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A Friend in Need is a Friend Indeed: How Does Online Social Capital Affect the Resilience of Individual Investors on Social Media

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1 Abstract

We examine how online social capital affects online individual investor resilience on social media. Compared with offline social capital, online social capital is more fragile. We find no evidence that online social capital accumulated prior to a stock market crash improves online investor resilience during the crash period. However, online social capital established during the crash period (referred to as post-event online social capital) does improve online investor resilience. The effect of post-event online social capital varies systematically with network size, investor experience and investor's offline social capital. Online investor resilience also improves investor well-being.

2 Introduction

Due to the rapid deterioration of natural environment and technological disruptions, investors are facing a world with enhanced volatility, uncertainty, complexity and ambiguity (commonly referred to as VUCA). Natural disasters and financial crises have become increasingly common. Hence, investor resilience, defined as an investor's ability to withstand and bounce back from negative shocks, has become very important in the VUCA world. The ongoing Covid-19 pandemic highlights the importance of individual resilience (Lancet Editorial 2020; Nauck et al. 2021). Compared with institutional investors, many individual investors could be more vulnerable to negative shocks due to their lower level of sophistication and economic wealth. Hence, understanding how individual investors respond to negative external shocks is important to the welfare of individual investors and inclusive economic development. In addition, individual investor resilience also matters to financial market development because prior research (see review of Goldstein and Yang 2017) shows that individual investors' participation in financial markets is critical to the efficient functioning and risk sharing of capital markets.

Despite the importance of investor resilience, the prior accounting and finance literature has predominantly focused on economic efficiency and paid little attention to investor resilience. The objective of this study is to examine whether social capital that individual investors develop on social media (referred to as online social capital) affects their resilience on social media (referred to as online investor resilience). We focus on social capital because prior research (e.g., Aldrich 2019) shows that social capital matters to individual resilience in general. However, different from the prior social capital literature, we focus on *online* social capital and *online* investor resilience because social media platforms are becoming popular destinations for people to make friends and seek investment advice from complete strangers (Lim 2021; McCabe et al. 2021; Beals 2012; Huang 2015; Langton 2015). However, as we detail in the next section, the structure and content of online social networks are fundamentally different from those of offline social networks (Kane et al. 2014) and hence our knowledge about offline social capital may not apply to online social capital. Furthermore, Hobbs et al. (2016) find that online social integration is associated with reduced mortality risk, suggesting that online investor resilience could also influence offline investor resilience (i.e., investor resilience in offline communities). Therefore, it is important to understand how online social capital affects online investor resilience.[1]

We test our research question using China's 2015 stock crash as the setting. During the stock crash in 2015, the Shanghai Stock Exchange Composite Index dropped over 40% within two months. To measure individual investors' online social capital and resilience on social media, we employ a proprietary database from iMaibo, one fast-growing social investing platform in

[1] While it is also interesting to study the effect of online investor resilience on *offline* investor resilience, it is beyond the scope of the current study due to lack of data on individual investors' offline activities in our setting.

China during our sample period, covering close to 11,000 active individual investors at the onset of the stock market crash.

Following the extant disaster and infrastructure literature (e.g., Bruneau et al. 2003; Ouyang et al. 2012), we define online investor resilience based on the activeness function. Specifically, we define an investor's activeness function as the composite function of her social media activities on iMaibo (i.e., comments, likes, following, tweets and articles) over a specified time interval t (e.g., a day). Using each investor's social media activities prior to the 2015 stock market crash, we construct a machine learning prediction model to measure each investor's target activeness function following the onset of the stock market crash (i.e., the counterfactual). We define an individual investor's online resilience as the ratio of the investor's activeness function to her *target* activeness function for each week following the onset of the stock market crash. Our investor resilience definition is quite intuitive because it captures how "live and well" an investor is after experiencing a negative shock, using their expected social media activities in the absence of the shock as a benchmark.

To measure an individual investor's online social capital, we use each investor's social interactions with other investors on iMaibo: following, comments and likes. Consistent with prior research that examine offline social capital (e.g., Borgatti et al. 1998; Burt 2000; Easley and Kleinberg 2010; Larcker et al. 2013; El-Khatib et al. 2015; Jackson 2008 and 2019), we define an investor's online social capital based on the first principal component of five types of social network centrality proxies: degree centrality, closeness centrality, eigenvector centrality, betweenness centrality and local clustering coefficient. These five proxies are selected to capture different forms of social capital: network closure, structural holes and network centrality (see Section 4.1 for more details). We construct two types of online social capital in our setting. First, we construct an investor's online social capital over a 180-calendar day period prior to the onset of the stock market crash (referred to as pre-event online social capital). Second, we construct an investor's online social capital weekly following the onset of the stock market crash (referred to as post-event online social capital). As the 2015 stock market crash ends six months after the onset, our sample ends six months after the onset of the stock market crash, though inferences are qualitatively similar if we use 12 months as an alternative cutoff.

As noted above, the prior offline social capital literature typically assumes that an individual's offline social capital is highly persistent (Burt 2000; Di Maggio et al. 2019). In contrast, we find that individual investors' online social capital is quite fragile. Specifically, we find that the correlation between the pre-event and post-event online social capital is only 0.281.[2] This

[2] Although a large number of studies have reported positive and persistent performance effect of offline social capital (e.g., Burt 2000; Larcker et al. 2013; El-Khatib et al. 2015), not many studies report the time series correlation between social capital and lagged social capital. An exception is Di Maggio et al. (2019), who report in Figure A2 (in online appendix) the beta coefficients from broker eigenvector centrality regressed on its lags, ranging from 1-month to 36-month lags. Broker eigenvector centrality is highly persistent: 1) Beta coefficient on one-month lag is around 0.9; 2) Beta coefficients gradually decrease as the number of lags increases. Beta coefficients on 6-

finding suggests that the role of online social capital may not be the same as the role of offline social capital examined in the extant offline social capital literature, consistent with Kane et al.'s (2014) argument that online social networks are fundamentally different from offline social networks.

We next examine the impact of online social capital on online investor resilience during the 2015 stock market crash. While social capital is a positive word and hence one would expect the effect of social capital on investor resilience to be positive, the extant *offline* social capital literature actually shows that social capital is a double-edged sword (Portes 1998; Villalonga-Olives and Kawachi 2017). Accordingly, we do not make any ex-ante prediction on the effect of online social capital on online investor resilience. We find little evidence that pre-event online social capital positively affects online investor resilience. However, we find that post-event online social capital positively affects online investor resilience. Inferences are qualitatively similar if we use a two-stage-least-square regression approach to dealing with potential endogeneity of post-event online social capital. Our finding on pre-event online social capital does not appear consistent with several studies that find a positive impact of offline social capital on offline individual resilience (Aldrich and Meyer 2014; Also see the reviews by Ledogar and Fleming 2008 and Kerr 2018). Our findings support Kane et al.'s (2014) argument that online social communities are fundamentally different from offline social communities and more fragile; therefore, "a friend in need is a friend indeed".

As explained above, there is overlap in the data used to construct investor resilience and online social capital. Hence, one concern is whether the relationship between online social capital and online investor resilience is mechanical. We do not believe this is the case because we find different results for pre-event online social capital and post-event online social capital. To fully address this concern, we remove each investor's comments, likes and following when measuring online investor resilience so that the data used to construct online social capital and online investor resilience have zero overlap. We obtain qualitatively similar inferences using this alternative definition of investor resilience.

We perform several cross-sectional regression analyses to better understand the boundaries of the impact of post-event online social capital on investor resilience. First, we examine whether the relationship between online investor resilience and post-event online social capital varies with stock market index return. During the 2015 stock market crash period, the stock market index became volatile with multiple ups and downs on its way to more than 40% drop over a six-month window. Hence, we examine whether the ups and downs of the stock market index have differential effects on the relationship between investor resilience and post-event online social capital. Empirically, we find no evidence that the performance of the market index return has any differential effects on this relationship. This evidence suggests

and 12-month lag are around 0.75 and 0.6, respectively. In contrast, the beta coefficient in a regression of post-event online social capital on lagged post-event online social capital is 0.252 while the beta coefficient in a regression of post-event online social capital on pre-event online social capital is 0.295.

that the effect of post-event online social capital on online investor resilience is not related to the sign of the stock market index performance per se.

Second, we examine whether the relationship between online investor resilience and post-event online social capital varies with the iMaibo platform's network size. We define network size as total number of active users (including investors and SMAs) in the last week divided by total healthy users before the stock crisis. As the unfolding of the 2015 stock market crash was quite uncertain, network size could shrink rapidly over time, which in turn could lessen the impact of online social capital on online investor resilience. Consistent with this conjecture, we find a significant decline of network size during the course of the stock market crash. More importantly, we find that the positive effect of post-event online social capital declines when network size shrinks.

Third, we examine whether the relationship between online investor resilience and post-event online social capital varies with an investor's experience on iMaibo, which is a dummy variable that equals one for investors whose number of days since joining iMaibo is above the sample median and zero otherwise. We conjecture that individual investors who joined the platform earlier (i.e., more experienced) could have more alternative ways to deal with negative market shocks and hence the benefit of online social capital could be smaller. On the other hand, recently joined investors may need stronger social support and hence the benefit of online social capital could be larger. Consistent with this conjecture, we find that the effect of post-event online social capital on online investor resilience is more positive for less experienced investors.

Fourth, we examine whether the relationship between online investor resilience and post-event online social capital varies with an investor's offline social capital. We conjecture that the effect of post-event online social capital on online investor resilience is stronger if iMaibo investors also share strong offline social network connections. Due to lack of data, we cannot directly measure an investor's offline social capital. However, our proprietary database allows us to infer the city locations of iMaibo investors based on their IP addresses. We assume that two iMaibo investors are likely to have offline social network connections if they live in the same city and also interact with each other on iMaibo. Hence, we define an iMaibo investor to have offline social capital if she interacts with at least one investor living in the same city on iMaibo. Consistent with our conjecture, we find that the effect of post-event online social capital on investor resilience is stronger for investors with higher offline social capital.

The broad resilience literature assumes that resilience matters to individual well-being, as emphasized by psychologists (See Masten 2014). In this study we shed light on this important assumption within the context of social media. Specifically, we test two hypotheses. First, we examine whether more resilient investors are happier on social media. Consistent with this hypothesis, we find a positive relationship between online investor resilience and investor sentiment based on investors' online expressions on iMaibo. Second, we examine whether more resilient investors are more likely to pay for information products offered by social media analysts on iMaibo. This prediction is based on prior marketing research that shows that consumers are more likely to purchase products when they are happier (e.g., Homburg et al.

2005; Seiders et al. 2005). Consistent with this prediction, we find a positive relationship between online investor resilience and investors' purchasing of SMA reports.

Our study makes two important contributions to two streams of existing literature. First, we contribute to the literature on the determinants of individual investor resilience during financial crises.[3] While there are many studies that examine individual investor behavior (See the reviews by Barber and Odean 2013, Guiso and Sodini 2013 and Beshears et al. 2019), very few examine investor resilience, let alone online investor resilience. A stream of economics and finance papers (Malmendier and Nagel 2011; Hoffmann et al. 2013; Weber et al. 2013; Knupfer et al. 2017; Guiso et al. 2018) examine how individual investor perceptions change and drive trading and risk-taking behavior during financial crises but they do not examine why some investors are more resilient than others during financial crises. Bucher-Koenen and Ziegelmeyer (2014) use German household survey data to show that financially illiterate investors are more likely to suffer permanent losses during the 2008 financial crisis and do not participate in stock markets' resurgence, suggesting that financially illiterate investors are less resilient. We contribute to this literature by documenting the role of online social capital, an important theoretical construct in the broad resilience literature, on online investor resilience. Moreover, we show that online investor resilience matters to investor well-being.

Second, we contribute to the broad and highly interdisciplinary social capital literature (Coleman 1988; Portes 1998; Burt 2000; Granovetter 2005; Villalonga-Olives and Kawachi 2017; Kerr 2018). Different from most studies in this literature that focus on offline social capital, we examine online social capital, a theoretical construct that is gaining increasing importance due to the rise of social media. The findings from our study show that online social capital is more fragile than offline social capital and hence should be treated separately. In addition, we show that it is post-event online social capital but not pre-event online social capital that matters to online investor resilience during financial crises. This finding is new to the social capital literature.

Our results also have important policy implications for platform operators and securities regulators who care about the long-term well-being of individual investors. We provide a validated proxy for online investor resilience that policy makers can adopt. Our results also confirm that online investor resilience matters to investor well-being. Moreover, our results suggest that timely interventions during a financial crisis matter more than pre-crisis interventions in fostering online investor resilience.

The rest of the paper is organized as follows. Section 2 discusses related literature and develops the hypothesis on the effect of online social capital on online investor resilience. Section 3 describes the sample selection procedures. Section 4 explains how we define online social capital and online investor resilience. Section 5 presents the results on the effect

[3] Though not directly related to this study, we note a growing literature in accounting and finance that analyzes corporate responses to the global financial crisis of 2007–2008 (e.g., Balakrishnan et al. 2016; Duchin et al. 2010).

of online social capital on online investor resilience. Section 6 discusses the impact of online investor resilience on investor well-being. Section 7 concludes.

3 Related literature and hypothesis development

We examine the effect of social capital on online investor resilience. Resilience is defined as an individual's ability to withstand and bounce back from negative shocks. Social capital represents resources that one accumulates through relationships among people (Coleman 1988; Portes 1998). In this paper, we focus on individual social capital rather than collective social capital defined by Putnam (2000) that measures social integration and trust of a group (e.g., the whole society considered by Guiso et al. 2004).

An individual's social capital stock is a function of her position in a social network. The structural holes theory (Burt 2000) argues that an individual who is in a brokering position (i.e., a person who connects two or more otherwise disconnected individuals) possesses more social capital than others. Similarly, positions with a high network centrality are associated with higher social capital (e.g., Larcker et al. 2013; Rossi et al. 2018). The most important benefit of being in a structural hole or central position is a person's ability to receive information quickly and control the information flow in a social network. In contrast to the information advantage offered by structural holes and network centrality, network closure (i.e., a network position that connects densely with people in the same group) is another form of social capital that facilitates mutual trust and mutual support (e.g., Coleman 1988; Burt 2000; Xiao and Tsui 2007).

Prior to the rise of social media, researchers focus on social capital in offline social communities (i.e., offline social capital). In a systematic review of social network studies, Borgatti and Foster (2003) classify the mechanisms of social network influences along two dimensions: network structure, which enables network users to reach or control important resources, and network content, which flows through a network. Borgatti and Foster (2003) show that both mechanisms can explain diversity and homogeneity in individual user behaviors in a network. The extant literature shows that social capital is a double-edged sword with both positive and negative consequences. For example, Portes (1998) identifies four types of negative effects of higher social capital, including excessive demands on group members, restriction of freedom resulting from excessive informal control, exclusion of out-group members, and down-leveling of norms due to the demand for group conformity. Villalonga-Olives and Kawachi (2017) further show that social networks could facilitate negative social contagion (e.g., the spread of rumors and misinformation).

Prior studies have examined how offline social capital affects offline resilience of individuals and communities (Aldrich and Meyer 2014; Also see the reviews by Ledogar and Fleming 2008 and Kerr 2018). The dominant finding is that offline social capital helps improve offline individual and community resilience. For example, in his study of Japan's Tohoku earthquake in March 2011, Aldrich (2019) finds that offline social capital promotes mutual trust and a sense of belongingness, facilitates collective actions, and serves as a kind of informal insurance; as a result, offline social capital helps individuals and communities recover from the shock of the earthquake. However, similar to the general literature on social capital, some studies also document negative consequences of social capital. For example, strong bonding links can worsen elderly health during heat wave, and this negative effect arises because elderly people do not take heat wave seriously, and their views are echoed and reinforced by their neighbors (Wolf et al. 2010).

While individual investors constitute an important part of financial markets and often suffer substantial losses during stock market crashes (Hoffmann et al. 2013; Bucher-Koenen and Ziegelmeyer 2014),[4] research on individual investor resilience (offline or online) has been surprisingly scant, presumably because mainstream finance research focuses on performance and efficiency.[5] More importantly, we are not aware of any study that examines the effect of online social capital on online individual investor resilience. Building on the research of boyd and Ellison (2007) and Ellison and boyd (2013), Kane et al. (2014) identify several key features of online social networks that are fundamentally different from offline social networks. First, an online social network allows users to have unique user profiles that are constructed by users, by members of their networks, and by the platform. Many users on social media are pseudonymous. Hence, a user's social media profile could be significantly different from her offline true self. Second, an online social network allows users to access digital content through, and protect it from, various search mechanisms provided by the platform, at low costs. Third, an online social network allows users to articulate a list of other users with whom they share a relational connection, which could be altered at any time. Fourth, an online social network allows users to view and traverse their connections and those made by others on the platform.

These distinctive features of online social networks could have significant economic consequences because they will shape both the structure and content of online social networks, which in turn drive social capital effects (Borgatti and Foster 2003). For example, features one and two discussed above allow users to control network content at low costs (i.e., how digital resources are shared and accessed through a network). Similarly, features three and four allow users to easily visualize and manipulate network structure (i.e., how people establish and manage the connections between others in a network). In addition, features two and four imply that online social networks are more transparent than offline social networks. Moreover, users on online social networks have low commitment because

[4] According to Bucher-Koenen and Ziegelmeyer (2014), "20.5% of households in Germany suffered financial losses due to the financial crisis in 2008 and on average households lost about 2,562 Euros or 3.6% of their financial assets (p. 2217)." Similar findings are also reported in other countries. For example, Dutch retail investors lost almost half of their portfolio values during the first several months of the 2007-2008 financial crisis (Hoffmann et al. 2013).

[5] Several studies have examined how financial crises affect the risk preferences and beliefs of investors (e.g., Malmendier and Nagel 2011; Hoffmann et al. 2013; Weber et al. 2013; Guiso et al. 2018), but these studies are silent on why some investors are more resilient to financial crises than others.

they typically use pseudonyms and can enter and exit online social networks at any time. Therefore, online social capital could be more fragile than offline social capital.

Because of these fundamental differences between online social networks and offline social networks, it is unclear whether the relationship between offline individual (investor) resilience and offline social capital documented in the extant literature can be generalized to online social networks. Hence, we state the following hypothesis in the null form:
H1: There is no relationship between online investor resilience and online social capital.

The extant offline social capital literature implicitly assumes and also finds evidence that social capital is relatively stable over time (Burt 2000; Di Maggio et al. 2019) and hence effects of social capital are assumed to be relatively stable too. However, as we have argued above, this assumption may not be appropriate for online social networks. Specifically, strong negative shocks such as stock market crashes could significantly reshape the structure of fragile online social networks and hence online social capital following the occurrence of a negative shock (i.e., post-event online social capital) could have little resemblance to online social capital accumulated prior to the negative shock (i.e., pre-event online social capital). Accordingly, pre-event online social capital may carry less weight than post-event online social capital in helping improve the online resilience of individual investors during the negative shock. Accordingly, we revise the null hypothesis of H1 as follows by distinguishing pre-event and post-event online social capital:
H1a: There is no relationship between online investor resilience and pre-event online social capital.
H1b: There is no relationship between online investor resilience and post-event online social capital.

4 Sample selection procedures

The sample used in this study is based on a proprietary database provided by iMaibo, a fast-growing social investing platform in China during the sample period. We refer readers to Chen et al. (2021) for a more detailed introduction of the platform. iMaibo has two types of users: suppliers of research on individual stocks and macro analyses (i.e., SMAs) and consumers of research provided by SMAs (i.e., individual investors). These two categories of users are mutually exclusive. SMAs produce both free and paid content (in the form of short tweets or long articles). Anyone can register an account on iMaibo free of charge. All users (including SMAs) use pseudonyms on iMaibo and therefore their real identities are unknown.

The iMaibo database records information about each registered user’s social media interaction behaviors (i.e., follow/comment/like), posting behaviors (i.e., post articles and tweets) and information purchasing behaviors (i.e., subscription to research insights of SMAs). In this paper, we focus on individual investors, though we include SMAs when constructing the social capital proxies because SMAs are also an integral part of social networks within the iMaibo platform.

Our sample covers the period from January 2, 2014 to December 6, 2015, including the pre-event period January 2, 2014-June 14, 2015 and the post-event period June 15, 2015-December 6, 2015. June 15, 2015 represents the onset of China's largest stock market crash since 2010. As shown in Figure 1, the Shanghai Stock Composite Index lost approximately 40% of its value from its peak within a short period of two calendar months. The pre-event period starts on January 2, 2014 because it is the first trading day when we have data on all behavior records (i.e., follow/comment/like/ articles/tweets). We select a 180-day duration (approximately 6-month) for the post-event period for two reasons. First, the stock market crash is pretty much over by the end of the 6-month period. Second, our definition of online investor resilience requires the prediction of the counterfactuals of each investor's social media behaviors without the stock market crash in the post-event period. As the performance of any prediction model declines with the prediction horizon, we choose six months for our main analyses. However, inferences are qualitatively similar if we use a post-event period of 360 days (untabulated).

We select our sample of individual investors using the following steps. First, we require each investor to be active in the pre-event period. An investor is active if she satisfies any of the following conditions: (i) the investor followed any other investors (including SMAs) on at least two different days, which is used to filter out potential bots that follow other investors only at the time of account creation; or (ii) the investor had comment or like on any day; or (iii) the investor posted articles or tweets on any day. Second, we require each active investor to be healthy right before the onset of the stock market crash. If an investor had already left the platform by the time of the stock market crash, it might be difficult to measure her resilience during the post-event period. Specifically, we impose the following two criteria: (i) the investor must have at least 14 active days during the pre-event period;[6] and (ii) the investor must have at least one of the five behavioral records during the last 90 calendar days of the pre-event period. Third, we exclude a small number of investors whose target activeness function (defined in Section 4.2) is always zero in the post-event period because resilience is not defined for these investors. These sample selection conditions result in a final sample of 10,953 individual investors. As the post-event period contains 25 weeks, our investor-week panel data set for the post-event period contains 273,825 (i.e., 10,953×25) investor-week observations.

5 Key variable definition

[6] An investor has an active day if he/she conducted any of the five behaviors (i.e., follow/comment/like/articles/tweets) at least once in a day.

This section describes how we construct the two key regression variables: online social capital and online investor resilience.

5.1 Definition of social capital

To construct any social capital proxies, one first needs to define the nodes and edges of a social network. The nodes in our setting are individual investors. Prior research often uses homophily (e.g., common interests) to define the edges of a social network. Homophily-based social network definitions could be noisy because individuals with common interests are not necessarily socially connected. In this study we define the edges of our social network based on each investor's actual interactions with others. Specifically, we use the following three interaction behaviors to construct the edges of the social network: following, comments and likes. As tweet posting and article posting by individual investors (non-SMAs) are not 1-to-1 directed interactions with specific individuals, they are excluded from the definition of online social capital. We first construct a pre-event social network based on the three interaction behaviors during the 180-day period before June 15, 2015. We also construct weekly post-event social network based on the same three interaction behaviors in the post-event period.

As discussed in Section 2, the prior literature identifies three types of social network positions that may offer social capital: structural holes, network centrality and network closure. We use betweenness centrality to proxy for structural holes because betweenness centrality calculates how often a node (i.e., an investor in our setting) falls on the shortest path that connects two other nodes. Network centrality measures the importance of a node in a network. To proxy for network centrality, we use degree centrality, closeness centrality and eigenvector centrality. Degree centrality is simply the total number of links a node has. Closeness centrality measures the reciprocal of the total distance from the current node to all other nodes in the network, and eigenvector centrality measures a node's importance by calculating the importance of the immediate neighbours of the current node. Degree centrality, closeness centrality and eigenvector centrality are commonly used in previous studies (e.g., Jackson 2008). Network closure refers to how closely connected a node is within its community, which can be measured by the local clustering coefficient. Local clustering coefficient calculates how many friends of one node are friends themselves. If two friends of one node are also friends themselves, then these three nodes are densely connected to each other, consistent with network closure.

We calculate the five social capital proxies based on the social network defined above (see appendix 1 for the details). To facilitate comparison and interpretation, we normalize each social capital proxy to have a mean of zero and a standard deviation of one. Even though the five social capital proxies are conceptually distinct, they are highly correlated with each other. Hence, we follow prior research by constructing a composite social capital using Principal Component Analysis (see appendix 2 for the detail).

5.2 Definition of online investor resilience

At the highest level, resilience is a system property. For example, the Singapore-ETH Center (SEC) defines resilience as the capability of a socio-technical system to maintain and reconfigure its essential functions, structures and feedback loops in the face of acute shocks and chronic strains (SEC 2019). For real-world systems, resilience typically consists of both biophysical and cognitive functionalities. The biophysical functions include (1) resistance within the acceptable limits of degradation, (2) restabilization of critical functions, (3) rebuilding of degraded functions, and (4) reconfiguration of substance, energy and service flows while the cognitive functions include (1) staying aware, (2) sense-making, (3) response, and (4) updating and adaptation (SEC 2019). While the concept of resilience is very intuitive, its measurement is challenging and could vary by discipline. The infrastructure resilience literature (e.g., Bruneau et al. 2003; Ouyang et al. 2012) defines a system's resilience (R_i) as follows based on an activeness function:

$$R_i = \frac{\int_{t_0}^{T_c} AF_i(t)dt}{\int_{t_0}^{T_c} TAF_i(t)dt} \tag{1}$$

Intuitively, R_i measures a system's performance following a negative shock (i.e., the active function AF_i) relative to its target performance without the negative shock (i.e., the target activeness function TAF_i) over a specified time interval starting from the onset of the negative shock (t_0). R_i would be equal to one or higher for a fully resilient system. Equation (1) allows a system to perform even better than the pre-shock period (i.e., R_i>1) due to updating and adaptation.

Even though we study resilience of an individual investor rather than resilience of a system, we believe that the definition of resilience in equation (1) can still be applied to an individual investor. As we examine online social networks, the cognitive functions of resilience are most relevant. Following the infrastructure resilience literature, we define an investor's active function (AF_i) on social media over a day using the following five types of social media behaviors: comments, likes, following, tweets and articles. AF_i is computed based on each investor's (a node) out-degree because out-degree is initiated by an investor and thus better captures the investor's activeness. Specifically, the activeness function AF_i for investor i on day t is defined as follows:

$$AF_i(t) = \log\left(\sum_j b_{i,j}(t) + 1\right), \tag{2}$$

where $b_{i,j}(t)$ is the number of behavior j for investor i on day t. The active function is expressed in logarithm to reduce the influence of extreme values. TAF_i represents an investor's activeness function if the negative shock did not occur (i.e., the counterfactual). We use machine learning to predict the target activeness function (TAF_i) in the post-event period. As this portion of the discussion is relatively technical, we relegate it to appendix 3 to increase the readability of the main text.

Our definition of resilience is quite intuitive because higher R_i represents more active information search and communications by an investor on social media. Prior social media research indicates that lack of communication and information search could lead to dysfunctional effects that reduce the welfare of individual investors. For example, a recent review by Verduyn et al. (2017) shows that social media usage has two contrasting effects on individual well-being. On one hand, social media usage may entail social comparison, which could lead to envy or anxiety. On the other hand, social media usage may create social capital and gives a sense of being socially connected. Verduyn et al. (2017) argue that passive usage (monitoring other people's lives without actively engaging with others) leads to envy or anxiety, while active usage creates social capital.[7] In Section 6 we provide direct evidence on the effect of online investor resilience on investor well-being in our setting.

We calculate online investor resilience using equation (1) for the entire post-event period. In addition, to understand how investor resilience evolves over the course of the stock market crash, we also calculate investor resilience for every week of the post-event period. Past resilience research typically does not have the luxury to measure individual resilience frequently. For example, Iwasaki et al. (2017) rely on a one-time survey only to measure individual mental health following the March 2011 meltdowns at the Fukushima nuclear power plants in Japan. As we can measure investor resilience weekly, we can better understand the evolution of investor resilience over the post-event period.

5.3 The effect of online social capital on online investor resilience

This section tests the effect of online social capital on online investor resilience (H1a and H1b) as well as the cross-section effects.

5.3.1 Tests of H1a and H1b

To test H1a and H1b, we use the following regression model:

$$RESILIENCE_{it} = \beta_1 * SOCIALCAPITAL + \beta_2 * RESILIENCE_{it-1} + \beta_3 * AGE_{it-1} + \gamma_i + \theta_t + \varepsilon_{it} \quad (3)$$

The unit of observation is an investor-week in the post-event period. Variable definitions are provided in appendix 2. *SOCIALCAPITAL* is our key variable of interest and represents online social capital in the pre-event period ($PRE\text{-}EVENT\_SOCIALCAPITAL_i$) for H1a and online social capital in the post-event period ($POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$) for H1b. Due to lack of time-variant data on each investor, we can only control for investor age on the platform

[7] Our activeness function does not include an investor's stock trading. Prior research (e.g., Odean 1999; Barber et al. 2009) shows that excessive trading could hurt investors. Hence, an investor's trading activeness is not necessarily a good measure of investor resilience. Unfortunately, we do not have access to iMaibo investors' stock trading records and hence cannot directly test this conjecture.

(*AGE*) and lagged dependent variable. We use investor fixed effects to account for any omitted time-invariant individual characteristics and week fixed effects to account for potential time-variant confounding factors (e.g., market sentiment, common time trends). Standard errors are clustered by investor and week.

Table 1 reports the summary statistics of the investor-week sample used in the subsequent regression models. Panel A shows the summary statistics for the regression variables. In addition to showing the distribution of $RESILIENCE_{it}$ at the investor-week level, we also tabulate the distribution of $RESILIENCE_{i}$ at the investor level. If an investor were not negatively affected by the stock market crash, $RESILIENCE_{i}$ should equal one or higher. Hence, the median of 0.204 for $RESILIENCE_{i}$ suggests that many investors cut back their social media activeness following the onset of the stock market crash. However, the variance of $RESILIENCE_{i}$ is very high, suggesting significant divergence in the online resilience of individual investors during the stock market crash period.

Panel B of Table 1 reports the correlations among the regression variables of model (3). The correlation between $PRE\text{-}EVENT\_SOCIALCAPITAL_{i}$ and $POST\text{-}EVENT\_SOCIALCAPITAL_{it}$ is 0.281. While this correlation is statistically significant, the magnitude is not large relative to the time-series persistence of offline social capital reported by prior literature (see footnote 2). This finding suggests that online social capital is relatively fragile and hence there is a possibility that it may not be as effective as offline social capital in improving investor resilience. Consistent with this hypothesis, the correlation between $RESILIENCE_{it}$ and $POST\text{-}EVENT\_SOCIALCAPITAL_{it}$ is much larger in magnitude than the correlation between $RESILIENCE_{it}$ and $PRE\text{-}EVENT\_SOCIALCAPITAL_{i}$ (0.004 vs. 0.141).

Panel A of Table 2 formally tests H1a and H1b. As $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$ in model (3) is lagged by one period, we exclude the first week of the post-event period in Table 2. The regression model in column (1) uses $PRE\text{-}EVENT\_SOCIALCAPITAL_{i}$ only, the regression model in column (2) includes $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$ only, and the regression model in column (3) includes both $PRE\text{-}EVENT\_SOCIALCAPITAL_{i}$ and $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$. The coefficient on $PRE\text{-}EVENT\_SOCIALCAPITAL_{i}$ in column (1) is insignificant. On the other hand, the coefficient on $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$ is significantly positive in column (2). In addition, after including both social capital measures in the same model in column (3), the coefficient on $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$ continues to be significantly positive while the coefficient on $PRE\text{-}EVENT\_SOCIALCAPITAL_{i}$ becomes significantly negative. These results suggest that it is online social capital at the time of a crisis that helps improve online investor resilience. There is no evidence that pre-event online social capital helps improve online investor resilience. In terms of economic magnitude, a standard deviation increase in post-event social capital is associated with 10.21% increase in online investor resilience relative to the unconditional mean value.

$POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$ could be subject to the concern of endogeneity. As $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$ is constructed from an investor's social network, this endogeneity concern is typically difficult to deal with in the absence of exogenous shocks. Luckily, we manage to identify several exogenous disruptions specific to some SMAs in the post-event period that could affect individual investors' online social networks on iMaibo and hence could serve as a valid instrument for $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$. The disruption events are disclosed by SMAs in their iMaibo tweets and cover various relatively random reasons that are specific to individual SMAs, including electricity blackout, internet failure, computer breakdown and phone breakdown.[8] For simplicity, we call these disruption events as SMA disruption events. Remember that SMAs are not part of our individual investor sample. The SMA disruption events occurred during the following seven weeks in the post-event period ending on June 28, August 2, September 13, October 18, November 1, November 15 and November 29. The number of individual investors affected by these SMA disruption events ranges from 15 to 130.

We use the following procedures to identify the individual investors affected by the SMA disruption events. Let's assume that week [0] is the week when one or more SMA disruptions occur. First, we identify all the SMA friends of an individual investor in week [-1]. We define the SMA friends of an individual investor to be those who interacted (i.e., comments, likes and following) with the individual investor in week [-1]. If the SMA friends of an individual investor experience one or more disruption events in week [0], this individual investor would be negatively affected and hence she could turn to other SMAs for social interactions and reduce her interest to interact with the disrupted SMA friends in the future. Therefore, there could be a permanent shift in the social network structure of the platform and hence the degree of individual investors' online social capital. As a result, an instrument variable based on the SMA disruption events (denoted as $DISRUPTION_{it-1}$) will satisfy the relevance condition of a valid instrument variable. In addition, as the disruption events are idiosyncratic to an SMA (i.e., friends of an individual investor), we have no reason to expect $DISRUPTION_{it-1}$ to be systematically correlated with the error term of the second-stage regression for a focal investor. In other words, $DISRUPTION_{it-1}$ should also satisfy the exclusion condition of a valid instrument.

Panel B of Table 2 shows the 2SLS regression results of model (3). Consistent with our prediction, the coefficient on $DISRUPTION_{it-1}$ is significantly negative in the first-stage regression, suggesting that the idiosyncratic network disruptions to some SMAs had permanently altered the social network structure of many individual investors. More importantly, the coefficient on $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$ is still significantly positive in the second-stage regression. This finding suggests that the inference of Panel A of Table 2 is robust to controlling for the endogeneity of $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$.

The unit of analysis in Table 2 is an investor-week, but $PRE\text{-}EVENT\_SOCIALCAPITAL_i$ is defined at the investor level. To make sure this difference is not a cause of our surprising regression coefficient on $PRE\text{-}EVENT\_SOCIALCAPITAL_i$ in Table 2, we also estimate the following cross-sectional regression model (4) at the investor level:

[8] We find no evidence that individual investors disclose such disruptions on iMaibo in the post-event period, which may not be surprising because other users may not care about such events of a regular user on iMaibo. On the other hand, all SMAs should have an incentive to disclose such disruptive events due to their large followings.

$$RESILIENCE_i = \beta_1 * SOCIALCAPITAL_i + \beta_2 * PRE\text{-}EVENT\_ACTIVENESS_i + \beta_2 * AGE_i + \varepsilon_{it} \quad (4)$$

The unit of observation is an investor. Panel C of Table 2 shows the regression results. As $RESILIENCE_{it-1}$ is not defined at the investor level, we use $PRE\text{-}EVENT\_ACTIVENESS_i$ (i.e., the numerator of equation (1)) instead. Similarly, we use AGE_i defined at the beginning of the post-event period. As this is a cross-sectional regression model, investor and time fixed effects are excluded automatically. The coefficient on $PRE\text{-}EVENT\_SOCIALCAPITAL_i$ is positive but insignificant at the 10% significance level in column (1). Once we control for the average $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$, the coefficient on $PRE\text{-}EVENT\_SOCIALCAPITAL_i$ becomes even smaller while the coefficient on the average $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$ is significantly positive. Overall, we conclude that the inferences in Panel B and Panel A of Table 2 are qualitatively similar.

The definitions of online social capital and online investor resilience both use an investor's social media interactions (i.e., likes, comments, and following). Hence, one could wonder whether the relationship between online social capital and online investor resilience is mechanical due to this overlap in data usage. We do not believe this is the case because the definitions of online social capital and online investor resilience are constructed very differently. In addition, even though both $PRE\text{-}EVENT\_SOCIALCAPITAL_i$ and $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$ are constructed using similar data, we find different results for pre-event online social capital and post-event online social capital, which seems inconsistent with the mechanical relation hypothesis.

To deal with this concern completely, we also redefine $RESILIENCE_{it}$ by removing comments, likes and following so that there is no overlap in the used data for definitions of online social capital and online investor resilience. Panel D of Table 2 replicates the regression models in Panel A of Table 2. Our inferences in Panel D are qualitatively the same as in Panel A.

5.3.2 Boundary conditions for the effect of post-event online social capital

We next perform several cross-sectional tests of H1b to identify the boundary conditions for the effect of post-event online social capital. We consider four characteristics. The first two focus on macro conditions while the last two focus on investor characteristics. First, we examine whether the effect of H1b varies with lagged stock market index return ($MARKETRET_{t-1}$). Even though the stock market index lost more than 40% over a six-month period, the market index experienced several ups and downs over the course of the stock market's eventual decline (see Figure 1). As the impact of the index's ups versus downs could have differential effects on investor psychology, the effect of H1b could also differ for positive and negative market index returns. Column (1) of Table 3 shows the regression results of this test. The coefficient on $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1} \times MARKETRET_{t-1}$ is insignificant, suggesting that the effect of H1b is not sensitive to the change in the market index return in the post-event period per se.

Second, we examine whether the effect of H1b varies with the platform's network size ($NETWORKSIZE_{t-1}$), defined as total number of active users (including investors and SMAs) in the last week divided by total healthy users before the stock crisis. As shown in Figure 2, the network size declines sharply upon the onset of the stock market crash and stabilizes by around mid-October 2015. As the benefit of social capital should be greater for larger-size networks, we hypothesize that the effect of H1b increases with network size. Column (2) of Table 3 shows the regression results of this test. As predicted, the coefficient on $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1} \times NETWORKSIZE_{t-1}$ is significantly positive, suggesting that the positive effect of post-event online social capital is greater for larger networks.

Third, we examine whether the effect of H1b varies with an investor's experience on social media (EXP_{t-1}), which is a dummy variable that equals one for investors whose number of days since joining iMaibo is above the sample median and zero otherwise. We conjecture that individual investors who are more experienced (i.e., joining the platform earlier) could have found many different channels to help themselves weather through negative market shocks. As a result, the value of post-event online social capital to them could become smaller. Column (3) of Table 3 shows the regression results of this test. As predicted, the coefficient on $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1} \times EXP_{t-1}$ is significantly negative, suggesting that the positive effect of post-event online social capital is indeed smaller for more experienced investors.

Fourth, we examine whether the effect of H1b varies with an investor's offline social capital. All the analyses conducted so far focus on each investor's social media activities on iMaibo. However, all investors live in a specific physical environment with a particular amount of stock of offline social capital. Hence, an interesting question is whether the benefit of online social capital could be larger for investors who also have strong offline social capital. Obviously, this question is hard to test without detailed data on each iMaibo investor's offline social activities. In this study we shed light on this important question by exploiting the home/work locations of iMaibo investors, which can be inferred from their IP addresses used to log in to iMaibo. We assume that two iMaibo investors are likely to have offline social network connections if they live in the same city and interact with each other on iMaibo. Hence, we define an iMaibo investor to have offline social capital if she interacts with at least one iMaibo investor living in the same city (denoted by a dummy variable $OFFLINE\_SOCIALCAPITAL_{it-1}$). Column (4) of Table 3 shows the regression results of this test. As predicted, the coefficient on $POST\text{-}EVENT\_SOCIALCAPITAL_{it-1} \times OFFLINE\_SOCIALCAPITAL_{t-1}$ is significantly positive, suggesting that the positive effect of post-event online social capital is indeed larger for investors with higher offline social capital.

6 Consequences of online investor resilience

Does online investor resilience matter? Since the outbreak of Covid-19 pandemic, both media and policy makers emphasize the importance of building individual and social resilience. The implicit assumption is that resilience improves individual and societal well-being. One could extend the same line of logic to investor resilience. Hence, we examine whether individual investor resilience on social media matters to the well-being of individual investors. Due to lack of detailed data on iMaibo investors' offline activities, we cannot measure an investor's well-being directly. However, individual investors have been spending more and more of their time on online communities. Hence, their online well-being should be as important. In addition, one could argue that an investor's online well-being could partially reflect their offline well-being.

In this study, we consider two indicators of an investor's online well-being. First, we measure an investor's sentiment (or happiness) based on her posted messages on the iMaibo platform. We use the Chinese version of LIWC2015 dictionary (Huang et al. 2012; Pennebaker et al. 2015) to measure each investor's weekly sentiment score. Table 4 shows the regression results. We include lagged *AGE* and lagged positive and negative sentiment as well as investor and week fixed effects. The model in column (1) uses the full sample. As individual investors do not always express their views on iMaibo, the model in column (2) uses only the observations with non-zero messages to rule out the possibility that the regression results in column (1) are driven by the observations with zero messages. For both models, the coefficient on $RESILIENCE_{t-1}$ is always significantly positive, suggesting that more resilient investors on social media are happier.

Second, we use an investor's information purchase from SMAs as a proxy for the investor's well-being. Prior marketing research (Homburg et al. 2005; Seiders et al. 2005) shows that happier individuals are more likely to purchase consumer products. Hence, we examine whether more resilient investors are more willing to purchase information products from SMAs. The first two columns of Table 5 show the regression results. We measure an investor's information purchase using both *PURCHASE_COUNT* and *PURCHASE_AMOUNT*. We control for lagged *AGE* and lagged dependent variable. We also include investor and week fixed effects. Consistent with the marketing literature, we find that the coefficient on $RESILIENCE_{t-1}$ is always significantly positive, suggesting that more resilient investors on social media are more willing to purchase information products from SMAs.

Table 1 shows that $RESILIENCE_{t-1}$ contains a substantial number of zeros. To make sure that our results in Table 5 are not mechanically driven by zero $RESILIENCE_{t-1}$ observations, the last two columns of Table 5 replicate the models in the first two columns of Table 5 using the non-zero $RESILIENCE_{t-1}$ observations only. The coefficient on $RESILIENCE_{t-1}$ continues to be significantly positive for both dependent variables. Overall, our results in Tables 4 and 5 are consistent with the hypothesis that online investor resilience helps improve the well-being of individual investors.

7 Conclusion

Since the outbreak of the Covid-19 pandemic, resilience has become a salient concept to many investors and policy makers. The rise of social media in the past decade has also highlighted the importance of online social networks to the well-being of individuals. The objective of this study is to examine the impact of social capital that individual investors develop on social media (referred to as online social capital) on the online resilience of individual investors on social media. We test our research question within the context of China's largest stock market crash in the past decade that occurred in June 2015.

We measure both online social capital and online investor resilience using a proprietary database from iMaibo, a social investing platform in China. The extant social capital literature predominantly focuses on social capital in offline communities and hence implicitly assumes that offline social capital is a stable personal trait. However, Kane et al. (2014) show that online social networks are fundamentally from offline social networks. Hence, we distinguish online social capital one accumulates prior to the stock market crash (referred to as pre-event online social capital) and social capital one accesses to during the stock market crash (referred to as post-event online social capital). We show that online social capital is fragile because the correlation between pre-event online social capital and post-event online social capital is 0.281 only in our setting.

In contrast to prior offline social capital literature, we find little evidence that pre-event online social capital positively affects online investor resilience. However, we find that post-event online social capital positively affects online investor resilience, suggesting that online social capital behaves differently from offline social capital. We also examine the macro and individual investor characteristics that may affect the impact of post-event online social capital on online investor resilience. We find that network size but not market index return affects the effect of post-event online social capital. In addition, we find that the effect of post-event online social capital is more positive for newly joined investors and investors with higher offline social capital. We find that online investor resilience matters to investor well-being. Specifically, we show that more resilient investors are happier and purchase more information products from social media analysts.

We contribute to a small but growing literature in finance on investor resilience by showing the role of online social capital on individual investor resilience on social media. Our study is also complementary to the large social capital literature that predominantly focuses on offline social capital. To our best knowledge, we are the first study that examines how online social capital affects investor resilience in online social networks.

We expect our results to be of interest to social investment platforms and securities regulators. For example, we provide a validated measure of online investor resilience that can be used by platforms and regulators to monitor the health of online investors. In addition, our results suggest that if policy makers wish to shape investor resilience on social media, they need to pay more attention to post-event online social capital rather than pre-event social capital due to the fragility of online social capital.

Due to data limitations, we are not able to examine the relationships between online social capital/online investor resilience and offline social capital/offline investor resilience. With the rapid convergence of online and offline social communities, we believe that it is interesting to study the interactions of online and offline social capital and investor well-being in both online and offline communities.

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Appendices

Appendix 1 – Definitions of social network variables

We introduce concepts and definitions of social network measures, including degree centrality, closeness centrality, eigenvector centrality, betweenness centrality and local clustering coefficient based on directed networks. All individual centrality measures are normalized to have a mean of zero and standard deviation of one.

1. Degree centrality measures the total number of connections that a focal investor has with other investors. Degree centrality is defined as the number of links a node (i.e., an investor in our case) has. We use the following three interaction behaviors to define links between nodes: following, comments and likes. All interaction behaviors are treated as a one-shot event, so we do not assume the interaction is persistent for some extended period (i.e., an interaction is effective only in the current period). In-degree centrality is the number of inward links from other investors to a focal investor, and out-degree centrality is the number of outward links from the focal investor to other investors. Degree centrality is the sum of in-degree and out-degree scores.
2. Closeness centrality of a node u (i.e., a user) is the reciprocal of the average shortest path distance to u over all $n-1$ reachable nodes, namely,
$$C(u) = \frac{n-1}{\sum_{v=1}^{n-1} d(v,u)},$$
where $d(v,u)$ is the shortest-path distance between v and u, and n is the number of nodes that can reach u. Closeness centrality can help identify individuals who are best placed to influence the network most quickly (thinking about "broadcasters").
3. Eigenvector centrality measures a node's importance by calculating the importance of the immediate neighbors of the current node. Eigenvector centrality computes the centrality of a node based on the centrality of its neighbours. The eigenvector centrality for node i is the i-th element of the vector x defined by the equation
$$Ax = \lambda x,$$
where A is the adjacency matrix of the graph with eigen value λ. A high eigenvector score means that a node is connected to many nodes who themselves have high scores.
4. Betweenness centrality of a node u is the sum of the fraction of all-pairs shortest paths that pass through u, namely,
$$B(u) = \sum_{s,t \in V} \frac{\sigma(s,t|u)}{\sigma(s,t)},$$
where V is the set of nodes, $\sigma(s,t)$ is the number of shortest (s,t)-paths, and $\sigma(s,t|u)$ is the number of those paths passing through some node u other than s,t. If $s=t$, $\sigma(s,t)=1$, and if $u \in s,t$, $\sigma(s,t|u)=0$. Betweenness centrality is useful for

finding individuals who have more control over the network, because more information will pass through them.

5. Local clustering coefficient calculates how many friends of one node are friends themselves. The clustering coefficient of a node u is the fraction of possible triangles through that node that exist, namely,

$$c_u = \frac{2T(u)}{\deg(u)\,(\deg(u) - 1)},$$

where $T(u)$ is the number of triangles through node u and $\deg(u)$ is the degree of u.

By definition, local clustering coefficient does not distinguish directed versus undirected networks.

Appendix 2 – Variable Definition

Variable name	Description
$RESILIENCE_{it}$	Resilience score for investor i in week t during the post-event period. See more details in Section 4.2 and appendix 3.
$RESILIENCE_{i}$	Resilience score of the whole post-event period for investor i (defined according to equation (1) in Section 4.2).
Network variables	
$POST\text{-}EVENT\_SOCIALCAPITAL_{it}$	First principal component of degree centrality, closeness centrality, eigenvector centrality, betweenness centrality and local clustering coefficient (see appendix 1) for each investor i in week t. It is computed as 0.476 * degree $centrality_{it}$ + 0.523 * closeness $centrality_{it}$ + 0.407 * eigenvector $centrality_{it}$ + 0.421*betweenness $centrality_{it}$ + 0.397 * local clustering $coefficient_{it}$. The first principal component explains 57.53% of total variance. Since the coefficient before each proxy of social capital is always positive, the interpretation of this variable is similar to individual social capital proxies. All network measures have been standardized to have a mean of 0 and standard deviation of 1 in each week t before principal component analysis.
$POST\text{-}EVENT\_SOCIALCAPITAL_{i}$	Average of $POST\text{-}EVENT\_SOCIALCAPITAL_{it}$ in the entire post-event period.
$PRE\text{-}EVENT\_SOCIALCAPITAL_{i}$	First principal component of pre-event degree centrality, pre-event closeness centrality, pre-event eigenvector centrality, pre-event betweenness centrality and pre-event local clustering coefficient. The individual pre-event social capital proxies are defined over the 180-day period prior to the onset of the stock market crash (i.e., June 15, 2015). It is computed as 0.548 * pre-event degree $centrality_{i}$ + 0.423 * pre-event closeness $centrality_{i}$ + 0.527 * pre-event eigenvector $centrality_{i}$ + 0.478* pre-event betweenness $centrality_{i}$ + 0.123 * pre-event local clustering $coefficient_{i}$. The first principal component explains 54.82% of total variance. Since the coefficient before each proxy of pre-event social capital is always positive, the interpretation of this variable is similar to individual pre-event social capital proxies. All network measures have been standardized to have a mean of 0 and standard deviation of 1 before principal component analysis.
$DISRUPTION_{it}$	An indicator variable that is equal to 1 if an investor has SMA friends who experienced disruption events during or before week t, and 0 otherwise. We define SMA friends of an individual investor to be those who interacted (i.e., comments, likes and following) with the individual investor in week t-1.

Cross-section variables	
$MARKETRET_{t-1}$	Value-weighted market return (including Shanghai Stock Exchange and Shenzhen Stock Exchange) in week t-1.
$NETWORKSIZE_{t-1}$	Total number of active users (including investors and SMAs) in week t-1 divided by total healthy users before the stock crisis. There were 10,953 healthy investors and 120 healthy SMAs before the start of the crisis.
EXP_{it-1}	A dummy variable that is equal to one for investors whose number of days since joining iMaibo is above sample median and zero otherwise.
$OFFLINE\_SOCIALCAPITAL_{it-1}$	This variable is constructed using the following two steps: 1) Based on IP address data during the pre-event period, we define the location of a user to be the most frequent city in the user's IP address data. 2) $OFFLINE\_SOCIALCAPITAL_{it-1}$ is a dummy variable that is equal to one if an investor interacts (via following, likes and comments) with another user (including SMAs and investors) within the same location (specific to city) week t-1 and zero otherwise.
Information purchase	
$PURCHASE\_AMOUNT_{it}$	Total amount of money paid by investor i for information during week t. Log is taken later in regression analysis.
$PURCHASE\_COUNT_{it}$	How many times investor i pays for information during week t.
Investor sentiment	
$POSITIVE\_COUNT_{it}$[9]	Number of positive postings made by investor i during week t.
$NEGATIVE\ COUNT_{it}$	Number of negative postings made by investor i during week t.
$POSITIVE\_COUNT_{it}$ - $NEGATIVE\ COUNT_{it}$	The difference between $POSITIVE\_COUNT_{it}$ and $NEGATIVE\ COUNT_{it}$
$POSITIVE\_COUNT_{it}$ - $NEGATIVE\ COUNT_{it}$ Conditional on content > 0	Computed as the difference between $POSITIVE\_COUNT_{it}$ and $NEGATIVE\ COUNT_{it}$ if investor i creates at least one tweet/article during week t, and NA otherwise.
Other variables	
AGE_{it}	Age of investor i on the platform in week t, measured as number of days since joining iMaibo.

[9] Investors do not post many content in the majority of times, so it is not appropriate to scale these variables (denominator is too small).

AGE_i	Age of investor i on the platform (see above) measured on June 14, 2015.
$PRE\text{-}EVENT\_ACTIVENESS_i$	Total activeness score during the pre-event period. See more details in Section 4.2.

Appendix 3 – Measuring the target activeness function TAF_i

We predict an investor's target activeness function (TAF_i) in the post-event period using machine learning models trained using data in the pre-event period. Common prediction models (e.g., K-nearest neighbor, tree-based models and neural networks) use input variables in period t or earlier (e.g., lagged AF_i or time-variant individual investor characteristics) to predict an outcome variable in period t+1 or later (e.g., TAF_i in our setting). Unfortunately, this approach is not appropriate for our setting because both the outcome variable and the input variables are affected by the stock market crash itself. Hence, we consider the following three types of machine learning prediction models instead: (i) the baseline model; (ii) a clustering-based model; (iii) Facebook's Prophet model; and (iv) the combination of the Prophet model and a Lookalike model. Below we explain the details of each model. For all models, the sample is observations in the pre-event period (i.e., from January 2, 2014 to June 14, 2015). We split the sample into training and validation sets to perform cross-validation.

We adopt the approach of nested cross validation for time series, which is also known as "evaluation on a rolling forecasting origin" (Hyndman & Athanasopoulos 2018). Figure A3.1 illustrates this approach. Blue dots represent training data and red dots represent validation data. Due to the nature of time series data, each training set must precede the validation set to avoid look-ahead biases. As our data in the pre-event period have only a maximum of 529 days, we limit the length of the validation period to 90 days and conduct 3-fold cross validation. Another reason for selecting the 90-day cutoff is that this interval covers the first wave of the stock market crash that started on June 15, 2015. Cross-validation results are presented in Section A3.5 below.

A3.1. Baseline model

For each investor i on day t in the validation sets, the predicted TAF_{it} is simply the mean of her daily activeness score AF_i in the training sets. Note that for this baseline model, TAF_{it} only has cross-sectional variation: Each investor i has a constant TAF_i over the entire validation period.

A3.2. Clustering-based model

Clustering-based prediction model works as follows. First, we use K-means clustering to generate K clusters based on each investor's daily activeness scores in the training period. We select K to be 30 based on cross-validation. Second, we further split each of the K clusters into smaller clusters based on each investor's account creation time. Investors who created their accounts in the same quarter will be clustered together. Although we can also conduct the creation time clustering first and then followed by K-means clustering, this alternative approach would face a tricky problem when deciding K for each creation time cluster. Thus, we consider only the former clustering order for the ease of parameter tuning. For each investor i in cluster k on day t in the validation sets, the predicted TAF_{it} is simply the mean of the daily activeness score AF_k of all members in cluster k in the training sets. Note that for this clustering model, TAF_{it} only has cross-sectional variation across clusters: Each cluster k has the same TAF_k over the entire validation period.

K-means algorithm is a standard clustering algorithm, which iteratively minimizes the squared sum of distance between a data point and its assigned cluster. In our study, since different investors may have different creation time, thus different length of data, we cannot directly adopt Euclidean distance. Instead, we use the Dynamic Time Warping (DTW) distance, which is also widely used to measure similarity between two time series (even with different lengths).[10]

A3.3. Facebook's Prophet model

Facebook has proposed a forecasting procedure called Prophet (Taylor & Letham 2017). It is an additive deterministic time-series model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Thus, if we use the daily aggregated data, Prophet may provide better predictions given that we have sufficiently long training data. The Prophet model is expressed as follows:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t, \tag{3}$$

where $y(t)$ is the activeness score that we want to model. $g(t)$ is the trend function, which models non-periodic changes using a piecewise linear regression model. $s(t)$ is the seasonal function, which models the periodic changes in the value of the time series and is represented using a Fourier transformation. We only include weekly seasonality because 1) our training data is not enough to have annual seasonality and 2) we do not have within-day variations to model daily seasonality. $h(t)$ represents the function of modeling holidays and special impact events. ϵ_t is the model error which is assumed being normally distributed. The Prophet model is trained for each investor. For each investor i on day t in the validation sets, the predicted TAF_{it} is the predicted activeness score according to the trained model for each investor i. Prophet model produces both cross-sectional and time-series variations in TAF_{it}.

A3.4. Prophet + Lookalike

During preliminary experiments, we learned that Prophet performed better if there were sufficiently long training data. In our study, however, there are both investors who have a lot of historical data (i.e., accounts created early) and investors who have very few historical data (i.e., accounts created close to the end of the pre-event period). To improve the

[10] A drawback of DTW distance is that it might induce high computational costs and treat two time series similar if they share similar shapes with different time gaps. This feature may not help in our setting. Consider the following example. Investor A registered her account 200 days ago. Investor A was active for the first 100 days, and inactive for the remaining 100 days. Investor B registered her account 2 days ago, and investor B was active on the first day and inactive on the second day. DTW distance thinks that these two investors are the same because they have the same shape of activeness curve. In reality, however, these two investors might be quite indifferent in future behavior.

performance of our final machine learning prediction model, we consider a hybrid approach. Specifically, for investors who have sufficient historical data, we use the Prophet model, but for investors who have little historical data, we propose to adopt a Lookalike model. Consider the following example. An investor Bob's account was created on June 10, 2015 and had been active for five days in the pre-event period starting from the account creation date (i.e., 2015-06-10, 2015-06-11, 2015-06-12, 2015-06-13, 2015-06-14). Hence, we define a new variable called investor age relative to his account creation date. Bob's active age interval (i.e., the ages when he was active) is [0, 1, 2, 3, 4], corresponding to the five calendar days above. To predict Bob's daily activeness score for the first 90-day test period, we first find K lookalike investors for Bob. We calculate the similarity between different investors by comparing activeness scores in the same active age interval as Bob's, i.e., [0, 1, 2, 3, 4] in this example. Since the active age interval is identical, we adopt Euclidean distance function to compute the similarity to avoid the drawback of DTW distance discussed in footnote 10. To predict Bob's future 1-day AF (i.e., Bob's activeness with an age of 5), we calculate the average activeness score of the K lookalike investors when their age was 5. Similarly, to predict Bob's future n-day AF (i.e., Bob's activeness with an age of n+4), we calculate the average activeness score of the K lookalike investors when their age was n+4. As Bob grows older, there will be fewer lookalike investors available in the dataset, but there will be more historical training data for Bob and hence we can switch to the Prophet model for the older Bob as noted at the beginning of this paragraph.[11]

There are mainly two hyperparameters for the hybrid model of Prophet and Lookalike: 1) lower-bound length of the active age interval (la) and 2) number of lookalike investors (lk). Investors whose daily time-series in the training set is shorter than la use Lookalike method, and investors whose daily time-series in the training set is longer than or equal to la use Prophet model. Number of lookalike investors (lk) decides how many lookalike investors to find in Lookalike method.

Since we use the target activeness function (TAF_i) as a denominator when calculating resilience (R_i), the latter is not defined when TAF_i is zero. We deal with this missing value issue as follows: 1) Case 1: When both the activeness score and the target activeness score are zero, we set R_i to be zero; 2) Case 2: When the activeness score is positive but the target activeness score is zero, we set R_i to be equal to the activeness score only.11.4% of observations in our sample are affected by both cases. Case 1 comprises the super majority (99%).

A3.5. Cross validation performance results

To mitigate the influence of outliers, we use the standard mean absolute error (MAE) as the evaluation criterion of all machine learning models. MAE is defined as follows:

$$\frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y_j}\right|$$

[11] The Lookalike method cannot be used independently because for investors with very long active age intervals there may not exist any lookalike investors who satisfy sample selection conditions discussed in the text.

We conduct hyperparameter tuning for the Prophet+Lookalike model in order to achieve optimal performance. There are mainly two parameters to be tuned, including the lower-bound length of the active age interval (la) and number of lookalike investors (lk). We vary la from [14, 21, 28, 35, 42, 49, 56, 63, 70, 77, 84, 91, 98] and lk from [3, 5, 10]. The larger la is, the more accurate the Prophet model would be, but the number of available lookalike investors also decreases with *la*, which may negatively affect the performance of lookalike modeling, especially when the entire pool of investors is not large enough. The cross-validation performance results presented below are averages of the 3 folds reported in Panel B of Figure A3.1.

Panel A of Figure A3.2 shows that the best hybrid model requires the Prophet model to be built on more data (i.e., 98 days) and the lookalike model to be built on larger lk (i.e 10). Panel B of Figure A3.2 shows the cross validation results for individual investors with a prediction horizon of 90 days in the validation period. The statistics of MAE show that the Prophet+Lookalike model achieves the best cross-validation performance. Hence, we use this hybrid prediction model in the paper.

Table 1. Summary Statistics

This table reports summary statistics. Variable definition is in Appendix 2. All variables are winsorized at 1% and 99%. *p<0.1; **p<0.05; ***p<0.01.

Panel A. Summary Statistics

Variables	Mean	SD	Min	Q5	Q25	Median	Q75	Q95	Max	N
$RESILIENCE_{it}$	0.465	1.371	0.000	0.000	0.000	0.000	0.314	2.180	10.187	273825
$POST\text{-}EVENT\_SOCIALCAPITAL_{it}$	0.000	1.696	-0.731	-0.651	-0.476	-0.388	-0.281	1.351	36.482	273825
AGE_{it}	368.930	175.834	70.000	114.000	228.000	356.000	481.000	709.000	832.000	273825
$DISRUPTION_{it}$	0.038	0.191	0.000	0.000	0.000	0.000	0.000	0.000	1.000	273825
$RESILIENCE_{i}$	1.529	6.177	0.000	0.000	0.014	0.204	0.677	4.643	51.048	10953
$PRE\text{-}EVENT\_SOCIALCAPITAL_{i}$	0.000	1.656	-1.408	-1.377	-1.201	-0.294	0.516	3.016	10.066	10953
$POST\text{-}EVENT\_SOCIALCAPITAL_{i}$	0.000	1.174	-0.455	-0.455	-0.455	-0.388	-0.084	1.717	14.948	10953
AGE_{i}	277.707	168.401	26.000	51.000	139.000	272.000	375.000	631.200	703.000	10953
$PRE\text{-}EVENT\_ACTIVENESS_{i}$	0.259	0.261	0.004	0.012	0.069	0.165	0.373	0.777	1.263	10953
$MARKETRET_{t-1}$	-0.012	0.075	-0.159	-0.143	-0.071	0.011	0.052	0.072	0.091	262872
$NETWORKSIZE_{t-1}$	0.292	0.081	0.174	0.181	0.242	0.261	0.319	0.467	0.484	262872
EXP_{it-1}	0.492	0.500	0.000	0.000	0.000	0.000	1.000	1.000	1.000	262872
$OFFLINE\_SOCIALCAPITAL_{it-1}$	0.020	0.141	0.000	0.000	0.000	0.000	0.000	0.000	1.000	262872
$PURCHASE\_AMOUNT_{it}$	167.995	722.457	0.000	0.000	0.000	0.000	0.000	652.000	5980.000	273825
$PURCHASE\_COUNT_{it}$	0.533	1.361	0.000	0.000	0.000	0.000	0.000	4.000	6.000	273825
$POSITIVE\_COUNT_{it}$	0.081	0.422	0.000	0.000	0.000	0.000	0.000	0.000	3.000	273825
$NEGATIVE\_COUNT_{it}$	0.018	0.132	0.000	0.000	0.000	0.000	0.000	0.000	1.000	273825

Panel B. Correlation between Key Variables (N = 262,872)

	$PRE\text{-}EVENT\_SOCIALCAPITAL_{i}$	$POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$	$POST\text{-}EVENT\_SOCIALCAPITAL_{it}$
$PRE\text{-}EVENT\_SOCIALCAPITAL_{i}$	1.000		
$POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$	0.290***	1.000	
$POST\text{-}EVENT\_SOCIALCAPITAL_{it}$	0.281***	0.613***	1.000

$RESILIENCE_{it}$	0.004**	0.141***	0.212***

Table 2. The Effect of Online Social Capital on Online Investor Resilience

This table examines the effect of online social capital on online investor resilience. Variable definition is in Appendix 2. The sample size in Panel C is smaller than that in Panel A because we have to delete more individual investors whose target activeness scores in the post-event period are always zero. Standard error is clustered at both investor and week level (i.e., double clustering) for Panels A, C and D, and is clustered at investor level for Panel B. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Panel A. Investor-week Level Analysis

	Dependent variable:		
		$RESILIENCE_{it}$	
	(1)	(2)	(3)
PRE-EVENT_SOCIALCAPITAL$_{i}$	0.001		-0.007^{***}
	(0.002)		(0.002)
POST-EVENT_SOCIALCAPITAL$_{it-1}$		0.012^{***}	0.028^{***}
		(0.003)	(0.003)
RESILIENCE$_{it-1}$	0.509^{***}	0.277^{***}	0.502^{***}
	(0.019)	(0.015)	(0.018)
AGE$_{it-1}$	-0.00000	-0.001	-0.00001
	(0.00002)	(0.001)	(0.00002)
Week Fixed effects	Yes	Yes	Yes
Investor Fixed effects	No	Yes	No
Observations	262,872	262,872	262,872
Adjusted R^2	0.281	0.372	0.282

Panel B. Instrumental Variable Analysis

	Dependent variable:	
	POST-EVENT_SOCIALCAPITAL$_{it-1}$	RESILIENCE$_{it}$
	(1)	(2)
DISRUPTION$_{it-1}$	-0.643^{***}	
	(0.234)	
RESILIENCE$_{it-1}$	0.207^{***}	0.230^{***}
	(0.007)	(0.028)
AGE$_{it-1}$	0.001	-0.001
	(0.001)	(0.001)
POST-EVENT_SOCIALCAPITAL$_{it-1}$ `(instrumented)`		0.238^{**}

		(0.117)
Week Fixed effects	Yes	Yes
Investor Fixed effects	Yes	Yes
Observations	262,872	262,872
Adjusted R^2	0.479	0.331

Panel C. Investor-level Analysis

	Dependent variable:		
	RESILIENCE$_i$		
	(1)	(2)	(3)
PRE-EVENT_SOCIALCAPITAL$_i$	0.055		0.012
	(0.035)		(0.038)
POST-EVENT_SOCIALCAPITAL$_i$		0.204***	0.200***
		(0.028)	(0.032)
PRE-EVENT_ACTIVENESS$_i$	-2.170***	-2.315***	-2.357***
	(0.222)	(0.228)	(0.229)
AGE$_i$	0.0001	0.00000	-0.00000
	(0.0003)	(0.0003)	(0.0003)
Constant	2.056***	2.129***	2.141***
	(0.153)	(0.147)	(0.155)
Observations	10,953	10,953	10,953
Adjusted R^2	0.007	0.008	0.008

Panel D. Define Resilience with only Tweets and Articles

	Dependent variable:		
	RESILIENCE$_{it}$		
	(1)	(2)	(3)
PRE-EVENT_SOCIALCAPITAL$_i$	0.007***		0.001
	(0.002)		(0.002)
POST-EVENT_SOCIALCAPITAL$_{it-1}$		0.010***	0.019***
		(0.002)	(0.002)
RESILIENCE$_{it-1}$	0.382***	0.158***	0.376***
	(0.029)	(0.012)	(0.029)
AGE$_{it-1}$	-0.0001***	-0.001	-0.0001***

	(0.00002)	(0.0004)	(0.00002)
Week Fixed effects	Yes	Yes	Yes
Investor Fixed effects	No	Yes	No
Observations	244,800	244,800	244,800
Adjusted R^2	0.166	0.288	0.167

Table 3. Cross-sectional Variation of the Effect of Online Social Capital on Online Investor Resilience

This table examines cross-sectional variation of the effect of social capital on investor resilience on social media. Variable definition is in Appendix 2. Standard error is clustered at both investor and week level (i.e., double clustering). $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

	Dependent variable:			
	$RESILIENCE_{it}$			
	(1)	(2)	(3)	(4)
$POST\text{-}EVENT\_SOCIALCAPITAL_{it-1}$	0.012^{***} (0.003)	-0.024 (0.016)	0.019^{***} (0.004)	0.011^{***} (0.003)
$POST\text{-}EVENT\_SOCIALCAPITAL_{it-1} \times MARKETRET_{t-1}$	0.009 (0.043)			
$POST\text{-}EVENT\_SOCIALCAPITAL_{it-1} \times NETWORKSIZE_{t-1}$		0.123^{**} (0.053)		
$POST\text{-}EVENT\_SOCIALCAPITAL_{it-1} \times EXP_{it-1}$			-0.014^{***} (0.004)	
EXP_{it-1}			-0.036^{**} (0.016)	
$POST\text{-}EVENT\_SOCIALCAPITAL_{it-1} \times OFFLINE\_SOCIALCAPITAL_{it-1}$				0.013^{**} (0.006)
$OFFLINE\_SOCIALCAPITAL_{it-1}$				-0.107^{**} (0.045)
$RESILIENCE_{it-1}$	0.277^{***} (0.015)	0.276^{***} (0.015)	0.276^{***} (0.015)	0.278^{***} (0.015)

AGE_{it-1}	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Week Fixed effects	Yes	Yes	Yes	Yes
Investor Fixed effects	Yes	Yes	Yes	Yes
Observations	262,872	262,872	262,872	262,872
Adjusted R^2	0.372	0.373	0.373	0.373

Table 4. The Effect of Online Investor Resilience on Investor Happiness

This table examines the effect of online investor resilience on investor happiness. Variable definition is in Appendix 2. Standard error is clustered at both investor and week level (i.e., double clustering). $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

	Dependent variable:	
	$POSITIVE\_COUNT_{it}$ - $NEGATIVE\_COUNT_{it}$	$POSITIVE\_COUNT_{it}$ - $NEGATIVE\_COUNT_{it}$ Conditional on Content>0
	(1)	(2)
$RESILIENCE_{it-1}$	0.002^{**}	0.018^{***}
	(0.001)	(0.007)
AGE_{it-1}	0.00001	-0.002^{*}
	(0.0002)	(0.001)
$POSITIVE\_COUNT_{it-1}$	0.246^{***}	0.096^{***}
	(0.020)	(0.023)
$NEGATIVE\_COUNT_{it-1}$	-0.082^{***}	0.058^{*}
	(0.028)	(0.033)
Week Fixed effects	Yes	Yes
Investor Fixed effects	Yes	Yes
Observations	262,872	22,720
Adjusted R^2	0.516	0.577

Table 5. The Effect of Online Investor Resilience on Information Product Purchase

This table examines the effect of online investor resilience on information product purchase. To make sure that our results in Table 5 are not mechanically driven by zero $RESILIENCE_{t-1}$ observations, the last two columns of Table 5 replicate the models in the first two columns of Table 5 using the non-zero $RESILIENCE_{t-1}$ observations only. Variable definition is in Appendix 2. Standard error is clustered at both investor and week level (i.e., double clustering). $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

	Dependent variable:			
	$PURCHASE\_COUNT_{it}$	Log(1+ $PURCHASE\_AMOUNT_{it}$)	$PURCHASE\_COUNT_{it}$	Log(1+ $PURCHASE\_AMOUNT_{it}$)
	(1)	(2)	(3)	(4)
$RESILIENCE_{it-1}$	0.007^{***}	0.038^{***}	0.007^{*}	0.030^{***}
	(0.002)	(0.007)	(0.004)	(0.010)
AGE_{it-1}	0.001^{*}	0.003^{***}	0.002	0.007^{**}
	(0.001)	(0.001)	(0.002)	(0.003)
Lagged dependent variable	0.487^{***}	0.173^{***}	0.424^{***}	0.089^{**}
	(0.039)	(0.042)	(0.039)	(0.039)
Week Fixed effects	Yes	Yes	Yes	Yes
Investor Fixed effects	Yes	Yes	Yes	Yes
Observations	262,872	262,872	79,061	79,061
Adjusted R^2	0.808	0.586	0.807	0.550

Figure 1. Shanghai Composite Index Chart

This figure shows the change of Shanghai Composite Index during the 2015 stock market crash.

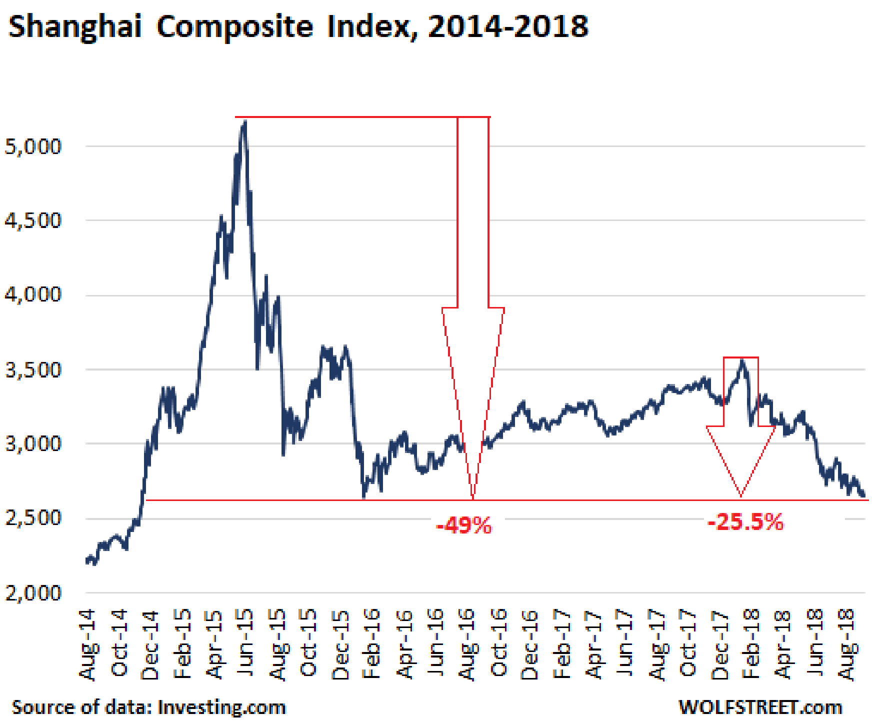


Figure 2. Change of Network Size Over Time

This figure plots the change of network size over time during the stock market crash period. Network size is the total number of active users (including investors and SMAs) in week t divided by total number of healthy users before the start of the financial crisis. There were 10,953 healthy investors and 120 healthy SMAs before the start of the crisis. The x axis is calendar time in the post-event period, and the y axis is the percentage of users that are active in week t.

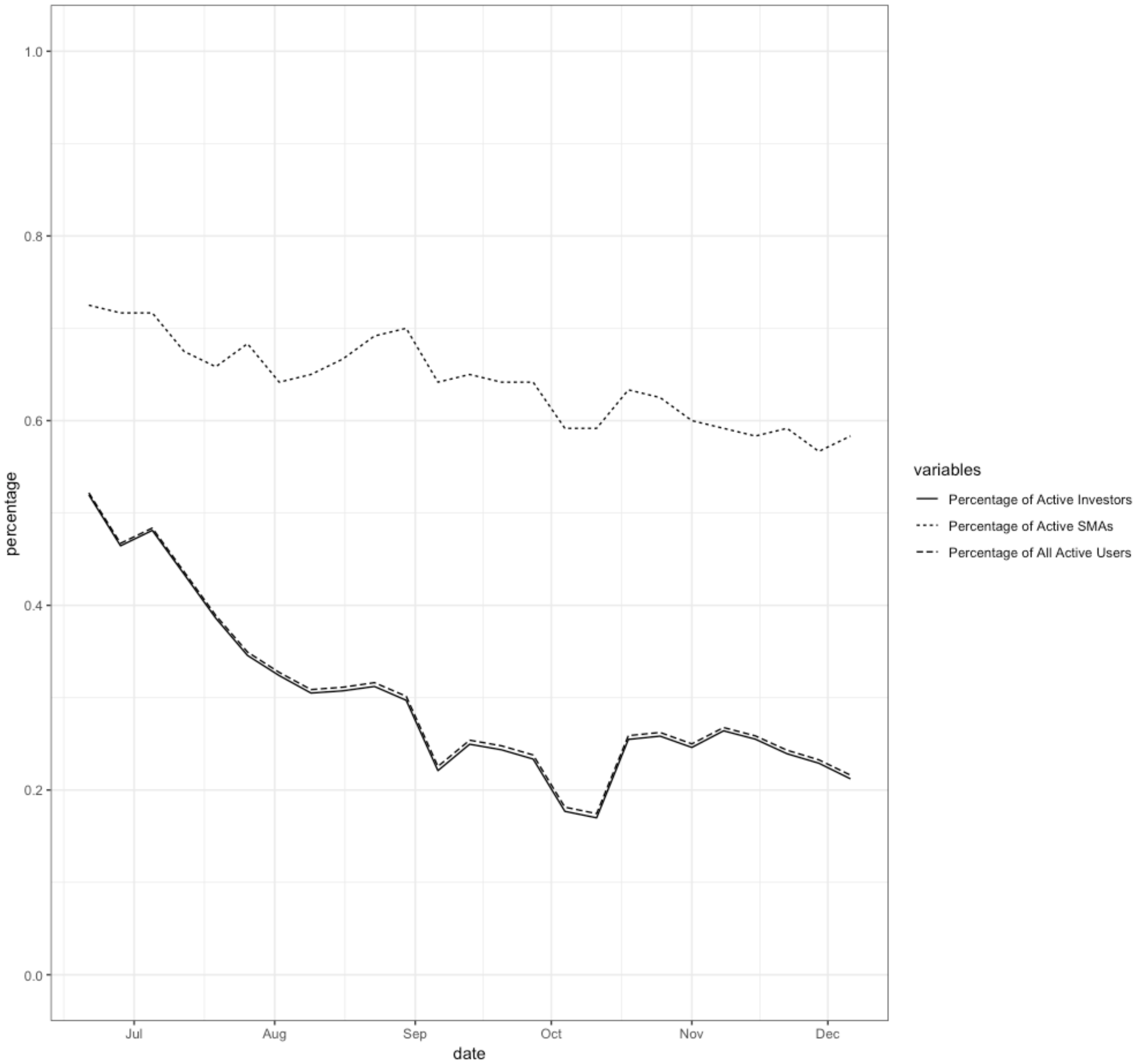
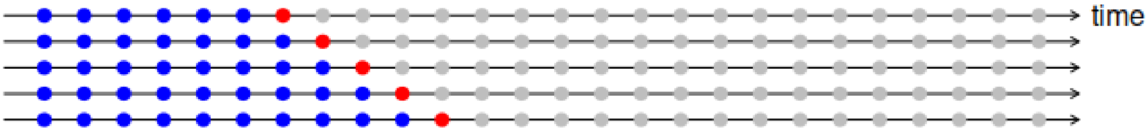


Figure A3.1. Nested Cross Validation for Time Series Prediction

Panel A. General Concept of Nested Cross Validation

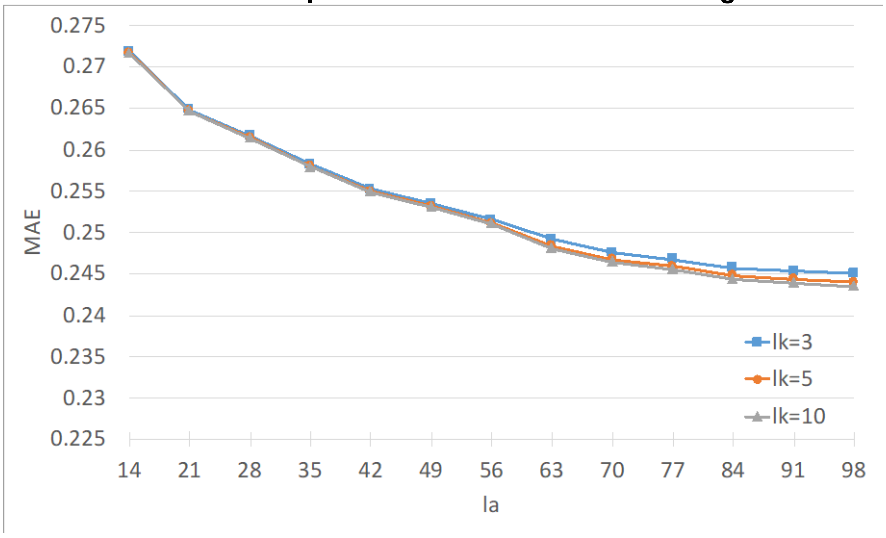


Panel B. Example of Cross-validation for 90-day Prediction in our Context

Fold	No. of Individual Investors	Training Period	Validation Period
1	9297 (/10953)	[2014-01-02, 2015-03-17)	[2015-03-17, 2015-06-15)
2	7331 (/10953)	[2014-01-02, 2014-12-17)	[2014-12-17, 2015-03-17)
3	5582 (/10953)	[2014-01-02, 2014-09-18)	[2014-09-18, 2014-12-17)

Figure A3.2. Target Activeness Function Prediction Results for Individual Investors

Panel A. Prophet+Lookalike Parameter Tuning



Panel B. Model Performance Comparison (90-day Prediction)

Model	Description	MAE
Clustering30+Q	30 KMeans and further split by quarterly	0.283
Clustering30+None	30 KMeans and no further split	0.290
Prophet+Lookalike	la=98, lk=10	**0.243**
Prophet	Pure Prophet	0.381
Baseline	Baseline	0.270

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