Retail Investors' Accessibility to the Internet and Firm-Specific Information Flows: Evidence from Google's Withdrawal in China*

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Abstract

Internet search is an important channel for retail investors to gather and process information. This paper investigates whether limiting retail investors' accessibility to the Internet could affect the incorporation of firm-specific information in prices, measured as the stock price synchronicity. Using Google withdrawing search services from China as an exogenous shock, I employ the matching-based difference-in-differences design and find an increase in synchronicity after Google's withdrawal, equivalent to a 4.6% growth in R^2. Further analysis shows that synchronicity measure arguably captures firm-specific information rather than noise, at least, in this setting. In addition, the improved synchronicity is concentrated in subsamples where corporate disclosures are verbose and few, firms are geographically inaccessible, and the controlling shareholder's ownership is moderate. The results are not driven by alternative explanations and are robust to alternative samples, alternative variable constructions, and the inclusion of more control variables.

Keywords: Retail Investors; Google Search; Firm-Specific Information; Synchronicity

JEL Classification: D83; G14; L86

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1. Introduction

In this paper, I investigate whether the retail investors' searching activities on the Internet affect the incorporation of firm-specific information in prices. Answering this research question is important for regulators, because it is conducive to understand retailer's behaviors given the base and role of retail investors grew up recently (Nasdaq 2020) and to limit the stock price co-movement, i.e., high R^2, which is considered a poor government indicator (Morck et al. 2000). Since retail investors typically suffer from information disadvantages relative to institutional investors who can get access to private information via various sources (e.g., Soltes 2014; Jung et al. 2018; Cheng et al. 2016), understanding this question is also helpful to level the playing field among investors (SEC 2020).

It is not clear, however, how Google's withdrawal affects the incorporation of firm-specific information in prices via investors' searching activities in China. On the one hand, since Google search provides more firm-specific information than the Chinese domestic search engine, Baidu (CNNIC 2011; Jiang 2013; Xu et al. 2021), Google's departure would render retailers lose a reliable way to solicit useful firm-level information. On the other hand, retail investors might be unsophisticated and are unable to analyze and process firm-specific information from the Internet where opaque, redundant, and fake messages blend into useful information. For example, Barber and Odean (2000, 2008) find that individual investors are highly interested in buying attention-grabbing stocks due to a search problem and generally have poor stock trading performance.[1] Da et al. (2011) suggest Google search could bias the investor trading behaviors by showing a within-year return reversal for high Google search firms. Overall, the effect of Google's withdrawal on the firm-specific information flows is essentially an empirical question.

[1] Search problem refers to the situation that although there are thousands of potential stocks that can be chosen, investors typically have limited cognition and time to process information and select stocks.

However, answering this question is empirically challengeable, because retail investors' searching activities are endogenously correlated with stock price co-movement. For example, retail investors could trade on the firm-specific information they obtain from the Internet, or the stock prices going up and down trigger their searching activities. To draw a causal inference, I exploit an exogenous shock that retail investors lost access to Google search after Google withdrew its services from mainland China in early 2010. Prior to 2010, Google search mainly competed with a domestic Internet engine, Baidu. Unforeseeably, Google withdrew its searching business after a failure of negotiation with the Chinese government on censorship issues in early 2010. The event of Google's departure is induced by the political excuse, not by any reasons regarding the retailers' behaviors, giving us a perfect quasi-natural experiment to study this research.

Specifically, I examine the effects of Google's withdrawal, which limits retail investors' accessibility to Internet search, on the incorporation of firm-specific information in prices, measure as stock price synchronicity. I employ the difference-in-differences (DiD) design and conduct the analyses using the propensity-score-matched sample. The original sample consists of all Chinese A-share listed firms from 2007 to 2012, where 2010 is the year of Google's withdrawal. Following Xu et al. (2021)[2], I identify the treatment firms and control firms based on the propensity that firms

[2] This paper is distinct from Xu et al. (2021), who document an increased crash risk due to Google's withdrawal, in two ways. First, conceptually, crash risk is the (negative signed) skewness of the distribution for residual from an (expanded) market model, where the residual is the component that cannot be explained by macro-level returns (Chen et al. 2001). Accordingly, the increased crash risk reflects a more skewed firm-specific information distribution. Unlike crash risk, synchronicity, which I used to proxy for firm-specific information flows in this paper, measures the log-transformed R^2 of the same (expanded) market model. Accordingly, synchronicity is more related to the amount of firm-specific information rather than the skewness of its distribution. Moreover, an untabulated analysis shows that, indeed, the synchronicity measure is weakly correlated with two crash risk measures (less than 10% for each pair) in my regression sample. Second, although prior literature documents a positive correlation between stock price synchronicity and crash risk, synchronicity is not considered to be caused by crash risk (Jin and Myers 2006). In Appendix Table A3, I provide evidence that my results are not driving by the likelihood of stock crash.

had higher Google's Search Volume Index (SVI) in 2009. The matching process makes treatment and control firms more comparable on the observable covariates (Rosenbaum and Rubin 1984).[3]

My first analysis is to examine the main effect of Google's withdrawal on stock price synchronicity. Using the propensity-score-matching sample and DiD design with firm and year fixed effects, I find that after Google removed its searching service from mainland China, Chinese listed firms with higher SVI before 2010 experience greater stock price synchronicity, i.e., have less incorporation of firm-specific information in prices.[4] The economic magnitude is also significant, about a 4.6% increase in R^2 estimated from a market model including market index and industry index. I also assess the dynamic effects and confirm that the parallel trend assumption is valid under my matching-based DiD design (Bertrand and Mullainathan 2003).

Next, I conduct several validation analyses to consolidate the baseline results. First, I address the concern that synchronicity measure might capture the firm-specific noise rather than information by examine the return-earnings association. The results show that the effect of Google's withdrawal on return-earnings association is negatively significant in both long- and short-window analyses, suggesting synchronicity arguably reflect the amount of firm-specific information rather than noise. Second, using a heterogeneity within treatment (i.e., treatment intensity), I examine whether the treatment firms with greater vis-à-vis less decline in Google SVI subsequent to Google's withdrawal will have higher synchronicity, compared to the control firms (Christensen et al. 2013; Lehmann 2019). The idea is that the more treatment firms suffer from Google's withdrawal, the greater treatment effects are. As expected, the evidence shows that treatment firms with a greater post-Google-withdrawal decline in SVI have less incorporation of

[3] Monthly Google SVI data for each Chinese listed-firm ticker is publicly available from http://jfe.rochester.edu/data.htm. I follow Xu et al. (2021) to use the median of the monthly SVI in the analysis.
[4] This result is robust to the sample extension, alternative variable constructions, and the inclusion of more control variables.

firm-specific information in prices. Last, since the Google search majorly benefits retail investors in China, Google effect should be concentrated in the subsample in which firms have less institutional ownership (i.e., more retail investor's ownership). Consistent with the conjecture, I find that Google effect only appears in the low institutional ownership group.

To explore the underlying mechanisms, I perform a bunch of cross-sectional analyses. First, I consider the Google search as an information hub to facilitate information acquisition and processing. If retail investors feel difficult to understand corporate disclosures, they are more likely to do some research through the Internet to get a better awareness of the target firms. To examine this conjecture, I partition the sample based on the median value of readability of corporate press releases. The result illustrates that Google's withdrawal has a greater impact on synchronicity in the low readability group, suggesting Google search could help the retail investors assess the firms with high textual complexity. Also, it is natural that retailers are more likely to use the Internet for searching additional information if corporate voluntary disclosures are rare. I partition the sample based on the median value of the count of corporate material events-related reports (like 8-K filings in the US) and examine the effects of Google's withdrawal on stock price synchronicity in both subsamples.[5] I observe that the coefficient on DiD estimator is only significant for firms with low voluntary disclosure and is significantly bigger than that for high voluntary disclosure firms. Overall, these findings are consistent with retail investors soliciting more information from the Internet when corporate disclosures are complex and deficient.

[5] In accounting literature, voluntary disclosure channels always refer to 8-K filings, management forecast, MD&A section in an annual report, conference calls, and investor days in the US (He and Plumlee 2020). However, in China, the management forecast is semi-mandatory, e.g., every firm should forecast if they expect an unexpectedly large positive or negative income for this fiscal year. Also, conference calls and investor days are nearly absent during my sample period. I do not consider MD&A a voluntary disclosure measure because it is semi-annually available and does not fully reflect the disclosure situation over an entire year. Accordingly, it is suitable to adopt material event disclosure (like 8-K filings) to proxy for voluntary disclosure.

Second, I consider the Internet search as a substitute for individual site visits. One possible way for retail investors to talk with management is through personal site visits. In China, the site visit is not the dedicated channel for analysts but is also open to retail investors. In light of the money and temporal limits, it is hard for retail investors to visit a firm located in a transportation-inconvenient city. In this case, they might rely more on the Internet to collect information. Accordingly, firms with headquarters located in the transportation-inconvenient city will suffer more from Google's withdrawal, thus having higher synchronicity. Based on the past city-level GDP performance, I categorize Beijing, Shanghai, Guangzhou, and Shenzhen as transportation-convenient cities (Banerjee et al. 2012) and use this classification to partition the sample. As expected, I find a significant treatment effect only for firms located in a transportation-convenient city, consistent with the argument that Google search complements retail investors' information set in the absence of individual site visits.

Finally, I consider the role of controlling shareholders in shaping the firm's synchronicity in China. Gul et al. (2010) document that synchronicity is a concave function of ownership concentration of controlling shareholders in China. In other words, high and low controlling shareholder's ownership may both lead to a small synchronicity. Based on this argument, I partition the sample based on whether a firm has a high (4^{th} quartile) or low (1^{st} quartile) controlling shareholder's ownership. The evidence shows that only when the controlling shareholder's ownership is concentrated around the sample's median value (i.e., 2^{nd} and 3^{rd} quartiles), the effects of Google's withdrawal on synchronicity is significant, consistent with Gul et al. (2010).

I also perform a bunch of tests to rule out several alternative explanations. First, one could argue that Google's withdrawal, in effect, discourages retailers from trading on the market, thus causing the informed traders cannot find people to arbitrage, suppressing the firm-specific information to be impounded into prices. I tease out this alternative interpretation by examining the effect of Google's withdrawal on the number of shareholder accounts and the number of comments on East Money stock forum. The result reveals that Google effect increases the investor attention, working against the alternative explanation. To further dissect the treatment effects, in a dynamic DiD model, I find that the Google effect on the number of shareholder accounts increases gradually in the pre-period and remains steady in the post-period. Meanwhile, Google's withdrawal has no impact on investor comments.

Second, prior studies document that more analyst forecasting activities will lead to high synchronicity in both the US and emerging market settings (Piotroski and Roulstone 2004; Chan and Hameed 2006). Accordingly, Google's withdrawal possibly cut off one of the information channels for retail investors, which in turn incentivizes analysts to dig into more information in response to the increased investor demand. Given that analyst activity is more act as a "conduit" for intra-industry information transfers (Piotroski and Roulstone 2004), one would expect that, after Google removes its searching services from mainland China, analyst forecast activities will become more prevalent and thereby carry more market- and industry-wide information. Meanwhile, analyst forecasts might be less accurate and dispersed because more macro-information is reflected in prices. Inconsistent with these arguments, I find that Google's withdrawal has no effect on analyst reports. Furthermore, there is no evidence that analyst forecast accuracy and dispersion are affected by Google's withdrawal.

Third, it could be the case that firms strategically change their voluntary disclosure strategy in response to the loss of exposure to Google search. Wang et al. (2020) document that Chinese listed firms with greater foreign sales are prone to release more optimistic corporate press releases and have lower stock informativeness (measured by R^2 from a market and industry return model) after Google's withdrawal. To ensure that corporate disclosure strategy does not systemically change after Google's withdrawal for treatment firms versus control firms, I regress the count of corporate press releases, the count of corporate press releases only on material events, and the word count of MD&A section on DiD estimator. I observe that the coefficient on DiD estimator is insignificant despite three models, indicating that the voluntary disclosure strategies do not change in response to Google's withdrawal.

Finally, one could argue that losing Google search would discourage media from covering firms because the audience may have less chance to reach media reports. Prior literature document a negative relation between media coverage and stock price synchronicity in both international and Chinese settings (Kim et al. 2016; Dang et al. 2020). To rule out this explanation, I assess the effects of Google's withdrawal on media coverage. I do not find any significant Google effect on media coverage.[6]

To provide solid inference, I also conduct some robustness analyses. My results are robust to the sample extension, alternative variable constructions, and the inclusion of more control variables.

This paper contributes to three strands of literature. First, it contributes to the synchronicity literature. Prior research emphasizes the importance of analysts (Piotroski and Roulstone 2004; Crawford et al. 2012), media (Kim et al. 2016; Dang et al. 2020), intuitional investors and insiders (Piotroski and Roulstone 2004), accounting quality (Jin and Myers 2006; Hutton et al. 2009; Gul

[6] Previous research also implied a positive relation between stock price crash risk and synchronicity, although synchronicity is not considered to be caused by stock price crash risk (Jin and Myers 2006; Hutton et al. 2009). Given that a positive causal link between Google's withdrawal and stock price crash risk has been shown in Xu et al. (2021), I check whether my sample and measure essentially mirror their sample and measures. In doing so, I first replicate Xu et al. (2021) and obtain quantitively and qualitatively similar results, indicating my original data is comparable to theirs. Next, I compare the correlation coefficients between my synchronicity measure and two crash risk measures in their paper, and find correlation coefficients are less than 10% for two pairs. Last, I use my regression sample to repeat the baseline test in Xu et al. (2021). The result, as shown in Appendix Table 3A, reveals that the effect of Google's withdrawal on crash risk is insignificant, confirming that crash risk cannot drive my results in this study.

et al. 2010), ownership structure (Gul et al. 2010), and political events (Piotroski et al. 2015) in shaping firm's stock price synchronicity. In particular, poor private property rights and public investor protections are considered the key institutional factors driving the synchronicity upward in the emerging market (Morck et al. 2000).[7] In this paper, I argue that, in the absence of superior Internet engine in China, retail investors are limited to obtain firm-specific information which curbs the information flowing into prices. Accordingly, this paper highlights the role of superior Internet engine in reducing stock price synchronicity in an emerging market.

Second, it contributes to the Internet search literature. Previous research documents that investor's searching activities on the Internet could predict future stock returns and other economic indicators (Da et al. 2011; Choi and Varian 2012), aid taxpayers to comply with laws and plan their tax (Hoopes et al. 2015), help decrease corporate stock price crash risk (Xu et al. 2021), and bias corporate disclosure behaviors (Wang et al. 2020). This paper provides distinct insight into the role of Internet search in shaping firm-specific information flows into prices, and the firm-specific information is arguably not the noise.

Third, it contributes to a growing body of literature on the impact of individual investors on stock returns (Kaniel et al. 2008; Kaniel et al. 2012; Barrot et al. 2016; Boehmer et al. 2021). Although prior research documents retail investors generally make irrational, biased, and unformed trading decisions (Barber and Odean 2000, 2008), more recent papers claim that retail trading are informed and can predict future stock returns (Barber et al. 2009; Kaniel et al. 2012; Kelley and Tetlock 2013; Barrot et al. 2016; Boehmer et al. 2021). This paper adds the supporting evidence on the latter argument by showing that retail investors could leverage the Internet search to discover firm-specific information and facilitate price discovery.

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[7] A related study by Wurgler (2000) shows that the efficiency of capital allocation is positively associated with minority investor protection and negatively associated with stock price synchronicity.

2. Institutional Background

Retail investors in China impose more impacts on the stock market relative to those in the US. According to the statistics from China Securities Depository and Clearing Corporation Limited (CSDC), the number of equity trader's accounts belong to retail investors hit 98.82 million by the end of 2015, accounting for more than 99% of total investor accounts. As a result, the vast majority of stock trades, around 85%, are made by retail investors (CNBC 2015).[8]

One of the most important ways for retail investors to search for information is through the Internet. A survey from Shenzhen Stock Exchange (SZSE) shows that 91% of respondents who are individual investors used the Internet to obtain stock information in 2010 (SZSE 2011).[9,10] In China, two Internet searching engine giants, Baidu and Google, monopolized the market together. According to the data from iReserch, a Chinese leading consulting firm, by the end of 2009, Baidu owns the largest market shares, around 63%, while Google makes up 33%.[11]

Since Google China (www.google.cn) was launched in January 2006, it has provided censored search results, along with the domestic Internet engine Baidu (www.baidu.com), to comply with Chinese censorship laws. Nonetheless, the information that two Internet engines offered essentially differentiates from one another. China Internet Network Information Center (CNNIC), a Chinese administration in charge of Internet affairs, conducted a national telephone survey and reported that 44% of search engine users complain the too much spam or false information on Baidu, while this percentage for Google is less than half of Baidu, around 20.9%

[8] Also, Chinese retail investors trade more frequently than US retail investors, according to a survey by State Street (CNN 2015).
[9] This survey was conducted by Nielsen Company which SZSE commissions.
[10] By the end of 2010, China has 457.30 million netizens, 81.9% of which reports the search engine is one of their network applications (CNNIC 2012).
[11] iResearch is a professional market research and consulting firm and focuses on the Internet industry in China. Its reports are cited by various media such as The New York Times, The Economist, Forbes, Harvard Business Review, etc.

(CNNIC 2011). Based on the first 10 results of searching 316 Chinese Internet events on Baidu and Google in 2010, Jiang (2013) documents low overlapped search results. The paper also shows that Baidu apparently avoids displaying the information of which data source comes from its competitors while Google does not have the same scheme, suggesting more comprehensive search results from Google than Baidu. Xu et al. (2021) provide a more detailed comparative analysis regarding the effectiveness of Internet searching on stock market information. They compare the first three pages of search results on Google versus Baidu by inputting all stock ticker of Chinese listed firms in 2019. They conclude three major advantages of Google engine vis-à-vis Baidu engine: Google search results illustrated less advertising (more informative message), less data source concentration (broader information references), more data from international websites (greater additional and perhaps professional information). Collectively, Google engine is more likely a superior information provider relative to Baidu engine.[12] It indeed became more and more popular among Chinese netizens as the market shares increased from 2007 to 2009.

On January 12, 2010, Google reported that it is unwilling to provide filtered information, because of the concerns about Chinese hacking attacks on human rights activists' Gmail accounts, if the agreement with the Chinese government does not work out. After negotiating with the Chinese government, on March 22, 2010, Google announced that it stopped providing censored search services for mainland China's users and redirected traffic to its Hong Kong server, where the information is uncensored.[13] The duopoly situation was then break up. Although Chinese netizen can technologically get access to Google's Hong Kong server, they have to face low

[12] Several Chinese studies made similar arguments that Google is better than Baidu in terms of information accuracy and relevance (e.g., Liu et al. 2010; Fei 2010).
[13] The negotiation failed because "the Chinese government has been crystal clear throughout our discussions that self-censorship is a non-negotiable legal requirement," according to the statement made by David Drummond, the senior vice president of Google, on March 22, 2010.

internet response, much server downtime (CNNIC 2011; Jiang 2013), and even the blocked access caused by Great Fire Wall (Reuters 2010; Fortune 2020) which is considered the Achilles' heel of Google engine after the withdrawal (CNNIC 2011). These suggest that the absence of Google engine reduces the information accessibility for retail investors to more useful information.

3. Data and Variable Construction

3.1 Sampling and PSM

I start the sample selection process by obtaining the necessary data for all Chinese A-share listed firms between 2007 and 2012 from CSMAR, WIND, CCER, and CNRDS databases.[14] This yields 11,861 firm-year observations with 2,496 unique firms as the original sample. I then remove financial firms which have distinct accounting method and regulation. Additionally, I eliminate the firm-year observations with missing values for regressions. Finally, I drop the observations that only occur in the pre- or post-period, allowing the firm to be its own control. After these deletions, I obtain the full sample composed of 7,897 observations with 1,425 unique firms. Da et al. (2011) suggest that Google SVI likely measures the retailer's attention. Accordingly, if retail investors search and collect firm-specific information via Google engine, firms with greater exposure to Google's search would be more vulnerably influenced by Google's departure. The SVI data in this paper comes from Xu et al. (2021) and is collected based on the searches for stock tickers of Chinese A-share listed firms on Google. In line with Xu et al. (2021), I identify treatment firms if the firm's SVI was above the sample median in 2009 and acquire 755 treatment firms as well as 670 control firms.

[14] The sample begins in 2007 because the new accounting standards took effect at that time. The sample ends in 2012 in order to construct a time-balanced dataset.

To mitigate the concern that treatment firms are not randomly assigned, I apply the propensity-score-matching (PSM) approach to refine the treatment and control sample further. First, I employ a logit model to estimate the propensity of being a treatment firm (i.e., a high SVI firm) using all of the sample firms in the year before Google's withdrawal. I consider a large spectrum of covariates in the selection model, including market to book ratio (*MtB*), SOE dummy (*SOEDummy*), firm size (*Size*), leverage (*Lev*), institutional ownership (*IH*), analyst coverage (*Analyst*), share turnover (*Turnover*), return volatility (*Volatility*), accrual quality (*DA_abs*), and investor comment in a stock forum (*Comment*). In addition, I include industry fixed effects and province fixed effects. The selection of the above covariates derives from economic intuition and the extant literature (Chan and Hameed 2006; Gul et al. 2010; Xu et al. 2021). All variable definitions are described in Appendix Table A1.

Then I match treatment firms and control firms based on a one-to-one nearest neighbor matching criterion with the caliper equals 0.25*standard error of propensity score (Dehejia and Wahba 2002; Chen et al. 2018), but without replacement. This results in the final (PSM) regression sample of 5,068 firm-year observations, 2,588 of which belongs to the treatment group and 2,480 of which belongs to the control group. Panel A of Table 1 presents the sample selection process.

I provide the sample composition by year and by industry sector in Panel B and Panel C of Table 1, respectively. The number of treatment firms and control firms are similar over time and within industry, suggesting a (closely) balanced panel dataset.

[Insert Table 1 here]

Panel A of Appendix Table A2 presents the result of a logit model for calculating propensity scores. Consistent with Xu et al. (2021), I find that the propensity of being a treatment firm is negatively correlated with *Size*, and positively correlated with *Lev*, *IH*, *Analyst*, *Turnover*, *Volatility*, and *Comment*. To gauge the quality of matching, I perform the balance analysis for pre- and post-matching periods and report the results in Panel B and Panel C of Appendix Table A2, respectively. The results show that before matching, there are significant differences in seven out of ten covariates between treatment firms and control firms. However, after matching, the notable differences disappear, suggesting that the propensity-score-matching approach is effective and make treatment firms and control firms more comparable.

3.2 Measurement of Stock Price Synchronicity

To measure stock price synchronicity, I first estimate the expanded market model taking the following form:

$$Return_{it} = \alpha + \beta_1 Market_t + \beta_2 Industry_{it} + \varepsilon_{it}, \quad (1)$$

where $Return_{it}$ is the weekly individual return for firm *i* in week *t*, $Market_t$ is the value-weighted market return in week *t*, and $Industry_{it}$ is the value-weighted return of the industry to which firm *i* belongs in week *t*. $Industry_{it}$ is measured using all firms within the same one-digit China Securities Regulatory Commission (CSRC) industry, excluding the firm *i* per se.[15] I estimate the Eq. (1) for each firm-year with a minimum of 40 weekly observations (Chan and Hameed 2006). Following Morck et al. (2000), the dependent variable, stock price synchronicity (*Synch*), is defined as

$$Synch = \ln(R^2 / (1 - R^2)),$$

[15] I adopt the one-digit industry code designed by CSRC in 2012, which includes 19 unique industries.

where R^2 is the coefficient of determination from the estimation of Eq. (1). By construction, high *Synch* indicates that a firm's price movement is highly correlated with the market index and the industry index, i.e., less firm-specific information impounded into prices.

3.3 Descriptive Statistics

Table 2 reports the descriptive statistics for variables. All the continuous variables are winsorized at the 1% and 99% levels. The mean (median) value of *Synch* is -0.085 (-0.061) for my regression sample for the period 2007-2012, which is greater than that in Gul et al. (2010) where they report -0.232 (-0.151) in mean (median) *Synch* for the period 1996-2003.[16] This may imply that stock price synchronicity in China experiences an increase from the post-1997 Asian financial crisis to the post-2007 global financial crisis.[17] The distribution of other variables is comparable to prior studies (e.g., Piotroski et al. 2015; Xu et al. 2021).

[Insert Table 2 here]

4. Empirical Analysis

In the empirical section, I first examine the effects of Google's withdrawal on stock price synchronicity under a DiD research design. I then perform several validation tests to lend support to my baseline results. Next, I conduct a bunch of cross-sectional analyses to explore the underlying mechanisms. Finally, I consider the alternative explanations and empirically rule them out.

[16] The summary statistics for the pre-matched sample show a similar distribution of *Synch* with mean (median) of -0.085 (-0.062).
[17] I note to cautiously explain this phenomenon, because Gul et al. (2010) only report non-wonsorized synchronicity, and their calculation of synchronicity is slightly different from mine.

4.1 Baseline Regression

The main goal of this paper to investigate whether the absence of Google engine, which limits retail investor's accessibility to superior Internet search engine, affects stock price synchronicity. In doing so, I apply the following fixed effect-based DiD model:

$$Synch_{it} = \alpha + \beta GoogleShock_{it} + \gamma Controls_{it} + Firm\ Fixed\ Effects + Year\ Fixed\ Effects + \varepsilon_{it}, \qquad (2)$$

where $GoogleShock_{it}$ is an indicator, equal to 1 if a firm belongs to the treatment group and over the post-period, and 0 otherwise.[18] Following prior literature (Chan and Hameed 2006; Gul et al. 2010), I include a battery of control variables: *Size*, *MtB*, *Lev*, *Turnover*, *Volatility*, *stdROA*, *NumInd*, and *IndSize*. In addition, I control for time-invariant firm characteristics and market-wide unobservable heterogeneity by adding firm fixed effects and year fixed effects. Standard errors are clustered at the firm level. The coefficient of interest is β which represents the effect of Google's withdrawal on synchronicity.

Panel A of Table 3 presents the results for Eq. (2). In Column 1, I exclude the control variables but with the inclusion of two-way fixed effects. The coefficient on *GoogleShock* is 0.071 at the 5% significance level (*t*-stat = 2.05). Given the fixed effects structure, this result suggests that Google's withdrawal increases the synchronicity for firms more subject to Google search before the shock. In Column 2, I add the full set of control variables that likely affect the stock price synchronicity. The coefficient on *GoogleShock* remains positive (coefficient = 0.090) and significant at the 1% level (*t*-stat = 2.80). The economic magnitude is also meaningful: the coefficient on *GoogleShock* in Column 2 means, on average, synchronicity grows from -0.085 (mean synchronicity in PSM sample) to 0.005, equivalent to 47.9% and 50.1% return variations explained by the market index and industry index. That is, R^2 of Eq. (1) increases by 4.6%

[18] *Treat* and *After* are subsumed to firm fixed effects and year fixed effects, respectively.

subsequent to Google's withdrawal. The magnitude is reasonable given China has a relatively high synchronicity base.[19] The loadings on control variables are much comparable to those in prior research (e.g., Gul et al. 2010; Kim et al. 2021). Firm size (*Size*) is positively correlated with synchronicity, while growth (*MtB*), leverage (*Lev*), and return volatility (*Volatility*) are negatively correlated with synchronicity.

To ensure the common trend assumption is not violated, I use the specification from Column 2 in Panel A of Table 3 with others equal but decompose *GoogleShock* into several dummy variables (Bertrand and Mullainathan 2003): $GoogleShock^{-3}$, $GoogleShock^{-2}$, $GoogleShock^{-1}$, $GoogleShock^{0}$, $GoogleShock^{+1}$, and $GoogleShock^{+2}$. $GoogleShock^{n}$ is defined as 1 if a firm belongs to the treatment group and in the year *n*+2010 (*n* = -3, -2, -1, 0, 1, or 2), and 0 otherwise. $GoogleShock^{-1}$ is set to 0 as the benchmark year. Panel B of Table 3 presents the results of the dynamic effects. The coefficients on $GoogleShock^{-3}$ and $GoogleShock^{-2}$ are both insignificant, suggesting that there are no changes of synchronicity in the pre-period. Meanwhile, the coefficients on $GoogleShock^{0}$, $GoogleShock^{+1}$, and $GoogleShock^{+2}$ are positive and significant at the conventional level. In particular, the coefficients on these three dummies map out a convex curve that the effect of Google's withdrawal on synchronicity drops from 0.116 to 0.087 for the first two years after the shock and then increase to 0.140 in the third year. These results imply that Google's withdrawal has a long-term effect.

[Insert Table 3 here]

[19] Another way to interpret the economic magnitude is to follow Xu et al. (2021), who studies the effect of Google's withdrawal on crash risk in China. Based on the rationale from them, the coefficient 0.090 is equivalent to 12.7% (= 0.090 / 0.709) of the standard deviation of *Synch* in the regression sample. The value is similar if using the standard deviation of *GoogleShock* in the full sample, 0.725, to gauge the economic magnitude.

4.2 Validation Analysis

To support the baseline results, I perform three validation tests. First, I investigate whether firm-specific return variations reflect information other than noise. Second, I explore the treatment intensity by focusing the heterogeneity in SVI declines. Finally, I provide evidence that retail investors rely more on Google engine rather than institutional investors.

4.2.1 Information or Noise?

Roll (1988) notes that lower R^2 (equivalent to lower synchronicity) could either represent the noise or information. On the one hand, Durnev et al. (2003) empirically test the association between synchronicity and stock price informativeness (measured by the further earnings response coefficient) and conclude that lower synchronicity reflects more informative stock prices. On the other hand, Ashbaugh-Skaife et al. (2005) document the mixed relation between synchronicity and informativeness in the five non-US (i.e., Australia, France, Germany, Japan, and the UK) stock markets. To ensure that the synchronicity measure captures the amount of firm-specific information rather than noise (at least in this setting), I examine the Google effects on return-earnings association which is considered the most value relevant firm-specific information (Gul et al. 2010). If synchronicity reflects the information, I would expect the return-earnings association reduces for the treatment firm subsequent to Google's withdrawal. The following model is specified to subject this expectation to an empirical test.

$$AbnReturn_{it} = \alpha + \beta GoogleShock_{it} \times UE_{it} + \delta GoogleShock_{it} + \eta UE_{it} + \omega Controls_{it} \times UE_{it} + \gamma Controls_{it} + Firm\ Fixed\ Effects + Year\ Fixed\ Effects + \varepsilon_{it}, \quad (4)$$

where *AbnReturn* denotes the long-run window abnormal return (*BHAR[MayToApril]*), measured by the market-adjusted monthly returns compounded from May to the next year's April,[20] and

[20] Chinese listed firms are required to announce annual earnings by the end of April after the fiscal year-end.

short-run window abnormal return (*CAR[*-1, +1*]*), measured by the market-adjusted daily returns around earnings announcement three-day window [-1, +1], *UE* denotes the unexpected earnings based on the analyst forecast census supplemented by seasonal random walk if the census is not available, and *Controls* denotes other explanatory variables including treatment firm dummy (*Treat*), post dummy (*After*), market capitalization (*MV*), growth (*MtB*), and leverage (*Lev*).[21]

Panel A of Table 4 presents the estimates of Eq. (4). The coefficients on the interaction term *GoogleShock* × *UE* is consistently negative and significant at better than the 10% level across four columns, indicating that Google's withdrawal lowers the response of stock prices to earnings in both the long- and short-run window. It also suggests that retail investors are limited to learn and gather the value relevant information after Google's withdrawal.

4.2.2 Treatment Intensity: Declines in Google SVI

If Google's withdrawal matters, it is natural to expect treatment firms which experience a *bigger decline in Google SVI subsequent to the shock* would have a greater increase in synchronicity. To test this conjecture, I utilize the treatment intensity and partition the treatment group based on the sample median value of the declines in SVI in the post-period (i.e., the negative ΔSVI). Specifically, I use Eq. (2) but replace *GoogleShock* with two dummy variables, *GoogleShock*[*HighDeclineSVI*] and *GoogleShock*[*LowDeclineSVI*]. *GoogleShock*[*HighDeclineSVI*] (*GoogleShock*[*LowDeclineSVI*]) is defined as 1 if firms belong to treatment group and experiences above-median (below-median) SVI declines in the post-period, and 0 otherwise.

The results are reported in Panel B of Table 4. The average treatment effects are significantly positive only for firms with high SVI decline after Google's withdrawal. The

[21] *Treat* and *After* are absorbed by firm and year fixed effects, respectively. However, *Treat* × *UE* and *After*× *UE* survive in the specification.

difference between the coefficients on *GoogleShock*[*HighDeclineSVI*] and *GoogleShock*[*LowDeclineSVI*] is also statistically significant at the 1% level (*F*-stat = 18.57). These results are consistent with the idea that greater decline in SVI, higher treatment effects firms have.

4.2.3 Google's Users: Retail Investors?

One underlying assumption in this paper is that retail investors are more likely to use Google search to obtain information rather than institutional investors. If so, I would expect firms with low institutional holdings (i.e., high retailer's holdings) have greater Google effects. To examine my conjecture, I partition the sample based on the median value of institutional holdings (*IH*) in 2009. Panel C of Table 4 presents the results. For low institutional holdings firms (Column 1), the coefficient on *GoogleShock* is 0.136 and nearly three times bigger than that in high institutional holdings firms (Column 2). The difference between two coefficients is statistically significant at the 10% level (*Chi-squared* stat = 2.79). These confirm the argument that retail investors make more use of Google engine, compared to institutional investors. Meanwhile, these findings are consistent with the notation that the Internet searching behaviors of retail investors are captured by SVI (Da et al. 2011).

[Insert Table 4 here]

4.3 Cross-Sectional Variations

So far, we have examined the effects of Google's withdrawal on stock price synchronicity and provided the evidence to validate the results. In this subsection, I focus on the mechanisms behind the Google effects.

4.3.1 Reporting Readability and Voluntary Disclosure

As discussed above, Internet search is a common tool for retail investors to obtain information, because it is easy and cheap to use. Accordingly, I expect Google search becomes more important if retail investors are difficult to understand or extract firm-specific information through corporate disclosures, in particular, when the disclosure information is complex and the voluntary disclosures are deficient. To investigate these potentially mechanisms, I examine the effect of Google's withdrawal on synchronicity but conditional on (1) the reporting readability, *Press Release Readability*, measured as the average word count per corporate press release, or (2) the degree of voluntary disclosure, *# Material Events*, measured as the average count of material events disclosed.[22] Here, I do not use the readability of annual reports because it only measures the textual complexity of annual reports, not the overall level of readability across a year. Other common voluntary disclosure proxies in studies, such as, management forecast, MD&A section, conference calls, and investor days, are also not suitable for either the Chinese setting or this story: management forecast is semi-mandatory; conference calls and investor days are deficient in my sample period; MD&A section is only available semi-annually thus does not capture the voluntary disclosure situation over a whole year.

I partition the sample based on the sample median value of readability measure (voluntary disclosure measure) in 2009 and report the results in Column 1 and Column 2 (Column 3 and Column 4) in the Panel A of Table 5. For low readability firms and high textually complexity firms, the coefficients on *GoogleShock* are 0.135 and 0.128, respectively, both significant at the 1% level. In contrast, the coefficients on *GoogleShock* for high readability firms and low textually complexity firms are both insignificant. The differences of coefficients on *GoogleShock* between

[22] The disclosure of material events in China is much similar to 8-K filings in the US. The number of 8-K filings is considered a measure of voluntary disclosure in prior literature (e.g., Guay et al. 2016; He and Plumlee 2020).

Column 1 and Column 2 and between Column 3 and Column 4 are statistically significant at the 10% level, with *Chi-squared* stat equals 2.86 and 2.94, respectively. The evidence in Panel A suggests that Google search serves as an additional information hub for retail investors to gather and process information if corporate disclosures are textually complex and few.

4.3.2 Geographic Difficulty for Individual's Site Visit

Although retail investors have information disadvantages relative to sophisticated institutional investors, they still have the chance to visit firm and talk with management. If a firm is located in a transportation-inconvenient city, retail investors are more likely to gather information online instead of personally visit the firm. I expect the Google effect to be significantly positive for firms located in a transportation-inconvenient city. Due to the data availability, I classify the city as a transportation-inconvenient city (*Transportation-Inconvenient City*) if it does not belong to the top four GDP cities, i.e., Shanghai, Beijing, Guangzhou, and Shenzhen.[23] The idea is that GDP level is correlated with transportation infrastructure development (e.g., Banerjee et al. 2012). I partition the sample based on whether the headquarter of a firm is located in a transportation-inconvenient city for a given year. The results are presented in Panel B of Table 5. Firms with headquarter in a transportation-inconvenient city have s strong Google effect (coefficient = 0.116, *t*-stat = 3.074), while the Google effect in a transportation-convenient city group is indistinguishable with zero. The difference of the coefficients on *GoogleShock* between two columns is significant at the 10% level (*Chi-squared* stat = 3.01). The results in Panel B suggest that Google engine serves as a substitute for retail investors to obtain information when the personally site visit are costly because of geographic difficulty.

4.3.3 Ownership Structure

[23] According to National Bureau of Statistics of China, these four cities consecutively occupied the top four economic development city list between 2007 and 2012. The sum of their GDP accounts for one-eighth of China's national GDP.

Gul et al. (2010) document synchronicity is a concave function of ownership concentration of controlling shareholders in China. In the spirit of Gul et al. (2010), I consider the role of controlling shareholders in shaping the firm's synchronicity. Specifically, I first partition the sample based on the ownership of controlling shareholders, *Top1*, by quartile and by year, and identify the firms subject to higher synchronicity due to the ownership structure as the ones falling into the second or third quartile. Panel C of Table 5 reports the results. I find that only if the firm's ownership is concentrated on the second and third quartile value of sample distribution, the effects of Google's withdrawal on synchronicity is significant (coefficient = 0.110, *t*-stat = 2.255). The difference of coefficients on *GoogleShock* in two columns, however, is not statistically distinguishable from zero. The results in Panel C suggest a moderating role of the controlling shareholder's ownership structure in Google effects, consistent with Gul et al. (2010).

[Insert Table 5 here]

5. Alternative Explanations and Robustness Checks

In this section, I discuss several alternative explanations that might drive the results, and empirically rule them out. In the end, I also provide some robustness checks.

5.1 Whether Investor Attention Decreases after Google's Withdrawal

One may argue that since Google's withdrawal limits the ability of retail investors to obtain information from the Internet, it could also discourage retail investors from participating in the stock market. To alleviate this concern, I examine the effects of Google's withdrawal on the number of shareholders (*Shareholder*) and retailers' comments from an active online stock forum (*Comment*), respectively. Control variables are adopted as the same as the baseline model. The data, with regard to investors' trading accounts and comments, is retrieved from WIND and CNRDS, respectively.

Panel A of Table 6 presents the results. As shown in Column 1 and 2, Google effects increase the participation of investors in the stock market, which works against the alternative explanation. To further explore the dynamic changes, I decompose the *GoogleShock* into five dummy variables as defined in Section 4.1 and re-run the regression analyses. Column 3 and 4 show that, in effect, the positive effects in Column 1 and 2 are due to the lower *Shareholder* in the first two years of the pre-period relative to the year of 2009. Meanwhile, the effects on *Shareholder* are stable in the post-period. Column 5 and 6 report the results of the model with *Comment* as dependent variable. No matter the inclusion of control variables, there is no evidence to show that retail investors' attention significantly changes because of Google's withdrawal.

5.2 Whether Analysts' Behaviors Change after Google's Withdrawal

Previous literature argues a positive association between analyst forecasting activities and stock price synchronicity in the US (Piotroski and Roulstone 2004) and emerging markets (Chan and Hameed 2006). In particular, Piotroski and Roulstone (2004) interpret this association as an analyst's industry affiliation and expertise allow them to convey industry-level information better, consequently improve the intra-industry information transfers. Accordingly, it could be a concern that retail investors may elevate their demand for soliciting more firm-specific information due to the loss of Google engine, which in turn incentivizes analysts to produce more reports. Moreover, analyst forecast accuracy and dispersion may decline because more market- and industry-wide information (i.e., less firm-specific information) are incorporated into forecasting activities. To get rid of this alternative explanation, I assess the effects of Google's withdrawal on the number of analyst reports (*Analyst Report*), analyst forecast error (*Forecast Error*), and analyst forecast dispersion (*Dispersion*). The sample size reduces significantly when the dependent variable is *Forecast Error* or *Dispersion*, because analyst forecast activities are still underdeveloped in China. The variable definitions are described in Appendix Table A1.

Panel B of Table 6 reports the results. Following prior literature (Behn et al. 2008; Dhaliwal et al. 2012), I add firm size (*Size*), earnings volatility (*stdROE*), institutional holdings (*IH*), auditor (*Big4*), and loss (*Loss*) to Column 4 to 6, and include analyst following (*Analyst*) and forecast horizon (*FHorizon*) as additional controls to Column 5 and 6. In Panel B, the coefficients on *GoogleShock* are insignificant across all columns. Accordingly, the evidence contradicts the argument that the positive synchronicity is driven by the changes of analyst forecasting activities due to the Google's withdrawal.

5.3 Whether Corporate Disclosure Strategies Change after Google's Withdrawal

Chan and Hameed (2006) argue that high synchronicity in the emerging market can be attributed to the lower voluntary disclosure. It is possible that firms alter the disclosure strategies, for instance, increase the voluntary disclosure, in response to the high demand from the investor side result from the loss of superior Internet search engine. Wang et al. (2020) find that Chinese public firms which announce foreign transactions issue more optimistic corporate press releases after Google's withdrawal relative to firms which announce domestic transactions, suggesting a strategic corporate disclosure in the absence of Google engine. To ensure that the disclosure strategy is not systemically changed because of Google's withdrawal, I assess the Google effects on three disclosure measures, i.e., natural log of the count of material event disclosures (*# Material Events*), natural log of the word count of MD&A section in the annual report (*# WC MD&A*), the average word count of corporate press release (*# WC Press Release*), and the word count of an annual report (*# WC Annual Report*). The first two measures capture the extent to which firms are inclined to voluntarily disclose information.[24] The last two measures capture the extent to which disclosure contains verbose text, that is, reporting readability. Control variables include firm size (*Size*), growth (*MtB*), leverage (*Lev*), profitability (*ROA*), operational complexity (*Segment*), analyst following (*Analyst*), institutional holdings (*IH*), and media coverage (*News*). The variable definitions are described in Appendix Table A1.

In Panel C of Table 6, I present the results of DiD estimations, beginning with the model without any control variables in Column 1 to 4, and then including a battery of controls in Column 5 to 8. Inconsistent with the alternative explanation, I do not observe the statistically significant change in voluntary disclosures and reporting readability under the DiD design. The evidence shown in Panel C indicates that my inference is not affected by changes in corporate disclosure strategy.

5.4 Whether Media Coverages Decrease after Google's Withdrawal

It could be a case that Google's withdrawal discourages media from covering firms with *ex ante* high SVI, because media expect audience may have less chance to read news via the Internet. Kim et al. (2016) and Dang et al. (2020) provide evidence that media coverage would decrease stock price synchronicity by using samples of Chinese listed firms and international firms from 40 countries, respectively. Accordingly, media coverage could be a potential driver of my results. To exclude this possibility, I examine the effects of Google's withdrawal on media coverage using the same DiD specification as the baseline model. I define media coverage (*News*) as the number of financial news that mentions a firm at least one time. Data with regard to media coverage is obtained from Datago, a Chinese data vendor focusing on big data analyses.[25] I adopt

[24] Material events are disclosed more timely, while MD&A section only occurs in semi-annual or annual reports.
[25] Datago is founded by accounting researchers from the University of Southern California, the Chinese University of Hong Kong, and other business schools. Detailed information regarding *News* is described in Piotroski et al. (2017).

the same control variables as in Column 5 to 8 in Panel C with the exclusion of *News* per se. The results in Panel D of Table 6 exhibit that the coefficients on *GoogleShock* in Column 1 and 2 are both indistinguishable from zero, suggesting that media coverage does not experience significant changes subsequent to Google's withdrawal.

[Insert Table 6 here]

5.5 Robustness Tests

I perform additional robustness tests in this subsection. Specifically, I first use the full sample and repeat the baseline analysis. Then I employ an alternative dependent variable, *Synch_dr*, measured via the Eq. (1) but using daily return data. In addition, I include more control variables in the model. Last, I further extend the Eq. (1) by including the lagged market return and lagged industry return and yield an alternative dependent variable, *Synch_fourfactors*. Table 7 present the results of robustness tests. Similar to the main results, in Column 1, the coefficient on *GoogleShock* remains positive (coefficient = 0.131) and significant at the 1% level. In Column 2, I use a daily return-based synchronicity measure as the dependent variable and re-run Eq. (2). The inference is unchanged. In Column 3, following the literature (Jin and Myers 2006; Gul et al. 2010), I add more control variables to the model, including cross listing indicators (*H_Dummy* and *B_Dummy*), controlling shareholder's ownership and its square (*Top1* and *Top1_Square*), auditor (*Big4*), and stock price crash risk (*NCSKEW*). The magnitude of the main effect is similar to what I observe in the baseline model, suggesting these additional controls have little explanatory power. At the same time, consistent with Gul et al. (2010), *Top1* is the concave function of synchronicity. The loading on *NCSKEW* is also in line with the findings, documented by Jin and Myers (2006), that crash risk is correlated with synchronicity. In Column 4, I replace the dependent variable with an alternative measure, *Synch_fourfactors*, and find that the coefficient on GoogleShock is positive and significant at better than the 5% level. Combined, the evidence suggests that my inference is robust to the sample extension, alternative variable definitions, and the inclusion of more control variables.

[Insert Table 7 here]

7. Conclusion

The Internet is an important tool for gathering and processing information (Hoopes et al. 2015; Xu et al. 2021). But still, it could manipulate or mislead people by displaying much misleading and fake news without effective filtering. Given the increased role of retail investors in the stock market, it is curial to understand whether and how retail investors affect stock prices through the Internet search. This paper sheds light on this matter from the perspective of how retail investor's searching activities influence firm-specific information flows.

Exploiting the unforeseen withdrawal of Google search services from China in 2010 as an exogenous shock, I examine the effects of limiting retail investors' accessibility to superior Internet search engine on stock price synchronicity. A fixed effects-based difference-in-differences analysis shows that Google's withdrawal increases the synchronicity, that is, suppress the firm-specific information impounded into prices. The validation checks further support this inference. In the cross sections, I find the effects become more pronounced when the corporate disclosure is textually complex and few, the firm is located in a transportation-inconvenient city, the firm is state-owned, and the controlling shareholder's ownership is moderate. Finally, after ruling out several alternative explanations, I provide additional evidence to corroborate that less synchronicity arguably represents more firm-specific information, rather than noise, incorporated into prices, at least in this setting.

My findings should be of interest to governors and regulators. On the one hand, politics-induced government action could protect national interests and maintain national authority; on the other hand, it might be harmful to the majority of individual participants in the stock market, thereby lowering the market efficiency. How to trade off national interests and individual investors' benefits is a critical issue for future studies.

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Table 1 Sample Selection and Composition

This table reports the sample selection process and sample composition. Panel A presents the sampling procedure. My final regression sample includes 5,068 firm-year observations (912 unique firms) with the sample period 2007 to 2012. Panel B (Panel C) presents the distribution of regression sample by year (by industry sector).

Panel A: Sampling

Sample Selection	# of obs.	# of firms
Original sample from 2007 to 2012	11,861	2,496
Exclude:		
Financial firms	202	
Missing values of variables required for the regressions	3,183	
Firms only appearing in the pre- or post-period	579	
Full sample	7,897	1,425
Exclude:		
Unmatched observations	2,829	
Regression sample	5,068	912

Panel B: Distribution by year

Year	Treatment	Control	Total
2007	393	325	718
2008	422	368	790
2009	456	456	912
2010	448	446	894
2011	437	441	878
2012	432	444	876
Total	2,588	2,480	5,068

Panel C: Distribution by industry sector

Industry sector	Treatment	Control	Total
A	48	43	91
B	67	66	133
C	1,652	1,553	3,205
D	89	63	152
E	68	71	139
F	215	172	387
G	104	109	213
I	71	81	152
K	153	186	339
L	27	30	57
N	5	5	10
R	3	1	4
S	86	100	186
Total	2,588	2,480	5,068

Table 2 Descriptive Statistics

This table summarizes the descriptive statistics of the main variables for regression sample. All the continuous variables are winsorized at the 1% and 99% levels. All variables are defined in Appendix Table A1.

	N	Mean	Std. Dev.	Q1	Median	Q3
Synch	5068	-0.085	0.709	-0.535	-0.061	0.393
Treat	5068	0.511	0.500	0.000	1.000	1.000
After	5068	0.522	0.500	0.000	1.000	1.000
Size	5068	21.754	1.213	20.927	21.650	22.444
MtB	5068	3.683	3.472	1.787	2.907	4.632
Lev	5068	0.522	0.214	0.376	0.523	0.659
Turnover	5068	0.553	0.356	0.268	0.473	0.786
Volatility	5068	1.907	0.317	1.685	1.910	2.150
stdROA	5068	0.040	0.055	0.012	0.023	0.045
NumInd	5068	6.071	1.388	4.585	6.883	7.182
IndSize	5068	28.662	1.224	27.945	29.083	29.563

Table 3 The Effect of Google's Withdrawal on Stock Price Synchronicity

This table shows the results of Google's withdrawal on stock price synchronicity. Panel A reports the DiD estimation. The dependent variable, *Synch*, equals ln(R^2 / (1 – R^2)), where R^2 is the coefficient of determination from Eq. (1). The independent variable, *GoogleShock*, is an indicator equal to one if a firm belongs to the treatment group and in the post-period, and zero otherwise. Panel B reports the results of common trend test. The dependent variable, *Synch*, is defined as before. The independent variable, $GoogleShock^n$, is defined as one if a firm belongs to the treatment group and in the year *n*+2010 (*n* = -3, -2, -1, 0, 1, or 2), and 0 otherwise, where $GoogleShock^{-1}$ is set to 0 as the benchmark year. All other variables are defined in Appendix Table A1. *t*-statistics are shown in parentheses and are based on standard errors clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A Baseline Results

	(1)	(2)
Dep Var. =	*Synch*	*Synch*
GoogleShock	0.071**	0.090***
	(2.054)	(2.804)
Size		0.159***
		(4.479)
MtB		-0.023***
		(-4.894)
Lev		-0.482***
		(-4.431)
Turnover		-0.224***
		(-4.823)
Volatility		-0.685***
		(-11.391)
stdROA		-0.330
		(-1.208)
NumInd		0.038
		(0.941)
IndSize		-0.059
		(-1.531)
FirmFE	Yes	Yes
YearFE	Yes	Yes
Adj. R^2	0.393	0.454
N	5068	5068

Panel B Common Trend Test

	(1)
Dep Var. =	*Synch*
$GoogleShock^{-3}$	0.058
	(1.092)
$GoogleShock^{-2}$	0.024
	(0.505)
$GoogleShock^{0}$	0.116**
	(2.263)
$GoogleShock^{+1}$	0.087*
	(1.668)
$GoogleShock^{+2}$	0.140***
	(2.676)
Size	0.159***
	(4.500)
MtB	-0.023***
	(-4.894)

Lev	-0.484***
	(-4.457)
Turnover	-0.220***
	(-4.740)
Volatility	-0.685***
	(-11.391)
stdROA	-0.337
	(-1.236)
NumInd	0.038
	(0.934)
IndSize	-0.059
	(-1.534)
FirmFE	Yes
YearFE	Yes
Adj. R^2	0.454
N	5068

Table 4 Validation Checks

This table reports the results of validation checks. Panel A shows the effects of Google's withdrawal on the return-earnings association. The dependent variables are *BHAR*[*MayToApril*] and *CAR*[-1, +1], measuring the long-run and short-run window association, respectively. The production of UE and other explanatory variables are also included in the model. Panel B reports the tests of treatment intensity based on the extent to which SVI declines for treatment firms. The dependent variable, *Synch*, equals ln(R^2 / (1 – R^2)), where R^2 is the coefficient of determination from Eq. (1). The independent variable, *GoogleShock*[*HighDeclineSVI*] (*GoogleShock*[*LowDeclineSVI*]), is an indicator equal to one if a firm belongs to the treatment group and experiences above-median (below-median) SVI declines in the post-period, and zero otherwise. Panel C reports the DiD estimation for low (high) and high (low) institutional holdings (retail investors' holdings) firms. The dependent variable, *Synch*, is defined as before. The independent variable, *GoogleShock*, is an indicator equal to one if a firm belongs to the treatment group and in the post-period, and zero otherwise. The sample partitioning is based on the variable *IH*, defined as the number of shares owned by institutional investors divided by total outstanding shares. All other variables are defined in Appendix Table A1. *t*-statistics are shown in parentheses and are based on standard errors clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Return-Earnings Association: Long-Window and Short-Window

	(1)	(2)	(3)	(4)
Dep Var. =	*BHAR*[*MayToApril*]	*CAR*[-1, +1]	*BHAR*[*MayToApril*]	*CAR*[-1, +1]
GoogleShock×UE	-0.514*	-0.076*	-0.612**	-0.071*
	(-1.776)	(-1.902)	(-2.087)	(-1.773)
GoogleShock	-0.021	-0.002	-0.019	-0.002
	(-1.323)	(-0.687)	(-1.160)	(-0.704)
Treat×UE	0.497***	0.015	0.480**	0.020
	(2.725)	(0.557)	(2.542)	(0.748)
After×UE	0.177	0.056*	0.285	0.066**
	(0.928)	(1.899)	(1.450)	(2.228)
UE	0.494***	-0.028	0.112	-0.403
	(4.752)	(-1.548)	(0.065)	(-1.497)
MV			0.029	-0.011***
			(1.464)	(-4.080)
MtB			0.019***	0.000
			(5.604)	(0.086)
Lev			0.139**	-0.007
			(2.176)	(-0.821)
MV×UE			0.012	0.017
			(0.160)	(1.452)
MtB×UE			0.020	-0.001
			(1.507)	(-0.258)
Lev×UE			-0.017	0.020
			(-0.066)	(0.526)
FirmFE	Yes	Yes	Yes	Yes
YearQtrFE	Yes	Yes	Yes	Yes
Adj. R^2	0.099	0.020	0.120	0.024
N	5068	5068	5068	5068

Panel B: Treatment Intensity: Declines in Google SVI

Dep Var. =	*Synch*
GoogleShock[*HighDeclineSVI*]	0.137***
	(3.996)
GoogleShock[*LowDeclineSVI*]	-0.020
	(-0.484)
Size	0.161***
	(4.533)
MtB	-0.023***

	(-4.910)
Lev	-0.491***
	(-4.495)
Turnover	-0.205***
	(-4.399)
Volatility	-0.649***
	(-10.641)
stdROA	-0.316
	(-1.151)
NumInd	0.041
	(0.992)
IndSize	-0.060
	(-1.540)
FirmFE	Yes
YearFE	Yes
Adj. R^2	0.457
N	5068

Panel C: Google's Users: Retail Investors or Institutional Investors?

	(1)	(2)
Dep Var. = *Synch*	Low *IH*	High *IH*
GoogleShock	0.136***	0.046
	(2.940)	(1.042)
Size	0.198***	0.073
	(4.648)	(1.275)
MtB	-0.014**	-0.046***
	(-2.567)	(-5.170)
Lev	-0.577***	-0.175
	(-3.917)	(-1.073)
Turnover	-0.230***	-0.269***
	(-3.503)	(-3.430)
Volatility	-0.801***	-0.529***
	(-9.179)	(-5.992)
stdROA	-0.005	-0.787
	(-0.014)	(-1.491)
NumInd	0.049	0.004
	(0.883)	(0.080)
IndSize	-0.015	-0.070
	(-0.295)	(-1.381)
FirmFE	Yes	Yes
YearFE	Yes	Yes
Adj. R^2	0.456	0.462
N	2464	2604

Table 5 The Cross-Sectional Variation of Google's Withdrawal on Stock Price Synchronicity

This table reports the results of cross-sectional analyses examining the underlining mechanisms. The dependent variable, *Synch*, equals $\ln(R^2 / (1 - R^2))$, where R^2 is the coefficient of determination from Eq. (1). The independent variable, *GoogleShock*, is an indicator equal to one if a firm belongs to the treatment group and in the post-period, and zero otherwise. Panel A reports the DiD estimation conditional on press release readability and voluntary disclosure. Panel B reports the DiD estimation conditional on the transportation-convince of a city where a firm' headquarter is located. Panel C reports the DiD estimation conditional on the controlling shareholder's ownership. All variables are defined in Appendix Table A1. *t*-statistics are shown in parentheses and are based on standard errors clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Press Release Readability and Voluntary Disclosure: High vs. Low

Dep Var. = *Synch*	(1) Low # *WC Press Release*	(2) High # *WC Press Release*	(3) Low # *Material Events*	(4) High # *Material Events*
GoogleShock	0.135***	0.044	0.128***	0.028
	(3.092)	(0.944)	(3.260)	(0.503)
Size	0.137**	0.159***	0.100*	0.171***
	(2.579)	(3.137)	(1.837)	(3.816)
MtB	-0.037***	-0.015***	-0.034***	-0.016**
	(-4.011)	(-2.788)	(-4.580)	(-2.475)
Lev	-0.492***	-0.421***	-0.302**	-0.582***
	(-2.647)	(-2.982)	(-2.036)	(-3.450)
Turnover	-0.226***	-0.225***	-0.280***	-0.114
	(-3.581)	(-3.294)	(-4.849)	(-1.464)
Volatility	-0.644***	-0.707***	-0.550***	-0.943***
	(-7.596)	(-8.307)	(-7.461)	(-9.225)
stdROA	-0.018	-0.588	-0.714*	0.008
	(-0.043)	(-1.591)	(-1.825)	(0.022)
NumInd	0.033	0.023	0.049	0.046
	(0.607)	(0.377)	(0.965)	(0.709)
IndSize	-0.038	-0.062	-0.074	-0.054
	(-0.690)	(-1.153)	(-1.451)	(-0.915)
FirmFE	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes
Adj. R^2	0.441	0.469	0.450	0.459
N	2525	2543	3350	1718

Panel B: Firm's Location in Transportation-Inconvenient City vs. Transportation-Convenient City

Dep Var. = *Synch*	(1) Transportation-Inconvenient City	(2) Transportation-Convenient City
GoogleShock	0.116***	0.007
	(3.074)	(0.119)
Size	0.172***	0.082
	(4.237)	(1.178)
MtB	-0.021***	-0.030***
	(-3.837)	(-3.090)
Lev	-0.561***	-0.112
	(-4.498)	(-0.597)
Turnover	-0.226***	-0.214**
	(-4.091)	(-2.410)
Volatility	-0.682***	-0.717***
	(-9.781)	(-5.854)
stdROA	-0.326	-0.031
	(-1.145)	(-0.040)
NumInd	0.032	0.091

	(0.642)	(1.197)
IndSize	-0.059	-0.083
	(-1.273)	(-1.126)
FirmFE	Yes	Yes
YearFE	Yes	Yes
Adj. R^2	0.444	0.482
N	3778	1290

Panel C: Controlling Shareholder's Ownership: (1st Quartile + 4th Quartile) vs. (2nd Quartile + 3rd Quartile)

	(1)	(2)
Dep Var. = *Synch*	1st Quartile + 4th Quartile	2nd Quartile + 3rd Quartile
GoogleShock	0.073	0.110**
	(1.538)	(2.255)
Size	0.176***	0.168***
	(3.138)	(3.029)
MtB	-0.023***	-0.024***
	(-2.858)	(-3.740)
Lev	-0.707***	-0.371**
	(-3.849)	(-2.507)
Turnover	-0.199***	-0.238***
	(-2.940)	(-3.537)
Volatility	-0.600***	-0.758***
	(-6.558)	(-8.953)
stdROA	0.293	-0.786**
	(0.605)	(-1.980)
NumInd	0.018	0.137**
	(0.350)	(2.040)
IndSize	-0.044	-0.163**
	(-0.871)	(-2.529)
FirmFE	Yes	Yes
YearFE	Yes	Yes
Adj. R^2	0.436	0.481
N	2483	2492

Table 6 Rule Out Alternative Explanations

This table presents the results of analyses conducted to rule out several alternative explanations. Panel A shows the results from examining whether investor attention decreases subsequent to Google's withdrawal. The dependent variables are *Shareholder* and *Comment*. Panel B shows the results from examining whether analysts' behaviors change subsequent to Google's withdrawal. The dependent variables are *Analyst Report*, *Forecast Error*, and *Dispersion*. Panel C shows the results from examining whether corporate disclosure strategies change subsequent to Google's withdrawal. The dependent variables are *# Material Events*, *# WC MD&A*, *# WC Press Release*, and *# WC Annual*, all of which are defined in Appendix Table A1. Panel D shows the results from examining whether median following changes subsequent to Google's withdrawal. The dependent variable is *News*, defined in Appendix Table A1. All other variables are defined in Appendix Table A1. *t*-statistics are shown in parentheses and are based on standard errors clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Whether Investor Attention Decrease after Google's Withdrawal

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var. =		*Shareholder*				*Comment*
GoogleShock	0.172***	0.133***			0.027	-0.012
	(5.639)	(4.749)			(0.623)	(-0.328)
GoogleShock^{-3}			-0.292***	-0.222***		
			(-8.410)	(-6.725)		
GoogleShock^{-2}			-0.200***	-0.175***		
			(-7.593)	(-6.737)		
GoogleShock^{0}			0.031	0.031		
			(1.174)	(1.253)		
GoogleShock^{+1}			0.019	0.008		
			(0.619)	(0.264)		
GoogleShock^{+2}			0.022	0.006		
			(0.701)	(0.191)		
Size		0.116***		0.112***		0.058
		(4.233)		(4.103)		(1.632)
MtB		-0.020***		-0.020***		-0.003
		(-6.460)		(-6.590)		(-0.803)
Lev		-0.268***		-0.266***		-0.212*
		(-3.475)		(-3.442)		(-1.718)
Turnover		0.429***		0.413***		0.906***
		(12.926)		(12.459)		(16.085)
Volatility		0.082**		0.082**		0.941***
		(2.270)		(2.254)		(15.625)
stdROA		-0.203		-0.184		-0.624
		(-0.893)		(-0.801)		(-1.505)
NumInd		0.086***		0.083**		0.012
		(2.604)		(2.489)		(0.219)
IndSize		-0.070**		-0.065**		-0.006
		(-2.260)		(-2.110)		(-0.117)
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.857	0.876	0.860	0.877	0.673	0.765
N	4966	4966	4966	4966	4350	4350

Panel B: Whether Analysts' Behaviors Change after Google's Withdrawal

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var. =	*Analyst Report*	*Forecast Error*	*Dispersion*	*Analyst Report*	*Forecast Error*	*Dispersion*
GoogleShock	-0.966	-0.001	-0.004	-0.647	-0.001	-0.006
	(-1.322)	(-0.938)	(-0.444)	(-0.934)	(-0.839)	(-0.571)

Size				5.404***	-0.002	0.003
				(8.889)	(-1.228)	(0.193)
stdROE				0.385	0.006**	0.018**
				(1.401)	(2.157)	(2.064)
IH				7.534***	-0.008***	-0.009
				(5.287)	(-3.046)	(-0.500)
Big4				-2.458	0.001	0.016
				(-1.036)	(0.654)	(1.114)
Loss				-1.527***	0.041***	0.096***
				(-4.470)	(9.698)	(4.289)
Analyst					0.000**	0.001***
					(2.259)	(2.709)
FHorizon					0.002**	0.007
					(2.189)	(0.727)
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.729	0.221	0.222	0.744	0.388	0.245
N	5068	2999	1924	5068	2999	1924

Panel C: Whether Corporate Disclosure Strategies Change after Google's Withdrawal

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep Var. =	*# Material Events*	*# WC MD&A*	*# WC Press Release*	*# WC Annual Report*	*# Material Events*	*# WC MD&A*	*# WC Press Release*	*# WC Annual Report*
GoogleShock	-0.050	0.021	-0.103	-0.005	-0.049	0.020	-0.104	-0.004
	(-1.164)	(0.915)	(-1.552)	(-0.544)	(-1.150)	(0.893)	(-1.576)	(-0.574)
Size					-0.079*	0.091***	0.174***	0.073***
					(-1.694)	(3.628)	(3.645)	(7.898)
MtB					0.001	-0.001	0.011**	0.001
					(0.161)	(-0.242)	(2.105)	(1.472)
Lev					0.319**	-0.099	-0.125	0.058**
					(2.003)	(-1.206)	(-0.775)	(2.359)
ROA					0.194	-0.085	0.267	-0.009
					(0.797)	(-0.683)	(0.882)	(-0.207)
Segment					0.021	-0.003	0.058	0.060***
					(0.555)	(-0.115)	(0.981)	(6.736)
Analyst					-0.004	-0.003*	-0.005	0.000
					(-1.404)	(-1.800)	(-1.053)	(0.558)
IH					-0.071	0.066	0.017	0.008
					(-0.806)	(1.477)	(0.126)	(0.498)
News					0.274***	0.046***	0.161***	0.019***
					(9.666)	(3.156)	(3.473)	(3.810)
FirmFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.280	0.634	0.773	0.773	0.299	0.638	0.775	0.799
N	5068	5007	5068	5027	5068	5007	5068	5027

Panel D: Whether Media Coverages Decrease after Google's Withdrawal

	(1)	(2)
Dep Var. =	*News*	*News*
GoogleShock	-0.008	0.013
	(-0.261)	(0.465)
Size		0.193***
		(7.274)
MtB		0.031***

		(7.466)
Lev		-0.163*
		(-1.890)
ROA		0.494***
		(3.491)
Segment		-0.022
		(-0.946)
Analyst		0.019***
		(10.770)
IH		0.186***
		(3.520)
FirmFE	Yes	Yes
YearFE	Yes	Yes
Adj. R^2	0.771	0.798
N	5068	5068

Table 7 Robustness Checks

This table presents the results of robustness tests. All variables are defined in Appendix Table A1. *t*-statistics are shown in parentheses and are based on standard errors clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

	(1) Full Sample	(2) Daily Return-Based Measure	(3) More Controls	(4) Add Lagged Market Return and Lagged Industry Return in Market Model
Dep Var. =	*Synch*	*Synch_dr*	*Synch*	*Synch_fourfactors*
GoogleShock	0.131***	0.053**	0.080**	0.074**
	(4.856)	(2.135)	(2.515)	(2.389)
Size	0.144***	0.065**	0.139***	0.148***
	(4.829)	(2.137)	(4.141)	(4.387)
MtB	-0.024***	-0.024***	-0.023***	-0.023***
	(-6.402)	(-6.342)	(-4.856)	(-5.235)
Lev	-0.382***	-0.444***	-0.464***	-0.467***
	(-4.458)	(-4.876)	(-4.285)	(-4.559)
Turnover	-0.177***	0.023	-0.224***	-0.239***
	(-4.635)	(0.650)	(-4.852)	(-5.454)
Volatility	-0.715***	-0.860***	-0.594***	-0.623***
	(-13.941)	(-20.059)	(-9.882)	(-10.827)
stdROA	-0.324	-0.720***	-0.424	-0.280
	(-1.294)	(-2.932)	(-1.590)	(-1.044)
NumInd	0.022	0.031	0.037	0.057
	(0.627)	(0.949)	(0.915)	(1.549)
IndSize	-0.026	-0.028	-0.059	-0.068*
	(-0.767)	(-0.843)	(-1.540)	(-1.960)
H_Dummy			0.142	
			(0.442)	
B_Dummy			-0.458	
			(-1.372)	
Top1			0.014*	
			(1.893)	
Top1_Square			-0.000	
			(-1.561)	
Big4			-0.016	
			(-0.147)	
NCSKEW			0.124***	
			(8.430)	
FirmFE	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes
Adj. R^2	0.448	0.637	0.457	0.446
N	7897	4986	5068	5068

Appendix

Table A1: Variable Definitions

Variables	Definition
Synch	$\ln(R^2 / (1 - R^2))$, where R^2 is the coefficient of determination from Eq. (1) using weekly return data
GoogleShock	An indicator equal to one if a firm belongs to the treatment group and in the post-period, and zero otherwise
Treat	An indicator equal to one if Google's Search Volume Index (SVI) of a firm is lower than the sample median in 2009, and zero otherwise
After	An indicator equal to one if the year after 2010, and zero otherwise
Size	Natural logarithm of total assets
MtB	Market to book ratio
Lev	Total liabilities divided by total assets
Turnover	Average monthly share turnover, which is defined as the total share trading volume divided by the total tradable shares at the end of the month
Volatility	Standard deviation of weekly returns times 100
stdROA	Standard deviation of return on assets over the past five years, including the current year, with at least three years data available
NumInd	Natural logarithm of the number of one-digit CSRC industry peers
IndSize	Natural logarithm of total assets of all Chinese A-shared listed firms in the one-digit CSRC industry
DA_abs	The sum of the absolute value of discretionary accruals, estimated from modified Jones model, over the past three years, excluding the current year
Analyst	The number of analysts covering a firm
IH	The number of shares owned by institutional investors divided by total outstanding shares
SOEDummy	An indicator equal to one if a firm is under government control, and zero otherwise
Comment	Natural logarithm of the number of investor comments in East Money which is a popular stock forum in China
GoogleShock[*HighDeclineSVI*]	An indicator equal to one if a firm belongs to treatment group and experiences above-median SVI declines in the post-period, and zero otherwise
GoogleShock[*LowDeclineSVI*]	An indicator equal to one if a firm belongs to treatment group and experiences below-median SVI declines in the post-period, and zero otherwise
# WC Press Release	Natural logarithm of the word count of corporate press releases
# Material Events	Natural logarithm of the count of material event disclosure

Transportation-Inconvenient City	An indicator equal to one if a city does not belong to Shanghai, Beijing, Guangzhou, or Shenzhen, and zero otherwise
Top1	The number of shares owned by controlling shareholders divided by total shares
Top1_Square	The squared value of *Top1*
Shareholder	Natural logarithm of the number of shareholders
Analyst Report	The number of analyst reports
Forecast Error	The absolute value of the difference between actual EPS and analyst EPS consensus, divided by the stock price at the beginning of the fiscal year. Each analyst EPS forecast is required to be issued prior to corresponding earnings announcement up to 270 calendar days
Dispersion	Standard deviation of all the analyst EPS forecasts. Each analyst EPS forecast is required to be issued prior to corresponding earnings announcement up to 270 calendar days
FHorizon	Natural logarithm of the average number of calendar days between forecasting issuing date and corresponding earnings announcement date
stdROE	Standard deviation of return on equity over the past five years including the current year, with at least three years data available
Loss	An indicator equal to one if a firm has negative net income in a given year, and zero otherwise
Big4	An indicator equal to one if a firm's annual report is audited by a Big 4 accounting firm
# WC MD&A	Natural logarithm of the word count of MD&A section in the annual report
# WC Annual Report	Natural logarithm of the word count of the annual report
Segment	Natural logarithm of the number of business segments
News	Natural logarithm of one plus the number of financial articles mentioning the firm. Data are retrieved from Datago database
ROA	Return on assets
NCSKEW	Negative of the third moment of firm-specific weekly returns for each year, divided by the standard deviation of firm-specific weekly returns raised to the third power, for a given firm in a fiscal year
DUVOL	Natural logarithm of the ratio of the standard deviation on the down weeks to the standard deviation on the up weeks. The weeks with firm-specific weekly returns below (above) the annual mean are down (up) weeks
BHAR[*MayToApril*]	Market-adjusted monthly returns compounded from the May to the next year's April
CAR[-1, +1]	Cumulative market-adjusted daily return around earnings announcement three-day window [-1, +1]

UE	The difference between actual EPS and analyst EPS consensus. Analyst EPS consensus is replaced with seasonal random walk if census is not available
MV	Market capitalization
Synch_dr	The same calculation as *Synch*, but estimating R^2 from Eq. (1) using daily return data
Synch_fourfactors	The same calculation as *Synch*, but estimating R^2 from the extended Eq. (1), that is, $Return_{it} = \alpha + \beta_1 Market_t + \beta_2 Market_{t-1} + \beta_3 Industry_{it} + \beta_4 Industry_{it-1} + \varepsilon_{it}$, using weekly return data
H_Dummy	An indicator equal to one if a A-listed firm also issues H shares, and zero otherwise
B_Dummy	An indicator equal to one if a A-listed firm also issues B shares, and zero otherwise

Table A2: Propensity-Score-Matching Approach

This table presents the results for propensity-score-matching approach. Panel A reports the results of the logit model. The dependent variable, *Treat*, is an indicator equal to one if Google's Search Volume Index (SVI) of a firm is lower than the sample median in 2009, and zero otherwise. All the explanatory variables are defined in Appendix Table A1. Industry FE and Province FE indicate the industry fixed effects and province fixed effects. Panel B (Panel C) reports the results of balance analyses for pre-matching (post-matching) sample. *z* statistics are shown in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Logit Model for Estimating Propensity Score

Dep Var. =	*Treat*
MtB	-0.004
	(-0.246)
SOEDummy	-0.220
	(-1.611)
Size	-0.341***
	(-4.272)
Lev	0.767***
	(2.589)
IH	1.726***
	(5.094)
Analyst	0.065***
	(7.047)
Turnover	1.115***
	(4.580)
Volatility	1.146***
	(3.213)
DA_abs	0.150
	(0.176)
Comment	0.685***
	(7.508)
Industry FE	Yes
Province FE	Yes
Pseudo R^2	0.123
N	1406

Panel B: Pre-Matching Balance Test

	N		Mean		Diff	*t*-Value	*p*-Value
Variable	Treat	Control	Treat	Control			
MtB	746	662	4.875	4.484	0.391	1.88	0.060
SOEDummy	746	662	0.597	0.642	-0.045	-1.75	0.080
Size	746	662	21.752	21.644	0.108	1.59	0.112
Lev	746	662	0.532	0.516	0.016	1.37	0.171
IH	746	662	0.365	0.322	0.043	3.58	0.001
Analyst	746	662	9.380	6.222	3.158	6.07	0.000
Turnover	746	662	0.830	0.776	0.054	2.98	0.003
Volatility	746	662	1.990	1.938	0.052	4.96	0.000
DA abs	746	662	0.077	0.072	0.005	1.40	0.161
Comment	746	662	10.175	9.901	0.274	6.28	0.000

Panel C: Post-Matching Balance Test

	N		Mean		Diff	*t*-Value	*p*-Value
Variable	Treat	Control	Treat	Control			
MtB	456	456	4.642	4.412	0.230	0.93	0.354
SOEDummy	456	456	0.627	0.614	0.013	0.41	0.683
Size	456	456	21.587	21.642	-0.055	-0.68	0.500

Lev	456	456	0.515	0.523	-0.008	-0.53	0.595
IH	456	456	0.334	0.330	0.004	0.25	0.805
Analyst	456	456	6.774	6.974	-0.200	-0.34	0.737
Turnover	456	456	0.792	0.814	-0.022	-1.00	0.316
Volatility	456	456	1.954	1.962	-0.008	-0.69	0.493
DA abs	456	456	0.072	0.075	-0.003	-0.56	0.577
Comment	456	456	9.958	9.969	-0.011	-0.20	0.842

Table A3: Whether Crash Risk Drives the Results

This table reports the DiD estimation of stock price crash risk. The analysis mirrors specification and variable constructions in Xu et al. (2021) but using my regression sample. The dependent variable is *NCSKEW* or *DUVOL*. *NCSKEW* is defined as the negative of the third moment of firm-specific weekly returns for each year, divided by the standard deviation of firm-specific weekly returns raised to the third power, for a given firm in a fiscal year. *DUVOL* is defined as the natural logarithm of the ratio of the standard deviation on the down weeks to the standard deviation on the up weeks. The weeks with firm-specific weekly returns below (above) the annual mean are down (up) weeks. The independent variable, *GoogleShock*, is an indicator, equal to one if a firm belongs to the treatment group and in the post-period, and zero otherwise. All other variables are defined in the same way in Xu et al. (2021). *t*-statistics are shown in parentheses and are based on standard errors clustered by firm. ***, **, * indicate significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)
Dep Var. =	*NCSKEW*	*DUVOL*	*NCSKEW*	*DUVOL*
GoogleShock	0.052	0.037	0.063	0.041
	(1.401)	(1.437)	(1.438)	(1.374)
lagRet			1.385**	1.035***
			(2.481)	(2.840)
lagSigma			9.641***	6.346***
			(2.706)	(2.739)
lagSize			0.091***	0.063***
			(2.597)	(2.693)
lagLev			-0.034	-0.014
			(-0.248)	(-0.149)
lagROA			0.141	0.248*
			(0.673)	(1.708)
lagMtB			0.008*	0.008***
			(1.815)	(2.628)
lagDA_abs			-0.122	-0.119
			(-1.033)	(-1.482)
lagAge			0.635*	0.420*
			(1.814)	(1.799)
lagDturn			-0.043	-0.024
			(-1.121)	(-0.913)
lagNCSKEW			-0.171***	-0.111***
			(-9.844)	(-9.298)
FirmFE	Yes	Yes	Yes	Yes
YearFE	Yes	Yes	Yes	Yes
Adj. R^2	0.106	0.106	0.140	0.136
N	5068	5068	4381	4381