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Learning, Price Discovery, and Macroeconomic Announcements

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Keywords: Learning, Macroeconomic announcements, Price informativeness, Market efficiency
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 the well-functioning of the capital market (Fama 1970). The existing literature predominantly emphasizes the central role of trading for facilitating the price discovery in the stock markets.[1] The key benefit is that private information can be efficiently aggregated in the market equilibrium through trading across investors of varied types (Grossman and Stiglitz 1980; Kyle 1985; Biais, Hillion, and Spatt 1999 and more recently, Goldstein and Yang 2015). Nonetheless, across a wide class of models and the empirical explorations, the implications of learning and trading for price discovery are largely intertwined.[2]

Our paper, however, isolates and explicitly studies the channel of *learning* for shifting the process of price discovery in the stock market. We frame our study by focusing on China's stock market and exploit its important and unique institutional features. First, given China's underdeveloped derivatives markets, we are able to disentangle the correlations between the learning dynamics while market is closed and the return performance once trading session begins. Our identification using Chinese data is little confounded by the high trading volume during market close as observed in the advanced markets. Second, by focusing on macroeconomics announcements in China, our study builds upon the very facts that China's stock markets are very prone to aggregate risk and the benefits of trading on price discovery for aggregating private information in the windows of macro announcements are very much attenuated. Third, macroeconomic announcements in China arrive to the market with significant timing variations.[3] As macro announcements in China can be well

[1]Boehmer and Wu (2012) and Beber and Pagano (2013) show that trading frictions such as the constrained short sales prevent the efficient price discovery. Barclay and Hendershott (2003) and Barclay and Hendershott (2008) highlight that price discovery consistently benefits from trading during and outside the trading sessions and during the pre-opening period. Brogaard, Hendershott, and Riordan (2014) and Brogaard, Hendershott, and Riordan (2019) identify the contributions of high-frequency traders for elevating the efficient price discovery.

[2]For example, to rationalize the role of trading for aggregating information, the framework of rational expectation equilibrium (REE) models with costly information acquisition is derived from a critical assumption that investors *immediately* act upon informative signals through trading. In addition, the empirical evidences on price discovery are established based on the specifications that asset prices could potentially react to news within minutes upon data release (e.g. Hu, Pan, and Wang 2017).

[3]First, unlike the U.S. market, macro announcements in China that regularly release the economic and financial statistics can fall outside its regular trading hours of China-listed stocks, which start from 9:15 am to 3:30 pm including its pre-trading and post-trading sessions. 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, National Bureau of Statistics of China publishes the PMI data as early as 8:20 AM and as late as 8:00 PM. China's central bank, People's Bank of China (PBOC) routinely releases monetary and financial statics such as the monetary aggregates and the total social financing data after

made in non-trading hours, investors cannot promptly respond in trading. Such market setting renders us the leverage to explore the impacts of "learning without trading" on price discovery across events for causal inference.

Our paper documents important empirical evidence. First, we show that the more distant the macroeconomic announcements are released before trading, the quicker and more efficient price discovery can be obtained upon market opening. Second, we demonstrate that the differences in the speed of price discovery is not driven by the differences between off-hours and regular hours announcements or by the presence of information aggregation in the pre-opening sessions. Rather, the speed and efficiency of price discovery increases with the distance-to-trading, which captures the length of duration between the arrival of an announcement and market opening. More importantly, it is shown that the distance-to-trading is negatively correlated with degree of investors disagreement in the pre-opening sessions as reflected by the bid-ask spread. This confirms the learning channel that the information quality upon market opening is improved as an announcement is made earlier. Third, we present additional facts based on the Propensity-Score-Matching (PSM), which ensures the comparability of the post-announcement cumulative returns in both U.S. and China. We show that China's stock market excels the U.S. counterpart by having quicker price discovery in response to macro news as long as a macro announcement is made over non-trading hours and leaves investors more time for processing information before trading.

We then rationalize our documented facts in a simple model. Our model extends Vayanos and Wang (2012) by introducing a single parameter to capture the distance-to-trading. We allow for two different types of liquidity supplying traders differed in the sophistication of processing the macro announcement, who jointly accommodate the trading needs of liquidity demanding traders. Distance-to-trading over non-trading hours gives time to less informed traders to learn and extract useful information from a macro announcement before trading. Therefore, upon market opening, increasing number of liquidity supplying traders are better informed for trading with news incorporated. On the contrary, if an announcement is made just within trading sessions, only those sophisticated traders who are well informed of the macro news immediately would respond through trading in the very short period of window. Our model finds that greater distance-to-trading gives less informed investors more time to process the information, which generates larger price informativeness of the fundamentals in equilibrium upon market opening. Our paper thus highlights learning as the fundamental

market-close, before market-open, and even over the weekends (Guo, Jia, and Sun 2022).

driver of those factors that help explain the degree of price discovery.

Relate Literature. Our paper is related to several strands of literature. First, our paper is the first to identify the learning channel for price discovery and show that the distance-to-trading of information arrivals is a measure of learning intensity before trading. Learning significantly shifts the price discovery upon market opening even if trading is absent. The previous literature has well documented that the market trading is critical for strengthening the information aggregation process for efficient price discovery. Biais, Hillion, and Spatt (1999) identify the benefits of having pre-opening sessions in the stock market for efficient price disovery. Barclay and Hendershott (2003) find that trading day realizes the largest component of price discovery while price discovery is quicker and more efficient during the pre-open sessions. Barclay and Hendershott (2008) document that high trading volume in pre-trading sessions is critical for ensuring the opening price to be efficient and for generating greater price discovery before market opening. Brogaard, Hendershott, and Riordan (2014) and Brogaard, Hendershott, and Riordan (2019) study price discovery by highlighting the role of High-Frequency Trading who submit limit orders with information advantage. While the channels of learning and trading are jointly studied in the literature, our paper exploits the market structure in China and isolates the learning channel. We provide an learning-based interpretation on why pre-open trading enhances the price discovery. Our paper also contributes to the literature by providing an explanation on why the efficiency in price discovery differs between cases when information arrives in mid of trading sessions and when information falls outside trading sessions.

Second, a number of empirical work identified important facts related to risk and return profiles of the stock market in response to macroeconomic announcements. Our paper examines the price discovery process in the post-announcement days and explores the timing variations of macro announcements in China for implications on price discovery. Savor and Wilson (2013) and Savor and Wilson (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 equity premium before the FOMC statement release. Cieslak, Morse, and Vissing-Jorgensen (2019) find that the equity premium realized before and on the FOMC days is part of a larger FOMC premium cycle. Ernst, Gilbert, and Hrdlicka (2019) document a great proportion of the U.S. FOMC-related premium can be byproduct of post-announcement performance of many other macro announcements. Hu, Pan, Wang, and Zhu (2022) emphasize the heightening and the subsequent reduction of market uncertainty before the FOMC announcements. Brusa, Savor, and Wilson (2020) show that the stock markets of thirty-five countries exhibit strong reactions to the FOMC announcements. Boguth, Gregoire, and Martineau (2022) investigate the post-announcement returns of FOMC, and argue that equity prices following FOMC announcements are less informative about future indicative prices than those before announcements. Guo, Jia, and Sun (2022) highlight the fact that macro announcements in China can randomly arrive to markets with timing variations. Our paper is the first to ransack and study a comprehensive list of macro announcements in both China and the U.S. and show that the timing variations of macro announcements generate varied efficiencies of price discovery in the stock markets. Moreover, since the trading of the market index or derivatives is largely unavailable during the non-regular trading hours in the Chinese market, our paper helps to disentangle the two potential channels, investors learning or off-hours trading, that both may attribute to the faster price discovery. Our results show that, in our setting, investors learning during the non-trading hours – rather than the trading itself – is what speeds up the price discovery once the trading session begins.

Third, our paper is also related to the broad literature on the earnings announcements and the associated market reactions, including Patell and Wolfson (1982), Greene and Watts (1996), Dellavigna and Pollet (2009), Jiang, Likitapiwat, and McInish (2012), among others. Two recent papers, Lyle, Stephan, and Yohn (2021) and Drummond (2022), study the speed of the market reactions to earnings announcements released at different calendar time and find that more time to process information and trade would lead to faster market reactions. Different from their focus, we study the market reactions to the public macroeconomic announcements ex-post. Our frame of study helps attenuate the confounding factors of trading and aggregating private information and isolates the impact of learning from macro announcements for price discovery.

Lastly, our paper contributes to an emerging stream of work that evaluate the efficiency of financial markets in China. Based on earlier data, Allen, Qian, and Qian (2005) and Allen, Jun, Zhang, and Zhao (2012) provide comprehensive overviews of China's financial system and conclude that China's stock markets are inefficient for 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 increasing the divergence of cost of borrowing for state-owned and non-state owned firms. In addition, the identified inefficiencies are largely driven by the poor and ineffective regulation in China. Carpenter, Lu, and Whitelaw (2021) find that China's stock markets have become increasingly efficient in the way that the stock prices are informative about firms' future profits and the market is effectively aggregating the relevant information. Liu, Stambaugh, and Yuan (2019) construct the well-tailored size and value factors for stocks in China and show that a large proportion of individual investors makes China's stock market susceptible to investor sentiments. He and Wei (2022) 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 developments in more recent years. Our paper shows that the institutional design for releasing important economic and financial data increases the efficiency of price discovery in China's stock markets. Importantly, we demonstrate that studying China could help improve our understanding of the functioning of the capital markets in general.

The rest of the paper is structured as follows. In Section 2, we highlight the asset pricing implications of distance-to-trading for information arrivals in a simple model framework and derive the testable hypotheses. We summarize our data and introduce the institutional background in Section 3. In Section 4, we document the empirical evidence that are consistent with our hypotheses. Section 6 concludes the paper. In the Appendix, we provide additional theoretical results, empirical evidence and the proofs.

2 Model

In a simple framework, we examine the asset pricing implications of an environment when an important macro announcement is made outside the trading hours. Our model extends Vayanos and Wang (2012) by allowing for two types of liquidity supplying traders who differ in the sophistication of processing a macro announcement, though they jointly accommodate the trading needs of liquidity demanding traders. Specifically, if an announcement is made within trading sessions, only those sophisticated traders who are informed of the macro news would immediately respond through trading in a short window. On the contrary, those non-trading hours after the announcement but before trading give time to less informed traders to learn from the public announcement without trading. Therefore, a significantly larger fraction of liquidity supplying traders can be well informed with the macro news incorporated for trading.

2.1 Environment

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 period 2 with $D \sim \mathbf{N}(0, \sigma^2)$. The supply of risky asset is normalized to be a unit share. The return on the risk-free asset is normalized for $r = 0$ such that the risk-free asset has a constant price of 1 and serves as the numeraire. The financial market opens for trading in three periods for $t = 0, 1, 2$. The price of the risky asset is denoted by p_t and is endogenously determined in equilibrium through market clearing. In case of no uncertainty regarding the risky asset payoff once period 2 unfolds, $p_2 = D$. We therefore focus on the equilibrium price of the risky asset in period 1, i.e., p for which we suppress the period index for simplicity.

We assume there is a unit measure of investors who have CARA preference and derive utility from wealth in period 2. Without the loss of generality, we simply set the risk aversion to be one for the ease of notation. All traders are homogeneous in period 0 and become heterogeneous in period 1, which then justifies the need for trading in period 1. The heterogeneity across traders is driven by the information heterogeneity and the realizations of endowment shocks. Specifically, a total fraction $1-\pi \in [0, 1]$ of traders receive an endowment of $z \cdot D$ in period 2 with shocks to endowment $z \sim \mathbf{N}(0, \sigma_z^2)$ which is independent of the asset payoff D and realized in period 1. On the other hand, the fraction π of traders receive no endowment. Traders receiving endowment shocks would initiate trading in period 1 and demand for market liquidity and thus they are considered liquidity demanders. Therefore, z shocks can be interpreted as liquidity shocks. In equilibrium, traders receiving no such liquidity shocks would accommodate the risk-sharing trading needs and provide liquidity. They are considered the liquidity suppliers.

In addition, our model entertains the fact that an announcement may fall outside the trading session. Without the loss of generality, we allow for an announcement to arrive *before* the trading period at $t = 1$. In the following, we model a macro announcement as a signal s that partially reveals the dividend payoff D subject to a noise ϵ:

$$s = D + \epsilon, \quad \text{s.t.} \quad \epsilon \sim \mathbf{N}(0, \sigma_\epsilon^2) \tag{1}$$

where σ_ϵ^2 denotes the variance of the signal noise. Figure 1 summarizes a timeline along which a macro announcement may fall prior to trading sessions. In particular, we introduce a parameter λ, to capture the duration of time between the arrival of an announcement and the beginning of the next trading session, i.e., "distance-to-trading".

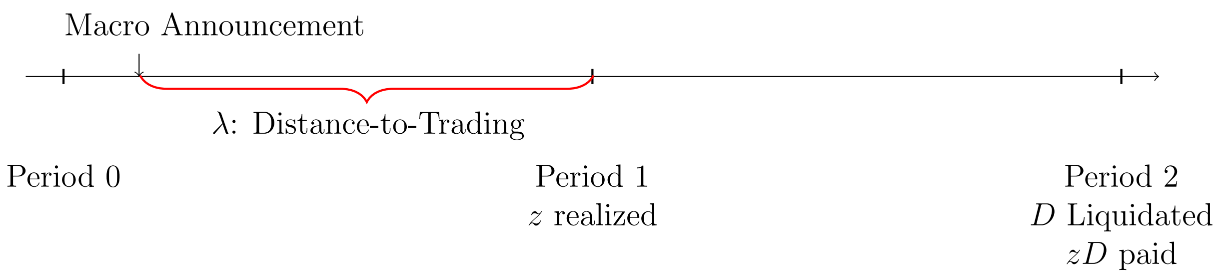


Figure 1: A Timeline

2.2 Market Equilibrium with Different Types of Learning Investors

Importantly, in line with Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), we further assume that a fraction $\delta \in (0, 1)$ of liquidity supplying traders of mass π are less sophisticated. It takes more time for them to be attentive to public signals and then extract information from the macro announcement, i.e. these traders as indexed as n. On the other hand, a fraction $1 - \delta$ of liquidity suppliers would be sophisticated enough to immediately process macro announcements and draw useful information, i.e. sophisticated traders as indexed as a. For simplicity, we denote a constant hazard rate of "learning from the signal" per infinitesimal time among the less sophisticated investors, i.e. $\alpha > 0$. Hence, the fraction of less sophisticated investors who stay uninformed from the macro announcement upon market trading follows that

$$\delta(\lambda) = \delta e^{-\alpha\lambda} \in [0, \delta] \tag{2}$$

A faster learning ratio α with more extended duration of distance-to-trading λ trigger a stronger learning effect, which increases the total size of informed investors among those unsophisticated ones upon market trading. Therefore, our derived hazard rate of learning implies that information processing takes time before trading but it eventually reduce the number of less informed traders over time in the market, which is in line with Dugast and Foucault (2018). Therefore, across announcement events, we should see a greater fraction of less informed liquidity supplying traders in case the investors are left with too short distance-to-trading. As λ is larger, they are given more time to turn themselves into more informed liquidity suppliers. We then label the liquidity demanding traders as type d. Following Vayanos and Wang (2012), we assume that all liquidity demanders are informed of the macro announcement. This holds because these traders can infer s perfectly from the price because they also observe their own liquidity shock realizations. Therefore, investors' sophistication matters for those less informed liquidity supplying traders only.

For trader type $i = n, a, d$, upon trading opens in period 1, a trader optimizes the demand q of the risky asset conditional on her information set adjusted for learning, $\mathcal{I}$. It follows that investors solve the following utility maximization problem in a general form.

$$\max_{q_i} U(W_{2,i}) = -\mathbb{E}_{\mathcal{I}} e^{-W_{2,i}} \tag{3}$$

$$\text{s.t.} \quad W_{2,i} = W_1 + q_i(D - p) + \mathbb{I}_{i=d} \cdot zD \tag{4}$$

Accordingly, W_1 is the initial wealth that is common to all traders. $\mathbb{I}_{i=d} = 1$ if the trader is a liquidity demander conditional on receiving shocks realization z in period and $\mathbb{I}_{i=d} = 0$ for liquidity supplying traders. While sophisticated liquidity supplying traders are able to incorporate the signal s in its information set, the less informed traders are thus taking the market price as given. Therefore, the information heterogeneity and the liquidity shocks are driving traders apart, which deliver the following the optimal asset demands of trader types

$$q_n(p) = \frac{\mathbb{E}(D|p) - p}{\sigma^2_{D|p}} \tag{5}$$

$$q_a(p) = \frac{\mathbb{E}(D|s) - p}{\sigma^2_{D|s}} \tag{6}$$

$$q_d(p) = \frac{\mathbb{E}(D|s) - p}{\sigma^2_{D|s}} - z \tag{7}$$

The financial market equilibrium is then determined given the asset demands of different types of traders and the market equilibrium price in period 1 satisfies the market-clearing condition such that

$$\pi\delta(\lambda)q_n(p) + \pi(1 - \delta(\lambda))q_a(p) + (1 - \pi)q_d(p) = 1 \tag{8}$$

2.3 Equilibrium Solutions

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

$$p = a + b(s - c \cdot z) \tag{9}$$

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

Applying the Bayes's rule, we have the conditional expectations and posterior variances regarding dividend among sophisticated investors who act upon the signal:

$$\mathbb{E}(D|s) = \gamma_S \cdot s \tag{10}$$

$$\sigma^2_{D|s} = \frac{1}{1/\sigma^2 + 1/(\sigma^2_\epsilon)} = (1 - \gamma_S)\sigma^2 \tag{11}$$

where $\gamma_S = \frac{\sigma^2}{\sigma^2+\sigma_\epsilon^2}$. Given the equilibrium price of the risky asset as in Equation (9), the expectation and variances regarding D among those uninformed investors are

$$\mathbb{E}(D|p) = \gamma_N(s - cz) \tag{12}$$

$$\sigma^2_{D|p} = \frac{1}{1/\sigma^2 + 1/(\sigma_\epsilon^2 + c^2\sigma_z^2)} = (1-\gamma_N)\sigma^2 \tag{13}$$

where $\gamma_N = \frac{\sigma^2}{\sigma^2+\sigma_\epsilon^2+c^2\sigma_z^2}$.

Plugging these equations into Equation (8), we can solve for the coefficients such that

$$a = -\frac{\sigma^2_{D|s}\sigma^2_{D|p}}{\pi\delta(\lambda)\sigma^2_{D|s} + (1-\pi\delta(\lambda))\sigma^2_{D|p}} = -(1-b)\sigma^2 \tag{14}$$

$$b = \frac{\gamma_N\pi\delta(\lambda)\sigma^2_{D|s} + \gamma_S(1-\pi\delta(\lambda))\sigma^2_{D|p}}{\pi\delta(\lambda)\sigma^2_{D|s} + (1-\pi\delta(\lambda))\sigma^2_{D|p}} \tag{15}$$

$$c = \frac{1-\pi}{1-\pi\delta(\lambda)}\sigma_\epsilon^2 \tag{16}$$

2.4 Model Predictions

Next, we examine the asset pricing implications of varying the distance-to-trading λ given some learning ratio of α among unsophisticated investors. Intuitively, we see that $\lambda \to \infty$ captures the extreme scenario when all less informed traders eventually are aware of the informative signals delivered through macro announcements upon trading. To the other extreme, when an announcement exactly falls within the trading session in period 1, $\lambda \to 0$ gives that a sizable fraction of liquidity supplying traders are not able to incorporate the macro announcements immediately for trading, i.e., $\delta(\lambda) \to \delta$. We then derive the theoretical results by focusing on a few market statistics: first, the measures of the price informativeness, which capture the degree of efficiency for the equilibrium price to reflect the fundamentals; second, the quantity of trading volume; and third, the volatility of returns.

We evaluate the stock price informativeness (PI) using the following two metrics. Both measures are to reflect the degree of information quality of stock prices revealing the dividend payoff.

$$PI_1 = \frac{1}{\sigma^2_{D|p}} = \frac{1}{\sigma^2} + \frac{1}{\sigma_\epsilon^2 + c^2\sigma_z^2} \tag{17}$$

$$PI_2 = \frac{cov(P,D)}{\sigma_P} = \frac{\sigma}{\sqrt{\sigma^2+\sigma_\epsilon^2+c^2\sigma_z^2}} \tag{18}$$

Given that $\delta'(\lambda) < 0$, 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 an macro announcement arrives much earlier before a trading session begins, traders are give more time to start processing the news and extract new information. As a result, upon market opening, more traders would be able to supply liquidity by trading upon the macro announcement. Hence the noise component is reduced in the equilibrium price. Stock prices become more informative of the asset payoffs.

Second, since we have normalized the total number of shares of risky asset to one, the trading volume denotes the turnover rate. Given that the trading takes place between the liquidity suppliers of two types on one side and the liquidity demanders on the other side. For tractability, we examine the variance of directional quantity trading of the liquidity demanders and see how the distance-to-trading affects this measure.

$$Volume = Var\{(1-\pi)[\frac{(\gamma_s - b)s - a + bcz}{\sigma^2_{D|s}} - z]\} \tag{19}$$

$$= [\frac{1-\pi}{\sigma^2_{D|s}}]^2[(\gamma_s - b)^2(\sigma^2 + \sigma^2_\epsilon) + [bc - \sigma^2_{D|s}]^2\sigma^2_z] \tag{20}$$

Equation (20) suggests that the depth of trading volume is driven by two forces. In case of greater distance-to-trading for a larger λ, the first term in the bracket reflects the degree of noise reduction in which uncertainty about asset payoff is lowered. This mitigates the trading volume driven by price uncertainty. The second term captures the market liquidity increase driven by liquidity supplying trades due to increased price responsiveness to dividend payoff.

Third, we examine the variance of gross returns of the risky asset $D - p$, which reflects the return volatility ($RetVol$) upon market opening. In specific, it gives that

$$RetVol = Var(D - p) = (1 - b)^2\sigma^2 + b^2[\sigma^2_\epsilon + c^2\sigma^2_z] \tag{21}$$

Equation (21) suggests that the return volatility is driven by two forces. In case of greater distance-to-trading for larger λ, the first term reflects the degree of noise reduction in which uncertainty about asset payoff σ^2 is scaled down as we can show that $\frac{\mathrm{d}b}{\mathrm{d}\lambda} > 0$. The second term captures the return volatility driven by price responsiveness to dividend payoff for increased price informativeness. This precisely defines the trade-off between reduction of dividend uncertainty, i.e. noise reduction, and increased price informativeness for greater volatility, i.e. information-driven volatility.

2.5 Discussions and Hypotheses

We have shown in a simple model structure that the duration of information processing before trading as measured by distance-to-trading well affects the price informativeness of the payoff fundamentals. In addition, the trading volume and the return volatility in equilibrium are shifted both by the effect of the increased price informativeness and that of the reduced market uncertainty given that learning can happen before trading. It can be well the facts that the effect of increased price informativeness dominates through market clearing upon market opening, which later on drives down the market noise and leads to lowered trading volume and the return volatility as time evolves. In the following, we lay out the hypothesis to be tested against the data.

Hypothesis 1. *When macro announcements are made outside the trading hours, the speed of price discovery, thus the price informativeness, is larger than the case when announcements fall within trading hours.*

Hypothesis 2. *When macro announcements are made outside the trading hours, the speed of price discovery, thus price informativeness, increases with distance-to-trading upon market opening.*

Hypothesis 3. *When macro announcements are made outside the trading hours, the market return volatility and trading volume upon market opening increases with distance-to-trading and then declines over time as time evolves.*

Our empirical exercises then exploit the differences of announcement timing across macro announcements in China, and make fair comparisons between market impacts of macro announcements for China and those of the U.S. announcements.

3 Data

3.1 Macroeocnomic Announcements in China

We consider the release of major macroeconomic indicators in China. To identify the set of important market-moving macroeconomic indicators, we include fifteen Chinese macroeconomic indicators with relevance scores from Bloomberg, which tracks the number of subscriptions on the Bloomberg terminal and represents the top China macroeconomic indexes that investors pay attention to. The fifteen economic indicators are: 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), foreign exchange settlement and sales by banks (FESS). We supplement the set of indicators with five additional monetary policy announcements from the People's Bank of China (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).[4]

We collect the date and time of individual macroeconomic announcements between January 2009 and December 2020 from the Bloomberg terminal and the website of PBOC. The announcement time are with minute-level timestamps. Unlike many developed countries, most macroeconomic announcements in China do not follow a fixed timetable, and the actual release time may vary substantially between announcements, as shown in Table 1. For the macroeconomic announcements released in our sample, the earliest release time is 6:40 am, the median is 10:00 am, and the latest is 9:07 pm.

We separate the macroeconomic announcements into two groups based on their release time: those within the regular trading hours and those outside of the regular trading hours. Announcements released outside of the trading hours include three cases: 1) released before the stock market opens (9:30 am) on a trading day, 2) released after the stock market closes (3:00 pm) on a trading day, 3) released on a non-trading day. In our sample, 1,048 announcements are made during the regular trading hours, while 854 announcements are made during the non-trading hours.[5]

3.2 The Financial Markets and Trading Hours in China

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

[4]The People's Bank of China employes many monetary policy tools, and we only include the ones that have regular releasing schedule and contain information that can potentially move the market. For example, we didn't include the announcements of Short-term Liquidity Operation, issuance of central-bank bills, and repos because PBOC has stopped using these monetary tools in recent years. We also exclude the announcements of targeted medium-term lending facility because they are very infrequent in our sample period. Lastly, we exclude the announcements of reverse repos because they are announced typically every two to three days in our sample period.

[5]There are 15 macroeconomic announcements are released during the noon break, between 11:30 am and 1:00 pm, in our sample period. We exclude these 15 announcements in our analysis.

Table 1: Release Time of Major Macroeconomic Indicators in China

Announcement	MinT	MedT	MaxT	#Trd	#NonTrd	#Open	#Close	#Weekend	Score	Source	Sector
CPI/PPI	9:30	9:30	13:30	122	22	0	0	22	98	National Bureau of Statistics	Public
GDP	10:00	10:00	15:00	47	1	0	1	0	96	National Bureau of Statistics	Public
PMI	9:00	9:00	20:00	0	179	113	1	65	94	Federation of Logistics & Purchasing	Public
Caixin	9:45	9:45	10:30	312	11	0	0	11	92	Markit	Private
IP	10:00	10:00	15:40	109	14	0	3	11	88	National Bureau of Statistics	Public
M2	8:00	16:00	20:00	33	111	6	94	11	86	The People's Bank of China	Public
Trade	9:32	10:58	17:30	96	33	0	3	30	82	General Administration of Customs	Public
FER	8:00	16:00	18:27	11	77	6	51	20	69	The People's Bank of China	Public
PI	9:30	9:30	11:00	85	28	0	0	28	51	National Bureau of Statistics	Public
RRR	12:12	18:06	20:01	0	26	0	18	8	41	The People's Bank of China	Public
FDI	6:40	10:16	20:30	90	46	2	41	3	36	Ministry of Commerce	Public
BOP	14:30	16:46	19:05	1	37	0	37	0	35	State Administration of Foreign Exchange	Public
Swift	9:00	9:00	21:07	1	60	58	2	0	33	SWIFT	Private
SPRB	9:30	9:30	9:30	30	3	0	0	3	29	National Bureau of Statistics	Public
FESS	10:00	15:53	19:52	10	34	0	34	0	27	State Administration of Foreign Exchange	Public
OMO	9:10	9:46	9:46	46	8	8	0	0	-	The People's Bank of China	Public
SLF/MLF/PSL	9:23	15:51	19:12	11	62	1	57	4	-	The People's Bank of China	Public
CTCM	7:24	16:31	19:45	27	83	4	79	0	-	The People's Bank of China	Public
CBS	9:00	9:00	9:00	0	19	19	0	0	-	The People's Bank of China	Public
LPR	9:30	9:30	9:30	17	0	0	0	0	-	The People's Bank of China	Public
All	6:40	10:00	21:07	1048	854	217	421	216			

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 announcements by 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 the regular trading hours. "#NonTrd" refers to the number of announcements released during the non-regular trading hours. "#Open" refers to the number of announcements released before the stock market opens (9:30 am) on a trading day. "#Close" refers to the number of announcements released after the stock market closes (3:00 pm) on a trading day. "#Weekend" 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. "Sector" indicates whether the announcement is issued by a public or a private entity. The sample period is from January 2009 to December 2020.

Exchange (SSE) and the Shenzhen Stock Exchange (SZSE), are now second globally in terms of market capitalization, behind only the United States. Despite its 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.[6]

Stock trading can only take place on the two stock exchanges during the regular trading hours in China. The regular trading hours include two sessions: the morning session from 9:30 am to 11:30 am, and the afternoon session from 1:00 pm to 3:00 pm.[7] The total trading session is therefore only four hours (240 minutes) per day, shorter than most of the developed markets. Also, it's worth noting that financial futures and options can only be traded in the regular trading hours in China, in contrast to many developed countries (including the U.S.), where the financial markets are open almost 24 hours around the clock.[8]

The under-developed financial markets, coupled with short trading hours, make China a unique laboratory to study the information transmission mechanism when trading is not available at the time information arrives the market. For macroeconomic announcements released during non-trading hours, Chinese investors have to wait until the stock market opens to trade because both the stock and derivatives markets are close. This is very different from the macroeconomic announcements 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 payrolls, GDP, CPI, etc.), from 8:30 am to 9:15 am Eastern Time, or within the regular trading hours (FOMC, ISM, CSI, etc.). As a result, the US investors can immediately trade on the news using, for instance, the liquid market index ETFs which are actively traded during both the trading and the pre-trading hours, or the market index futures contracts that are open to trade almost around-the-clock.

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

[7] Before the market opens, there is a ten-minute pre opening trading sessions takes from 9:15 am to 9:25 am, during which orders are placed in advanced and an opening price of the stock is decided based on a call auction process.

[8] The CSI 300 index futures are launched in April 16, 2010, and are traded from 9:15 am to 11:30 am and 1:00 pm to 3:15 pm from 2010 to 2015. After 2016, the trading hours for the CSI 300 index futures are changed to 9:30 am to 11:30 am and 1:00 pm to 3:00 pm. The CSI 300 index options are launched much later, in December 23, 2019, and are traded from 9:30 am to 11:30 am and 1:00 pm to 3:00 pm.

3.3 Summary Statistics

Our main empirical results are based on the high-frequency intra-day tick data 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, as well as the high-frequency tick data of the index's component stocks. The high frequency data, including both price and volume, is provided by the RESSET Financial Database. The data for the CSI 300 index, with second-level timestamps, is available for every five-second time interval from January 2009 to December 2020. The data for the component stocks, with minute-level timestamps, is available for every one-minute time interval from January 2012 to December 2020.

In Table 2, we report the average return, volatility, and trading volume of the CSI 300 Index of five different post-announcement time windows for our sample of major macroeconomic announcements in China. "0" denotes the first minute of trading after the release of macroeconomic indicators at $t = 0$; "[1,59]" denotes the trading window from the beginning of the second minute to the end of the 60th minute; "[60,119]" denotes the trading window from the beginning of the 61th to the end of the 120th minute; "[120,179]" denotes the trading window from the beginning of 121th to the end of 180th minute; "[180,239]" denotes the trading window from the beginning of 181th to the end of 240th minute.

For announcements made in non-trading hours, "0" refers to the first minute return after the stock market opens in the next trading day, i.e., from 3:00 pm of the last trading day to the end of 9:30 am of the next trading day, and all other trading windows are relative to the market opening time at 9:30 am. For announcements made during trading hours, all trading windows are relative to the actual announcement time. "0" refers to the one-minute return after the news announcement, from the end of the last minute before the actual announcement time to the end of the first minute after the actual announcement time, and all other time windows are defined in similar ways.

For each of the five post-announcement time windows, we report the return ("Return"), the volatility ("Volatility"), and the trading volume per minute for CSI 300 Indexes, averaged across the Chinese macroeconomic announcements released in the trading and non-trading hours, separately.[9] The t-values for the average returns are also reported in the squared

[9]Returns are reported as log returns. Volatility of each time window 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 $N + 1$ number of minute-end prices within the given time window.

brackets. For comparison, we also report the statistics of return, volatility, and trading volume for the same calendar time window on the trading day without announcements one week prior each announcement day ("Non-Ann"), and compare then with the statistics on the announcement day ("Ann"). The returns and volatilities are reported in basis points, and the volumes are reported as millions of shares per minute. All continuous variables are winsorized at the 1% and 99% levels.

Panel A of Table 2 shows that the return volatilities and volume are significantly higher around the opening hours on the trading day following non-trading-hours macroeconomic announcements in China. After the release of an non-trading-hours announcement, the average return volatility at 9:30 am is 45.33 basis points, significant higher than the average one-minute volatility of 37.07 on the non-announcement days. The average volatility remains higher for approximately half-an-hour, and then reduces to levels similar to the non-announcement days. The trading volume exhibits a very similar pattern. The trading volume after an non-trading-hours macroeconomic announcement is significantly higher from 9:30 am to 10:29 am, and then quickly converge to a level indifferent from the non-announcement days. The average returns are similar on announcement and non-announcement days, suggesting that there is a balanced mixture of good- and bad-news announcements. Overall, the statistics confirm that market moving information revealed by macroeconomic announcements during non-trading-hours is indeed incorporated into market prices through trading at the market opening time.

For macroeconomic announcements released within the regular trading hours, there is similar, albeit much weaker, increase in volatility and trading volume after the announcement time, as shown in Panel B of Table 2.

We also use the macroeconomic announcements released in the U.S. as the benchmark case whereas investors trade immediately after the news release. Following the literature, we include the announcements of important macroeconomic indicators, Federal Open Market Committee (FOMC), total nonfarm payroll employment (NFP), initial claims for unemployment insurance (INC), gross domestic production (GDP), consumer price index (CPI), the Institute for Supply Management's manufacturing index (ISM), and the preliminary release of the consumer sentiment index (CSI), industrial production (IP), personal income (PI), housing starts (HST), and producer price index (PPI). For FOMC announcements, the release time are based on the time-stamp of Bloomberg and news wires. For all other announcements, the release time are obtained from Bloomberg.

We report the summary statistics of the market returns on the U.S. macroeconomic announcements days at Panel C of Table 2. The return statistics are based on the transaction-level E-mini S&P 500 index futures from January 2009 to December 2020 from the Chicago Mercantile Exchange (CME). Since the E-mini S&P 500 index futures are traded almost around the clock, all returns are measured relative to the actual release time of macroeconomic announcements. As shown in Panel C, the average volatility are significantly higher on announcement days than on non-announcement days, peak in the first minute after the release, and remain higher and statistically significant for the next one hour. The trading volume remains at higher levels even longer, lasting for hours on the announcement day.

4 Empirical Results

4.1 The speed of price discovery: non-trading-hours and trading-hours announcements

Hypothesis 1 of our model predicts that the speed of discovery for announcements released during non-trading hours will be faster than those released during trading hours. To test this hypothesis, we rely on an unbiased regression model similar to Biais, Hillion, and Spatt (1999) and Boguth, Gregoire, and Martineau (2022). 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 t:

$$R_i^{[-10,239]} = \alpha_t + \beta_t R_i^{[-10,t]} + \epsilon_{i,t}, \tag{22}$$

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 minutes after the release time for the announcement i. Time 0 is the market opening time at 9:30 am 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, Gregoire, and Martineau (2022), we focus on the R-squared of the regression (22), denoted as R_t^2, which measures the price informativeness at the time t. By construction, R_t^2 always starts from zero and coverages towards 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. Figure 2 compares the R_t^2 of the unbiased

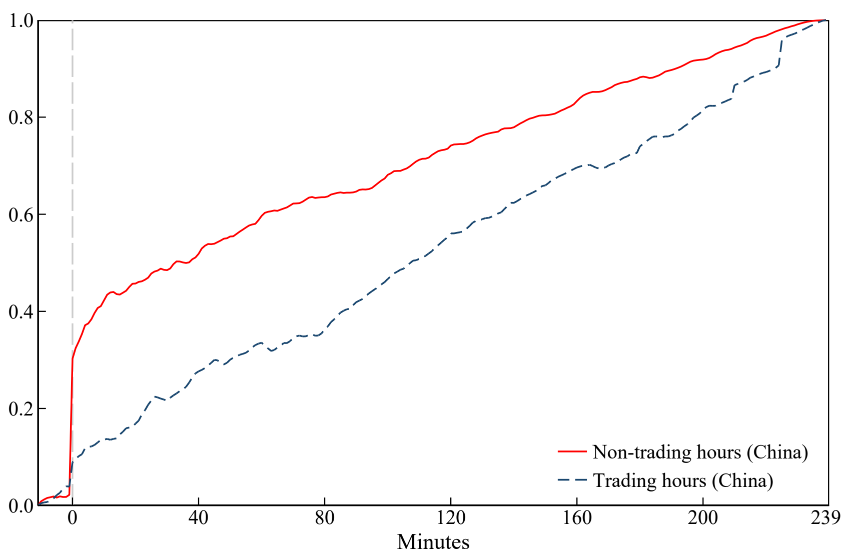
Table 2: Market Returns on Macroeconomic Announcement Days

	Return			Volatility			Volume		
Minutes	Ann	Non-Ann	Diff	Ann	Non-Ann	Diff	Ann	Non-Ann	Diff
Panel A: China announcements released within non-regular trading hours									
0	0.41	-4.17*	4.58	45.33	37.07	8.26***	2.87	2.46	0.41***
3:00pm-9:30am	[0.15]	[-1.88]	[1.28]			[3.36]			[3.25]
[1, 59]	8.31***	9.74***	-1.43	32.84	32.48	0.35	0.67	0.62	0.05**
9:31am-10:29am	[3.65]	[5.22]	[-0.49]			[0.77]			[2.16]
[60, 119]	0.54	-3.13*	3.67	28.32	28.32	-0.00	0.38	0.36	0.02
10:30am-11:29am	[0.27]	[-1.74]	[1.37]			[-0.01]			[1.58]
[120, 179]	1.15	0.70	0.45	27.57	27.90	-0.33	0.36	0.35	0.01
13:00am-13:59am	[0.63]	[0.43]	[0.18]			[-0.83]			[1.14]
[180, 239]	1.99	1.54	0.45	27.31	27.52	-0.21	0.46	0.45	0.01
14:00am-14:59am	[1.03]	[0.85]	[0.17]			[-0.50]			[0.55]
Panel B: China announcements released within regular trading hours									
0	-1.37	-0.12	-1.25	11.72	7.82	3.90***	1.12	0.89	0.23***
	[-1.28]	[-0.18]	[-0.99]			[3.90]			[3.35]
[1, 59]	2.32	1.42	0.90	31.43	30.90	0.53	0.50	0.48	0.02
	[1.35]	[0.79]	[0.36]			[1.20]			[1.07]
[60, 119]	-2.00	2.39	-4.38*	30.02	29.96	0.06	0.36	0.36	0.00
	[-1.10]	[1.24]	[-1.66]			[0.10]			[0.16]
[120, 179]	-3.15*	1.20	-4.34	31.61	32.33	-0.72	0.39	0.39	-0.00
	[-1.70]	[0.60]	[-1.59]			[-0.79]			[-0.24]
[180, 239]	2.26	1.61	0.65	47.60	49.27	-1.68	0.55	0.56	-0.02
	[0.87]	[0.61]	[0.17]			[-0.92]			[-0.74]
Panel C: US announcements									
0	0.37	-0.04	0.41	11.08	5.37	5.71***	6.78	2.47	4.30***
	[1.28]	[-0.29]	[1.28]			[19.75]			[20.09]
[1, 59]	-0.44	1.07*	-1.50*	39.27	35.74	3.54***	2.31	1.92	0.39***
	[-0.75]	[1.93]	[-1.87]			[3.46]			[5.60]
[60, 119]	-1.17	0.83	-2.00*	49.36	48.16	1.20	5.43	5.13	0.30***
	[-1.39]	[0.98]	[-1.68]			[0.87]			[4.07]
[120, 179]	0.48	0.35	0.13	41.54	41.53	0.02	3.52	3.38	0.14**
	[0.74]	[0.50]	[0.14]			[0.01]			[2.44]
[180, 239]	-0.07	0.74	-0.82	37.60	37.53	0.07	2.53	2.40	0.13***
	[-0.13]	[1.33]	[-1.02]			[0.07]			[2.88]

This table reports the summary statistics of market returns on the macroeconomic announcement days in China and the U.S.. The market returns are based on the CSI 300 ETF for the Chinese announcements and on the E-mini S&P 500 index futures for the U.S. announcements. The full list of Chinese and US macroeconomic indicators are reported in the text of Section 3. “Ann” refers to the announcement days, and “Non-Ann” refers to the trading day without announcements one week prior each announcement day. For the announcements released in the non-regular hours in China, “0” refers to the one-minute period from 3:00 pm of the previous trading day to the end of 9:30 am of the next trading day. For the announcements released in the regular trading hours in China and the announcements in the U.S., “0” refers to the first minute window after the actual release time. Other trading windows are defined in the similar way. Returns and volatilities are reported in basis points, and volume is reported as millions of shares per minute. All continuous variables are winsorized at the 1% and 99% levels. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. The sample period is from January 2009 to December 2020.

regressions (22) for macroeconomic announcements released during non-trading and trading hours. For announcements made during non-trading hours, R_t^2 jumps immediately by 28% at the market opening time 9:30 am and stays above the R_t^2 of trading hours announcements for the entire post-announcement time window. R_t^2 also increases at the time of release for announcements made during trading hours, but the increase is much smaller, only about 5% in size. Clearly, the announcements made during non-trading hours experience a much quicker price discovery process than those made during trading hours.

Figure 2: Cumulative R-squared Around Chinese Macroeconomic Announcements



Notes: This figure shows R-squared $R^2{}_t$ of the unbiased regressions. The dependent variables are the macroeconomic announcements window t returns of CSI 300 index from 10 minutes prior to the end of 240th minutes after the announcement, 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: $R_i^{[-10,239]} = \alpha_t + \beta_t R_i^{[-10,t]} + \epsilon_{i,t}$, where $R_i^{[-10,t]}$ denotes the return from 10 minutes prior to the announcement i to minute t around the announcement i. "Non-trading hours (China)" refers to the Chinese macroeconomic announcement released during the non-trading hours; "Trading hours (China)" refers to the Chinese macroeconomic announcements released during the regular trading hours. The time "0" is the opening time of stock market (9:30 am) for announcements released during the non-trading hours, and is the actual announcement time for announcements released during the trading hours. The sample period is from January 2009 to December 2020.

To further pin down the effect of announcement time on the spread of price discovery, we regress the returns at different post-announcement windows on the information content of individual news announcements, proxied by the total return in the window $[-10, 239]$ around the release time. The regression is specified below:

$$R_i^t = \alpha^t + \beta_1^t R_i^{[-10,239]} + \beta_2^t R_i^{[-10,239]} \times Non_i + \beta_3^t Non_i + \epsilon_i^t, \tag{23}$$

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, Non_i is a dummy variable that equals one if the announcement i is released in non-trading hours, $R_i^{[-10,239]}$ denotes the total return of CSI 300 index from ten minute prior to the release time to the end of the 240th minute after the announcement. The regression coefficient β_1^t measures the average proportion of price discovery occurring in time window t for announcements released during trading hours; $\beta_1^t + \beta_2^t$ measures the average proportion of price discovery occurring in time window t for the announcement released during non-trading hours. Our focus is therefore on the coefficient β_2^t, which captures the difference in the speed of price discovery between the announcements within non-trading hours and trading hours. In particular, we split the four hours trading window after announcement into the following five periods:

Time window "0": The initial one minute of trading right after the announcement. If the announcement is released during trading hours, for example at 10:00 am on Monday, the initial one-minute return, which can be denoted by R_i^0, is calculated using the last transaction prices at the end of 9:59 am and the end of 10:00 am, respectively. If the announcement is released during non-trading hours, for example at 5:00 pm on Friday, the initial one-minute return is calculated using the last transaction prices at the market closing time 3:00 pm on Friday and the end of 9:30 am on the following Monday.

Time window "$[1, 59]$", "$[60, 119]$", "$[120, 179]$", "$[180, 239]$": Following the initial minute, we label the fifty-nine minutes trading window from the beginning of minute "1" to the end of minute "59" by "[1,59]", and denote the market return by $R_i^{[1,59]}$; the sixty minutes trading window from the beginning of minute "60" to the end of minute "119" by "[60,119]", and denote the market return by $R_i^{[60,119])}$; the sixty minutes trading window from the beginning of minute "120" to the end of minute "179" by "[120,179]", and and denote the market return by $R_i^{[120,179]}$; the last sixty minutes trading window from the beginning of minute "60" to the end of minute "239" by "[180,239]", and denote the market return by $R_i^{[180,239]}$.

Table 3 Panel A shows that 5.1% of the price discovery occurs at the first minute of trading ("0") for announcements released during trading hours, whereas 27.7% (0.051+0.226) of the price discovery occurs at the first minute of trading for announcements released during non-trading hours. The difference in the speed of price discovery in the first minute is 22.6% with a significant t-stat of 8.90. In terms of economic magnitudes, the coefficient implies that the speed of price discovery is more than five times faster for announcements released during non-trading hours. Consistent with faster price discovery in the first minute of trading, the coefficients of β_2^t are negative significant for trading windows "[180,239]".

Consistent with Hypothesis 1, our results show that the speed of price discovery is faster for announcements released during the non-trading hours, compared to the ones released during the trading hours. The latter is an extreme case where the distance-to-trading equals zero, as investors can trade immediately after the release of these news.

Table 3: The Impact of Distance-to-trading on the Speed of Price Discovery

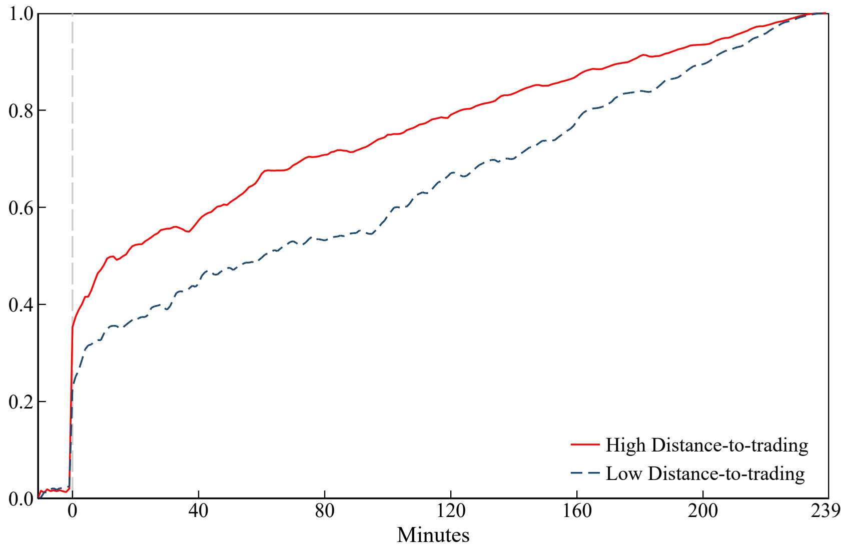
	Post-announcement time windows				
	(1) 0	(2) $[1,59]$	(3) $[60,119]$	(4) $[120,179]$	(5) $[180,239]$
Panel A: Non-trading-hours v.s. trading-hours announcements					
$R^{[-10,239]}$	0.051***	0.164***	0.187***	0.183***	0.381***
	[4.422]	[11.074]	[13.915]	[10.273]	[18.567]
$R^{[-10,239]} \times Non$	0.226***	0.034	-0.013	-0.031	-0.198***
	[8.901]	[1.399]	[-0.664]	[-1.394]	[-7.549]
Non	-3.087	2.422	-0.630	1.507	-3.741
	[-1.163]	[0.933]	[-0.264]	[0.652]	[-1.491]
Constant	-1.329	2.438	-1.856	-3.009*	2.539
	[-1.283]	[1.601]	[-1.184]	[-1.848]	[1.394]
$Adj.R^2$	0.242	0.221	0.240	0.222	0.449
N	1677	1677	1677	1677	1677
Panel B: The impact of distance-to-trading					
$R^{[-10,239]}$	0.104***	0.176***	0.181***	0.181***	0.329***
	[8.304]	[13.808]	[16.868]	[13.302]	[19.630]
$R^{[-10,239]} \times Dur$	0.071***	0.004	-0.001	-0.016***	-0.052***
	[6.794]	[0.565]	[-0.204]	[-2.674]	[-4.503]
Dur	-0.417	0.174	2.565**	-1.395	-1.475
	[-0.208]	[0.134]	[2.478]	[-1.407]	[-1.141]
Constant	-1.986	3.511***	-3.332***	-1.752	1.124
	[-1.620]	[2.656]	[-2.599]	[-1.343]	[0.762]
$Adj.R^2$	0.209	0.218	0.242	0.225	0.425
N	1677	1677	1677	1677	1677

Notes: Panel A reports the regression results of $R_i^t = \alpha^t + \beta_1^t R_i^{[-10,239]} + \beta_2^t R_i^{[-10,239]} \times Non_i + \beta_3^t Non_i + \epsilon_i^t$. Panel B report the regression results of $R_i^t = \alpha^t + \beta_1^t R_i^{[-10,239]} + \beta_2^t R_i^{[-10,239]} \times Dur_i + \beta_3^t Dur_i + \epsilon_i^t$. 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 in non-trading hours. Dur_i is the time between announcement time and the first trading time after the announcement and is in days. 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.

4.2 The speed of price discovery: relation to the distance-to-trading

In this section, we test Hypothesis 2 and investigate further on the quantitative relation between the speed of price discovery and the distance-to-trading, utilizing the rich variations in the releasing time of macroeconomic announcements in China. We divide the announcements released during non-trading hours into high and low groups according to the distance-to-trading, then estimate the unbiasedness regressions, respectively. Figure 3 shows R-squared R_t^2 from the unbiased regression (22). "High Distance-to-trading" refers to the announcement with distance-to-trading above the median; "Low Distance-to-trading" refers to the announcement with distance-to-trading below the median. The path of R_t^2 shows that the price discovery speed is faster for announcemnets with high distance-to-trading.

Figure 3: The Impact of Distance-to-trading on Cumulative R-squared Around Macroeconomic Announcements



Notes: This figure shows R-squared R_t^2 from unbiasedness regressions based on the sample of announcements released during non-trading hours. The dependent variables are the macroeconomic announcements window t returns of CSI 300 index from 10 minutes prior to 240 minutes after the announcement, 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: $R_i^{[-10,239]} = \alpha^t + \beta^t R_i^{[-10,t]} + \epsilon_i^t$, where $R_i^{[-10,t]}$ denotes the return from 10 minutes prior to the announcement i to minute t around the announcement i. "High Distance-to-trading" refers to the Chinese macroeconomic announcement released during non-trading hours with high distance-to-trading; "Low Distance-to-trading" refers to the Chinese macroeconomic announcement released during non-trading hours with low distance-to-trading. The time "0" is the opening time of stock market (9:30 am) for announcements released during the non-trading hours. The sample period is from January 2009 to December 2020.

To further pin down the effect of distance-to-trading on the spreed of price discovery, we replace the dummy variable Non_i with the distance-to-trading Dur_i in Equation (23). In particular, Dur_i is zero for announcements released during trading hours, and is the time between the release time and the market opening time (9:30 am) on the next trading day for announcements released during non-trading hours. We estimate the impact of the distance-to-trading on the speed of price discovery through the following regression:

$$R_i^t = \alpha^t + \beta_1^t R_i^{[-10,239]} + \beta_2^t R_i^{[-10,239]} \times Dur_i + \beta_3^t Dur_i + \epsilon_i^t, \tag{24}$$

where our interest is on the coefficient β_2^t, which captures the impact of distance-to-trading on the the speed of price discovery.

We report the estimation results in Panel B of Table 3. The results paint a clear picture that the speed of price discovery is faster when the distance-to-trading increases. The proportion of price discovery occurring in time window "0" increases by 7.1% with a significant t-value of 6.79, when the distance-to-trading increases by one day. Consistent with the faster price discovery at time "0", there is less price discovery in the subsequent time windows"[120,179]" and "[180,239]" as the distance-to-trading increases. The coefficients β_2^t are significantly negative for these time windows.

We further test the robustness of the above results using only the announcements released during the non-trading hours, and report the results of Table 4. The relation between the speed of discovery and distance-to-trading remains robust. Time window "close-to-open" denotes the close-to-open return. For example, if the announcement is released at 5:00 pm on Friday, the close-to-open return is calculated using the last transaction prices at the market closing time 3:00 pm on Friday and the market opening price on the following Monday.

As the distance-to-trading increases by one day, the proportion of price discovery occurring in time window "close-to-open" increases by 2.9%, and is statistically significant with a t-value of 3.10. The results confirm that the strong relation between price discovery speed and distance-to-trading is not driven entirely by the differences between non-trading-hours and trading-hours announcements. In fact, within the sample of announcements all released during non-trading hours, the calendar time duration between the announcement time and the market opening time still has a considerable impact on the speed of price discovery.

Table 4: The Impact of Distance-to-trading on the Speed of Price Discovery (Non-Trading-Hours Only)

	Post-announcement time windows					
	(1) close-to-open	(2) [open, 0]	(3) $[1, 59]$	(4) $[60, 119]$	(5) $[120, 179]$	(6) $[180, 239]$
$R^{[-10,239]}$	0.178***	0.056***	0.204***	0.169***	0.172***	0.203***
	[7.167]	[4.931]	[8.223]	[9.907]	[9.984]	[9.617]
$R^{[-10,239]} \times Dur$	0.029***	0.002	-0.004	0.002	-0.013**	-0.014*
	[3.095]	[0.589]	[-0.483]	[0.383]	[-1.989]	[-1.728]
Dur	0.566	0.217	-0.606	3.768***	-2.512**	-0.883
	[0.297]	[0.363]	[-0.403]	[3.152]	[-2.174]	[-0.778]
Constant	-5.818**	0.463	5.515**	-6.469***	1.196	-0.220
$Adj.R^2$	0.270	0.124	0.222	0.231	0.216	0.270
N	717	717	717	717	717	717

Notes: This table reports the regression results of $R_i^t = \alpha^t + \beta_1^t R_i^{[-10,239]} + \beta_2^t R_i^{[-10,239]} \times Dur_i + \beta_3^t Dur_i + \epsilon_i^t$ 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. 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.

4.3 Distance-to-trading and information quality

In this section, we investigate the relation between distance-to-trading and information quality. Our main proxy of information quality is the bid-ask spreads of the index component stocks, which reflects the degree of investors disagreement. We calculate the bid ask spreads as, $Spreads = \frac{ask-bid}{(ask+bid)/2}$, where ask and bid are the order-volume weighted averages of ask and bid prices. The data is based on the high-frequency minute-by-minute quotes of the CSI 300 component stocks, which is available from January 2012 to December 2020. Since bid-ask spreads have strong intra-day pattern, we further subtract the average bid-ask spreads of the same calendar time from the bid-ask spreads, and normalize them by their respective standard deviations in our sample period, so that the normalized bid ask spreads are comparable across different trading windows.

We estimate the following regressions to quantify the impact of distance-to-trading on the bid ask spreads:

$$Spreads_{i,s}^t = \alpha^t + \beta_1^t Non_i + \gamma_s^t + \epsilon_{i,s}^t \tag{25}$$

$$Spreads_{i,s}^t = \alpha^t + \beta_1^t Dur_i + \gamma_s^t + \epsilon_{i,s}^t, \tag{26}$$

where $Spreads_{i,s}^t$ denotes the average scaled bid-ask spreads of stock s for time window t after announcement i, Non_i is a dummy variable which equals one if announcement i is released during non-trading hours, and Dur_i is the calendar time between the release time and the market opening time (9:30 am) on the next trading day for non-trading-hours announcements and is zero for trading-hours announcements.

Panel A of Table 6 reports the estimation results of Equation (25), Panel B and C report the estimation results of Equation (26). Panel C reports the regression results based on the sample of announcements released during non-trading hours. Time window "0" in Panel C denotes the pre-opening centralized competitive pricing time (9:25am).

The results in Table 6 show that the first minute post-announcement bid asks spreads of the tend to be smaller for announcements released in non-trading hours. The differences of the scaled bid ask spreads, between non-trading and trading hours announcements, is 0.038 for the first-minute trading time window "0", and is strongly significant. When the distance-to-trading increases by one day, the scaled bid ask spreads decrease by 0.017.

We provide further evidences on the bid ask spreads by focusing on the sample of Chinese announcements released during non-trading hours. As shown in Panel C, as the time during between announcement time and the pre-opening time (9:25am) increases by one day, the scaled bid ask spreads based decreases by 0.027.

Table 5: The Impact of Distance-to-trade on Post-Announcement Bid-ask Spreads

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Non-trading-hours v.s. trading-hours announcements						
		0	$[1, 59]$	$[60, 119]$	$[120, 179]$	$[180, 239]$
Non		-0.038**	-0.020	-0.014	-0.018	-0.026
		[-2.132]	[-1.059]	[-0.741]	[-0.967]	[-1.440]
Constant		-0.014	0.008	0.003	0.002	0.003
		[-1.183]	[0.604]	[0.253]	[0.144]	[0.217]
$Adj.R^2$		0.004	0.005	0.005	0.005	0.006
N		390025	390025	390025	390025	390025
Panel B: The impact of distance-to-trading						
		0	$[1, 59]$	$[60, 119]$	$[120, 179]$	$[180, 239]$
Dur		-0.017**	-0.010	-0.013	-0.013	-0.014*
		[-2.094]	[-1.168]	[-1.413]	[-1.505]	[-1.709]
Constant		-0.024**	0.003	0.003	-0.000	-0.002
		[-2.484]	[0.339]	[0.266]	[-0.014]	[-0.262]
$Adj.R^2$		0.004	0.005	0.005	0.006	0.006
N		390025	390025	390025	390025	390025
Panel C: The impact of distance-to-trading (Non-Trading-Hours Only)						
	open	open-to-0	$[1, 59]$	$[60, 119]$	$[120, 179]$	$[180, 239]$
Dur	-0.027***	-0.009	-0.006	-0.012	-0.012	-0.010
	[-2.724]	[-0.935]	[-0.656]	[-1.185]	[-1.147]	[-1.043]
Constant	-0.021	-0.043***	-0.005	0.002	-0.003	-0.012
	[-1.203]	[-2.748]	[-0.300]	[0.132]	[-0.205]	[-0.802]
$Adj.R^2$	0.009	0.011	0.019	0.018	0.019	0.019
N	174987	174987	174987	174987	174987	174987
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panel A reports the regression results of $Spreads^t_{i,s} = \alpha^t + \beta^t_1 Non_i + \gamma^t_s + \epsilon^t_{i,s}$. Panel B and Panel C report the regression results of $Spreads^t_{i,s} = \alpha^t + \beta^t_1 Dur_i + \gamma^t_s + \epsilon^t_{i,s}$. Panel C reports the regression results based on the sample of announcements released during non-trading hours. The dependent variables are the average scaled bid-ask spreads of CSI 300 components stocks for the respective time intervals, and are based on the order-volume weight average bid and ask prices. Non_i equals 1 if the announcement is released in non-trading hours. Dur_i is the time between announcement time and the first trading time after the announcement and is in days. The sample period is from January 2012 to December 2020. Standard errors are clustered at the announcement and stock level. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

In the cross section, we find that the improvement in post-announcement bid ask spreads is mainly for low-price stocks. As shown in Table **??**, the estimated coefficients β^t_1 are only significant for stocks with prices in the bottom 50%. Since low-price stocks tend to be stocks with higher volatility, more information asymmetry, and higher retail trading, our resutls suggest that these stocks benefit more from longer distance-to-trading on the announcement days.

Table 6: The Impact of Distance-to-trade on Post-Announcement Bid-ask Spreads for High- and Low-Price Stocks

	0		0		open	
	(1) Low	(2) High	(3) Low	(4) High	(5) Low	(6) High
Non	-0.075***	-0.005				
	[-3.408]	[-0.269]				
Dur			-0.035***	0.001	-0.037***	-0.017
			[-3.580]	[0.179]	[-3.402]	[-1.645]
Constant	0.141***	-0.169***	0.124***	-0.171***	0.082***	-0.125***
	[9.282]	[-15.245]	[10.597]	[-19.036]	[4.188]	[-7.068]
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Empirical p-value	0.000		0.000		0.000	
$Adj.R^2$	0.058	0.060	0.058	0.060	0.042	0.038
Observations	195426	194599	195426	194599	87626	87361

Notes: Column (1) and (2) report the regression results of $Spreads_{i,s}^t = \alpha^t + \beta_1^t Non_i + \gamma_s^t + \epsilon_{i,s}^t$. Column (3) - (6) report the regression results of $Spreads_{i,s}^t = \alpha^t + \beta_1^t Dur_i + \gamma_s^t + \epsilon_{i,s}^t$. Column (5) and (6) report the regression results based on the sample of announcements released during non-trading hours. Column (1), (3) and (5) report the regression results based on the sample of stocks with low nominal prices. Column (2), (4) and (6) report the regression results based on the sample of stocks with high nominal prices. The dependent variables are the average scaled bid-ask spreads of CSI 300 components stocks for the respective time intervals, and are based on the order-volume weight average bid and ask prices. Non_i equals 1 if the announcement is released in non-trading hours. Dur_i is the time between announcement time and the first trading time after the announcement and is in days. Empirical p-value of Fisher's permutation test for the difference in coefficients of Non or Dur between stocks with high nominal prices and stocks with low nominal prices is calculate by 1000 bootstrapping procedure. The sample period is from January 2012 to December 2020. Standard errors are clustered at the announcement and stock level. The t-statistics are reported in square brackets, and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

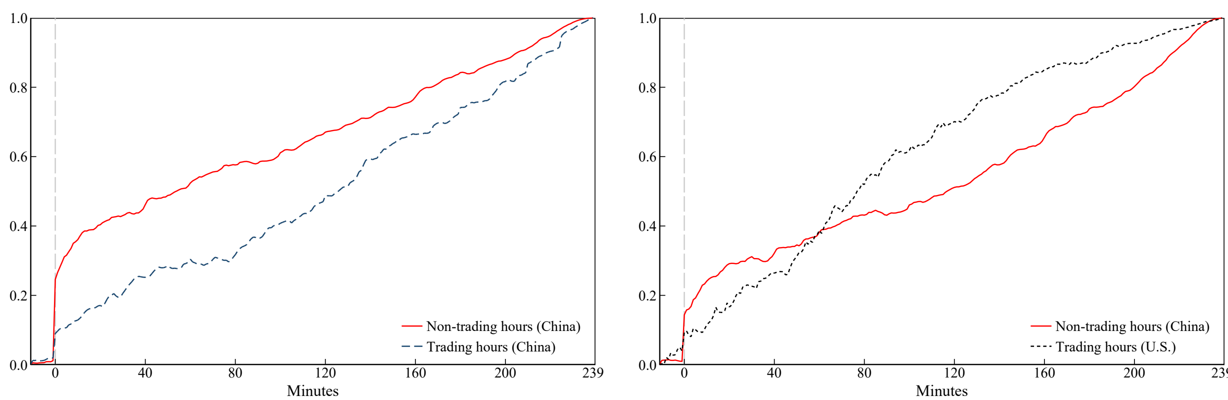
5 Robustness Tests and Additional Discussions

5.1 Analysis based on a matched sample

One may concern that the releasing time of macroeconomic news are related to their information content. In particular, regulators many intentionally release important news during non-regular trading hours, and hope to minimize the news impact on the market. If the releasing time is endogenously related to their market impact, our previous analysis might be biased. In this section, we address this concern by using a matched sample of macroeconomic announcements that share similar overall market impact but differ in releasing time. We use the 250 minutes returns of the CSI 300 index as the measure of total market impact, and require the differences between the matched pairs of announcements are within the 1 basis point threshold. For announcements released in non-trading hours, the 250 minutes return is from 2:50 pm of the previous trading day to 2:59 pm of the following trading day. For announcements released in trading hours, the 250 minutes post-announcement return is from ten minutes prior to the actual announcement time to the end of the 240th minute afterward. For the 717 non-trading-hours announcements, we perform an one-to-one matching with replacement based on the 960 trading-hours announcements and obtain 644 pairs of matched announcements. As shown in appendix Table B.1.T, the matched announcements are comparable in terms of market impact, the average 250 minutes return are 11.81 basis points for both announcements released in non-trading and trading hours.

Panel (a) of Figure 4 shows R-squared R_t^2 from unbiasedness regressions based on the matched samples. Table 7 report the results of the regression estimation of Equation (23) and (24) based on the matched samples of macroeconomic announcements. Overall, the results are robust and similar to the baseline results discussed in Section 4.

Figure 4: Cumulative R-squared Around Matched Macroeconomic Announcements



(a) Trading hours (China)

(b) Trading hours (U.S.)

Notes: This figure shows R-squared R_t^2 from unbiasedness regressions using matched samples with Chinese and U.S. announcements released during trading hours in panels (a) and (b). The dependent variables are the macroeconomic announcements window t returns of CSI 300 index and E-mini S&P 500 index futures from 10 minutes prior to 240 minutes after the announcement, 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: $R_i^{[-10,240)} = \alpha^t + \beta^t R_i^{[-10,t)} + \epsilon_i^t$ denotes the return from 10 minutes prior to the announcement i to minute t around the announcement i. "Non-trading hours (China)" refers to the matched Chinese macroeconomic announcement released during the non-trading hours; "Trading hours (China)" refers to the matched Chinese macroeconomic announcements released during the regular trading hours; "Trading hours (U.S.)" refers to the matched U.S. macroeconomic announcements released during the regular trading hours. The time "0" is the opening time of stock market (9:30 am) for announcements released during the non-trading hours, and is the actual announcement time for announcements released during the trading hours. The sample period is from January 2009 to December 2020.

5.2 Compare with U.S. macroeconomic announcements

In this section, we test the prediction of Hypothesis 2 by investigating the relation between the speed of price discovery and the distance-to-trading using the macroeconomic announcements in China and their counterparts in the U.S.. The very deep and extremely liquid financial markets in the U.S., including various market index ETFs, futures, and options, allow investors to trade immediately following the release of important macroeconomic indicators. As a result, although many important indexes, such as Non-farm payrolls and GDPs, are announced at 8:30 Eastern Time, one hour before the stock market opens, the

Table 7: The Impact of Distance-to-trade on the Speed of Price Discovery: Matched Sample

	Post-announcement time windows									
	(1) 0	(2) [1, 59]	(3) [60, 119]	(4) [120, 179]	(5) [180, 239]	(6) 0	(7) [1, 59]	(8) [60, 119]	(9) [120, 179]	(10) [180, 239]
	Panel A: Non-trading-hours v.s. trading-hours (China)					**Panel C: Non-trading-hours v.s. trading-hours (U.S.)**				
$R^{[-10,239])}$	0.082***	0.174***	0.163***	0.202***	0.352***	0.044***	0.227***	0.321***	0.193***	0.189***
	[3.937]	[8.767]	[7.377]	[10.294]	[14.521]	[4.899]	[10.838]	[11.343]	[11.228]	[10.274]
$R^{[-10,239]} \times Non$	0.214***	0.025	0.013	-0.054**	-0.183***	0.229***	-0.013	-0.175***	-0.057*	0.026
	[6.032]	[0.770]	[0.430]	[-2.095]	[-5.954]	[5.704]	[-0.345]	[-4.547]	[-1.818]	[0.840]
Non	-2.777	1.377	-2.929	7.280***	-4.195*	-2.352	1.111	-3.190	0.905	-0.166
	[-0.985]	[0.494]	[-1.071]	[2.993]	[-1.663]	[-0.904]	[0.458]	[-1.264]	[0.424]	[-0.081]
Constant	-0.745	2.091	0.317	-8.701***	3.678**	1.165**	0.247	-0.145	-2.430**	-0.321
	[-0.535]	[1.185]	[0.159]	[-4.981]	[1.965]	[1.971]	[0.217]	[-0.090]	[-2.098]	[-0.282]
$Adj.R^2$	0.207	0.158	0.138	0.179	0.341	0.129	0.174	0.203	0.128	0.199
	Panel B: Non-trading-hours v.s. trading-hours (China)					**Panel D: Non-trading-hours v.s. trading-hours (U.S.)**				
$R^{[-10,239]}$	0.151***	0.188***	0.162***	0.182***	0.295***	0.114***	0.232***	0.241***	0.177***	0.213***
	[7.565]	[10.554]	[9.596]	[12.070]	[16.118]	[5.522]	[11.331]	[11.082]	[10.745]	[12.961]
$R^{[-10,239]} \times Dur$	0.063***	-0.001	0.011	-0.012	-0.057***	0.077***	-0.020	-0.014	-0.022*	-0.019
	[3.206]	[-0.094]	[1.024]	[-1.147]	[-4.401]	[2.880]	[-1.343]	[-0.989]	[-1.950]	[-1.597]
Dur	0.369	0.214	1.399	-0.338	-1.437	1.834	-0.639	0.245	-1.555	-0.341
	[0.165]	[0.142]	[1.254]	[-0.297]	[-1.165]	[0.790]	[-0.485]	[0.207]	[-1.576]	[-0.339]
Constant	-2.437	2.674*	-1.878	-4.866***	2.415*	-0.992	1.138	-1.850	-1.184	-0.217
	[-1.614]	[1.780]	[-1.235]	[-3.532]	[1.657]	[-0.751]	[0.924]	[-1.335]	[-1.043]	[-0.199]
$Adj.R^2$	0.179	0.157	0.139	0.171	0.320	0.117	0.176	0.176	0.130	0.201
N	1288	1288	1288	1288	1288	1148	1148	1148	1148	1148

Notes: Panel A and C reports the regression results of $R_i^t = \beta_0 + \beta_1 R_i^{[-10,239]} + \beta_2 R_i^{[-10,239]} \times Non_i + \beta_3 Non_i + \epsilon_i$. Panel B and D reports the regression results of $R_i^t = \beta_0 + \beta_1 R_i^{[-10,239]} + \beta_2 R_i^{[-10,239])} \times Dur_i + \beta_3 Dur_i + \epsilon_i$. Panel A and B use the matched sample of Chinese announcements released during the non-trading hours and trading hours. Panel C and D use the matched sample of Chinese announcements released during the non-trading hours and U.S. announcements released during trading hours. The dependent variables are the log returns of of CSI 300 (China) and S&P 500 futures (U.S.) for the respective time intervals and are in basis points. Dummy variable Non_i equals 1 if the announcement is released in non-trading hours. Dur_i is the time between announcement time and the first trading time after the announcement and is in days. 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.

distance-to-trading is close to zero for investors in the U.S. market. We argue that, despite the apparent institutional differences between the two markets – such as the investor composition and overall market efficiency – a comparison of the two markets can still offer some insights on how investors' distance-to-trading affects the speed of price discovery.

For each Chinese macroeconomic announcement released during the non-trading hours, we match it with an U.S. announcement with similar total market impact, proxied by the 250 minutes returns of the CSI 300 index and the S&P 500 index. We obtain 574 pairs of matched announcements. Panel C of appendix Table B.1.T shows that the matched Chinese and U.S. announcements have very similar total market impact.

For this matched sample of announcements, we perform similar tests specified in the previous sections and report the results in Panel (a) of Figure 4 and Panel C and D of Table 7.

The results are consistent and all suggest that the Chinese announcements made in the non-trading hours have faster speed of price discovery than their counterparts in the US market, once the market opens to trade. While we knowledge that many institutional differences between the two markets might affect the estimation, we think the effect of distance-to-trading is more likely to be underestimated because the Chinese stock market is often considered as being less efficient than the US market. The fact that the price discovery process is still faster for the Chinese non-regular-hours announcements highlights the important role of distance-to-trading on the speed of price discovery.

5.3 Fixed macroeconomic announcement type

Our baseline regressions are based on the a pooled sample of 20 most important macroeconomic announcements in China. One concern is that different sorts of macroeconomic announcements may be fundamentally different from one another, and this cross-type difference may have an impact on our baseline findings. To address this concern, we examine the robustness of our results by restricting ourselves to macroeconomic announcements of the same index but with various release times.

Panel (A) of Table 8 reports the results for PMI announcements. Given that all 179 PMT announcements are released during non-trading hours, we focus on Equation (24) to estimate the relation between the price discovery speed and the duration of distance-to-trade. In Panel (B) - (D) of Table 8, we report the estimation results for (24) using only the Trade Balance (Trade), Industrial Production (IP) or Central Treasury Cash Management

(CTCM) announcements. In our sample period, there are 109 IP, 96 Trade and 27 CTCM announcements released during regular trading hours, and 14 IP, 33 Trade and 83 CTCM announcements released during non-trading hours. The large variations in the announcement time of IP, Trade and CTCM provide identification we need for the estimation. Overall, the results are robust for both PMI, IP Trade and CTCM. For announcements with long distance-to-trade, the speed of price discovery is significantly faster. In unreported results, we have also performed the tests on foreign exchange settlement and sales by banks (FESS) and profit of industrial enterprises (PI), the relation between the price discovery speed and the distance-to-trade remains robust.

5.4 The impact of distance-to-trading on market volatility and trading volume

Per our derived Equations (20) and (21), we show that the trading volume and the return volatility in equilibrium are shifted both by the effect of the increased price informativeness and that of the reduced market uncertainty given that learning can happen before trading. These results well suggest that the effect of increased price informativeness dominates through market clearing upon market opening, which later on drives down the market noise and leads to lowered trading volume and the return volatility as time evolves. It therefore implies that compared to the announcements that fall closer but before trading sessions, those announcements that arrive much earlier generate larger effect of price informativeness by triggering greater price discovery upon market opening. As a result, the subsequent reduction of market noise is larger, which lead to relatively lighter trading volume and lowred return volatility after the market opening.

In this section, we investigate the impact of distance-to-trading on the market volatility and trading volume. Since return volatility and trading volume have strong intra-day pattern, we further subtract the average return volatility and trading volume of the same calendar time from the return volatility and trading volume, and normalize them by their respective standard deviations in our sample period, so that the normalized return volatility and trading volume are comparable across different trading windows.

Figure 5 reports the average normalized return volatility and trading volume for the respective time interval. Comparing announcements released during non-trading and trading hours, the average volatility of non-trading hours announcements spikes more at the first minute, but declines quickly and remains lower for the next four hours. The trading volume

Table 8: The Impact of Distance-to-trade on the Speed of Price Discovery: for Fixed Macroeconomic Announcement Type

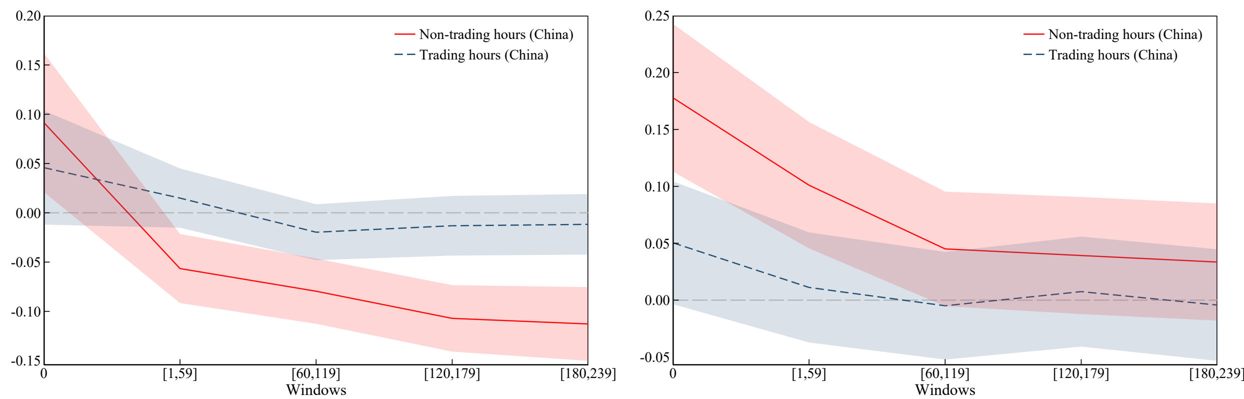
	Post-announcement time windows									
	(1) 0	(2) $[1, 59]$	(3) $[60, 119]$	(4) $[120, 179]$	(5) $[180, 239]$	(6) 0	(7) $[1, 59]$	(8) $[60, 119]$	(9) $[120, 179]$	(10) $[180, 239]$
	Panel A: PMI (Non-Trading-Hours Only)					**Panel C: Trade**				
$R^{[-10,240)}$	0.249***	0.201***	0.148***	0.144***	0.232***	0.007	0.157***	0.201***	0.332***	0.262***
	[5.489]	[4.683]	[5.268]	[5.672]	[6.024]	[0.674]	[3.776]	[4.983]	[7.537]	[6.345]
$R^{[-10,240)} \times Dur$	0.034***	-0.005	0.008	-0.015**	-0.018*	0.150***	0.017	-0.017	-0.056**	-0.092***
	[3.483]	[-0.477]	[1.273]	[-2.277]	[-1.877]	[6.940]	[0.545]	[-0.696]	[-2.339]	[-4.421]
Dur	2.212	-3.556	3.510**	-1.875	0.361	-1.281	-6.022	6.857	3.979	-6.450
	[0.672]	[-1.426]	[2.318]	[-1.051]	[0.222]	[-0.225]	[-0.978]	[1.192]	[0.811]	[-1.317]
Constant	-9.932*	18.680***	-7.461*	-0.856	-6.407	1.839	4.120	-1.700	-13.423**	9.039*
	[-1.847]	[3.614]	[-1.725]	[-0.211]	[-1.314]	[0.960]	[0.794]	[-0.396]	[-2.507]	[1.799]
$Adj.R^2$	0.363	0.250	0.244	0.168	0.342	0.468	0.179	0.298	0.437	0.328
N	179	179	179	179	179	129	129	129	129	129
	Panel B: IP					**Panel D: CTCM**				
$R^{[-10,240)}$	-0.010	0.140***	0.289***	0.202***	0.338***	0.013	0.177***	0.198***	0.299***	0.264***
	[-0.762]	[3.805]	[4.885]	[6.039]	[5.724]	[0.536]	[4.786]	[4.266]	[8.360]	[9.241]
$R^{[-10,240)} \times Dur$	0.103**	0.066***	-0.068*	-0.001	-0.098***	0.224***	-0.014	0.002	-0.130**	-0.051
	[2.574]	[3.172]	[-1.964]	[-0.072]	[-2.850]	[4.743]	[-0.360]	[0.046]	[-2.062]	[-0.811]
Dur	-9.622	-8.468*	-1.623	6.072	9.354	-12.949*	6.259	3.462	-3.517	3.691
	[-1.241]	[-1.799]	[-0.212]	[1.204]	[1.355]	[-1.870]	[1.147]	[0.700]	[-0.500]	[0.508]
Constant	2.623*	-1.960	2.751	-0.235	-2.681	-0.249	-3.743	-4.839	11.646*	-2.458
	[1.758]	[-0.466]	[0.449]	[-0.052]	[-0.479]	[-0.054]	[-0.640]	[-0.840]	[1.842]	[-0.468]
$Adj.R^2$	0.271	0.264	0.294	0.303	0.361	0.222	0.213	0.256	0.371	0.421
N	123	123	123	123	123	110	110	110	110	110

Notes: The table reports the regression results of $R_i^t = \beta_0 + \beta_1 R_i^{[-10,239]} + \beta_2 R_i^{[-10,239]} \times Dur_i + \beta_3 Dur_i + \epsilon_i$. 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 in non-trading hours. Dur_i is the time between announcement time and the first trading time after the announcement and is in days. Panel A, Panel B, Panel C and Panel D are based on the sample of PMI announcements, industrial production announcements, trade balance announcements and central treasury cash management announcements, respectively. 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.

of non-trading hours announcements, however, spikes immediately and remains higher for the next four hours.

In Table 9, we report the impact of distance to trade on the the volatility and trading volume of the CSI 300 Index. The results are consistent with Figure 5. For announcements with longer distance-to-trade, the volatility and trading volume are substantially higher at the first minute but become insignificantly different afterward.

Figure 5: Return Volatility and Trading Volume



(a) Return Volatility

(b) Trading Volume

Notes: Panel (a) and (b) report the average normalized return volatility and trading volume for the respective time interval, respectively. "Non-trading hours (China)" refers to the Chinese macroeconomic announcement released within the non-trading hours; "Trading hours (China)" refers to the matched Chinese macroeconomic announcements released during the regular trading hours. The sample period is from January 2009 to December 2020.

Table 9: The Impact of Distance-to-trading on Return Volatility and Trading Volume

	Post-announcement time windows									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	0	[1, 59]	[60, 119]	[120, 179]	[180, 239]	0	[1, 59]	[60, 119]	[120, 179]	[180, 239]
	Panel A: Volatility					**Panel C: Volume**				
Dur	0.137***	-0.018	-0.027*	-0.026*	-0.032**	0.076***	0.025	0.004	0.005	-0.002
	[3.400]	[-1.457]	[-1.906]	[-1.870]	[-2.198]	[2.823]	[1.142]	[0.238]	[0.242]	[-0.094]
Constant	0.003	-0.008	-0.033**	-0.042***	-0.040**	0.070***	0.038	0.014	0.019	0.013
	[0.106]	[-0.494]	[-2.253]	[-2.717]	[-2.541]	[2.598]	[1.595]	[0.627]	[0.804]	[0.536]
$Adj.R^2$	0.014	0.000	0.002	0.002	0.002	0.005	0.000	-0.001	-0.001	-0.001
N	1677	1677	1677	1677	1677	1677	1677	1677	1677	1677
	Panel B: Volatility (Non-Trading-Hours Only)					**Panel D: Volume (Non-Trading-Hours Only)**				
Dur	0.173***	0.001	-0.016	-0.002	-0.008	0.059*	0.002	-0.012	-0.005	-0.016
	[3.551]	[0.087]	[-0.935]	[-0.105]	[-0.481]	[1.956]	[0.066]	[-0.590]	[-0.218]	[-0.791]
Constant	-0.092	-0.058**	-0.062**	-0.105***	-0.104***	0.115**	0.099**	0.058	0.044	0.051
	[-1.576]	[-2.101]	[-2.287]	[-3.868]	[-3.538]	[2.401]	[2.393]	[1.546]	[1.165]	[1.343]
$Adj.R^2$	0.037	-0.001	0.000	-0.001	-0.001	0.004	-0.001	-0.001	-0.001	-0.001
N	717	717	717	717	717	717	717	717	717	717

Notes: Panel A and C report the regression results of $Volatility_i^t = \alpha^t + \beta_1^t Dur_i + \epsilon_i^t$ based on full sample and sample of announcements released during non-trading hours, respectively. Panel B and D report the regression results of $Volume_i^t = \alpha^t + \beta_1^t Dur_i + \epsilon_i^t$ based on full sample and sample of announcements released during non-trading hours, respectively. The dependent variables are the normalized return volatility and trading volume of CSI 300. Dummy variable Non_i equals 1 if the announcement is released in non-trading hours. Dur_i is the time between announcement time and the first trading time after the announcement and is in days. 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.

6 Conclusion

We document that the degree of efficient price discovery increases with the duration of investors' information processing time before the pre-opening and the continuous trading sessions in the stock market. Our paper isolates and identifies the impacts of learning on shifting the process of price discovery in absence of the confounding factor of market trading. In particular, we exploit the unique institutional feature of China's capital market for the significant timing heterogeneity of its macro announcements, which gives us the leverage to explore the efficiency differential of price discovery driven by the fact that new information may or may not arrive in active trading sessions. We show that investors' learning before the pre-opening facilitates the price discovery process. We find that the more distant the macroeconomic announcements are released before trading, the quicker and more efficient price discovery can be obtained upon market opening. We then rationalize the facts and show in a model that the increased learning among less informed investors over the span between the announcement arrivals and the market opening enhances the price informativeness of the equity prices.

Our paper makes the following contributions. First, while the channels of learning and trading are intertwined for understanding the price discovery in the existing literature, our paper exploits the market structure in China and isolates the learning channel. We provide an learning-based interpretation on why pre-open trading enhances the price discovery. Second, our paper is the first to ransack and study a comprehensive list of macro announcements in both China and the U.S. and highlights the fact that timing variations across macro announcements affect the efficiency of price discovery in the stock markets. Third, our results show that, in our setting, investors learning during the non-trading hours – rather than the trading itself – is what speeds up the price discovery once the trading session begins. Last but not least, our paper finds that the Chinese way of scheduling data releases of economic and financial statistics gives China greater price efficiency in its stock markets.

Appendix

A Welfare Derivations and Discussions

Considering the optimal asset demands, we compute the unconditional expected utilities of sophisticated informed and non-sophisticated uninformed investors, i.e. $\mathbb{E}[U(c_S)]$ and $\mathbb{E}[U(c_N)]$.

First, we derive $\mathbb{E}(c_S|s)$ and $\mathbb{E}(c_S|p)$. By Equation () and $p = a + be$ with $e = s - \bar{D} - c \cdot x$, it follows that

$$\mathbb{E}(c_S|s) = W + \frac{[\mathbb{E}(D|s) - p]^2}{\alpha\sigma^2_{D|s}}$$

$$\mathbb{E}(c_S|p) = W + \frac{[\mathbb{E}(D|p) - p]^2}{\alpha\sigma^2_{D|p}}$$

Second, we derive conditional variance $\sigma^2_{c_S|s}$ and $\sigma^2_{c_N|p}$. Plugging in the equilibrium conditions, we have

$$\sigma^2_{c_S|s} = \frac{[\mathbb{E}(D|s) - p]^2}{\alpha^2\sigma^2_{D|s}}$$

$$\sigma^2_{c_N|p} = \frac{[\mathbb{E}(D|p) - p]^2}{\alpha^2\sigma^2_{D|p}}$$

Taking the expectations of the CARA utilities of investors for both types conditional on their information set, we have

$$\mathbb{E}[U(c_S)|s] = -\exp(-\alpha W - \frac{1}{2}\frac{[\mathbb{E}(D|s) - p]^2}{\sigma^2_{D|s}})$$

$$\mathbb{E}[U(c_N)|p] = -\exp(-\alpha W - \frac{1}{2}\frac{[\mathbb{E}(D|p) - p]^2}{\sigma^2_{D|p}})$$

By the law of iterative expectations, we further compute the unconditional expectations by doing integration over space of signals s, e and asset supply shocks x. It follows that

$$\mathbb{E}[U(c_S)] = -\exp(-\alpha W) \cdot \mathbb{E}\exp(-\frac{1}{2}\frac{[(\bar{D} - a) + (\gamma_S - b)e + c \cdot \gamma_S \cdot x]^2}{\sigma^2_{D|s}})$$

$$\mathbb{E}[U(c_N)] = -\exp(-\alpha W) \cdot \mathbb{E}\exp(-\frac{1}{2}\frac{[(\bar{D} - a) + (\gamma_N - b)e]^2}{\sigma^2_{D|p}})$$

By defining $y_s = \frac{(\bar{D}-a)+(\gamma_S-b)e+c\cdot\gamma_S\cdot x}{\sqrt{(\gamma_S-b)^2(\sigma^2+e^{-\lambda}\sigma^2_\epsilon)+b^2\cdot c^2\cdot\sigma^2_x}}$, we have $y_s \sim \mathbf{N}(\frac{(\bar{D}-a)}{\sqrt{(\gamma_S-b)^2(\sigma^2+e^{-\lambda}\sigma^2_\epsilon)+b^2\cdot c^2\cdot\sigma^2_x}}, 1)$. It follows that

$$-\mathbb{E}\exp(-\frac{1}{2}\frac{[(\bar{D} - a) + (\gamma_S - b)e + c \cdot \gamma_S \cdot x]^2}{\sigma^2_{D|s}}) = -\mathbb{E}\exp(-\frac{(\gamma_S - b)^2(\sigma^2 + e^{-\lambda}\sigma^2_\epsilon) + b^2 \cdot c^2 \cdot \sigma^2_x}{2\sigma^2_{D|s}}y_s^2)$$

By the moment generating function of non-central χ^2 distribution, we have

$$- \mathbb{E}\exp(-\frac{1}{2}\frac{[(\bar{D}-a)+(\gamma_S-b)e+c\cdot\gamma_S\cdot x]^2}{\sigma^2_{D|s}}) =$$

$$- \frac{1}{\sqrt{1+\frac{(\gamma_S-b)^2(\sigma^2+e^{-\lambda}\sigma^2_\epsilon)+b^2\cdot c^2\cdot\sigma^2_x}{\sigma^2_{D|s}}}}\exp(-\frac{(\bar{D}-a)^2}{2\{(\gamma_S-b)^2(\sigma^2+e^{-\lambda}\sigma^2_\epsilon)+b^2\cdot c^2\cdot\sigma^2_x+\sigma^2_{D|s}\}})$$

By defining $y_e = \frac{(\bar{D}-a)+(\gamma_N-b)e}{(\gamma_N-b)\sigma_e}$, we have $y_e \sim \mathbf{N}(\frac{(\bar{D}-a)}{(\gamma_N-b)\sigma_e}, 1)$. It follows that

$$-\mathbb{E}\exp(-\frac{1}{2}\frac{[(\bar{D}-a)+(\gamma_N-b)e]^2}{\sigma^2_{D|p}}) = -\mathbb{E}\exp(-\frac{(\gamma_N-b)^2\sigma^2_e}{2\sigma^2_{D|p}}y^2_e)$$

By the moment generating function of non-central χ^2 distribution, we have

$$-\mathbb{E}\exp(-\frac{1}{2}\frac{[(\bar{D}-a)+(\gamma_N-b)e]^2}{\sigma^2_{D|p}}) = -\frac{1}{\sqrt{1+\frac{(\gamma_N-b)^2\sigma^2_e}{\sigma^2_{D|p}}}}\exp(-\frac{(\bar{D}-a)^2}{2[(\gamma_N-b)^2\sigma^2_e+\sigma^2_{D|p}]})$$

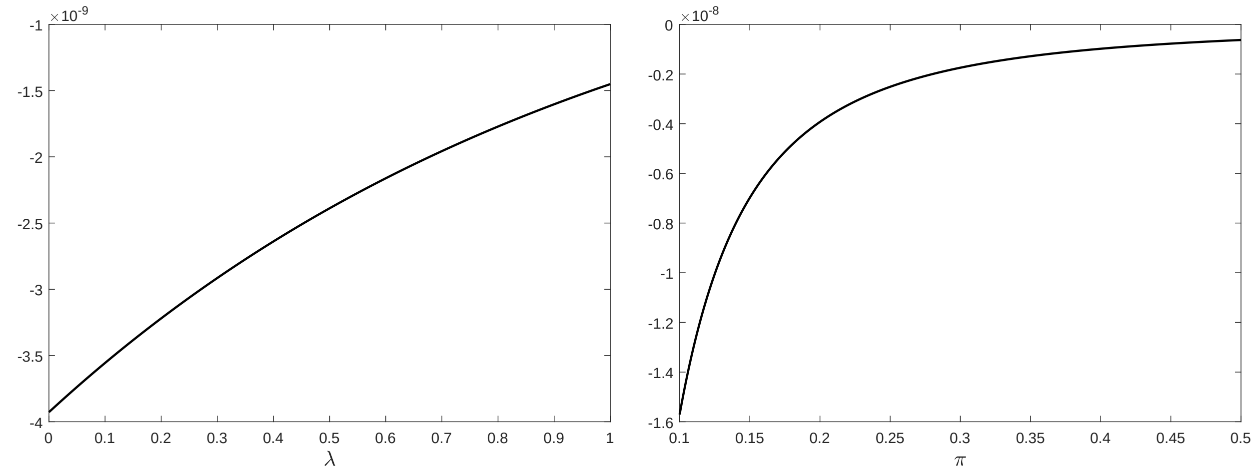
Next, we examine the welfare of uninformed investors relative to that of informed investors, i.e., $\mathbb{E}[U(c_N)] - \mathbb{E}[U(c_S)]$.In particular, we have

$$\mathbb{E}[U(c_S)] = -\frac{1}{\sqrt{1+\frac{(\gamma_S-b)^2(\sigma^2+e^{-\lambda}\sigma^2_\epsilon)+b^2c^2\sigma^2_x}{\sigma^2_{D|s}}}}\exp(-\alpha W - \frac{(\bar{D}-a)^2}{2\{(\gamma_S-b)^2(\sigma^2+e^{-\lambda}\sigma^2_\epsilon)+b^2c^2\sigma^2_x+\sigma^2_{D|s}\}}) \tag{A.1.E}$$

$$\mathbb{E}[U(c_N)] = -\frac{1}{\sqrt{1+\frac{(\gamma_N-b)^2(\sigma^2+e^{-\lambda}\sigma^2_\epsilon+c^2\sigma^2_x)}{\sigma^2_{D|p}}}}\exp(-\alpha W - \frac{(\bar{D}-a)^2}{2[(\gamma_N-b)^2(\sigma^2+e^{-\lambda}\sigma^2_\epsilon+c^2\sigma^2_x)+\sigma^2_{D|p}]}) \tag{A.2.E}$$

According to Equations (A.1.E) and (A.2.E), the investors' welfare are determined by the ratio of the expected gain from trade over the posterior variance conditional on their information set. Distance to trading λ increases the information quality of informed investors and this also raises the informativeness of the stock prices. More informative prices move closer to the true valuation of dividend payouts and thus reduce the profitable trading opportunities, even though both types of investors have lowered perceived risk from trading. We then numerically show in Figure A.1.F that the relative welfare of uninformed investors increases with the duration of trading-to-distance of announcement arrivals. Importantly, while the market is having greater proportion of sophisticated and informed investors π, this relative welfare of uninformed is further increased as the market price would be less affected by the noisy trading.

Figure A.1.F: Difference: Welfare of the Uninformed Relative to Welfare of the Informed



(a) λ (b) π

B Other Results

In this section, we report the summary statistics for the returns on the full sample and the matched sample of macroeconomic announcement days at Table B.1.T, the relation of distance-to-trading and the speed of price discovery with additional controls for pre-scheduled announcements at Table B.2.T and Table B.3.T. The pre-scheduled announcements include those for the CPI/PPI, Caixin, GDP, IP, LPR, PI, PMI, SLF/MLF/PSL, and SPRB, for which the announcement days are preset but the actual announcement time varies throughout the day.

Table B.1.T: Post-announcement Market Returns on Macroeconomic Announcement Days in China

Post-Ann Return$^{[-10,239]}$	Obs	Mean	Std.	Min	P25	P50	P75	Max
Panel A: Full Sample								
Non-Trd (China)	717	17.40	145.90	-553.80	-50.69	14.02	90.88	635.59
Trd(China)	960	-0.74	150.22	-713.54	-77.47	-3.68	78.25	645.46
Trd(U.S.)	1899	-0.28	62.02	-295.36	-30.83	2.07	33.85	508.12
Panel B: Matched Sample with Chinese Announcements within trading hours								
Non-Trd (China)	644	11.81	114.05	-417.50	-45.25	11.12	75.97	389.23
Trd(China)	644	11.81	114.04	-417.50	-45.31	11.13	76.05	389.29
Panel C: Matched Sample with U.S. Announcements within trading hours								
Non-Trd (China)	574	10.71	83.13	-295.58	-37.89	10.79	64.23	299.37
Trd(U.S.)	574	10.72	83.15	-295.36	-37.77	10.84	64.46	299.26

We match the sample of announcements released during the non-trading hours with announcements within the regular trading hours (matching with replacement) based on the $[-10, 239]$ returns of the CSI 300 index and E-mini S&P 500 index futures. The $[-10, 239]$ trading window is extending from 2:50 pm of the previous trading day to 2:59 pm of the following trading day for non-trading-hours announcements, and is from ten minutes prior to the actual announcement time to the end of the 240th minute afterward for trading hours announcements. The distribution of the $[-10, 239]$ returns are reported for the full sample of announcements in Panel A. The distribution of the $[-10, 239]$ returns are reported for the matched sample of announcements with Chinese and U.S. announcements released during trading hours in Panel B and Panel C, respectively. The sample period is from January 2009 to December 2020.

Table B.2.T: The Impact of Distance-to-trading on the Speed of Price Discovery: Pre-Scheduled

	Post-announcement time windows				
	(1)	(2)	(3)	(4)	(5)
	0	$[1,59]$	$[60,119]$	$[120,179]$	$[180,239]$
Panel A: Non-trading-hours v.s. trading-hours announcements					
$R^{[-10,239]}$	0.024*	0.155***	0.194***	0.225***	0.368***
	[1.670]	[7.831]	[9.853]	[10.095]	[15.547]
$R^{[-10,239]} \times Non$	0.232***	0.034	-0.014	-0.039*	-0.194***
	[9.194]	[1.414]	[-0.718]	[-1.806]	[-7.438]
Non	-4.351	3.966	-0.706	2.276	-5.580**
	[-1.563]	[1.427]	[-0.284]	[0.925]	[-2.093]
$R^{[-10,239]} \times Pre$	0.041*	0.014	-0.010	-0.063***	0.020
	[1.871]	[0.585]	[-0.484]	[-2.717]	[0.776]
Pre	-4.062*	5.436**	-0.338	2.188	-6.203**
	[-1.653]	[2.028]	[-0.138]	[0.874]	[-2.297]
Constant	1.377	-1.343	-1.600	-4.373*	6.770***
	[0.828]	[-0.554]	[-0.719]	[-1.799]	[2.670]
$Adj.R^2$	0.245	0.222	0.239	0.229	0.451
N	1677	1677	1677	1677	1677
Panel B: The impact of distance-to-trading					
$R^{[-10,239]}$	0.097***	0.170***	0.186***	0.216***	0.302***
	[5.406]	[9.661]	[11.240]	[11.489]	[15.469]
$R^{[-10,239]} \times Dur$	0.071***	0.004	-0.001	-0.016***	-0.052***
	[6.748]	[0.541]	[-0.206]	[-2.814]	[-4.673]
Dur	-0.549	0.473	2.591**	-1.370	-1.810
	[-0.269]	[0.350]	[2.513]	[-1.392]	[-1.415]
$R^{[-10,239]} \times Pre$	0.011	0.010	-0.008	-0.058**	0.044
	[0.443]	[0.418]	[-0.394]	[-2.483]	[1.625]
Pre	-2.165	4.521*	0.489	1.040	-5.711**
	[-0.880]	[1.765]	[0.209]	[0.439]	[-2.174]
Constant	-0.727	0.787	-3.600**	-2.199	4.396**
	[-0.398]	[0.382]	[-2.026]	[-1.149]	[2.196]
$Adj.R^2$	0.208	0.219	0.241	0.230	0.428
N	1677	1677	1677	1677	1677

Notes: This table reports the regression results based on sample of Chinese macroeconomic announcements released during the non-trading hours and the regular trading hours. Panel A reports the regression results of $R_i^t = \alpha^t + \beta_1^t R_i^{[-10,239]} + \beta_2^t R_i^{[-10,239]} \times Non_i + \beta_3^t Non_i + \beta_4^t R_i^{[-10,239]} \times Pre_i + \beta_5^t Pre_i + \epsilon_i$. Panel B reports the regression results of $R_i^t = \alpha^t + \beta_1^t R_i^{[-10,239]} + \beta_2^t R_i^{[-10,239]} \times Dur_i + \beta_3^t Dur_i + \beta_4^t R_i^{[-10,239]} \times Pre_i + \beta_5^t Pre_i + \epsilon_i$. 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 in non-trading hours. Dur_i is the time between announcement time and the first trading time after the announcement and is in days. Dummy variable Pre_i equals 1 if the announcement is pre-scheduled. 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 B.3.T: The Impact of Distance-to-trade on the Speed of Price Discovery: Pre-Scheduled (Non-Trading-Hours Only)

	Post-announcement time windows					
	(1) close-to-open	(2) open-to-0	(3) $[1, 59]$	(4) $[60, 119]$	(5) $[120, 179]$	(6) $[180, 239]$
$R^{[-10,239]}$	0.186***	0.055***	0.191***	0.165***	0.172***	0.219***
	[6.273]	[3.340]	[6.421]	[7.400]	[7.563]	[9.196]
$R^{[-10,239]} \times Dur$	0.029***	0.002	-0.004	0.002	-0.013**	-0.013
	[3.045]	[0.601]	[-0.506]	[0.252]	[-1.966]	[-1.521]
Dur	0.628	0.216	-0.739	3.850***	-2.469**	-0.925
	[0.329]	[0.367]	[-0.490]	[3.114]	[-2.118]	[-0.806]
$R^{[-10,239]} \times Pre$	-0.013	0.002	0.020	0.012	0.001	-0.031
	[-0.325]	[0.145]	[0.515]	[0.408]	[0.034]	[-0.922]
Pre	-5.315	0.341	10.355**	-3.556	-2.529	-1.049
	[-1.201]	[0.198]	[2.317]	[-0.944]	[-0.741]	[-0.277]
Constant	-3.700	0.317	1.424	-5.184**	2.158	0.378
	[-1.308]	[0.228]	[0.465]	[-2.093]	[0.903]	[0.158]
$Adj.R^2$	0.270	0.122	0.227	0.230	0.215	0.270
N	717	717	717	717	717	717

Notes: This table reports the regression results of $R_i^t = \alpha^t + \beta_1^t R_i^{[-10,239]} + \beta_2^t R_i^{[-10,239]} \times Dur_i + \beta_3^t Dur_i + \beta_4^t R_i^{[-10,239]} \times Pre_i + \beta_5^t Pre_i + \epsilon_i$ based on the sample of announcements made within 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. Pre_i equals 1 if the announcement is pre-scheduled. 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.

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