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Trading without meeting friends: Empirical evidence from the wuhan lockdown in 2020

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ABSTRACT

Using a unique proprietary dataset of daily mutual fund trading records and the COVID-19 pandemic-triggered lockdown in Wuhan (China) as a natural experiment, we find that individual mutual fund investors in Wuhan significantly reduced their daily trading frequency, total investment of their portfolios, and risk level of their invested funds during the lockdown period as compared to investors in other cities. The results suggest that the elimination of face-to-face interaction among individual investors during the lockdown reduced their information sharing, which led to more conservatism in their financial trading. We rule out alternative explanations of salience bias due to limited investor attention and temporary changes in personal circumstances such as depression and/or income reduction, during the lockdown period. Finally, consistent with the theory of naïve investor trading, we also find that investors received higher trading returns during the lockdown as they reduced trading aggressively in the absence of face-to-face interactions.

1. Introduction

Social interactions play a crucial role in shaping investors' trading behavior by influencing their beliefs, perceptions, emotions, and decisions. These interactions often amplify herding behavior, where decision-makers tend to follow others (Banerjee, 1992; Bikhchandani et al., 1998). The financial economics literature has extensively examined how social interactions impact trading behavior through mechanisms such as information sharing, social learning, herding, and emotional contagion (Heimer, 2016; Kaustia and Rantala, 2015; Noorderhaven and Harzing, 2009; Pool et al., 2015). However, prior studies have largely treated social interactions as a single, undifferentiated concept, without exploring the distinct effects of face-to-face (henceforth, F2F) versus digital communications. This paper aims to fill that gap by exploiting the Wuhan (China) lockdown from January to April 2020 as a natural experiment, using a difference-in-differences (DID) framework to investigate how these two modes of communication affect investors' trading behavior.

The influence of F2F interactions on investors' trading behaviour operates through two key channels: richer information and enhanced social capital. F2F communication conveys not only verbal content but also non-verbal cues such as facial expressions and tone, allowing investors to assess credibility and sincerity more effectively than digital platforms (Daft & Lengel, 1986). Real-time feedback in F2F settings further reduces uncertainty, facilitating better-informed decisions (Bushee, Jung, & Miller, 2011). In addition, F2F interactions build social capital by fostering trust, reciprocity, and emotional engagement, creating stronger obligations and accountability among investors (Coleman, 1988; Nahapiet & Ghoshal, 1998). In contrast, social media, while useful for quick exchanges, remains more transactional and less personal, limiting its ability to cultivate long-term cooperative networks (Antweiler & Frank, 2004). Social media platforms such as Twitter, Facebook or WeChat have deeply penetrated the mechanics of everyday life over the past decade and greatly changed the norms of social interactions. While the gap in the "richness" of digital and F2F communications has been reduced over time, the differences between them still remain significant as F2F interactions help in developing trust and stronger social relationships (Urry, 2003; Storper and Venables, 2004).

We base our predictions on the theories related to the impact of social interactions on investors' trading behaviour and conjecture that F2F interactions has more significant impact than digital communication. F2F communication helps to reduce information cost barriers to stock

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market participation and leads to more frequent trading and higher investments (Hong et al., 2004, 2005; Georgarakos and Pasini, 2011; Kaustia and Torstila, 2011; Bushee et al., 2011; Mayew and Venkatachalam, 2012; Peng et al., 2021; Changwony et al., 2015). Consequently, the increased social engagement as a result of F2F interactions leads to increased social capital and common behaviour, as suggested by the herding behaviour literature, and investors tend to imitate the trading strategies of successful investors, whose higher returns are often associated with higher risk-taking behaviour (Apesteguia et al., 2020). Hence, we conjecture that investors with F2F interactions are more aggressive than their counterparts with little access to F2F interactions in terms of trading volume, frequency, and risks. The counterargument can be that the recent development of digital communications or social media means that investors rely little on F2F interactions, and we should not find any significant differences in their trading behaviour in the absence of F2F interactions. Hence, we try to explore these questions in our paper using the natural experiment of COVID-19 pandemic--triggered lockdown.

Wuhan experienced the world's first lockdown due to COVID-19 pandemic, from 23 January to 8 April 2020. The Chinese central government decided to isolate Wuhan, where COVID-19 had broken out, by locking it down from the outside world. Wuhan is the most populous city in Central China and is also the capital and biggest city of Hubei province, with a population of more than 11 million people. All forms of public transport, such as buses, trains, and planes, were stopped during the lockdown, including the Wuhan airport, railway station, and metro. The authorities did not allow Wuhan residents to exit the city without permission. Only stores that sold essential goods, such as food items and medicine, remained open, while all others were closed. The roads were empty and silent as private vehicles needed special authorization to drive around. At first, people could leave their homes, but soon they had to stay indoors as the restrictions became stricter. Some areas allowed one family member to go out every two days to buy necessities, while others required residents to stay home and order food and other necessary items through delivery services. This was the first time in history that such large number of people were locked down for about three months. The consequence of such a lockdown meant that there were no F2F interactions at all among anyone except the household members living together. We exploit the location of investors to generate variation in the treatment effect and hence, use investors located in Wuhan as our treatment group and investors in other cities constitute the control group in our DID setting.

Using a unique proprietary dataset on individual investors and their comprehensive daily mutual fund trading records from a large Chinese NY brokerage company, we find that investors in Wuhan significantly reduced their daily trading frequency, the total investment of their portfolio, and the risk profile of their invested funds during the lockdown period as compared to investors in other cities. These results support our hypothesis that investors become more conservative in their trading behaviour after the disruption of information sharing with peer investors during the lockdown period due to elimination of F2F interactions. We use extensive data at the individual investor-level to account for three set of fixed effects. First, we eliminate any potential concern that our main results may be influenced by unobservable and unchanged investor characteristics, such as trading behaviour differences across gender (Barber and Odean, 2001; Niederle and Vesterlund, 2007; Beck et al., 2013), by using individual investor fixed effects. Second, we capture all possible economic and market changes that occurred at the national- and international- levels that can drive our main results by using daily fixed effects. For instance, Huber et al. (2021) find that, in their controlled experiment, professional participants significantly reduce their investment during the COVID-19 market crash period. Third, we use mutual fund company fixed effects to account for possible characteristics at the mutual fund level. For example, investors may expose themselves to higher risks during the lockdown period if they hold mutual funds with companies which have higher risk-taking attitude. Our results are also robust to an alternative definition of control group that includes other cities in the same province as Wuhan (Hubei province), as the whole Hubei province experienced a more serious COVID-19 situation than the rest of China in early phases of the pandemic (Lau et al., 2020).

Also, as Wuhan was experiencing the highest level of lockdown with little F2F interactions as compared to other parts of China due to the severity of pandemic, this consequently impacted the F2F interactions to different levels in different regions. Hence, following Au et al. (2023), we use an alternative measure of treatment classified as "*hotspot* cities" based on the number of COVID-19 cases. We define *hotspot* cities as the ones that have at least 2,000 cumulative COVID-19 cases reported by April 8, 2020. We expect that investors located in hotspot cities were more negatively impacted by the restrictions of the lockdown, and hence, affected their trading behaviours. Our analysis supports this conjecture.

We then provide some indirect evidence to support our main argument. We expect that a senior (or retired) investor would depend more on F2F interactions than a younger investor who are more familiar with various technology-supported electronic communication platforms, e.g., WeChat. Therefore, we predict that a senior or retired investor would experience more significant changes in trading behaviour during the lockdown period than their younger counterparts. Our results also confirm this prediction.

Next, we investigate whether our main results can be explained by salience bias, where investors overweight salient information when making investment decisions (Kahneman and Tversky, 1973; Grether, 1980; Seasholes and Wu, 2007; Bordalo et al., 2012, 2013). At the beginning of the Wuhan lockdown, fear and anxiety spread rapidly among residents, especially within Wuhan.[1] These effects were overwhelming and it is likely that investors were drawn to the COVID-related statistics and non-salient information such as stock market performance were neglected, which resulted in more conservative trading behaviour during the lockdown.[23] We test this salience hypothesis by utilizing the Baidu Search Index to quantify search volumes for each fund name by investors in different locations. The empirical analysis reveals a significant decline in fund-related searches by Wuhan residents during the lockdown period as compared to the residents in other cities, highlighting reduced investor attention. However, we do not find any subsequent significant impact of this reduced investor attention on their trading behaviour in Wuhan during the lockdown period as compared to investors in other cities. Overall, these results provide limited support for the argument related to salience bias and investor attention as a key driver of the observed trading behaviour during the Wuhan lockdown.

Further, we also explore other possible explanations for our main findings besides the F2F interaction arguments. The lockdown in Wuhan could have also affected other aspects of investors' personal lives, such as depression or temporary changes in income and employment, etc., which can also discourage participation in the financial markets. For instance, previous studies have shown that workers who face a higher risk of income loss are less likely to invest in the stock market (Catherine et al., 2022), and that people's financial risk-taking is negatively influenced by their personal experiences of macroeconomic shocks (Malmendier and Nagel, 2011). These personal aspects are different from F2F interactions, as they tend to worsen as the period of lockdown

[1] Fear may include, but not limited to, fear of the unknown (the transmission and severity of the new virus), fear of shortages, fear of being trapped, fear of overwhelmed healthcare, fear of infection in hospital, fear of misinformation, and fear for loved ones, among others.

[2] Au et al. (2023) shows social interaction spread fear about COVID-19 disease among institutional investors and reduce their trading.

[3] Literature has mixed findings on retail investors' trading behavior during the COVID-19 lockdown (see Barber et al., 2022; Ozik et al., 2021; Welch, 2022; Glossner et al., 2022, among others).

Table 1
Definitions of variables.

Variables	Definition
Dependent variables	
Trading frequency	Daily trading frequency of individual investors
Investment	Natural logarithm of net amount invested by individual investors in mutual funds
Fund risk	The mutual funds are classified into five categories according to their risk level by the fund management company: low, low to median, median, median to high, and high. We therefore construct an index to capture the fund risk, ranging from one (lowest risk) to five (highest risk).
Trading return	The holding period return (adjusted by risk level of the fund) from the fund purchasing date to the date when the fund is sold.
Search	Baidu Search Index, which is obtained by calculating the number of daily searches for specific keywords of the fund by the investors in different cities
Explanatory variables	
Treat	A dummy that takes the value of one if the investor lives in Wuhan, and zero for investors living in other cities in China.
Hotspot	A dummy variable which equals to one if the investor lives in cities that have atleast 2,000 cumulative COVID-19 cases reported by April 8, 2020.
Lockdown	A time dummy which takes the value of one for the lockdown period from 23 January 2020 to 8 April 2020, and zero for the pre-lockdown period from 4 September 2019 to 22 January 2020.
Post lockdown	A time dummy variable which takes the value of one for the post-lockdown period from 8 April 2020 to 21 July 2020, and zero for the period 23 January 2020 to 7 April 2020.
Old	A dummy variable that takes the value of one if investors are over the age of 60 years, and zero otherwise.

increases; for example, as income may decline and depression may rise. If these personal aspects are the main drivers of our results, we expect a downward trend in trading for individual investors during the lockdown period. However, this trend cannot be easily reversed immediately after the lockdown is lifted, as it takes time for businesses to recover and for people to overcome anxiety and depression. Our results do not support this alternative explanation, as we find that trading frequency, investment, and fund risk increases back to pre-lockdown levels shortly after the lockdown ends, with no significant differences between the treated and control groups.

Finally, we explore the impact on realized trading returns and find that individual investors' realized trading returns increased during the lockdown period compared to the non-lockdown period. This result is consistent with the literature on naïve investor trading about how naïve investors, upon receiving more information, become overconfident, trade aggressively and speculatively, reduce their trading profits and transfer more wealth to well-informed investors (Barber and Odean, 2000; Bloomfield et al., 1999; Smith, 2010; Langnickel, 2018; Eyster et al., 2019; Han et al., 2022). There is also evidence that this trading aggressiveness by naïve investors is greatly exacerbated by social interactions and connectedness (Hong et al., 2004, Kaustia and Knüpfer, 2012).

The remainder of this paper is organized as follows: In Section 2, we mention the theoretical framework, research hypothesis and contributions of the paper. Section 3 discusses the data and summary statistics. In Section 4, we describe our empirical methodology and present the empirical results with their robustness tests. In Section 5, we report the results of various alternative explanations, and Section 6 provides the empirical findings on trading returns of investors during the lockdown. Finally, Section 7 provides the conclusion and policy implications.

2. Theoretical framework, research hypothesis and contributions

2.1. Theoretical framework

This section outlines the two primary economic channels through which F2F interactions influence investor behaviour more effectively than other communication mediums, such as social media. These channels are: (1) the richness of information conveyed during F2F interactions, and (2) the enhancement of social capital through trust, reciprocity, emotional engagement, and enforcement of social norms. Each of these factors play a crucial role in shaping the decision-making processes of investors.

F2F interactions are considered the richest form of communication due to their ability to convey not only verbal content but also non-verbal cues, which provide additional context and depth to information exchanges. This richness influences investor behaviour through three specific mechanisms: First, in F2F settings, investors gain access to non-verbal cues such as facial expressions, gestures, eye contact, and tone of voice, all of which contribute to a more nuanced understanding of information (Daft & Lengel, 1986). These cues help investors to assess the confidence, sincerity, and credibility of their counterparts, leading to better-informed decisions. Social media interactions, in contrast, lack this non-verbal dimension, making it harder for participants to fully interpret the intent or reliability behind the messages.

Second, the real-time nature of F2F communication allows for immediate feedback, enabling participants to clarify misunderstandings or probe deeper into specific details on the spot. This dynamic exchange of information leads to greater clarity and reduces uncertainty in decision-making (Bushee, Jung, & Miller, 2011). By comparison, social media interactions often involve delays in response or less direct feedback, which can limit the quality and timeliness of the information exchanged (Antweiler & Frank, 2004).

Third, F2F interactions often take place in more controlled, private environments, facilitating the sharing of sensitive or proprietary information. Investors are more willing to disclose valuable insights during in-person meetings, where the risk of unintended exposure is lower compared to online forums or social media platforms (Burt, 2000). The private nature of F2F discussions can lead to more actionable and high-quality trading decisions, as investors exchange information with greater confidence.

In addition to the richness of information, F2F interactions significantly enhance social capital, which plays a crucial role in shaping cooperative behaviours and trust within investor networks. This enhancement occurs through following key mechanisms: First, F2F interactions help in building trust through personal connections and accountability. Trust is more effectively built in F2F settings through repeated personal interactions, where individuals observe each other's behaviours and develop a sense of reliability (Coleman, 1988). Furthermore, F2F interactions create a stronger system of accountability, as the physical presence of peers increases the pressure to follow through on commitments and act in good faith (Granovetter, 1985). In contrast, social media interactions allow for greater anonymity and less accountability, reducing the strength of trust built through these platforms (Antweiler & Frank, 2004).

Second, F2F interactions help in fostering reciprocity, which is a key component of social capital. In-person exchanges create stronger social obligations to return favours or share information, as the effort and personal investment involved in F2F communications reinforce mutual obligations (Burt, 2000). On the other hand, social media, while facilitating exchange, tends to be more transactional and less personal, weakening the long-term reciprocity that sustains cooperative investor networks (Nahapiet & Ghoshal, 1998).

Third, F2F interactions facilitate deeper emotional engagement, allowing investors to share and respond to each other's emotional states, which influences risk-taking behaviours (Kaustia & Knüpfer, 2012). This

Table 2
Summary statistics.

	Full Sample (N = 199,112)		Pre-lockdown Treated group (N = 1,445)		Pre-lockdown Control group (N = 120,134)		Pre-lockdown Diff	Lockdown Treated group (N = 935)		Lockdown Control group (N = 78,978)		Lockdown Diff
	Mean (1)	Std (2)	Mean (3)	Std (4)	Mean (5)	Std (6)	(7)	Mean (8)	Std (9)	Mean (10)	Std (11)	(12)
Trading frequency	7.0306	8.5096	5.6459	3.0154	7.5711	8.5507	-1.9252***	4.2470	3.6445	6.8651	6.0510	-2.6181***
Investment	7.7252	3.5444	8.5715	2.9654	8.4219	2.9377	0.1496	6.3226	3.6361	7.3517	4.3029	-1.0291***
Fund risk	1.4565	0.8722	1.4885	0.8938	1.5252	0.7792	-0.0367	1.3363	1.1561	1.4964	0.9974	-0.1600***
Search	55.4549	54.5424	135.4391	28.6090	60.5005	55.6173	74.9386***	118.5757	22.2539	48.3131	42.1847	70.2626***

This table reports the descriptive statistics for all variables used in the regression analysis. *Treated group* is a dummy variable which equals one if the investor lives in Wuhan, and zero for investors living in other cities of China. *Lockdown* is a dummy variable which equals one if the investment transaction was made during the period of lockdown from 23 January 2020 to 8 April 2020, and zero for the pre-lockdown period from 4 September 2019 to 22 January 2020. *Trading frequency* measures the daily mutual fund trading frequency of an investor, *investment* is measured as the natural logarithm of net amount invested by individual investors in mutual funds, and *fund risk* is measured by an index capturing the riskiness of funds ranging from one (lowest risk) to five (highest risk). Detailed definitions of variables are provided in Table 1. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % level, respectively.

emotional contagion aligns investors' sentiments, leading to coordinated trading strategies, whether in times of optimism or caution (Heimer, 2016). Additionally, the physical presence in F2F settings reinforces social norms more directly. The immediacy of social feedback—whether approval or disapproval—creates a powerful mechanism for enforcing norms of trustworthiness and cooperation (Ostrom, 2000). Social media, by comparison, offers more flexibility for individuals to navigate between groups or disengage from feedback, making it harder to enforce such norms consistently.

2.2. Hypothesis development

The previous financial economics literature combines F2F and digital interactions when studying the impact of social interactions on investors' investment/trading behaviour. Some authors (e.g., Brown et al., 2008; Hong et al., 2004, 2005; Ivković and Weisbenner, 2007) study how F2F interactions with neighbours, friends, communities, and families generate social capital, while other studies (such as Antweiler and Frank, 2004; Barber and Odean, 2008; Da et al., 2011; Amman and Schaub, 2020) mainly focus on digital interactions through social platforms and trading forums. Steiger and Pelster (2020) have made some efforts to distinguish between the two different communications, but within a laboratory setting. Such rare evidence of experiments is not surprising because these two modes of social interactions are empirically difficult to separate. It is also difficult to imagine a setting where an investor can exclusively utilize either F2F or virtual interactions but not both. Hence, in this paper, we aim to tackle this empirical challenge and provide the first empirical evidence on how (the elimination of) F2F interactions can have an impact on investors' daily trading behaviour using the COVID-19 pandemic-triggered lockdown in Wuhan (China) as a natural experiment.

The richer information provided by F2F interactions—through verbal and non-verbal signals, immediate feedback, and access to sensitive information—enables investors to gain deeper insights into the credibility and confidence of the information source. This enhanced understanding encourages investors to trade in larger positions and engage in trades more frequently due to the greater clarity and reliability of the information they receive. Additionally, the social trust established in F2F interactions fosters bolder investment decisions. When investors trust the information and believe the group shares a common risk tolerance, they are more inclined to take riskier positions. F2F interactions also create opportunities for emotional engagement, which can lead to emotional contagion and herd behaviour, resulting in coordinated trading strategies that amplify both risk-taking and trading frequency. Moreover, the obligation to act on information shared by trusted peers further increases the likelihood of more frequent trading and riskier decisions. In summary, F2F interactions influence investor behaviour which leads to more informed, coordinated, and confident trading decisions as investors benefit from clearer communication, stronger trust, and a deeper sense of accountability and reciprocity. Based on the above theoretical discussion, we frame the following hypothesis:

Hypothesis 1. The elimination of F2F interactions significantly reduces daily trading frequency, total amount of investments, and investments in risky funds by the investors in Wuhan during COVID-19 lockdown period as compared to investors in other cities.

2.3. Contributions to the literature

Our study examines the economic role of social interactions in financial decision-making, which ties into broader theories on information asymmetry, market participation, and behavioural finance. It adds to the literature by isolating the impact of F2F interactions from digital communications, emphasizing the importance of non-verbal cues, trust, and reciprocity in financial behaviour. Our empirical findings support the hypothesis that investors in Wuhan become more conservative in their trading behaviour after the disruption of information sharing during the lockdown period as compared to investors in other cities. Concurrent papers by Bai and Massa (2022) and Lee (2023) examine mutual fund managers' trading behaviour during the pandemic-triggered lockdown in the US and exploit variation in social interactions driven by COVID-19 lockdowns. Our paper differs from these papers as we examine individual investors' trading behaviour during the lockdown, but our conclusions are similar that investors (individual or institutional) become less aggressive in the stock market during the lockdown period. Also, what differs in our findings is that individual investors tend to (partially) withdraw from participation in the market and invest in less risky funds, while institutional investors tend to hold more passive and diversified portfolios to reduce fund risks.

Our paper also contributes to the debate over the reasons for naïve investors' excessive trading in the financial markets (French, 2008). It may be because they are overconfident in their judgement of public information (Scheinkman and Xiong, 2003) or the precision of their private information (Daniel et al., 1998; Odean,1998). It is also likely that they may also downplay the precision of other investors' private signals (Odean, 1998; Banerjee et al., 2009; Banerjee and Kremer, 2010; Banerjee, 2011). Another reason can also be that they are "cursed" when they do not fully appreciate what prices convey about others' private information and hence, tend to rely more on their own signals than on market signals (Eyster et al., 2019). Our findings tend to be consistent with this "cursed" model, because investors tend to rely more on the "private" information through F2F interactions, be it material information or trading strategies, than the signals through market prices, in their trading.

Table 3
Baseline regression.

	Trading frequency (1)	Investment (2)	Fund risk (3)	Trading frequency (4)	Investment (5)	Fund risk (6)
*Treat*Lockdown*	-0.4761***	-0.1862**	-0.1300***	-0.5040***	-0.1769*	-0.0835***
	(0.090)	(0.085)	(0.023)	(0.093)	(0.102)	(0.025)
Lockdown	-0.2236**	0.0793	-0.2452***	-	-	-
	(0.090)	(0.085)	(0.023)			
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Daily FE	No	No	No	Yes	Yes	Yes
Fund Company FE	Yes	Yes	Yes	Yes	Yes	Yes
N	198,728	199,112	198,728	198,728	199,112	198,728
R-squared	0.521	0.391	0.663	0.563	0.401	0.676

This table reports the estimations for difference-in-differences regressions using individual, daily, and fund company fixed effects. The dependent variables are *Trading frequency*, measuring the daily mutual fund trading frequency of an investor; *Investment*, measured as the natural logarithm of net amount invested by individual investors in mutual funds; and *fund risk*, which is measured by an index capturing the riskiness of funds ranging from one (lowest risk) to five (highest risk). We use the enactment of lockdown in January 2020 in Wuhan when the COVID-19 pandemic first broke as a quasi-natural experiment. *Treat* is a dummy variable which equals one if the investor lives in Wuhan, and zero for investors living in other cities of China. *Lockdown* is a dummy variable which equals one if the investment transaction was made during the period of lockdown from 23 January 2020 to 8 April 2020, and zero for the pre-lockdown period from 4 September 2019 to 22 January 2020. The heteroscedasticity robust standard errors are clustered at the city level and are shown in parentheses. Detailed definitions of all variables are provided in Table 1. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % level, respectively.

Our research provides empirical evidence that confirms the findings from existing management and communication literatures that, despite the increased use of digital communications in the past decade, F2F human interactions, being a richer communication medium with superior clarity and engagement, is still most effective for complex and high-stakes interactions, especially in the context of student learning (Yuan and Wu, 2020), consultation in health care, international relations (Holmes, 2020), and work productivity (Morikawa, 2022), etc. Our paper also adds depth to the literature on behavioural finance that incorporates psychological and social factors into traditional financial theories. This aligns with the works of Kahneman (2011) and Thaler and Sunstein (2008), expanding on how non-economic factors, such as emotional and psychological comfort, affects financial decision-making.

3. Data and summary statistics

3.1. Data

The unique proprietary dataset used in this study comes from Jinniu Financial Management Company [4], a large Chinese online brokerage company controlled by China Securities Journal, which is a national securities newspaper sponsored by Xinhua News Agency and authorized by the China Securities Regulatory Commission to disclose information related to listed companies. We acquire individual investors' information and comprehensive daily mutual fund trading records from this platform. The investors are anonymized, and only partial ID numbers are provided for each trading record. However, we are still able to identify general information about investors from their incomplete ID numbers, including their age, gender, and household register. To remove potential outliers, we winsorize observations at the 1 % level from upper and lower tails of the distribution for all variables used in the regression models. Hence, our final dataset contains 199,112 daily trading records of 17,562 investors over 839 mutual funds issued by 64 fund management companies over the sample period of 4 September 2019 to 21 July 2020, including the Wuhan lockdown period from 23 January to 8 April 2020.

We also incorporate data from the Baidu Search index. Most Chinese Internet users use Baidu, which is a search engine like Google. Data such as the number and regional distribution of certain keywords searched by Chinese users will be reflected through the Baidu Search index. The Baidu Search index allows us to collect data about user searches. The data collected from the Baidu Search index is standardized, and we collect data from different geographic regions covering our sample period. To examine Chinese people's attention to mutual fund investment, we choose fund names as search keywords from 4 September 2019 to 21 July 2020. Finally, we collect the data of number of COVID-19 cases from CSMAR dataset to classify cities into COVID hotspots and non-hotspots. We provide the definitions of all variables used in our regression models in Table 1.

3.2. Summary statistics

Table 2 reports descriptive statistics for the main variables of interest. We report mean and standard deviation for the whole sample (column 1), the treated (Wuhan) and control groups (all other places in China) before the lockdown (columns 2 and 3, respectively), and during the lockdown (columns 5 and 6). We also report p-values for testing the equality of means between the treated and control groups (columns 4 and 7). To begin with, we find no significant difference in investment amount and fund risk between the investors in Wuhan and investors in other cities, while the trading frequency is lower in Wuhan than in other cities in the pre-lockdown period. However, during the lockdown, trading frequency, investment amount, and fund risk significantly declined among the investors in Wuhan compared to other investors. In the following sections, using a formal regression analysis based on a DID model, we explore the impact of lockdown during the COVID-19 pandemic on investors' trading behaviour.

4. Empirical methodology and findings

4.1. Lockdown and investor behaviour

We begin our empirical analysis by investigating the impact of lockdown during the COVID-19 pandemic on investor behaviour. The empirical strategy employed in this paper is a DID methodology as it estimates the true impact of an exogenous intervention which is widely used in the economics and finance literature (Angrist and Krueger, 2001, Wooldridge, 2010). Since, it is not obvious a priori whether an intervention is expected to have any impact, the DID method exposes the treatment group to the intervention and leaves the control group out of the intervention. The intervention is then considered to have a significant impact if there are differences in outcomes between the treatment and control groups, which occur between pre-treatment and post-treatment periods. In our setting, DID methodology is more appropriate as it is well-suited to estimate the effects of COVID-19 lockdown on the investors located in Wuhan as compared to investors in other cities. The COVID-19 lockdown is a unique window for our

[4] The website of the company is http://www.jnlc.com.

Table 4
Alternative control group.

	Trading frequency (1)	Investment (2)	Fund risk (3)
Treat Lockdown*	-0.3085***	-0.0494***	-0.0119***
	(0.023)	(0.004)	(0.001)
Individual FE	Yes	Yes	Yes
Daily FE	Yes	Yes	Yes
Fund Company FE	Yes	Yes	Yes
N	10,322	10,268	10,322
R-squared	0.761	0.474	0.901

This table reports the estimations for difference-in-differences regressions using individual, daily, and fund company fixed effects. The dependent variables are *Trading frequency*, measuring the daily mutual fund trading frequency of an investor; *Investment*, measured as the natural logarithm of net amount invested by individual investors in mutual funds; and *fund risk*, which is measured by an index capturing the riskiness of funds ranging from one (lowest risk) to five (highest risk). We use the enactment of lockdown in January 2020 in Wuhan when the COVID-19 pandemic first broke as a quasi-natural experiment. *Treat* is a dummy variable which equals one if the investor lives in Wuhan, and zero for investors living in non-Wuhan cities but in the Hubei province. *Lockdown* is a dummy variable which equals one if the investment transaction was made during the period of lockdown from 23 January 2020 to 8 April 2020, and zero for the pre-lockdown period from 4 September 2019 to 22 January 2020. The heteroscedasticity robust standard errors are clustered at the city level and are shown in parentheses. Detailed definitions of all variables are provided in Table 1. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % level, respectively.

study as this event was a sudden exogenous shock to the economy that caused unprecedented fear and movements in the financial markets, creating a rare opportunity to examine investment behaviour associated with lockdown and elimination of F2F interactions.

We consider the daily trading behaviour of investors by focusing on their trading frequency, total investments in mutual funds, and risk preference. *Trading frequency* captures the daily mutual fund trading frequency of an investor, and *investment* is measured as the natural logarithm of the net investment amount of individual investors in mutual funds. *Fund risk* is measured by constructing an index that captures the riskiness of funds, ranging from one (lowest risk) to five (highest risk).[5] The estimated model is the following:

$$Trading\ behaviour_{ift} = a_0 + a_1 Treat_{ic} * Lockdown_t + \mathscr{X}_f + \gamma_i + \delta_t + \epsilon_{ift}, \quad (1)$$

where $i = 1, 2, \ldots, N$ refers to the cross-section of investors trading fund f, in city c, at daily time-frequency t. *Treat* is a dummy that takes the value of one if the investor lives in Wuhan, and zero for investors living in other cities in China[6]. *Lockdown* is a time dummy which takes the value of one for the lockdown period from 23 January 2020 to 8 April 2020, and zero for the pre-lockdown period from 4 September 2019 to 22 January 2020.[7] The main variable of interest is the coefficient of '$Treat * Lockdown$', which captures the impact of the lockdown period on investor behaviour in Wuhan as compared to investors in other cities. We estimate the above models using individual investor (γ_i) fixed effects to control for unobserved heterogeneity at investor level, such as gender. Next, we control for mutual fund company ($\mathscr{X}_f$) fixed effects to capture characteristics at the mutual fund company level, such as risks associated with certain high-risk mutual funds. Finally, we include daily (δ_t) time-fixed effects to account for possible economic and market changes occurring on a daily-basis at both national and international levels, such as changes in stock market volatility, and we cluster the standard errors at city level.

The empirical results of Eq. (1) are reported in Table 3. We report the results for *trading frequency* (columns 1 and 4), *investment* (columns 2 and 5), and *fund risk* (columns 3 and 6) by including different fixed effects that strengthen our identification in the subsequent columns of Table 2. We find a negative and significant impact of the lockdown on trading frequency and risk preference of investors as captured by the variable '*Lockdown*' in columns 1-3, indicating investors on average became more conservative in their daily financial trading during the lockdown period as compared to the pre-lockdown period. What is more interesting is that we find that the coefficients of our main variable of interest '$Treat * Lockdown$' show a negative and significant effect on the dependent variables, suggesting that during the lockdown, investors in Wuhan reduced their daily trading frequency, total amount of investments in mutual funds, and investments in risky mutual funds as compared to investors in other cities. The economic magnitudes of the interacted coefficients in columns 4-6 suggest that during the lockdown, trading frequency reduced by 7.2 % in terms of the sample mean, the total investment amount declined by 16.3 %[8], and investments in risky mutual funds reduced by 5.7 % in terms of sample mean for investors in Wuhan as compared to investors living in other cities. These coefficients are statistically significant at the 1 % level of significance, except investment amount, which is significant at the 10 % level. Hence, these results support our hypothesis 1 that during the lockdown, investors become more conservative in their daily trading behaviour in Wuhan due to the disruption of information sharing with peer investors and the elimination of F2F interactions as compared to investors in other cities.

4.2. Alternative measure of control group

It could be argued that our results are sensitive to the construction of the control group, which consists of investors living in other cities in China other than Wuhan. Hence, we use an alternative definition of control group for robustness that includes other cities in the same province as Wuhan (Hubei province), as the whole Hubei province experienced a more serious COVID-19 situation than the rest of China. This allows us to control for any bias that may exist between the treatment and control groups due to different government policies and macroeconomic environments across different regions during the lockdown period. The empirical results for these estimations are provided in Table 4, and they are consistent with our main results, which are also statistically significant at the 1 % level. Hence, our results are robust to an alternative definition of control group.

4.3. Alternative measure of treatment

While Wuhan was experiencing the highest level of lockdown with little F2F interactions, other parts of China were experiencing different levels of lockdown based on the severity of pandemic, which consequently impacted F2F interactions to different levels in different regions. To check whether our results are robust to an alternative measure of treatment, we use the number of COVID-19 cases to classify cities into

[5] The China Securities Regulatory Commission requires fund management companies to explicitly show the risk level of each mutual fund to investors, from low (Rating 1) to high (Rating 5). In principle, money market funds are classified as 1, pure bond funds are classified as 2, mixed bond-stock funds with a low percentage of shares in stocks are classified as 3, mixed bond-stock funds with a high percentage of shares in stocks are classified as 4, and pure stock funds are classified as Rating 5.

[6] Our results are also robust to an alternative control group that includes other cities in the same province as Wuhan (Hubei province). These results are reported in Table 4.

[7] We exclude the data from 9 April 2020 onwards for these regressions.

[8] The economic magnitudes in Table 3 are calculated as follows: the average trading frequency is 7.03, and the DID coefficient is -0.504 (column 4). Dividing the coefficient of -0.504 with mean 7.03 shows a decline of 7.2% in trading frequency. Further, since the total investment is measured in log form and the DID coefficient is -0.1769 (column 5), the magnitude is calculated as $e^{-0.1769} - 1 = -0.1629$ which shows a decline of 16.3% in total investment.

Table 5
Alternative measure of treatment.

	Trading frequency (1)	Investment (2)	Fund risk (3)	Trading frequency (4)	Investment (5)	Fund risk (6)
*Hotspot*Lockdown*	-0.1158**	-0.2216**	-0.1910**	-0.4153***	-0.1898**	-0.0647**
	(0.046)	(0.102)	(0.082)	(0.026)	(0.087)	(0.029)
Lockdown	-0.2151**	-0.1411	-0.1717***	-	-	-
	(0.107)	(0.124)	(0.038)			
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Daily FE	No	No	No	Yes	Yes	Yes
Fund Company FE	Yes	Yes	Yes	Yes	Yes	Yes
N	198726	198728	197557	198726	198728	197559
R-squared	0.795	0.370	0.897	0.815	0.417	0.899

This table reports the estimations for difference-in-differences regressions using individual, daily and fund company fixed effects. The dependent variables are *Trading frequency* measuring the daily mutual fund trading frequency of an investor; *Investment* measured as the natural logarithm of net investment amount of individual investors in mutual funds; and *fund risk* which is measured by an index capturing the riskiness of funds ranging from 1 (lowest risk) to 5 (highest risk). We use the enactment of lockdown in January 2020 in Wuhan when the COVID-19 pandemic first outbreak as quasi-natural experiment. *Hotspot* is a dummy variable which equals to one if the investor lives in cities that have atleast 2,000 cumulative COVID-19 cases reported by April 8, 2020. *Lockdown* is a dummy variable which equals to one if the investment transaction made during period of lockdown from January 23rd of 2020 to April 8^{th} of 2020, and zero for the pre-lockdown period from 4 September 2019 to 22 January 2020. The heteroscedasticity robust standard errors are clustered at the city level and are shown in parentheses. *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively.

COVID hotspots and non-hotspots. Following Au, Dong and Zhou (2023), we define COVID hotspot cities as the ones that have at least 2,000 cumulative COVID-19 cases reported by April 8, 2020. Thus, *hotspot* is a dummy variable that takes value one when the investor is located in a hotspot city, and zero otherwise. We estimate the following model to study the trading behaviour of investors in COVID-19 hotspots during the lockdown:

$$\textit{Trading behaviour}_{ift} = a_0 + a_1 \textit{Hotspot}_{ict} * \textit{Lockdown}_{\ell} + \mathscr{X}_f + \gamma_i + \delta_t + e_{if\ell}, \tag{2}$$

The empirical results of Eq. (2) are reported in Table 5. The main variable of interest '*Hotspot* $*$ *Lockdown*' shows a negative and significant effect on the dependent variables, suggesting that during the lockdown investors located in COVID-19 hotspots reduced their daily trading frequency, total amount of investments in mutual funds, and investments in less risky mutual funds as compared to investors in non-hotspot cities. Given that COVID-19 lockdown is more salient in cities with significantly higher cases and deaths, the results show that investors in these cities become much more conservative in their trading than investors in non-hotspot cities. Hence, these results also support our main findings that during the lockdown, investors living in COVID-19 hotspot cities became more risk-averse due to the elimination of F2F interactions and reduced their daily trading behaviour.

4.4. Indirect evidence of F2F interactions

The findings above provide suggestive evidence for the hypothesis that elimination of F2F interactions during the lockdown would result in more conservative behaviour by investors. Although we do not have a direct measure for F2F interactions in our dataset, we provide some indirect evidence to strengthen this explanation. We argue that older (or retired) investors are more dependent on F2F and social interactions than younger investors who rely more on technology-supported electronic communication platforms such as WeChat. There is a wide literature that studies how social networks have a contingent effect on individual's decision to participate in the stock markets (Li, 2014; Hong et al., 2004), which can vary across gender, age, wealth, and education of individuals. Empirical evidence confirms that ownership of risky assets among older investors is positively associated with the size of their social network (Ostrovsky-Berman and Litwin, 2019). Hence, following this argument, we expect older (or retired) investors to experience more significant changes in trading behaviour during the lockdown period than their younger counterparts due to disruption of F2F interactions. We test this hypothesis by constructing a dummy variable, *Old*, that takes the value of one if investors are over the age of 60 years, and zero otherwise. We then interact this dummy with our main DID coefficient and estimate a difference-in-difference-in-differences (DDD) model as provided in the following model-

$$\begin{aligned}\textit{Trading behaviour}_{ift} = {} & a_0 + a_1 \textit{Old}_{ift} * \textit{Treat}_{ic} * \textit{Lockdown}_{\ell} + a_2 \textit{Old}_{ift} \\ & * \textit{Lockdown}_{\ell} + a_3 \textit{Treat}_{ic} * \textit{Lockdown}_{\ell} + \mathscr{X}_f + \gamma_i \\ & + \delta_t + e_{if\ell},\end{aligned} \tag{3}$$

We report the estimation results of Eq. (3) in Table 6. The main variable of interest is the coefficient of the triple interaction term '*Old* $*$ *Treat* $*$ *Lockdown*', which shows that old (or retired) investors in Wuhan are more likely to reduce their daily *trading frequency, investment*, and *fund risk* during the lockdown period as compared to their younger peers (coefficients of -1.668, -1.783, and -0.078, respectively). In terms of economic magnitude, an old investor over the age of 60 years in Wuhan during the lockdown period on average reduces trading frequency by 24 % in terms of sample mean, investment amount by 83.2 %, and investments in risky funds by 5.5 % in terms of sample mean as compared to a younger investor located in a different city during the pre-lockdown period. Hence, these results confirm that the disruption of F2F interaction negatively affects the trading behaviour of older investors more than the younger investors.

5. Alternative explanations

The results reported in the previous section suggest more conservative behaviour by investors in Wuhan during the lockdown period than investors in other cities. We argue that this is because of the elimination of F2F interaction, which reduces information sharing, among investors. This section explores other possible explanations that can also influence these results. First, we test whether the results are driven by salience bias due to limited attention among the investors. Second, we test to what extent our results are driven by the fact that the lockdown may result in changes in personal circumstances, such as depression, employment termination, income reduction, etc.

5.1. Salience bias

One possible explanation for the conservative behaviour of investors in Wuhan during the lockdown can be explained by salience theory,

Table 6
Indirect evidence of F2F interactions.

	Trading frequency (1)	**Investment** (2)	**Fund risk** (3)
*Old * Treat*Lockdown*	-1.6677***	-1.7825***	-0.0777***
	(0.357)	(0.274)	(0.025)
*Old * Lockdown*	0.0854	0.1445	0.0053
	(0.318)	(0.265)	(0.021)
*Treat * Lockdown*	-0.7799***	0.6408***	0.0069
	(0.133)	(0.087)	(0.007)
Individual FE	Yes	Yes	Yes
Daily FE	Yes	Yes	Yes
Fund Company FE	Yes	Yes	Yes
N	198,728	199,112	198,728
R-squared	0.816	0.419	0.899

This table reports the estimations for difference-in-differences regressions using individual, daily, and fund company fixed effects. The dependent variables are *Trading frequency*, measuring the daily mutual fund trading frequency of an investor; *Investment*, measured as the natural logarithm of net amount invested by individual investors in mutual funds; and *fund risk*, which is measured by an index capturing the riskiness of funds ranging from one (lowest risk) to five (highest risk). *Treat* is a dummy variable which equals one if the investor lives in Wuhan, and zero for investors living in other cities in China. *Lockdown* is a dummy variable which equals one if the investment transaction was made during the period of lockdown from 23 January 2020 to 8 April 2020, and zero for the pre-lockdown period from 4 September 2019 to 22 January 2020. *Old* is a dummy variable that takes the value of one if investors are over the age of 60 years, and zero otherwise. The heteroscedasticity robust standard errors are clustered at the city level and are shown in parentheses. Detailed definitions of all variables are provided in Table 1. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % level, respectively.

which is based on agents' paying more attention to the salient attributes/states (Seasholes and Wu, 2007; Bordalo et al., 2012, 2013). As the COVID-19 lockdown created an unprecedented fear and increase in pandemic attention, it is likely to have intensified salient prospects of illness, death, or economic ruin among investors resulting in suboptimal and conservative investment decisions during this period especially among investors in Wuhan which were at the epicentre of this pandemic outbreak as compared to investors in other cities.

We investigate this potential explanation by conducting the following analysis. We create a variable '*search*' using the Baidu Search Index[9], which is obtained by calculating the number of daily searches of specific keywords of the fund by investors in different cities. We start by studying the impact on mutual fund searches by investors in Wuhan as compared to investors in other cities by estimating a DID model as provided in Eq. (4). Next, we estimate a DDD model by interacting the *'search'* variable with '*Treat*' and '*lockdown*' dummies as provided in Eq. (5)-

$$Search_{ift} = a_0 + a_1 Treat_{ic} * Lockdown_t + \mathscr{X}_f + \gamma_i + \delta_t + \varepsilon_{ift}, \tag{4}$$

$$\begin{aligned} Trading\ behaviour_{ift} = {} & a_0 + a_1 Search_{ift} * Treat_{ic} * Lockdown_t \\ & + a_2 Search_{ift} * Lockdown_t + a_3 Treat_{ic} * Lockdown_t \\ & + a_3 Search_{ift} * Treat_{ic} + a_4 Search_{ift} + \mathscr{X}_f + \gamma_i + \delta_t \\ & + \varepsilon_{ift}, \end{aligned} \tag{5}$$

We report the estimation results of Eqs. (4) - (5) in Table 7. In column 1, we provide the estimations for Eq. (4). We find a significant decline in fund-related searches by Wuhan residents during the lockdown period as compared to residents in other cities, as suggested by the negative and significant coefficient of '*Treat* ∗ *Lockdown*'. These results indicate the presence of salience bias among investors located in Wuhan as fund-related searches reduce under the influence of fear during lockdown. Next, in columns 2-4, the main variable of interest is the coefficient of the triple interaction term '*Search* ∗ *Treat* ∗ *Lockdown*', which shows an insignificant impact on daily *trading frequency, investment*, and *fund risk,* implying that there is no significant impact of fund-related searches on the trading behaviour of investors in Wuhan as compared to investors in other cities in China. These results suggest that even though there has been a decline in fund-level searches among investors in Wuhan during the lockdown period, it did not have any significant impact on the daily trading behaviour among investors in Wuhan as compared to investors in other cities. Hence, the theory of salience bias and reduced investor attention does not influence our main empirical findings.

5.2. *Changes in personal circumstances*

Another possible explanation for the conservative behaviour of investors during the lockdown can be changes in their personal circumstances, such as depression, temporary termination of employment, and income reduction. Depression or anxiety triggered due to the imposing of lockdown may discourage investors from actively trading in financial markets. Similarly, temporary termination of employment and income reduction of investors during the lockdown may negatively impact investors' trading in financial markets. If this explanation holds, we expect this conservatism to continue during the post-lockdown period, because it takes time for businesses to get back to normal, and the recovery from depression can be rather difficult (Malmendier and Nagel, 2011). Hence, to test this potential explanation, we extend our sample to include the post-lockdown period, which is three months after the lifting of lockdown, i.e., the period from 9 April 2020 to 21 July 2020, and study the daily trading and risk preference of investors during the pre-lockdown, lockdown, and post-lockdown periods.

We estimate the following equation, which includes separate monthly dummies for each month in the pre-lockdown (4 September 2019 to 22 January 2020), lockdown (23 January to 8 April 2020), and post-lockdown (9 April to 21 July 2020) periods. For example- '*Dec_pre*' is a dummy variable which equals one if the trading was done in the pre-lockdown period before December 2019, and zero otherwise, '*Jan*' is a dummy variable which equals one if the trading was done in January but after 23 January 2020, when the lockdown started, and zero otherwise. '*Apr_post*' is a dummy variable which equals one if the transactions were made in the post-lockdown period after April 8 2020, and zero otherwise, etc.

$$\begin{aligned} Trading\ behaviour_{ift} = {} & a_0 + a_1 Treat_{ic} * Dec\_pre_t + a_2 Treat_{ic} * Jan\_pre_t \\ & + a_3 Treat_{ic} * Jan_t + a_4 Treat_{ic} * Feb_t + a_5 Treat_{ic} \\ & * Mar_t + a_6 Treat_{ic} * Apr_t + a_7 Treat_{ic} * Apr\_post_t \\ & + a_8 Treat_{ic} * May\_post_t + a_9 Treat_{ic} * Jun\_post_t \\ & + a_{10} Treat_{ic} * Jul\_post_t + \mathscr{X}_f + \gamma_i + \delta_t + \varepsilon_{ift} \end{aligned} \tag{6}$$

The estimation results of Eq. (6) are reported in Fig. 1(a) - (c). The results show insignificant coefficients for '$Treat_{ic} * Dec\_pre_t$' and '$Treat_{ic} * Jan\_pre_t$' on daily *trading frequency, investment*, and *fund risk,* implying there is no significant difference between treated and control groups during the pre-lockdown period. However, this effect reverses after the enactment of lockdown from 23 January 2020 to 8 April 2020, as we find negative and significant effects on daily *trading frequency, investment*, and *fund risk* during the lockdown period, implying that the investors in Wuhan reduced their trading frequency, total investment in mutual funds, and investments in risky mutual funds as compared to investors in other cities. In the post-lockdown period from April 2020 to July 2020, we find that *trading frequency, investment*, and *fund risk* increase and revert back to the pre-lockdown levels, with no significant differences between treated and control groups. Hence, as we find that investors' trading behaviours return back to pre-lockdown levels soon

[9] We use the web scraping techniques to obtain the data from Baidu website.

Table 7
Salience bias based on investors' attention.

	Search (1)	Trading frequency (2)	Investment (3)	Fund risk (4)
Search Treat*Lockdown*		0.0058	0.0029	-0.0003
		(0.005)	(0.002)	(0.000)
*Search * Lockdown*		-0.0022	0.0006	0.0001
		(0.002)	(0.002)	(0.000)
*Treat * Lockdown*	-4.4088***	-1.4760**	-1.4078***	-0.0009**
	(1.254)	(0.650)	(0.267)	(0.000)
*Search*Treat*		-0.0143***	-0.0004	-0.0004
		(0.004)	(0.002)	(0.000)
Search		0.0047**	0.0000	0.0000
		(0.002)	(0.001)	(0.000)
Individual FE	Yes	Yes	Yes	Yes
Daily FE	Yes	Yes	Yes	Yes
Fund Company FE	Yes	Yes	Yes	Yes
N	179,630	179,628	178,552	179,628
R-squared	0.810	0.829	0.827	0.898

This table reports the estimations for difference-in-differences regressions using individual, daily, and fund company fixed effects. The dependent variables are *Trading frequency*, measuring the daily mutual fund trading frequency of an investor; *Investment*, measured as the natural logarithm of net amount invested by individual investors in mutual funds; and *fund risk*, which is measured by an index capturing the riskiness of funds ranging from one (lowest risk) to five (highest risk). *Treat* is a dummy variable which equals one if the investor lives in Wuhan, and zero for investors living in other cities in China. *Lockdown* is a dummy variable which equals one if the investment transaction was made during the period of lockdown from 23 January 2020 to 8 April 2020, and zero for the pre-lockdown period from 4 September 2019 to 22 January 2020. *Search* is Baidu Index value, which is obtained by calculating the number of daily searches for specific keywords of the fund by investors in different cities. The heteroscedasticity robust standard errors are clustered at the city level and are shown in parentheses. Detailed definitions of all variables are provided in Table 1. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % level, respectively.

after the lifting of lockdown, we confirm that our results are not driven by any changes in personal circumstances, such as depression or income reduction.[10]

6. Trading return during the lockdown period

To be consistent with the theory of naïve investor trading, we study the trading return of investors during the lockdown. The main idea is that naïve investors tend to trade excessively based on new information, as they overestimate the precision of this information. Empirical evidence shows that retail investors have a competitive disadvantage to professional investors both in terms of information processing and market access (Ben-Rephael et al., 2017). As naïve investors fail to recognize their inferior situation, they underestimate the reaction of other market participants to the new information. Hence, naïve investors falsely believe that they have an informational advantage and trade too much in response to the information earning reduced trading profits (Langnickel, 2018). The literature also shows that investors' trading aggressiveness is greatly exacerbated by social interactions (Hong et al., 2004, Kaustia and Knüpfer, 2012, Han et al., 2022).

To study the influence of naïve investor trading in the absence of F2F interactions, we estimate the following regression model, where the dependent variable of *trading return* is defined as the holding period return (adjusted by risk level of the fund) from the fund purchasing date to the date when the fund is sold, and uses similar specifications as in Eq. (1) -

$$\textit{Trading return}_{ift} = a_0 + a_1 \textit{Treat}_{ic} * \textit{Lockdown}_t + \mathscr{X}_f + \gamma_i + \delta_t + \varepsilon_{ift}, \tag{7}$$

We report the estimation results of Eq. (7) in Table 8. The main variable of interest is the coefficient of the interaction term '*Treat ∗Lockdown*', which shows a positive and significant impact, implying that during the lockdown, investors in Wuhan increased their trading return as compared to investors in other cities. These results support our argument that during the lockdown and disruption of F2F interactions, naïve investors traded less, increased their trading returns, and consequently transferred less wealth to more-informed investors. Hence, these results confirm the findings from the existing literature by Barber and Odean (2000), among others.

7. Conclusion and policy implications

Using a unique dataset of 17,562 individual investors' information and 199,112 daily trading records from China, this paper provides the first empirical study to examine the effects of the COVID-19 pandemic-triggered lockdown and the consequent elimination of F2F interactions on the daily trading behaviour of individual investors in a natural randomized setting. We classify investors located in Wuhan as our treatment group, while investors in other cities form a part of the control group in our DID setting. We find that investors in Wuhan significantly reduced their daily trading frequency, total investment amount, and investments in risky mutual funds during the lockdown period as compared to investors in other cities. These results strongly support the argument that investors become more conservative after the lockdown due to disruption of information-sharing with peer investors and the elimination of F2F interactions.

To rule out any other alternative explanations that may affect our main results, we take into account salience bias due to limited attention of investors as well as any changes in personal circumstances of investors, such as depression, employment termination, income reduction, etc., which may discourage investors from actively engaging in the financial market. We do not find any empirical support related to the argument of salience bias due to limited investor attention. Even though, we find that there was a decline in investor attention during the lockdown period among Wuhan investors, these did not have any significant impact on their daily trading behaviour during the lockdown period as compared to investors in other cities. We also find no evidence in support of the other alternative explanation related to changes in personal circumstances, as the results show that investors' trading behaviour returned to pre-lockdown levels soon after the end of lockdown. If the alternative argument of changes in personal circumstances holds, we would expect a decreasing trend of individual investors engaging in the financial markets over a continued period even after the end of lockdown. Finally, consistent with the theory of naïve investor trading, we

[10] These results also support the parallel trends assumption in our DID models, as we do not find any significant differences between the treated and control groups in the pre-lockdown and post-lockdown periods, while this effect reverses after the enactment of lockdown.

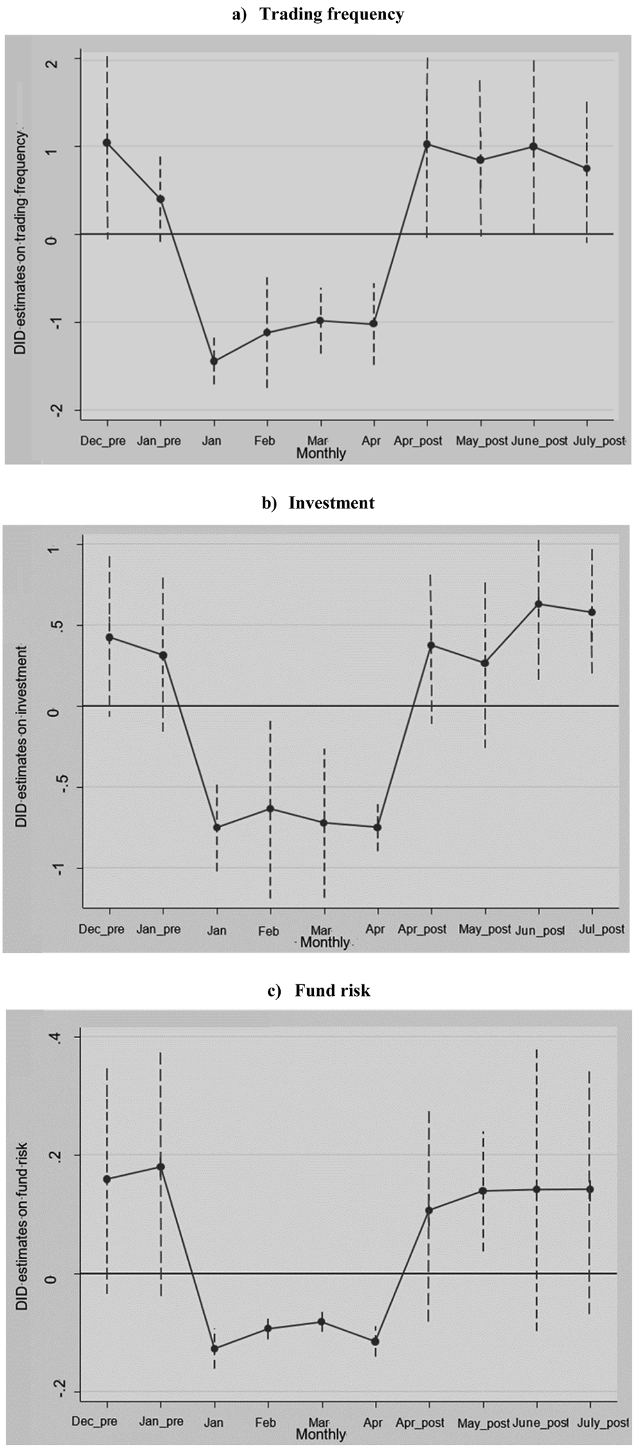

Fig. 1. Changes in personal circumstances
Notes: The figure provides the DID estimates for the effects of the changes in personal circumstances such as depression or temporary termination of employment and income reduction on investors' trading behaviour. The x-axis provides separate monthly dummies for each pre-lockdown (4 September 2019 to 22 January 2020), lockdown (23 January to 8 April 2020), and post-lockdown (9 April to 21 July 2020) periods. For example- 'Dec_pre' is a dummy variable which equals one if the trading was done in the pre-lockdown period before December 2019, and zero otherwise, 'Jan' is a dummy variable which equals one if the trading was done in January but after 23 January 2020 when the lockdown started, and zero otherwise. 'Apr_post' is a dummy variable which equals one if the transactions were made in the post-lockdown period of April 2020 but before April 8, and zero otherwise, etc.

Table 8
Investors' trading return.

	Trading return	
	(1)	(2)
*Treat*Lockdown*	0.0056***	0.0036**
	(0.002)	(0.002)
Lockdown	0.0027***	-
	(0.001)	
Individual FE	Yes	Yes
Time FE	No	Yes
Fund Company FE	Yes	Yes
N	19,697	19,697
R-squared	0.539	0.587

This table reports panel regression results of face-to-face interaction on individual investment return in the sample period of 23 September 2019 to 8 April 2020. We use the enactment of lockdown in January 2020 in Wuhan when the COVID-19 pandemic first broke as a quasi-natural experiment. *Treat* is a dummy variable which is equal to one if the investor lives in Wuhan. *Lockdown* is a dummy variable which is equal to one if the investment transaction was made during the period of lockdown (from 23 January 2020 to 8 April 2020). *Trading return* is defined as the holding period return (adjusted by risk level of the fund) from the fund purchasing date to the date when the fund is sold. Definitions of all variables are provided in Table 1. The heteroscedasticity robust standard errors are clustered at the city level and are shown in parentheses. *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % level, respectively.

also find that investors received higher trading returns during the lockdown as they reduced trading aggressively in the absence of F2F interactions.

The findings of this study have important policy implications for financial institutions, regulatory authorities, and policymakers concerned with promoting market stability and managing investor behaviour. Our results indicate that policies supporting in-person financial advisory services may play a critical role in maintaining market participation, particularly during times of crisis or heightened market uncertainty. Conversely, the observed increase in trading returns during the lockdown suggests that regulators could leverage these insights to develop investor education programs aimed at mitigating overconfidence and reducing excessive trading, thereby fostering more prudent investment practices.

Moreover, the evidence that older investors are disproportionately affected by the elimination of F2F interactions highlights the need for targeted policies that enhance digital literacy and provide remote advisory support for vulnerable groups. By improving both digital and in-person communication infrastructures, regulatory bodies could mitigate the uneven effects of information disruptions across different investor demographics.

During the preparation of this work the authors used ChatGPT in order to refine the language and ensure the manuscript is free from grammatical errors. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Yichu Huang: Data curation, Formal analysis, Methodology, Writing – review & editing. **Udichibarna Bose:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Zeguang Li:** Data curation, Resources. **Frank Hong Liu:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Data availability

The authors do not have permission to share data.

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