Antitrust Platform Tech Regulation and Competition: Evidence from China

Ke Rong (Tsinghua)
D. Daniel Sokol (USC)
Di Zhou (Tsinghua)
Feng Zhu (HBS)

Abstract. Many jurisdictions have launched antitrust enforcement and introduced ex ante regulation against large tech platforms. As a quasi-natural experiment, the quick and strict implementation of China's "Anti-Monopoly Guidelines for Platform Economy" provides an opportunity to evaluate the impact of antitrust regulation on platform competition. This paper addresses how government regulation impacts the number of investments and the entry of start-ups to measure competition. It adopts a Difference-in-Differences (DID) method to empirically explore the impact of China's Platform Guidelines. The results show that overall, China's Platform Guidelines did not achieve the expected result of greater competition. Rather, competition weakened in markets covered by the guidelines with less venture capital and corporate venture capital investment flowing into these markets. Moreover, the guidelines not only restricted the expansion of the existing big tech digital platforms, but also negatively impacted complementor markets in which covered companies were not allowed to enter. Our study suggests that governments consider more carefully the potential unintended consequences of ex ante antitrust platform regulation.

Keywords: Platform, Monopoly, Antitrust, Complementor, Competition, CVC, venture capital, Platform Ecosystem

1. Introduction

Globally there has been growing concern about the power of tech giants. Government responses have included calls for greater ex ante regulation for antitrust (Parker et. al 2021; Deutsch 2021, Jacobides 2020). The study of the effects of such regulation remains nascent but the potential impact on innovation relating to competition has potentially profound effects for innovation in platform markets globally.

This paper investigates and explores the impact of China's “Anti-Monopoly Guidelines for Platform Economy”[1] (Platform Guidelines) on market competition of Internet-related industries. A number of Chinese tech firms such as Tencent and Alibaba, whether through investing via corporate venture capital (CVC), acquiring smaller firms with growth potential, or by launching new features in adjacent platform-related industries, have reached a level of scope and scale that has led to them being dubbed “Digital Giants” (Weiss et al. 2004). Such firms have a significant influence across significant areas of the Chinese digital economy (Chen 2022; Zeng 2018).

Compared to the policies or acts proposed or implemented in elsewhere globally, the Platform Guidelines have been strictly and quickly implemented in China, which provides us a very rare quasi-natural experiment to explore the impact of Platform Guidelines on the entire markets that used to be touched by the market power from the Chinese tech giants. Our focus is not how the Platform Guidelines influence the behaviors of the covered digital platforms but how the Platform Guidelines influence competition from other firms in the industries that where there was entry via investment or operations by the Digital Giants. The tech platforms that constitute the digital giants for purposes of the Platform Regulation are Alibaba, Tencent, ByteDance, DiDi, Meituan and Jingdong.

Officially implemented on February 7, 2021, China’s Platform Guidelines ended the unregulated expansion Chinese platform companies by putting into place a system to limit certain behavior by large platforms designated under the regulation. These include limits on price discrimination (to punish non-cooperating sellers), “self preferencing” (where a platform favors its on service or product), and merger and acquisitions (including CVC investments). Soon after implementation of the Platform Guidelines, Chinese tech giants have been subject to enforcement actions. The lack of warning of the Platform Guidelines and its immediate enforcement make academic study of the impact of enforcement an event study of particular interest because of similar interest in such regulatory actions globally. What is different in China relative to other jurisdictions is that unlike Europe, India or elsewhere, US

[1] The text of “Anti-Monopoly Guidelines for Platform Economy” can be found in the official Chinese government website: http://www.gov.cn/xinwen/2021-02/07/content_5585758.htm.

tech companies are insignificant in China so claims cannot be made that ex ante regulation is based on protectionist grounds (McGill and Gold 2021; Nikkei 2021).

Table 1 offers specific cases related with the Platform Guidelines against covered firms. In the first enforcement action, Alibaba was fined 18.228 billion RMB, which accounted for 4% of the Alibaba's total sales. In addition to the cases listed in Table 1, Jingdong, DiDi and Bilibili have all been fined for violating the Platform Guidelines. In Figure 1, we calculate the average number of investments by platform CVC[2] and other VC (venture capital) in each month before and after 12 months of the implementation of the Platform Guidelines. Figure 1 illustrates that after the implementation of the Platform Guidelines, the overall trend of the average number of investments by CVC and VC from the covered platforms significantly declined.

Table 1. Specific Cases Related to the Platform Guidelines

Date	Platform Companies	Punishments/Actions
2021.04.10	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".
2021.10.08	Meituan	Meituan was fined 3.443 billion RMB for abusing its dominant market position in the catering industry.
2021.12.24	Tencent	Tencent's shareholding in Jingdong was reduced from 17% to 2.3%, and Tencent was no longer the largest shareholder in Jingdong.
2022.01.19	Bytedance	Bytedance disbanded its own strategic investment department.

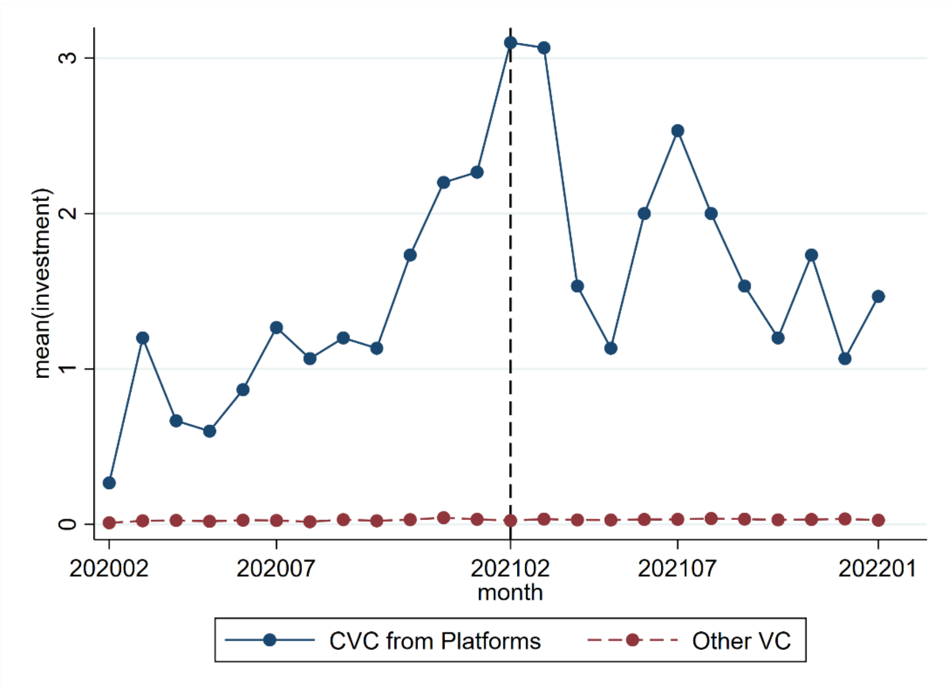

Figure 1. Mean Investments for CVC from Platforms and Other VC

[2] We classify venture capital from Alibaba, Tencent, ByteDance, DiDi, Meituan and Jingdong as CVC. The data is from IT Juzi database. We only include investment events in mainland China and consider investments prior to an Initial Public Offering.

2. Perspectives and Related Literature

2.1 Platforms and entrepreneurship

The VC and CVC structure is influential on M&A activity of technology based start-ups. The nature of VC is that such funds typically invest in a portfolio of firms with a return horizon of approximately ten years. This return horizon is critical as passive VC investors eventually expect a return of their capital (and profit) at the end of the fund lifecycle. In terms of a successful it, M&A is the primary opportunity for passive VC investors. The exit period at the end of the lifecycle of VC funds is also important for VC fund managers. Successful exits allow such managers the opportunity to establish a strong reputation and to attract new investors for future funds they manage.

CVC is a mechanism by which established firms make equity investments in entrepreneurial ventures. The motivation of such firms may be to gain increasing awareness of new ventures and their related technologies or alternatively to leverage the investment into a long term alliance or potential acquisition (Dushnitsky and Lenox, 2005a; Dushnitsky and Lenox, 2005b). Compared to VCs, CVC fundings not only provide financial capital, but also complementary assets (Park and Steensma 2012). Relatedly, Kim et al. documented in their study that IT companies utilized their CVC arms to supplement in house R&D efforts in a hyper competitive market of technology based products as they provide flexibility, technological knowledge and other strategic benefits through exposure of innovation of those companies in which they invest.

VC and CVC are part of the entrepreneurial ecosystem but mergers by larger platforms of entrepreneurial ventures also plays a critical role. Often these acquired firms are complementary to existing platforms, which allows for scale and scope economies (Ahuja and Katila 2001; Miric et al., 2021) through integration with the larger acquiring firm. The integration may introduce increased process innovation (Cassiman et al. 2005). For example, the Li and Agarwal (2018) study of Facebook's integration of Instagram showed that some competing third party companies were able to drive value from Facebook's acquisition of Instagram as demand by consumers in the photo sharing industry increased following the merger. They concluded that Facebook's increased role in the photo sharing ecosystem through the acquisition of Instagram ultimately benefited the complementary market overall by increasing overall foot traffic in the space.

Nevertheless, the existing literature has taken a mixed view about the role of mergers as to competitive effects within a platform ecosystem. Current empirical findings related to the outcomes of big tech acquisitions are either on a product level (Kamepalli et al. 2021) or on the investor side (Prado and Bauer 2022). Some papers argue that tech acquisitions serve to shield incumbent platforms from competition (Kamepalli et al. 2020, Koski et al. 2020). By acquiring potential competitors, the platform companies gain market power, deter market entry, and further weaken the innovation across the entire industry. By acquisition, platform forms a more complicated platform ecosystem with multiple complementors inside (Kretschmer et al. 2022, Wang and Miller 2020). So, compared to traditional firms, platform's market power has extended beyond the platform's own market to affect the complementor markets (Eisenmann et al. 2011, Katila et al. 2022). Specifically, the complementors' rivals may attract less investment (Zhu 2019), thus hinter the growth of these rivals (Adner and Lieberman 2021).

Other papers suggest that tech acquisitions do not have such an effect (Jin et al. 2022; Prado and Bauer 2022) and that such acquisitions are value creating. Offering policy lessons, Cabral (2022) argues that acquisitions by platform companies frequently brings 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.

2.2 Relationship Between Platforms and Complementors

Platforms offer incentives and rules via contractual mechanisms to value (Cusumano et al. 2019; Bhargava 2021). When the incentives are properly aligned the platform orchestrates behavior in a way that create value across the ecosystem (Parker et al. 2017). Platforms adopt strategies to attract different kinds of complementors to build an even more powerful platform ecosystem (Ceccagnoli et al. 2012, Rong et al. 2021). These complementors may come from different industries and work with the platforms to provide a bundle of products or services with high complementarity (Boudreau and Jeppesen 2015, Jacobides et al. 2018). In turn, the platforms provide digital infrastructure for these complementors (Ceccagnoli et al. 2012, Zhu 2019) and balance the benefits of these complementors (Chen et al. 2022, Zhang et al. 2020).

In some cases, the platforms may compete with their complementors (Wen and Zhu 2019, Zhu and Liu 2018), while in most situations, platforms tend to cooperate with their complementors and balance the benefits among them to enhance the market power of the entire platform ecosystem (Chen et al. 2022, Wang and Miller 2020, Zhang et al. 2020). Since independent complementors can choose a multi-homing strategy (Li and Zhu 2021), a feasible way for a digital platform to ensure their high-performing complementors to exclusively choose only one platform is to invest and exert influence on those complementors. By investing and supporting the complementors, digital platforms can quickly obtain market power in those industries where the complementors belong (Langley and Leyshon 2017).

Under certain circumstances, platforms may create potential anti-competitive effects. platform may envelope adjacent markets (Eisenmann et al., 2011) by pushing out existing firms. In other settings, platforms may overall create value even when there are some negative effects for complementors. The theory and empirical work is mixed relating to the overall relationship between platforms and complementors depending on the setting (He et al. 2020; Huang et al. 2022; Cheng et al. 2023; Zhu et al. 2021; Cennamo et al 2018). Some of these papers suggest that there are policy implications, which include either antitrust or regulation.

2.3 Platform regulation

While much of platform orchestration is contractual, there is also a related literature that focuses on the impacts of government regulation of platforms. A series of works focus on how privacy regulation impacts platform competition. The regulation of technology by governments implicates the nature of innovation that is industry wide, beyond that of the firms being regulated. For example, a number of papers identify the impact of privacy regulation on markets. such as GDPR with regard to the effects of regulation on competition (e.g., Aridor, Che and Salz 2020; Puekert et al. 2022; Janßen et al 2022). Each of the GDPR studies find that regulation had unintended consequences as GDPR reduced competition.

Other work examines the impact of regulation and competitive consequences for complementors in 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 hurts the small businesses that regulation was intended to protect.

3. Empirical Background and Data Description

The impact of regulation of tech platforms may encourage other firms to erode the market share of the tech platforms by entering tech platform markets more aggressively as incumbent response has been damped by regulation. As a result, these firms may attract more VC investments or more startups may choose to enter the related industries. However, there may also be a negative effect (Sine et al. 2003) as the crackdowns on tech platforms may cause firms to fear that regulation in the industries in which existing tech platforms operate may create potential uncertainty going forward for all entrants into those areas, especially if the entrants grow to significant market presence (Gulen and Ion 2016). Further, policymakers may create uncertainty by implementing policies at macroeconomic level or industry level (Brogaard and Detzel 2015). In China, the government has launched multiple official documents to encourage the development of digital economy and a quick and strict Platform Guidelines may elevate uncertainty in the platform-related markets more generally, thereby undermining the confidence of investors and entrepreneurs.

Thus, potentially new firms in the covered platform industries may become less attractive to VC and CVC investors and there will be fewer entrants as a result. Since the impact of Platform Guidelines remains unclear, based on this research gap, **we propose the following research questions: (1) How does platform antitrust regulation shape competition in platform industries?; and (2) Will regulation open up markets in which tech giants are present, per the objective of the regulation, for new entrants and hence through increased venture capital?**

In this section, we will first introduce the data and variables used in this paper. Then, we proceed the collected data and give the descriptive statistics.

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/). Both the two databases include many startups according to their own criteria and collect all the investment events occur in mainland China. Based on the two databases, our dataset covers all the company information and investment events from 12 months before the Platform Guidelines to 12 months after the platform antitrust policy. As the Platform Guidelines were officially implemented on February 7, 2021, the range of the dataset is from February 2020 to January 2022. Specifically, the 12 months from February 2020 to January 2021 refers to the period before the platform antitrust policy, while the 12 months from February 2021 to January 2022 refers to the period after the platform antitrust policy.

The IT Juzi database has very exclusive industry categories, which means each company belongs to only one industry category. The problem with the IT Juzi database is that it only collects a relatively small number of companies. We find that the IT Juzi database only contains 7484 newly established companies during the above mentioned 24-month period. As for the Jingzhun database, it has a greater collection of companies, and we can obtain 19196 companies in the same period. However, in the Jingzhun database, each company may belong to several different industry categories, which in turn leads to a similar company entry trend across different industries. For example, in the Jingzhun database, a startup that mainly run e-commerce business for agriculture products may be divided into both the traditional agricultural industry and the e-commerce industry. We code such startup as more of 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 the company in the IT Juzi database with the highest similarity, thus classifying all the companies in the Jingzhun database to the industry categories in the IT Juzi database.

After merging the two databases, we then further adjusted the industry categories based on the industry scale. We find some industries in our database have nearly no industry entry or investment during the 24-month period of our study. To reduce the influence of these outliers, we merged industries with fewer than 5 investments and fewer than 5 industry entries during the entire 24-month period to other industries similar to them. Moreover, considering the potential of impacts from other policies, we have also removed those industries that have been consistently supported by the Chinese government. Specifically, we identified these industries supported by the Chinese government from an official document named “Made in China

2025."[3] After data cleaning, we obtain a final dataset that contains 19,196 companies and 16,984 investments across 168 industry categories from February 2020 to January 2022. We conduct our study based on this dataset, and then subject all industry categories to robustness testing. Next, we give the detailed data processing process below.

3.2 Industries Affected by the Covered Platforms

To compare the differentiated impact that the Platform Guidelines has on the industries deeply and not deeply influenced by the monopolist platforms, we need to identify which platforms are covered platforms and which industries are deeply influenced by the monopolist platforms before the platform antitrust policy.

Though several Chinese platforms have been punished for violating the "Anti-Monopoly Guidelines for Platform Economy", there is no officially recognized list of covered platforms currently. According to the existing enforcement actions, as well as the amount and the frequency of the historical platform CVC investment, we identify six Chinese platforms as the covered platforms covered by the Platform Regulations, namely Alibaba, Tencent, ByteDance, DiDi, Meituan and Jingdong.[4]

Based on the six covered platforms, we further define three kinds of industries as industries with a presence by the covered platforms before the promulgation of the Platform Guidelines: (1) industries in which the core of the covered platform belongs (e.g., Alibaba and e-commerce), (2) industries to which the subsidiaries of the covered platforms belong (e.g., video games of Tencent), (3) industries in which the unicorns or listed companies in which there were CVC investments. Collectively, we call these industries ones in which there was "deep influence" by covered platforms. Among all the 168 industries, Table 2 shows in detail the 41 industries that were considered as the industries deeply influenced by the covered platforms before the platform antitrust policy. Most of the 41 industries are business to consumer. Nevertheless, there are a few business to business industries, such as Integrated Financial Services, Logistic Information Technology, and Storage Services. We then define the treatment variable $platin = 1$ if a certain company belongs to the 41 industries and $platin = 0$ if the company belongs to the rest of the 127 industries.

Table 2. 41 Industries Covered by Platform Regulation

Industries	Companies/apps	Information
Integrated Education Services	Tencent Classroom	Launched by Tencent in Jul. 2014. Daily active users ranked top one in China online education market in

[3] Proposed in May 2015, "Made in China 2025" is a national strategic plan and industrial policy of the Chinese government to further develop the high-tech manufacturing industries. Industries from ten areas are involved, they are new generation of 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, biomedical and high-performance medical devices.

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

		2020 Q1.
Integrated Logistics	Cainiao	Co-founded by Alibaba in May. 2013. In Dec. 2019, Alibaba invested 23.3 billion RMB, raises 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 raised 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 covered 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 Jingdong 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 Jingdong 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 covered 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	Jingdong Logistics	Launched by Jingdong in Apr. 2017. The full year revenue of Jingdong 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 Jingdong in Jan. 2012. One of the largest cross-border e-commerce platforms in Jingdong 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, Jingdong 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.

3.3 Measuring Competition

According to Porter (2008), an industry with growth potential often has a strong industry attractiveness. In the GE McKinsey Matrix, industry attractiveness represents the profit potential of the industry for a business to enter and compete in that industry.[5] An industry with high attractiveness usually attracts more start-ups and VC investments and thus has more

[5] GE McKinsey Matrix: https://thinkinsights.net/strategy/ge-mckinsey-matrix/

intense competition. Following Koski *et al.* (2020), we use the number of investment and the entry number of the start-ups in the industry level to measure competition. Following this logic and based on our dataset, we construct two variables $investment$ and $newentry$.

For $investment$, we calculate the number of the monthly investments from other VC institutions after excluding the platform CVC investments from covered platforms in each industry. Since one of the Platform Guideline's policy goals is to prevent covered platforms' further CVC investment, the Platform Guidelines directly hit the investment behavior of the covered platforms. Using 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. To obtain investment behaviors from other VCs and CVCs, we first discard those investment events that have no specific VC institutions named as we cannot judge if the covered platforms were involved in these anonymous investments. There are 414 anonymous investment events among the total of 13,022 investment events, which is 3.18%. Then, to better reflect the attractiveness of the industry to venture capital, we focus only on those investments prior to an IPO.[6] Finally, we obtain 6,794 investment events and 16,984 investments, which indicates on average, 2.50 VC institutions are involved in each investment event.

For $newentry$, we calculate the number of the monthly entry of startups in each industry. As the Platform Guidelines only has an impact on companies in mainland China, we exclude all companies that established outside mainland China. Also, as explained above, we match and classify all the companies in the Jingzhun database to the industry categories in the IT Juzi database. We adopt a text similarity analysis, which can be considered as an unsupervised machine learning method, to obtain the similarity of the business descriptions between different companies. We detail our matching steps in the Appendix. Ultimately, our merged dataset contains 19,196 startups distributed among 168 different industries.

3.4 Descriptive Statistics

After we define the industries that were deeply influenced by the covered platforms, as well as the two monthly variables $investment$ and $newentry$ that measure the industry competition, we now have a panel data with 168 industries × 24 months. Furthermore, we set the policy shock variable $policy = 0$ for the first 12 months before the implementation of the platform antitrust policy, while $policy = 1$ for the rest of 12 months. The specific day that the policy was officially implemented was February 7, 2021, we set $policy = 1$ for February 2021 and regard this month as the first month influenced by the antitrust policy.

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[6] Specifically, we only consider the following types of investments: seed round, angel round, A round to H round, and strategic investments.

Table 3 reports summary statistics for both the $investment$ and $newentry$. We give the mean value and standard error of $investment$ and $newentry$ for the two groups of industries whether deeply or not deeply influenced by the covered platforms in the table, respectively. We also conduct paired t-tests to compare $investment$ and $newentry$ for each industry group before and after the platform antitrust policy. The $investment$ for industries deeply influenced by the covered platforms shows no significant difference after the platform antitrust policy, while a significantly increase of the $investment$ for industries not deeply influenced by the covered platforms is observed. As for the $newentry$, both the two groups of industries show a significantly increase after the policy. Overall, the disparities of the mean values of both the $investment$ and $newentry$ become larger after the policy, which indicates the Platform Guidelines may pose a negative policy impact on the industries deeply influenced by the covered platforms.

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

4. Empirical Results

We adopt a Difference-in-Differences (DID) model to identify the causal influence of the Platform Guidelines on the industry competition.

4.1 Difference-in-Differences Estimation

With the treatment variable $platin$ and the policy variable $policy$ defined in the previous section, we can have the following regression framework.

$$comp_{it} = \alpha policy_t + \beta policy_t \times platin_i + \gamma t + \mu_t + \delta_i + \varepsilon_{it} \qquad (1)$$

where i indexes the industries and t indexes the months. $comp_{it}$ means the monthly competition level of each industry in our dataset. Specifically, follow Koski, *et al.* (2020), we use $ln\_investment_{it}$ and $ln\_newentry_{it}$ in this paper as our dependent variables to proxy industry competition. The reason why we adopt the logarithms of the monthly $investment$ and $newentry$ is to avoid potential heteroskedasticity problems. Follow Zhang and Zhu (2011), we add one to the monthly $investment$ and $newentry$ before taking logarithms. As defined above, $policy_t$ is a dummy that equals one if the months are after the platform antitrust policy, and zero otherwise. Similarly, $platin_i$ is also a dummy that equals one if a certain industry belongs to the industry categories that are deeply influenced by the covered platforms before the antitrust policy (treatment group), and zero otherwise (control group). 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 for we believe the investment or the company establishment in mainland China has a strong monthly pattern. For example, the investment or the company establishment will usually reach a peak after the Chinese New Year holiday. Besides, based on our interviews with several VC investors and entrepreneurs in mainland China, the main issues that influence their decision for investing or establishing a company are economic environment and the industrial potential. Therefore, no other control variables are considered in regression model (1) after we control industry level fixed effects and month level fixed effects.

Table 4 reports the regression results. Models 1 and 2 use the number of investments as dependent variable, while Models 3 and 4 use the number of new entries as the dependent variable. We only control month level fixed effects in Models 1 and 3, and control both the month level and industry level fixed effects in Models 2 and 4. Month trend is controlled in all the regression models. All regression results show a similar pattern: after the platform antitrust policy, compared to the industries not deeply influenced by the covered platforms, the industries deeply influenced by the covered platforms have a significantly 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 attracted by the industries deeply influenced by the covered platforms 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 the newly established companies in the industries deeply influenced by the covered platforms is 18.72% lower than that in the other industries after the platform antitrust policy.

Table 4. Difference-in-Differences Estimations

VARIABLES	(1) *ln_investment*	(2) *ln_investment*	(3) *ln_newentry*	(4) *ln_newentry*
policy	5.1829***	5.1845***	4.0842***	4.0853***
	(1.6322)	(1.6323)	(1.2039)	(1.2037)
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: Robust standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

The regression results imply that though the Platform Guidelines aims to restrain the behavior of these covered platforms, it causes a wider negative impact at the industry level. VC institutions show less interest in these industries that are deeply influenced by the covered platforms, and startups are no longer willing to entry these industries. A reasonable explanation for our results is that when the covered 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. In our paper, the pre-assumption for parallel trends means that before the platform antitrust policy, both the $investment$ and $newentry$ in the industries deeply influenced by the covered platforms (treatment group) and the industries not deeply influenced by the covered platforms (control group) have a same trend. 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 $newentry$ in the industry level in each month and further plot folded line charts in Figures 2 and 3. The vertical dashed lines in Figures 2 and 3 show the month when the Platform Guidelines was officially implemented by the Chinese government. The solid bule lines reflect the monthly trends of industries deeply influenced by the covered platforms, while the dashed red lines present the monthly trends of industries not deeply influenced by the covered platforms. In Figure 2, we observe almost parallel trends for the two groups of industries before the Platform Guidelines. Once the policy was implemented, we can find a very clear and stable divergence between the solid blue line and dashed red line. Similarly, in Figure 3, 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 industries not deeply influenced by the covered platforms is larger than that in the industries deeply influenced by the covered platforms.

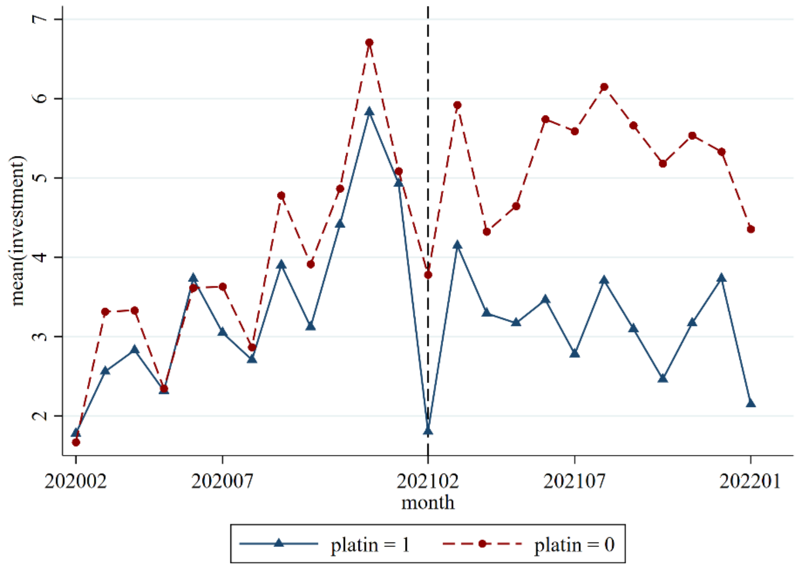

Figure 2. The Monthly Trends of *investment*

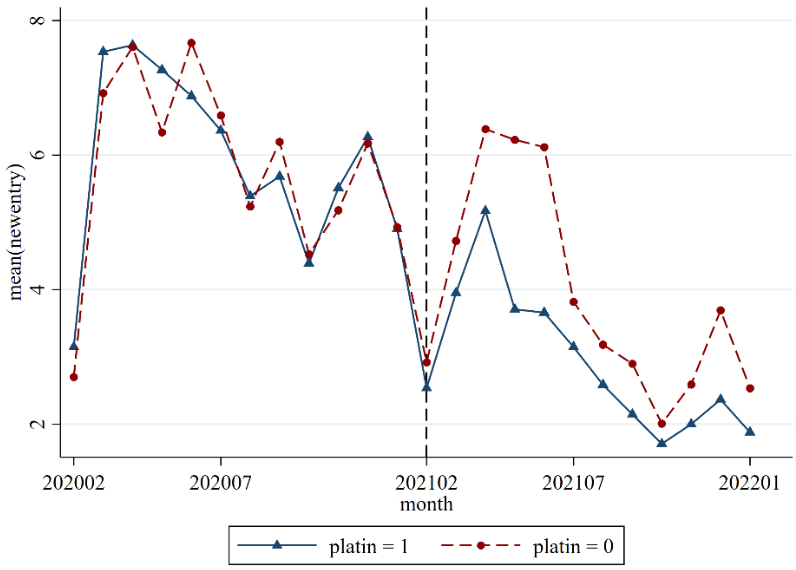

Figure 3. The Monthly Trends of new*entry*

Secondly, we verify the parallel trend assumption with an event study (Binder 1998, Liu and Bharadwaj 2020, Seamans and Zhu 2014). An event study help ensure whether the $investment$ and $newentry$ of the treated and control groups are dynamically comparable in the pre-treatment period, and whether the policy effect lasts in the post-treatment period. The specific regression model for the event study in our research is as follows:

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

In regression model (2), we replace $policy_t$ with a series of re-constructed 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 5th month before the platform antitrust policy. 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 values of $k < 0$ in Models 1 and 2 show no effect in the months leading up to the platform antitrust policy, which provides suggestive evidence to support the parallel trends for both the $investment$ and $newentry$. As for the results for values of $k > 0$ in Models 1 and 2, we observe an immediate impact on $investment$, while a gradually showing up impact on $newentry$. Taken together, these results still provide evidence to support the impact of Platform Guidelines on market competition in industries that were deeply influenced by the platform giants.

Table 5. Event Study Estimations

VARIABLES	(1) *ln_investment*	(2) *ln_newentry*
policy_-6$^+$	Omitted	Omitted
policy_-5	1.8908***	1.7482***
	(0.5201)	(0.3867)
policy_-4	2.0092***	1.7667***
	(0.5923)	(0.4343)
policy_-3	2.4457***	2.0708***

	(0.6534)	(0.4856)
policy_-2	2.8760***	2.4045***
	(0.7313)	(0.5410)
policy_-1	2.9141***	2.3894***
	(0.8182)	(0.5935)
policy_0	2.8796***	2.2530***
	(0.8771)	(0.6501)
policy_1	3.3644***	2.7019***
	(0.9474)	(0.6993)
policy_2	3.4252***	3.0514***
	(1.0276)	(0.7577)
policy_3	3.6002***	3.1529***
	(1.1043)	(0.7955)
policy_4	4.0071***	3.3349***
	(1.1637)	(0.8605)
policy_5	4.1586***	3.3331***
	(1.2386)	(0.9102)
*policy_*6^{+}	5.1773***	4.0950***
	(1.6354)	(1.2042)
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: Robust standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

To intuitively observe the results in Table 5, we also visualize all the coefficients of the interaction terms and their 90% confidence intervals in Figures 4 and 5. The two figures clearly show insignificant coefficients leading up to the Platform Guidelines and significant coefficients after the promulgation of the Platform Guidelines in most of the months.

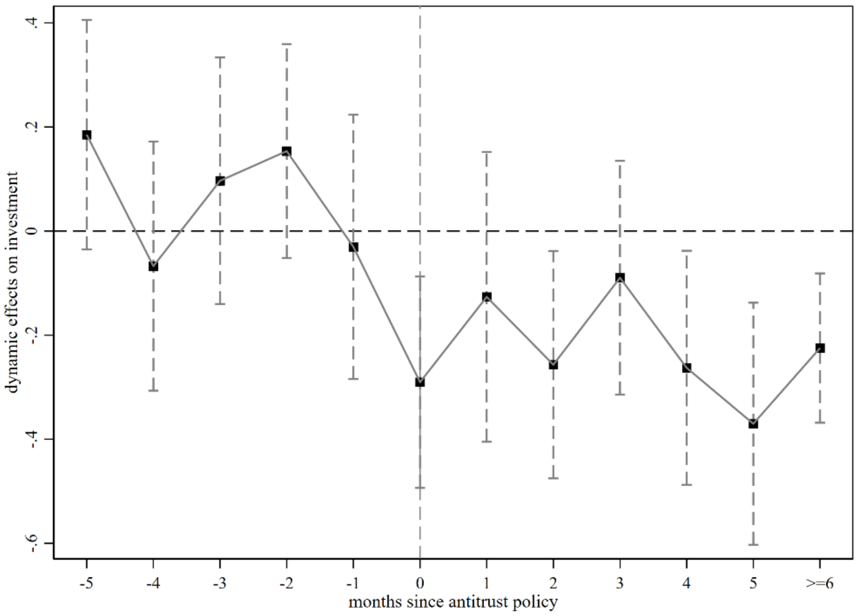

Figure 4. Event Study: Estimates of Platform Guidelines on *investment*

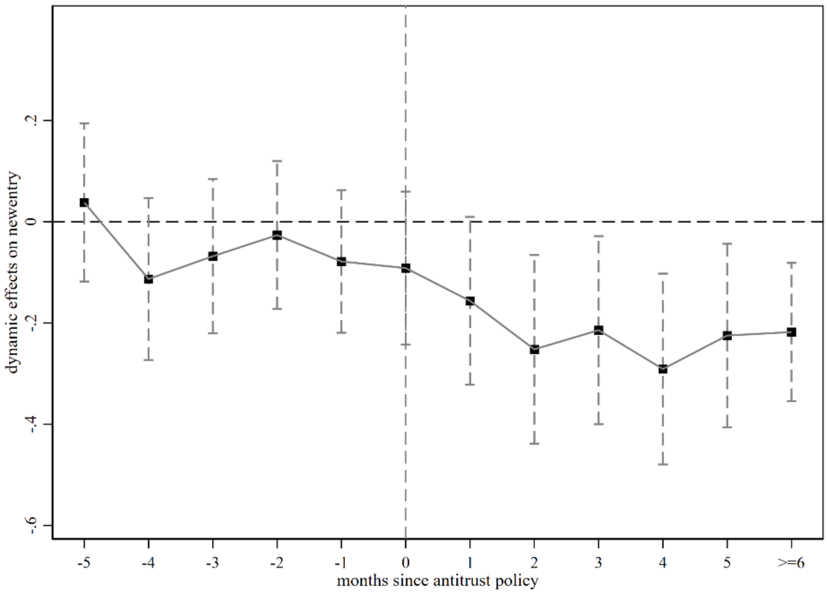

Figure 5. Event Study: Estimates of the Platform Guidelines on *newentry*

Thirdly, Roth (2022) pointed out that event study may have low statistical power to check the parallel trends, which indicates the distributions of the event-study estimates and the confidence intervals we obtain in Table 5, as well as showed in Figures 4 and 5 may be distorted and unreliable. We follow Thatchenkery and Katila (2020) and use the *pretrends* R package provided in Roth's GitHub website.[7] Specifically, we first import the coefficients and variance-covariance matrix of the event study estimations and then calculate the ratios of the likelihood of the observed coefficients under the hypothesized trend relative to under parallel

[7] Jonathand Roth provides the *pretrends* package in his GitHub website: https://github.com/jonathandroth/pretrend s

trends. We finally obtain small likelihood ratios (0.049 for $investment$ and 0.013 for $newentry$), which provides further support to the pre-assumption for parallel trends.

4.3 Random Implementation Tests

Another concern for the DID estimation in Table 4 is the spurious regression and false significance. Our dataset covers 12 months before and after the Platform Guidelines. It is possible that other potential shocks happened during this period are driving the results that we observe in the DID estimation. For example, instead of the Platform Guidelines, maybe an economic recession for platform related industries lead to the results. A feasible way to rule out this concern is to exert placebo intervention and conduct random implementation tests to improve the confidence of the DID estimations (Bertrand et al. 2004, Burtch et al. 2018). We mainly conduct two kinds of 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 $\times$ 12 months) to create a placebo treatment and then re-estimate the DID model with month and industry fixed effects again. We replicate the procedure 500 times and store all the coefficients of the placebo-treatment. Follow Burtch et al. (2018), we show the results of the random implementation test in Table 6. From Table 6, we first find the all the estimated coefficients of the placebo-treatment are quite small and not significantly different from zero, which indicates the DID estimations we obtain in Table 4 are unlikely to be caused by other unobserved policies or shocks and they are reliable. Also, we find the DID estimations (estimated βs) are significantly different with the coefficients of the placebo-treatment.

Table 6. Random Implementation Test

	Randomly create a placebo treatment group		Randomly create a placebo treatment	
VARIABLES	*ln_investment*	*ln_newentry*	*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

As the empirical results we obtain from the DID regression framework have passed the tests for parallel trends and the random implementation tests, we believe we have identified the causal relationship between the Platform Guidelines and competition.

5. Robustness Checks

In this section, we further conduct robustness checks to support the results we obtain from the DID regression model.

5.1 Robustness Test One: Change the Sample Range

Though we conduct and pass the random implementation tests in the previous section, we still believe that other policies implemented by the Chinese government may potentially bias our results. In the first robustness test, we change the sample range based on two policies and the results are shown in Table 6. Firstly, as we explained before, we drop the 16 industries that are impacted by the “Made in China 2025” during the data processing, as we believe these industries are supported by the Chinese government. But given the timing of growing U.S.-China trade tensions, the Chinese government may not be able to provide sustained support for these industries after the U.S.-China trade agreement reached in January 2020. Therefore, we add back the 16 industries into our sample and the results are shown in Models 1 and 2. Another policy that may bias our results is the “double reduction” policy implemented in July 2021. The “double reduction” aims to limit schoolwork outside of the classroom in China and hit hard on the education-related industries, which also belong to the industries that receive large amount of investment from platform CVC. In Models 3 and 4, we drop 6 education-related industries to rule out the potential influence of the “double reduction” policy. Finally, we also consider shortening the sample period to reduce the potential influence of other policies. In Models 5 and 6, we only measure only six months before and after the Platform Guidelines. As shown in Table 6, the results remain robust after we change the sample range.

Table 6. Robustness Test One

	(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*
policy	5.5831***	4.4963***	5.8473***	4.3424***	1.2391	1.6521***
	(1.5258)	(1.1298)	(1.6506)	(1.2254)	(0.7625)	(0.5613)
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: Robust standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

5.2 Robustness Test Two: Industrial Similarity

Another concern about our dataset is that the differences between the treatment group and control group comes from the features of the industries. For example, the industries in the treatment group are likely to be Internet-related industries while the industries in the control group may not so closely related to the Internet. Though we control industry fixed effects in our baseline regressions, such kind of bias may still exist.

A feasible way to rule out this concern is to narrow our industry scope. In our dataset, we now have 41 and 127 industries in the treatment and control group. Based on the company descriptions in each industry, we can conduct a similarity analysis to select industries having high similarities with those in the treatment group to reconstruct a control group. After we obtain the similarities among all the industries, we can then conduct similarity matching without or with replacement (DeFond et al. 2017) to construct a new control group. Table 7 shows the results. In Models 1 and 2, we conduct a 1:1 similarity matching without replacement 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 can observe significantly negative coefficients of the interaction term in all the four regression models, which provides empirical evidence to support our main results.

Table 7. Robustness Test Two

	(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*
policy	7.6544***	4.2474**	7.8241***	4.7507***
	(2.3895)	(1.6359)	(2.2050)	(1.5121)
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: Robust standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

5.2 Robustness Test Three: Change in the Measurement of the Dependent Variable

In the previous part we introduced how we processed our data and how we measured industry development. We use $investment$ and $entrance$ as our dependent variable. Specifically, for $investment$, we use the number of VC institutions that participate in the investment events, rather than the number of investment events. As for $entrance$, we use an unsupervised machine learning and based on the similarities of the business descriptions to match the companies in the Jingzhun database into the IT Juzi database. In robustness test two, we reconstruct the measurement of $investment$ and $entrance$. We use the number of investment events to measure $investment$ and for $entrance$, we first use the companies in the IT Juzi database, then use the companies matched from the Jingzhun database with a highest similarity larger than 0.75.

Table 7 gives the new estimations after we change the measurement of the two dependent variables. In Models 1 and 2, we still observe significantly negative coefficients of the interaction term with p-value smaller than 0.01, which implies using the number of investment events does not change the results we find in the DID regression model (2). However, in Models 3 and 4, though the interaction terms are still significantly negative, they only have p-values between 0.05 and 0.1. The significance level decrease is partly due to the small number of newly established companies in the IT Juzi database. We have 7,484 newly established companies in IT Juzi database, which means the monthly average number of entrants in each industry is only 1.64. In Models 5 and 6, when we matched companies from Jingzhun database with a highest similarity larger than 0.75 into the IT Juzi database, we then reacquired negative coefficients of the interaction term with *p*-value smaller than 0.01. Overall, we can still obtain robust results after we change the measurement of the dependent variable.

Table 8. Robustness Test Three

	(1)	(2)	(3)	(4)	(5)	(6)
	Use number of investment events, rather than the number of investment behaviors		Use the number of startups in the IT Juzi database		Use the companies matched from the Jingzhun database with a highest similarity larger than 0.75	
VARIABLES	*ln_investment*	*ln_ investment*	*ln_ newentry*	*ln_newentry*	*ln_ newentry*	*ln_newentry*
policy	5.1662***	5.1671***	0.6594	0.6618	3.6514***	3.6522***
	(1.6323)	(1.6324)	(0.4260)	(0.4262)	(1.1760)	(1.1759)
platin × policy	-0.1797***	-0.1833***	-0.1054*	-0.1152*	-0.1716***	-0.1748***
	(0.0618)	(0.0621)	(0.0600)	(0.0685)	(0.0495)	(0.0514)
Observations	4,032	4,032	4,032	4,032	4,032	4,032
R^2	0.063	0.063	0.271	0.271	0.227	0.227
Month Trend	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Industry FE	NO	YES	NO	YES	NO	YES

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

5.3 Robustness Test Four: Change the Criteria for Industries

When we identify the 41 industries that are deeply influenced by the covered platforms, we identify three kinds of firms. Another way to identify the industries is to use historical investment data. We change the criteria to re-identify industries deeply influenced by the covered platforms. The new criteria are: (1) the industries to which the covered platforms belong; (2) the industries at least one investment from the covered platforms is higher than round D; (3) the industries that the ratio of investment from the covered platforms in higher than the 75% quantile. The last two criteria are based on interviews that we have with the experts from Tencent, Alibaba, and ByteDance. Table 8 shows the regression results and the coefficients of the interaction term in all the four Models remain significantly negative, with *p*-values smaller than 0.05.

Table 9. Robustness Test Four

	(1)	(2)	(3)	(4)
VARIABLES	*ln_investment*	*ln_investment*	*ln_newentry*	*ln_newentry*
policy	5.1645***	5.1662***	4.0682***	4.0693***
	(1.6327)	(1.6328)	(1.2043)	(1.2042)
platin × policy	-0.2284***	-0.2373***	-0.1429**	-0.1490**
	(0.0717)	(0.0720)	(0.0716)	(0.0741)
Observations	4,032	4,032	4,032	4,032
R^2	0.064	0.064	0.268	0.268
Month Trend	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Industry FE	NO	YES	NO	YES

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

5.4 Robustness Test Five: Use Poisson Regression

The traditional OLS regression assumes the dependent variable follows a normal distribution. When dependent variable is count data, or the dependent variable contains a substantial number of zeros (Silva and Tenreyro 2011), Poisson regression should be considered. So, we switch our log-OLS regressions in Table 4 to a fixed effects Poisson regressions to further check the robustness. Table 10 shows the results. We still find significantly negative coefficients for interaction terms in Models 1-4, which again prove the reliability of our empirical results.

Table 10. Robustness Test Five

VARIABLES	(1) *investment*	(2) *investment*	(3) *newentry*	(4) *newentry*
policy	6.8497	6.8296***	7.9343*	7.9414***
	(4.1922)	(2.3989)	(4.4651)	(2.4280)
platin × *policy*	-0.5018***	-0.4121***	-0.2929***	-0.3233***
	(0.0761)	(0.0768)	(0.0797)	(0.0515)
Observations	4,032	4,032	4,032	4,032
Pseudo R^2	0.038	0.529	0.068	0.603
Month Trend	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Industry FE	NO	YES	NO	YES

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

6. Conclusion and Discussion

Using the investments and market entrance data from IT Juzi database and Jingzhun database, this paper uses a DID model and explores the impact of China's "Anti-Monopoly Guidelines for Platform Economy" on competition in the Internet-related industries. We find that China's Platform Guidelines results in a less attractive investment climate for start up entrants to compete against covered platform companies reduces competition. Specifically, our empirical results show that compared to the industries that not deeply influenced by the covered platforms, the monthly number of investments and the monthly number of newly established companies in the industries deeply influenced by the covered platforms are 26.73% and 18.72% lower respectively. Overall, our results show that China's Platform Guidelines did not achieve the expected effect of creating more competition. Instead, the Platform Guidelines hardened the existing market structure in industries influenced by the coered platforms. Moreover, the Platform Guidelines not only restrict the expansion of the digital platforms, but also impacted complementor markets.

6.1 Contributions

As a quasi-natural experiment, the implementation of China's Platform Regulation is to our knowledge the first study of the effects of antitrust platform regulation in any jurisdiction. Our study makes the following contributions. Firstly, our study contributes to the literature specific to understanding platform related VC and CVC and their impact on competition and the entrepreneurial ecosystem.

Secondly, we contribute to platform antitrust research by systematically analyzing the policy shock of platform antitrust ex ante regulation as a mechanism to solve for anti-competitive behavior by platforms against complementors. We find that China's Platform Regulation "achieve the opposite of the intended effect and that the guidelines negatively impacted the Internet-related industries.

6.2 Practical Implications

First, governments need to consider more carefully the potential unintended consequences of ex ante platform regulation. We observe that in China regulatory uncertainty due to the Platform Guidelines changed start-up expectations for the future of these industries. Indeed, these expectations seem to have been undermined by the Platform Guidelines.

Another practical implication is for the digital platforms themselves. To maintain growth, digital platforms rely heavily on the network effects, which drives platforms to seek profitability in both existing and related industries. Even if platforms and consumers are better off, if some competitors are worse off, such competitors can leverage political channels to impose regulatory penalties on successful platforms. Platforms may be well advised to more effectively self regulate in ways that do not allow competitors easy targets for more severe government regulation.

6.3 Limitations and Direction for Future Research

Our study is not without limitations. First, though we use similarity analysis to match the companies in the Jingzhun database to the IT Juzi database, we still need to manually adjust those companies with low similarity. Therefore, a better database to duplicate our results can provide better robustness support. Second, the results are from antitrust regulation in China. While the general mechanisms are similar to other attempts at ex ante antitrust regulation, there may be some uniquely Chinese factors that might influence results. Finally, the results focus on short term effects rather than long term ones.

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Appendix

Appendix A: 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 $s_{i,j}$:

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

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 2 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 2. 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 Highest Similarity in IT Juzi Database	Industry Categories in IT Juzi Database
1	Integrated circuit chip	0.833	Engaged in integrated circuit chip	Integrated Circuit

	design manufacturer		production and design	
2	Internet information service provider	1.000	Internet information service provider	Enterprise IT Service
3	Intelligent driving system developer	0.889	Intelligent driving system research and development provider	Automatic/Unmanned
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

As in Figure 1, we also draw a cumulative distribution curve based on all the highest similarities we obtain. Basically, 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.

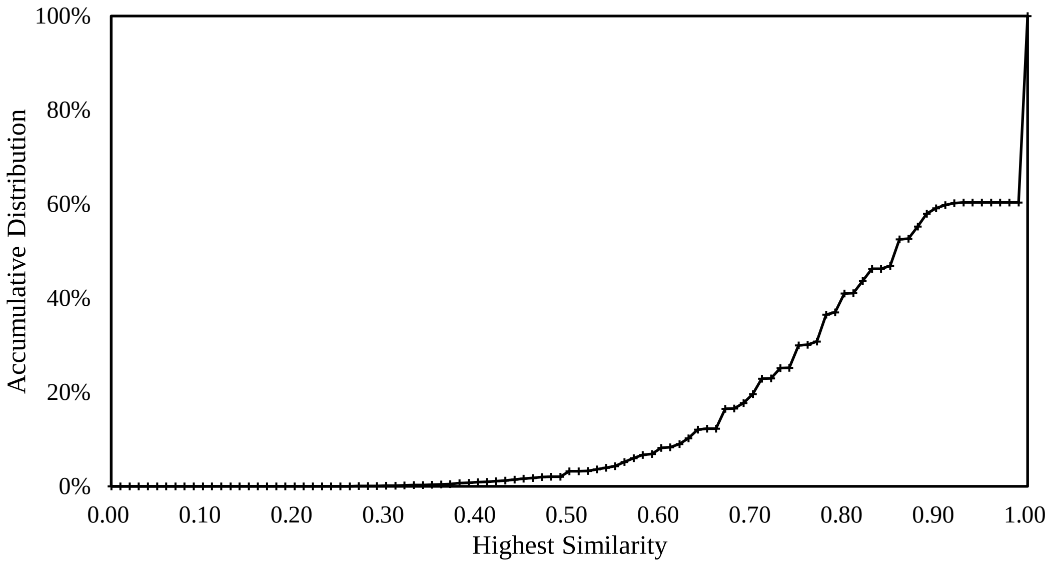

Figure A1. A Cumulative Distribution Curve for the Highest Similarity