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Top executives on social media and information in the capital market: Evidence from China

Xunan Feng[a], Anders C. Johansson[b,*,1]

[a] Shanghai University of Finance and Economics, China
[b] Stockholm School of Economics, Sweden

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ABSTRACT

Social media platforms are becoming increasingly important channels for information dissemination. This study examines how microblogging by top executives affects the information environment for listed firms in an emerging market. Using a manually collected data set of Sina Weibo, one of China's most popular and largest social media platforms, we find that a board chair having a Weibo account is associated with the dissemination of more firm-specific information to the capital market. This result holds up to a battery of robustness tests, including an alternative noise-trading explanation and alternative measures of information flows and definitions of Weibo usage. We also show that the relationship between board chairs' Weibo usage and information dissemination is stronger for smaller firms, firms that went public more recently, and firms characterized by less analyst coverage. In addition, Weibo usage primarily disseminates firm-specific news rather than industry news. Finally, we document that institutional trading is an important channel through which private information is incorporated into stock prices. Findings in this study have important implications for the understanding of the role of social media in the dissemination process of corporate information and corporate communication strategy.

1. Introduction

Over the last decade, the internet has become the most important source for financial news, with thousands of websites providing information that can be accessed by all types of investors (Drake et al., 2017). More generally, it has been shown that consumers increasingly turn to fellow customers rather than expert advice when making their buying decisions (Chen et al., 2014). The growing importance of social media in information dissemination and the influence it has on buy and sell decisions in all walks of life have also transformed how financial information is disseminated and utilized. Previous studies have shown that the internet and social media act as channels for dissemination of corporate information, which in turn may affect the capital market (e.g. Hu et al., 2013; Blankespoor et al., 2014; Chen et al., 2014). The Securities and Exchange Commission (SEC) in the United States recognized the growing importance of this new information channel and announced that it would allow firms to disclose news through social media in 2013.

The goal of this study is to examine how social media usage by top executives acts as an information intermediary for the firms

* Corresponding author at: Stockholm School of Economics, P.O. Box 6501, Stockholm SE-113 83, Sweden.
E-mail address: anders.johansson@hhs.se (A.C. Johansson).

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they control. To do this, we collect official Sina Weibo accounts of board chairs in Chinese listed firms and analyze how the activation of a microblog account influences the dissemination of information. Sina Weibo is the largest microblogging service in China with 361 million monthly active users as of June 2017. Similar to Twitter, it is a popular platform for quick dissemination of news and opinions and is thus suitable for examining the research questions in this study.

A priori, there are several reasons why Weibo usage by board chairs could lead to more firm-specific information incorporated into stock prices. First, a Weibo account implies a higher probability of more news release, which may incentivize investors to analyze and trade more. Second, a Weibo account could indicate that investors find a new channel to communicate with top executives. For example, an anonymous investor can ask any question with board chair directly over the platform. Investors may acquire more firm-specific information through online communication. Weibo usage may thus incentivize investors to collect firm-specific information, which is a central determinant of information being incorporated into the stock price. When trading activity increases, it also contributes to further information transmission. Third, if a board chair uses Weibo, it may suggest that he or she is taking a more open approach to investors in general, leading investors to assume that firms under their control are more open to sharing more information, e.g. when firms issue public announcements. Openness can, in turn, encourage trading, thereby providing more cover for, and indirectly encouraging, privately informed trading. Last but not least, users can express their opinions in the comment section of Weibo messages. A board chair being active on Weibo may result in an increase in protection because of the possibility of insiders expropriating outside investors may be reduced under social pressure due to the possibility of commenting on posts. Grossman and Stiglitz (1980) argue that when information is inexpensive or when traders obtain precise information, the market price will reveal most of the information that is available to traders. Roll (1988) argues that private information is likely more common with respect to firms than to the overall market. Based on this, we hypothesize that microblogging by board chairs in Chinese listed firms complements traditional information sources by helping to improve firm-specific information dissemination to the market. Moreover, if microblogging by board chairs indeed helps decrease information asymmetries in the financial markets, we believe that the impact of board chairs' activity over social media on firm-specific information dissemination will increase for firms characterized by low transparency. Typical firms with lower transparency include smaller firms, firms that recently went public, and firms with less analyst coverage.

We collect data on board chairs' Weibo accounts and analyze their effect on information pertaining to stock price returns between 1 January 2010 and 31 December 2016. We find that only a small percentage (from 1% in 2010 to approximately 2.5% in 2016) of the board chairs of all listed firms have signed up for a Weibo account. In our benchmark analysis, we find that there is a significant and negative relationship between board chairs on Weibo and stock return synchronicity. This means that a board chair with a Weibo account is positively related to a better information environment for the firms under his or her control. We confirm this result with several robustness tests, including a firm fixed effect regression analysis, an instrument variable two-stage least square analysis, various matching methods, and an event study. Next, we examine how firm heterogeneity influence the relationship between board chair' Weibo usage and firm-specific information dissemination. We find that the effect of Weibo usage by board chairs is significantly stronger for smaller firms, newly listed firms, and firms with less analyst coverage. These findings are closely related to Jin and Myers (2006), who provide cross-country evidence showing that low levels of transparency and poor investor protection result in less firm-specific information dissemination. Our firm-level findings are consistent with their country-level results: a new channel for information disclosure in the form of a board chair's Weibo account is associated with decreased levels of return synchronicity. This information encouragement effect is especially prominent for firms characterized by higher information asymmetry. In addition, we find that the relationship between board chair Weibo usage and information dissemination is greater for family firms. For additional robustness, we also carry out an analysis in which we exclude firms in the finance industry, firms in the manufacturing industry and observations from 2015 as that was an unusually turbulent year for the Chinese stock market.

We also conduct additional robustness checks to take limits to arbitrage, pricing errors, and noise manifested in stock return synchronicity into account. We provide evidence that an alternative noise-trading argument does not explain our initial results. Our findings are also robust for several alternative variables that measure information flow more directly. These results support the proposition that Weibo usage by board chairs function as a driver of private information flows.

Considering that board chairs may discuss industry and market conditions on Weibo, we then use a return-earnings framework to examine whether board chair Weibo postings influence the timing relation by mainly disseminating industry-level, firm-specific, or both types of information. We find that Weibo usage primarily disseminates firm-specific rather than industry-level news. Considering the diversity of the content found on Weibo, we also redefine Weibo usages by measuring the density of Weibo postings. There is no fundamental effect on our initial results when we do this. Last but not least, we document an underlying mechanism which supports the relationship between Weibo usage and information dissemination. Institutional trading, especially trading by hedge funds, function as an important channel through which firm-specific information is incorporated into stock prices.

To sum up, our empirical findings support the hypothesis that activity over social media by board chairs in Chinese listed firms helps improve the information environment for the firms in question and that this relationship is dependent on several firm characteristics that are associated with transparency.

This study connects to several strands of literature. First, we contribute to a large body of literature that examines the information environment for listed firms. Previous research has analyzed capital market effects of professional reports (e.g., Drake et al., 2014; Dai et al., 2015), press coverage (Fang and Peress, 2009; Kothari et al., 2009; Bushee et al., 2010), and different types of internet intermediaries (Drake et al., 2017). Our study builds on this research by examining how social media usage by top executives affects the incorporation of firm-specific information in the capital market. Second, we extend the literature on social media and corporations. Previous studies have shown that firms use social media to reduce information asymmetry and increase the liquidity of their stocks (Blankespoor et al., 2014), engage their customers (Lee et al., 2017), attempt to control the negative effects of product recalls (Lee et al., 2015), and for the strategic dissemination of news (Jung et al., 2017). We contribute to this strand of literature by providing evidence for how corporations can utilize social media to improve their information environment.

Third, there is a growing literature on the relationship between social media and capital markets. For example, Bollen et al. (2011) examine how the mood on Twitter can help predict future stock market movements. Park et al. (2013) conduct an experiment on a stock message board to analyze the role of confirmation bias among investors. Chen et al. (2014) and Jame and Wolfe (2016) analyze how crowdsourced opinions of investors relate to stock market movements. Blankespoor et al. (2014) show how firm news disseminated via Twitter is related to lower bid-ask spreads and higher market liquidity. We extend this burgeoning literature by shedding light on how social media usage by key personnel in listed firms affects firm-specific information dissemination in the stock market.

Fourth, we add to the growing literature on how a firm's information disclosure or its institutional environment (e.g. legal origin, property rights protection, and quality of government) affects the relative importance of firm-specific as opposed to industry-level and market-wide factors (Jin and Myers, 2006; Piotroski and Roulstone, 2004; Chang et al., 2006; and Morck et al., 2000). We build on previous studies in this literature by examining if board chair Weibo postings lead to stock prices aggregating more firm-specific information, which would mean that market and industry factors explain less of the variation in stock returns. Our findings highlight that it is important to understand the nature of voluntary disclosure of information on a social media platform in trying to interpret any particular association between information flow and stock return synchronicity. To the best of our knowledge, this is the first study that examines how social media relates to firm-specific information capitalization in the market.

Last but not least, this paper improves our understanding of how social media and informed trading interact to influence the incorporation of information into stock prices. We reason that Weibo usage creates incentives to collect private information, which is a prerequisite for information dissemination. When trading activity is generated, it contributes to return synchronicity and the flow of private information. To corroborate this reasoning, we provide direct evidence on trading as a mechanism through which Weibo usage is related to stock return synchronicity. Specifically, this relationship persists and is stronger for stocks that are intensely traded by hedge funds that are involved in arbitrage. We show that at least one of the links between Weibo and information flow is via arbitrage institutions. To the best of our knowledge, such a link has not been sufficiently documented in previous studies.

The rest of the study is organized as follows. Section 2 introduces the Chinese microblogging service provided by Sina Weibo and explains why we have chosen this particular social media platform for our analysis. Section 3 presents the data and methodological approach. Section 4 provides the results of the benchmark model as well as alternative model specifications and robustness tests to alleviate concerns for endogeneity. A fixed effect model, an instrumental variable (IV) regression, several methods of matching, and an event study analysis are all implemented to verify our findings. Section 5 examines firm heterogeneity that may influence the relationship between board chairs' Weibo usage and private information dissemination in the capital market. Section 6 provides further robustness tests that focus on the data sample, alternative noise-trading explanation, several other measures of information flows, and a discussion on industry-specific versus firm-specific information dissemination. In addition, we also look at alternative definitions of Weibo usage. Finally, Section 7 concludes the study.

2. Sina Weibo - microblogging in China

The Chinese government has long enforced a policy of both encouraging the use of the internet while also maintaining vigorous control (Sullivan, 2012). One direct effect of this strategy is that the ecological social media system found in most other countries around the world is not present in China. The global microblogging platform Twitter was established in 2006 and was soon used by Chinese netizens as well. As early as 2007, several Chinese microblogs services (including TaoTao, Jiwai, Fanfou, and Zuosa) similar to Twitter were operational (Qin et al., 2017). However, none of these platforms managed to attract a larger user base. In 2009, microblogging had begun to play an important role as a channel for free-flowing information on current events.

However, this was not to last. In July 2009, a series of violent riots broke out in Urumqi, the capital city of the Xinjiang Uyghur Autonomous Region in China. The Chinese government quickly blamed the ethnic riots that resulted in the death of > 200 people on the uninhibited flow of information and rumors online. Subsequently, the use of international social media platforms such as Twitter and Facebook were banned. The news portal Sina.com presented a plan for a new microblog social media platform that would control incoming posts by tracking and blocking content that was deemed to be too sensitive (Sullivan, 2012). The company's CEO was well trusted by the government and Sina Weibo was launched in August 2009. Several competitors including NetEase, Sohu and Tencent soon launched similar services. However, Sina Weibo has remained the most popular platform for microblogging in China.

Today, Sina Weibo, typically called Weibo, is one of China's biggest social media platforms. While it is often called "China's Twitter", Weibo is more versatile and can in many ways be regarded as a combination of Twitter and Facebook. Weibo posts are limited to 140 characters, and photos, videos, images, and gifs can be uploaded as well. There are also significant differences between Twitter and Weibo in terms of user behavior (Gao et al., 2012). Weibo users tend to be more active and disclose more information about themselves (in contrast to Twitter users, Weibo users also post more during the weekends). While Twitter is a popular channel for political news flows and opinions, Weibo users, for natural reasons, tend to avoid issues that relate to political organizations and other institutions.

While some observers have argued that new rules established in 2015 requiring users to register with their real names would result in a strong decline and even death of Weibo, user trends between 2015 and 2017 say otherwise. In the 2017 June-ended quarter, Sina Weibo reported that it had reached 361 million monthly active users, an increase of 28% from the same period the previous year. This can be compared to Twitter reporting 319 million monthly active users for the same quarter. A 2016 report from China Internet Network Information Center (CNNIC) shows that the main purpose of using Weibo is to obtain trending news in time.

Thus, Weibo constitutes a dominant source of news content which enables its users to acquire, share, and comment on a variety of subjects. The importance of Weibo as a channel for dissemination of new information also means that it is suitable for the analysis of how top executives' use of social media affects the information environment of their firms.

3. Data and methodology

3.1. Board Chairs' Sina Weibo usage

We first identify the board chair for all listed companies during the period 2010–2016. The sample starts in 2010 since Sina Weibo was launched the previous year. The main reason we focus on the board chair rather than the CEO is that the chair often has the most authority in terms of making operational decisions in Chinese companies (Kato and Long, 2006; Feng and Johansson, 2017).[2] For each board chair, we then collect information on whether he or she has opened up an official Weibo account.[3] Panel A in Table 1 presents the number of all listed firms and the number of board chairs with Weibo accounts for each year throughout the sample period. As is evident in the table, only a small fraction of board chairs in listed companies have a Weibo account. In 2010, as few as 18 or < 1% of the total number of board chairs had a Weibo account. The number of board chairs with Weibo accounts has increased slowly but steadily throughout the sample period, with a total of 67 or 2.7% of the total number of board chairs having a Weibo account in 2016.

Panel B in Table 1 presents the distribution of listed firms by industry and the number of firms characterized by having a board chair with a Weibo account. Most of the firm observations are within manufacturing and that is also where most of the observations of firms with a board chair using Weibo is found. However, the highest percentage of firms characterized by having a board chair with a Weibo account is found in the hotel and catering, culture, sports and entertainment, and information technology industries.

3.2. Stock return synchronicity

To measure informativeness in the capital market, we use a firm-specific return variation measure. A similar approach has been used in several studies on stock market information (e.g., Durnev et al., 2003; Durnev et al., 2004; Jin and Myers, 2006; Feng et al., 2016). More specifically, we follow Morck et al. (2000) and calculate the stock return synchronicity for each firm. We first obtain the R^2 from an expanded index model:

$$r_{i,t} = \alpha + \beta_{m,t} r_{m,t} + \beta_{IND,t} r_{IND,t} + \varepsilon_{i,t}. \tag{1}$$

Here, $r_{i,\ t}$ is the return of stock *i* in week *t*. $r_{m,\ t}$ is the market return in week *t*, calculated as the weekly tradable market value-weighted returns of all Chinese A-share. Finally, $r_{IND,\ t}$ is the industry return in week *t*, calculated as the tradable market value-weighted industry index, excluding firm *i*. R^2 is the coefficient of determination from the estimation of model (1). Roll (1988) argues that the effect of broad, pervasive economic influences and of industry-wide influences on stock return changes are reflected in R^2. Consequently, the remainder is closely related to firm-specific information. As R^2 ranges from 0 to 1, we then follow Morck et al. (2000) and use a logistic transformation to obtain a suitable measure of stock return synchronicity:

$$Synch = LOG(R^2/(1 - R^2)). \tag{2}$$

When there is no firm-specific news, all of the observed changes in stock prices would presumably be explained by pervasive factors (Roll, 1988). A high value of Synch suggests that less firm-specific information is included in the stock return and that it is instead market-wide or industry-level information that is driving the price (Morck et al., 2000). Correspondingly, a smaller value means that more firm-specific information is incorporated into the stock market. In addition to our analysis on market-model stock return synchronicity, we examine the robustness of our results using other models, such as the Fama and French (1992) three-factor model, Carhart (1997) four-factor model and the French et al. (1987) estimator in which the additional terms adjust for biases that result from autocorrelation and cross-autocorrelations of weekly returns. Estimation of stock return synchronicity for these multi-factor models is analogous to that of the market model. In addition, we deal with the concern that *Synch* possibly acts as a proxy for noise-trading in Section 6.

3.3. Firm data

We obtain firm-level data for all listed firms with A-shares on the Shenzhen and Shanghai stock exchanges from the China Security Market and Accounting Research (CSMAR) database. CSMAR provides detailed annual financial information on all listed firms in

[2] Feng and Johansson (2016) note that the board chair in Chinese companies is often called *yi ba shou* (number one), while the CEO is *er ba shou* (number two).

[3] We investigate board chairs' personal Weibo account rather than firms' accounts for several reasons. First, most Weibo users are individuals rather than institutions or firms due to the nature of that particular social media platform. Second, board chairs can post a wide variety of content on their personal Weibo account, including issues pertaining to work as well as their private life. It is therefore interesting to investigate whether firm-specific information is incorporated into the stock price via Weibo. We thank an anonymous reviewer for suggesting that we explain this in more detail.

Table 1
The sample.

Panel A: Distribution of Firms with a Board Chair on Sina Weibo[a]

Year	Number of all listed firms	Firms with Board Chair Weibo	
		Number	As percentage of all listed firms (%)
2010	1858	18	0.969
2011	2013	46	2.285
2012	2101	54	2.570
2013	2114	58	2.744
2014	2178	65	2.984
2015	2306	67	2.905
2016	2447	67	2.738
Total	15,017	375	2.497

Panel B: Industry Distribution of Firms with a Board Chair on Sina Weibo[b]

Industry	Number of all listed firms	Firms with Board Chair Weibo	
		Number	As percentage of all listed firms (%)
Agriculture, Forestry, farming & fishery	240	0	0.000
Mining	441	0	0.000
Manufacturing	9065	224	2.471
Utilities	626	12	1.917
Construction	442	10	2.262
Wholesale and retail	955	25	2.618
Transportation	540	12	2.222
Hotel & catering industry	76	6	7.895
Information transmission、software & information technology service	586	26	4.437
Finance	369	0	0.000
Real estate	864	36	4.167
Leasing & commerce service	196	6	3.061
Scientific research & technology service	70	0	0.000
Water conservancy, environment & public facilities management	141	5	3.546
Education	15	0	0.000
Hygienism & social work	28	0	0.000
Culture, sports & entertainment	202	13	6.436
Comprehensive	161	0	0.000
Total	15,017	375	2.497

[a] This panel presents the distribution of A-share listed firms by year during 2010–2016. Firms with Board Chair are defined as firms whose board chair has opened a Sina Weibo account.

[b] This panel presents the distribution of A-share listed firms by industry in 2010–2016. Firms with Board Chair are defined as firms whose board chair has opened a Sina Weibo account.

China. Appendix 3 presents summary statistics for the variables used in the empirical analysis and Appendix 4 displays the correlation between them. All continuous variables are winsorized at the bottom and top 1% levels to avoid spurious results.

Synch is the measure for stock return synchronicity defined in the previous section and *Weibo* is a dummy variable that equals one if the firm has a board chair with a Weibo account and zero otherwise. Appendix 3 shows that the mean and median R^2 are 0.347 and 0.348 during 2006–2016, respectively. This is comparable to the reported mean R^2 of 0.453 for China in the 1995 sample of Morck et al. (2000). China's stock market has developed rapidly during the last two decades, and this development is a reasonable explanation for the decrease of R^2. It should be noted that it remains much larger than the reported mean R^2 of 0.193 in the US sample of Piotroski and Roulstone (2004). The mean and median *Synch* are -0.375 and -0.273, respectively, and it is computed using the specification of the market model in Piotroski and Roulstone (2004). They a mean and median of -1.742 and -1.754, respectively. This suggests that, compared with US firms, stock prices of firms in China tend to comove more with market-wide and/or industry level information. The standard deviation of *Synch* is 0.538, suggesting that the flow of firm-specific information into the stock market varies widely across firms even in a single country.

The remaining variables are firm-specific control variables and include: *Size*, the natural logarithm of total assets of the firm; *Leverage*, the ratio of total liabilities to total assets; *ROE*, net profits divided by total equity; *Sales Growth*, or the growth in sales over the last year; *Segments*, used to capture firm-level complexity, measured as the number of business segments exceeding 30% of the firm's total sales; *Volume*, defined as the natural logarithm of trading volume of the firm; *Volatility*, the standard deviation of the stock return of the firm; *Illiquidity*, the average ratio of daily absolute returns to the daily trading volume, multiplied by 10^9; *%INST*, the ratio of mutual funds' holdings, measured as the aggregate number of shares held by mutual funds, scaled by outstanding shares of the firm; *Analyst*, the natural logarithm of one plus the number of analysts that cover the firm, *Investability*, the ratio of shares which can be traded in the secondary market; *HHI*, the Herfindahl-Hirschman Index, an indicator of competition estimated by using all listed firms' sales from the same industry; *Family Firm*, a dummy variable which equals one if the firm is ultimately controlled by individuals and zero otherwise; *Control-Ownership*, a proxy for the ultimate owner's control in excess of their ownership rights, defined as the difference between the ultimate owner's control rights and ownership; *Ownership*, the cash flow rights owned by the ultimate owner; *Synchronous Fundamentals*, the Spearman correlation between the firm's ROA and its industrial average ROA over the past ten quarters.

4. Microblogging and the capital market

In this section, we provide empirical evidence on the negative relation between microblogging board chairs and stock return synchronicity. A firm fixed-effect model is provided in the next subsection to reduce the concern of unobservable firm-related factors. Subsection 4.3 presents an IV analysis, and subsection 4.4 presents a matching method analysis to further reduce endogeneity concerns. Finally, results from an event study are provided in subsection 4.5. The main finding in this section is clear: firms with microblogging board chairs exhibit a lower level of stock return synchronicity.

4.1. Baseline results

We begin our analysis of the relationship between board chair' Weibo usage and stock return synchronicity with an overview of R^2 and *Synch* for firms with and without board chairs with a Weibo account. Panel A in Table 2 presents the mean and median, as well as tests for differences between the two groups of firms. The results show that firms characterized by having a board chair with a Weibo account have a smaller R^2 and *Synch*. The difference is significant for both the mean and median values of the two measures. While preliminary, these findings indicate that board chairs using Weibo is associated with more firm-specific information in their stock prices and thus provide a better information environment for investors.

Clearly, the univariate comparisons are subject to observed bias due to the differences in sample characteristics which may influence the outcome. Statistical estimators can be used to control for this bias. In other words, while the univariate results support our research hypothesis, we need to control for firm-specific variables that may influence stock return synchronicity. To do this, we run a baseline pooled ordinary least square (OLS) regression and a Fama and MacBeth (1973) panel regression using the following model specification:

$$Synch_{i,t} = \alpha + \beta_0 Weibo_{it} + \beta \mathbf{x}_{it} + \gamma \mathbf{z}_i + \varepsilon_{it}. \tag{3}$$

$Synch_{it}$ is the measure for stock return synchronicity for firm *i* in year *t*, which is defined in Section 3.2 and $Weibo_{it}$, the main explanatory variable, is a dummy variable which equals one if the board chair of firm *i* had a Weibo account in year *t* and zero otherwise. $\mathbf{x}_{it}$ is a vector of the additional control variables introduced in Section 3.3, $\mathbf{z}_i$ is a vector of year- and industry-fixed effects. We cluster standard errors by firm and year where appropriate (Petersen, 2009; Thompson, 2011). The results for two regressions are presented in Panel B of Table 2. Results from a Fama and MacBeth (1973) regression are provided to ensure that the results are not driven by errors-in-variables and autocorrelation. In addition, board chairs' microblogging activities may cluster through time and the impact of macroeconomic conditions may vary across time. The Fama and MacBeth (1973) procedure provides a flexible specification for macrolevel changes. As can be seen in Table 2, the main explanatory variable *Weibo* is significantly negative in both estiations. We can thus conclude that Weibo usage by board chairs is a statistically significant determinant of stock return synchronicity. This relation is also economically significant: controlling for other firm characteristics, Weibo usage by board chairs reduces stock return synchronicity by 0.06, or about two percentages (see Appendix 3 for the mean variable). Weibo usage by board chairs result in more information flowing to the market via trading on private information. These multivariate regression results corroborate the initial findings of a significant positive relationship between board chairs' Weibo usage and firm-specific information imputed in the market. Microblogging board chairs are thus associated with a better information environment for investors.

These findings also have policy implications for regulators in transitional economies. Efficient allocation of scare capital is an important policy objective in emerging economies. Lower levels of stock return synchronicity are associated with a more efficient allocation of capital. Our results suggest that the capitalization of firm-specific information into stock prices in emerging markets could be facilitated via board chairs' activity on social media. Information disclosure via social media is thus a feasible way to improve the informational and functional efficiency of stock markets.

4.2. Fixed-effect analysis

While the empirical analysis in the preceding section supports our hypothesis, it assumes that Weibo usage is exogenously and randomly determined. To see if the baseline results are robust, we now relax this assumption. In addition, it is possible that unobserved or omitted variables that are difficult to measure affect our main explanatory variable *Weibo* as well as the dependent variable *Synch*. For example, it could be argued that it is not Weibo usage by the board chair, but instead good corporate governance that results in a higher level of firm-specific information transmission in the capital market. To remedy this potential issue, we have included *Control-Ownership* and *Ownership* as control variables as well since expropriation by the ultimate owner is a key corporate governance issue in China.

To further handle with the potential endogeneity problem, we run a fixed-effect regression. The fixed-effect model allows us to

Table 2
Stock Return Synchronicity and Board Chair Weibo.

Panel A: Summary Statistics

Mean

	Weibo		T-statistic for the difference between(1)and(2)
	With (1)	Without (2)	
R^2	0.325	0.347	2.31**
Synch	−0.446	−0.373	2.91***

Median

	Weibo		Wilcoxon-Mann-Whitney test for the difference between (1) and (2)
	With (1)	Without (2)	
R^2	0.321	0.348	2.14**
Synch	−0.324	−0.272	2.11**

Panel B: Multivariate Regression Analysis

	OLS	Fama and MacBeth (1973)
	(1)	(2)
Weibo	−0.069***	−0.067***
	(−3.11)	(−3.09)
Size	−0.023***	−0.024*
	(−2.66)	(−1.78)
Leverage	−0.060***	−0.056**
	(−3.25)	(−2.42)
ROE	0.096	0.088
	(1.19)	(1.23)
Sales Growth	−0.009	−0.002
	(−1.51)	(−0.06)
Segments	−0.010	−0.008
	(−0.98)	(−0.20)
Volume	0.110***	0.130***
	(16.47)	(7.86)
Volatility	−6.427***	−7.992***
	(−29.14)	(−13.18)
Illiquidity	−1.487	−1.144
	(−1.44)	(−0.72)
%INST	−0.341***	−0.233***
	(−8.77)	(−5.43)
Analyst	0.012***	0.011**
	(3.41)	(2.10)
Investability	−0.059***	−0.034***
	(−3.07)	(−2.82)
HHI	−1.269***	−1.650***
	(−5.11)	(−4.25)
Family Firm	−0.086***	−0.084***
	(−10.34)	(−4.11)
Control – Ownership	0.203***	0.207**
	(3.97)	(2.32)
Ownership	0.016	0.023
	(0.60)	(0.24)
Synchronous fundamentals	0.040***	0.037**
	(2.89)	(2.18)
Intercept	−1.757***	−2.345***
	(−10.03)	(−5.07)

(continued on next page)

Table 2 *(continued)*

Panel B: Multivariate Regression Analysis		
	OLS	Fama and MacBeth (1973)
	(1)	(2)
Year Dummy	Yes	No
Industry Dummy	Yes	Yes
N	15,017	15,017
Adjusted R^2	0.391	0.226

Panel A: This panel presents the summary statistics for the sample portfolios with and without board chair Weibo. Mean (median) is the average (median) value across all firms and years. All continuous variables are winsorized at the top and bottom 1%. The last column reports *T*-test/ Wilcoxon-Mann-Whitney test for the difference between *with* and *without* board chair Weibo. ***,** and * denote significance at 1%, 5%, and 10%, respectively.
Panel B: This table presents the multivariate regression results for board chair Weibo and stock return synchronicity. The sample period is from 2010 to 2016. The dependent variable is *Synch*, a commonly used stock return synchronicity measure calculated as $\log(R^2/(1 - R^2))$. R^2 is from regressions of the market model of return of the firm against the stock market index and industry index using weekly data. *Weibo* is a dummy variable which equals one when the board chair of firm *i* posted on Weibo at year *t,* and zero otherwise. *Size* is the natural logarithm of the market capitalization of firm *i* at the beginning of year *t. Leverage* is defined as the book value of all liabilities scaled by total assets, again measured at the beginning of the year *t. ROE* is the ratio of net profits divided by total equities at the beginning of the year *t. Sales Growth* is the ratio of sales growth from last year to this year. *Segments* is the number of segments, including only those with sales that exceed 30% of firm *i*'s total sales at the beginning of year *t. Volume* is the natural logarithm of trading volume of firm *i* at year *t. Volatility* is the standard deviation of the stock return of firm *i* at year *t. Illiquidity* is defined as the average ratio of daily absolute returns to the daily trading volume at year *t,* multiplied by 10^9. *%INST* is the ratio of mutual funds' holdings, measured as the aggregate number of shares held by mutual funds, scaled by outstanding shares of firm *i* in year *t. Analyst* is the natural logarithm of one plus the number of analysts that cover firm *i* at year *t. Investability* is the investability measure of firm *i* at year *t. HHI* (Herfindahl-Hirschman Index) is an indicator of competition, estimated by using all listed firms' sales from the same industry at the beginning of year *t. Family Firm* is a dummy variable which equals one if the firm is ultimately controlled by individuals and zero otherwise. (C*ontrol* – *Ownership*) is the difference between the ultimate owner's control rights and ownership. *Ownership* is defined as the cash flow rights of the ultimate owners. *Synchronous fundamentals* is defined as the Spearman correlation between the firm's ROA and its industrial average ROA over the past ten quarters. Model (1) presents the results from the OLS in which year and industry dummies are included but not reported. *t*-statistics are given in parentheses and computed using heteroskedasticity-robust standard errors clustered by firm and year (Petersen, 2009; Thompson, 2011). Column (2) presents Fama and MacBeth (1973) panel results. Industry dummies are included but not reported and *t*-statistics are computed using heteroskedasticity-robust standard errors clustered by industry. All continuous variables are winsorized at the top and bottom 1%.***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

control for firm-specific effects, and thereby to control for unobservable firm-related factors that may influence stock return synchronicity. It also helps us address the issue of potential reverse causality in the baseline regression. The fixed-effect regression model includes the same dependent variables as the benchmark regression, but excludes *Control-Ownership* and *Segments*, as these typically change very slowly.[4] The number of reservations in the fixed-effect regression is reduced somewhat since each firm needs at least two observations to be included. The fixed-effect regression results are presented in Table 3. The key explanatory variable *Weibo* is still negatively significant at the 1% level, suggesting that the initial results supporting our hypothesis are robust. These results again support the hypothesis that social media activity by top executives can enhance the information environment in an emerging market characterized by relatively poor investor protection.

4.3. Instrumental variable analysis

The results from the fixed-effect regression at least partially alleviate the concerns for potential endogeneity. However, the model specification in that analysis assumes that the potential unobserved heterogeneity we address is constant over time. To address the possibility of time-varying omitted variables, we also conduct a two-stage instrumental variable (IV) analysis. In the first stage, we construct a selection model for board chairs to open a Weibo account. In the second stage, we include predicted Weibo as an independent variable. We construct a measure for board chair personality by identifying his or her personal characteristics in the news. We first flag all news articles we find that contain at least the company name/abbreviation/code and the name of the board chair. Several individuals involved in the project then read the articles in detail to ascertain the personal characteristics of the board

[4] As suggested by an anonymous referee, we can keep *Control-Ownership* and *Segments* in the model specifications because these characteristics likely vary between firms. When doing so, our findings still remain qualitatively the same.

Table 3
Firm fixed effects.

	Firm fixed effect
Weibo	−0.014***
	(−5.19)
Size	0.209***
	(12.50)
Leverage	−0.141***
	(−3.02)
ROE	0.149***
	(3.77)
Sales Growth	0.015**
	(1.99)
Volume	0.168***
	(19.52)
Volatility	0.528***
	(2.91)
Illiquidity	26.680***
	(17.04)
%INST	−0.077
	(−1.50)
Analyst	0.036***
	(5.86)
Investability	0.174***
	(5.96)
HHI	−0.778**
	(−2.37)
Synchronous fundamentals	0.182***
	(10.06)
Intercept	−9.347***
	(−22.95)
Year Dummy	Yes
N	13,748
Adjusted R^2	0.527

This table presents the firm fixed effect regression results for board chair Weibo and stock return synchronicity. The sample period is from 2010 to 2016. The dependent variable is *Synch*, a commonly used stock return synchronicity measure, calculated as $\log(R^2/(1-R^2))$. R^2 is from regressions of the market model of return of the firm against the stock market index and industry index using weekly data. *Weibo* is a dummy variable which equals one when the board chair of firm *i* posted on Weibo in year *t* and equals zero otherwise. *Size* is the natural logarithm of the market capitalization of firm *i* at the beginning of year *t. Leverage* is defined as the book value of all liabilities scaled by total assets, again measured at the beginning of the year *t. ROE* is the ratio of net profits divided by total equities at the beginning of the year *t. Sales Growth* is the ratio of sales growth from last year to this year. *Volume* is the natural logarithm of trading volume of firm *i* at year *t. Volatility* is the standard deviation of the stock return of firm *i* at year *t. Illiquidity* is defined as the average ratio of daily absolute returns to the daily trading volume at year *t,* multiplied by 10^9. *%INST* is the ratio of mutual funds' holdings, measured as the aggregate number of shares held by mutual funds, scaled by outstanding shares of firm *i* in year *t. Analyst* is the natural logarithm of one plus the number of analysts that cover firm *i* at year *t. Investability* is the investability measure of firm *i* at year *t. HHI* (Herfindahl-Hirschman Index) is an indicator of competition, estimated by using all listed firms' sales from the same industry at the beginning of year *t. Synchronous fundamentals* is defined as the Spearman correlation between the firm's ROA and its industrial average ROA over the past ten quarters. Year dummies are included but not reported and *t*-statistics are computed using heteroskedasticity-robust standard errors clustered by year. All continuous variables are winsorized at the top and bottom 1%.***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 4
Two-stage regression analysis.

Panel A: Summary Statistics of Instrument Variables[a]

	Weibo		T-statistic(Wilcoxon-Mann-Whitney test) for the difference between (1) and (2)
	With	Without	
Social	0.384 (0.000)	0.102 (0.000)	11.12*** (17.17***)

Panel B: Two-stage Regression Results[b]

	First stage	Second stage
	Weibo	***Syn***
Predicted Weibo		−0.084***
		(−12.75)
Social	0.015***	
	(7.68)	
Size	0.005	−0.019***
	(1.54)	(−2.81)
Leverage	0.012	−0.053***
	(0.34)	(−3.62)
ROE	0.003	0.097
	(0.70)	(1.03)
Sales Growth	0.006	−0.009
	(1.19)	(−1.41)
Segments	0.021	−0.010
	(0.79)	(−1.24)
Volume	0.041	0.103***
	(1.24)	(12.63)
Volatility	0.168	−6.234***
	(0.95)	(−18.32)
Illiquidity	−0.018	−1.439
	(−0.50)	(−1.21)
%INST	0.035	−0.343***
	(1.26)	(−5.69)
Analyst	0.061	0.014***
	(1.08)	(3.75)
Investability	0.007	−0.063***
	(1.34)	(−3.21)
HHI	0.040	−1.261***
	(0.25)	(−5.85)
Family Firm	0.043	−0.081***
	(0.28)	(−9.40)
Control – Ownership	0.006	0.214***
	(0.17)	(3.65)
Ownership	0.006	0.013
	(0.15)	(0.83)
Synchronous fundamentals	0.001	0.045**
	(0.76)	(2.17)
Intercept	−0.134*	−2.566***
	(−1.79)	(−18.54)
Year Dummy	Yes	Yes
Industry Dummy	Yes	No
N	15,017	15,017
Pseudo /Adjusted R^2	0.281	0.415

(continued on next page)

Table 4 *(continued)*

Panel B: Two-stage Regression Results[b]

	First stage	Second stage
	Weibo	***Syn***
Tests of Exogeneity, Relevance, and Validity of Instruments		
Partial F-statistic: First Stage	31.654	
Partial R^2: First Stage	0.227	
Anderson–Rubin F-statistic		25.492
Hansen J-statistic		0.237

[a] Panel A: This panel presents the summary statistics of instrumental variables. The mean value is provided in column (1) and (2), and the corresponding median value is in parenthesis. The last column provides T-statistic(Wilcoxon-Mann-Whitney test)for the difference between firms with and without board chair Weibo. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

[b] Panel B: This panel presents the two-stage regression results of Weibo and stock return synchronicity. Predicted Weibo is the predicted probability of Weibo based on the estimation in the first-stage model. The dependent variables in the second stage model are stock return synchronicity. The lower part of this panel shows the partial *F*-statistic and the partial *R*2 from the first stage regression and the values for Anderson–Rubin *F*-statistic test and Hansen *J*-statistic.

chair. If at least three different sources claim that the board chair is good at social interaction (*shejiao*), we define the dummy variable *Social* as one and zero otherwise. We use the following news sources for the collection of this data: GTA Financial News Database, Genius Finance, INFOBANK, and China Core Newspapers Full-text Database.

Panel A in Table 4 presents the summary statistics of the IV *Social*. On average, board chairs with a Weibo account are clearly seen as better at social interaction in Chinese media. Board chairs with a Weibo account have higher mean and median scores for Social and simple tests for difference in mean and median of Social are significant at the 1% level. Next, we run the two-stage regression analysis. Panel B in Table 4 presents the results, with the first column displaying the first-stage results and the second column showing the second-stage results. In the first-stage regression, the coefficient for Social is positively significant at the 1% level, indicating that the IV Social indeed is strongly related to Weibo usage. In the second-stage regression, Predicted Weibo is negatively significant at the 1% level. To be sure of the suitability of the estimation, we also carry out tests for exogeneity, relevance, and validity of instruments. The Shea partial R^2 values and the *F*-statistic provide further support for the relevance of our IV in the first stage. The Anderson–Rubin *F*-statistic rejects the null hypothesis, thereby indicating that the endogenous regressor is relevant. Finally, the Hansen *J*-statistic is unable to reject the null hypothesis that the instrument is valid and orthogonal to the residuals. The exclusion of them in the main estimated equation is thus appropriate. To conclude, the two-stage regression again supports the main initial result, namely that microblogging board chairs are positively associated with a better information environment.

4.4. Matching method analysis

It is always a challenge to identify a good IV for a two-stage regression analysis. We acknowledge this and conduct additional robustness tests based on matching samples. Our main aim here is to use matching methods to identify samples of control firms with similar characteristics but without board chairs who have Weibo accounts. If the matching models are well designed, the difference between the treatment sample and the control sample will be driven by the key explanatory variable *Weibo*. A common approach is that of dimensional matching, which compares ex-post stock return synchronicity of treated firms with control firms having similar ex-ante characteristics such as industry, firm size, etc. However, this traditional matching method may potentially not yield good matches ex-ante because of a multi-dimensional matching problem. For comprehensiveness, we use four alternative matching methods commonly found in the literature: (1) firm size and industry; (2) firm size, industry, board chair age, and board chair education; (3) caliper matching; (4) Kernel matching. The first two matching methods are based on firm- and individual-specific characteristics, while the latter two are statistical propensity score matching (PSM) methods. In caliper matching, a common support condition is imposed which helps us avoid bad matches. This, in turn, results in a higher matching quality. In kernel matching, we instead construct a counterfactual outcome by applying nonparametric matching estimators based on weighted averages of most firms in the control group. One major advantage of kernel matching is the lower variance which is achieved since more information is used (Caliendo and Kopeinig, 2008).

The purpose of the different matching approaches is the same, namely to select a matching firm with similar ex-ante firm characteristics as those of non-Weibo firms. The variables selected in estimating a propensity score include those affecting both the propensity to use Weibo and the ex-post effect (Heckman and Navarro-Lozano, 2004). Finance theory and previous empirical studies suggest that a suitable propensity score can be estimated using the prediction model in the first stage as seen in Table 3.

Panel A of Table 5 presents the average treatment effects or the difference between the outcome of treated and non-treated (control) firms. Rows (1) and (2) in Table 5 show that the level of stock return synchronicity is significantly lower for treated firms, i.e. firms characterized by a board chair with a Weibo account. The results from these dimensional matchings are consistent with our

Table 5
Matching method for effects of Weibo on Stock return synchronicity.

Panel A. Differences in Stock Return Synchronicity[a]

Matching methods	Stock return synchronicity
(1) Size/Industry matching	−0.073***
(2) Size/Industry and Chair Age/Gender/Education matching	−0.076***
(3) Caliper matching	−0.082***
(4) Kernel matching	−0.084***

Panel B: Mean (Median) Tests[b]

	Treated firms	Control firms	T-statistic (Wilcoxon-Mann-Whitney test)
Social	0.384	0.392	0.22
	(0.000)	(0.000)	(0.22)
Size	22.782	22.729	0.34
	(22.667)	(22.538)	(0.26)
Leverage	0.471	0.476	0.27
	(0.455)	(0.461)	(0.30)
ROE	0.077	0.079	0.20
	(0.082)	(0.086)	(0.22)
Sales Growth	0.170	0.176	0.35
	(0.137)	(0.141)	(0.31)
Segments	1.156	1.142	0.11
	(1.000)	(1.000)	(0.16)
Volume	23.858	23.805	0.89
	(23.735)	(23.721)	(0.77)
Volatility	0.066	0.068	0.29
	(0.059)	(0.062)	(0.24)
Illiquidity	0.005	0.005	0.35
	(0.004)	(0.004)	(0.21)
%INST	0.128	0.125	0.74
	(0.039)	(0.034)	(0.53)
Analyst	2.442	2.430	0.36
	(2.861)	(2.836)	(0.40)
Investability	0.818	0.811	0.48
	(0.982)	(0.976)	(0.37)
HHI	0.045	0.042	0.34
	(0.005)	(0.004)	(0.51)
Family Firm	0.639	0.629	0.13
	(1.000)	(1.000)	(0.12)
Control – Ownership	0.039	0.037	0.82
	(0.000)	(0.000)	(0.84)
Ownership	0.329	0.324	0.29
	(0.342)	(0.340)	(0.35)
Synchronous fundamentals	0.075	0.073	0.21
	(0.091)	(0.087)	(0.28)

This table presents average treatment effects, i.e. the difference between outcomes of treated and control firms with similar characteristics or propensity scores. (1) and (2) are dimension-by-dimension matching methods. (3) and (4) are propensity score matching methods. “Size/Industry matching” matches each treated firm with control firm which has the nearest market capitalization and is also in the same industry. “Size/Industry and Chair Age/Gender/Education matching” matches each treated firm with a control firm that has the nearest market capitalization, is in the same industry, and whose chair has the nearest age, same gender, and educational attainment. The propensity score is estimated using the prediction model in the first stage as seen in Table 3. “Caliper matching” presents the treatment effect using caliper matching with a caliper of 0.05. “Kernel matching” gives the treatment effect using kernel matching. *T*-statistics are calculated using bootstrapping. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

[a] This panel presents the mean (median) differences in stock return synchronicity between treated and matching firms using four different matching methods.

[b] This panel presents results for tests for the difference in ex-ante firm characteristics between treated and matching firms using propensity score matching. A T-test (Wilcoxon-Mann-Whitney test) is used to examine the mean (median) difference after matching.

working hypothesis. However, the matching quality for our treated sample may be questioned. As mentioned earlier, we thus use propensity score matching to cope with the multi-dimensional matching problem (e.g., Rosenbaum and Rubin, 1983; Rosenbaum and Rubin, 1985; Heckman et al., 1997). Rows (3) and (4) in Table 5 display the results from caliper matching and kernel matching, respectively. Our results still remain qualitatively the same: board chairs' Weibo disseminates firm-specific information into the stock market. Panel B in Table 5 then presents the matching quality of ex-ante firm characteristics using propensity score matching. The paired *t*-test and Wilcoxon-Mann-Whitney test are used to investigate the mean and median difference between Weibo and matching

Table 6
Change in stock return synchronicity after activation of Weibo account.

Panel A. Size/Industry matched (N = 62)[a]

	Pre-Weibo usage	Post-Weibo usage	Difference between post- and pre-Weibo
(1) Firms with Weibo	−0.377	−0.552	2.76***
	(−0.329)	(−0.505)	(2.62***)
(2) Firms without Weibo	−0.381	−0.401	0.45
	(−0.338)	(−0.352)	(0.22)
Difference (1) and (2)	0.04	2.03**	3.18***
	(0.08)	(2.42**)	(3.57***)

Panel B. Size/Industry and Chair Age/ Gender/Education Matched (N = 56)[b]

	Pre-Weibo usage	Post-Weibo usage	Difference between post- and pre-Weibo
(1) Firms with Weibo	−0.376	−0.550	2.79***
	(−0.327)	(−0.501)	(2.68***)
(2) Firms without Weibo	−0.380	−0.397	0.24
	(−0.331)	(−0.348)	(0.16)
Difference (1) and (2)	0.05	2.06**	3.21***
	(0.07)	(2.51**)	(3.62***)

Panel C. Caliper matching (N = 52)[c]

	Pre-Weibo usage	Post-Weibo usage	Difference between post- and pre-Weibo
(1) Firms with Weibo	−0.378	−0.554	2.75***
	(−0.331)	(−0.509)	(2.60***)
(2) Firms without Weibo	−0.380	−0.391	0.45
	(−0.336)	(−0.347)	(0.22)
Difference	0.04	2.35**	3.31***
(1) and (2)	(0.06)	(2.51**)	(3.72***)

Panel D. Kernel matching (N = 54)[d]

	Pre-Weibo usage	Post-Weibo usage	Difference between post- and pre-Weibo
(1) Firms with Weibo	−0.378	−0.553	2.73***
	(−0.331)	(−0.507)	(2.58***)
(2) Firms without Weibo	−0.382	−0.390	0.41
	(−0.336)	(−0.344)	(0.20)
Difference (1) and (2)	0.05	2.01**	3.28***
	(0.06)	(2.37**)	(3.67***)

This table presents average treatment effects, using an event study method. "Pre-Weibo usage" is the three-year average stock return synchronicity before the board chair opened a Weibo account. "Post-Weibo usage" is the three-year average stock return synchronicity after the board chair opened a Weibo account. The corresponding median is given in parentheses. The last column reports a T-test (Wilcoxon-Mann-Whitney test) for the difference between "Post-Weibo usage" and "Pre-Weibo usage", which is a difference-in-means (medians) test. The last row reports a T-test (Wilcoxon-Mann-Whitney test) for the difference between Firms with and without Weibo, respectively for the three years before and after the activation of a Weibo account. The statistics on the last row and the last column is the Difference in Difference (DiD) test. All variables are winsorized at the top and bottom 1%. ***, **, and * denote significance for the difference between two samples at 1%, 5%, and 10%, respectively.

[a] "Size/Industry matching" matches each treated firm with a control firm that has the nearest market capitalization and is in the same industry.

[b] "Size/Industry and Chair Age/Gender/Education matching" matches each treated firm with a control firm that has the nearest market capitalization, is in the same industry, and whose board chair has the nearest age, same gender, and education degree.

[c] The propensity score is estimated using the prediction model in the first stage as seen in Table 3. "Caliper matching" presents the treatment effect using caliper matching with a caliper of 0.05.

[d] The propensity score is estimated using the prediction model in the first stage as seen in Table 3. "Kernel matching" gives the treatment effect using kernel matching.

firms for ex-ante firm characteristics. It is shown that the ex-ante variables are well balanced in terms of means and medians. We can thus conclude that the propensity score matching balances ex-ante variables simultaneously, suggesting that there is no treatment effect introduced by firm characteristics.

To sum up, the findings in this subsection holds up for all four alternative matching methods, thus providing further support to our previous findings.

4.5. Event study analysis

To test whether board chairs' Weibo cause stock return synchronicity, we study the change in return synchronicity following the opening of Weibo account by a board chair. We argue that setting up a new Weibo account represents a significant change in the information provided by board chairs, i.e., new firm-specific information is contained in the posts. Our tests focus on changes in return synchronicity that are likely attributable to the opening of Weibo accounts by board chairs. If what we are observing can simply be attributed to it (i.e., board chairs in firms which have more private information transmitted into the market are prone to use Weibo), stock return synchronicity should not shift when the board chair opens a Weibo account. Moreover, the Weibo accounts identified in the data sample are activated in different years, further reducing endogeneity concerns.

To do this, we first construct firm samples for “Pre-Weibo usage”, with the three-year average stock return synchronicity before the board chair of the firm in question opens up a Weibo account. We create corresponding subsamples for “Post-Weibo usage”. We then match each of these subsamples using the four different matching methods discussed earlier. By doing this, we can analyze the difference between pre- and post-Weibo usage by board chairs and compare this difference for the treatment and control groups.

Table 6 presents the results for the event study analysis results. Panel A presents the results for the size- and industry-matched firm groups. A difference-in-means test of the stock return synchronicity between the three-years before and three years after the opening of a Weibo account is reported in the final column. Looking at the first two lines, we find that the difference in stock return synchronicity is highly significant for the treatment group but insignificant for the control group. That is, Weibo significantly reduces stock return synchronicity for treated firms but not for control firms. A difference-in-means test of the stock return synchronicity between treated firms and control firms during the three-years before or after the activation of a Weibo account is reported in the final row. In Table 6, the first two columns show that the difference in stock return synchronicity for treated and control firms is not significant before Weibo usage, but their difference becomes significant after Weibo usage. That is, the information environment is similar for treated and control firms before Weibo usage, but after a board chair opens a Weibo account, more firm-specific information is incorporated into the stock market. The DiD test presented in the last column on the last row shows that stock return synchronicity decreases significantly after a board chair opens up a Weibo account.

The remaining three panels exhibit the same results for tests using alternative matching methods. These results show that firms experience a significant improvement in the dissemination of information to the market when their board chair opens up a Weibo account. This event study suggests that earlier panel-based results are not likely driven by reverse causality, lending further support to the argument that more firm-specific information is incorporated into the stock price after a board chair opens up a Weibo account.

5. The role of firm-specific characteristics: information asymmetry

Having established a significant relationship between board chairs' Weibo usage and firm-specific information dissemination in the capital market, we now examine firm-specific characteristics that may influence this relationship. A deeper analysis of firm heterogeneity can improve our understanding of the nature of private information flows. Previous studies have argued that information asymmetry is associated with costs due to adverse selection (e.g., Milgrom and Stokey, 1982; Copeland and Galai, 1983). Thus, Weibo usage by board chairs can be used as a tool for firms to overcome the reluctance of potential investors to hold firm shares.

As mentioned in the introduction, we hypothesize that Weibo usage by board chairs is likely to influence stock return synchronicity more for small firms, recently listed firms, and firms with less analyst coverage. The main premise behind this hypothesis is that these firms are typically characterized by a poorer information environment, suggesting that introducing a new channel such as a microblog by their leading figure may have a relatively larger impact. To analyze this, we create three new variables: *Smaller Firm*, a dummy variable that equals one if the firm's market capitalization is less than the median value of the sample and zero otherwise; *Younger Firm*, a dummy variable that equals one if the firm's listing year is lower than the corresponding median value of the sample and zero otherwise; *Fewer Analysts*, a dummy variable that equals one if the number of analyst covering a firm is less than the median value of the sample and zero otherwise. We then run separate OLS and two-stage regressions in which we include the interaction between *(Predicted)Weibo* and each of these variables, in Columns (1) and (2), respectively.

The results of the regressions that focus on these firm characteristics are presented in Table 7. Panel A displays the result for the analysis of firm size. The interaction variable *(Predicted)Weibo*Smaller Firms* is negatively significant at the 1% level, suggesting that the size of the firm is driving the influence board chairs' Weibo usage has on the information environment. Indeed, when we include the interaction term, the coefficient for *(Predicted)Weibo* on its own is no longer statistically significant. This result suggests that more information is flowing from board chairs' Weibo accounts when facing a higher level of information asymmetry.

Panel B presents the results for the analysis that focuses on the age of firms. Firm age can be used to capture the degree of the firms' information asymmetries. Basically, the older a firm is, the lower the degree of information asymmetry is associated with it on average (Datta and Iskandar-Datta, 1999). The interaction variable *(Predicted)Weibo*Younger Firm* is negatively significant at the 1% level, suggesting that how recent the firm is listed influences the effect board chair usage has on firm-specific information dissemination. Again, a new channel for information disclosure encourages the collection of private information and accelerates firm-specific information dissemination, leading to less stock return synchronicity, especially for opaque firms.

Finally, Panel C presents the results for the analysis of analyst coverage. Previous studies (e.g., Bhushan, 1989; Brennan and Subramanyam, 1995; Healy and Wahlen, 1999; Chang et al., 2006) have found that analysts follow firms that are easier to understand and argue that firms receiving less analyst coverage are subject to more information asymmetry. The variable *Fewer Analysts* can thus act as a proxy for higher opaque. Similar to the previous two firm characteristics, the interaction variable *(Predicted)Weibo*Fewer*

Table 7
Firm heterogeneity.

Panel A. Small firms[a]

	OLS	2SLS: Second stage
	(1)	(2)
Weibo	−0.051	
	(−1.08)	
Predicted Weibo		−0.069
		(−1.51)
Weibo Smaller Firm*	−0.085***	
	(−7.97)	
Predicted Weibo Smaller Firm*		−0.118***
		(−12.43)
Size	−0.021***	−0.022*
	(−2.59)	(−1.71)
Leverage	−0.061***	−0.056**
	(−3.03)	(−2.23)
ROE	0.096	0.089
	(1.15)	(1.27)
Sales Growth	−0.007	−0.002
	(−1.22)	(−0.13)
Segments	−0.011	−0.008
	(−0.83)	(−0.43)
Volume	0.104***	0.137***
	(12.65)	(9.42)
Volatility	−6.234***	−7.853***
	(−21.86)	(−14.65)
Illiquidity	−1.429	−1.126
	(−1.35)	(−0.95)
%INST	−0.335***	−0.231***
	(−7.46)	(−5.97)
Analyst	0.011***	0.015**
	(3.62)	(2.36)
Investability	−0.054***	−0.037***
	(−3.51)	(−3.92)
HHI	−1.282***	−1.654***
	(−5.43)	(−4.72)
Family Firm	−0.082***	−0.089***
	(−12.90)	(−4.01)
Control – Ownership	0.203***	0.211**
	(3.13)	(2.64)
Ownership	0.018	0.023
	(0.74)	(0.69)
Synchronous fundamentals	0.041**	0.058**
	(2.43)	(2.39)
Intercept	−1.987***	−2.362***
	(−16.86)	(−5.91)
Year Dummy	Yes	Yes
Industry Dummy	Yes	No
N	15,017	15,017
Adjusted R^2	0.395	0.421

Panel B. Newly Listed Firms[b]

	OLS	2SLS: Second Stage
	(1)	(2)
Weibo	−0.037***	
	(−2.96)	
Predicted Weibo		−0.072***
		(−3.52)
Weibo Younger Firm*	−0.089***	
	(−4.74)	
Predicted Weibo Younger Firm*		−0.113***
		(−18.95)
Size		

(continued on next page)

Table 7 *(continued)*

Panel B. Newly Listed Firms[b]

	OLS	2SLS: Second Stage
	(1)	(2)
	−0.020***	−0.021***
	(−2.61)	(−2.93)
Leverage	−0.053***	−0.058***
	(−3.76)	(−3.82)
ROE	0.091	0.095
	(1.04)	(1.38)
Sales Growth	−0.008	−0.009
	(−1.43)	(−1.28)
Segments	−0.012	−0.013
	(−0.83)	(−1.05)
Volume	0.104***	0.104***
	(15.63)	(10.32)
Volatility	−6.351***	−5.127***
	(−25.86)	(−13.04)
Illiquidity	−1.445	−1.407
	(−1.39)	(−1.35)
%INST	−0.337***	−0.321***
	(−8.82)	(−4.37)
Analyst	0.015***	0.010***
	(3.28)	(3.21)
Investability	−0.056***	−0.057***
	(−3.58)	(−3.92)
HHI	−1.253***	−1.265***
	(−5.03)	(−3.43)
Family Firm	−0.082***	−0.065***
	(−9.51)	(−7.76)
Control – Ownership	0.201***	0.225***
	(3.82)	(3.97)
Ownership	0.013	0.015
	(0.37)	(0.93)
Synchronous fundamentals	0.043***	0.052**
	(3.91)	(2.43)
Intercept	−1.986***	−2.834***
	(−14.51)	(−12.76)
Year Dummy	Yes	Yes
Industry Dummy	Yes	No
N	15,017	15,017
Adjusted R^2	0.397	0.416

Panel C. Analyst Coverage[c]

Firm characteristics

	OLS	2SLS: Second stage
	(1)	(2)
Weibo	−0.043**	
	(−2.07)	
Predicted Weibo		−0.071***
		(−4.25)
Weibo Fewer Analysts*	−0.086***	
	(−5.31)	
Predicted Weibo Fewer Analysts*		−0.114***
		(−18.50)
Size	−0.021***	−0.021***
	(−2.71)	(−3.65)
Leverage	−0.054***	−0.053***
	(−3.21)	(−3.37)
ROE	0.091	0.084
	(1.24)	(1.42)
Sales Growth	−0.009	−0.012
	(−1.32)	(−0.78)

(continued on next page)

Table 7 *(continued)*

Panel C. Analyst Coverage[c]		
Firm characteristics		
	OLS	2SLS: Second stage
	(1)	(2)
Segments	−0.011	−0.010
	(−0.92)	(−1.15)
Volume	0.104***	0.103***
	(15.82)	(11.72)
Volatility	−6.246***	−6.221***
	(−21.82)	(−19.37)
Illiquidity	−1.433	−1.484
	(−1.24)	(−1.54)
%INST	−0.351***	−0.347***
	(−8.07)	(−5.86)
Analyst	0.013***	0.014***
	(3.97)	(3.75)
Investability	−0.052***	−0.067***
	(−3.41)	(−4.97)
HHI	−1.281***	−1.268***
	(−5.92)	(−6.93)
Family Firm	−0.087***	−0.082***
	(−8.95)	(−10.09)
Control – Ownership	0.205***	0.212***
	(3.41)	(3.80)
Ownership	0.012	0.034
	(0.45)	(1.25)
Synchronous fundamentals	0.053**	0.042**
	(2.25)	(2.35)
Intercept	−1.865***	−2.543***
	(−12.38)	(−19.92)
Year Dummy	Yes	Yes
Industry Dummy	Yes	No
N	15,017	15,017
Adjusted R^2	0.396	0.418

This table presents the multivariate regression results of the effect of board chair Weibo on stock return synchronicity by firm heterogeneity. The sample period is from 2010 to 2016. The dependent variable is *Synch*, a commonly used stock return synchronicity measure, calculated as $\log(R^2/(1-R^2))$. R^2 is from regressions of the market model of return of the firm against the stock market index and industry index using weekly data. *Weibo* in Column 1 is a dummy variable which equals one when the board chair of firm *i* posted on Weibo in year *t* and equals zero otherwise. *Predicted Weibo* in Column 2 is the predicted probability of Weibo based on the estimation in the first-stage model of Table 4. The second stage of a 2SLS is reported for robustness.

The focus in this table are *(Predicted) Weibo*Smaller Firm* (in Panel A), *(Predicted) Weibo* Younger Firm* (in Panel B) *and (Predicted) Weibo* Fewer Analysts* (in Panel C), which are the interaction terms of *(Predicted)*Weibo and different firm characteristics. *Size* is the natural logarithm of the market capitalization of firm *i* at the beginning of year *t. Leverage* is defined as the book value of all liabilities scaled by total assets, again measured at the beginning of the year *t*. *ROE* is the ratio of net profits divided by total equities at the beginning of the year *t*. *Sales Growth* is the ratio of sales growth from last year to this year. *Segments* is the number of segments, including only those which sales that exceed 30% of firm *i*'s total sales at the beginning of year *t. Volume* is the natural logarithm of trading volume of firm *i* at year *t. Volatility* is the standard deviation of the stock return of firm *i* at year *t. Illiquidity* is defined as the average ratio of daily absolute returns to the daily trading volume at year *t,* multiplied by 10^9. *%INST* is the ratio of mutual funds' holdings, measured as the aggregate number of shares held by mutual funds, scaled by outstanding shares of firm *i* in year *t. Analyst* is the natural logarithm of one plus the number of analysts that cover firm *i* at year *t. Investability* is the investability measure of firm *i* at year *t. HHI* (Herfindahl-Hirschman Index) is an indicator of competition, estimated by using all listed firms' sales from the same industry at the beginning of year *t*. *Family Firm* is a dummy variable which equals one if the firm is ultimately controlled by individuals and zero otherwise. (C*ontrol – Ownership*) is the difference between the ultimate owner's control rights and ownership. *Ownership* is defined as the cash flow rights of the ultimate owners. *Synchronous fundamentals* is defined as the Spearman correlation between the firm's ROA and its industrial average ROA over the past ten quarters. Column (1) presents the results from the OLS in which year and industry dummies are included but not reported. Column (2) presents the second stage OLS regression results where the predicted Weibo in Table 4 is used. *t*-statistics are given in parentheses and computed using heteroskedasticity-robust standard errors clustered by firm and year (Petersen, 2009; Thompson, 2011). All continuous variables are winsorized at the top and bottom 1%.***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

[a] Smaller Firm is a dummy variable which equals one if the firm's market capitalization is less than the corresponding median value of the sample and zero otherwise.

[b] Younger Firm is a dummy variable which equals one if the firm's listing year is less than the corresponding median value of the sample and zero otherwise.

[c] Fewer Analysts is a dummy variable which equals one if the number of analysts covering the firm is less than the corresponding median value for the sample and zero otherwise.

Table 8
Type of ownership – family and non-family firms.

	Family Firms			Non-Family Firms		
	OLS	Fama-MacBeth (1973)	2SLS: Second Stage	OLS	Fama-MacBeth (1973)	2SLS: Second Stage
	(1)	(2)	(3)	(4)	(5)	(6)
(Predicted) Weibo	−0.117***	−0.116***	−0.179***	−0.011*	−0.006*	−0.021**
	(−3.99)	(−3.50)	(−21.50)	-(1.73)	(1.91)	(−2.42)
Size	−0.020**	0.004*	−0.012**	−0.044***	−0.050**	−0.037**
	(−2.44)	(−1.91)	(−2.23)	(−3.94)	(−2.19)	(−2.34)
Leverage	−0.080***	−0.077	−0.046***	−0.009	0.006	−0.013
	(−2.98)	(−1.33)	(−3.74)	(−0.37)	(−0.12)	(−1.42)
ROE	0.103**	0.112	0.114	0.094**	0.058	0.062
	(2.31)	(0.88)	(1.52)	(2.34)	(0.62)	(1.51)
Sales Growth	−0.014*	−0.008	−0.010	0.002	0.007	−0.004
	(−1.71)	(−0.53)	(−1.06)	(0.21)	(0.27)	(−1.53)
Segments	−0.058***	−0.058	−0.035*	0.028	0.033	−0.007
	(−3.65)	(−1.36)	(−1.71)	(2.10)	(0.96)	(−1.32)
Volume	0.115***	0.130***	0.108***	0.115***	0.130***	0.123***
	(11.58)	(5.36)	(10.23)	(12.92)	(5.74)	(11.79)
Volatility	−6.024***	−7.589***	−6.651***	−6.921***	−8.564***	−6.753***
	(−19.30)	(−8.64)	(−13.91)	(−22.34)	(−10.17)	(−14.80)
Illiquidity	0.764	6.538	−0.206	−8.314***	−2.887	−1.307
	(0.55)	(1.37)	(−1.36)	(−4.49)	(−1.21)	(−1.95)
%INST	−0.298***	−0.313**	−0.304***	−0.310***	−0.346***	−0.340***
	(−6.02)	(−2.56)	(−4.81)	(−5.94)	(−2.72)	(−5.05)
Analyst	0.001***	0.002**	0.002*	0.021***	0.022*	0.017***
	(3.26)	(2.03)	(1.75)	(4.17)	(1.74)	(3.36)
Investability	−0.045	−0.005	−0.051***	−0.103***	−0.093*	−0.082***
	(−1.56)	(−0.136)	(−3.85)	(−3.98)	(−1.65)	(−3.18)
HHI	−1.322***	−1.545	−1.472***	−1.146***	−1.245	−1.234***
	(−3.80)	(−0.89)	(−5.93)	(−3.30)	(−0.71)	(−4.46)
Control – Ownership	0.269***	0.246	0.243***	0.124*	0.150	0.206
	(3.68)	(1.23)	(3.92)	(1.73)	(0.83)	(1.35)
Ownership	0.017	0.012	0.015	−0.003	0.021	0.009
	(0.43)	(0.73)	(0.94)	(−0.09)	(0.19)	(0.45)
Synchronous fundamentals	0.056***	0.045*	0.048**	0.012*	0.019**	0.032**
	(2.68)	(1.73)	(2.42)	(1.67)	(2.41)	(2.17)
Intercept	−1.996***	−3.073***	−3.075***	−1.376***	−1.631**	−3.368***
	(−7.12)	(−4.428)	(−11.03)	(−5.90)	(−2.39)	(−14.76)
Year Dummy	Yes	No	Yes	Yes	No	Yes
Industry Dummy	Yes	Yes	No	Yes	Yes	No
N	7759	7759	7759	7258	7258	7258
Adjusted R^2	0.390	0.194	0.423	0.382	0.253	0.401

This table presents the regression results for board chair Weibo and stock return synchronicity, for subsamples with family and non-family firms. All variables are defined in Appendix 2. Columns (1) and (4) present the OLS results. Columns (2) and (5) present the Fama and MacBeth (1973) panel results. Columns (3) and (6) present the 2SLS second-stage result where predicted Weibo is included as an independent variable. Year/Industry dummies are included but not reported, and *t*-statistics are given in parentheses and computed using heteroskedasticity-robust standard errors clustered by firm/industry and year where appropriate (Petersen, 2009; Thompson, 2011). All continuous variables are winsorized at the top and bottom 1%. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Analysts is negatively significant at the 1% level, indicating that the effect board chairs' Weibo usage has on stock return synchronicity and thereby the firm-specific information environment is influenced by the number of analysts covering the firm.

6. Further robustness checks

In this section, we provide additional tests to substantiate the negative relationship between board chair Weibo usage and stock return synchronicity. We first present evidence that the characteristics of sample distribution do not fundamentally change our initial findings. We then show that the noise-trading argument cannot explain our results. We also provide evidence that several direct measures of information flow are associated with Weibo usage the same was as stock return synchronicity is. Finally, we show that that board chairs use of Weibo better relay firm-specific news compared to industry news.

Fig. 1. The Shanghai Composite Index.
Note: This figure illustrates the Shanghai Composite Index during the period 1 January 2010 to 31 December 2016.

Table 9
Excluding observations.

	Excluding Observations in the finance industry			Excluding Observations for the Year 2015		
	OLS	Fama-MacBeth (1973)	2SLS: Second Stage	OLS	Fama-MacBeth (1973)	2SLS: Second Stage
	(1)	(2)	(3)	(4)	(5)	(6)
(Predicted) Weibo	−0.065***	−0.062***	−0.089***	−0.081***	−0.080***	−0.132**
	(−2.96)	(−3.05)	(−13.26)	(−3.29)	(−3.53)	(−6.86)
Size	−0.020**	−0.018**	−0.019***	−0.014**	−0.022**	−0.032**
	(−2.33)	(−2.31)	(−2.94)	(−2.31)	(−2.54)	(−2.48)
Leverage	−0.043**	−0.041	−0.051***	−0.059***	−0.055	−0.015
	(−2.32)	(−1.10)	(−3.97)	(−2.96)	(−1.37)	(−1.37)
ROE	0.103***	0.098	0.086	0.088***	0.081	0.054
	(3.39)	(1.32)	(1.51)	(2.70)	(1.10)	(1.31)
Sales Growth	−0.009	−0.003	−0.008	−0.006	−0.002	−0.006
	(−1.45)	(−0.16)	(−1.26)	(−0.94)	(−0.10)	(−1.27)
Segments	−0.012	−0.008	−0.011	−0.018	−0.012	−0.011
	(−1.15)	(−0.19)	(−1.36)	(−1.56)	(−0.33)	(−1.09)
Volume	0.110***	0.129***	0.143***	0.125***	0.145***	0.115***
	(16.36)	(7.70)	(15.52)	(17.17)	(8.72)	(10.28)
Volatility	−6.718***	−8.154***	−6.579***	−8.503***	−8.944***	−5.342***
	(−30.21)	(−13.25)	(−17.21)	(−32.27)	(−14.38)	(−15.17)
Illiquidity	−0.845	−1.745	−1.548	−0.628	4.053	−1.525
	(−0.80)	(−0.93)	(−1.35)	(−0.57)	(0.64)	(−1.24)
%INST	−0.299***	−0.322***	−0.361***	−0.339***	−0.357***	−0.301***
	(−8.34)	(−3.65)	(−6.58)	(−8.90)	(−4.17)	(−5.29)
Analyst	0.010***	0.009**	0.011***	0.013***	−0.009	0.012***
	(2.84)	(2.17)	(3.21)	(3.26)	(−0.94)	(3.80)
Investability	−0.055***	−0.028***	−0.024**	−0.076***	−0.061*	−0.078***
	(−2.75)	(−2.85)	(−2.20)	(−3.67)	(−1.73)	(−3.25)
HHI	−1.324***	−1.616**	−1.012***	−1.340***	−1.919	−1.323***
	(−5.35)	(−2.23)	(−4.43)	(−5.21)	(−1.46)	(−3.31)
Family Firm	−0.079***	−0.079***	−0.080***	−0.080***	−0.077***	−0.085***
	(−9.45)	(−3.84)	(−9.76)	(−8.77)	(−3.67)	(−7.62)
Control – Ownership	0.193***	0.202**	0.212***	0.212***	0.226*	0.235***
	(3.75)	(2.49)	(3.98)	(3.79)	(1.86)	(4.97)
Ownership	0.018	0.026	0.019	0.002	0.020	0.011
	(0.66)	(0.27)	(1.26)	(0.28)	(0.49)	(0.65)
Synchronous fundamentals	0.035**	0.029**	0.049**	0.040***	0.028	0.031**
	(2.47)	(2.32)	(2.45)	(2.67)	(0.70)	(2.12)
Intercept	−1.803***	−2.455***	−2.678***	−2.201***	−2.691***	−2.952***
	(−10.15)	(−5.16)	(−22.47)	(−11.58)	(−5.85)	(−14.31)
Year Dummy	Yes	No	Yes	Yes	No	Yes
Industry Dummy	Yes	Yes	No	Yes	Yes	No
N	14,648	14,648	14,648	12,711	12,711	12,711
Adjusted R^2	0.396	0.221	0.417	0.410	0.250	0.411

This panel presents the regression results of board chair Weibo and stock return synchronicity, for a sample that excludes observations in the finance industry and a sample that excludes observations in 2015. All variables are defined in Appendix 2. Columns (1) and (4) presents the OLS results, Columns (2) and (5) presents the Fama and MacBeth (1973) panel results, and Columns (3) and (6) presents the 2SLS second stage result where the Predicted Weibo as the independent variable. Year/Industry dummies are included but not reported, and *t*-statistics are given in parentheses and computed using heteroskedasticity-robust standard errors clustered by firm/industry and year where appropriate (Petersen, 2009; Thompson, 2011). All continuous variables are winsorized at the top and bottom 1%. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

6.1. Sample selection

It could be argued that certain characteristics of the data sample are driving our results. To test the robustness of our results further, we look at three potential issues with the firm sample: firm ownership, financial firms, and extreme market events. For firm ownership, it could, for example, be argued that the general information environment differs between firms under private and state control, respectively. This is important in the Chinese context, as SOEs still constitute an important part of listed firms in the country. We separate the sample into two groups, family and non-family firms, and run new estimations on each of the two subsamples.

Table 10
Stock return synchronicity and return-earnings associations.

	MAR
NI	2.175***
	(3.24)
*NI*Syn_decile*	−0.196***
	(−5.71)
*NI*MCap*	0.108***
	(3.83)
*NI*Leverage*	−0.009
	(−1.05)
*NI*Tobin's Q*	0.072***
	(5.79)
Intercept	−0.307***
	(−2.68)
Year Dummy	Yes
Industry Dummy	Yes
N	14,878
Adjusted R^2	0.062

This table presents the regression results about the effect of stock return synchronicity on return-earnings associations. The dependent variable is MAR, defined as market-adjusted monthly returns compounded over the 12-month period ending the fourth month after the end of a firm's fiscal year; NI is net income deflated by the market value of equity at the beginning of the fiscal year; *Syn_decile* is the scaled decile rank score. Control variables include *MCap*, measured by the natural log of market capitalization; *Leverage*, measured as the ratio of total liabilities over total assets; and *Tobin's Q*, measured as the ratio of the sum of market value of equities and book value of liabilities over book value of total assets. Year and Industry dummies are included but not reported, and *t*-statistics are given in parentheses and computed using heteroskedasticity-robust standard errors clustered by firm and year (Petersen, 2009; Thompson, 2011). All continuous variables are winsorized at the top and bottom 1%. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 8 presents the results for three different estimations for each of the two subsamples: a standard OLS, a Fama-MacBeth, and a two-stage OLS regression.[5] The coefficient for the main explanatory variable *Weibo (Predicted Weibo)* is negatively significant in all six estimations. The significance is somewhat weaker in the case of non-family firms.[6] This could suggest that Weibo usage may play a larger role as a complementary information channel for family firms compared to non-family firms. Overall, however, the results indicate that the relationship between board chairs' Weibo usage and information efficiency is not driven by ownership type.

Next, we exclude financial firms. It is generally argued that including them may lead to spurious results as they typically exhibit skewed fundamentals, including very high leverage. In addition, the finance industry in China is highly regulated, resulting in financial firms exhibiting significantly different characteristics from other firms. Second, periods of unusual stock market activity may affect the analysis. During the sample period used in this study, 2015 marked a year with very high turbulence. As Fig. 1 shows, there was an extremely strong bull-market run leading to what many regarded as the burst of a bubble in June that year. A third of the value of A-shares was lost within a month and market volatility remained high for an extended period.

To take these potential sample issues into account, we run two new sets of regressions, one without financial firms and one in which we exclude all firm observations for 2015. For each of these new samples, we run three separate regressions: a standard OLS regression, a Fama-MacBeth regression, and a two-stage OLS regression. The results of these estimations are presented in Table 9. As can be seen in the table, the coefficient for our key explanatory variable *Weibo (Predicted Weibo)* is negatively significant at the 1% level in all six estimations. As seen in Panel B of Table 1, most of our sample firms are concentrated in the manufacturing industry. Our results still remain qualitatively the same after excluding manufacturing industry.[7] We can thus conclude that our initial results on the relationship between board chairs' Weibo usage and firm-specific information in the stock market also hold up when we take potential data sample issues into consideration.

[5] Since this is mainly a robustness check, we leave the first stage result of the 2SLS estimation out for brevity. The main variable in the second stage is the Predicted Weibo.

[6] Unreported tests show that the Weibo coefficient for the family firm sample is significantly different from that for non-family firms at the 1% level.

[7] While we do not report these results for the sake of brevity, we thank an anonymous referee for suggesting that we check it the potential impact on our findings.

6.2. Alternative explanation of stock return synchronicity

Another crucial issue is the question of what stock return synchronicity actually signifies. In this study, we have used it as a measure of firm-specific information dissemination. However, it has been argued that a low R^2, and a correspondingly high level of synchronicity, may not constitute a good measure of information content in stock prices (e.g., Ashbaugh-Skaife et al., 2005; Kelly, 2014). In our setting, when a board chair opens a Weibo account, noise-trading may for example increase as a result because the board chair may post publicly disclosed information. That is, if individual investors fail to realize that the information already is publicly disclosed, noise trading will increase, which may lead to a decrease in stock return synchronicity. This conjecture could provide an alternative explanation for the negative relationship between board chairs' Weibo usage and stock return synchronicity.

To verify that our synchronicity measure indeed does capture the amount of firm-specific information impounded in firms' stock prices, we run a new test that focuses on the association between returns and earnings. Gul et al. (2010) argue that if the synchronicity measure captures firm-specific information, the return-earnings association should be weaker for firms with high synchronicity. This is because corporate earnings are typically regarded as the most important firm-specific information that is publicly available. To test this, we run a model similar to that of Gul et al. (2010):

$$MAR_{i,t} = \alpha_0 + \alpha_1 NI_{i,t} + \alpha_2 NI_{i,t} * Syn\_Decile_{i,t} + \sum_k \alpha_k NI_{i,t} * Control_{i,t}^k + Industry + Year + \varepsilon_{i,t}. \tag{4}$$

Here, $MAR_{i,\ t}$ is the market-adjusted monthly returns compounded over a 12-month period that ends the fourth month after the end of firm i's fiscal year; NI is net income deflated by the market value of equity for firm i at the beginning of year t; $Syn\_Decile_{i,\ t}$ is the scaled decile rank score. To control for determinants of the relationship between returns and earnings, we include a set of control variables, $Control_{i,\ t}^{k}$: ***Firm Size***, defined as the natural logarithm of the market capitalization; ***Tobin's Q***, the ratio of the sum of market value of equity and book value of liabilities over the book value of total assets; ***Leverage***, the ratio of total liabilities to total assets. Finally, we control for industry and year fixed effects by including dummies for each of them.

The results of the regression on the return-earnings association are presented in Table 10. The coefficient for $NI_{i,\ t}$ is significantly positive, suggesting that earnings are associated with stock returns. Moreover, the coefficient for $NI_{i,\ t} * Syn\_Decile_{i,\ t}$ is significantly negative, indicating that the market assigns a lower value to earnings of firms characterized by a higher stock return synchronicity, and that information on corporate earnings is less impounded in stock prices for them. These findings support the argument that our measure of stock return synchronicity captures the extent to which firm-specific information incorporated into stock prices in our sample.

6.3. Weibo and alternative definitions of information flow

Next, we test for the relationship between board chair Weibo usage and several dependent variables that measure information flow more directly. First, we use turnover as one alternative to stock return synchronicity in proxying for the intensity of private information flowing the market. Trading is theoretically linked to the quality or extent of private information (e.g., Blume et al., 1994), and can thus be used as a measure of private information flow. We investigate unsigned firm-level yearly turnover (*TURNOVER*), defined as share volume over the number of shares outstanding. We also use alternative measures found in the literature in the form of private information flow indexes (in particular, *PIN*) and indexes of future earnings information contained in stock prices (such as *FINC* and *FERC*).[8]

To confirm our initial interpretation of the relationship between board chair Weibo usage and stock return synchronicity, we estimate the following regression model:

$$INF_{i,t} = \alpha + \beta_0 Weibo_{it} + \beta \mathbf{x}_{it} + \gamma \mathbf{z}_i + \varepsilon_{it}. \tag{5}$$

The variable *INF* refers to one of the measures just discussed (*TURNOVER*, *PIN*, *FINC*, *FERC* and ψ), and t refers to an annual index. $\psi_{i,\ month}$is a monthly idiosyncratic volatility measure as seen in Ferreira and Laux (2007). We include the same control variables as in Model (3) in the regressions.

Columns (1) of Table 11 report results for the turnover regressions. The coefficient on Weibo is positive and significant. Thus, the evidence suggests that trading activity is higher in stocks of firms in which the board chair is active on Weibo. Coefficients on control variables are mostly consistent with expectations. Columns (2) of Table 11 present estimates of Eq. (4) using the *PIN* measure of Easley et al. (2002). We find that *PIN* is also positively related to Weibo, which supports our hypothesis that open firms are more subject to private information trading. Columns (3) of Table 11 present estimates of Eq. (4) using idiosyncratic volatility (ψ) measure of Ferreira and Laux (2007). We find that ψ is positively and significantly related to Weibo, which supports our hypothesis that open firms are more subject to private information trading.

Columns (4) and (5) in Table 11 test whether firms with board chairs who use Weibo have stock prices that contain more

[8] Easley et al. (1996, 1997a, 1997b) develop a model on the probability of informed trading (PIN), which has since then become a widely used measure of the amount of private information that is available in the market. By applying their model, we can use observable trade and quote data on the number of buys and sells to make inferences about unobservable information events and the frequency of informed and uninformed trades. In addition, Ferreira and Laux (2007) argue that idiosyncratic volatility is a good proxy for a summary measure of information flow, especially for firm-specific information.

Table 11
Panel regression of alternative information measures on Weibo.

	TURNOVER	*PIN*	$\psi_{i,\ month}$	*FERC*	*FINC*
	(1)	(2)	(3)	(4)	(5)
Weibo	0.083*	0.003***	−0.011***	0.018***	0.007***
	(1.71)	(2.98)	(−6.29)	(3.75)	(6.49)
Size	−1.375***	−0.021***	0.247	−1.063	0.102***
	(−30.37)	(−17.92)	(1.26)	(−1.39)	(1.76)
Leverage	−0.682***	−0.013	0.118***	3.25	0.028
	(−6.98)	(−7.74)	(5.22)	(0.64)	(0.59)
ROE	0.369**	0.002	0.0147*	1.007	0.208
	(2.30)	(0.63)	(1.76)	(0.82)	(0.59)
Sales Growth	0.004	−0.003	−0.015	0.897*	−0.014
	(0.14)	(−1.46)	(−1.22)	(1.82)	(−0.53)
Segments	−0.019	−0.001	−0.0481	0.380	0.027
	(−0.34)	(−1.28)	(−0.76)	(0.57)	(0.82)
Volume	1.721***	−0.012**	0.087	0.091	0.015
	(48.43)	(−2.35)	(1.01)	(0.14)	(0.46)
Volatility	45.782***	0.787**	3.208***	−0.187	−0.209
	(39.15)	(2.39)	(9.29)	(−0.49)	(−0.11)
Illiquidity	11.051**	−0.306	0.209	−0.005	0.021
	(2.01)	(−1.29)	(0.65)	(−0.24)	(0.38)
%INST	−0.155	1.087	0.298***	0.027	−0.001
	(−0.81)	(0.72)	(2.80)	(0.40)	(−0.25)
Analyst	−0.212***	0.010	−0.008***	0.001	−0.002
	(−11.46)	(0.34)	(−3.79)	(0.16)	(−0.47)
Investability	0.684***	0.029	0.027	0.006	−0.001
	(6.70)	(1.32)	(1.49)	(0.52)	(−0.31)
HHI	−0.511	−0.892	0.185	−0.028	−0.025
	(−0.39)	(−1.25)	(1.38)	(−1.03)	(−0.53)
Family Firm	−0.258***	−0.029	0.036***	−0.027	−0.021
	(−5.86)	(−1.42)	(5.82)	(−1.24)	(−0.15)
Control –Ownership	−3.425***	0.084	−0.108***	0.082	0.053
	(−12.57)	(1.06)	(−3.20)	(0.34)	(1.08)
Ownership	−2.987***	0.021	0.021	0.016	0.007
	(−20.86)	(0.48)	(0.72)	(0.37)	(0.39)
Synchronous fundamentals	−0.232***	−0.071	−0.012**	0.001	−0.003
	(−3.11)	(−0.84)	(−2.31)	(0.12)	(−0.09)
Intercept	−8.367***	−2.589***	2.107***	−1.087	−0.951**
	(−9.03)	(−18.65)	(5.69)	(−1.27)	(−2.03)
Year Dummy	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes
N	15,017	15,017	165,180	118	118
Adjusted R^2	0.499	0.325	0.445	0.129	0.161

This table presents the panel regression results of the effect of Weibo on other alternative definition of information flow.

$$INF_{i,t} = \alpha + \beta_0 Weibo_{it} + \beta \mathbf{x}_{it} + \gamma \mathbf{z}_i + \varepsilon_{it}.$$

Turnover is the yearly share volume divided by shares outstanding. *PIN* is the annual probability of information-based trading of Easley et al. (2002). $\psi_{i,\ month}$ is the idiosyncratic volatility measure of Ferreira and Laux (2007). *FERC* is the annual future earnings response coefficient, and *FINC*, the annual futures earnings incremental explanatory power. *FERC* and *FINC* regressions are estimated at the industry-level. Columns (4) and (5) report estimates of coefficients of the time-series cross-sectional industry-level regression. *Weibo* is a dummy variable which equals one when the board chair of firm *i* posted on Weibo in year *t,* and zero otherwise. Definitions for the remaining variables are presented in Appendix 2. Columns (1)–(5) present the results from the pooled OLS in which year and industry dummies are included but not reported. *t*-statistics are given in parentheses and computed using heteroskedasticity-robust standard errors clustered by firm and year (Petersen, 2009; Thompson, 2011). All continuous variables are winsorized at the top and bottom 1%.***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

information about future earnings. Following Durnev et al. (2003), *FERC* is the annual future earnings response coefficient, and *FINC* is the annual future earnings incremental explanatory power. Appendix 2 provides more detailed definitions of the measures. Columns (4) and (5) in Table 11 show that board chair Weibo usage is positively associated with future earnings response measures. The Weibo coefficients are 0.018 in the *FERC* regression and 0.007 in the *FINC* regression, respectively, and both coefficients are statistically significant at the 1% level. These results provide further support to our earlier findings by showing how board chairs' social media activity is closely related to alternative measures of information flow intensity. In particular, several of the measures focus on private information, thus supporting the proposition that firm-specific information flows are facilitated by board chairs being active on Weibo.

Table 12
Impact of Board Chair Weibo on the timing of the incorporation of industry and firm-specific earnings components into prices.

	$CAR_{i,\ t}$	
	OLS	Fama and MacBeth (1973)
	(1)	(2)
$I_{i,\ t}$	2.184***	2.075***
	(7.72)	(5.91)
$I_{i,\ t+1}$	0.593	0.524
	(0.45)	(0.73)
$F_{i,\ t}$	0.871**	0.697***
	(12.29)	(12.45)
$F_{i,\ t+1}$	0.094***	0.052***
	(3.16)	(2.97)
$I_{i,t}$*Weibo	−0.641	−0.593
	(−0.60)	(−0.72)
$F_{i,t}$*Weibo	1.287***	1.062***
	(13.62)	(11.90)
$I_{i,t+1}$*Weibo	−0.319	−0.287
	(−0.37)	(−0.45)
$F_{i,t+1}$*Weibo	0.115**	0.126**
	(2.93)	(3.54)
Weibo	0.381	0.374
	(0.97)	(0.82)
$CAR_{i,\ t+1}$	−0.019	−0.011
	(−0.84)	(−0.73)
$Log(\mathrm{MVE}_{i,\ t-1})$	0.102	0.086
	(0.43)	(0.91)
$Log(\mathrm{MB}_{i,\ t-1})$	0.009	0.007
	(0.82)	(0.53)
Adj. R^2	11.87%	12.52%

This table presents the coefficients from the estimation of the following model:

$$CAR_{i,t} = \alpha + \lambda_1 I_{i,t} + \lambda_2 I_{i,t+1} + \gamma_1 F_{i,t} + \gamma_2 F_{i,t+1} + \lambda_3 I_{i,t}{}^{*}weibo + \gamma_3 F_{i,t}{}^{*}weibo + \lambda_4 I_{i,t+1}{}^{*}weibo + \gamma_4 F_{i,t+1}{}^{*}weibo + \beta_1 CAR_{i,t+1} + \beta_2 weibo + \beta_3 Log(\mathrm{MVE}_{i,t-1}) + \beta_2 Log(\mathrm{MB}_{i,t-1}) + \varepsilon_{i,t}$$

Variables are defined in the study. Column (1) presents the results from the OLS. *t*-statistics are given in parentheses and computed using heteroskedasticity-robust standard errors clustered by firm and year (Petersen, 2009; Thompson, 2011). Column (2) presents Fama and MacBeth (1973) panel results. *t*-statistics are computed using heteroskedasticity-robust standard errors clustered by industry. All continuous variables are winsorized at the top and bottom 1%.***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

6.4. Industry vs. firm-specific information dissemination

Board chairs may discuss industry conditions (e.g., technology trend) and market conditions (e.g., interest rate policy) on their Weibo accounts. If Weibo primarily facilitates the incorporation of industry-level and market-wide information into prices, stock returns will display greater synchronicity. Conversely, firm prices will exhibit less synchronous movement if board chairs Weibo usage primarily contributes to firm-specific rather than intra-industry information. The main finding in the preceding sections is that the main explanatory variable *Weibo* is significantly and negatively associated with *Synch.* This suggests that it is the firm-specific information rather than industry- and market- information that is incorporated into the stock price.

In addition to the variable construction of *Synch*, we discuss the industry or firm-specific information dissemination via Weibo using a return-earnings framework. Ball and Brown (1967) suggest that a firm's annual earnings innovation can be decomposed into a market component, an industry component, and a firm-specific component. Therefore, the return-earnings relationship framework can be used to test what type of information that board chairs post on Weibo is incorporated into stock prices.

Following Ayers and Freeman (1997) and Piotroski and Roulstone (2004), the following specification is used in the multivariate analysis:

$$CAR_{i,t} = \alpha + \lambda_1 I_{i,t} + \lambda_2 I_{i,t+1} + \gamma_1 F_{i,t} + \gamma_2 F_{i,t+1} + \lambda_3 I_{i,t}{}^{*}weibo + \gamma_3 F_{i,t}{}^{*}weibo + \lambda_4 I_{i,t+1}{}^{*}weibo + \gamma_4 F_{i,t+1}{}^{*}weibo + \beta_1 CAR_{i,t+1} + \beta_2 weibo + \beta_3 Log(\mathrm{MVE}_{i,t-1}) + \beta_2 Log(\mathrm{MB}_{i,t-1}) + \varepsilon_{i,t}, \quad (6)$$

where $CAR_{i,\ t}$ is the value-weighted market-adjusted return for firm *i* in fiscal year *t*. Firm and market index returns are measured from the start of the fifth month of year *t* to the end of the fourth month of year $t + 1$.

To calculate the industry- and firm-specific components of each year's earnings innovation, we follow Ayers and Freeman (1997). Specifically, the industry component of the current earnings innovation $I_{i,\ t}$ is measured as $\Delta IE_{j,\ t} - \Delta ME_t$, where $\Delta IE_{j,\ t}$ is the median annual change in firm earnings for all firms in the same industry *j* in year *t*. ΔME_t is the median $\Delta IE_{j,\ t}$ for all industries in year *t*. Price-deflated change in firm *i*'s earnings, denoted $\Delta FE_{i,\ t}$, is defined as the difference in firm *i*'s earnings divided by market value at the beginning of the year for firm *i* (Christie, 1987). $F_{i,\ t}$ represents the firm-specific component of firm *i*'s change in earnings and is measured as $\Delta FE_{i,\ t} - \Delta IE_{j,\ t}$. That is, each firm's earning change less the change in market-wide earnings ($\Delta FE_{i,\ t} - \Delta ME_t$) is partitioned into two parts: industry performance relative to the market ($I_{i,\ t}$) and firm performance relative to the industry ($F_{i,\ t}$).

The one-year lead and contemporaneous regression coefficients provide estimates of price responses in year *t* due to industry and firm earnings changes from years *t* and $t + 1$. We extend Ayers and Freeman's (1997) methodology to examine whether board chair Weibo usage influences these timing relations by mainly disseminating industry-level, firm-specific information, or both. The next period returns ($CAR_{i,\ t+1}$) are also included to control for the unexpected components of future earnings news (Collins et al., 1994). This approach has been applied in studies that examine the timeliness of earnings (e.g., Lundholm and Myers, 2002; Gelb and Zarowin, 2002). We also include the log of firm size ($Log(\mathrm{MVE}_{i,\ t-1})$) and market-to-book ratios ($Log(\mathrm{MB}_{i,\ t-1})$) to control for differences in returns due to these factors.

Table 12 presents the return-earnings evidence conditional on Weibo usage. Consistent with our conjecture that board chair Weibo usage transmits firm-specific information, we find that the relation between current returns and the firm-specific components of contemporaneous and next year's earnings innovations strengthens when the board chair posts on Weibo ($\gamma_3 > 0$ and $\gamma_4 > 0$). The coefficients for industry earnings interacted with Weibo usage are negative ($\lambda_3 < 0$ and $\lambda_4 < 0$), which is consistent with Weibo usage transmitting firm-specific news rather than industry news. This finding also contributes to the literature (e.g. Peterson, 1987; Crawford et al., 2012) by identifying how the mixture of firm-, and industry-based information is transmitted via social media.

7. Mechanism of Weibo and information flows: the trading-link argument

Institutional trading is an important channel through which information is incorporated into stock prices. Piotroski and Roulstone (2004) find that institutional trading is negatively associated with stock return synchronicity, indicating that institutions trade on firm-specific information. In addition, Hartzell and Starks (2003) find that institutional investors contribute to private information collection and trading. Based on this, we argue that institutional trading constitutes a mechanism in which board chairs' social media activity contributes to the flow of private information. In other words, at least one of the links between Weibo usage and stock return synchronicity or between Weibo usage and information flow is via arbitrage institutional trading.

To examine this issue and verify the robustness of the relationship between Weibo usage and stock return synchronicity, we introduce institutional trading as an additional control in our baseline model. Additionally, we test our trading link hypothesis by including an interaction variable between Weibo usage and institutional trading. If, in fact, institutional trading contributes to the incorporation of information into stock prices of firms with board chairs who are active on Weibo, we expect that the coefficient for this interaction variable to be negative. We use two measures for institutional trading, one broad measure and one that focuses on the trading of arbitrage-active institutions, namely hedge funds. We estimate the following regression equation:

$$Synch_{i,t} = \alpha + \beta_0 Weibo_{it} + \lambda * Weibo_{it} * Insti_{it} + \beta \mathbf{x}_{it} + \gamma \mathbf{z}_i + \varepsilon_{it}. \tag{7}$$

Here, %Insti is the annual absolute change in the number of a firm's shares held by institutional investors as a fraction of the stock's annual trading volume. Correspondingly, we run a second regression in which we instead use *%Hedge,* defined as the annual absolute change in the number of firm's shares held by hedge funds as a fraction of the annual trading volume.

Columns 1 and 2 of Table 13 report estimates of Eq. (7) using *%Insti*, the broad measure of institutional trading, with and without the interaction regressor *Weibo* ×*%Insti*, respectively. The estimate of the Weibo coefficient β_0 is significantly negative in both cases, i.e. institutional trading is associated with less stock return synchronicity. The interaction variable is also significantly negative. This suggests that institutional trading adds to the negative statistical effect of *Weibo* on *Syn*, in that institutional trading accelerates the incorporation of firm-specific information into stock prices and, consequently, decreases stock return synchronicity. Columns 3 and 4 in Table 13 report analogous results, this time using *%Hedge*. The relation between *Weibo* and *Syn* remains strong after controlling for this narrower proxy for institutional trading. The results support our trading-link hypothesis in that the Weibo–information flow relation is stronger in the presence of high levels of arbitrage-active institutional trading at the firm level. These results improve our understanding of the underlying mechanism as it shows that board chair Weibo usage and institutional trading have mutually reinforcing effects on firm-specific information flows.

8. Alternative definition of Weibo

While we have provided evidence that board chair Weibo usage accelerates firm-specific information dissemination in the capital market, a remaining concern could be that the way we construct the proxy *Weibo* means that we lose a lot of information related to the content of Weibo posts (we did look at content when we discussed firm-specific news versus industry news dissemination in

Table 13
Mechanism of Weibo and information flow: the trading-link argument.

	(1)	(2)
Weibo	−0.019**	−0.012**
	(−2.03)	(−2.25)
Weibo%INST*	−0.350***	
	(−4.79)	
Weibo%Hedge*		−0.585***
		(−7.94)
Size	0.125***	0.120***
	(12.98)	(12.25)
Leverage	−0.158***	−0.161***
	(−3.17)	(−3.46)
ROE	0.125***	0.120***
	(3.65)	(3.38)
Sales Growth	0.018*	0.015*
	(1.79)	(1.83)
Volume	0.110***	0.121***
	(16.58)	(11.35)
Volatility	−0.487	−0.452
	(−0.91)	(−0.68)
Illiquidity	15.682**	13.405**
	(2.07)	(2.07)
%INST	−0.282***	
	(−7.73)	
%Hedge		−0.653***
		(−4.83)
Analyst	0.019***	0.014***
	(2.81)	(2.95)
Investability	0.167***	0.161***
	(3.51)	(3.74)
HHI	−0.778**	−0.746**
	(−2.37)	(−2.43)
Synchronous fundamentals	0.141***	0.136***
	(12.87)	(13.94)
Intercept	−11.427***	−12.750***
	(−5.28)	(−8.92)
Year Dummy	Yes	Yes
N	13,748	13,748
Adjusted R^2	0.557	0.552

This table presents the firm-fixed effect results of the mechanism of Weibo and information flow. The sample period is from 2010 to 2016. The dependent variable is *Synch*, a commonly used stock return synchronicity measure, calculated as $\log(R^2/(1-R^2))$. R^2 is from regressions of the market model of return of the firm against the stock market index and industry index using weekly data. *Weibo* is a dummy variable which equals one when the board chair of firm *i* posted on Weibo in year *t*, and equals zero otherwise. *%INST* in Column (1) is the ratio of mutual funds' buying holdings, measured as the aggregate purchasing number of shares held by mutual funds, scaled by outstanding shares of firm *i* at the beginning of year *t*. *%Hedge* in Column (2) is the ratio of mutual funds' buying holdings, measured as the aggregate purchasing number of shares held by hedge funds, scaled by outstanding shares of firm *i* at the beginning of year *t*. The focus of this table is the interaction term of *Weibo*%INST* in Column (1) and *Weibo*% Hedge* in Column (2). Year dummies are included but not reported and *t*-statistics are computed using heteroskedasticity-robust standard errors clustered by year. All continuous variables are winsorized at the top and bottom 1%.***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Section 6.4). To remedy this, we examine content in Weibo posts using textual analysis.

Board chairs, like most other people, do not only post work-related content, but also content that has personal information. For instance, as illustrated by Fig. 1 in Appendix 6, Mr. Li Dongsheng, the board chair of TCL posted about the progress in an important project on 22 May 2018. This could thus be classified as firm-specific information that is not disclosed via other channels. Fig. 2 in Appendix 6 displays another posting by Mr. Li in which he writes about TCL's annual report and discusses it briefly on 28 April 2018. Although it is related to TCL, we classify it as second-hand information because TCL publicly announced its annual report on the previous day. Finally, Fig. 3 in Appendix 6 provides an example of a post with personal information, as Mr. Li shows how he and his family celebrated the Spring Festival.

Using Python and Java, we downloaded all the relevant Weibo content in May 2017. The total number of postings is 147,698 and include texts, pictures, videos, and links. A group of research assistants was then trained to read each post and classify its content. A

Table 14
Work-related Weibo and stock return synchronicity.

	Firm fixed effect	
	(1)	(2)
Firm-Related Weibo	−0.025***	
	(−17.64)	
Number of Firm -related posts		−0.007***
		(−9.25)
Size	0.204***	0.201***
	(13.18)	(11.64)
Leverage	−0.137***	−0.140***
	(−3.25)	(−3.41)
ROE	0.144***	0.141***
	(3.42)	(3.59)
Sales Growth	0.016*	0.015**
	(1.92)	(2.24)
Volume	0.159***	0.154***
	(12.64)	(13.87)
Volatility	0.517***	0.511***
	(2.78)	(3.32)
Illiquidity	26.087***	26.397***
	(14.46)	(18.76)
%INST	−0.085	−0.072
	(−1.21)	(−1.08)
Analyst	0.032***	0.039***
	(5.19)	(4.34)
Investability	0.164***	0.178***
	(5.37)	(5.05)
HHI	−0.725**	−0.739**
	(−2.48)	(−2.24)
Synchronous fundamentals	0.171***	0.190***
	(8.85)	(12.31)
Number of Firm Announcements	−0.012**	−0.010*
	(−2.14)	(−1.89)
Number of News	−0.019	−0.027
Coverage	(−0.85)	(−1.32)
Intercept	−11.964***	−18.047
	(−37.31)	(−26.93)
Year Dummy	Yes	Yes
N	13,748	13,748
Adjusted R^2	0.631	0.732

This table presents the firm-fixed effect regression results for alternative definitions of Weibo and stock return synchronicity. The sample period is from 2010 to 2016. The dependent variable is *Synch*, a commonly used stock return synchronicity measure, calculated as $\log(R^2/(1-R^2))$. R2 is from regressions of the market model of return of the firm against the stock market index and industry index using weekly data. *Firm-Related Weibo* is a dummy variable which equals one when the board chair of firm *i* posted at least five firm-related Weibo at year *t*, and equals zero otherwise. *Number of Firm-related posts* is the number of firm-related Weibo information posted by the board chair of firm *i* in year *t*. *Size* is the natural logarithm of the market capitalization of firm i at the beginning of year *t*. *Leverage* is defined as the book value of all liabilities scaled by total assets, again measured at the beginning of the year t. *ROE* is the ratio of net profits divided by total equities at the beginning of the year t. *Sales Growth* is the ratio of sales growth from last year to this year. *Volume* is the natural logarithm of trading volume of firm *i* at year *t*. *Volatility* is the standard deviation of the stock return of firm i at year t. *Illiquidity* is defined as the average ratio of daily absolute returns to the daily trading volume at year t, multiplied by 109. *%INST* is the ratio of mutual funds' holdings, measured as the aggregate number of shares held by mutual funds, scaled by outstanding shares of firm *i* in year *t*. *Analyst* is the natural logarithm of one plus the number of analysts that cover firm *i* at year *t*. *Investability* is the investability measure of firm *i* at year *t*. *HHI* (Herfindahl-Hirschman Index) is an indicator of competition, estimated by using all listed firms' sales from the same industry at the beginning of year t. *Synchronous fundamentals* is defined as the Spearman correlation between the firm's ROA and its industrial average ROA over the past ten quarters. *Number of Firm Announcements* is the number of public announcements for firm i in year t. Number of News Coverage is the number of news reports for firm i in year t. Year dummies are included but not reported and t-statistics are computed using heteroskedasticity-robust standard errors clustered by year. All continuous variables are winsorized at the top and bottom 1%.***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

post is defined as having firm-related information if at least three research assistants verify that it is related to the firm.[9] *Number of firm-related posts* is defined as the number of firm-related posts for each firm per year. If this number is larger than 5, the dummy variable *firm-related weibo* is defined as one, and zero otherwise. In contrast to the dummy variable *firm-related weibo* that simply indicates whether firm-related content has been posted, the variable *Number of firm-related post* measures the actual density of Weibo posts.

We also need to consider potential omitted variables when we examine the content of Weibo posts. For example, board chairs disclose firm-specific information selectively, and therefore official channels for public information disclosure should not be ignored in our analysis. Previous studies also argue that financial reports are important ways for top executives to communicate information with outside investors (e.g., McNichols and Trueman, 1994; Healy and Palepu, 2001). Furthermore, and as discussed previously, some of the information that board chairs post on is just second-hand information that has already been published somewhere else. In fact, we do find that board chairs repost news, explain traditional news report, or rebut rumors over Weibo. Whether our results remain robust after controlling for public disclosure is thus an important question. Similarly, Gong et al. (2018) argue that the financial news media plays a disciplining role in China. Thus, since the incremental information disclosure is the main focus of this study, traditional media reports should also be controlled for. Here, *Number of Firm Announcements* is the number of public announcements for firm i in year t and is obtained from the GTA database. *Number of News Coverage* is the number of news reports for firm i in year t. The following news sources are used to calculate the measure: GTA Financial News Database, Genius Finance, INFOBANK, and China Core Newspapers Full-text Database.

We thus use the following regression model to take Weibo content into account:

$$Synch_{i,t} = \alpha + \beta_0 Firm - Related\ Weibo_{it}\,(or\ Number\ of\ firm - related\ post_{it}) + \beta \mathbf{x}_{it} + \gamma \mathbf{z}_i + Number\ of\ Firm\ Announcements_{it} + Number\ of\ News\ Coverage_{it} + \varepsilon_{it}. \tag{8}$$

All control variables are the same as in Eq. (3). *Firm-Related Weibo* is constructed to precisely describe the firm-specific information flowing to the stock market, excluding noise (e.g., jokes, greetings). *Number of firm-related posts* is used to measure the density of firm-related information disclosure via Weibo.

Table 14 presents the stock return synchronicity regression results controlling for the firm's public announcements and traditional news coverage. The table is set up the same way as in the earlier tables and reports variations on the same basic model in eq. (6). The key difference is that $Firm - Related\ Weibo_{it}$ is used in Column 1, and $Number\ of\ firm - related\ post_{it}$ is used in Column 2.As seen in the table, our initial results hold up across all model variations. The measures for Weibo are still strongly correlated with stock return synchronicity, even after controlling for the firm's officially public announcement and traditional news coverage. Estimates of the coefficient for $Firm - Related\ Weibo_{it}$ is negative and significant in Column 1. This suggests that the level of stock return synchronicity is reduced significantly in the presence of firm-related Weibo posts. Within the interpretation of stock return synchronicity as flows of private information, this is indicative of more information flowing to the market via Weibo when board chairs post firm-related information. In Column 2, the coefficient for $Number\ of\ firm - related\ post_{it}$is -0.002 with a robust t-statistic of -9.25. Higher levels of $Number\ of\ firm - related\ post_{it}$suggest more firm-related Weibo posts. Increasing the frequency of firm-related information disclosure on board chairs' Weibo accounts contributes to more firm-specific information being incorporated in the stock price. To sum up, these results verify that our findings are not dependent on the way we defined Weibo usage in our baseline estimation.

9. Conclusion

This study examines how the usage of social media in the form of microblogging by corporate executives in China is affecting the information environment for their firms. We provide strong empirical evidence that Chinese listed firms with a board chair who owns a Weibo account are characterized by significantly better dissemination of information compared to other listed firms. This finding holds up to a battery of robustness tests, including tests on the measure for firm-specific information dissemination itself. In addition, we find that certain characteristics such as firm size, how recent a firm went public, and analyst following are influential factors behind the relationship between board chairs' social media usage and firm-specific information dissemination. A plausible reason for these findings is that the potential effect on information dissemination for smaller firms, firms that were listed more recently, and firms with less analyst coverage is larger. This is likely they case as they are characterized by a lower level of information being disseminated to the market in general.

These findings suggest that social media can act as an effective information channel that complements traditional channels such as public information by the firm, the media, and analyst reports. The results also show the importance for firms to have top executives who understand and can use social media as a platform for information dissemination. This is especially true for firms with certain characteristics, including being of smaller size, having gone public recently, or having fewer analysts following them. Finally, and on a more general note, our findings show that the role of social media for companies has gone beyond that of being solely a channel to reach and engage with customers. The potential advantages of disseminating selected information over social media can have direct effects on how the market perceives the company and it should thus be considered to play a possible role in companies' overall communication and operational strategy.

[9] Our results remain unchanged if we increase that to all five research assistant being required to label the content in a post as firm-related.

Appendix 1: Stock return synchronicity

Panel A: Distribution of Sample by Year[a]

		Synch			R^2		
Year	Number	Mean	Median	STD	Mean	Median	STD
2010	1858	−0.418	−0.369	0.434	0.313	0.301	0.171
2011	2013	−0.232	−0.190	0.347	0.390	0.393	0.150
2012	2101	−0.210	−0.166	0.358	0.401	0.406	0.162
2013	2114	−0.544	−0.469	0.497	0.270	0.254	0.163
2014	2178	−0.913	−0.808	0.642	0.168	0.135	0.137
2015	2306	−0.174	−0.096	0.421	0.427	0.445	0.170
2016	2447	−0.166	−0.061	0.520	0.442	0.466	0.202
Total	15,017	−0.375	−0.273	0.538	0.347	0.348	0.191

Panel B: Distribution of Sample by Industry[b]

		Synch			R^2		
Industry	Number	Mean	Median	STD	Mean	Median	STD
Agriculture, Forestry, farming & fishery	240	−0.462	−0.387	0.502	0.305	0.291	0.177
Mining	441	−0.258	−0.127	0.557	0.403	0.428	0.194
Manufacturing	9065	−0.399	−0.292	0.546	0.338	0.338	0.190
Utilities	626	−0.309	−0.280	0.497	0.369	0.345	0.194
Construction	442	−0.316	−0.212	0.504	0.369	0.381	0.187
Wholesale and retail	955	−0.352	−0.264	0.519	0.353	0.352	0.193
Transportation	540	−0.220	−0.130	0.469	0.407	0.426	0.197
Hotel & catering industry	76	−0.514	−0.449	0.584	0.295	0.262	0.191
Information transmission, software & information technology service	586	−0.484	−0.388	0.588	0.310	0.291	0.198
Finance	369	−0.122	−0.066	0.387	0.449	0.463	0.167
Real estate	864	−0.312	−0.220	0.467	0.365	0.376	0.175
Leasing & commerce service	196	−0.434	−0.288	0.496	0.318	0.340	0.177
Scientific research & technology service	70	−0.378	−0.243	0.599	0.355	0.364	0.191
Water conservancy, environment & public facilities management	141	−0.406	−0.289	0.527	0.332	0.340	0.180
Education	15	−0.486	−0.447	0.498	0.292	0.263	0.197
Hygienism & social work	28	−0.432	−0.355	0.485	0.313	0.307	0.173
Culture, sports & entertainment	202	−0.561	−0.434	0.677	0.294	0.269	0.211
Comprehensive	161	−0.396	−0.294	0.559	0.339	0.337	0.192
Total	15,017	−0.375	−0.273	0.538	0.347	0.348	0.191

[a] This panel presents the distribution of our sample by year during 2010–2016. *Synch* is a commonly used stock return synchronicity measure, calculated as $\log(R^2/(1-R^2))$. R^2 is from regressions of the market model of return of the firm against the stock market index and industry index using weekly data.

[b] This panel presents the distribution of the sample by industry during 2010–2016. Industry is classified according to the Guidelines for the Industry Classification of Listed Companies by CSRC (2012 Revision).

Appendix 2: Definition of variables

Variable	Definition
Syn	A commonly used stock return synchronicity measure calculated as $\log(R^2/(1-R^2))\log(R^2/(1-R^2))$. R^2 is from regressions of the market model of return of the firm against the stock market index and industry index using weekly data.
Weibo	A dummy variable which equals one if the firm's board chair opens a Weibo account, and zero otherwise.
Size	The natural logarithm of the market capitalization of firm *i* at the beginning of year *t*.
Leverage	The book value of all liabilities scaled by total assets at the beginning of the year *t*.
ROE	Net profits divided by total equity at the beginning of the year *t*.
Sales Growth	Sales growth during the last year.
Segments	The number of segments, including only those with sales that exceed 30% of firm *i*'s total sales at the beginning of year *t*.
Volume	The natural logarithm of trading volume of firm *i* at year *t*.

Volatility	The standard deviation of the stock return of firm i at year t.
Illiquidity	The average ratio of daily absolute returns to the daily trading volume at year t, multiplied by 10^9.
%INST	Mutual funds' holdings, measured as the aggregate number of shares held by mutual funds divided by outstanding shares of firm i in year t.
Analyst	The natural logarithm of one plus the number of analysts that cover firm i at year t.
Investability	The investability measure of firm i at year t, i.e. the ratio of shares which can be traded in the secondary market.
HHI	Abbreviation for Herfindahl-Hirschman Index, an indicator of competition, estimated by using all listed firms' sales from the same industry at the beginning of year t.
Family Firm	A dummy variable which equals one if the firm is ultimately controlled by individuals and zero otherwise.
Control – Ownership	A proxy for the ultimate owner's control in excess of ownership rights, defined as the difference between the ultimate owner's control rights and ownership (similar to that of La Porta et al., 1999).
Ownership	The cash flow rights owned by the ultimate owner (similar to that of La Porta et al., 1999).
Synchronous fundamentals	The Spearman correlation between the firm's ROA and its industrial average ROA over the past ten quarters.
Turnover	Monthly share volume divided by shares outstanding
PIN	Annual probability of information-based trading as seen in Easley et al. (2002)
FERC	Sum of the coefficients on future changes in earnings $\sum_{\tau=1}^{3} b_{2,\tau}^{b}$ of the annual regression on each industry with at least 10 firms: $r_{i,t} = b_0^b + b_1^b \Delta E_{i,t} + \sum_{\tau=1}^{3} b_{2,\tau}^{b} \Delta E_{i,t+\tau} + \sum_{\tau=1}^{3} b_{3,\tau}^{b} r_{i,t+\tau} + \varepsilon_{i,t}^{b}$ where $r_{i,\ t}$ is annual stock return calculated from fiscal year-end share price plus dividends adjusted by stock splits and distributions, and $\Delta E_{i,\ t}$ is the annual change in earnings before interest, taxes, depreciation, and amortization scaled by previous fiscal year-end market capitalization.
FINC	Increase in the coefficient of determination (R^2) of the annual regression on each industry with at least 10 firms: $r_{i,t} = b_0^b + b_1^b \Delta E_{i,t} + \sum_{\tau=1}^{3} b_{2,\tau}^{b} \Delta E_{i,t+\tau} + \sum_{\tau=1}^{3} b_{3,\tau}^{b} r_{i,t+\tau} + \varepsilon_{i,t}^{b}$ relative to the base regression: $r_{i,\ t} = b_o{}^c + b_1{}^c \Delta E_{i,\ t} + \varepsilon_{i,\ t}{}^c$

Appendix 3: Summary statistics

Variable	Number	Mean	Median	STD	Q1	Q3
R^2	15,017	0.347	0.348	0.191	0.195	0.491
Syn	15,017	−0.375	−0.273	0.538	−0.595	−0.007
Weibo	15,017	0.025	0.000	0.156	0.000	0.000
Size	15,017	22.470	22.331	1.010	21.731	23.032
Leverage	15,017	0.485	0.487	0.219	0.319	0.648
ROE	15,017	0.059	0.065	0.131	0.024	0.111
Sales Growth	15,017	0.198	0.096	0.628	−0.047	0.258
Segments	15,017	1.136	1.000	0.343	1.000	1.000
Volume	15,017	23.645	23.563	1.043	22.914	24.336
Volatility	15,017	0.065	0.058	0.026	0.048	0.075
Illiquidity	15,017	0.007	0.005	0.006	0.003	0.009
%INST	15,017	0.074	0.019	0.125	0.002	0.086
Analyst	15,017	1.742	1.792	1.430	0.000	2.996
Investability	15,017	0.790	0.936	0.257	0.599	1.000
HHI	15,017	0.038	0.005	0.065	0.005	0.045
Family Firm	15,017	0.516	1.000	0.500	0.000	1.000
Control – Ownership	15,017	0.052	0.000	0.077	0.000	0.093
Ownership	15,017	0.327	0.314	0.164	0.199	0.439
Synchronous fundamentals	15,017	0.096	0.104	0.286	−0.094	0.275

This appendix presents the summary statistics for the main variables in this study.

Appendix 4: Correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)Syn	1.000***	−0.027***	0.249***	0.030***	0.054***	−0.013	−0.004	0.347***	0.002
(2)Weibo	−0.020***	1.000***	0.052*	−0.011	0.023	−0.007	0.009	0.035*	0.007
(3)Size	0.288***	0.058*	1.000***	0.077	0.251	0.078	0.022	0.745***	−0.078***
(4)Leverage	0.034***	−0.011	0.051	1.000***	−0.139***	0.051	0.016	0.063	−0.031
(5)ROE	0.030***	0.042	0.330	−0.062***	1.000 ***	0.173***	−0.006	0.105***	−0.110***
(6)Sales Growth	−0.007	0.024	0.135	0.030	0.343	1.000***	0.002	−0.015	−0.011
(7)Segments	−0.002	0.009	0.019	0.014	−0.011	0.018	1.000***	0.028	0.003
(8)Volume	0.371***	0.031**	0.735***	0.060	0.135***	0.036	0.030	1.000***	−0.009
(9)Volatility	−0.016	0.005	−0.037***	−0.029	−0.160**	−0.084	0.000	0.053	1.000***
(10)Illiquidity	−0.204***	−0.060	−0.853	−0.132	−0.273***	−0.090	−0.031***	−0.646	0.214***
(11)%INST	0.125	0.067	0.554	−0.064	0.379***	0.221***	−0.007	0.371***	−0.063***
(12)Analyst	0.050***	0.081	0.566	−0.054	0.457***	0.242**	−0.017	0.318***	−0.107***
(13)Investability	0.065***	0.018	−0.056	0.200	−0.129*	−0.152**	0.049	0.090***	−0.034
(14)HHI	0.140	0.011	0.207	0.123	0.071**	0.056*	0.072	0.199***	0.043
(15)Family Firm	−0.134***	0.042*	−0.160***	−0.217	0.032***	0.036**	−0.036**	−0.136***	0.102
(16)Control – Ownership	0.004***	−0.018	−0.015	0.032***	0.016	−0.006	−0.002	−0.025***	0.009***
(17)Ownership	0.019	0.010	0.193	−0.023	0.096	0.030***	−0.011	−0.002	−0.023
(18)Synchronous fundamentals	0.163***	−0.009	0.148	0.064	0.097	0.025	−0.012	0.166	0.079

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)Syn	−0.162***	−0.028***	0.053***	0.054***	−0.010	−0.135***	0.023**	0.022	0.152***
(2)Weibo	−0.053	0.072	0.083	0.018	0.016	0.042*	−0.028	0.003	−0.012
(3)Size	−0.680	0.342	0.567	−0.041	0.075	−0.174***	−0.003	0.218	0.126
(4)Leverage	−0.136	−0.071	−0.057	0.208	0.003	−0.210	0.023***	−0.033	0.064
(5)ROE	−0.147***	0.253**	0.326**	−0.108**	0.046*	0.027**	0.029	0.072	0.078
(6)Sales Growth	0.001	0.097***	0.074**	−0.171**	0.046**	0.036*	0.007	0.024***	0.013
(7)Segments	−0.029**	−0.005	−0.017	0.047	0.068	−0.036***	0.000	−0.009	−0.016
(8)Volume	−0.559	0.165***	0.327***	0.128***	0.048***	−0.136***	−0.024***	0.006	0.140
(9)Volatility	0.131***	−0.082***	−0.100***	0.005	0.014	0.105	0.029**	−0.016	0.053
(10)Illiquidity	1.000***	−0.222***	−0.415***	−0.411***	−0.016	0.256	−0.055***	−0.020	−0.059***
(11)%INST	−0.448	1.000***	0.514***	−0.194***	0.046***	0.036***	0.002	0.009	0.078
(12)Analyst	−0.517***	0.646***	1.000***	−0.089***	0.047***	−0.007	0.032	0.113	0.078
(13)Investability	−0.291***	−0.151***	−0.120***	1.000***	−0.004	−0.214	0.071	−0.231	−0.019
(14)HHI	−0.189***	0.027***	0.031**	0.072	1.000***	−0.055***	−0.076	0.037	−0.010
(15)Family Firm	0.247	−0.034**	−0.008	−0.238	−0.133***	1.000***	0.129***	−0.239	−0.036
(16)Control – Ownership	−0.020**	−0.011	0.003	0.062	−0.072	0.215***	1.000***	−0.379	−0.003
(17)Ownership	−0.083	0.066	0.116	−0.152	0.089	−0.244	−0.422	1.000***	0.039
(18)Synchronous fundamentals	−0.093***	0.111	0.077	−0.009	0.245	−0.039	−0.014	0.038	1.000***

Appendix 5: Idiosyncratic volatility

We estimate each stocks' idiosyncratic volatility for each month using daily data. Our measure of idiosyncratic volatility is based on a regression projection of stock returns on the returns of the market index, an industry index, and other factors. In the case of the market model, we have the following model for stock *i*,

$$r_{i,t} = \alpha_i + \beta_i R_{M,t} + \varepsilon_{i,t}.$$

where $E(\varepsilon_{i,\ t}) = Cov(\mathrm{R}_{\mathrm{M},\ t}, \varepsilon_{i,\ t}) = 0$. Here, $r_{i,\ t}$ is the excess return for stock *i* on day *t* and $R_{M,\ t}$ is the value-weighted excess market index return on day *t*. Then $\beta_i = \frac{\sigma_{i,m}}{\sigma_M^2}$, where $\sigma_{i,\ m} \equiv \mathrm{Cov}(\mathrm{r}_{i,\ t}, \mathrm{r}_{\mathrm{M},\ t})$ and $\sigma_m{}^2 \equiv Var(\mathrm{r}_{\mathrm{M},\ t})$. Idiosyncratic variance is defined as $\sigma_{i,\mathrm{e}} \equiv \sigma_i^2 - \frac{\sigma_{i,\mathrm{M}}^2}{\sigma_M^2}$, where $\sigma_i{}^2 \equiv Var(\mathrm{r}_{i,\ t})$. We use sums of squares of daily returns in each month to estimate monthly return variances, and sums of cross-products to estimate return covariances.

From idiosyncratic volatility, we then calculate each stock's relative idiosyncratic volatility as the ratio of idiosyncratic volatility to total volatility, $\frac{\sigma_{ie,month}^2}{\sigma_{i,tmonth}^2}$. This is $1 - R_{i,\ \mathrm{month}}{}^2$ of Eq. (1). Given the bounded nature of R^2, we thus carry out regression tests using the logistic transformation of $1 - R_{i,\ \mathrm{month}}{}^2$.

$\psi_{i,month} \equiv \ln\left(\frac{1-R^2_{i,\text{month}}}{R^2_{i,\text{month}}}\right) = \ln\left(\frac{\sigma^2_{ie,month}}{\sigma^2_{i,month}-\sigma^2_{ie,month}}\right)$ Our dependent variable $\psi_{i,\ month}$ measures idiosyncratic volatility relative to market-wide variation. One important reason for scaling idiosyncratic volatility by the total variation in returns is that firms in some industries are more subject to economy-wide shocks than others and firm-specific events may be correspondingly more intense. Furthermore, scaling this way makes it possible to compare the results with those found in previous studies (e.g., Durnev et al., 2004).

Appendix 6: Examples of different types of Weibo content

This appendix presents three different Weibo posts by Mr. Li Dongsheng, the board chair of Chinese listed company TCL. In the first figure, *firm-specific information* is provided when Mr. Li writes about a firm project. In the second figure, *second-hand firm information* is provided when Mr. Li writes about the firm's annual report that was made public the previous day. In the third figure, *personal information* is conveyed when Mr. Li writes about how he and his family celebrated the Spring Festival.

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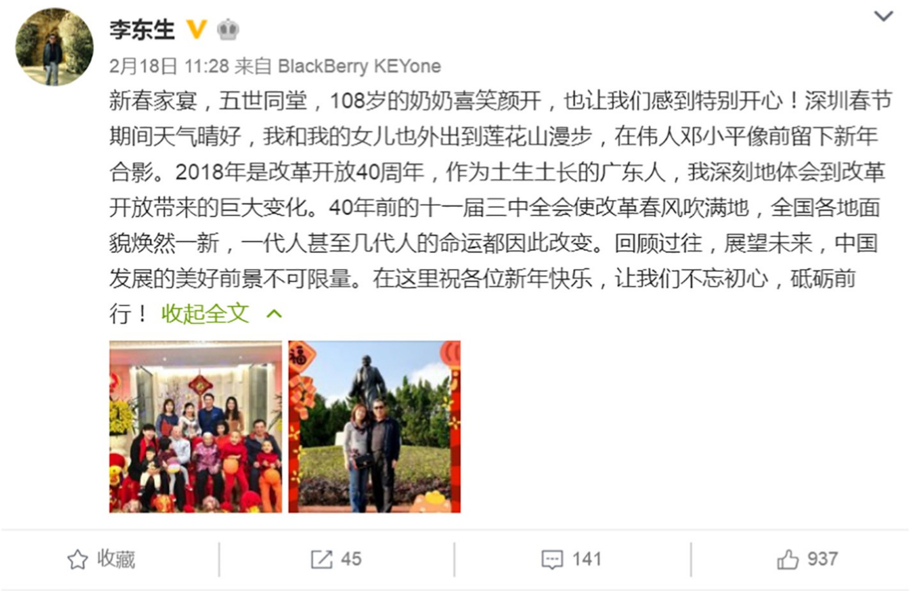

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