Front. Econ. China 2021, 16(4): 714–743
https://doi.org/10.54605/fec20210406

RESEARCH ARTICLE

Nan Li[a], Yuhong Zhu[b]

The Impact of COVID-19 on Stock Market in China

Abstract This paper studies the impact of the COVID-19 on the stock ambiguity, risks, liquidity, and stock prices in China stock market, before and after the outbreak of COVID-19 during the Chinese Spring Festival holidays in 2020. We measure stock ambiguity using the intraday trading data. The outbreak of COVID-19 has a significant impact on the average stock ambiguity, risk, and illiquidity in China and induces structural break in the market average ambiguity. However, the equity premium and liquidity premium change little during the same period. The market average stock ambiguity and risks decrease, and stock liquidity improves to pre-pandemic levels as the pandemic is under control in China. The market average stock ambiguity and risks in China increase again when the confirmed new cases in the U.S. surge in the second half of 2020. We also find a "flight-to-liquidity" phenomenon, and the equally-weighted (value-weighted) 20-trading-day liquidity premium declined significantly to about –4.42% (–6.48%) during the fourth quarter of 2020.

Keywords ambiguity, Knightian uncertainty, liquidity, liquidity premium, COVID-19
JEL Classification D53, D81, G11, G12

1 Introduction

In 2020, the outbreak of the COVID-19 pandemic had a profound impact on the uncertainty in the whole world. In early January 2020, information about the nature of this SARS-like disease was limited. As a result, if not all, most people

Received May 11, 2021

[a] Department of Finance, Antai College of Economics and Management, Shanghai Jiao Tong University, Shanghai 200030, China
[b] School of Economics, Singapore Management University, 178903, Singapore
E-mail: nanli@sjtu.edu.cn (Nan Li, corresponding author), yhzhu.2021@phdecons.smu.edu.sg (Yuhong Zhu)

do not know the severity and possible impact of the COVID-19. How do investors and other economic decision-makers respond to the changes in uncertainty? How much is the impact on the stock risk, uncertainty, liquidity, and stock prices? To answer these questions, we need first to measure stock risks and uncertainty.

Knight (1921) is the first to emphasize that "*Uncertainty* must be taken in a sense radically distinct from the familiar notion of *Risk*, from which it has never been properly separated." According to Knight (1921), risk refers to the random events to be realized with a probability distribution, unique and known to all the decision-makers; while (Knightian) uncertainty refers to random events a priori unknown, and the probability distribution is either not uniquely assigned or unknown. Financial economists have made important theoretical progress in understanding the investment decision and asset pricing under (Knightian) uncertainty or ambiguity during the past one hundred years. Since the 2008 Global Financial Crisis, the uncertainty in the stock market has attracted the attention of investors, academic researchers, and policymakers. Hansen and Sargent (2021) show that market prices of uncertainty are time-varying and distinct from that of risks, and investors like uncertainty in low-growth-rate states and fear uncertainty in high-growth-rate states.

However, the main challenge to empirically test the theoretical predictions of Knight (1921), Hansen and Sargent (2021), and many others is to quantify the degree of uncertainty different from the conventional measure of risk using data from the financial markets. To meet this challenge, Izhakian (2020) proposes the ambiguity measure based on the intraday stock return data, risk-independent, and attitudes-independent[1].

The classical finance theory assumes that the daily stock return distribution is unique and known to all investors. If we assume that daily stock returns follow a normal distribution and are stationary, then the unique distribution of stock returns is solely determined by the expected return (μ_0 .) and risk or return volatility (σ_0 .), which can be estimated by the sample mean and standard deviation of the historical daily returns. However, the distribution of daily stock returns may not be unique and known to the investors. Thus investors are ambiguous about the distribution of the daily stock returns. If we maintain the

[1] Izhakian (2020) provides the theoretical foundation and points out that "these qualities are necessary for any study investigating the effect of ambiguity without confounding it with risk or with attitudes toward ambiguity and risk."

assumption that daily stock returns follow normal distributions and are stationary while relaxing the assumption that the distribution is unique, then we are in a world with ambiguity or (Knightian) uncertainty. In this world, the means and standard deviations of daily stock returns are not unique but taken from a group of possible values. For example, the mean can be any value in ($\underline{\mu}$, $\overline{\mu}$) while the standard deviation can be any value in ($\underline{\sigma}$, $\overline{\sigma}$), where $\overline{\mu} > \underline{\mu}$ and $\overline{\sigma} > \underline{\sigma}$. The world of classical finance theory is a special case where $\overline{\mu} = \underline{\mu} = \mu_0$ and $\overline{\sigma} = \underline{\sigma} = \sigma_0$.

Figure 1 illustrates the probability distribution(s) of the stock market index in the world without (with) ambiguity[2]. The red dotted line depicts the (unique) normal Probability Distribution Function (PDF) of stock returns of the market index in the classical world without ambiguity, where the mean and standard deviation is estimated by the sample mean and sample standard deviation of daily returns of the market index (CSI800). The solid lines depict a group of normal PDFs of the stock market index in a world with ambiguity. This group of PDFs has the same mean as the sample mean of the market index but different standard deviations, the average of which equals the sample standard deviation of the market index.

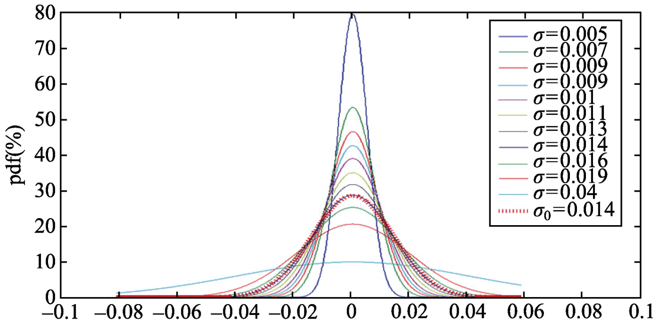

Figure 1 Probability Density Functions of Stock Market Index Return

Note: The red dotted line depicts the normal PDF with sample mean and sample standard deviation of daily returns of CSI800, the solid lines depict a group of normal PDFs with sample mean of daily returns of CSI800 and a group of standard deviation, the average of which equals the sample standard deviation of daily returns of CSI800.

[2] We assume daily stock returns are stationary (over time) and follow normal distribution. For illustrative purposes, we assume there is no ambiguity in the mean and only the standard deviation or volatility is ambiguous.

In Figure 2, we compare the histogram of the daily return of CSI800 and that of the simulated data drawn from the unique PDF (without ambiguity, bottom panel) and a group of PDFs (with ambiguity in volatility, middle panel). The top panel shows the histogram of daily returns of CSI800. The daily return has a fatter tail than the normal distribution with a kurtosis of 6.71. The middle panel shows that simulated returns from a group distribution with ambiguity have a similar fatter tail with a kurtosis of 6.63. The histogram matches much better with the data than the simulated returns without ambiguity (bottom panel). Thus, by just relaxing the assumption that the distribution is unique and known and allowing for ambiguity in distribution, we can generate daily returns with the similar fat-tail property as the observed data. This feature is convenient in asset pricing literature, as maintaining the normal assumption is fundamental to obtain explicit solutions and testable implications of many asset pricing models.[3]

Izhakian (2020) proposes to use dispersion in the PDFs to measure the ambiguity. As an illustration, if the group of PDFs in Figure 1 corresponds to the estimated PDFs of daily returns from intraday trading data[4], then Izhakian (2020)'s ambiguity measure of the daily return of the market index is computed as the dispersion[5] of this group of PDFs.

In this paper, we use the measure proposed by Izhakian (2020) to quantify stock ambiguity and study the impact of the COVID-19 pandemic on the stock ambiguity, risk, liquidity, and equity premium. In particular, we focus on the difference between the cross-section average of individual stock ambiguity and ambiguity of market index and the relationship between stock ambiguity, risk, and liquidity. The stock market in China during the period of the COVID-19 pandemic provides us with an ideal experiment field. The movements in stock

[3] In most of the existing literature in asset pricing with ambiguity, it is assumed that the ambiguity is only about the expected return or drift, not about the variance or volatility, so that the linear expectation operator and Itô's lemma works well in the world with ambiguous mean or drift. However, Anderson et al. (2020) and others find that ambiguity in volatility is essential to quantitatively explain the observed anomalies in the financial markets, such as the family firm ownership puzzle and other under-diversification puzzles. Peng (2006) establishes the theoretical foundation of the nonlinear expectation (G-Expectation) associated with the G-normal distribution with ambiguous variance and G-Brownian Motion with ambiguous volatility. Epstein and Ji (2013) study asset pricing in continuous time with ambiguous volatility.

[4] Under the assumption that stock returns follow normal distribution, we just need to estimate a group of means and standard deviations of daily returns using the intraday trading data.

[5] Izhankian (2020) uses the expected variance of the PDFs to measure the dispersion of the PDFs.

prices, risks, ambiguity, and liquidity help us deduce how the information is incorporated in the equilibrium stock prices and the trading behavior of investors facing unprecedented uncertainty. Furthermore, China is the first country hit on a large scale by the COVID-19, which provides us a cleaner environment to test the impact of COVID-19 on the stock market. When the COVID-19 later hits European countries and the U.S., it is much harder to separate the uncertainty from the COVID-19 and policies in different countries.

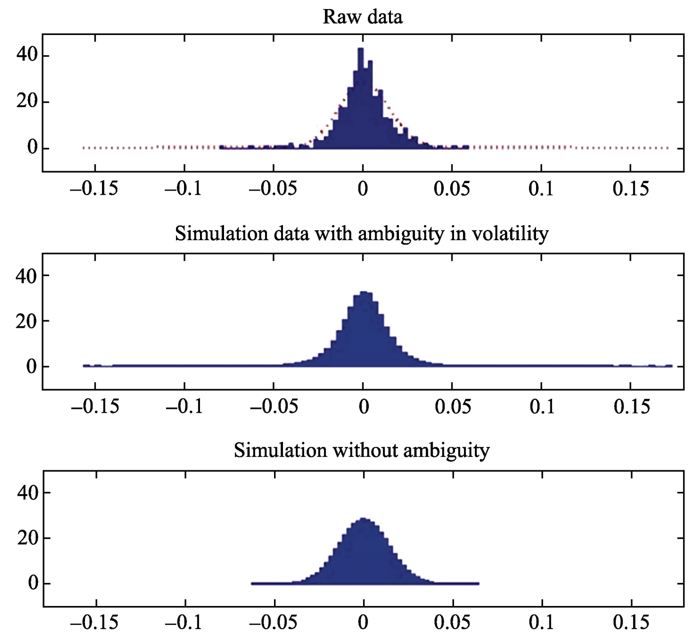

Figure 2 Histogram of Data and Simulated Data on Market Index Returns

Note: In the top panel, the blue bar depicts the histogram of daily returns of CSI800, in the middle panel, the blue bar depicts the histogram of simulated returns with ambiguity in standard deviation, that is, the returns are drawn from a group of normal PDFs with a unique mean (sample mean of the daily return of CSI800) and ambiguous volatility (a group of standard deviation with average equals to the sample standard deviation); the bottom panel depicts the histogram of simulated returns without ambiguity, that is, the returns are drawn from a unique normal PDF with mean and standard deviation equal sample mean and standard deviation of the daily return of CSI800, respectively.

Hansen and Sargent (2021) show that ignorance about the ambiguity of the probability distributions of risks[6] adds to the "equilibrium prices of those risks." In fact, stock ambiguity is usually positively correlated with stock illiquidity as the information asymmetry between informed traders and non-informed traders is likely to be higher when the stock returns are more ambiguous. Hansen and Sargent (2010) show that investors are more reluctant to trade stocks with higher ambiguity when they are concerned about ambiguity regarding the estimation of the asset value, which leads to higher illiquidity levels for these stocks. Kang et al. (2019) find that stock ambiguity and illiquidity are positively related, but the ambiguity premium is negative, and the illiquidity premium is positive. They propose to correct the measure liquidity premium by controlling for the information uncertainty or ambiguity.

If the stock ambiguity increases uniformly for all stocks during the COVID-19 period, then the overall market illiquidity should increase as stocks become more illiquid. However, the liquidity premium should not change if the cross-section difference in stock ambiguity does not change. Hence, we test the impact of the COVID-19 on the stock liquidity and liquidity premium in the China stock market, in addition to the tests on stock ambiguity, risks, and the equity premium.

Brenner and Izhakian (2018) apply the ambiguity measure of Izhakian (2020) to the market index (S&P500) in the US stock market and study the relationship between equity premium, risks, and ambiguity of stock market index over time. Li and Zhu (2020) find the cross-section relationship between stock return and ambiguity is different. They investigate the price of ambiguity using cross-section data in the China stock market and find that stocks with more ambiguity have a lower return, or the ambiguity premium is negative in the China stock market due to the binding short-sale constraints[7].

In this paper, we study both the ambiguity of the market index and the cross-section average of individual stock ambiguity and test whether these two respond differently to the shock in ambiguity caused by COVID-19. We modify Brenner and Izhakian's (2018) implementation method to accommodate the stock market characteristics in China as Li and Zhu (2020). We measure the stock

[6] Hansen and Sargent (2021) discuss and distinguish two types of ignorance about probability distributions of risks, "ambiguity concerns" and "misspecification concerns". In this paper, we focus on the ambiguity concerns.

[7] Li and Zhu (2020) argue that if investors' beliefs about stock prices are more dispersed when stock ambiguity is larger, then Miller (1977)'s model implies that more ambiguous stocks are overpriced in the market with binding short-sale constraints.

ambiguity by the dispersion in the probability distributions of the daily stock returns over the 20-trading-day window. To test the changes in the stock ambiguity before and after the Chinese Spring Festival (CSF), we do not construct the monthly stock ambiguity as Brenner and Izhakian (2018), but separate the trading days based on the CSF holiday schedule in 2019 and 2020, and compute the stock ambiguity over the 20-trading-day window.[8] Hence, no window includes the non-trading days in the CSF holidays in 2019 and 2020. As the lockdown in Wuhan and the nationwide social distancing measure took place during the CSF holidays in 2020, we can identify the changes in the stock ambiguity and liquidity before and after the outbreak of COVID-19 in China.

First, we find significant differences between stock ambiguity and risks. The risks of the stock market index and the cross-section average of the individual stock risk move together and increase right after the CSF holidays, while the increase in 2020 is much larger and significant. On the other hand, the cross-section average of the individual stock ambiguity increases after the CSF holiday in 2019 and 2020, with the increase much larger and significant in 2020, while the ambiguity of the market index *increases significantly before* the CSF holidays and *drops significantly after* the CSF holidays.

We examine further movements of the average ambiguity of each stock and the market index ambiguity before and after the outbreak of the COVID-19 pandemic in 2020. To our surprise, we find that the market index ambiguity increases from September to early December 2019, then declines right before the CSF holidays, and drops significantly after the CSF holidays when the outbreak of COVID-19 in China is confirmed. Then, it increases from March to June 2020 when the confirmed new cases in China decrease, but the COVID-19 starts in Europe and the U.S. The market index ambiguity declines when the confirmed new cases in the U.S. in June and July 2020 surge.

On the other hand, the market average ambiguity of individual stocks remains calm before the CSF holiday, increases significantly after the CSF holidays when the confirmed new cases of COVID-19 surge in February 2020, and declines when the confirmed new cases of COVID-19 in China decrease. Furthermore, the average stock ambiguity in China increases when the confirmed new cases of COVID-19 in the U.S. surge in June and July 2020.

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[8] There was no trading in the China stock market from February 2 to February 10, 2019, or from January 24 to February 2, 2020.

The ambiguity of the market index measures the dispersion of the probability distributions of the average stock returns. In contrast, the average of stock-level ambiguity measures the average dispersion of the probability distributions of each stock returns. The dramatic differences we observed in the movements of these measures imply that the information drives the movements in the average individual stock prices and the average movements of individual stock prices are different. Hence, it is necessary to study both the relationship between the prices and ambiguity of the market index (Brenner and Izhakian, 2018) and the cross-section relationship between stock prices and ambiguity (Li and Zhu, 2020). Furthermore, we do not observe such kind of difference in the movements of market index risks versus the average of stock risks.

The cross-section average of the stock returns and the value-weighted market index return move together as we expect. We find that 20-trading-day returns on average increase significantly after the CSF holidays in 2019 but change little after the CSF holidays in 2020, although the market risks and the cross-section average of stock ambiguity increase significantly. This result is consistent with the findings of Li and Zhu (2020) that the ambiguity premium is negative due to biding short-sale constraints in China. Hence, when both the cross-section average and dispersion of stock ambiguity increase[9] with risks, the impact on the equity premium is ambiguous.

We also find that both the average stock illiquidity and the market index illiquidity increase significantly right after the Chinese Spring Festival holidays in 2020 but decrease in 2019. Wu (2013) and others find mixed evidence on the "Chinese Spring Festival Effect" in the Chinese stocks[10], and there is no consensus. During the Chinese Spring Festival holidays, stock trading is suspended for about ten days. There are usually important monetary policies and economic statistics published before and after the CSF holidays. Hence, some investors prefer to hold cash before the CSF holidays to make better investment decisions after the CSF holidays when new information reduces economic and

[9] The difference between the cross-section mean and median of stock ambiguity increases significantly after the 2020 CSF holidays. We also find the 95% confidence interval of the cross-section stock ambiguity increases significantly after the 2020 CSF holidays. Data is available upon request.

[10] Wu (2013) finds that Chinese ADRs have significantly higher average returns in the week prior to the festival, but lower average returns in the post-festival week than the rest of the year using data from 1993 to 2011.

policy uncertainty, which may explain the improvement of stock liquidity after the CSF holidays in 2019. In 2020, due to the outbreak of COVID-19, the overall uncertainty increased significantly after the CSF holidays, and investors were uncertain about the impact of the COVID-19.[11] When the new confirmed cases surged, and little information was available to gauge the severity of the situation in Wuhan city, Hubei province, the stock illiquidity increased significantly. Later, as more information about the situation in Wuhan city and Hubei province were available, the new confirmed cases declined, the stock liquidity on average improved.

We further investigate the movement in liquidity premium. We find that the value-weighted liquid premium increases significantly as the equity premium in 2019 after the CSF holidays, but the equally-weight liquidity premium does not change much. However, in 2020, the liquidity premium, value-weighted or equally weighted, and equity premium remain the same after the CSF holidays. In the second half of 2020, we find a significant “flight-to-liquidity” phenomenon. The large and liquid stocks outperform the small and illiquid stocks, and the liquidity premium becomes negative.

Our study relates closely to a growing literature on the dynamics of stock prices, economic activity, and policy actions during the COVID-19 pandemic. Davis et al. (2021) comprehensively summarize the related literature and compare about 40 countries. We focus on the China stock market and contribute in several ways: First, we measure the ambiguity or Knightian Uncertainty based on the intraday trading data that are risk-independent and risk-attitude-independent and find that stock ambiguity and risks differ significantly in response to the outbreak of COVID-19 pandemic in China and the U.S. Second, we show that the information contained in the cross-section stock ambiguity and market index ambiguity differs significantly. Third, we find that the equity premium remains unchanged when the market risks and ambiguity increase by 70% and 200% after the outbreak of COVID-19 in China, which may imply that ambiguity and risks are priced differently in the market. Fourth, stock liquidity is closely related to stock ambiguity. Average stock liquidity decreases as the average and dispersion of stock ambiguity increase, and stock liquidity improves as more information is available to reduce the stock ambiguity in the market.

[11] They didn’t even know the name of this new disease.

Lastly, we find a significant “flight-to-liquidity” phenomenon in the China stock market, that is, the equally-weighted (value-weighted) 20-trading-day liquidity premium decline significantly to about –4.42% (–6.48%), during the fourth quarter of 2020 when the COVID-19 is well under control in China, and the stock market attracts more foreign investors who prefer large and liquid stocks.

The rest of the paper is organized as follows. Section 2 describes the data source, construction of stock ambiguity, and other key variables in the empirical analysis. Section 3 presents the results of empirical analysis. Section 4 concludes.

2 Data Construction

This section describes the data source and the methods to construct the stock-level ambiguity, risk, and liquidity in the China stock market.

2.1 Data Sources

Our primary data set is the high-frequency trading data for stocks listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange. We obtain this data set from the Gaotime database[12], which contains complete intraday trading data for all the stocks from February 2007 onward. Our data sample is from July 11, 2018, to December 22, 2020, so that it contains the CSF holidays and half-year period before and after the CSF holidays in 2019 and 2020. In addition, we restrict our analysis to the non-financial and non-Special-Treatment (NST) stocks[13] in the China stock market. After cleaning the data, we have an average of 3,399 stocks during the sample period from July 2018 to December 2020.

2.2 Stock-Level Ambiguity and Market Index Ambiguity

Jurado et al. (2015) employ a large set of macroeconomic and financial variables to estimate the macro and financial uncertainty index (JNL Index) as the variance of the unpredictable component of these variables. Baker et al. (2016) estimate the economic policy uncertainty from newspaper articles and tax code

[12] http://www.gaotime.com

[13] Under the administrative delisting process of Shanghai and Shenzhen Stock exchanges, stocks in danger of being delisted are put in a “special treatment” or “ST” category, and undergo administrative review over a certain time period.

provisions' expiration. Andreou et al. (2014) and Driouchi et al. (2018) estimate market ambiguity using data on the S&P 500 Market Index options. However, all these measures of ambiguity or uncertainty either only measure aggregate-level ambiguity or rely on the option data, which is usually not available at the stock level, especially in China stock market.

As for the stock-level ambiguity, some studies use dispersion in analysts' forecasts (Diether et al., 2002; Doukas et al., 2006; Berkman et al., 2009) as a proxy, Bali et al. (2017) use the correlation between stock returns and the JNL Index to measure the stock-level uncertainty. Izhakian (2020) proposes to measure the ambiguity of stock returns as the dispersion of the probability distributions of daily stock returns, under the assumption that daily stock returns follow Normal distribution with a group of means and variances. Izhakian (2020) builds a theoretical foundation of this measure and shows that this measure is risk independent and risk-attitude independent. Brenner and Izhakian (2018) use high-frequency (5-minute) trading data on the S&P 500 market index to estimate the market-level ambiguity and find that ambiguity is priced in the US stock market.

We apply the Izhakian (2020) method to construct the stock-level ambiguity of each stock and market index based on the high-frequency trading data in the China stock market. Assuming the daily stock return follows normal distributions with ambiguous mean and standard deviation, we use the 5-minute returns in day t to estimate the mean and standard deviation of day-t stock return. Then, we calculate the expected variance of the probability distribution of the daily stock return for each stock or market index over a 20-trading-day window. Finally, the cross-section average of stock ambiguity is computed as the cross-section average of the stock-level ambiguity of each stock in every 20-trading-day window.

We design 20-day intervals and let the 10-day CSF holidays separate two different intervals so that the CSF holidays in 2020 are not in any interval. In China, the government started the lockdown in Hubei and social distancing in the rest of China right before the CSF holidays, during which period the stock market was closed. Therefore, if we followed the conventional approach to estimate the monthly ambiguity, the February data would be messed up with the period before the outbreak of COVID-19 and the period with tremendous uncertainty after the CSF holidays when investors came back to the stock market.

This unique feature allows us to identify the event time, separate the data samples, and study the stock ambiguity, risks, liquidity before and after the outbreak of COVID-19. In particular, we can test whether the ambiguity increases or decreases after investors have learned the measures taken by the government and the latest information about the COVID-19.

2.2.1 Mean and Standard Deviation of Daily Returns

We first estimate the mean and variance of 5-minute returns in each trading day using the high-frequency trading data in the China stock market. Andersen et al. (2001) argue that the 5-minute horizon is short enough to keep track of the fluctuations in the stock price and long enough to reduce the confounding influences from market microstructure frictions, such as discrete clustering of prices and bid-ask bounce effects; Brenner and Izhakian (2018) use 5-minute returns to estimate the ambiguity of the S&P 500 index.

There is a lunch break from 11:30 am to 1:00 pm on each trading day in the China stock market. The morning trading session is between 9:30 am, and 11:30 am, and the afternoon trading session is between 1:00 pm and 3:00 pm. In total, the stock market trades for 4 hours on each trading day.

We exclude the price changes during the lunch break and the overnight break and focus on the ambiguity in the trading hours. We divide the trading session into 48 five-minute intervals per day, involving a series of price records at 50 timestamps. In general, there are 24 5-minute (log) returns in both the morning session (9:30 am–11:30 am) and the afternoon session (1:00 pm–3:00 pm).

If no trading occurs during a 5-minute interval for some inactive stock, then the 5-minute return of that interval will be omitted. We only keep the data on the trading days with more than 14 records of 5-minute returns for each stock. For the market index, there are valid records on all trading days. Then we estimate the mean and variances of the 5-minute returns on each trading day d for each stock or market index using the sample mean (μ_{5min}) and variance (σ^2_{5min}), and normalize as following,

$$\mu_d = n \cdot \mu_{5min}, \sigma^2_d = n \cdot \sigma^2_{5min}, \tag{1}$$

where n is the number of 5-minute returns on each trading day, n is no less than 15 and no more than 48. For most of the observations in our data set, n equals 48.

2.2.2 Stock-Level Ambiguity

We measure the ambiguity of each stock as the expected variance of the probability distributions of the daily stock returns over 20 trading days. Assume the day-*d* stock return follows the normal distribution, with estimates of the mean and standard deviation of the 5-minute stock returns in that day (μ_d, σ_d), we can compute the cumulative probability of (favorable) return on day *d*, that is, the probability of day-*d* return r_d is larger than *x,* as following,

$$Prob\left(r_d \geqslant x\right) = 1 - \Phi\left(x; \mu_d, \sigma_d\right), \textit{for any } x \in \left(-\infty, +\infty\right), \tag{2}$$

where Φ is the cumulative density function of the normal distribution with a mean of μ_d and a standard deviation of σ_d. We divide the range of daily returns $\left(-\infty, +\infty\right)$ into 82 bins to get the discretized (normal) probability density functions.[14] There are 80 bins from –8% to 8%, with an equal width *w* of 0.2%. Apart from these bins, we ao compute the probability of the return lower than –8% and higher than 8%, so there are altogether 82 bins. We calculate the mean ($\hat{E}_t\left[\varphi\left(x_i\right)\right]$) and variance ($\widehat{Var}_t\left[\varphi\left(x_i\right)\right]$) of the probabilities that day-*d* return falls in bin *i* in period *t* as follows:

$$\hat{E}_t\left[\varphi\left(x_i\right)\right] = \begin{cases} \dfrac{1}{n}\sum_{d=1}^{n}\Phi\left(x_0; \mu_d, \sigma_d\right), if\ i = 0 \\ \dfrac{1}{n}\sum_{d=1}^{n}\left[\Phi\left(x_i; \mu_d, \sigma_d\right) - \Phi\left(x_{i-1}; \mu_d, \sigma_d\right)\right], if\ i = 1, \ldots, 80 \\ \dfrac{1}{n}\sum_{d=1}^{n}\left[1 - \Phi\left(x_{80}; \mu_d, \sigma_d\right)\right], if\ i = 81 \end{cases} \tag{3}$$

[14] Brenner and Izhakian (2018) divide the range of daily returns of S&P 500 index into 62 intervals including one bin smaller than -6%, 60 equal bins from -6% to 6%, and one bin larger than 6%. However, as the volatility of individual stocks is usually larger than that of market portfolio and the volatility of the stocks in the China stock market is larger than that of the U.S. stock market, we find it is more reasonable to divide the range from stock returns into 80 intervals from -8% to 8%. The ambiguity estimated using our method has lower variance than using the method of Brenner and Izhakian (2018). Furthermore, the daily price change limit of ±10% started from December 16, 1996, in the China stock market. This regulation is valid for most stocks until now. China allowed the stocks of on the growth enterprise market (GEM) in the Shenzhen Stock Exchange to rise or fall by 20%, up from 10% in August, 2020. For Special Treatment stocks, the price change limit is ±5%. But Special Treatment stocks are excluded from this analysis.

$$\widehat{Var}_t\left[\varphi\left(x_i\right)\right] = \begin{cases} \frac{1}{n-1}\sum_{d=1}^{n}\left(\Phi\left(x_0;\mu_d,\sigma_d\right)-\hat{E}_t\left[\varphi\left(x_0\right)\right]\right)^2, for\, i=0 \\ \frac{1}{n-1}\sum_{d=1}^{n}\left(\Phi\left(x_i;\mu_d,\sigma_d\right)-\Phi\left(x_{i-1};\mu_d,\sigma_d\right)-\hat{E}_t\left[\varphi\left(x_i\right)\right]\right)^2, for\, i=1,\ldots,80 \\ \frac{1}{n-1}\sum_{d=1}^{n}\left(1-\Phi\left(x_{80};\mu_d,\sigma_d\right)-\hat{E}_t\left[\varphi\left(x_{80}\right)\right]\right)^2, for\, i=81, x_{80}=8\% \end{cases} \tag{4}$$

where

$$x_0=-8\%, x_{i+1}=x_i+0.2\%$$

for i = 0, 1, 2,…,79. The ambiguity of stock j in period t, $\mho^2_{t,j}\left[r\right]$, is then computed as the weighted average of the variance of the probabilities in each bin $\widehat{Var}_{t,j}\left[\varphi\left(x_i\right)\right]$, with the weight equal to the mean of the probabilities in each bin ($\hat{E}_{t,j}\left[\varphi\left(x_i\right)\right]$), that is,[15]

$$\mho^2_{t,j}\left[r\right]=\frac{1}{w\left(1-w\right)}\times\sum_{i=0}^{81}\hat{E}_{t,j}\left[\varphi\left(x_i\right)\right]\widehat{Var}_{t,j}\left[\varphi\left(x_i\right)\right]. \tag{5}$$

The sample includes all non-financial, non-ST, A-share stocks. For each stock j, we keep only the intervals with more than 10 records of different trading days to calculate the degree of ambiguity.[16] A newly listed stock would be included in the da from the second month after its IPO.

2.2.3 Market Index Ambiguity

We also compute the ambiguity of the market index and compare it with the cross-section average of stock ambiguity. We use the value-weight returns of stocks in CSI 800 as a proxy for the market index returns. CSI 800 consists of the

[15] Brenner and Izhakian (2018) show that the cumulative probabilities of favorable return $Prob\left(r_d \geqslant x\right)$. are uniformly distributed over the month if the daily ratios of the sample mean and standard deviation, μ_d/σ_d, follow student's t-distribution, which assigns lower weights to values of μ_d/σ_d that deviate from the monthly mean of μ_d/σ_d. They also show that it is better to use the scaling of $1/(w(1-w))$ than $1/(w\ln(1/w))$, as it is analogous to Sheppard's correction and minimizes the effect of the bin size on the vues of the ambiguity measure.

[16] For each stock, we only keep these trading days with more than 14 records of 5-minute returns, and we drop all trading periods that do not have more than 10 days tt satisfy this condition.

top 800 stocks by the total market capitalization. CSI800 is designed to reflect the overall performance of the large-, mid-, and small-cap A-share stocks in the Shanghai and Shenzhen Stock Exchanges. The market value of stocks in CSI 800 is about 70% of all the stocks in the Shanghai and Shenzhen Stock Exchanges, while the share of the profit of stocks in the CSI800 is more than 90% in 2020.

We divide the range of daily returns of CSI 800 into 62 bins to get the discretized (normal) probability density functions. There are 60 bins from –6% to 6%, with an equal width w of 0.2%, and two additional bins with returns lower than –6% and higher than 6%, so there are 62 bins in total. We then calculate the mean ($\hat{E}_t\left[\varphi\left(x_i\right)\right]$) and variance ($\widehat{Var}_t\left[\varphi\left(x_i\right)\right]$) of the probabilities that day-d return falls in bin i in period t. Our choice of bin numbers and bin width is the same as that of Brenner and Izhakian (2018), who estimate the ambiguity of the S&P 500 market index. As the volatility of individual stocks is usually larger than that of the market portfolio, it is reasonable to use a broader range and more bins when computing the ambiguity of individual stocks.

In summary, we use 5-minute returns of each stock to estimate the probability distributions of returns on each trading day and then compute the variance of dispersion of the probability distributions of daily returns over each 20-trading-day period to measure the ambiguity of each stock.

2.3 Stock Risk and Liquidity Measure

We measure the risks of stocks as the conventional standard deviation of daily stock returns in the given period (20 trading days). The underlying assumption of this conventional risk measure is that all daily returns in the same period follow a unique distribution with the mean estimated by the sample mean and the variance by the sample variance.

The risk of stock i in period t, $Risk_{i,t}$ does not rely on the high-frequency trading data; the risk measure is computed as the standard deviation of daily returns in the 20-trading-day period, that is,

$$Risk_{i,t} = \sqrt{\frac{1}{N_{i,t}-1}\sum_{d=1}^{N_{i,t}}(r_{i,d} - \overline{r}_{i,t})^2} \tag{6}$$

where $N_{i,t}$ and $\overline{r}_{i,t}$ are the numbers of trading days, and the sample mean of daily returns for stock i in the 20-trading-day period t, respectively.

We use the Amihud (2002) illiquidity ratio as the stock liquidity measure. The

Amihud measure is defined as the average ratio of the absolute daily stock return to the daily trading volume, reflecting the price impact of a monetary unit of trade:

$$ILLIQ_{i,t} = \frac{1}{N_{i,t}} \sum_{d=1}^{N_{i,t}} \frac{|r_{i,d}|}{Volume_{i,d}}, \tag{7}$$

$$MarketILLIQ_t = \frac{1}{M_t} \sum_{i=1}^{M_t} ILLIQ_{i,t} \tag{8}$$

where $|r_{i,d}|$ and $Volume_{i,d}$ are the absolute value of the return and the trading volume of stock *i* on day *d*, $N_{i,t}$ is the number of trading days for stock *i* in the 20-trading-day period *t*, M_t is the number of stocks in the 20-trading-day period *t*.

3 Empirical Analysis and Results

To test the impact of the COVID-19 pandemic on the stock ambiguity, risk, liquidity, and equity premium, we separate the sample periods based on the CSF-holiday schedule in 2019 and 2020, then compute the stock ambiguity and other variables over the 20-trading-day window. As there is no trading during the CSF holidays in 2020, when the lockdown in Hubei and the nationwide social distancing took place, our approach effectively investigates the influence of the outbreak. We also identify the differences between the ambiguity and the risks and the differences between the cross-section average of stock ambiguity and market index ambiguity.

3.1 Stock Market Before and After COVID-19

We test the significance of the changes in the market index and cross-section mean and median of the ambiguity, risk, liquidity, and return before and after the Chinese Spring Festival in 2019 and 2020.

The first column of Table 1 shows that the cross-section mean (median) of stock ambiguity increases by 0.782 (0.35), both economically and statistically significant, about 3 (13) times of the increase in 2019. In addition, the 95% confidence interval of the cross-section stock ambiguity also increases dramatically. Hence, both the average and dispersion of the cross-section stock ambiguity increase significantly after the outbreak of COVID-19 during the

Chinese Spring Festival holidays in 2020. However, the market index ambiguity *decreases* significantly by 0.587 in 2020, double the decrease in 2019. The market index ambiguity measures the ambiguity in the market index return, which is the value-weighted average returns of stocks in the market index. Since the ambiguity measures the dispersion in the probability distributions of the daily stock returns, our findings imply that the ambiguity about the average stock returns and the average of stock ambiguity convey different information about the uncertainty regarding the stock market. The market index is a value-weighted

Table 1 Summary Statistics (2018/07–2020/12)

		Ambiguity	Risk	Illiquidity	Return
Cross-section mean		0.536***	0.027***	0.045***	0.011
		–11.397	–27.21	–12.968	–0.861
Cross-section median		0.186***	0.024***	0.034***	–0.005
		–10.092	–23.863	–13.539	(–0.416)
Market index		0.574***	0.013***	0.039***	0.012
		–11.073	–14.281	–10.392	–1.218
Difference in mean before and after CSF	2019	0.243	0.002	–0.025	0.263***
		–0.879	–0.31	(–1.441)	–2.784
	2020	0.782***	0.017***	0.048***	–0.016
		–2.829	–2.784	–2.814	(–0.174)
Difference in median before and after CSF	2019	0.027	0.002	–0.018	0.237**
		–0.217	–0.283	(–1.592)	–2.593
	2020	0.350***	0.018***	0.031**	–0.027
		–2.819	–2.774	–2.628	(–0.297)
Difference in market index before and after CSF	2019	–0.216	0.009	–0.005	0.131*
		(–0.885)	–1.505	(–0.416)	–1.868
	2020	–0.587**	0.013**	0.01	–0.02
		(–2.408)	–2.126	–0.837	(–0.287)

Note: Ambiguity, Liquidity, Risk, and Return are the full-sample time-series average of the market index and cross-section mean or median of the stock ambiguity, liquidity, return volatility, and returns in each 20-trading-day window, respectively. The difference in the market index and mean (median) before and after CSF is the difference between each variable in the 20-day-trading windows before and after the Chinese Spring Festival Holiday in 2019 and 2020. The t-statistics are given in parentheses. *** stands for significant at 1%, ** stands for significant at 5%, * stands for significant at 10%.

portfolio of all the stocks, and the ambiguity of the market index measures the systematic ambiguity, with idiosyncratic information about individual stocks averaged out. On the other hand, the stock-level ambiguity contains information about both the systematic and individual-stock ambiguity.

The second column of Table 1 shows that both the market index risks and the cross-section average of stock risks increase in 2019 and 2020 after the CSF holidays. The market index risks and the cross-section mean (median) of stock risks increase in 2020 by 1.3% and 1.7% (1.8%), respectively, both economically and statistically significant, and about 1.4 and 9.0 (9.8) times of the increase in 2019. Comparing Column 1 and Column 2 in Table 1, we find that Izhakian's (2020) measure of stock ambiguity is fundamentally different from the conventional measure of stock risks, as Knight (1921) suggests. Izhakian's (2020) measure of stock ambiguity allows us to extract the information in the intraday trading, which is missing in the daily returns.

The third column of Table 1 shows that both the market index liquidity and the cross-section average of stock liquidity improve in 2019 but deteriorate in 2020, after the CSF holidays, while only the change in the cross-section average of stock liquidity in 2020 is significant. Hence, in 2020, the cross-section average of stock risks and ambiguity increases, and individual stocks are more illiquid on average. On the other hand, for the market index, its risk increases, ambiguity decreases, and the liquidity does not change significantly.

In the fourth column of Table 1, we test the changes in the 20-trading-day market index returns and the cross-section average of the stock returns after the CSF holidays. The changes in market index returns and the average (mean) of stock returns are the same as expected, and neither changed significantly in 2020. However, the equity premium increases significantly in 2019 after the CSF holidays when none of the stock ambiguity, risks, or liquidity changes significantly. The significant changes in the equity premium in 2019 after the CSF holidays are worth further investigation but are not the focus of this paper.

We focus on the insignificant change in equity premium in 2020. Hansen and Sargent (2021) show that equity premium contains both risk premium and ambiguity premium. Li and Zhu (2020) find that the ambiguity premium is negative in the China stock market due to binding short-sale constraints, while the conventional risk premium is always positive. Hence, when both market risks and ambiguity increase after the outbreak of COVID-19 during the CSF holidays, the change in the equity premium is ambiguous.

Table 2 presents the time-series correlation between the average stock ambiguity, market index ambiguity, average stock risks, average stock returns,[17] average stock illiquidity, market index illiquidity, and the confirmed new cases in China and the U.S. Consistent with what we find in Table 1, the market average ambiguity negatively correlates with the market index ambiguity. The market risks correlate positively (negatively) with the market average ambiguity (market index ambiguity). The market index illiquidity and the average illiquidity correlate positively with the market average ambiguity and risks, negatively with the market index ambiguity. Furthermore, the market average ambiguity, risks, and illiquidity positively correlate with the number of new cases confirmed in China.

Table 2 Correlation Coefficient Matrix after Chinese Spring Festival in 2020

	Average ambiguity	Market index ambiguity	Average risk	Average illiquidity	Market index illiquidity	Average return	New cases in China
Market index ambiguity	–0.791***						
	(–3.872)						
Average risk	0.917***	–0.767***					
	(6.901)	(–3.586)					
Average illiquidity	0.410	–0.160	0.640**				
	(1.350)	(–0.485)	(2.497)				
Market index illiquidity	0.685**	–0.523*	0.748***	0.547*			
	(2.822)	(–1.841)	(3.377)	(1.962)			
Average return	0.043	–0.212	0.091	–0.304	–0.218		
	(0.130)	(–0.650)	(0.275)	(–0.958)	(–0.672)		
New cases in China	0.552*	–0.357	0.729**	0.915***	0.394	–0.098	
	(1.987)	(–1.146)	(3.195)	(6.817)	(1.286)	(–0.295)	
New cases in the US	–0.470	0.276	–0.493	–0.365	–0.574*	–0.278	–0.320
	(–1.597)	(0.861)	(–1.699)	(–1.178)	(–2.103)	(–0.867)	(–1.014)

Note: The sample period is from February 3, 2020, to December 22, 2020. The *t*-statistics are given in parentheses. *** stands for significant at 1%, ** stands for significant at 5%, * stands for significant at 10%.

[17] As shown in Figure 3 and Figure 4, the movements in the market index risks (return) and the cross-section average stock risks (returns) are about the same, so we only include the cross-section average stock risks (returns) in the correlation calculation.

Next, we investigate the dynamics of stock ambiguity, risks, liquidity, and equity premium before and after the COVID-19 outbreak in China in 2020.

3.2 Dynamics of Stock Ambiguity and Risks

We first study the time series of the stock ambiguity and risks in each before and after the COVID-19 outbreak. In Figure 3, the yellow bars indicate the non-trading periods during the Chinese Spring Festival holidays. Panel A of Figure 3 shows that the cross-section average of the stock ambiguity increases after the Chinese Spring Festival in both 2019 and 2020, while the increase is more than tripled and statistically significant in 2020. From March to June, the market average ambiguity decreases as the confirmed new cases in China decrease due to the strict and effective social distancing. From July to September, the market average ambiguity increases when the pandemic was already under control in China, but the confirmed new cases in the U.S. surged. Besides, the cross-section variation in the stock-level ambiguity is much higher during these high-ambiguity periods. On the contrary, the market index ambiguity increases significantly before the CSF holidays in 2020 and drops significantly after the CSF holidays. From March to June, the market index ambiguity increases when the market average ambiguity decreases. These dramatic differences imply that the information drives the movements in the average individual stock prices and the average movements of individual stock prices are different.

Panel B of Figure 3 shows that the cross-section mean and median of stock-level and market index risks move together. Both measures of market risks increase right after the CSF holidays, while the increase in 2020 is much larger and significant. Comparing Panel B with Panel A, we find that apparently, the ambiguity of the index is different from the conventional measure of risks. The ambiguity of the market index increases significantly before the CSF holidays and drops significantly after the CSF holidays, while the market index risks increases after the CSF holidays.

Figure 4 depicts the cross-section average of stock return and the value-weighted market index (CSI 800) returns from mid-2018 to 2020, which move together as expected. The equity premium surges on average after the CSF holidays in 2019. However, in 2020, the equity premium changes little when both the market risks and the cross-section average of stock ambiguity increase significantly.

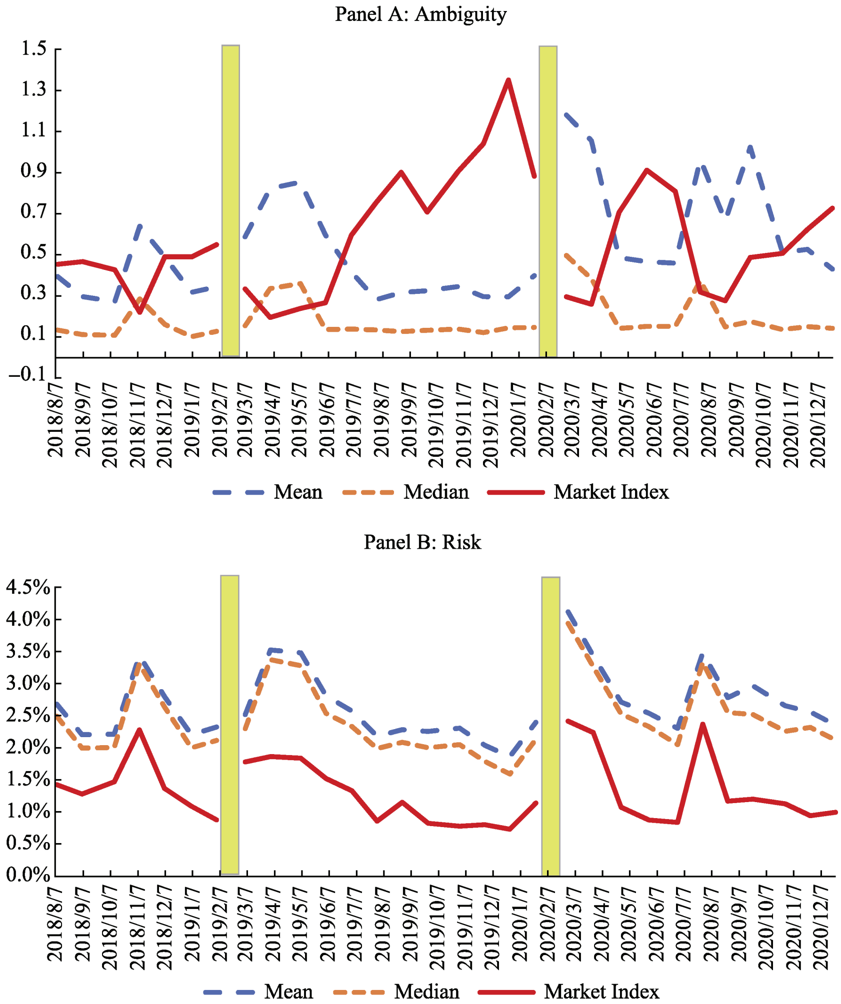

Figure 3 Stock Ambiguity and Stock Risk

Note: In both panels, the yellow bars indicate the non-trading periods during the Chinese Spring Festival Holiday. In Panel A, the dotted and dashed line depicts the cross-section median and mean, respectively, of the stock-level ambiguity, the solid line depicts the ambiguity of the market index. In Panel B, the dotted and dashed lines depict the cross-section median and mean, respectively, of the stock-level risk, the solid line depicts the risk of the market index.

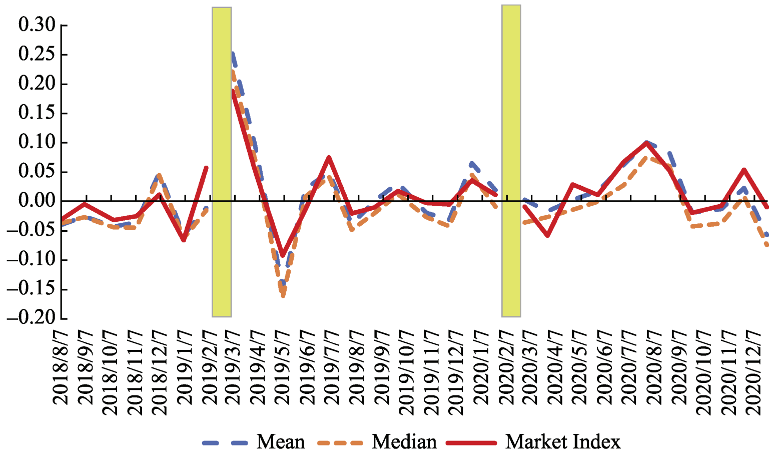

Figure 4 Cross-Section Average of Stock Return and Market Index Return

Note: The yellow bars indicate the non-trading periods during the Chinese Spring Festival Holidays. The dashed and dotted lines depict the cross-section mean and median of 20-trading-day stock returns, respectively. The solid line depicts the 20-trading-day returns of the market index.

Figure 5 depicts the market average ambiguity and the number of daily new COVID-19 cases in China and the U.S. The market average ambiguity increased dramatically after the CSF holiday in 2020 when confirmed new cases surged in China. It then gradually decreased to the pre-pandemic level in May and June when the number of new cases in China was low. From July to September 2020, the market average ambiguity in China increases again when the confirmed new cases in the U.S. surge.

Figure 6 presents the CSI 800 index ambiguity and the number of daily new COVID-19 cases in China and the U.S. The market index ambiguity increases from September to early December 2019, about two months before the outbreak of COVID-19 is confirmed in China. It then declines before the CSF holidays and drops after the CSF holiday. The market index ambiguity increases from March to June 2020 when the confirmed new cases in China decrease, but the COVID-19 starts in Europe and the U.S. The market index ambiguity declines when the confirmed new cases in the U.S. in June and July 2020 surge.

It seems that the market index ambiguity “predict” the outbreak of the COVID-19 in China and in the U.S 2–3 month in advance. However, we should also note that during in the fourth quarter of 2019, the election in the U.S. and the trade friction between China and the U.S. drive up the uncertainty globally, while from March to June, the uncertainty regarding the COVID-19, monetary and fiscal policies are possible driving forces of the ambiguity in the stock market.

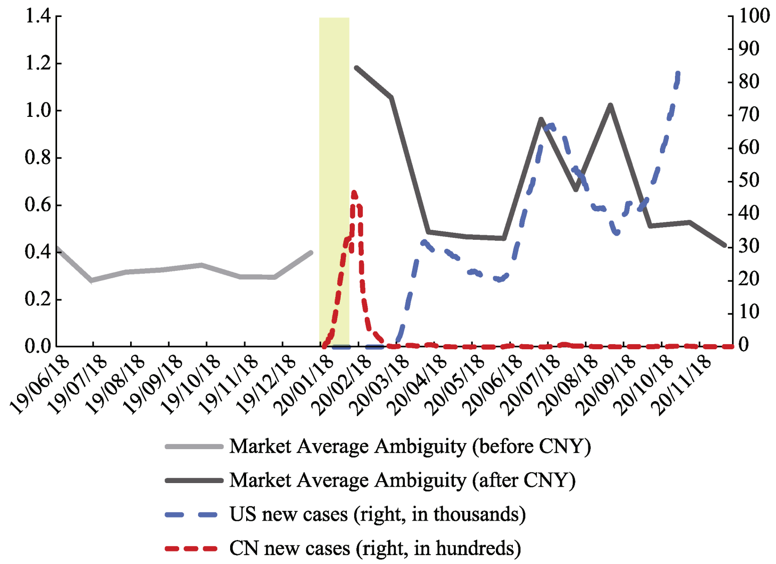

Figure 5 Cross-Section Average Stock Ambiguity and Confirmed New COVID-19 Cases, 2019/06–2020/12

Note: The yellow bar indicates the non-trading periods during the Chinese Spring Festival Holidays in 2020. The dotted and dashed lines depict the sum of confirmed new cases of COVID-19 in the 20-trading-day periods in China and the U.S., respectively. The solid line depicts the cross-section average of the stock ambiguity.

3.3 Structural Breaks in Stock Ambiguity

We use the Bai-Perron test to detect structural changes in the stock ambiguity. Bai and Perron (1998, 2003) propose to test possible breaks in a time series sequentially. First, we test the null hypothesis of no structural break against five breaks. Then, if we reject this null hypothesis, we keep testing the null hypothesis of m structural breaks against m+1 breaks until we cannot reject the null hypothesis.

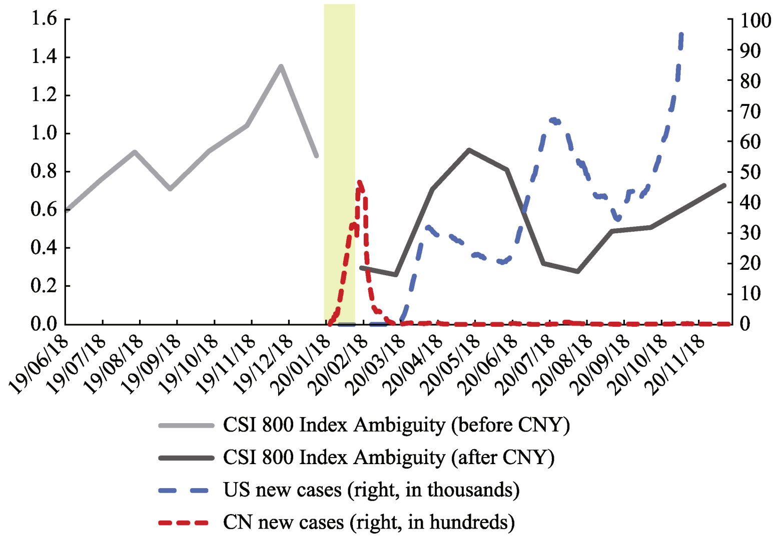

Figure 6 Market Index Ambiguity and Confirmed New COVID-19 Cases, 2019/06–2020/12

Note: The yellow bar indicates the non-trading periods during the Chinese Spring Festival Holidays in 2020. The dotted and dashed lines depict the confirmed new cases of COVID-19 in the 20-trading-day periods, respectively. The solid line depicts the market index ambiguity.

Table 3 shows the results of the Bai-Perron tests. We find two breakpoints in the time series of the cross-section average ambiguity and no structural break in the time series of market index ambiguity. For the market average ambiguity, the first break occurs at the start of the outbreak of COVID-19, from 2019/12/26 to 2020/01/23. This result implies that the stock prices in the China stock market respond quickly to the uncertainty regarding a possible pandemic before the official announcement of the outbreak of COVID-19 and lockdown in Wuhan. Thus, the stock ambiguity measure provides a systematic way to extract information from the vast high-frequency trading data of each stock.

3.4 Impact of COVID-19 on Stock Liquidity

Lastly, we investigate the impact of COVID-19 on stock liquidity. Figure 7 depicts the market average illiquidity and the liquidity of CSI 800, along with the index return from July 2018 to December 2020. We find that both the market average illiquidity and the market index illiquidity increased immediately after the outbreak of COVID-19 during the CSF holidays in 2020. Furthermore, both measures of market liquidity improve from March 2020 onwards when the COVID-19 is under control in China. The deterioration of stock liquidity at the start of the outbreak of the COVID-19 implies that investors are very uncertain about the impact of COVID-19 right after the Chinese Spring Festival holidays.

Table 3 Bai-Perron Test of Structural Breaks in the Stock Ambiguity

Break test	Test statistics	Critical value for significance level 5%	Breakpoint	Break Yes or No
Panel A: Cross-section mean of stock ambiguity				
0 vs [1,5]	11.53	8.88	2019/12/26–2020/01/23	Yes
0 vs 1	12.81	8.58	2019/12/26–2020/01/23	Yes
1 vs 2	11.63	10.13	2019/12/26–2020/01/23, 2020/08/25–2020/09/21	Yes Yes
2 vs 3	9.05	11.14		No
Panel B: Market index ambiguity				
0 vs [1,5]	7.22	8.88		No
0 vs 1	6.35	8.58		No

Note: In Panel A, we test whether there is a structural break in the cross-section mean of the stock-level ambiguity in each 20-trading-day window. In each row, we test whether there are 1, 2, or 3 breaks. The periods in which there is a break are listed in the Breakpoint column. In Panel B, we test whether there is a structural break in the ambiguity of the market index (CSI 800). We test whether there is one break.

In China, trading in the stock market is usually suspended for about ten days during the CSF holidays. In addition, there are usually important monetary policies and economic statistics published before and after the CSF holidays. Therefore, some investors prefer to hold cash before the CSF holidays to avoid economic and policy uncertainty, which may explain the improvement of stock liquidity after the CSF holidays in 2019. However, in 2020, due to the pandemic, the overall uncertainty increases significantly after the CSF holidays, and investors are clueless about the impact of the COVID-19. With a surge of confirmed cases and little information to forecast the situation in Hubei, the stock illiquidity increases significantly. Later, when the number of confirmed new cases declined during late February and March 2020 and the uncertainty about the pandemic gradually resolved, the stock liquidity on average improved.

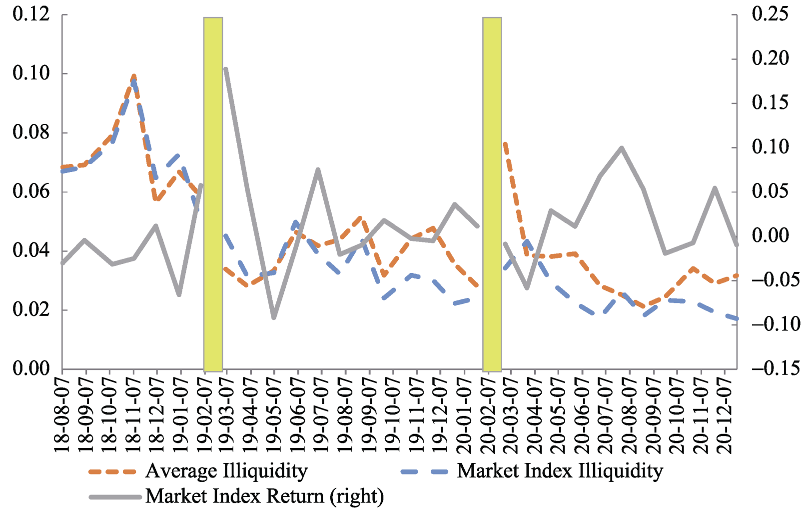

Figure 7 Stock Illiquidity and Market Index Return

Note: The yellow bars indicate the non-trading periods during the Chinese Spring Festival Holidays. The dotted and dashed lines depict the cross-section average of 20-trading-day stock illiquidity and the market index illiquidity, respectively. The solid line depicts the 20-trading-day returns of the market index.

We further investigate the impact of COVID-19 on the liquidity premium. We construct ten portfolios based on the three-month Amihud Illiquidity using the non-ST and non-financial stocks in June each year. The portfolios at rebalanced annually. We exclude the stocks with the Amihud measure in the extreme 1% of observations in the three months from April to June of that year. Then we measure the liquidity premium as the 20-trading-day return spread between the most illiquid portfolio (Portfolio 10) and the most liquid portfolio (Portfolio 1).

Figure 8 shows the monthly value-weighted and equally-weighted liquidity premium from January 2018 to December 2020. We find that the value-weighted liquid premium increases significantly as the equity premium in 2019 after the CSF holidays, but the equally-weighted liquidity premium does not change much. However, in 2020, the liquidity premium and the equity premium remain the same after the CSF holidays.

More importantly, we find a significant "flight-to-liquidity" phenomenon in the stock market in China after July 2020. The liquidity premium declines, and returns of liquid stocks are even higher than that of illiquid stocks in the last quarter of 2020. The equally-weighted (value-weighted) 20-trading-day liquidity premium declined significantly to about –4.42% (–6.48%) during the fourth quarter of 2020.

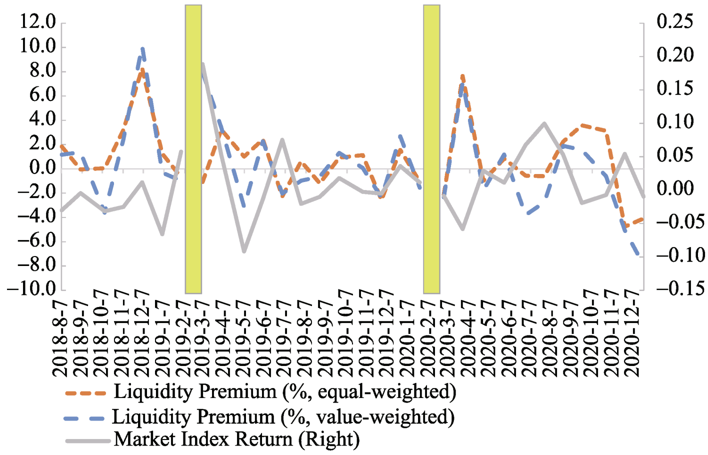

Figure 8 Liquidity Premium and Market Index

Note: The yellow bars indicate the non-trading periods during the Chinese Spring Festival Holidays. The dotted and dashed lines depict the equally- and value-weighted liquidity premium, respectively. The solid line depicts the 20-trading-day returns of the market index.

We conjecture that this “flight-to-liquidity” phenomenon is partly related to the complete openness of the financial market to the world starting April 1, 2020, based on the agreement between China and U.S. signed in January 2020. China is relatively in good shape during the second half of 2020 after the lockdown in the first half of 2020, so foreign investors may increase their investment in the China stock market. As foreign investors prefer large liquid stocks, the prices of these stocks are driven up by the surge in demand. At the same time, the revision of the Security Law was effective as of March 1, 2020, so the changes in policies and uncertainty about the COVID-19 in the world make it difficult to pinpoint precisely the cause of the decrease in the liquidity premium.

4 Conclusion

In this paper, we study the impact of the COVID-19 on the stock ambiguity, risks, liquidity, and stock prices in China stock market, before and after the outbreak of the COVID-19 pandemic in China around the Chinese Spring Festival in 2020.

We measure the stock ambiguity by the dispersion in the probability distribution of the daily stock returns estimated from the intraday trading data, using the method proposed by Izhakian (2020), and measure the stock liquidity using the Amihud (2002) liquidity measure.

We find that the average stock ambiguity, risks, and illiquidity increase significantly after Chinese Spring Festival holidays in 2020, but the market index ambiguity decreases. At the same time, the equity premium and liquidity premium change little. The market index ambiguity contains different information about the market uncertainty, and the stock risks and ambiguity are fundamentally different. The market average ambiguity increases with the number of confirmed new cases in China and in the U.S. The market average stock ambiguity and risks decrease, and stock liquidity improves to pre-pandemic levels as the pandemic is under control in China.

We also find a significant “flight-to-liquidity” phenomenon, and the equally-weighted (value-weighted) 20-trading-day liquidity premium declined significantly to about –4.42% (–6.48%) during the fourth quarter of 2020.

Our results contribute to growing literature on the dynamics of stock prices, economic activity, and policy actions during the COVID-19 pandemic period. We focus on the China stock market, as the outbreak of COVID-19 is confirmed right before the Chinese Spring Festival holidays, when there is no trading in the stock market. We thus separate the trading days based on the Chinese Spring Festival holiday schedule in 2019 and 2020 and compute the stock ambiguity over the 20-trading-day window to design clean tests of the impact of COVID-19 on the stock market.

In addition, our findings that the ambiguity and (conventional) risks respond differently to the COVID-19 outbreak, and cross-section average of the stock ambiguity moves differently from the market index ambiguity, imply that ambiguity measure provides us a systematic method to extract information from the high-frequency trading data. Furthermore, the equity premium and liquidity premium change little when the market average risks, ambiguity, and illiquidity increase significantly, implying that the risks and ambiguity are priced differently in the stock market, and both positive risk premium and negative ambiguity premium are important components of the equity premium.

Acknowledgments Nan Li acknowledges financial support from the National Natural Science Foundation of China (No. 72073097) and Antai College of Economics and

Management, Shanghai Jiao Tong University.

References

Amihud Y (2002). Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets, 5(1): 31–56

Anderson R, Karim M, Li N, Reeb D (2020). Ambiguity about return volatility and the family firm ownership puzzle. Working Paper

Andersen T G, Bollerslev T, Diebold F X, Ebens H (2001). The distribution of realized stock return volatility. Journal of Financial Economics, 61(1): 43–76

Andreou, P C, Kagkadis, A, Maio, P F, Philip, D (2014). Stock market ambiguity and the equity premium. Working Paper, Durham University

Bai J, Perron P (1998), Estimating and testing linear models with multiple structural changes. Econometrica, 66: 47–78

Bai J, Perron P (2003). Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18: 1–22

Bali T G, Brown S J, Tang Y (2017). Is economic uncertainty priced in the cross-section of stock returns? Journal of Financial Economics, 126(3): 471–489

Baker S R, Bloom N, Davis S J (2016). Measuring economic policy uncertainty. The Quarterly Journal of Economics, 131(4): 1593–1636

Berkman H, Dimitrov V, Jain P C, Koch P D, Tice S (2009). Sell on the news: Differences of opinion, short-sales constraints, and returns around earnings announcements. Journal of Financial Economics, 92(3): 376–399

Brenner M, Izhakian Y (2018). Asset pricing and ambiguity: Empirical evidence. Journal of Financial Economics, 130(3): 503–531

Davis S J, Liu D, Sheng X S (2021). Stock prices and economic activity in the time of Coronavirus. NBER Working Paper, No. 28320

Diether K B, Malloy C J, Scherbina A (2002). Differences of opinion and the cross section of stock returns. Journal of Finance, 57(5): 2113–2141

Doukas J A, Kim C, Pantzalis C (2006). Divergence of opinion and equity returns. The Journal of Financial and Quantitative Analysis, 41: 573–606

Driouchi T, Trigeorgis L, So R H (2018). Option implied ambiguity and its information content: Evidence from the subprime crisis. Annals of Operations Research, 262(2), 463–491

Ellsberg D (1961). Risk, ambiguity, and the savage axioms. Quarterly Journal of Economics, 75, 643–669

Epstein L G, Ji S (2013). Ambiguous volatility and asset pricing in continuous time. Review of Financial Studies, 26 (7): 1740–1786

Guidolin M, Rinaldi F (2013). Ambiguity in asset pricing and portfolio choice: A review of the literature. Theory Decision, 74: 183–217

Hansen L P, Sargent T J (2010). Fragile beliefs and the price of uncertainty. Quantitative

Economics, 1(5): 129–162

Hansen L P, Sargent T J (2021). Macroeconomic uncertainty prices when beliefs are tenuous. Journal of Econometrics, 223(1): 222–250

Izhakian Y (2020). A theoretical foundation of ambiguity measurement. Journal of Economic Theory, 187: 105001

Jurado K, Ludvigson S C, Ng S (2015). Measuring uncertainty. American Economic Review, 105(3): 1177–1216

Kang W, Li N, Zhang H (2019). Information uncertainty and the pricing of liquidity. Journal of empirical finance, 54: 77–96

Knight F M (1921). Risk, Uncertainty and Profit. Boston, MA: Houghton Mifflin

Li N, Zhu Y (2020). The pricing of stock ambiguity and short-sale constraints in China. Working Paper

Peng S (2006). G-Expectation, G-Brownian motion and related stochastic calculus of Ito's type. Working Paper, arXiv:math/0601035

Wu C (2013). The Chinese New Year holiday effect: Evidence from Chinese ADRs, Investment Management and Financial Innovations, 10(2): 8–14