leading to greater degree of price discovery near market opening. Brogaard et al. (2014, 2019) find that price discovery benefits from high-frequency traders who can submit limit orders with information advantage. While the channels of learning and trading are jointly studied in the literature, little is known if the improved investors' information position in absence of trading helps with price discovery upon market opening. Our paper exploits the unique market setting in China and is the first to identify and to highlight the importance of the overnight learning on price discovery. More importantly, as investors in our setting won't observe the equilibrium market prices or price quotes until the market reopens, We identify a "learning from the non-price" channel that is immune from a few confounding effects, i.e. "learning from the price", or the "information paradox" that increased price informativeness deters continuous learning among less informed investors (Grossman and Stiglitz, 1980). Hence, our paper demonstrates that overnight learning from non-price sources is a distinctive and under-explored mechanism that contributes to price discovery even when market trading is closed.

Second, an important stream of literature is devoted to studying the risk and return profiles of stocks in response to macroeconomic announcements. Savor and Wilson (2013, 2014) first document that the U.S. equity market exhibits larger excess returns on days of data releases for inflation, unemployment, and various interest rates. Lucca and Moench (2015) detect a pre-announcement drift of the equity premium before the FOMC statement release. Ai and Bansal (2018) and Ai et al. (2022) theoretically show the asset pricing implications of recursive preferences in windows of macroeconomic announcements. Cieslak et al. (2019) find that the equity premium realized before and on FOMC days is part of a larger FOMC premium cycle. Hu et al. (2022) emphasize the heightening and subsequent reduction of market uncertainty before the FOMC announcements. Brusa et al. (2020) show that the stock markets of 35 countries all exhibit strong reactions to the FOMC announcements. Boguth et al. (2023) find that equity prices following FOMC announcements are less informative. Guo et al. (2023) first study the asset pricing implications of a market setting that macro announcements in China randomly arrive to the markets with significant timing variations. They document positive returns accrued prior to PBOC's monthly releases of monetary aggregates data. Our paper is the first to show that the stock market dynamics after macro announcements can be driven by the investors' learning over a duration of an information-sensitive period, which is after the announcement arrival but before market trading (i.e., the distance-to-trading). Our results show that investor learning during non-trading hours – rather than the trading itself – helps generate sizable price discovery upon the release of macroeconomic data once market trading resumes.

Lastly, our paper contributes to the series of work that evaluate the efficiency of financial markets in China. Based on an earlier sample, Allen et al. (2005) and Allen et al. (2012) provide comprehensive overviews of China's financial system and conclude that the Chinese stock markets are less efficient for its stock prices are not reflective of fundamental values of listed firms. Geng and Pan (2019) find improved price efficiency in China's bond markets but at a cost of the increased divergence of the cost of borrowing between state-owned and non-state-owned firms. Carpenter et al. (2021) document that China's stock markets have become increasingly efficient as stock prices are more informative of firms' future profits and the market is effectively aggregating the relevant information. Liu et al. (2019) construct the relevant size and value factors for valuing stocks in China. He and Wei (2023) and Hu and Wang (2022) provide very detailed reviews of major markets in China. They show that China's capital markets have experienced significant growth and development in recent years. Importantly, our paper highlights the market setting in China with unscheduled releases of macroeconomic data facilitates the evaluation of a general learning channel that affects the stock price efficiency. In addition, in spite of the frictions that negatively affect the Chinese stock market performance (Allen et al., 2023), our findings however suggest that retail investors can still benefit from the timing arrangements of macro announcements in China. Greater distance-to-trading leaves investors more time to learn from relevant source for trading, which helps level the information playing field across investors. If overnight learning makes the large share of retail investors in China learn more about market fundamentals after important macro announcements before trading, such a setting of macro announcements at least partially offsets the social welfare loss driven by the excessive noisy trading in Chinese markets as highlighted in Brunnermeier et al. (2021). Particularly, we emphasize that our paper is also the first that systematically summarizes the impacts of a comprehensive list of macro announcements in China on its stock markets.

The rest of the paper is structured as follows. We summarize our data on macroeconomic announcements in China and introduce the institutional background in Section 2. In Section 3, we document our main findings regarding the impacts of distance-to-trading on price discovery. Section 4 presents a model to show the importance of overnight learning in the distance-to-trading for rationalizing our main findings. We provide important empirical evidence to test the model-implied hypotheses in Section 5. We show additional test results in Section 6. Finally, Section 7 concludes. In the Appendix and the Internet Appendix, we provide additional theoretical results and empirical evidence.

2 Data

2.1 Macroeconomic Announcements in China

We consider the release of major macroeconomic indicators in China. To pinpoint important market-moving macroeconomic indicators in China, we first include 15 Chinese macroeconomic indicators covered by the Bloomberg relevance scores. These scores track the number of subscriptions on the Bloomberg terminal and thereby represent the top China macroeconomic indexes that investors pay attention to. These 15 economic indicators are: the consumer price index and producer price index (CPI/PPI), gross domestic production (GDP), purchasing managers' index (PMI), Caixin China purchasing managers' index (Caixin), industrial production (IP), broad money supply (M2), trade balance (Trade), foreign exchange reserves (FER), required reserve ratio (RRR), profit of industrial enterprises (PI), foreign direct investment (FDI), balance of payments (BOP), Swift global payments CNY (Swift), sales prices of residential buildings (SPRB), and foreign exchange settlement and sales by banks (FESS). We supplement the set of indicators with 5 additional monetary policy announcements from the PBOC: open market operations of medium-term lending facility (OMO), monthly summary of standing lending facility/medium-term lending facility/pledged supplementary lending operations (SLF/MLF/PSL), central treasury cash management (CTCM), central bank bills swap (CBS), and loan prime rate (LPR).[6]

We collect the release date and time of the macroeconomic announcements between January 2009 and December 2020 from the Bloomberg terminal and the website of the PBOC. The announcement times are with minute-level time stamps. Unlike many developed countries, most macroeconomic announcements in China do not follow a fixed timetable, and the actual release calendar date and time may vary substantially between announcements. In Table 1, we report the timing distribution of the 20 major macroeconomic indicators covered in our sample. It shows that the earliest macroeconomic announcement in our sample arrives on a day at 6:40 a.m., the median is at 10:00 a.m., and the latest is at 9:07 p.m.

Based on the release time, we divide the macroeconomic announcements into two groups: those within regular trading hours and those outside of regular trading hours. In our sample, 1,044 announcements are made during regular trading hours, while 854 announcements are

[6]The People's Bank of China employs many monetary policy tools, and we only include the ones that have a regular releasing schedule and contain information that can potentially move the market.

made during non-trading hours. There are three scenarios for announcements made outside of trading hours: 1) 217 announcements are made before the stock market opens (9:30 a.m.) on a trading day; 2) 421 announcements are made after the stock market closes (3:00 p.m.) on a trading day; and 3) 216 announcements are made on a non-trading day, which includes both weekends and holidays.[7]

2.2 The Financial Markets and Trading Hours

Along with its fast economic development, China's financial markets have grown tremendously in recent years. Established in 1990, the two stock exchanges, the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE), are now second globally in terms of market capitalization, second only to the United States. Despite their large size and growing importance, China's financial markets, the derivatives market in particular, remain largely underdeveloped. The Chinese financial futures and options markets, launched in 2010 and 2015, respectively, have a very short history and are significantly smaller compared to its own stock market and the derivatives market in other developed countries.[8]

Stock trading can only take place on the two stock exchanges during regular trading hours in China. Regular trading hours include two sessions: the morning session from 9:30 a.m. to 11:30 a.m., and the afternoon session from 1:00 p.m. to 3:00 p.m. The total trading session is therefore only four hours (240 minutes) per day, shorter than most of the developed markets. Before the market opens, there is a pre-opening auction session that runs from 9:15 to 9:25 a.m., during which orders are placed in advance and an opening price of the stock is decided based on a call auction process. There is no after-hours trading session in China.[9] Moreover, financial futures and options can only be traded during regular trading hours in China, in contrast to many developed countries (including the U.S.), where the derivatives

[7]Fifteen macroeconomic announcements are released during the noon break, between 11:30 a.m. and 1:00 p.m., in our sample period. We exclude these announcements in our analysis.

[8]Interested readers can refer to Hu and Wang (2022) for a review on the development and characteristics of the financial derivatives market in China.

[9]In addition to the main board on Shanghai and Shenzhen stock exchanges, ChinNext and The Science and Technology Innovation Board (STAR) are two separate boards of the stock markets in China established in 2009 and 2019, respectively. As part of the Shenzhen Stock Exchange, ChinNext is focused on small and medium-sized enterprises in innovative and high-growth industries. The companies listed on ChinNext are often in emerging industries. STAR is part of the Shanghai Stock Exchange and is designed to support the development of innovative companies in the country. The STAR market focuses on high-tech and strategic emerging industries. For stocks listed on ChinNext and STAR, there is an after-hours fixed-price trading session from 3:05 p.m. to 3:30 p.m.

Table 1: Release Time of Major Macroeconomic Indicators in China

Announcement	MinT	MedT	MaxT	#Trd	#NonTrd	#Open	#Close	#Weekend/Holiday	Score	Source
CPI/PPI	9:30	9:30	13:30	122	22	0	0	22	98	National Bureau of Statistics
GDP	10:00	10:00	15:00	47	1	0	1	0	96	National Bureau of Statistics
PMI	9:00	9:00	20:00	0	179	113	1	65	94	Federation of Logistics & Purchasing
Caixin	9:45	9:45	10:30	308	11	0	0	11	92	Markit
IP	10:00	10:00	15:40	109	14	0	3	11	88	National Bureau of Statistics
M2	8:00	16:00	20:00	33	111	6	94	11	86	The People's Bank of China
Trade	9:32	10:58	17:30	96	33	0	3	30	82	General Administration of Customs
FER	8:00	16:00	18:27	11	77	6	51	20	69	The People's Bank of China
PI	9:30	9:30	11:00	85	28	0	0	28	51	National Bureau of Statistics
RRR	12:12	18:06	20:01	0	26	0	18	8	41	The People's Bank of China
FDI	6:40	10:16	20:30	90	46	2	41	3	36	Ministry of Commerce
BOP	14:30	16:46	19:05	1	37	0	37	0	35	State Administration of Foreign Exchange
Swift	9:00	9:00	21:07	1	60	58	2	0	33	SWIFT
SPRB	9:30	9:30	9:30	30	3	0	0	3	29	National Bureau of Statistics
FESS	10:00	15:53	19:52	10	34	0	34	0	27	State Administration of Foreign Exchange
OMO	9:10	9:46	9:46	46	8	8	0	0	-	The People's Bank of China
SLF/MLF/PSL	9:23	15:51	19:12	11	62	1	57	4	-	The People's Bank of China
CTCM	7:24	16:31	19:45	27	83	4	79	0	-	The People's Bank of China
CBS	9:00	9:00	9:00	0	19	19	0	0	-	The People's Bank of China
LPR	9:30	9:30	9:30	17	0	0	0	0	-	The People's Bank of China
All	6:40	10:00	21:07	1044	854	217	421	216		

Notes: This table reports the summary statistics on the release time of 20 major macroeconomic indicators in China: 15 indicators with Bloomberg subscription scores and 5 monetary policy tools of the People's Bank of China. "MinT", "MedT", and "MaxT" refer to the minimum, median, and maximum of the release time. "#Trd" refers to the number of announcements released during trading hours. "#NonTrd" refers to the number of announcements released during non-trading hours. "#Open" refers to the number of announcements released before the stock market opens (9:30 a.m.) on a trading day. "#Close" refers to the number of announcements released after the stock market closes (3:00 p.m.) on a trading day. "#Weekend/Holiday" refers to the number of announcements released on weekends and holidays. "Score" refers to the subscription scores by Bloomberg. "Source" is the official releasing entity of the indicator. The sample period is from January 2009 to December 2020.

markets are open almost 24 hours around the clock.[10]

The under-developed financial markets, coupled with short trading hours, make China a unique laboratory for studying the information transmission mechanism when trading is not available at the time information arrives to the market. For macroeconomic announcements released during non-trading hours, Chinese investors have to wait until the stock market opens for trading because both the stock and derivatives markets are close. This setup is very different from the way macroeconomic announcements are released in other developed countries. In the U.S., for example, important macroeconomic announcements are released either shortly before the stock market opens (non-farm payroll, GDP, CPI, etc.), from 8:30 a.m. to 9:15 a.m. eastern time, or within regular trading hours (FOMC, ISM, CSI, etc.). U.S. investors could therefore immediately trade on the news using, for instance, the market index futures contracts that are open to trade almost around-the-clock or the market index ETFs that are actively traded during both trading and pre-trading hours.

In summary, we can characterize the environment of interest in which a macroeconomic announcement arrives in between regular trading hours using a timeline. Specifically, according to Figure 1, an announcement is released outside the trading session. That is, it is released to the public after a regular trading day $t-1$ and before the next trading day t. In addition, we highlight a period of time to denote the duration of time between the arrival of an announcement and the beginning of the next trading session (i.e., distance-to-trading). The distance-to-trading is of great interest of our paper as it captures the duration of hours during which investors cannot observe and learn from asset prices for investment decisions but some important macro news has arrived that potentially moves the asset valuation. In particular, while the market is yet to incorporate the information of the newly arrived macroeconomic announcements released overnight, it is important to examine the implications of such an information-sensitive period overnight in the absence of trading for the price discovery process once market resumes trading on the next trading day.

[10]CSI 300 index futures were launched on April 16, 2010, and were traded from 9:15 a.m. to 11:30 a.m. and 1:00 p.m. to 3:15 p.m. from 2010 to 2015. After 2016, the trading hours for the CSI 300 index futures were changed to 9:30 a.m. to 11:30 a.m. and 1:00 p.m. to 3:00 p.m. CSI 300 index options were launched much later, on December 23, 2019, and are traded from 9:30 a.m. to 11:30 a.m. and 1:00 p.m. to 3:00 p.m.

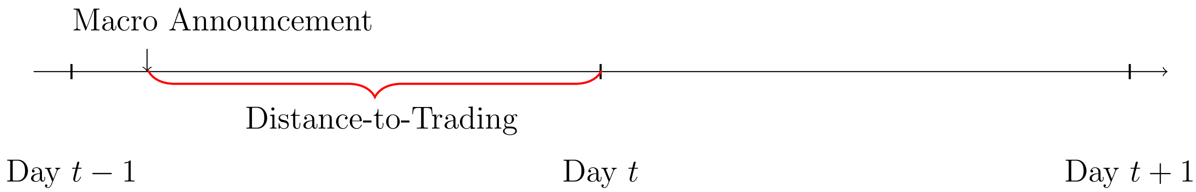


Figure 1: A Timeline

2.3 Market Responses on Macroeconomic Announcement Days

Our main empirical results are based on the return of the CSI 300 index, the capitalization-weighted index tracking the performance of the 300 largest stocks listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange. We obtain the high-frequency intraday tick data of the index, including both price and volume, from the RESSET Financial Database. The CSI 300 index data are with second-level time stamps and available for every five-second time interval from January 2009 to December 2020. We complement the index data with high-frequency tick data for its constituent stocks, provided by RESSET and with minute-by-minute time stamps for each one-minute interval from January 2009 through December 2020. Based on the high-frequency data, we calculate the returns for the CSI 300 index and its constituent stocks at a daily frequency as well as for different time windows around the release of macroeconomic announcements. We winsorize returns at the 1% and 99% levels to mitigate the potential large impact driven by a few extreme values.

We report the summary statistics of the daily market returns on the macroeconomic announcement days in Table 2. For the announcements released during regular trading hours, the daily market returns are calculated as the percentage returns of the CSI 300 index from the close (3 p.m.) of the previous trading day to the close (3 p.m.) of the announcement day. For the announcements made outside trading hours, the daily market returns are calculated as the percentage returns of the CSI 300 index from the close of the previous trading day to the close of the next trading day after the announcement release time.

The average market return is 5.23 basis points (bps) on the announcement days, which is positive but not statistically significant with a t-value of 1.63. Out of the 20 announcements tracked in our sample, the PMI announcement days elicit the most positive market reactions, yielding an average of 34.20 bps, which is significant at the 5% level. While the market returns are large on several announcement days, specifically positive on SLF/MLF/PSL, LPR, and Trade release days, and negative on OMO, RRR, and Swift release days, none of these results are statistically significant. The overall daily market returns are close to zero on the non-announcement days, with an average of -0.77 bps with a small t-value of -0.22.

Table 2: Daily Market Returns and Distance-to-Trading on Macroeconomic Announcement Days

		Market Return (daily)			Distance-to-Trading (Dur)	
	N	Mean	Std	TStat	Mean	Std
Ann	1898	5.23	140	1.63	0.56	1.18
CPI/PPI	144	-1.50	142	-0.13	0.29	0.76
GDP	48	-12.95	150	-0.60	0.02	0.11
PMI	179	34.20	150	3.04	0.96	1.78
Caixin	319	14.43	144	1.79	0.20	1.16
IP	123	-1.41	131	-0.12	0.19	0.61
M2	144	12.84	134	1.15	1.15	1.30
Trade	129	16.89	138	1.39	0.42	0.83
FER	88	4.56	135	0.32	1.01	1.09
PI	113	-1.43	145	-0.10	0.39	0.83
RRR	26	-24.99	161	-0.79	1.73	1.85
FDI	136	-11.85	140	-0.99	0.40	0.81
BOP	38	7.08	163	0.27	2.34	2.14
Swift	61	-20.12	110	-1.43	0.04	0.10
SPRB	33	5.72	155	0.21	0.18	0.58
FESS	44	4.59	129	0.24	1.23	1.11
OMO	54	-28.44	121	-1.72	0.00	0.00
SLF/MLF/PSL	73	26.64	135	1.68	1.06	1.35
CTCM	110	-19.04	138	-1.44	0.64	0.71
CBS	19	3.97	133	0.13	0.02	0.00
LPR	17	23.01	124	0.77	0.00	0.00
Non-ann	1600	-0.77	139	-0.22		

Notes: This table reports the summary statistics of market returns and distance-to-trading on the macroeconomic announcement days and other days in China. The market returns are the average log returns of CSI 300 and are in basis points. Dur is the time (in unit of calendar days) between announcement time and the first trading time after the announcement. "Ann" refers to the announcement days, and "Non-ann" refers to the trading day without announcements. The sample period is from January 2009 to December 2020.

Table 2 also shows large variations in the distance-to-trading among macroeconomic announcements in China. We measure the distance-to-trading (Dur) for each announcement as the number of calendar days between the actual release time and the first instance that investors can trade, which equals zero for announcements released during trading hours. For the 1,898 macroeconomic announcement in our sample, the average distance-to-trading is 0.56, with a large standard deviation of 1.18. The large variations in distance-to-trading are a result of differences across announcement types as well as variations within fixed macroeconomic announcement types.

To further pin down the magnitudes of market reactions on macroeconomic announcement days, we group announcement days based on the surprise component of the releases and investigate the corresponding market returns. The index surprise δ is calculated as the difference between the actual release and the median of Bloomberg economists' forecasts, normalized by its full-sample standard deviation. Because of Bloomberg coverage limits, we can only calculate index surprises for CPI/PPI, GDP, PMI, Caixin, IP, M2, Trade, FER, and FDI announcements.[11] Based on the index surprise, we divide the announcement days into three different groups: the bad news group with δ less than -0.5, the neutral news group with δ between -0.5 and 0.5, and the good news group with δ larger than 0.5.

We observe significant market movement on the macroeconomic announcement days that deliver unexpected information, as presented in Panel A of Table 3. The average returns on these announcement days are -20.27 bps for the bad news group and 26.14 bps for the good news group. The return differences between groups of good and neutral news and between groups of neutral and bad news are significant. The majority of these market reactions occur after the release of the macro news. The average post-announcement return, $R^{[0,239]}$, which captures the 240-minute (4 trading hours) return after the regular trading hours announcement and the 240-minute return (4 trading hours) after 9:30 a.m. of the following trading day for after-hours announcements, is -23.69 bps and 23.66 bps for the bad and good news groups, respectively. Both numbers and their between group differences are statistically significant.

Conversely, no significant pre-announcement returns are observed before macroeconomic announcements. The average pre-announcement return, $R^{[-240,-1]}$, measuring the 240-minute return before the release time for announcements made during regular trading hours and the

[11]For the CPI/PPI announcement days, we calculate the index surprises based on the surprise component of the CPI release and forecast, considering that the CPI receives high Bloomberg relevance scores. It is also worth noting that the market may not always view higher than expected CPI as good news. In unreported robustness tests, we exclude the CPI/PPI announcement days in our sample and obtain results similar to those reported in Table 3.

Table 3: Macroeconomic Index Surprises and Announcement Returns

Panel A: Market returns for announcements sorted based on index surprises

	Bad $\delta < -0.5$	**Neutral** $-0.5 \leq \delta \leq 0.5$	**Good** $\delta > 0.5$	**B−N**	**G−N**
δ	-1.15***	0.01	1.07***		
	[-28.23]	[0.54]	[15.16]		
Dur	0.59***	0.64***	0.59***	-0.05	-0.05
	[7.25]	[11.25]	[6.42]	[-0.46]	[-0.47]
R^{ann}	-20.27**	8.86	26.14***	-29.13***	17.28*
	[-2.17]	[1.57]	[2.98]	[-2.69]	[1.67]
$R^{[-240,-1]}$	-3.49	8.07	11.44	-11.56	3.37
	[-0.40]	[1.54]	[1.44]	[-1.15]	[0.35]
$R^{[0,239]}$	-23.69***	0.93	23.66***	-24.61**	22.73**
	[-2.64]	[0.16]	[2.60]	[-2.21]	[2.10]
N	182	485	207		

Panel B: The impact of index surprises on market returns

	Ann-day R^{ann}		**Pre-ann** $R^{[-240,-1]}$		**Post-ann** $R^{[0,239]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
δ	11.63***	11.68***	3.83	3.91	14.56***	14.50***
	[2.60]	[2.59]	[0.88]	[0.90]	[3.17]	[3.14]
Dur	5.71	6.32	0.03	-4.62	7.96*	5.20
	[1.33]	[1.03]	[0.01]	[-1.14]	[1.83]	[0.83]
Constant	3.19		6.38		-3.93	
	[0.70]		[1.44]		[-0.83]	
Index FE		Yes		Yes		Yes
Year FE		Yes		Yes		Yes
Month FE		Yes		Yes		Yes
Day FE		Yes		Yes		Yes
R^2	0.01	0.09	0.00	0.08	0.02	0.09
N	874	872	874	872	874	872

Notes: Panel A reports the summary statistics of market returns for sorted groups on macroeconomic announcement days. The announcement days are sorted into bad news ($\delta < -0.5$), neutral news ($-0.5 \leq \delta \leq 0.5$), and good news ($\delta > 0.5$) grouped by index surprise δ. The index surprise δ is calculated as the difference between the actual release and the median of Bloomberg economists' forecasts, normalized by its full sample standard deviation. The market returns are the average log returns of CSI 300 and are reported in basis points. "B−N" and "G−N" indicate the difference between the bad and neutral group and the good and neutral group, respectively. R^{ann} refers to the daily return on announcement days. $R^{[-240,-1]}$ and $R^{[0,239]}$ refer to returns from the beginning of minute "-240" to the end of minute "-1", and from the beginning of minute "0" to the end of minute "239". The minute "0" is the opening time of the stock market (9:30 a.m.) for announcements released during non-trading hours and is the actual announcement time for announcements released during trading hours. Dur is the time (in unit of calendar days) between announcement time and the first trading time after the announcement. Panel B reports the regression results of $R_i = \alpha + \beta_1 \delta_i + \beta_2 Dur_i + \epsilon_i$. The sample period is from January 2009 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

240-minute return before 3 p.m. of the previous trading day for after-hours announcements, stands at -3.49 bps and 11.44 bps for the bad and good news groups, respectively. Neither of these numbers are statistically significant. As expected, for neutral announcements with no surprising information, no significant market movements are observed either prior to or following the announcements.

Putting all the evidence together, it is clear that macroeconomic announcements in China carry important informational content and could result in substantial price movement in the equity market. This observation aligns with the findings from our regression analysis where the returns of different announcement windows are regressed on the surprise component of macroeconomic announcements. As shown in Panel B of Table 3, a one-unit increment in the index surprise δ is associated with an increase of approximately 15 bps in the post-announcement returns, yet it exhibits no significant effect on the pre-announcement returns.

It's also worth emphasizing that we observe no significant difference in the release timing among macroeconomic announcements with varying information content. For both the bad and good news groups, the average distance-to-trading is around 0.59 days (or 850 minutes), and it does not statistically differ from that of the neutral group. In a regression setup, we also find that the distance-to-trading does not affect the announcement returns of macroeconomic releases. In other words, the information content and the market response to macroeconomic announcements are not directly associated with the timing of their release.

3 Price Discovery Speed and Distance-to-trading

3.1 Preliminary Evidences Based on R-squared

To investigate the impact of distance-to-trading of macro announcements on the speed of stock price discovery after market reopening, we first rely on an unbiasedness regression model similar to Biais et al. (1999) and Boguth et al. (2023). Formally, for given $-10 \leq t \leq 239$, we regress the total returns surrounding the announcements' release time on the cumulative announcement returns ending at time stamp t, which is defined relative to the release time of an announcement $t = 0$:

$$R_i^{[-10,239]} = \alpha_t + \beta_t R_i^{[-10,t]} + \epsilon_{i,t}, \tag{1}$$

where $R_i^{[-10,t]}$ denotes the cumulative return of the CSI 300 index from 10 minutes before the release to the time t after the release for the announcement i; $R_i^{[-10,239]}$ denotes the cumulative return of the CSI 300 index from 10 minutes before the release time to the 240th minute after the release time for the announcement i. Time 0 is the market opening time at 9:30 a.m. on the following trading day after the release for announcements released during non-trading hours and is the actual release time for announcements released during trading hours.

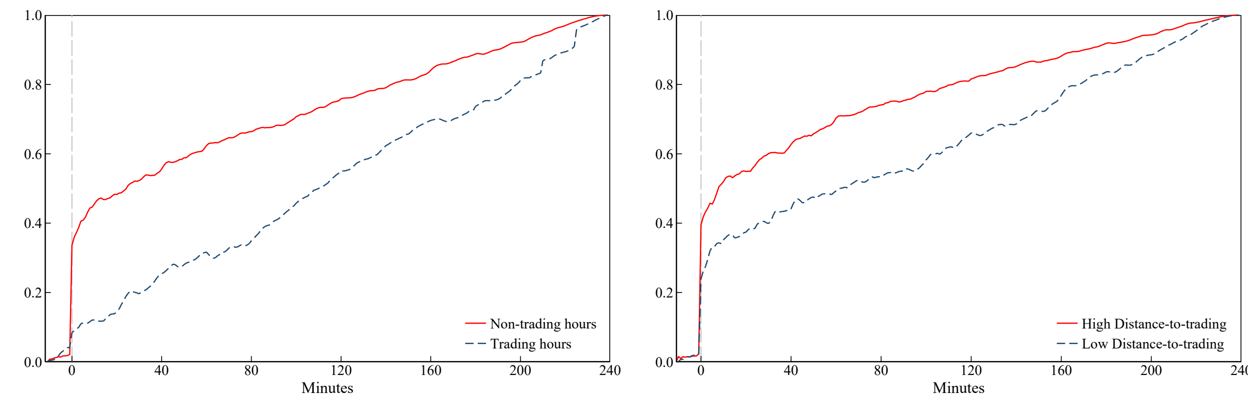
Following Boguth et al. (2023), we focus on the R-squared of the regression (1), denoted as R_t^2, which measures the price informativeness at time t. By construction, R_t^2 always starts from zero and coverages toward one as t moves from the beginning to the end of the time window. The path of R_t^2, however, provides useful information on the speed of price discovery. Panel (a) of Figure 2 compares the R_t^2 of the unbiasedness regressions (1) for macroeconomic announcements released during non-trading and trading hours. For announcements made during non-trading hours, R_t^2 jumps immediately by 31% at the market opening time at 9:30 a.m. and stays above the R_t^2 of trading hours announcements for the entire post-announcement time window. By comparison, R_t^2 also increases at the release time for announcements made during the trading hours, but the increase is much smaller, only about 4% in size. Clearly, the announcements made during non-trading hours exhibit a much quicker price discovery process than those made during trading hours.[12]

To avoid potential bias in comparing non-trading-hours and trading-hours announcements, we further divide the non-trading-hours announcements into high and low groups according to the distance-to-trading and estimate the unbiasedness regression (1) for each group. Panel (B) of Figure 2 shows R_t^2 based on the sample of non-trading-hours announcements: "High Distance-to-trading" refers to the announcements with distance-to-trading above the median; "Low Distance-to-trading" refers to the announcements with distance-to-trading below the median. The path of R_t^2 shows that the price discovery speed is faster for non-trading-hours announcements with high distance-to-trading. In Internet Appendix Table IA.I, we present evidences that the excess change in R-squared (R_t^2) at first trading minute (9:30 am) is significantly higher for announcements with high distance-to-trading.[13]

[12]One interpretation is that in mid of trading sessions, bounded rational investors still cannot costlessly process information from asset prices even if they observe the real-time price signals. Their interpretation of asset prices brings in additional noises into the equilibrium prices, leading to increased endogenous noise trading at least in the short-run. See more details in Mondria et al. (2022).

[13]We conduct a bootstrapping procedure that randomly assigns each announcement released during non-

Figure 2: Unbiasedness Regression R-squared around Chinese Macroeconomic Announcements



(a) Non-trading-hours vs. trading-hours announcements

(b) Non-trading-hours announcements only

Notes: This figure shows the R-squared (R_t^2) estimated from unbiasedness regressions: $R_i^{[-10,239]} = \alpha_t + \beta_t R_i^{[-10,t]} + \epsilon_{i,t}$ based on the sample of announcements released during both non-trading hours and trading hours in Panel (a), and only non-trading hours in Panel (b). The dependent variables are the returns of the CSI 300 index from 10 minutes prior to the announcement to the end of the 240th minute after the announcement, $R_i^{[-10,239]}$, and the independent variables are the returns of the partial announcement window from 10 minutes prior to the announcement to minute t around the announcement i, $R_i^{[-10,t]}$. "Non-trading hours" refers to the macroeconomic announcements released during non-trading hours; "Trading hours" refers to the macroeconomic announcements released during regular trading hours. "High Distance-to-trading" refers to the macroeconomic announcements released during non-trading hours with high distance-to-trading; "Low Distance-to-trading" refers to the macroeconomic announcements released during non-trading hours with low distance-to-trading. The time "0" is the opening time of the stock market (9:30 a.m.) for announcements released during non-trading hours and is the actual announcement time for announcements released during trading hours. The sample period is from January 2009 to December 2020.

3.2 Regression Analysis

In the following analysis, we will focus exclusively on announcements released during non-trading hours for several reasons. Firstly, the first post-announcement return (return at time "0") observed for macroeconomic news made during non-trading-hours include the overnight close-to-open periods, which could make them fundamentally different from the intra-day returns of announcements released during trading hours. Secondly, since investors cannot trade immediately following the release of announcements during non-trading hours, these announcements provide a unique opportunity to better understand the impact of investor learning from non-price sources on the speed of price discovery. Lastly, the variations in the release time of macroeconomic announcements during non-trading hours in China offers sufficient variation to study the relation between distance-to-trading and the efficiency of price discovery.

To pin down the effect of distance-to-trading on the speed of price discovery, we regress the returns at different post-announcement windows on the information content of individual news announcements. We use the total post-announcement return of the CSI 300 index – from the previous market close to the market close of the first trading day after the news release time, denoted as R_i^{ann} for announcement i – as a proxy for this information content. We estimate the impact of the distance-to-trading on the speed of price discovery through the following regression:

$$R_i^t = \alpha^t + \beta_1^t R_i^{ann} + \beta_2^t R_i^{ann} \times Dur_i + \beta_3^t Dur_i + \epsilon_i^t, \tag{2}$$

where R_i^t denotes the return of the CSI 300 index on a given time interval t around the release of the announcement i, distance-to-trading Dur_i denotes the calendar time between the actual index announcement time and the market opening time (9:30 a.m.). We include time and macroeconomic index dummies to control for potential calendar and announcement type specific effects. The regression coefficient β_1^t measures the average proportion of price discovery occurring in different post-announcement time window t. We focus on the coefficient β_2^t, which captures the impact of distance-to-trading on the speed of price discovery

trading hours to either high or low groups, repeating this process for 1000 times. We then calculate empirical p-values for the likelihood of observing higher excess ΔR_0^2 difference between the assigned high and low groups in the bootstrapped distribution compared to the actual data. As shown in Table IA.I, the excess ΔR_0^2 is indeed significantly higher for announcements with longer distance-to-trading.

for time window t. We split the four-hour post-announcement windows into the following five periods.

The market opening time "0": This is the earliest time investor can trade on news released during non-trading hours. For such announcements, the return at the market opening time is calculated as the close-to-open return based on the previous market closing price and the next trading day's market opening price.

Other post-announcement windows Following the market opening, we cut the remaining four hours of trading into four one-hour time windows. We label the first trading hour from 9:30 a.m. to 10:29 a.m. by "1^{st}"; the second hour from 10:30 a.m. to 11:29 a.m. by 2^{nd}; the third trading hour from 1:00 p.m. to 1:59 p.m. by 3^{rd}; and the last trading hour from 2:00 p.m. to the market close by 4^{th}.

We report the estimation results in Table 4. The results paint a clear picture that the speed of price discovery is faster when the distance-to-trading increases. As the distance-to-trading increases by one day, the proportion of price discovery occurring at time "0" increases by 3.8% and is statistically significant with a t-value of 3.90. Consistent with the faster price discovery at time "0", there is less price discovery in the subsequent time windows as the distance-to-trading increases. The coefficients β_2^t is significantly negative for the third- and fourth-hour post announcement.

The above results show that, within the subsample of non-trading-hours announcements, the calendar time duration between the actual announcement time and the market opening time has a considerable impact on the speed of price discovery.[14] In Internet Appendix Table IA.II, we present further evidences based on the full sample of non-trading-hours and trading-hours announcements. The latter is an extreme case where the distance-to-trading equals zero, as investors can trade immediately after the release of this news. we find that the speed of price discovery is significantly faster for non-trading-hours announcements when the market reopens for trade, compared to the ones released during trading hours.

[14]We have 854 announcements made during non-trading hours. After controlling for fixed effects of announcement types, the sample size reduced to 853 because the GDP announcement are made only once during non-trading hours.

Table 4: The Impact of Distance-to-trading on the Speed of Price Discovery

	Market Opening	**Other Post-ann Windows**			
	close-to-open (“0”)	1^{st}	2^{nd}	3^{rd}	4^{th}
$R^{ann} \times Dur$	0.038***	0.001	0.002	-0.017**	-0.023***
	[3.90]	[0.12]	[0.23]	[-2.53]	[-2.77]
R^{ann}	0.175***	0.252***	0.179***	0.177***	0.216***
	[7.09]	[10.67]	[9.66]	[9.87]	[10.18]
Dur	-1.644	-0.787	4.969***	-2.460*	-0.078
	[-0.76]	[-0.44]	[3.25]	[-1.66]	[-0.05]
Index FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
R^2	0.362	0.455	0.311	0.275	0.354
N	853	853	853	853	853

Notes: This table reports the regression results of $R_i^t = \alpha^t + \beta_1^t R_i^{ann} + \beta_2^t R_i^{ann} \times Dur_i + \beta_3^t Dur_i + \epsilon_i^t$ based on the sample of announcements released during non-trading hours. The dependent variables are the log returns of CSI 300 for the respective time intervals and are in basis points. Dur_i is the time between the actual announcement time and the market opening time after the announcement (9:30 am) and is measured in days (i.e., distance-to-trading). The sample period is from January 2009 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

3.3 Robustness

We further explore the robustness of our main results. One potential issue is the varying degrees of attention that macroeconomic announcements receive, as higher attention could accelerate price discovery for certain announcements. In our baseline analysis, we control for cross-index differences using index type dummies. To further mitigate this concern, we added additional controls for the attention received by each type of announcements, using Bloomberg subscription scores $Score$ and the interaction term between $Score$ and the total return impact $R_i^{[-10,239]}$. The results are presented at Panel A of Table 5. After controlling for attention, the pattern of price discovery remain consistent with our baseline results.

A related concern is the release schedule of macroeconomic news on the speed of price discovery. We investigate whether our findings are influenced by the fact that some macroeconomic announcements in China, such as CPI/PPI, GDP, and Caixin, are released according to a fixed, pre-announced schedule well known to investors, while other announcements like M2, Trade and FDI appear to arrive randomly. Panel B of Table 5 examines the impact of time-to-trading on the speed of price discovery, with additional controls for pre-scheduled announcements. The findings confirm the robustness of our results, aligning closely with our baseline analysis.

Next, we address potential impact related to trading before market opening. First, we control for pre-opening trading impact by including the total trading volume during the market opening call auction as additional controls. The results are reported in Panel C of Table 5. Second, since U.S.-listed China concept stocks could be traded during the overnight period when the Chinese stock markets are close, the trading information of these U.S.-listed China concept stocks could potentially attribute to the price discovery process in the Chinese stock market when the market reopens. In Panel D of Table 5, we report the results for the subsample of macroeconomic announcements made between Saturday 4:00 am to Monday 9:30 am – the period when the U.S. stock market is also closed. Results in Panel C and D confirm that our baseline results remain robust.

We also test the robustness of our results by replacing the continuous distance-to-trading measure Dur with a discrete indicator AMC. This indicator takes value of one for announcements released after market closes, during weekends, or on holidays, and zero to those released before the market opens. The findings, presented in Panel E of Table 5, align with our baseline results: announcements made after market closes or during week-

Table 5: Distance-to-trading and the Speed of Price Discovery: Robustness Tests

	Market Opening	**Other Post-ann Windows**			
	close-to-open ("0")	1^{st}	2^{nd}	3^{rd}	4^{th}
Panel A: Controlling for attention					
$R^{ann} \times Dur$	0.036***	0.002	0.004	-0.020***	-0.022**
	[3.67]	[0.21]	[0.52]	[-3.09]	[-2.56]
$R^{ann} \times Score$	0.000	-0.000	0.000	-0.001*	0.000
	[0.08]	[-0.08]	[0.81]	[-1.71]	[0.59]
Panel B: Controlling for pre-scheduled news					
$R^{ann} \times Dur$	0.038***	0.001	0.001	-0.017**	-0.023***
	[3.98]	[0.15]	[0.21]	[-2.57]	[-2.69]
$R^{ann} \times Pre$	0.043	-0.028	0.015	-0.016	-0.014
	[1.25]	[-0.82]	[0.51]	[-0.65]	[-0.44]
Pre	-15.921	23.456**	-27.062**	9.737	9.791
	[-1.13]	[1.98]	[-2.34]	[0.95]	[0.82]
Panel C: Controlling for opening call auction trading volume					
$R^{ann} \times Dur$	0.034***	0.003	0.004	-0.019**	-0.023***
	[3.63]	[0.37]	[0.59]	[-2.58]	[-2.79]
$R^{ann} \times OCAV$	0.099**	-0.054*	-0.064**	0.024	-0.005
	[2.35]	[-1.76]	[-2.22]	[1.01]	[-0.15]
$OCAV$	22.077**	1.659	2.909	-5.143	-21.503***
	[2.52]	[0.24]	[0.38]	[-0.89]	[-3.23]
Panel D: Excluding the impact of China concepts stock					
$R^{ann} \times Dur$	0.047***	0.001	-0.016	-0.013	-0.019
	[2.77]	[0.08]	[-1.33]	[-1.30]	[-1.48]
Panel E: Results based on a discrete indicator					
$R^{[-10,239]} \times AMC$	0.100***	-0.024	0.028	-0.035	-0.069**
	[2.59]	[-0.68]	[0.83]	[-1.17]	[-2.18]
Panel F: Results based on the matched sample					
$R^{ann} \times Dur$	0.045***	-0.003	0.007	-0.010	-0.039***
	[3.17]	[-0.20]	[0.68]	[-0.97]	[-3.02]

Notes: This table reports the robustness results based on the sample consisting of announcements released during non-trading hours. Specifically, Panel A controls for Bloomberg subscription score's interaction with R^{ann}; Panel B controls for a variable $OCAV_i$ indicating opening call auction trading volume and its interaction with R^{ann}; Panel C controls for a dummy variable Pre_i indicating pre-scheduled announcement and its interaction with R^{ann}; Panel D reports results based on the sample of announcements made within Saturday 4:00 a.m. to Monday 9:30 a.m (after the U.S. stock market close on Friday); Panel E replaces Dur_i with a discrete measure AMC indicating announcement released after market closes, during weekends, or on holidays; Panel F reports results based on a matched sample. The dependent variables are the log returns of CSI 300 for the respective time intervals and are in basis points. Dur_i is the time between the actual announcement time and the market opening time (9:30 am) and is in days (i.e., distance-to-trading). The sample period is from January 2009 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

ends/holidays, which have a longer non-trading period before the market opens, exhibit a faster price discovery than those made just before market opens.

In the last Panel of Table 5, we address the concern that the timing of macroeconomic news release might be endogenously determined by their information content. Specifically, regulators may schedule important news during non-trading hours to mitigate market impact. Such timing could bias our previous analysis. To address this, we construct a matched sample of macroeconomic announcements with similar market impacts but differing in release time. As shown in Internet Appendix Table IA.IV, the matched pairs show a comparable market impact: average post-announcement market returns are 19.59 and 19.54 bps for announcements with high and low distance-to-trading. Panel F of Table 5 confirms that the findings based on this matched sample align with our baseline results.

4 Model

In a simple framework, we examine the asset pricing implications of an environment when an important macro news announcement is made outside of the trading hours. Our model demonstrates that once the market reopens for trading, the equilibrium price of a risky asset becomes more informative of the payoff fundamentals if an overnight announcement gives investors more time to process the related information by leaving a longer distance-to-trading.

Extending the three-period model of Vayanos and Wang (2012) in which investors trade for liquidity needs, our model introduces an additional ingredient of investors' heterogeneities, driven by their differed information positions regarding the macro announcement released overnight. Two types of liquidity-supplying investors of differed information positions jointly accommodate the trading needs of the liquidity-demanding investors, who trade for hedging purposes given their private exposure to the risk. Our model shows that greater distance-to-trading of an announcement turns more under-informed investors to be better informed upon market opens. Increased learning among investors overnight enhances the price informativeness once market reopens.

4.1 Environment

Our model has three timestamps of interest as denoted by $t = 0, 1, 2$. $t = 0$ denotes the market close of a trading day. $t = 1$ marks the market opening of the next trading day.

An overnight macro announcement is released between $t = 0$ and $t = 1$ with its associated "distance-to-trading", $\lambda \in (0, 1)$. We consider a financial market with one risky asset (e.g., a stock market portfolio) and a risk-free asset. The risky asset pays off a random dividend D to be realized in $t = 2$ with $D \sim \mathbf{N}(0, \sigma^2)$. The interval between $t = 1$ and $t = 2$ therefore broadly captures the post-announcement period after market reopens. Importantly, a macro announcement is modelled as a public signal s that imperfectly reveals the risky payoff D subject to a noise ϵ such that:

$$s = D + \epsilon, \quad \text{s.t.} \quad \epsilon \sim \mathbf{N}(0, \sigma_\epsilon^2), \tag{3}$$

where σ_ϵ^2 denotes the variance of the signal noise.

We assume a total supply of a unit share of the risky asset. For simplicity, the return on the risk-free asset is normalized to $r = 0$ such that the risk-free asset has a constant price of 1 and serves as the numeraire. The price of the risky asset at different timestamps is denoted by p_t and is endogenously determined in equilibrium through market clearing. In case of the payoff uncertainty is fully resolved at $t = 2$, $p_2 = D$. Given any realized market close price p_0 at the market close of a previous trading day, we focus on the determination of the equilibrium price of the risky asset when market reopens at $t = 1$ (i.e., p) for which we suppress the timestamp index for simplicity.

4.2 Investor Heterogeneities and the Overnight Learning

There is a unit measure of investors who have CARA preferences and derive utility from $t = 2$ wealth in the post-announcement period after market reopens. Without loss of generality, we simply set the risk aversion to one for model tractability. In addition, investors are homogeneous at market close at $t = 0$ and become heterogeneous for different trading motives at $t = 1$ when market reopens. Relative to Vayanos and Wang (2012), investors' heterogeneities at $t = 1$ in our model are driven not only by some private liquidity shocks, but also by their different information positions as a result of overnight learning among investors. Specifically, a total fraction $1 - \pi \in [0, 1]$ of investors receive liquidity shocks $z \sim \mathbf{N}(0, \sigma_z^2)$ before $t = 1$ and then an endowment of $z \cdot D$ to be realized at $t = 2$. Investors receiving liquidity shocks possess private exposures to the payoff risk and initiate trading once market reopens at $t = 1$. For positive realizations of z, these investors in equilibrium may want to sell their shares of the risky asset for being exposed to the risk that the risky asset's payoff is low, who demand market liquidity. The liquidity shocks are therefore the source of trade at $t = 1$. Therefore, investors receiving the liquidity shocks before $t = 1$ are labelled the "liquidity demanders", indexed as type-d investors. Importantly, in the spirit of Vayanos and Wang (2012), we assume the liquidity-demanding investors are well informed of the extra signal s upon market opening at $t = 1$ after the announcement is released overnight.

On the other hand, the fraction π of investors receive no liquidity shocks by $t = 1$ and expect no additional endowment at $t = 2$. In equilibrium, these investors would accommodate the risk-sharing trading needs of the liquidity demanders and provide market liquidity. They are called the" liquidity suppliers". Importantly, we further assume that a measure of $\delta \in (0, 1)$ denotes the fraction of the liquidity-supplying investors who are "uninformed" of the macro announcement upon market opening at $t = 1$, indexed as type-n investors. A fraction $1 - \delta$ of liquidity suppliers are well informed of the macro announcement at $t = 1$, indexed as type-a investors.

We further assume that the fraction of uninformed investors δ is not a constant but a decreasing function of the distance-to-trading λ for $\delta'(\lambda) < 0$. This is to reflect the presence of "learning effects" by which it takes time for investors to filter out noise and become more informed of the public signals and then extract useful information for trading (Dugast and Foucault, 2018). This is particularly true that investors react with delays when unscheduled news arrives (Dugast, 2018). Therefore, we impose the assumption and later confirm that those announcements that arrive much earlier give investors more time to process the relevant information and learn from the macro announcement overnight before market reopens on the next trading day. As a result, more investors are better informed by the time of market opening for a lower δ under a larger λ. We denote a constant hazard rate of "learning from the overnight macro announcement" per an infinitesimal time among investors (i.e., $\alpha \geq 0$). Hence, the fraction of investors who stay uninformed of the macro announcement once market reopens at $t = 1$ follows that

$$\delta(\lambda) = \bar{\delta} e^{-\alpha\lambda}, \tag{4}$$

According to Equation (4), a faster learning ratio α with a more extended duration of distance-to-trading λ triggers a stronger learning effect overnight, which increases the total mass of informed investors by the market opening. $\bar{\delta}$ denotes an upper bound of the mass of uninformed investors when there is no learning effect ($\alpha = 0$) or when macro announcement right arrives at the market opening time ($\lambda = 0$). When $\delta = \bar{\delta} = 1$, our model nests the case when there is no overnight learning while the liquidity providing investors are fully uninformed in line with the baseline model studied in Vayanos and Wang (2012).

Importantly, when market trading is absent overnight, investors cannot observe the equilibrium asset prices that could have aggregated dispersed information across investors if otherwise trading is on and continuous. Investors therefore do not learn from the prices nor from the quotes for bids and asks. In particular, the "information paradox" that the increased price efficiency deters uninformed investors' learning as in Grossman and Stiglitz (1980) is not a confounding factor that applies in our model setting.

In summary, we feature a model environment in which investors' learning takes place overnight, with the degree of learning intensity increased with the length of distance-to-trading. This learning effect affects the relative size of uninformed investors upon market opening.

4.3 Market Equilibrium

For each investor type $i = d, n, a$ upon market opening at $t = 1$, they optimize the demand for the risky asset, q_i, conditional on her information set. It follows that investors solve the following utility maximization problem in a general form:

$$\max_{q_i} U(W_{2,i}) = -\mathbb{E}_{\mathcal{I}} e^{-W_{2,i}}, \tag{5}$$

$$\text{s.t.} \quad W_{2,i} = W_{1,i} + q_i(D - p) + \mathbb{I}_{i=d} \cdot zD. \tag{6}$$

Accordingly, $W_{1,i}$ is the initial wealth at the market opening. $\mathbb{I}_{i=d} = 1$ if an investor receives the liquidity shocks before $t = 1$ and may demand for market liquidity, and $\mathbb{I}_{i=d} = 0$ for investors who are providing market liquidity.

When market reopens for trading at $t = 1$, the equilibrium price p is observed by all investors. However, only those liquidity-supplying investors who are informed of the macro announcements along with liquidity-demanding investors carry the public signal s in their information set, whereas a margin of investors are uninformed of the signal. Therefore, the liquidity shocks and the information heterogeneity are both driving the trading investors apart, which delivers the following optimal asset demand function for each investor type:

$$q_n(p) = \frac{\mathbb{E}(D|p) - p}{\sigma^2_{D|p}}, \tag{7}$$
$$q_a(p) = \frac{\mathbb{E}(D|s) - p}{\sigma^2_{D|s}}, \tag{8}$$
$$q_d(p) = \frac{\mathbb{E}(D|s) - p}{\sigma^2_{D|s}} - z. \tag{9}$$

For liquidity-supplying investors $i = n, a$, they are willing to purchase the asset as long as their expected payoff is greater than the market price. For liquidity-demanding investors $i = d$, the positive risk exposure under a large z enables them to sell the asset for market liquidity. In addition, a larger posterior variance of the asset payoff D conditional on investors' information sets $\sigma^2_{D|p}$ or $\sigma^2_{D|s}$ decreases the asset demands across investors.

The financial market equilibrium price of the risky asset p satisfies the market-clearing condition that equates the supply and the demand such that

$$\pi\delta(\lambda)q_n(p) + \pi(1 - \delta(\lambda))q_a(p) + (1 - \pi)q_d(p) = 1. \tag{10}$$

4.3.1 Equilibrium Solutions

We then solve for the model equilibrium via the guess and verify method. We first conjecture the equilibrium price is in linear form such that

$$p = a + b(s - c \cdot z), \tag{11}$$

where a, b, and c are constants to be determined.

Applying the Bayes' rule, we have the conditional expectations and posterior variances regarding asset payoffs among investors informed of the macro announcement ($i = a, d$) such that:

$$\mathbb{E}(D|s) = \gamma_S \cdot s, \tag{12}$$
$$\sigma^2_{D|s} = \frac{1}{1/\sigma^2 + 1/\sigma^2_\epsilon} = (1 - \gamma_S)\sigma^2, \tag{13}$$

where $\gamma_S = \frac{\sigma^2}{\sigma^2+\sigma^2_\epsilon}$. Given the equilibrium price of the risky asset as implied by Equation (11), the expectation and variances regarding the asset payoff among the uninformed investors are

$$\mathbb{E}(D|p) = \gamma_N(s - cz), \tag{14}$$

$$\sigma^2_{D|p} = \frac{1}{1/\sigma^2 + 1/(\sigma^2_\epsilon + c^2\sigma^2_z)} = (1 - \gamma_N)\sigma^2, \tag{15}$$

where $\gamma_N = \frac{\sigma^2}{\sigma^2+\sigma^2_\epsilon+c^2\sigma^2_z}$.

Plugging these expectations and variances into Equation (10), we can solve for the coefficients such that

$$a = -\frac{\sigma^2_{D|s}\sigma^2_{D|p}}{\pi\delta(\lambda)\sigma^2_{D|s} + (1 - \pi\delta(\lambda))\sigma^2_{D|p}} = -(1 - b)\sigma^2, \tag{16}$$

$$b = \frac{\gamma_N\pi\delta(\lambda)\sigma^2_{D|s} + \gamma_S(1 - \pi\delta(\lambda))\sigma^2_{D|p}}{\pi\delta(\lambda)\sigma^2_{D|s} + (1 - \pi\delta(\lambda))\sigma^2_{D|p}}, \tag{17}$$

$$c = \frac{1 - \pi}{1 - \pi\delta(\lambda)}\sigma^2_\epsilon. \tag{18}$$

With a some constant indicating the unconditional mean of the equilibrium price, b and c are the risk loadings of the price on the divident payoff risk and the market liquidity risk, respectively. While the payoff risk carries a positive price of risk, the liquidity risk commands a negative price of risk given a larger z increases the supply of risky assets. One can show that $\frac{\mathrm{d}b}{\mathrm{d}\lambda} > 0$ and $\frac{\mathrm{d}c}{\mathrm{d}\lambda} < 0$. Intuitively, longer distance-to-trading triggers overnight learning which turns more uninformed liquidity-providing investors to be better informed of the dividend payoff by market opening, leading to a smaller δ. More informed investors providing liquidity therefore reduce the price sensitivity to liquidity risk resulting in a smaller c. In addition, a larger number of investors incorporating useful information from the macro announcements in trading helps strengthen the price co-movement with the payoff, leading to greater price sensitivity to fundamentals, a higher b.

4.3.2 Model Predictions

We then examine the asset pricing implications of changing distance-to-trading λ as associated with different macro announcements released overnight, given that some learning ratio of $\alpha > 0$ governs the learning effects among investors. Specifically, we derive the model predictions regarding several important market statistics: (1) the measures of the price informativeness, which reflect the degree of efficiency for the equilibrium price to reflect the fundamentals; (2) information asymmetry among investors, which affects the bid-ask spreads in trading; (3) the trading volume and the volatility of asset returns.

First, we evaluate the price informativeness (PI) using two different metrics. Both are measures of the degree of information quality in market prices in terms of revealing the dividend payoff conditional on price changes:

$$PI_1 = \frac{1}{\sigma^2_{D|p}} = \frac{1}{\sigma^2} + \frac{1}{\sigma^2_\epsilon + c^2\sigma^2_z}, \tag{19}$$

$$PI_2 = \frac{cov(p, D)}{\sigma_p} = \frac{\sigma^2}{\sqrt{\sigma^2 + \sigma^2_\epsilon + c^2\sigma^2_z}}. \tag{20}$$

Given that $\frac{\mathrm{d}\delta}{\mathrm{d}\lambda} < 0$, it's easy to show that $\frac{\mathrm{d}PI_1}{\mathrm{d}\lambda} > 0$ and $\frac{\mathrm{d}PI_2}{\mathrm{d}\lambda} > 0$ as c decreases in λ. That is, when a macro announcement arrives earlier before market opens, investors are given more time to process the macro news and extract new information. More investors are well informed of the signal by the market opening and the variation of market price driven by the liquidity risk is much reduced. The price of the risky asset at market opening becomes more informative of the fundamental payoffs.

Second, we measure the degree of information asymmetry among investors by the reciprocal of the covariance of the conditional expectations regarding the asset payoffs between informed and uninformed investors. This measure reflects the relative information gaps, which effectively determines the width of bid-ask spreads observable in the data.

$$IA = \frac{1}{cov[\mathbb{E}(D|p), \mathbb{E}(D|s)]} = \frac{\sigma^2 + \sigma^2_\epsilon + c^2\sigma^2_z}{\sigma^4}. \tag{21}$$

One can show that $\frac{\mathrm{d}IA}{\mathrm{d}\lambda} < 0$ as c decreases in λ. As overnight learning turns more uninformed investors to be fully informed of the signal at the market opening, the information asymmetry between informed and uninformed investors is mitigated.

Third, we examine the impacts of overnight learning associated with distance-to-trading on trading volume and the return volatility. Since we have a unit measure of total shares of the risky asset, the trading volume can be interpreted as the turnover rate. To measure the trading turnover, we focus on the variance of the directional trading of the liquidity demanding investors such that:

$$Volume = Var\{(1-\pi)[\frac{(\gamma_s - b)s - a + bcz}{\sigma^2_{D|s}} - z]\} \tag{22}$$

$$= [\frac{1-\pi}{\sigma^2_{D|s}}]^2[(\gamma_s - b)^2(\sigma^2 + \sigma^2_\epsilon) + (bc - \sigma^2_{D|s}]^2\sigma^2_z]. \tag{23}$$

Equation (23) implies that the depth of trading volume is driven by two forces. One can show that larger λ raises b as close as possible to γ_s. Therefore, the first term, $(\gamma_s - b)^2(\sigma^2 + \sigma^2_\epsilon)$, is smaller, which reflects the degree of noise reduction by which price increasingly co-moves with the payoff fundamentals. The second term $[bc - \sigma^2_{D|s}]^2\sigma^2_z$ captures trading surges among liquidity demanding investors who exhibit increased price sensitivities to dividend payoff conditional on reduction in c, as b is larger. This precisely defines the trade-off between a reduction in dividend uncertainty (i.e., noise reduction), and increased price informativeness for greater trading volatility (i.e., information-driven volatility).

Next, we examine the variances of overnight (close-to-open) and intraday (open-to-close) excess returns of the risky asset (relative to risk-free returns of 1), $p - p_0$ and $D - p$, respectively, such that

$$RetVol^{Overnight} = Var(p - p_0) = b^2[\sigma^2 + \sigma^2_\epsilon + c^2\sigma^2_z]. \tag{24}$$

$$RetVol^{Intraday} = Var(D - p) = (1-b)^2\sigma^2 + b^2[\sigma^2_\epsilon + c^2\sigma^2_z]. \tag{25}$$

Equations (24) and (25) both exhibit similar trade-off that we see for the trading volume. In case of greater distance-to-trading for larger λ, increased price sensitivity b raises the return volatility for both measures whereas a reduced noise component in price captured by a lower c dampens the return volatility measures.

In summary, our model finds that the price informativeness improves and the information asymmetry across investors is reduced after an overnight macro announcement associated with longer distance-to-trading. Our model also suggests that the trading volume and return volatility in equilibrium can be shifted by two off-setting channels, i.e., the increased price informativeness of payoff fundamentals, and the reduction in the posterior market uncertainty. We provide additional numerical results in the Appendix illustrating the trade-off of these two effects. In addition, in the later empirical sections, we provide evidence suggesting that trading for increased price informativeness dominates during hours close to the market opening but is quieted in later hours of a trading day. As a result, the effects of uncertainty reduction eventually lead to lowered trading volume and the return volatility as time evolves after announcements.

4.4 Testable Hypotheses

Based on our model predictions, we proceed to provide a range of testable hypotheses to identify the mechanism behind the empirics that stock price informativeness is correlated with the distance-to-trading of an overnight macro announcement.

We first hypothesize that a longer distance-to-trading of a macro announcement released overnight is associated with more intense learning among investors, a key assumption as captured by Equation (4). This hypothesis also reflects the presence of a learning ratio $\alpha > 0$ indicative of the learning effect among investors. In particular, we have this assumption derived from the premise that investors require time to sift through noise and identify relevant information, as noted by Dugast and Foucault (2018). With more time available before the market reopens, a greater number of investors can become well-informed about the macro announcements at market opening. Consequently, we explore the correlation between measures of overnight learning and the distance-to-trading for macro announcements, particularly focusing on retail investors who are generally less informed. We test whether distance-to-trading effectively captures the extent of retail investors' learning during the non-trading overnight period per the following hypothesis:

Hypothesis 1. *If announcements fall outside trading hours, the degree of overnight learning among retail investors increases with the duration of distance-to-trading.*

Our model also predicts that prices of risky assets at market opening will be more informative of payoff fundamentals if an overnight macro announcement provides investors a longer distance-to-trading to process information. Consequently, we should see faster price discovery upon market reopening for announcements with more intense overnight learning among investors. We then test the following hypothesis:

Hypothesis 2. *If announcements fall outside trading hours, greater overnight learning among retail investors leads to faster price discovery upon market opening.*

Our model also highlights that the information asymmetry between informed and uninformed investors should be reduced if more investors extract useful information from overnight macro announcements for trading decisions upon market reopening. Intense overnight learning, facilitated by a longer distance-to-trading, should increase the proportion of informed investors at market opening, thus reducing information disparities.

Hypothesis 3. *If announcements fall outside trading hours, greater overnight learning among retail investors reduces the information asymmetry among investors upon market opening.*

Further, as market opening prices become informative after more investors learn and be more informed given longer distance-to-trading, we explicitly test the existence of a few driving forces related to this learning channel. First, as our model suggests, if it is the retail investors who benefit from overnight learning, their trading should be more active after a macro announcement gives them more time to digest and respond. Second, if retail investors' learning is increased with the distance-to-trading, we should see their order imbalances of trading become more informative of asset payoffs and better aligned with the announcement returns. Third, in light of the differences of investor clienteles' trading at different times of a trading day leading to intra-day and over-night return reversals (Lou et al., 2019), our model also implies that a larger fraction of actively trading retail investors with improved information position at the market opening should lead to attenuated reversals between overnight and daytime returns after those macro announcements with longer distance-to-trading. Collectively, if the learning channel operates, we should see in the data that retail investors' trading becomes more active and more informative, leading to mitigated return reversals as a result of their increased overnight learning.

Hypothesis 4. *If announcements fall outside trading hours, greater overnight learning among retail investors leads to (1) more active trading among retail investors upon market opening; (2) improved alignment between retail investors' order imbalances and the announcement day returns; and (3) less reversals of open-to-close returns relative to the close-to-open returns.*

Lastly, our model suggests that heightened trading sensitiveness to payoff risk associated with announcements with longer distance-to-trading could enlarge both trading volume and return volatility. However, the improved price informativeness concurrently reduces noisy price variations, thereby decreasing volume and volatility. Given the theoretical ambiguity, we will present empirical evidence to show which effect dominates at market opening and how it evolves throughout the trading day.

5 Empirical Evidence of Overnight Learning

Our model features the importance of investors learning overnight for rationalizing our baseline empirical facts that longer distance-to-trading is associated with faster price discovery at market opening. In this section, we proceed to provide additional empirical evidence in supportive of the hypotheses derived from our model. We document direct evidence of the important learning channel among investors.

5.1 The Impact of Investor Learning on Speed of Price Discovery

To test our hypotheses, we rely on social media posts related to macroeconomic announcements to proxy for retail investors' learning activities around the news announcements' release time. Our web-scrapped data are from Weibo, a Chinese micro-blogging website and one of China's largest social media platforms, for the period from January 2018 to December 2020. We focus on three measures that proxy for investors' learning activities before they are able to trade on the news: 1) the total number of posts (*posts*) with keywords matched with the macroeconomic indexes; [15] 2) the number of fans (*fans*) following the bloggers who post the posts with keywords matched with the macroeconomic indexes; and 3) the total number of retweets, comments, and likes (*interactions*) of the posts with keywords matched with the macroeconomic indexes. The numbers of posts, fans, and interactions are calculated from the actual release time for announcements to the time when investors can trade on the news.[16]

[15] In Internet Appendix Table IA.V, we report the keywords that we use to match the 20 major macroeconomic indicators.

[16] We have experimented with the fixed 72-hour, 48-hour, or 24-hour pre-trading window, ensuring that both announcements with high distance-to-trading and low distance-to-trading have the same calculation

In Hypothesis 1, we expect non-trading-hours news announcements with higher distance-to-trading to have higher *posts*, *fans*, and *interactions* resulting from the news coverage of the just-released announcements, which provides the information and time for investors, especially retail investors, to digest the news before they trade on the following day. Indeed, as reported in Table 6, the number of *posts*, *fans*, and *interactions* are all positively related to the distance-to-trading (Dur). Without controlling for fixed effects, an increase of one day in the distance-to-trading is associated with 20 more related Weibo posts, 38 million more fans who tracked these posts, and 44 more retweets, comments, and likes following these posts. The results remain similar with controlling for fixed effects: an increase of one day in the distance-to-trading is associated with 13 more related Weibo posts, 19 million more fans who tracked these posts, and 30 more retweets, comments, and likes following these posts.

Table 6: Distance-to-trading and Investor Learning Before Trading

	posts		*fans*		*interactions*	
	(1)	(2)	(3)	(4)	(5)	(6)
Dur	0.020***	0.013***	0.038***	0.019**	0.044***	0.030**
	[3.66]	[2.87]	[3.67]	[2.44]	[2.67]	[2.08]
Constant	0.016***	0.022***	0.033***	0.048***	0.044***	0.055***
	[3.65]	[4.19]	[3.80]	[5.20]	[3.62]	[3.89]
Type FE		Yes		Yes		Yes
Year FE		Yes		Yes		Yes
Month FE		Yes		Yes		Yes
Day FE		Yes		Yes		Yes
R^2	0.063	0.841	0.058	0.853	0.040	0.807
N	311	309	311	309	311	309

Notes: This table reports the regression results of $Learning_i = \alpha + \beta_1 Dur_i + \epsilon_i$. The dependent variables $Learning_i$ are proxied by the number of related Weibo posts or fans of these posts or the retweets, comments, and likes of these posts between the announcement time and the first trading time after the announcement. The units for the number of posts, retweets, comments, and likes are in thousands and the unit for the number of fans is in billions. The sample period is from January 2018 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Next, we turn to Hypothesis 2 and investigate the impact of investor learning on the speed of price discovery. Similar to our previous discussions, we regress the log returns of the CSI 300 for different post-announcement time intervals on our three measures – *posts*, *fans*, and *interactions* – which all serve as proxies for investor learning before they trade on

window. The results remain similar.

the news. As shown in Table 7, more investor learning before trading is associated with faster post-announcement price discovery. With fixed effects controlled, an increase of one standard deviation in the pre-trading posts (75 posts), the fans following these posts (147 million), and retweets, comments, and likes following these posts (204 interactions) is associated with 5.03%, 5.25%, and 6.43% faster price discovery at the market opening time (9:30 am) of the next trading day.

In Internet Appendix Table IA.VI, we show our estimation results related to Hypotheses 1 and 2 are robust if the degree of retail investors' learning is measured differently. In specific, the learning intensity is instead measured by the number of the number of related articles of Weixin official accounts between the announcement time and the first trading time after the announcement. The results again suggest that learning from these articles of Weixin official accounts increases with the distance-to-trading and price discovery upon market opening is faster if more relevant articles of Weixin official accounts.

Lastly, it's important to clarify that we do not asume that retail investors' pre-trading learning comes exclusively from the Weibo posts and articles of Weixin official accounts. Rather, we view these posts and articles as a reflection of the collective efforts made by retail investors to extract and understand information relevant to stock investment, especially when macroeconomic news arrives during periods when trading is not active.

5.2 The Impact of Investor Learning on Information Outcomes

In this subsection, we explore the impact of distance-to-trading and investors' pre-trading learning activities on the information quality and the information asymmetry across investors as reflected by the underlying stocks after the stock market opens for trade. We use the bid-ask spreads of the CSI 300 index component stocks during the market opening call auction to proxy for the information asymmetry across investors. The spreads are calculated as $\frac{ask_s - bid_s}{(ask_s + bid_s)/2}$, where ask_s and bid_s are the order-volume weighted averages of ask and bid prices for stock s. We estimate the following regressions to quantify the impact of distance-to-trading and investors' learning activities on bid-ask spreads:

$$Spread_{i,s} = \alpha + \beta_1 Dur_i + \epsilon_{i,s}, \tag{26}$$

Table 7: The Impact of Distance-to-trading on the Speed of Price Discovery

	Market Opening	Post-ann Windows			
	Close-to-open	$[0, 59]$	$[60, 119]$	$[120, 179]$	$[180, 239]$
Panel A: Investor Learning Proxied by the Number of Related Posts					
$R^{[-10,239]} \times posts$	0.653***	-0.223*	-0.181	-0.101	-0.115
	[4.52]	[-1.81]	[-1.58]	[-0.90]	[-0.91]
$R^{[-10,239]}$	0.269***	0.249***	0.177***	0.159***	0.142***
	[8.85]	[9.61]	[7.38]	[6.29]	[5.75]
$posts$	-13.959	48.086	27.855	-47.271	-20.361
	[-0.18]	[0.70]	[0.48]	[-0.72]	[-0.42]
Constant	-1.061	-2.361	-1.391	0.113	1.425
	[-0.31]	[-0.63]	[-0.45]	[0.03]	[0.54]
R^2	0.591	0.573	0.417	0.385	0.377
Panel B: Investor Learning Proxied by the Number of Fans Following Related Posts					
$R^{[-10,239]} \times fans$	0.343***	-0.111	-0.071	-0.051	-0.093
	[4.65]	[-1.61]	[-1.25]	[-0.92]	[-1.28]
$R^{[-10,239]}$	0.267***	0.249***	0.176***	0.160***	0.144***
	[8.78]	[9.54]	[7.43]	[6.31]	[5.84]
$fans$	-18.030	6.994	54.391*	-15.601	-29.558
	[-0.42]	[0.14]	[1.66]	[-0.44]	[-0.98]
Constant	-0.374	-1.142	-3.981	-0.480	2.624
	[-0.10]	[-0.26]	[-1.28]	[-0.15]	[0.90]
R^2	0.593	0.572	0.420	0.385	0.379
Panel C: Investor Learning Proxied by the Number of Retweets, Comments, and Likes Following Related Posts					
$R^{[-10,239]} \times interactions$	0.322***	-0.131**	-0.098*	-0.030	-0.047
	[4.94]	[-2.23]	[-1.85]	[-0.61]	[-0.82]
$R^{[-10,239]}$	0.266***	0.252***	0.178***	0.158***	0.141***
	[8.66]	[9.41]	[7.33]	[6.32]	[5.63]
$interactions$	-26.273	9.050	5.793	-8.999	13.858
	[-1.26]	[0.41]	[0.33]	[-0.41]	[0.84]
Constant	0.682	-1.511	-0.941	-0.730	-0.422
	[0.21]	[-0.43]	[-0.33]	[-0.24]	[-0.16]
R^2	0.592	0.573	0.417	0.385	0.377
Type FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
N	309	309	309	309	309

Notes: This table reports the regression results of $R_i^t = \beta_0 + \beta_1 R_i^{[-10,239]} + \beta_2 R_i^{[-10,239]} \times Learning_i + \beta_3 Learning_i + \epsilon_i$. The dependent variables are the log returns of CSI 300 for the respective time intervals and are in basis points. $Learning_i$ is the number of related Weibo posts (or the fans of these posts, or the retweets, comments, and likes of these posts) between the announcement time and the first trading time after the announcement. The units for the number of posts, retweets, comments, and likes are in thousands and the unit for the number of fans is in billions. The sample period is from January 2018 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

where $Spread_i$ denotes the bid-ask spreads for the market opening call auction after announcement i, Dur_i is the calendar time between the release time and the market opening time (9:30 a.m.) on the next trading day for non-trading-hours announcements. Panel A of Table 8 Column (1) shows that the bid-ask spreads during the market opening call auction tend to be smaller for announcements with lower distance-to-trading. When the distance-to-trading increases by one day, the bid-ask spreads decrease by 0.003. In Internet Appendix Table IA.VII, we present the regression results based on the number of Weibo posts, the number of fans, the total number of retweets, comments, and likes, and the number of articles of Weixin official accounts. We also report the price discovery results during the opening call auction of individual stocks in Panel B of Table 8 Column (1), which are consistent with those at the index level.

In the cross section, we find that the improvement in speed of price discovery and post-announcement bid ask spreads is mainly for low institutional holdings and low-price stocks. As shown in Panel A of Table 8 Column (2) to (5), the estimated coefficients β_1 are significant smaller for stocks with institutional holdings and prices in the bottom. As shown in Panel B of Table 8 Column (2) to (5), the estimated coefficients β_2 are significant larger for stocks with institutional holdings and prices in the bottom. Since low institutional holdings and low-price stocks tend to be stocks with higher volatility, more information asymmetry, and higher retail trading, our results suggest that these stocks benefit more from longer distance-to-trading on the announcement days.[17]

5.3 The Impact of Investor Learning on Return Reversals

In this subsection, we explore the impact of distance-to-trading and investors' pre-trading learning activities on return reversals. Firstly, we use standard predictive regressions to connect the initial one minute return of trading right after the announcement with subsequent reversals. The predictive regressions are of the form:

$$R_i^t = \alpha^t + \beta_1^t R_i^{cto} + \epsilon_i^t, \tag{27}$$

[17] In this section, we report the results of bid-ask spreads and price discovery during the opening call auction. The results are similar if we use data from the first minute after the opening (i.e., at 9:30 a.m.).

Table 8: The Impact of Distance-to-trading on the Bid-ask Spreads and Price Discovery

		Institutional Holding		Stock Price	
	(1)	(2)	(3)	(4)	(5)
	Opening Call Auction	Low	High	Low	High
Panel A: Bid-Ask Spreads					
Dur	-0.003***	-0.004***	-0.001	-0.007***	0.001
	[-4.59]	[-4.88]	[-1.45]	[-9.08]	[1.23]
Constant	0.738***	0.806***	0.670***	0.947***	0.529***
	[1010.21]	[798.31]	[590.24]	[1047.86]	[472.52]
Empirical p-value		0.000		0.000	
R^2	0.474	0.515	0.451	0.491	0.304
Panel B: Price Discovery					
$R^{[-10,239]} \times Dur$	0.021***	0.023***	0.020***	0.023***	0.020***
	[14.88]	[11.06]	[9.84]	[12.14]	[10.31]
$R^{[-10,239]}$	0.184***	0.186***	0.183***	0.183***	0.185***
	[42.77]	[30.19]	[30.50]	[33.41]	[30.34]
Dur	0.283	0.579	-0.037	0.042	0.501
	[1.08]	[1.62]	[-0.10]	[0.13]	[1.24]
Constant	-5.977***	-6.072***	-5.856***	-5.933***	-6.002***
	[-18.88]	[-14.13]	[-12.72]	[-15.08]	[-12.31]
Empirical p-value		0.043		0.004	
R^2	0.119	0.139	0.112	0.127	0.119
Type FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
N	241172	120694	120478	120812	120360

Notes: Panel A reports the regression results of $Spread_{i,s} = \alpha + \beta_2 Learning_i + \epsilon_{i,s}$. The dependent variables are the bid asks spreads for the market opening call auction. Panel B reports the regression results of $R_{i,s} = \alpha + \beta_1 R_{i,s}^{[-10,239]} + \beta_2 R_{i,s}^{[-10,239]} \times Dur_i + \beta_3 Dur_i + \epsilon_{i,s}$. The dependent variables are the log returns of CSI 300 components stocks for the market opening call auctio and are in basis points. Dur_i is the time between announcement time and the first trading time after the announcement and is in days. Column (2) and (3) reports the regression results based on the sample of stocks with low and high institutional holdings. Column (3) and (5) report the regression results based on the sample of stocks with low and high nominal prices. Empirical p-values of Fisher's permutation test for the differences in coefficients of *Dur* (in Panel A) or $R^{[-10,239]} \times Dur$ (in Panel B) between stocks with high institutional holdings or nominal prices and stocks with low institutional holdings or nominal prices are calculate by 1000 bootstrapping procedure. The sample period is from January 2009 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

we further test whether price reversals following macro announcements can be linked to distance-to-trading by estimating the regression:

$$R_i^t = \alpha^t + \beta_1^t R_i^{cto} + \beta_2^t R_i^{cto} \times Dur_i + \beta_3^t Dur_i + \epsilon_i^t. \tag{28}$$

We report the estimation results in Table 9. Columns (1), (3), (5) and (7) show that in univariate regressions, the initial one minute return R_i^0 is negatively related to the returns of subsequent time windows "[1,29]" and "[1,59]", and is unrelated with the returns of subsequent time window "[120,239]". This indicates that return reversals exist within the shorter windows following the announcement. Columns (2), (4), (6) and (8) include interaction terms with distance-to-trading. The coefficients on the interaction terms are positive and statistically significant for time windows "[1,29]", "[1,59]", and "[1,119]", indicating that return reversals are less pronounced for announcement with higher distance-to-trading. Economically, if the distance-to-trading increases by one day, we anticipate smaller post-announcement reversal, in the amount of 4.7%, 4.5%, and 5.9% of return from time windows "[1,29]", "[1,59]", and "[1,119]". In Internet Appendix Table IA.VIII, we present the regression results based on the number of Weibo posts, the number of fans, the total number of retweets, comments, and likes, and the number of articles of Weixin official accounts. In Internet Appendix Table IA.IX, we present the regression results of long-term return reversals.

6 Additional Results

6.1 Volatility and Volume

In this section, we investigate the impact of distance-to-trading on the market volatility and trading volume. For each of the post-announcement trading hours, the return volatility is calculated as the squared root of the sum of return squared, $\sqrt{\sum_{i=1}^{N}(lnP_i - lnP_{i-1})^2}$, where $P_i (0 \leq i \leq N)$ denote the minute-end prices of CSI 300 index within the given time window. The trading volume is calculated as the total number of traded shares of the CSI 300 index component stocks within the given time window. For the market opening time ("0"), the return volatility is the squared root of the close-to-open return squared (or the absolute close-to-open return) for the CSI 300 market index and the trading volume is

Table 9: The Impact of Distance-to-trading on the Return Reversals

	[0, 29]		[0, 59]		[0, 119]		[0, 239]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R^{cto}	-0.153***	-0.244***	-0.081*	-0.158***	0.000	-0.110*	0.053	-0.050
	[-3.97]	[-6.49]	[-1.83]	[-3.35]	[0.00]	[-1.65]	[0.58]	[-0.51]
$R^{cto} \times Dur$		0.052***		0.044**		0.064**		0.060
		[3.34]		[2.26]		[2.32]		[1.49]
Dur		-1.605		0.097		5.704*		4.040
		[-0.95]		[0.05]		[1.91]		[0.93]
Constant	3.814**	5.661**	7.039***	6.882**	8.438***	1.638	12.570***	7.740
	[2.35]	[2.21]	[3.47]	[2.14]	[2.93]	[0.36]	[3.02]	[1.17]
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.152	0.165	0.155	0.161	0.128	0.138	0.113	0.117
N	853	853	853	853	853	853	853	853

Notes: This table reports the regression results of $R_i^t = \alpha^t + \beta_1^t R_i^{cto} + \epsilon_i^t$ and $R_i^t = \alpha^t + \beta_1^t R_i^{cto} + \beta_2^t R_i^{cto} \times Dur_i + \beta_3^t Dur_i + \epsilon_i^t$ based on the sample of announcements released during non-trading hours. The dependent variables are the log returns of CSI 300 for the respective time intervals and are in basis points. Dur_i is the time between announcement time and the first trading time after the announcement and is in days (i.e., distance-to-trading). The sample period is from January 2009 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

the total volume of the CSI 300 component stocks during their opening market call auction. In Panel A and B Table 10, we report the impact of distance to trade on the the volatility and trading volume.

First, we find that longer distance-to-trading lead to higher volatility and volume at the market opening time ("0"): an one-day increase in distance-to-trading leads to a 7.819 bps increase in volatility and a 0.026 million shares increase in volume. The higher volatility and trading volume are consistent with faster price discovery at the market opening time for announcements with longer distance-to-trading.

Interestingly, after the initial spike at time "0", the impact of distance-to-trading on stock volatility and volume turns negative. The impact on stock volatility turns negative from the second trading hour and reaches a significant negative level (-0.922 with t-stats of -2.15) at the fourth trading hour. Similarly, impacts on trading volume are negative across all trading hours, with significant decreases at the second trading hour (-11.9 with t-stats of -2.63) and marginally significant decrease for the fourth trading hour (-10.464 with t-stats of -1.94).

As discussed in Section 4, our model gives ambiguous predictions on the impact of investor learning on trading volume and volatility. The empirical evidence suggests that, shortly after the market opens, the first channel – heightened trading sensitivity to payoff risk – dominates, as indicated by higher volatility and trading volume for announcements with longer distance-to-trading. However, after the initial spike, the second channel—improved price informativeness—takes over, leading to lower volatility and trading volume for these announcements.

6.2 Heightened Uncertainty and Important Macro Announcements

We further examine the effect of varying degrees of uncertainty associated with different macroeconomic announcements on our results. We hypothesize that the mechanism driving the impact of distance-to-trading on the speed of price discovery is through investor learning. Consequently, we expect that this impact is more pronounced for announcements with heightened uncertainty before announcements, indicating they are important market anticipated news. To test this, we group macroeconomic announcements using three commonly used measures of uncertainty: the economic policy uncertainty index (EPU), abnormal volatility, and abnormal turnover, all measured on the day immediately before the announcement day.

Table 10: The Impact of Distance-to-trading on the Volatility and Volume

	Market Opening close-to-open ("0")	Other Post-ann Windows 1^{st}	2^{nd}	3^{rd}	4^{th}
Panel A: Volatility					
Dur	7.819***	1.050	-0.524	-0.075	-0.922**
	[3.99]	[1.40]	[-1.31]	[-0.18]	[-2.15]
Constant	33.470***	49.466***	32.738***	30.027***	30.295***
	[13.39]	[39.22]	[49.27]	[45.20]	[46.41]
R^2	0.239	0.324	0.347	0.390	0.383
Panel B: Volume					
Dur	0.026*	-5.239	-11.900***	-6.243	-10.464*
	[1.87]	[-0.75]	[-2.63]	[-1.23]	[-1.94]
Constant	0.348***	325.505***	208.906***	195.683***	252.979***
	[17.34]	[29.56]	[29.10]	[25.45]	[29.56]
R^2	0.468	0.820	0.842	0.836	0.866
Type FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
N	853	853	853	853	853

Notes: This table reports the regression results of $Y_i^t = \alpha^t + \beta_1^t Dur_i + \epsilon_i^t$ based on the sample of announcements released during non-trading hours. The dependent variables are the return volatility and volume of CSI 300 for the respective time intervals. Dur_i is the time between announcement time and the first trading time after the announcement and is in days (i.e., distance-to-trading). The sample period is from January 2009 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

We use the uncertainty measure by Huang and Luk (2020) to quantify economic policy uncertainty right before index releases. Evidences from the U.S. market indicate that the markets often exhibit low trading volume and volatility prior to important macroeconomic announcements – a phenomenon termed "quiet-before-the-storm" in studies by Bomfim (2003) and Jones et al. (1998). We therefore expect that announcements preceded by a day with lower abnormal volatility and abnormal turnover are associated with heightened uncertainty. To compute abnormal volatility and turnover, we first calculate the realized return volatility for each day as the square root of the sum of squared minute-end returns of the CSI 300 index. We calculate the daily turnover for the CSI 300 index by dividing the total daily trading volume of its component stocks by the total shares outstanding. We then calculate the abnormal volatility and abnormal turnover by subtracting their respective averages and dividing by the standard deviation from the past month.

As showing in Table 11, we find that the impact of distance-to-trading on the speed of price discovery is primarily driven by announcements characterized by higher EPU, lower abnormal volatility, and lower turnover before release – i.e., those associated with heightened uncertainty. For these announcements, each additional day of distance-to-trading results in increases of 0.055, 0.043 and 0.054 in the proportion of price discovery occurring at time "0". Conversely, for announcements characterized by lower EPU, higher abnormal volatility, and higher abnormal turnover, we observe no significant change in the speed of price discovery as distance-to-trading varies.

6.3 U.S. Macroeconomic Announcements

In this section, we examine the impact of distance-to-trading on the speed of price discovery for macroeconomic announcements in the U.S. Given the depth and liquidity of the U.S. financial markets, including market index ETFs, futures, and options, investors can immediately trade following the release of important macroeconomic indicators. Macroeconomic indexes such as Non-farm Payroll, Gross Domestic Production, Consumer Price index, Producer Price index, Personal Income, Housing Starts, and Initial Claims for Unemployment Insurance are uniformly announced at 8:30 a.m. Eastern Time – just one hour before the stock market opens. The only exception is Industrial Production, which is announced at 9:15 a.m. Eastern Time. In other words, the distance-to-trading in the U.S. market is very short and, more importantly, show little variations across indexes.

Table 11: The Impact of Distance-to-trading on the Speed of Price Discovery: Grouped by the Previous Day's Economic Policy Uncertainty, Abnormal Volatility and Abnormal Turnover

	Market Opening	**Other Post-ann Windows**			
	close-to-open ("0")	1^{st}	2^{nd}	3^{rd}	4^{th}
Panel A: Grouped by EPU at Day $t-1$					
High					
$R^{ann} \times Dur$	0.055***	-0.021*	0.005	-0.027**	-0.012
	[3.79]	[-1.85]	[0.45]	[-2.55]	[-1.15]
Low					
$R^{ann} \times Dur$	0.023	0.005	-0.006	0.006	-0.029**
	[1.41]	[0.33]	[-0.59]	[0.59]	[-2.03]
Panel B: Grouped by Abnormal Volatility at Day $t-1$					
Low					
$R^{ann} \times Dur$	0.043***	0.010	-0.017*	-0.017	-0.019*
	[3.25]	[0.78]	[-1.78]	[-1.60]	[-1.68]
High					
$R^{ann} \times Dur$	0.024	-0.005	0.023*	-0.018*	-0.024*
	[1.61]	[-0.37]	[1.74]	[-1.68]	[-1.79]
Panel C: Grouped by Abnormal Turnover at Day $t-1$					
Low					
$R^{ann} \times Dur$	0.054***	-0.008	-0.006	-0.003	-0.037***
	[3.73]	[-0.52]	[-0.52]	[-0.30]	[-2.88]
High					
$R^{ann} \times Dur$	0.024*	0.004	0.013	-0.017*	-0.024*
	[1.89]	[0.29]	[1.17]	[-1.80]	[-1.94]
Index FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the regression results of $R_i^t = \alpha^t + \beta_1^t R_i^{ann} + \beta_2^t R_i^{ann} \times Dur_i + \beta_3^t Dur_i + \epsilon_i^t$ based on the sample of announcements released during non-trading hours. The announcements are divided into high and low groups base on the median of the previous day's EPU, abnormal volatility and abnormal turnover. The dependent variables are the log returns of CSI 300 for the respective time intervals and are in basis points. Dur_i is the time between the actual announcement time and the market opening time after the announcement (9:30 am) and is measured in days (i.e., distance-to-trading). The sample period is from January 2009 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 12 reports the estimation results of Equation (2) based on non-trading-hours macroeconomic announcements in the U.S. We find that the coefficients of the interaction terms $R^{ann} \times Dur$ are not significant across all post-announcement windows, indicating that distance-to-trading does not influence price discovery in the U.S. stock market. This absence of impact is mainly due to the continuous trading in the U.S. financial market, which confound the effects of learning from price and non-price sources. By the time the stock market opens, investors can already infer the equilibrium stock price from the prices in the derivatives market.

Table 12: The Impact of Distance-to-trading on the Speed of Price Discovery: U.S. Macroeconomic Announcements

	Market Opening	**Other Post-ann Windows**			
	close to open ("0")	1^{st}	2^{nd}	3^{rd}	4^{th}
$R^{ann} \times Dur$	-2.586	2.068	0.130	-1.084	0.953
	[-1.57]	[1.25]	[0.09]	[-1.01]	[1.04]
R^{ann}	0.579***	0.090	0.140**	0.137***	0.040
	[8.81]	[1.37]	[2.31]	[3.23]	[1.13]
Constant	1.046	-1.828**	0.555	0.011	0.805
	[1.00]	[-2.05]	[0.79]	[0.02]	[1.39]
Type FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
R^2	0.553	0.221	0.220	0.140	0.139
N	1526	1526	1526	1526	1526

Notes: This table reports the regression results of $R_i^t = \alpha^t + \beta_1^t R_i^{ann} + \beta_2^t R_i^{ann} \times Dur_i + \beta_3^t Dur_i + \epsilon_i^t$ based on the sample of announcements released during non-trading hours. The dependent variables are the log returns of SPDR S&P 500 ETF for the respective time intervals and are in basis points. Dur_i is the time between announcement time and the first trading time after the announcement and is in days (i.e., distance-to-trading). The sample period is from January 2009 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

7 Conclusion

Exploiting a unique institutional feature of China's capital market, which exhibits significant timing heterogeneity with respect to its macro announcements, we isolate and identify the impacts of learning on shifting the process of price discovery in absence of the confounding factor of market trading. We show that investors' learning before trading, as proxied by the length of the non-trading period (distance-to-trading), could lead to faster and more efficient price discovery once the market opens for trading. Our paper shows that the distance-to-trading well proxies for the intensity of retail investors' learning, as measured by the number of related posts, fans, and interactions on China's social media regarding the newly released overnight macro announcements. Our documented empirical facts are consistent with the models that predict increased learning among less informed investors enhances the price informativeness of equity prices in equilibrium. As the timing arrangements of macroeconomic announcements in China can benefit retail investors by triggering learning and reducing noise trading, it contributes to the overall social welfare of the Chinese economy. Our paper is also the first to systematically study the impacts of a comprehensive list of macroeconomic announcements in China on its stock markets and could also be of general interest to other emerging market countries.

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Internet Appendix for "Learning, Price Discovery, and Macroeconomic Announcements"

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In this document, we report additional results of robustness. First, in Table IA.I, we explore the changes and excess changes in R-squared (R_t^2) at the first trading minute post-announcement, using unbiasedness regressions based on macroeconomic announcements made during non-trading hours. We find that announcements further from trading hours - categorized as "High Distance-to-trading" - show a significantly higher $Excess\Delta R_0^2$, suggesting a faster price discovery. We conduct 1000 bootstrapping procedures, randomly dividing each announcement released during non-trading hours into high or low group. We generate empirical p-values for the likelihood of observing, from the bootstrapped distribution, the difference between $Excess\Delta R_0^2$ statistics observed in the data or higher, further validate the statistical significance of our results. These results hold true across various event window lengths, confirming the robustness of our findings.

Second, Table IA.II shows the regression outcomes derived from announcements made both within and outside of trading hours. The findings indicate that price discovery occurs more rapidly for announcements issued during non-trading hours than for those released while markets are open.

Third, one may be concerned that the speed of price discovery is related to the release schedule of macroeconomic news. We explore if our results are driven by the fact that some of the macroeconomic announcements in China have their data release schedule pre-fixed and pre-informed to domestic investors. For example, the release time of major macroeconomic indicators from the National Bureau of Statistics is pre-scheduled. If the release time is endogenously related to their release schedule and market impact, our empirical results might be biased. Table IA.III first reports the median release time and the release schedule of the major macroeconomic indicators in China. The pre-scheduled announcements include those for the CPI/PPI, Caixin, GDP, IP, LPR, PI, PMI, SLF/MLF/PSL, and SPRB, for some of which the announcement dates are fixed but the actual announcement time varies throughout the day.

Fourth, we show the details of our matched and refined announcement samples for demonstrating the robustness of our main results. Table IA.IV reports the summary statistics of the

Table IA.I: The Change and Excess Change in R-squared around Chinese Macroeconomic Announcements

	High Distance-to-trading		Low Distance-to-trading			
$R^{[T_1,T_2]}$	ΔR_0^2	$Excess\Delta R_0^2$	ΔR_0^2	$Excess\Delta R_0^2$	H−L	p-value
$R^{[-10,119]}$	0.511	65.385	0.338	42.883	22.502***	0.008
$R^{[-10,239]}$	0.372	91.905	0.219	53.703	38.203**	0.023
$R^{[-10,479]}$	0.227	110.015	0.053	25.145	84.871***	0.002
$R^{[-30,119]}$	0.484	71.532	0.294	43.108	28.424***	0.007
$R^{[-30,239]}$	0.363	97.050	0.203	53.816	43.234**	0.019
$R^{[-30,479]}$	0.221	111.727	0.042	20.418	91.309***	0.003
$R^{[-60,119]}$	0.406	71.996	0.261	46.032	25.964**	0.029
$R^{[-60,239]}$	0.329	97.562	0.193	56.917	40.645**	0.030
$R^{[-60,479]}$	0.214	114.329	0.051	26.614	87.715***	0.002

Notes: This table reports the change and excess change in R-squared (R_t^2) at first trading minute after the announcement estimated from unbiasedness regressions: $R_i^{[T_1,T_2]} = \alpha_t + \beta_t R_i^{[T_1,t]} + \epsilon_{i,t}$ based on the sample of announcements released during non-trading hours. $R_i^{[t_1,t_2]}$ are the returns of the CSI 300 index from minute t_1 to minute t_2 in event time relative to the first trading time after the announcement i at time $t = 0$. $\Delta R_0^2(0,1) = R_0^2 - R_{-1}^2$. $Excess\Delta R_0^2 = T(R_0^2 - R_{-1}^2) - 1$, where $T = T_2 - T_1 + 1$ is the length of the event window. "High Distance-to-trading" refers to the macroeconomic announcements released during non-trading hours with high distance-to-trading; "Low Distance-to-trading" refers to the macroeconomic announcements released during non-trading hours with low distance-to-trading. "H−L" refers to the difference between the $Excess\Delta R_0^2$ of high and low group. Empirical p-value of Fisher's permutation test for the differences are calculate by 1000 bootstrapping procedure. The sample period is from January 2009 to December 2020.

Table IA.II: The Impact of Distance-to-trading on the Speed of Price Discovery

	First Post-ann Trading Minute	Other Post-ann Windows			
	0	1^{st}	2^{nd}	3^{rd}	4^{th}
Panel A: Non-trading-hours vs. trading-hours announcements					
$R^{[0,239]} \times Non$	0.251***	0.033	-0.029	-0.041*	-0.214***
	[10.50]	[1.53]	[-1.54]	[-1.90]	[-8.76]
$R^{[0,239]}$	0.048***	0.162***	0.207***	0.189***	0.394***
	[4.02]	[11.00]	[15.06]	[10.23]	[20.10]
Non	0.675	-3.740	4.642	3.680	-5.257
	[0.17]	[-0.94]	[1.20]	[0.96]	[-1.31]
R^2	0.306	0.277	0.286	0.251	0.480
Panel B: The impact of distance-to-trading					
$R^{[0,239]} \times Dur$	0.082***	0.009	-0.007	-0.020***	-0.064***
	[10.32]	[1.30]	[-1.22]	[-3.53]	[-7.03]
$R^{[0,239]}$	0.103***	0.171***	0.198***	0.186***	0.342***
	[8.23]	[13.56]	[17.86]	[13.25]	[21.30]
Dur	-0.317	-1.702	3.653***	-1.485	-0.148
	[-0.17]	[-1.26]	[2.97]	[-1.28]	[-0.11]
R^2	0.279	0.276	0.288	0.253	0.460
Index FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
N	1898	1898	1898	1898	1898

Notes: Panel A reports the regression results of $R_i^t = \alpha^t + \beta_1^t R_i^{[0,239]} + \beta_2^t R_i^{[0,239]} \times Non_i + \beta_3^t Non_i + \epsilon_i^t$. Panel B reports the regression results of $R_i^t = \alpha^t + \beta_1^t R_i^{[0,239]} + \beta_2^t R_i^{[0,239]} \times Dur_i + \beta_3^t Dur_i + \epsilon_i^t$. The dependent variables are the log returns of CSI 300 for the respective time intervals and are in basis points. Dummy variable Non_i equals 1 if the announcement is released during non-trading hours. Dur_i is the time between announcement time and the first trading time after the announcement and is in days (i.e., distance-to-trading). The sample period is from January 2009 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table IA.III: Release Time and Schedule of Major Macroeconomic Indicators in China

Announcement	MedT	Pre-scheduled
CPI/PPI	9:30	Pre-scheduled since 2012
GDP	10:00	Pre-scheduled since 2012
PMI	9:00	Pre-scheduled since 2012
Caixin	9:45	✓
IP	10:00	Pre-scheduled since 2012
M2	16:00	×
Trade	10:58	×
FER	16:00	×
PI	9:30	Pre-scheduled since 2012
RRR	18:06	×
FDI	10:16	×
BOP	16:46	×
Swift	9:00	Pre-scheduled with a few exceptions
SPRB	9:30	✓
FESS	15:53	×
OMO	9:46	×
SLF/MLF/PSL	15:51	×
CTCM	16:31	×
CBS	9:00	×
LPR	9:30	✓

Notes: This table reports whether the release time of 20 major macroeconomic indicators is pre-scheduled. "MedT" refers to the median of the release time. "Pre-scheduled" indicates whether the announcement time is pre-scheduled. "Since 2012" indicates, for announcements released by the National Bureau of Statistics, that only the announcement date was pre-scheduled before 2012, and both the announcement date and time are pre-scheduled from 2012 onward. "Few exceptions" indicates, for "Swift", that indicators are generally released at 9:30 a.m. on the fourth Thursday of each month, with nine exceptions. The sample period is from January 2009 to December 2020.

post-announcement returns for the full sample of macroeconomic announcements in China, as well as the matched sample of macroeconomic announcement.

Table IA.IV: Post-announcement Market Returns on Macroeconomic Announcement Days in China

Post-Ann Return^{ann}	Obs	Mean	Std.	Min	P25	P50	P75	Max
Panel A: Full Sample								
High Distance-to-trading	418	21.87	169.44	-555.76	-53.63	34.71	119.16	567.44
Low Distance-to-trading	436	5.51	128.19	-457.19	-61.57	2.79	72.05	642.64
Panel B: Matched Sample								
High Distance-to-trading	327	19.59	149.86	-441.32	-48.76	25.76	105.66	411.61
Low Distance-to-trading	327	19.54	150.16	-457.19	-48.97	25.75	106.29	412.75

Notes: We match the sample of announcements released during non-trading hours with high distance-to-trading with announcements released during non-trading hours with low distance-to-trading based on the returns of the return of the CSI 300 index from the market close of the previous trading day to the market close of the first trading day after announcement. The distribution of the returns is reported for the full sample of announcements in Panel A. The distribution of the returns is reported for the matched sample of announcements in Panels B. The sample period is from January 2009 to December 2020.

Table IA.V reports the keywords matched with the major macroeconomic indicators in China from Weibo.

In addition, we examine our measured learning intensity based on the related articles of Weixin official accounts. As shown in Table IA.VI, we run the estimation and find the results are robust and similar to the baseline results.

Finally, Table IA.VII and Table IA.VIII show the impact of investors' pre-trading learning activities, measured by the number of Weibo posts, the number of fans, the total number of retweets, comments, and likes, and the number of articles of Weixin official accounts, on the bid-ask spreads, opinion divergences and return reversals.

Table IA.V: Keywords for Matching Macroeconomic Indexes

Announcement	Keywords
CPI/PPI	CPI, PPI, Consumer Price Index, Producer Price Index
GDP	GDP, Gross Domestic Product
PMI	Manufacturing Purchasing Managers' Index, Bureau of Statistics Manufacturing Purchasing Managers' Index, Purchasing Managers' Index
Caixin	Caixin PMI, Caixin China PMI, Caixin China Manufacturing PMI, Caixin China Manufacturing Purchasing Managers' Index
IP	Industrial Value Added, Industrial Production, Industrial Value Added of Enterprises Above Designated Size
M2	M2, Broad Money, Aggregate Financing to the Real Economy, Money Supply, Monetary Aggregate
Trade	Export, Import, Balance of Trade, Trade Surplus, Total Value of Imports and Exports
FER	Foreign Exchange Reserves, Foreign Exchange Reserve Balance, Foreign Exchange Reserve Size
PI	Profit of Industrial Enterprises, Profit of Industrial Enterprises Above Designated Scale
RRR	Required Reserve Ratio, Required Reserve Ratio for RMB, Required Reserve Ratio for Deposit Financial Institution, Required Reserve Ratio for Financial Institution
FDI	FDI, Foreign Direct Investment
BOP	Balance of Payments, Balance of Payments Trade in Services, Balance of Payments Trade in Goods and Services
Swift	RMB Payment, RMB Settlement, Active Currency
SPRB	Sales Prices of Residential Buildings, Sales Price of Second-hand Residential Buildings, Sales Price of New Constructed Commodity Residential Buildings
FESS	Foreign Exchange Sales, Foreign Exchange Settlement, Foreign Exchange Sales by Banks, Foreign Exchange Settlement by Banks, Foreign Exchange Settlement and Sales by Banks
OMO	Open Market Operations
SLF/MLF/PSL	SLF, MLF, PSL, Standing Lending Facility, Medium-term Lending Facility, Pledged Supplementary Lending
CTCM	Central Treasury Cash Management, Central Treasury Cash Management Operation Announcement
CBS	Central Bank Bills Swap
LPR	LPR, Loan Prime Rate

Notes: This table reports the keywords that we use to match the 20 major macroeconomic indexes. The sample period is from January 2018 to December 2020.

Table IA.VI: The Impact of Pre-Trading Investor Learning Activities on the Speed of Price Discovery: Articles of Weixin Official Accounts

	Investor Learning	Market Opening	Other Post-ann Windows			
	weixin	close-to-open ("0")	1^{st}	2^{nd}	3^{rd}	4^{th}
Dur	0.045***					
	[3.09]					
$R^{ann} \times weixin$		0.552**	-0.206	-0.080	-0.040	-0.225*
		[2.51]	[-1.15]	[-0.52]	[-0.30]	[-1.72]
R^{ann}		0.258***	0.252***	0.174***	0.161***	0.156***
		[8.07]	[8.71]	[7.28]	[5.88]	[6.27]
$weixin$		-4.541	24.326	0.021	-7.753	-12.053
		[-0.18]	[1.06]	[0.00]	[-0.34]	[-0.62]
Index FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.648	0.586	0.573	0.414	0.390	0.391
N	309	309	309	309	309	309

Notes: Column (1) reports the regression results of $Learning_i = \alpha + \beta_1 Dur_i + \epsilon_i$. The dependent variables $Learning_i$ are proxied by the number of related articles of Weixin official accounts between the announcement time and the first trading time after the announcement. The unit for the number of articles is in thousands. Columns (2) to (6) report the regression results of $R_i^t = \beta_0 + \beta_1 R_i^{ann} + \beta_2 R_i^{ann} \times Learning_i + \beta_3 Learning_i + \epsilon_i$. The dependent variables are the log returns of CSI 300 for the respective time intervals and are in basis points. The sample period is from January 2018 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table IA.VII: The Impact of Pre-Trading Investor Learning Activities on Bid-ask Spreads and Opinion Divergences

	Spread				*Divop*			
posts	-0.056***				-0.026***			
	[-3.97]				[-3.48]			
fans		-0.040***				-0.020***		
		[-5.71]				[-5.42]		
interactions			-0.029***				-0.015***	
			[-6.23]				[-6.16]	
weixin				-0.031***				-0.017***
				[-5.02]				[-5.48]
$Spread_{d-1}$	0.351***	0.351***	0.351***	0.351***				
	[25.61]	[25.60]	[25.58]	[25.60]				
$Divop_{d-1}$					0.361***	0.361***	0.361***	0.361***
					[24.62]	[24.61]	[24.59]	[24.62]
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.682	0.682	0.682	0.682	0.712	0.712	0.712	0.712
N	91676	91676	91676	91676	91676	91676	91676	91676

Notes: This table reports the regression results of $Spread_{i,s} = \alpha + \beta_2 Learning_i + \beta_3 Spread_{i,s,d-1} + \epsilon_{i,s}$ and $Divop_{i,s} = \alpha + \beta_2 Learning_i + \beta_3 Divop_{i,s,d-1} + \epsilon_{i,s}$ based on the sample of announcements released during non-trading hours. The dependent variables are the bid asks spreads and opinion divergences for the market opening call auction. $Learning_i$ is the number of related Weibo posts (or the fans of these posts, or the retweets, comments, and likes of these posts, or the articles of Weixin official accounts) between the announcement time and the first trading time after the announcement. The sample period is from January 2018 to December 2020. The standard errors are clustered at the stock and announcement levels. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table IA.VIII: The Impact of Pre-Trading Investor Learning Activities on the Return Reversals

	$R^{[0,29]}$			
$R^0 \times posts$	1.853***			
	[3.16]			
$posts$	-154.290			
	[-1.49]			
$R^0 \times fans$		1.090***		
		[3.06]		
$fans$		-85.934		
		[-1.39]		
$R^0 \times interactions$			0.507**	
			[2.35]	
$interactions$			-61.575	
			[-1.65]	
$R^0 \times weixin$				0.807***
				[2.83]
$weixin$				-22.070
				[-0.68]
R^0	-0.142***	-0.153***	-0.116**	-0.133***
	[-2.98]	[-3.06]	[-2.53]	[-2.78]
Type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
R^2	0.349	0.352	0.342	0.340
N	309	309	309	309

Notes: This table reports the regression results of $R_i^{[0,29]} = \alpha + \beta_1 R_i^0 + \beta_2 R_i^0 \times Learning_i + \beta_3 Learning_i + \epsilon_i$ based on the sample of announcements released during non-trading hours. The dependent variables are the log returns of CSI 300 for the time interval $[0, 29]$ and are in basis points. $Learning_i$ is the number of related Weibo posts (or the fans of these posts, or the retweets, comments, and likes of these posts, or the articles of Weixin official accounts) between the announcement time and the first trading time after the announcement. The sample period is from January 2018 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table IA.IX: The Impact of Distance-to-trading on the Long-term Return Reversals

	$R^{[240,480]}$				$R^{[240,720]}$			
Panel A: Full announcement sample								
$R^0 \times Dur$		-0.012				-0.006		
		[-0.29]				[-0.09]		
R^0	-0.087	-0.065			0.065	0.077		
	[-1.01]	[-0.51]			[0.47]	[0.37]		
$R^{ann} \times Dur$				-0.022				-0.049
				[-1.01]				[-1.54]
R^{ann}			0.062	0.096*			0.087	0.164*
			[1.61]	[1.68]			[1.42]	[1.81]
Dur		2.152		2.130		6.827		6.713
		[0.46]		[0.45]		[1.08]		[1.05]
R^2	0.140	0.140	0.142	0.144	0.136	0.137	0.139	0.143
N	853	853	853	853	853	853	853	853
Panel B: Announcement sample with no other announcements within three trading days post-release								
$R^0 \times Dur$		-0.074				-0.050		
		[-0.62]				[-0.30]		
R^0	-0.153	-0.037			-0.083	0.000		
	[-0.83]	[-0.14]			[-0.29]	[0.00]		
$R^{ann} \times Dur$				0.002				-0.063
				[0.05]				[-1.24]
R^{ann}			0.072	0.068			0.005	0.121
			[0.96]	[0.64]			[0.05]	[0.88]
Dur		-8.588		-8.383		-2.107		-2.507
		[-0.95]		[-0.91]		[-0.19]		[-0.23]
R^2	0.323	0.328	0.325	0.328	0.302	0.302	0.301	0.306
N	284	284	284	284	284	284	284	284
Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the regression results of $R_i^t = \alpha^t + \beta_1^t R_i^0 + \epsilon_i^t$, $R_i^t = \alpha^t + \beta_1^t R_i^0 + \beta_2^t R_i^0 \times Dur_i + \beta_3^t Dur_i + \epsilon_i^t$, $R_i^t = \alpha^t + \beta_1^t R_i^{ann} + \epsilon_i^t$, and $R_i^t = \alpha^t + \beta_1^t R_i^{ann} + \beta_2^t R_i^{ann} \times Dur_i + \beta_3^t Dur_i + \epsilon_i^t$ based on the sample of announcements released during non-trading hours in Panel A and the sample of announcements released during non-trading hours with no other announcements within three trading days post-release. The dependent variables are the log returns of CSI 300 for the respective time intervals and are in basis points. Dur_i is the time between announcement time and the first trading time after the announcement and is in days (i.e., distance-to-trading). The sample period is from January 2009 to December 2020. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.