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Abstract

Many jurisdictions have launched antitrust enforcement and brought in regulation of large tech platforms. The swift and strict implementation of China's *Anti-Monopoly Guidelines for the Platform Economy* (Platform Guidelines) provides a quasi-natural experiment to evaluate the impact of antitrust regulation on platform competition. We adopt a difference-in-differences approach to empirically explore the impact of China's Platform Guidelines on the number of investments and the entry of startups in platform markets. The results show that the Platform Guidelines did not increase competition in these affected markets. Rather, competition weakened in these markets, with less venture capital investment flowing into them and fewer startups entering these markets. Our study suggests that governments should consider more carefully the potential unintended consequences of antitrust platform regulation.

Keywords: Platform, Antitrust, Regulation, Competition, Venture Capital

1. Introduction

There has been growing concern over the power of tech giants globally. Governments have responded to their power by calling for increased antitrust regulation (Parker et. al 2021; Deutsch 2021, Sokol and Van Alstyne 2021; Pan and Song 2023), among other responses, to restore competition. Empirical research on the efficacy of such regulations on market competition, however, remains nascent. This paper investigates and explores the impact of China's *Anti-Monopoly Guidelines for the Platform Economy*[1] (Platform Guidelines) on market competition. Whether through investment via corporate venture capital (CVC), acquiring smaller firms with growth potential, or launching new features in adjacent platform-related industries, a number of Chinese tech firms, including Tencent and Alibaba, have reached such a level of scope and scale that they have been dubbed "digital giants" (Weiss et al. 2004). Such firms have a significant influence across areas of the Chinese digital economy (e.g., Zeng 2018; Chen 2022).

Compared to policies or acts proposed or implemented elsewhere, such as the Digital Markets Act in Europe, China's Platform Guidelines have been strictly and swiftly implemented. This gives us a rare quasi-natural experiment to explore the impact of the guidelines on the markets in which those Chinese digital giants previously had significant presence. The tech platforms that constitute the digital giants,[2] for purposes of the Platform Guidelines, are Alibaba, Tencent, ByteDance, DiDi, Meituan, and JD.

Officially implemented on February 7, 2021, China's Platform Guidelines brought an end to the unregulated expansion of designated large Chinese platform companies by putting into place a system to limit certain behavior, including price discrimination (to punish noncooperating sellers), "self-preferencing" (where a platform favors its own service or product), and mergers and acquisitions (including CVC investments). Soon after the implementation of the platform guidelines, Chinese digital giants were subject to enforcement actions.[3] Table 1 shows significant cases related to the Platform Guidelines against affected firms. In the first enforcement action, Alibaba was fined RMB 18.228 billion, which accounted for 4% of its total sales. In addition to the cases listed in Table 1, JD and DiDi have all been fined for violating the Platform Guidelines.

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[1] The *Anti-Monopoly Guidelines for the Platform Economy* can be found at http://www.gov.cn/xinwen/2021-02/07/content_5585758.htm.

[2] The official *Guidelines for the Classification and Grading of Internet Platforms* released by the Chinese government set four criteria for digital giants in China—namely, that they had (1) no less than 500 million active users in China in the previous year; (2) at least two types of platform services in their core business; (3) no less than RMB 100 billion market capitalization (valuation) at the end of the previous year; and (4) platforms strongly capable to restrict merchants' access to consumers/users. These guidelines are available at https://www.samr.gov.cn/hd/zjdc/art/2023/art_c0086d02fcc544ea9506c997b3ac93c1.html.

[3] What is different in China relative to other jurisdictions is that US tech companies are insignificant in China, unlike in Europe, India, and elsewhere, and so the claim that regulation is based on protectionist grounds cannot be made (McGill and Gold 2021; Nikkei 2021).

---------Insert Table 1 here---------

This study seeks to explore how platform antitrust regulation shapes competition. Our evidence is derived from two Chinese enterprise databases, the IT Juzi database (https://www.itjuzi.com/) and the Jingzhun database (https://cloud.jingdata.com/), which have extensively compiled a substantial number of Chinese internet and technology-focused companies from China's official industrial and commercial enterprise registration records. Data these databases show that in the year preceding the implementation of the platform antitrust policy, there was notable monthly growth of 20.84% in CVC investments by platform giants. However, after the Platform Guidelines' enactment, such investments experienced a modest decline of 1.14% per month.

Based on the six platform giants affected by China's Platform Guidance, we identify 41 industries that were deeply influenced by the affected platforms prior to platform antitrust regulation, along with 127 uninfluenced industries. We follow Koski et al. (2020) and use investment numbers and startup entry to measure competition in each industry. We trace all the investment events and startups in all 168 industries, spanning from February 2020 to January 2022—that is, the year prior to and the year following the implementation of platform antitrust regulation.

We take a difference-in-differences (DID) approach to estimate the effect of this regulation on the treated group (41 influenced industries) relative to the control group (127 uninfluenced industries). The absence of pretrends in all outcome variables lends strong support to the validity of our estimation. We find that after the platform antitrust regulation implementation, the monthly number of investments in and startups entering the 41 influenced industries registered a substantial reduction, of 26.73% and 18.72%, respectively, in comparison to the 127 uninfluenced industries. Hence, in the industries influenced by the affected platforms, the market landscape became less competitive after platform antitrust regulation had been implemented.

In addition, we investigate the differentiation between new startups and the affected platforms in the 41 treated industries. New startups did not opt to engage in business in a similar way to the affected platforms after the platform antitrust regulation. Instead, they tended to engage in business distinct from the affected platforms.

Our study contributes to the literature examining platform-related VC and CVC and their impact on competition and the entrepreneurial ecosystem. Previous studies have concentrated on elucidating the decision-making processes associated with CVC investments within platform-based or IT enterprises (Dushnitsky and Lenox 2005b; Pan et al. 2019; Greenwood and Gopal 2017), while also exploring the consequential outcomes stemming from VC and CVC investments (Koski et al. 2020; Prado and Bauer 2022). Besides, some studies have established that platform giants have wielded their immense power through M&A activities across various industries, significantly impacting market competition within those industries (Kamepalli et al. 2020; Parker et al. 2021). There remains a dearth of research exploring effective regulatory measures to mitigate the adverse consequences of these VC and CVC investments. Our study empirically examines the regulation effects of the platform antitrust regulation implemented by the Chinese government and helps address this gap.

This paper also contributes to research on the impact of regulation of platform giants and IT-related industries. Some information systems scholars have explored the self-regulation of these platforms (Han et al. 2021; Ichihashi and Kim 2023). Meanwhile, as governmental oversight of platform giants intensifies, research efforts have emerged to investigate the impact of government regulatory policies on platforms and their associated industries (Buckman et al. 2023; Liu et al. 2023; Pan and Song 2023). The body of research predominantly focuses on data privacy regulation (Jassen et al. 2022; Johnson et al. 2023) or regulation within a specific industry, such as the sharing economy (Yu et al. 2019; Chen et al. 2023) and peer-to-peer lending platforms (Liu et al. 2023). Our research examines a comprehensive antitrust regulation initiative by the Chinese government that targets platform giants. In doing so, we uncover unintended policy outcomes that have implications on government regulation affecting platform giants, and IT-related industries more generally.

Finally, our paper relates to platform antitrust research (Bhargava et al. 2016; Parker et al. 2021) by systematically analyzing the policy shock of platform antitrust regulation as a mechanism to solve potential anticompetitive behavior by platforms against complementors. This study transcends a focus on the immediate repercussions of antitrust enforcement on platforms or platform complementors (Thatchenkery and Katila 2023), examining the ramifications of antitrust regulation on market competition at the industry level. We find that China's Platform Guidelines did not increase market competitiveness in tech related industries.

The remainder of the paper is organized as follows. Section 2 discusses the related literature. Section 3 describes the data. Section 4 depicts the empirical settings and outlines the empirical results. Section 5 discusses the robustness checks. Section 6 concludes the paper. Additional empirical results and the matching steps involved in the data processing are included in the online appendix.

2. Related Literature

2.1 Platforms and Entrepreneurship

CVC is a mechanism by which established firms make equity investments in entrepreneurial ventures to gain increasing awareness of new ventures and their related technologies or alternatively to leverage their investments into long-term alliances or potential acquisitions (Dushnitsky and Lenox 2005a, 2005b). Compared to VC, CVC funding not only provides financial capital but also complementary assets (Park and Steensma 2012). Relatedly, Kim et al. (2016) documented that IT companies utilized their CVC arms to supplement inhouse R&D efforts, since such investments provided flexibility, technological knowledge, and other strategic benefits through the exposure to innovation of those companies in which they invested.

In addition to CVC, large platforms tend to engage in many technology-related M&As, with a preference for younger, consumer-facing firms (Jin et al. 2023). Often, these acquired firms are complementary to existing platforms, which allows for economies of scale and scope (Ahuja and Katila 2001; Miric et al. 2021; Katila et al. 2022) and intellectual property and technology spillovers (Ceccagnoli et al. 2012; Parker et al. 2017; Huang et al. 2022) through integration with the acquiring firm. Such integration may be beneficial to competitors of acquired firms. For example, Li and Agarwal (2018) showed that some competing third-party companies were able to benefit from Facebook's acquisition of Instagram, since demand from consumers in the photo sharing segment increased following the merger. Further, Prado and Bauer (2021) found that platform acquisitions of startups had a positive influence on entrepreneurial innovation but that such influence may fade away over time.

2.2 Platform Regulation[4]

Digital platforms' M&A activities have facilitated the gradual formation of their platform ecosystems with strong network effects (Ceccagnoli et al. 2012; Parker et al. 2017; Zhu et al. 2021). Some papers have argued that tech acquisitions serve to shield incumbent platforms from competition (Kamepalli et al. 2020; Koski et al. 2020). Other studies offer an alternative viewpoint. For example, Cabral (2021) suggests that acquisitions by platform companies frequently bring significant synergies and efficiencies because the acquiring firms have the knowledge and capital to commercialize technology in ways that startups are not able to do.

The antitrust regulation of platforms is not the only area that implicates competition. A series of studies have studied privacy regulation. For example, several papers have identified the impact of the European Union's General Data Protection Regulation (GDPR) (e.g., Aridor et al. 2020; Jia et al. 2021; Janssen et al. 2022; Puekert et al. 2022). They have found that privacy regulation had unintended negative consequences on competition. GDPR has precipitated a decline in venture investment and amplified the challenges associated with securing financing for nascent startups (Jia et al. 2021; Kircher and Foerderer 2021). It also increased compliance costs regarding user data collection (Jassen et al. 2022; Puekert et al.

[4] Platform regulation differs from platform governance. Platform governance primarily involves the provision of incentives and rules via contractual mechanisms to create value and balance it among complementors (Ceccagnoli et al. 2012; Huang et al. 2013; Cennamo et al. 2018; Bhargava 2021). When the incentives are properly aligned, a platform orchestrates behavior in a way that creates value across the ecosystem (Parker et al. 2017; Jacobidies et al. 2018). For example, contractual mechanisms to address online quality requirements (Huang et al. 2022; Pu et al. 2022), certification (Rietveld et al. 2021), information disclosure for investors (Lu et al. 2022), unforeseen societal impacts (Han et al. 2021), and efforts to reduce customer complaints (Zhao et al. 2023) may be used. Unlike platform governance, platform regulations implemented by governments provide oversight of these contractual mechanisms and address the potential economic and social externalities that may arise.

2022; Johnson et al. 2023). Similarly, aligning with the evidence from GDPR, Bae et al. (2023) found that the California Consumer Privacy Act (CCPA) also led to an unintended negative impact on both firms and consumers.

In addition to privacy regulation, there are other kinds of government regulation of platforms and IT-related markets, such as social media platform regulation and COVID-19 (Buckman et al. 2021), and online peer-to-peer lending platform regulation (Liu et al. 2023). Further, related to the sharing economy, Yu et al. (2019) found that a cap on rideshare drivers hurt consumers. Similarly, Li and Wang (2021) identified that price caps on delivery fees for food delivery hurt the small businesses that regulation was intended to protect. Chen et al. (2023) found that regulation of professional hosts on Airbnb can increase supply from nonprofessional hosts, indicating that platform regulation can also influence the structure of market competition. Other studies have also emphasized the importance of platform self-regulation (Cohen and Sundararajan 2015; Cusumano et al. 2021). For instance, Han et al. (2021) identified that due to platform self-regulation, a decrease in Airbnb listings led to a decrease in crime. Ichihashi and Kim (2023) found that a cap on the maximum level of addictiveness can contribute to profit optimization for a platform.

Regulation of platforms may encourage other firms to erode the market share of such platforms by entering their markets more aggressively, since the incumbents' response has been damped by such regulation. As a result, these firms may attract more VC investment or more startups may choose to enter the related industries.

However, there may also be a negative effect (Sine et al. 2003), since the crackdowns on platforms may cause entrants to fear that regulation of the industries in which existing platforms operate may create potential uncertainty for all entrants (Brogaard and Detzel 2015), especially if the entrants grow to have a significant market presence (Gulen and Ion 2016). Thus, potential new firms in the industries affected by the Platform Guidelines may become less attractive to VC and CVC investors, and there will be fewer entrants as a result.

Therefore, the impact of the Platform Guidelines on market entry and venture investment becomes an empirical question.

3. Data Description

3.1 Data

We obtain our dataset from two Chinese enterprise databases, the IT Juzi database (https://www.itjuzi.com/) and the Jingzhun database (https://cloud.jingdata.com/). The IT Juzi database provides business information of IT-related startups in mainland China and has been widely used in media reports by reputable sources such as the Wall Street Journal (Yap, 2017), the New York Times (Qin, 2014), as well as some previous academic research (Dushnitsky and Yu, 2022; Wang et al., 2023a). The Jingzhun database collects business information of China's high-tech startups and has also been used by both mainstream media coverage such as the Bloomberg (Huang, 2021) and other academic scholars (Wang et al., 2023b). Specifically, each database includes the startups in mainland China according to its own data collection criteria and gathers related investment events. Our dataset ranges from the 12 months prior to and 12 months after the Platform Guidelines implementation. As the Platform Guidelines were officially implemented on February 7, 2021, the range of the dataset is from February 2020 to January 2022.

In the IT Juzi database, each company is assigned to one industry category. The database is relatively small and contains only 7484 newly established companies during the abovementioned 24-month period. The Jingzhun database, however, has a greater collection of companies, and contains 19,196 companies over the same period. However, in this database, each company may belong to several industry categories. For example, a startup that mainly runs e-commerce business for agriculture products may be classified in both the traditional agricultural industry and the e-commerce industry, although we typically consider such a startup as an e-commerce platform, rather than a traditional agricultural company. To overcome the shortcomings of the two databases, we develop a text similarity analysis based on the descriptions of the companies and match each company in the Jingzhun database to a company in the IT Juzi database with the closest similarity, thereby classifying all the companies in the Jingzhun database to the industry categories in the IT Juzi database.[5] We detail our matching steps in the appendix.

We remove industries that have been consistently supported by the Chinese government because they are likely to immune to regulations even platform giants have significant presence. Specifically, we remove industries included in the official government document "Made in China 2025."[6] After data cleaning, we obtain a final dataset containing 19,196 companies and 16,984 investments across 168 industry categories from February 2020 to January 2022.

3.2 Identifying Affected Industries

We then proceed to identify platform giants that are targets of the Platform Guidelines. Although several Chinese platforms have been punished for violating the Platform Guidelines, there is no officially recognized list of the affected platforms. According to the existing enforcement actions and the Guideline

[5] A small number of industry categories in our database have nearly no entry or investment during the 24-month period of our study. To reduce the influence of these outliers, we group industries with fewer than five investments and fewer than five entries during the entire 24-month period with other industries similar to them.
[6] Proposed in May 2015, "Made in China 2025" is a national strategic plan and industrial policy of the Chinese government to further develop high-tech manufacturing industries. Industries from ten areas are involved—namely, new-generation information technology, high-grade CNC machine tools and robots, aerospace equipment, marine engineering equipment and high-tech ships, advanced rail transportation equipment, energy saving and new energy vehicles, electric power equipment, agricultural equipment, new materials, and biomedical and high-performance medical devices.

for the Classification and Grading of Internet Platforms released by the Chinese government, as well as the amount and the frequency of historical platform CVC investment, we identify six Chinese platforms as the affected platforms covered by the Platform Guidelines—namely, Alibaba, Tencent, ByteDance, DiDi, Meituan, and JD.[7]

Based on this list, we define the following three kinds of industries as those in which the affected platforms had significant presence before the promulgation of the Platform Guidelines: (1) the industries in which the core of the affected platforms belong (e.g., Alibaba and e-commerce); (2) the industries in which the subsidiaries of the affected platforms belong (e.g., Tencent and video games); and (3) the industries in which belong unicorns or listed companies in which there have been CVC investments. We consider these industries as affected industries by the Platform Guidelines. Table 2 shows in detail the 41 affected industries out of 168 industries. Most of them are business to consumer, although there are a few business-to-business industries, such as Integrated Financial Services, Logistic Information Technology, and Storage Services. For each firm in our dataset, we create a dummy variable $platin$, which is equal to 1 if it belongs to the 41 industries and 0 otherwise. The Platform Guidelines were implemented on February 7, 2021, so we set the policy shock variable $policy$ to 0 for the months before February 2021 and 1 for the months in or after February 2021.

---------Insert Table 2 here---------

3.3 Measuring Competition

Following Koski et al. (2020), we use the amount of investment (*investment*) and the number of startups (*newentry*) at the industry level to measure competition. For *investment*, we calculate the number of monthly investments from VC and CVC investors after excluding the CVC investments of affected platforms in each industry. Since one of the Platform Guideline's policy goals is to prevent further CVC investment by the affected platforms, the guidelines directly restricted the investment behavior of the affected platforms. The use of investments from other VC and CVC investors can help capture the attractiveness of a certain industry. When an investment event involves multiple VCs, we count the number of investments by these VC institutions, rather than the number of investment events.[8] We obtain 6794 investment events and 16,984 investments, which indicates that on average, 2.50 VC institutions were involved in each investment event.

For $newentry$, we calculate the number of startups entering monthly in each industry. As the

[7] In robustness checks, we also determined that by increasing or decreasing the number of companies, these six comprise the correct number for which there is an effect.

[8] We discard the investment events that have no specific VC institutions named, since we cannot judge if the affected platforms were involved in these anonymous investments. There are 414 anonymous investment events among the total of 13,022 investment events, which amounts to 3.18%. We also focus on those investments prior to an IPO. Specifically, we only consider the following types of investments: seed round, angel round, A round to H round, and strategic investments.

Platform Guidelines have only had an impact on companies in mainland China, we exclude all companies that were established outside mainland China.

3.4 Descriptive Statistics

Table 3 reports summary statistics for the $investment$ and $newentry$ variables for the affected and unaffected industries. We also conduct paired t-tests to compare $investment$ and $newentry$ for each group before and after the platform antitrust policy. The $investment$ for affected industries shows no significant change after the platform antitrust policy, while we observe a significant increase in the $investment$ for unaffected industries. As for the $newentry$, both groups show a significant increase after the policy. Overall, the differences of the mean values of both the $investment$ and $newentry$ become larger after the policy, which indicates that the Platform Guidelines may have posed a negative impact on the affected industries.

---------Insert Table 3 here---------

4. Empirical Results

We adopt a DID model to identify the causal influence of the Platform Guidelines on market competition.

4.1 Difference-in-Differences Estimation

Using the treatment variable $platin$ and the policy variable $policy$ defined in the previous section, we have the following regression framework:

$$comp_{it} = \beta policy_t \times platin_i + \gamma t + \mu_t + \delta_i + \varepsilon_{it}, \tag{1}$$

where i indexes the industries and t indexes the months. $comp_{it}$ means the monthly competition level of each industry in our dataset. Specifically, following Koski et al. (2020), we use $ln\_investment_{it}$ and $ln\_newentry_{it}$ as our dependent variables to proxy industry competition. We adopt the logarithms of the monthly $investment$ and $newentry$ to minimize the impact of outliers.[9] In the regression model (1), we not only add industry-level fixed effects and month-level fixed effects but also include a month trend variable, since the investment or the company establishment in mainland China could exhibit time trends.

Table 4 reports the regression results. Models 1 and 2 use $ln\_investment_{it}$ as the dependent variable, while Models 3 and 4 use $ln\_newentry_{it}$ as the dependent variable. We control only month-level fixed effects in Models 1 and 3 and both the month- and industry-level fixed effects in Models 2 and 4. The month trend is controlled in all the regression models. All regression results show a similar pattern; after the platform antitrust policy, compared to the unaffected industries, affected ones have significantly

[9] Follow Zhang and Zhu (2011), we add 1 to the monthly *investment* and *newentry* before taking the logarithms to avoid taking logarithms of zeros.

lower $investment$ and $newentry$. The coefficient of $policy_t \times platin_i$ in Model 2 indicates that after the platform antitrust, the monthly number of investments in the affected industries is 26.73% lower than that in the other industries. Similarly, the coefficient of $policy_t \times platin_i$ in Model 4 indicates the monthly number of newly established companies in the affected industries is 18.72% lower than that in the other industries as a result of the platform antitrust policy.

---------Insert Table 4 here---------

The regression results imply that although the Platform Guidelines aimed to restrain the behavior of these affected platforms, they caused a wider negative impact at the industry level. VC institutions showed less interest in these affected industries, and startups were no longer willing to enter these industries. Our results suggest a chilling effect: when the affected platforms are fined or regulated by the Chinese government, investors or founders detect more risks in terms of regulatory uncertainty.

4.2 Test for Parallel Trends

The DID model supposes that the sample meets the assumption of parallel trends between affected and unaffected industries. We use three methods to test the pre-assumption for parallel trends.

Firstly, to intuitively observe the monthly trends of $investment$ and $newentry$ for the two groups of industries, we calculate the mean values of both the $investment$ and $newentry$ at the industry level for each month and plot folded line charts in Figures 1 and 2. The vertical dashed lines in Figures 1 and 2 show the month when the Platform Guidelines were officially implemented by the Chinese government. The solid blue lines reflect the monthly trends of affected industries, while the dashed red lines present the monthly trends of unaffected industries. In Figure 1, we observe almost parallel trends for the two groups of industries before the Platform Guidelines were implemented. Once the policy was realized, we find a clear and stable divergence between the solid blue line and dashed red line. Similarly, in Figure 2, before the platform antitrust policy, the two lines showing the trends of $newentry$ are almost the same. But after the platform antitrust policy, we can observe that the dashed red line is higher than the solid blue line, which indicates the $newentry$ per industry in the unaffected industries is larger than that in the affected industries.

---------Insert Figures 1 and 2 here---------

Secondly, we test the parallel trend assumption taking a regression approach following extant studies (e.g., Binder 1998; Seamans and Zhu 2014; Liu and Bharadwaj 2020). The specific regression model for the event study in our research is as follows:

$$comp_{it} = \sum_{k=-5}^{6} \beta_k' policy_{t}\_k \times platin_i + \gamma t + \mu_t + \delta_i + \varepsilon_{it}. \quad (2)$$

In regression model (2), we replace $policy_t$ with a series of reconstructed dummy variables, $policy_{t}\_k$, where $k \in \{-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, 6^+\}$, indicating whether month t is the kth month since the implementation of the platform antitrust policy. The omitted period is the months leading up to the fifth month before the platform antitrust policy. The analysis helps ensure whether the $investment$ and $newentry$ of the treated and control groups are dynamically comparable in the pretreatment period and whether the policy effect lasts in the post-treatment period. We report the estimated coefficients of a series of the interactions between $policy_t\_k$ and $platin_i$ ($\beta'_{-5}, \beta'_{-4}, \dots, \beta_{6^+}$) in Table 5. The results for the values of $k < 0$ in Models 1 and 2 show no effect in the months leading up to the platform antitrust policy, which supports the parallel trends for both the $investment$ and $newentry$. For $k > 0$ in Models 1 and 2, we observe an immediate impact on $investment$, while the impact on $newentry$ gradually shows up. Taken together, these results boost our confidence in the DID approach.

---------Insert Table 5 here---------

Thirdly, Roth (2022) points out that the regression estimates above may have low statistical power to check parallel trends. Similar to Thatchenkery and Katila (2023), we follow Roth's procedure[10] by importing the coefficients and variance–covariance matrix of the regression estimations and then calculating the ratios of the likelihood of the observed coefficients under the hypothesized trend relative to under parallel trends. We obtain small likelihood ratios (0.049 for $investment$ and 0.013 for $newentry$), which provide further support to the assumption for parallel trends.

4.3 Random Implementation Tests

One might also be concerned that other shocks during our study period that differentially impacted the affected and unaffected industries drive the results in the DID estimation. For example, instead of the Platform Guidelines, maybe an economic recession for platform-related industries led to the results. A feasible way to rule out this concern is to exert a placebo intervention and conduct random implementation tests to build more confidence of the DID estimations (Bertrand et al. 2004; Burtch et al. 2018). We conduct two random implementation tests.

Firstly, we randomly select 41 industries as the placebo treatment group and re-estimate the DID model with month and industry fixed effects. Secondly, we randomly select 492 observations (41 industries × 12 months) to create a placebo treatment and then re-estimate the DID model, again with month and industry fixed effects. We replicate the procedure 500 times and store all the coefficients of the placebo treatment. Following Burtch et al. (2018), we show the results of the random implementation test in Table 6. We find that all the estimated coefficients of the placebo treatment are quite small and not significantly different from zero, indicating that the DID estimations we obtained in Table 4 are unlikely to have been caused by other unobserved policies or shocks. We also find that the DID estimations (estimated βs) are significantly different from the coefficients of the placebo treatment.

[10] We use the *pretrends* package by Jonathan Roth at https://github.com/jonathandroth/pretrends.

---------Insert Table 6 here---------

4.4 Differentiation from Platform Giants

We also ask whether, after the Platform Guidelines were implemented, the new startups in the affected industries engaged in business that resembled that of the affected platforms or diverged significantly. On one hand, considering the government's efforts to curb the dominance of these platform giants, it seems plausible that these startups might emulate the platform giants to capture the market vacated by the retreat of the affected platforms. On the other, these startups might believe that by conducting business akin to the affected platforms, they could also face restrictions under China's Platform Guidelines as their market shares increase. This concern might lead the startups to consciously avoid business models similar to those of the affected platforms.

To analyze this, we calculate the similarity between each new startup and the existing companies/apps that represent the market impact of the affected platforms in the same industry. We denote this variable as $plat\_giants\_simi$. Our regression specification is as follows:

$$plat\_giants\_simi_{kit} = \beta policy_t + \delta_i + \varepsilon_{kit}, \tag{3}$$

where k denotes a company, i denotes an industry, and t denotes a month. Table 7 shows the regression results. Model 1 excludes industry fixed effects, while Model 2 includes them. In Model 3, we substitute $policy_t$ with a series of time dummies. The empirical findings suggest that post-antitrust policy, the similarity between startups and the affected platforms decreased significantly. Consistent with the chilling effect observed in our main results, we note that new market entrants tend to avoid direct competition with platform giants following the policy's enactment.

---------Insert Table 7 here---------

5. Additional Robustness Checks

In this section, we report several additional robustness checks.

5.1 Different Sample Range

Though we conducted the random implementation tests in the previous section, it is still possible that other policies implemented by the Chinese government may potentially bias our results. In the first robustness test (reported in Table A1), we change the sample range based on two policies. Firstly, in our main analysis, we dropped the 16 industries impacted by "Made in China 2025" because we believe these industries are supported by the Chinese government. Our results remain similar after adding back these industries (Models 1 and 2). Another policy that may bias our results is the "double reduction" policy implemented in July 2021. This policy aims to limit schoolwork outside the classroom in China and has had a significant impact on education-related industries, which also belong to industries that receive a large amount of investment from platform CVC. In Models 3 and 4 of Table A1, we drop six education-related industries to rule out the potential influence of the double reduction policy. Finally, we shorten the sample period to 6 months before and after the Platform Guidelines' implementation to reduce the potential influence of other policies (Models 5 and 6). Our results remain robust.

5.2 Using Matching to Construct the Control Group

Another concern is that our affected industries and unaffected ones are systematically different, and this difference could drive the outcome even after controlling for industry fixed effects. For example, the affected industries are more likely to be internet related, while these unaffected industries may not be so closely related to the internet.

As a robustness check, we match each affected industry with an unaffected industry based on the similarities of company descriptions in these industries and use the matched sample as our new control group. Table A2 presents the results. In Models 1 and 2, we conduct a 1:1 similarity matching without replacement (DeFond et al. 2017) and obtain a new control group with 41 industries. In Models 3 and 4, we conduct a 1:2 similarity matching with replacement and obtain a new control group with 54 industries. We continue to observe significantly negative coefficients of the interaction term in all the four regression models.

5.3 Dropping Immediate Months after the Policy Change

While companies in China often closely monitor and quickly respond to government policies, investment and market entry decisions might not be immediately impacted by the platform antitrust regulation. To account for this lag, we excluded data from several months following the policy change to reassess the effects of antitrust regulation. Specifically, in Table A3, we omitted data from the month of the policy change in Models 1 and 2, the two months following the change in Models 3 and 4, and the three months post-change in Models 5 and 6. The regression coefficients and their significance levels demonstrate that our DID estimation remains robust.

6. Conclusion

This paper examines the impact of China's Platform Guidelines on internet-related industries using a Difference-in-Differences (DID) model. We examine investment and market entry data to determine the guidelines' effect on competition. Our findings indicate that this regulation has made the investment climate less attractive for startups, evidenced by a 26.73% decrease in the monthly number of investments and an 18.72% drop in newly established companies in affected industries. Contrary to expectations, the Platform Guidelines have not fostered greater competition.

Our research has significant implications for policymakers, highlighting the necessity of considering the potential unintended consequences of platform regulation. In China, the uncertainty introduced by the Platform Guidelines has notably altered startup and investor expectations regarding uncertainties in operating such sectors, undermining their confidence. These unintended impacts are not unique to China; similar phenomena are observed in other countries' platform regulations, such as data privacy laws like GDPR and CCPA, which have also had unforeseen negative effects (Janssen et al. 2022; Puekert et al. 2022; Bae et al. 2023). Regulatory measures targeting platform giants must therefore account for potential adverse outcomes.

For digital platforms, our findings suggest the importance of effective self-regulation to mitigate regulatory targeting. Platforms should consider imposing stricter internal controls on practices like price discrimination, self-preferencing, and misuse of personal data. Additionally, they should account for rising antitrust risks in their M&A and CVC investment strategies, adjusting risk assessment models in line with government regulations.

Our study is not without limitations. For example, our findings are specific to China's antitrust regulation, and while the general mechanisms may be similar elsewhere, unique factors in China could have influenced our results. Secondly, given data limitation, our study focuses on the short-term effects of these regulations, not their long-term impacts.

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Figures and Tables

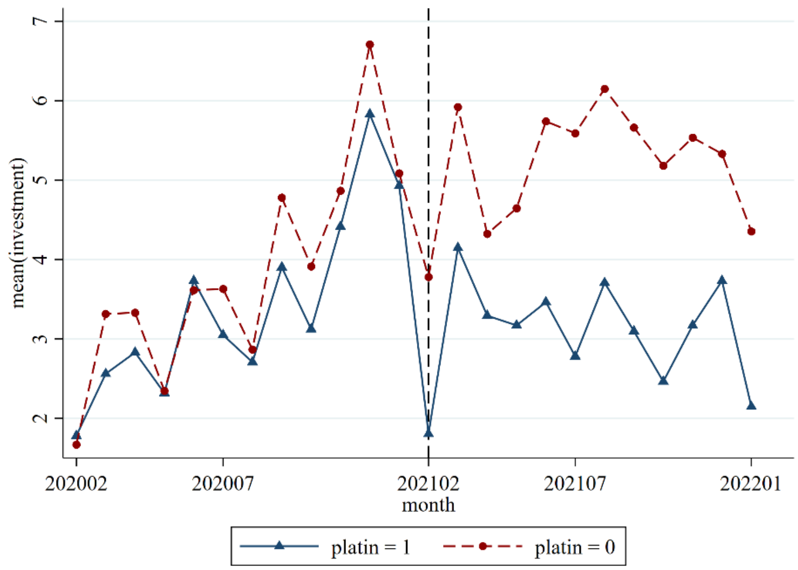

Figure 1. Monthly Trends of *investment*

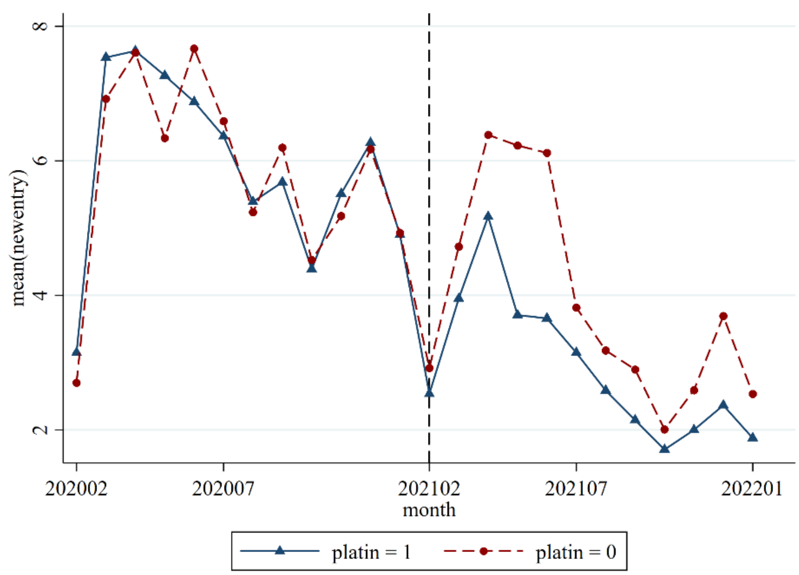

Figure 2. Monthly Trends of *newentry*

Table 1. Specific Cases Related to the Platform Guidelines

Date	Platform Companies	Punishments/Actions
04/10/2021	Alibaba	Alibaba was fined 18.228 billion RMB for forcing merchants to sell exclusively on its platform, a practice known as “pick one of two.”
10/08/2021	Meituan	Meituan was fined 3.443 billion RMB for abusing its dominant market position in the catering industry.
12/24/2021	Tencent	Tencent's shareholding in JD was reduced from 17% to 2.3%, and Tencent was no longer the largest shareholder in JD.
01/19/2022	Bytedance	Bytedance disbanded its own strategic investment department.

Table 2. 41 Industries Affected by Platform Regulation

Industries	Companies/apps	Information
Integrated Education Services	Tencent Classroom	Launched by Tencent in Jul. 2014. Daily active users ranked top in China online education market in 2020 Q1.
Integrated Logistics	Cainiao	Co-founded by Alibaba in May. 2013. In Dec. 2019, Alibaba invested 23.3 billion RMB, and raised Cainiao stake from 51% to 63%.
Integrated Tourism Services	Fliggy	Launched by Alibaba in Oct. 2014. Ranked top two in China’s online travel agency market in 2019.
Integrated Financial Services	Ant Group	Launched by Alibaba in Oct. 2014. Ant Group’s full-year revenue for 2019 was 120.6 billion RMB with a net profit of 18.07 billion RMB.
Transportation & Accommodation	Ele.me	Fully acquired by Alibaba and Ant Group in Apr. 2018. Ele.me’s take-out market share rose to 43.9% in 2019 Q3.
Freight Logistics	G7 Huitongtianxia	Tencent co-invested 30 million USD in May. 2015 (C round), co-invested 45 million USD in Apr. 2016 (C+ round), and co-invested 320 million USD in Dec. 2018 (strategic investment).
Game Developers	TiMi Studio Group	Launched by Tencent in Oct. 2014. TiMi’s full year revenue for 2020 reached about 10 billion USD and had become one of the world’s largest game developers.
Mobile and Online Advertising	Alimama	Launched by Alibaba in Aug. 2007. In 2020, Alimama helped Alibaba achieve 253.6 billion RMB in advertising revenue.
Other Advertising	Tikin Media	Invested by Tencent in Oct. 2019. Its advertising business had covered more than 60 cities all over the world in 2019.
Advertising Technology	Byte Advertising	Launched by ByteDance in Mar. 2015. In 2019, Byte Advertising helped ByteDance achieve 183.1 billion RMB in advertising revenue in Chinese market.
Second-hand E-commerce	Xianyu	Launched by Alibaba in Jun. 2014. In 2019, Xianyu captured about 60% of China’s second-hand e-commerce market.
Media & Reading	China Literature	Launched by Tencent in Mar. 2015. China Literature’s full year avenue for 2020 reached 8.53 billion RMB with a net profit of 0.92 billion RMB. Also, China Literature’s market share ranked first in 2020.
Video / Live Streaming	Douyin	Launched by ByteDance in Sep. 2016. Ranked first in China’s short video market in 2020.
Ride & Travel	DiDi	DiDi, one of the six Chinese affected platforms
Music	QQ Music	Launched by Tencent in Feb. 2005. Ranked first in China’s online music market in 2020.
Comic and Animation	Tencent Comic	Launched by Tencent in Mar. 2012. Captured 90% of China’s comic and animation market in 2020.
Integrated Game Services	Tencent Game	Launched by Tencent in Aug. 2003. Tencent Game ranked first in China’s game market in 2020 and its full year revenue for 2020 was 156.1 billion RMB.
E-commerce Solutions	Jingxitong	Launched by JD in Dec. 2015. By Nov. 2019, Jingxiton had covered more than 1800 counties in China.
Fresh	Fresh Hippo	Launched by Alibaba in Mar. 2015. Fresh Hippo’s full year revenue for 2019 was about 40 billion RMB.

Payment	Alipay	Launched by Alibaba in Dec. 2004. In Jun. 2019, the number of Alipay users reached 1.2 billion.
Video	Alibaba Pictures	Alibaba fully acquired China Vision Media Group and changed its name to Alibaba Pictures in Jun. 2014. Alibaba Pictures had a full year revenue of 2.875 billion RMB in 2020.
Other Tools	Amap	Fully acquired by Alibaba in Feb. 2014. Ranked first in China's mobile map market in 2019 Q3.
Office OA	Ding Talk	Launched by Alibaba in Dec. 2014. By Jun. 2019, Ding Talk had over 200 million registered users and over 10 million company users, with more active users than the sum of the second to tenth places.
Logistic Information Technology	Kaijing Group	Invested by Ant Group and Alibaba in Dec. 2018. Listed as unicorn company in 2019 Q2.
Community E-commerce	JD Daojia	Launched by JD in Apr. 2015.
Stranger Dating	MoMo	Before MoMo's IPO on NASDAQ in Dec. 2014, Alibaba hold a 20.74% stake in MoMo. MoMo's full year revenue for 2020 reached 15.024 billion RMB with a net profit of 2.896 billion RMB.
K12	Yuan Fudao	Tencent had participated in investing 3.91 billion USD in Yuan Fudao's several rounds of financing. In 2019 Q3, Yuan Fudao had been valued at 7.8 billion USD.
E-sports	VSPN	Before VSPN's IPO in the Hong Kong stock market, Tencent held a 13.54% stake in VSPN. In 2020, VSPN had a full year revenue of 0.892 billion RMB.
Other E-commerce Services	Yixun	Fully acquired by Tencent in May. 2012.
Integrated Life Services	Meituan	Meituan, one of the six Chinese affected platforms
Integrated E-commerce	Taobao	Launched by Alibaba in May. 2003. Still one of the largest e-commerce platforms in China.
Integrated Entertainment	Pengpai Audio Visual Technology	Established with investment from Bytedance in Dec. 2019.
Fitness	Keep	Tencent continued to participate in four rounds of financing after investing in Keep's C+ round in 2016. In F round, the investing amount reached 0.36 billion USD. In 2019, Keep had 0.165 billion registered users and captured 87.73% market share in China's fitness apps market.
Integrated Real Estate Services	BEKE	After D+ round investment in Nov. 2019, Tencent hold a 12.3% stake in BEKE and was the largest institutional shareholder. BEKE's full year revenue for 2020 reached 70.48 billion RMB and was one of the largest players in China's real estate service market.
Storage Services	JD Logistics	Launched by JD in Apr. 2017. The full year revenue of JD Logistics in 2020 reached 73.375 billion RMB.
Interest Community	RED	RED was invested by both Tencent and Alibaba. In 2021 Q4, RED had been valued at 20 billion USD.
Cross-border E-commerce	Minitiao	Fully acquired by JD in Jan. 2012. One of the largest cross-border e-commerce platforms in JD online shopping store.
Integrated Social Platform	WeChat	Tencent's largest social platform with over 1.1 billion daily active users in 2019.
Same-city Logistic	Dada Group	Before Dada's IPO on NASDAQ in Jun. 2020, JD held a 46.1% stake in Dada Group. Dada's full year revenue for 2020 was 5.74 billion RMB with a 85.18% annual growth rate.
Blockchain Application	Ant Chain	First launched by Alibaba in Dec. 2018 as Ant Blockchain and then renamed as Ant Chain in Jul. 2020. From 2016 to 2020, Ant Chain ranked first in global blockchain patent applications for four consecutive years.
Cross-border Logistic	Alog	Alibaba invested in Alog in the round A financing in Jun. 2014 and fully acquired Alog in Oct. 2019. Alog's overseas business covers 17 countries/regions and had 388 global supply chain networks with a 40-million-piece daily order processing capability.

Table 3. Summary Statistics and Paired t-test

	Pre-12 months	Post-12 months	Paired *t*-test	Increment
investment	Mean (S.E.)	Mean (S.E.)	t-stats	
platin = 1	3.43 (0.20)	3.08 (0.19)	1.28	-0.35
platin = 0	3.84 (0.17)	5.18 (0.23)	-4.64***	1.34
newentry				
platin = 1	5.91 (0.30)	2.90 (0.18)	8.63***	-3.01
platin = 0	5.84 (0.22)	3.93 (0.20)	6.48***	-1.91

Table 4. Difference-in-Differences Estimations

VARIABLES	(1) *ln_investment*	(2) *ln_investment*	(3) *ln_newentry*	(4) *ln_newentry*
platin × policy	-0.2604***	-0.2673***	-0.1827***	-0.1872**
	(0.0657)	(0.0661)	(0.0708)	(0.0732)
Observations	4,032	4,032	4,032	4,032
R^2	0.066	0.066	0.271	0.271
Month Trend	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Industry FE	NO	YES	NO	YES

Notes: Heteroskedasticity-adjusted standard errors, clustered at the industry level, are included in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5. Regression Test of Parallel Trends

VARIABLES	(1) *ln_investment*	(2) *ln_newentry*
platin × policy_-6+	Omitted	Omitted
platin × policy_-5	0.1851	0.0381
	(0.1332)	(0.0943)
platin × policy_-4	-0.0673	-0.1131
	(0.1447)	(0.0966)
platin × policy_-3	0.0966	-0.0681
	(0.1432)	(0.0922)
platin × policy_-2	0.1537	-0.0264
	(0.1242)	(0.0883)
platin × policy_-1	-0.0304	-0.0785
	(0.1536)	(0.0852)
platin × policy_0	-0.2904**	-0.0916
	(0.1228)	(0.0913)
platin × policy_1	-0.1265	-0.1563
	(0.1683)	(0.1002)
platin × policy_2	-0.2568*	-0.2521**
	(0.1320)	(0.1125)
platin × policy_3	-0.0896	-0.2142*
	(0.1358)	(0.1123)
platin × policy_4	-0.2628*	-0.2909**
	(0.1359)	(0.1140)
platin × policy_5	-0.3702***	-0.2247**
	(0.1406)	(0.1095)
platin × policy_6+	-0.2248**	-0.2179***
	(0.0867)	(0.0825)
Observations	4,032	4,032
R^2	0.068	0.272
Month Trend	YES	YES
Month FE	YES	YES
Industry FE	YES	YES

Notes: Heteroskedasticity-adjusted standard errors, clustered at the industry level, are included in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6. Random Implementation Test

VARIABLES	Randomly create a placebo treatment group *ln_investment*	*ln_newentry*	Randomly create a placebo treatment *ln_investment*	*ln_newentry*
mean of random β	-0.0037	-0.0019	0.0014	0.0171
s.d. of random β	0.0723	0.0633	0.1222	0.1141
Estimated β	-0.2673	-0.1872	-0.2673	-0.1872
Replications	500	500	500	500
Z-score	-3.638	-2.927	-2.194	-1.933
p-value	0.000	0.002	0.014	0.027

Table 7. Differentiation with Platform Giants

VARIABLES	(1) *plat_giants_simi*	(2) *plat_giants_simi*	(3) *plat_giants_simi*
policy	-0.0291***	-0.0263***	
	(0.0038)	(0.0031)	
policy_-6^{+}			Omitted
policy_-5			-0.0056
			(0.0077)
policy_-4			-0.0081
			(0.0104)
policy_-3			-0.0055
			(0.0073)
policy_-2			-0.0022
			(0.0072)
policy_-1			-0.0068
			(0.0086)
policy_0			-0.0175*
			(0.0090)
policy_1			-0.0199**
			(0.0078)
policy_2			-0.0329***
			(0.0062)
policy_3			-0.0370***
			(0.0078)
policy_4			-0.0404***
			(0.0078)
policy_5			-0.0325***
			(0.0080)
policy_6^{+}			-0.0236***
			(0.0048)
Observations	4,274	4,274	4,274
R^2	0.012	0.363	0.364
Industry FE	NO	YES	YES

Note: Robust standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Online Appendix A: Tables for Robustness Checks

Table A1. Robustness Test 1

	(1)	(2)	(3)	(4)	(5)	(6)
	Add 16 industries in the "Made in China 2025"		Drop 6 education-related industries influenced by the "double reduction" policy implemented in July 2021		Six months before and after the platform antitrust policy	
VARIABLES	*ln_investment*	*ln_newentry*	*ln_investment*	*ln_newentry*	*ln_investment*	*ln_newentry*
platin × policy	-0.2387***	-0.1918***	-0.2525***	-0.1454**	-0.3305***	-0.1853**
	(0.0659)	(0.0667)	(0.0615)	(0.0623)	(0.0794)	(0.0874)
Observations	4,416	4,416	3,888	3,888	2,016	2,016
R^2	0.079	0.263	0.070	0.261	0.063	0.084
Month Trend	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Notes: Heteroskedasticity-adjusted standard errors, clustered at the industry level, are included in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A2. Robustness Test 2

	(1)	(2)	(3)	(4)
	1:1 similarity matching without replacement to construct a new control group		1:2 similarity matching with replacement to construct a new control group	
VARIABLES	*ln_investment*	*ln_newentry*	*ln_investment*	*ln_newentry*
platin × policy	-0.2801***	-0.1681*	-0.2603***	-0.1561*
	(0.0816)	(0.0845)	(0.0798)	(0.0800)
Observations	1,968	1,968	2,280	2,280
R^2	0.080	0.296	0.072	0.299
Month Trend	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

Notes: Heteroskedasticity-adjusted standard errors, clustered at the industry level, are included in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A3. Robustness Test 3

	(1)	(2)	(3)	(4)	(5)	(6)
	Drop the month of policy change		Drop the two months after the policy change		Drop the three months after the policy change	
VARIABLES	*ln_investment*	*ln_newentry*	*ln_investment*	*ln_newentry*	*ln_investment*	*ln_newentry*
platin × policy	-0.2638***	-0.1947**	-0.2682***	-0.2012**	-0.2642***	-0.1907**
	(0.0688)	(0.0774)	(0.0698)	(0.0792)	(0.0745)	(0.0825)
Observations	3,864	3,864	3,696	3,696	3,528	3,528
R^2	0.066	0.274	0.067	0.285	0.070	0.293
Month Trend	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES

Notes: Heteroskedasticity-adjusted standard errors, clustered at the industry level, are included in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Online Appendix B: Matching Steps

Below are the detailed steps:

Step 1: for company i in the Jingzhun database, we calculate the text similarities between the business description of company i and the business descriptions of all the companies in the IT Juzi database one by one. Follow the method in Le and Mikolov (2014), we use doc2vec to obtain the Chinese words frequency vectors with k Chinese words decomposed from the company description texts. Then, we further calculate the Cosine similarity between the vector of company i and the vector of each of the company in the IT Juzi database. For example, V_i and V_j are the Chinese words frequency vectors of company i from Jingzhun database and company j from IT Juzi database, respectively. Then, for Chinese words w from 1 to k, we can obtain the text similarity $s_{i,j}$:

$$s_{i,j} = \cos(V_i, V_j) = \frac{V_i \cdot V_j}{\|V_i\| \|V_j\|} = \frac{\sum_{w=1}^{k} V_{iw} \times V_{jw}}{\sqrt{\sum_{w=1}^{k} (V_{iw})^2} \times \sqrt{\sum_{w=1}^{k} (V_{jw})^2}} \tag{B1}$$

Step 2: find the highest business description similarity among all the similarities we calculate for company i. For example, if company j^* from IT Juzi database has a highest similarity with company i, then we match company i with company j^*.

Step 3: categorize company i to a same industry that the company in the IT Juzi database with the highest similarity belongs to. In other words, we assign company i a same industry as company j^*.

Step 4: check the categorizing results, manually re-categorize if the highest business description similarity matched for company i is lower than 0.2.

Table A1 is a sample display of our matching results. Obviously, some of the companies in the two databases have exactly a same business description. Take company 2 as an example, the business description for company 2 in Jingzhun database and the business description for the company we matched in IT Juzi database are identical. We obtain a highest similarity of 1.000 and we can accurately categorize company 2 into the industry category of Enterprise IT Service in IT Juzi database. For company 8, the highest similarity is only 0.667 and we can visually find a slight difference between the two business descriptions. But a highest similarity of 0.667 is tolerable, as we can find both the company 8 and the matched company from IT Juzi database can be regarded as the sensor provider, which means that categorize company 8 to the industry category Sensor Device is still reasonable.

Table B1. Business Description Similarities and Matching Results

Company ID in Jingzhun Database	Business Description for Company in Jingzhun Database	Highest Similarity	Business Description for Company with the Highest Similarity in IT Juzi Database	Industry Categories in IT Juzi Database
1	Integrated circuit chip design manufacturer	0.833	Engaged in integrated circuit chip production and design	Integrated Circuit
2	Internet information service provider	1.000	Internet information service provider	Enterprise IT Service
3	Intelligent driving system	0.889	Intelligent driving system research and	Automatic/Unmann

	developer		development provider	ed
4	Integrated film and television company	0.857	Integrated film and television company	Video
5	Big data management service provider	0.875	Data management service provider	Data Service
6	Supply chain management service provider	1.000	Supply chain management service provider	Logistic Information Technology
7	Intelligent financial software	0.750	Intelligent financial management software	Integrated Financial Service
8	Micro differential pressure sensor provider	0.667	Tailpipe sensor provider	Sensor Device
9	Integrated circuit manufacturer	1.000	Integrated circuit manufacturers	Integrated Circuit
10	Internet learning platform	1.000	Internet learning platform	K12

Basically, our matching results show that for companies in Jingzhun database, nearly 40% have a highest similarity equals 1.00 while nearly 97% have a highest similarity higher than 0.50. Specifically, according to step 4, for all the 19196 companies in Jingzhun database, we only need to check and manually re-categorize 487 companies.

References

Le Q, Mikolov T (2014) Distributed representations of sentences and documents. *International conference on machine learning*. (PMLR), 1188–1196.