The Impact of Cloud Computing and AI on Industry Dynamics and Competition

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Abstract

We examine the rise of cloud computing and AI in China and its impact on industry dynamics. We find that industries that depend more on cloud infrastructure experience a higher increase in firm entry and exit after cloud computing expands in China. The positive relation with firm exit is driven by the increased exit through business failure and adjustments. We also compare cloud computing to artificial intelligence (AI) and show a differential effect of these technologies on exit. For AI, larger incumbents are less likely to exit. M&A is also more likely for cloud computing but not for AI. Concentration decreases post-cloud computing expansion but increases post-AI. These findings point to changes in competition from new technologies but with differential effects based on which types of firms are likely to adopt new technologies.

Keywords: Cloud computing, artificial intelligence, industry dynamics, competition, equity financing

JEL Codes: L11, G34, G32, L25, L26

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1 Introduction

Technological change is considered as an important factor affecting industry dynamics,[1] which can affect innovation, employment, product market competition, and total factor productivity.[2] Greenwood and Jovanovic (1999) show that information technology breakthroughs lead to a flood of entrants since they have more incentive to adopt new technologies unencumbered by suck costs in vintage capital. Hence, new firms could capture the rents and incumbents that don't adopt the new technologies may be forced to exit.[3] However, technological change may not always increase entry. Salgado (2020) shows that skill-biased technical change accounts for a significant fraction of the decrease in new business formation in the US over the last 30 years. In addition, computers, artificial intelligence, and robotics can increase the productivity of high-skill workers (Acemoglu 2002; Acemoglu and Restrepo 2020), thereby increasing their wages as workers and reducing their motivation to become entrepreneurs as in Krueger (1993). In sum, the impact of technological changes on firm entry and exit is controversial.

In this paper, we explore how new information technology adoption in China is related to industry dynamics and competition. We also examine subsequent changes in financing patterns in industries affected by cloud computing. Cloud computing is a newly emerging computing paradigm in which computing resources such as servers, storage, computing power, and software applications are provisioned in a pay-as-you-go manner over the Internet. Cloud computing providers centralize IT infrastructure in one region and distribute IT resources among a large pool of users on demand which contributes to resource utilization improvements and cost savings. Hence, cloud computing enables a shift from fixed costs to variable costs, which can lead to a decrease in the upfront fixed costs of information and communication technology (ICT) adoption. The variable costs for renting cloud computing

[1] See Jovanovic and MacDonald (1994) and Campbell (1998).

[2] See Peretto 1999; Shepherd (1984), Barseghyan and DiCecio (2011), Hjort and Poulsen (2019), Haltiwanger, Jarmin, and Miranda (2013); Hjort and Poulsen (2019), and Gourio, Messer, and Siemer (2016).

[3] In Africa, Hjort and Poulsen (2019) find that fast Internet increases firm entry but also increases the productivity of incumbents using the Internet.

are also lower than a comparable on-premise infrastructure due to the economies of scale of cloud computing providers and the cost savings of firms (e.g., hardware maintenance costs, licensing costs, and unplanned downtime costs).

We also examine whether the impact of another new technology, artificial intelligence (AI), has differing effects on the exit of differing sizes of firms. In the case of AI, Babina, Fedyk, He, and Hodson (2020) shows the benefits of AI accrue to larger firms. AI is a technology that requires more sophistication and more extensive amounts of data that large firms are disproportionately likely to have. Thus, in contrast to cloud computing, AI may have more fixed costs to effectively develop and use it. Thus, the benefits of AI may accrue to large firms while cloud computing may benefit smaller firms.

Following Melitz and Ottaviano (2008), our underlying conceptual framework is developed based on a monopolistically competitive model with heterogeneous firms. In the framework, fixed costs and variable costs affect potential entrants' expected future value, which can lead to the selection of heterogeneous entrants and incumbents. Firms face initial uncertainty about their productivity when making a costly investment prior to entry. Cloud infrastructure reduces the upfront cost of starting a new business, thus decreasing the entry barriers for potential entrants. Cloud computing also reduces variable marginal costs, leading to an increase in expected net entry value. Consequently, potential entrepreneurs are more likely to enter the market. Moreover, despite some incumbents still using outdated technologies, the adoption of cloud computing has enabled new entrants to leverage modern technologies, resulting in cost structures lower than those of incumbents. Hence, less productive incumbents are more likely to exit. Cloud computing may also reduce the average level of firm size in the industry as larger incumbents exit. In sum, both firm entry and exit can increase. In contrast, if AI has larger fixed costs and requires the use of more data, in many industries, it may be the larger incumbent firms that benefit.

The increase in average industrial productivity implies lower average prices in a monopolistically competitive market post-cloud computing, which can lead to greater market demand for varieties from consumers. Therefore, the resulting market competition increases with post-cloud computing. In addition, the mean size of firms tends to shrink as the percentage of small entrants using cloud computing increases. In contrast, AI may reduce market competition if there are fixed costs for its use and if its effectiveness increases with size given larger firms have more data available.

We empirically test the above predictions by using a large and comprehensive firm registration and cancellation database from China reported by the National Enterprise Credit Information Publicity System collected by the RESSET Enterprise Big Data Platform. The data covers all non-listed and listed firms, including small and micro firms as well as identifying entrants, surviving firms, and exits for all industries in China. We supplement these data with the National Tax Survey Database, which covers all two-digit industries and regions from 2007 to 2016. This dataset contains information on firms' performance, which allows us to calculate industry concentration measures and size distribution across industries.

China is a good laboratory to analyze the impact of new technologies on industry dynamics. First, China had the highest annual growth rate in the public cloud market from 2016 to 2020. China's cloud market size reached 133.4 billion RMB in 2019 and has become the world's second-largest cloud computing market.[4] In addition, China became the world's largest producer of AI research, with the largest number of AI paper output and the highest amount of financing. As of June 2018, China is the second-largest host of AI enterprises worldwide, with 1,011 firms.[5] Second, we have detailed and comprehensive firm registration and cancellation data covering the population of all firms in China, which allows us to measure firm entry and exit in each industry.

We study the relation of cloud computing with industry dynamics through cross-industry variation in the use of cloud computing since its expansion in 2013. There was a breakthrough in cloud computing technology and a wave of cloud computing providers entering the Chinese

[4]Source: China Academy of Information and Communications Technology (CAICT), the White Paper of Cloud Computing, published in July 2020.

[5]See the "China AI Development Report, 2018," available at https://ChinaAIDevelopmentReport2018.pdf.

cloud computing market, including Tencent cloud, AWS, UCloud, QingCloud, QiniuYun and others in 2013. The Chinese government also developed a series of policies to promote the development of cloud infrastructure and guide firms and the government to use cloud computing.[6] According to IDC China, the market size of cloud computing in China was about 4.76 billion yuan in 2013, with a growth rate of 36%, higher than the global growth rate of 29.7%.[7]

We exploit the cross-industry variation of cloud computing based on the condition that cloud computing mainly influences businesses with a strong online presence such as retail e-commerce websites, social networks, or Web-facing services. Following Ewens, Nanda, and Rhodes-Kropf (2018), we measure the influence of cloud computing on each two-digit industry based on whether the essential product or service the firm provides is highly related to software, network, web, or online using keywords in the text of the firm business descriptions. We use different set of keywords to measure the exposure to AI.

Our results show that both entry and exit increase for industries more exposed to cloud computing. The increase in firm exits after the sharp increase in cloud computing is mainly driven by the increase in voluntary exits, including firm failures and business adjustments. In addition, the positive effects of cloud computing on firm dynamics are larger when the price of cloud computing is lower.

When we examine the differences between cloud computing and artificial intelligence, our results show that cloud computing affects smaller firms while artificial intelligence relatively affects larger firms. Specifically, we find that cloud computing increases firm exit for both small and large firms, while artificial intelligence (AI) decreases the likelihood of firm exit for larger firms. The results are robust when accounting for changes in voluntary exit. The evidence is consistent with firms needing sufficient data and resources to use AI and as

[6]See, in July 2013, the Ministry of Industry and Information Technology issued the "Guidance on Promoting the Development of "Specialized and Specialized New" Small and Medium-sized Enterprises" to guide small and medium-sized enterprises to use cloud computing. In February 2013, the Ministry of Industry and Information Technology also issued the "Top-Level Design Guidelines for Cloud-based Public Platform for E-Government" to guide the government on how to use cloud computing.

[7]The detailed description of the background of cloud computing development in China is in Appendix 9.

such it reduces large firms likelihood of exit. The results for AI are consistent with Babina, Fedyk, He, and Hodson (2020) which show the benefits of AI for large firms. Thus, we show that there is a differing effect of these new technologies on whether or not new technologies relatively benefit large vs. small firms.

Our results also show that cloud computing increases the likelihood of being merged for both small and large firms, while AI only increases the likelihood of being merged for larger firms. This consistently supports the view that larger firms, with ample data and resources, become more attractive, thereby boosting their chances of being merged.

Furthermore, our results show that cloud computing decreases industry concentration while AI increases industry concentration. When we examine the changes in the size distribution of surviving firms across industries, our results show that cloud computing decreases the mean size across industries, and the size is concentrated on smaller firms, while AI has no impact on size distribution.

Finally, we examine how cloud computing and AI are associated with firms' external financing activities. We find that the probability of receiving equity financing increases signficantly for firms in industries more dependent on cloud computing. This result also holds when we examine venture capital equity financing.

This paper contributes to the literature in the following ways. A large literature acknowledges that technological changes are highly related to industry dynamics, but the relationship is controversial. Our paper finds strong empirical evidence that cloud computing usage can increase firm entry and exit, which is our first contribution. Hobijn and Jovanovic (2001), Kassem (2018) and Hjort and Poulsen (2019) find that electrification and IT can promote firm entry, while Salgado (2020) and Kamepalli, Rajan, and Zingales (2020) show that emerging technologies, such as computer, artificial intelligence, and digital platform, can decrease firm entry. Bessen (2020) finds that technological change can increase the productivity of top incumbents and thus improve their survival rate, while Hobijn and Jovanovic (2001), Samaniego (2010) and Kassem (2018) find that technological change increase firm exits.

Our results for cloud computing are consistent with this latter finding. We also show empirical evidence of differences in the effect of exit on cloud computing and AI. The likelihood of exit increases for cloud computing for both large and small firms, while AI reduces the likelihood of exit for large firms.

Our findings are also consistent with the previous studies which demonstrate that new technologies whose complementary assets are generic and can be transacted in the open market lead to a decline in the performance of incumbents (See Tushman and Anderson 1986; Rothaermel and Hill 2005). Cloud computing is publicly available and typically simple for firms to use by renting cloud services from cloud providers. Thus, cloud computing raises the likelihood of exit for incumbents. However, our results for AI are different. We find the probability of exit is reduced for firms in industries that use signficant AI as it requires substantial data and computational power for firms to train AI models. Certain critical AI technologies or applications are privately held, making them more advantageous to larger incumbents.

We also add to the growing literature on the economic effects of emerging technologies, such as artificial intelligence, robotics, big data, and cloud computing (see, e.g., Brynjolfsson and McAfee 2017; Yermack 2017 Graetz and Michaels 2018; Ewens, Nanda, and Rhodes-Kropf 2018; Acemoglu and Restrepo 2019; Cong and He 2019; Farboodi, Mihet, Philippon, and Veldkamp 2019; Acemoglu and Restrepo 2020). Our study examines the potential effect of emerging technologies on industry dynamics, studying both entry and exit as well as industry concentration and the size distribution of firms inside industries. We also examine how firm financing patterns change following large-scale innovation shocks.

Our study is also related to recent studies that examine the effects of broadband, information, and telecommunications infrastructure on economic growth. Röller and Waverman (2001) find that telecommunications infrastructure can lead to economic growth by reducing business transaction costs and increasing information intensity. Czernich, Falck, Kretschmer, and Woessmann (2011) also estimate the effect of broadband infrastructure, which enables high-speed internet, and find that a 10% increase in broadband penetration leads to an increase in annual per capita growth by 0.9% - 1.5%. Our paper finds that industry dynamics and concentration change and financing patterns change after large-scale technological shocks.

Finally, our study is also closely related to Ewens, Nanda, and Rhodes-Kropf (2018) who examine the impact of cloud computing and Amazon Web Services (AWS) on venture capital financed entry in the United States. Our study extends this study by examining overall firm entry and exit in China and how concentration and the size distribution of firms inside industries change following industry exposure to cloud computing. We also examine the differential effect of AI in addition to cloud computing, highlighting the differences between these two new technologies.

The rest of the paper is organized as follows. Section 2 discusses new technology use in China and develops our theoretical framework. Section 3 describes the data and outlines the empirical strategy. Section 4 presents the baseline results that show how entry and exit are related to cloud computing. Section 5 examines differences in exit and M&A between cloud computing and AI. Section 6 explores how industry concentration and the size distribution of firms change between cloud computing and AI. Section 7 investigates how equity financing of firms changes after large-scale innovation shocks. Section 8 describes robustness tests. Section 9 concludes.

2 New Technology Use in China

We first discuss the economics of cloud computing and develop hypotheses that we examine and then follow with a discussion of AI.

2.1 How Cloud Computing Affects Clients' Costs

Cloud computing, an infrastructure-biased technology, serves as the infrastructure of the "information superhighway" delivering virtualized resources, like software, computing resources, and storage, over the Internet. Cloud computing providers co-locate IT infrastructure to save costs. They distribute IT resources among a large pool of users in a pay-per-use business model with on-demand elasticity by which resources can be expanded or shortened based on users' requirements (see figure A.1, an overview of cloud computing). Hence, cloud computing providers transfer IT resources into a commodity and provide them to firms in a pay-as-you-go manner in the open market.

First, cloud computing enables a shift in the cost of IT resources away from fixed capital investments to variable services acquired over broadband networks from large-scale computing centers. Thus, Cloud computing decreases the upfront fixed cost of ICT adoption (see Bayrak, Conley, and Wilkie 2011; DeStefano, Kneller, and Timmis 2020).

Second, the variable costs for using cloud computing are much lower than what firms would pay to do it themselves. From the supply perspective, centralization of IT infrastructure in areas and distribution of IT resources among a large pool of users on demand contributes to resource utilization improvements and cost savings. Specialization of labor by cloud computing providers can also contribute to efficiency improvements. Hence, cloud computing providers can offer a lower unit price to users. The cost of operations per year per firm using cloud computing is much lower than before.

In a survey conducted by International Data Corporation (IDC) who interviewed 27 organizations around the world using AWS[8], annual IT infrastructure costs decreased by 31% with AWS vs. on-premise environment. Compared to AWS fees, these IT infrastructure costs included power, facilities, licensing, and hardware costs. The annual average number of unplanned outages per firm also decreased from 7 without AWS to 1.9 with AWS, thus

[8]The source is from the IDC White paper "Fostering Business and Organizational Transformation to Generate Business Value with Amazon Web Services".

leading to a 94% decrease in costs of lost productivity. Finally, IDC also found that cloud computing lowered time costs for IT staff by automating tasks, including patch automation, automated scaling, and monitoring.

2.2 Hypothesis Development

We draw on Melitz and Ottaviano (2008) to provide a conceptual framework from which we generate specific predictions that we test.

Cloud computing decreases not only fixed entry costs but also marginal variable costs. Potential entrants would prefer to use cloud services after the emergence of cloud computing out of cost savings. In contrast, incumbents that entered before cloud computing may not choose to transfer to cloud computing since the adjustment costs of abandoning their own on-premise infrastructure and transferring to cloud computing may be too high. Specifically, if incumbents want to transfer to cloud computing, they have to dispose of IT infrastructure, including server rooms, hardware, and software, transfer data from self-built servers to cloud platforms, fire some IT employees, and train employees to adapt to work in the cloud platform.

The decrease in variable costs improves the productivity of the entrants. The decrease in upfront fixed costs also lowers the entry barriers for potential entrants. Therefore, we predict that cloud computing leads to an increase in the competitiveness of entrants versus incumbents.

To derive the implications of these changes in firms' costs, we consider the underlying model of Melitz and Ottaviano (2008) in which firms maximize expected profits when considering entry and exit decisions. For simplicity, we assume that fixed costs are f_E and variable costs are c before cloud computing. After the sharp increase in cloud computing, fixed costs drop to μf_E and variable costs drop to τc where $\mu, \tau < 1$. Therefore, there is only one type of firm indexed by $\{(f_E, c)\}$ before cloud computing. However, there are two types of firms indexed by $\{(f_E, c), (\mu f_E, \tau c)\}$ post-cloud computing, where the former is the incumbents entering before cloud computing and the latter is the entrants using cloud computing.

A firm with a lower variable cost has higher productivity. We assume that the variable costs (or, productivity) are heterogeneous across firms, which is consistent with Melitz and Ottaviano (2008). Firms choosing to enter have to make the irreversible upfront fixed costs. After the fixed costs have been paid, firms learn about their productivity levels which represent firm technology.

From consumers' perspective, demand and price are negatively correlated and a maximum price exists in the market when the market demand for new varieties is zero. Following Melitz and Ottaviano (2008) the market size (respectively, the number of surviving firms) is endogenous. Suppose that the revenue function of firm i can be written as the following with no fixed costs for cloud computing:

$$[p_i(c_i) - c_i]\, q_i(c_i) \tag{1}$$

where $p_i(c_i)$ is the price charged by firm i with marginal costs c_i and $q_i(c_i)$ is the output of firm i. Market demand is then negatively correlated with the market price if the demand structure is a quadratic utility function.

We characterize the "toughness" of the market in terms of a marginal cost cut-off (or, the lowest productivity firm that survives) which is derived from a zero profit condition. Firms with marginal variable costs exceeding the cost cut-off will exit due to negative profits. In (2), the marginal cost cut-off for firms is the highest market price under a zero profit condition.

Both entrants and incumbents are faced with the same highest market price. However, the required smallest productivity to earn zero profit for entrants using cloud computing is smaller than that for incumbents without cloud computing because cloud computing can decrease variable costs. The difference in the required minimum productivity between entrants and incumbents increases as variable costs fall more and more post-cloud computing. Therefore, the productivity cut-off of entrants is lower than that of incumbents. This difference should be bigger for industries more affected by cloud computing.

We now characterize firm entry. Since cloud computing can lower the productivity cut-off by decreasing variable costs under a zero profit condition, some previously less productive firms that could not enter now enter successfully. In addition, the decrease in fixed entry costs increases the expected net entry value and lowers entry barriers under a free entry condition. Hence, we can obtain the first results summarizing the implications of cloud computing for the number of firms entering.

Prediction 1. Cloud computing is associated with an increase in firm entry. This increase is greater in industries that are more affected by cloud computing.

The increase in firm entry can also induce a larger number of product varieties. Under market clearing conditions, the higher demand by consumers for increasing product varieties leads to lower average prices. The market becomes tougher after more competitive entrants enter. Some less productive incumbents find it challenging to earn positive profits in a more competitive market with lower market prices. In addition, incumbents may have to make regular principal and interest payments because they previously borrowed a larger amount from banks to pre-build their own on-premise IT infrastructure. Hence, cloud computing decreases the relative competitiveness of incumbents and increases their productivity cut-off in a more competitive market.

Given a commonly known productivity distribution, incumbents with productivity between the productivity cut-offs before and after cloud computing choose to exit since their profits from staying in business become negative. The difference between the productivity cut-offs before and after cloud computing should be larger in industries more affected by cloud computing where cloud computing increases the productivity cut-off of incumbents more. Therefore, we can obtain the following result summarizing the implications of cloud computing for the number of exits.

Prediction 2. Cloud computing is associated with an increase in firm exit by all firms. This increase is greater in industries that are more affected by cloud computing.

We also examine an additional type of information technology: artificial intelligence (AI). If the use of artificial intelligence requires large amounts of data and significant financial resources to deploy and use effectively, we note that the revenue function of the firm will contain a fixed cost. AI could increase a firm's fixed costs, given the substantial amounts of data and computational power required to train AI models. We also predict that the marginal cost of using AI will be decreasing in size as more data is used and it becomes more effective. According to Babina, Fedyk, He, and Hodson (2020), firms investing in AI experience faster growth and AI tends to benefit larger firms given the high use of data used in AI. Under these conditions, the revenue function for a firm i using AI is as follows:

$$[p_i(c_i(q_i)) - c_i(q_i)]\, q_i(c_i) - F \tag{2}$$

with $c_i(q_i)$ decreasing in q_i as with more data from increased sales, firms become more effective in the use of AI. $p_i(c_i(q_i))$ is the price charged by firm i with marginal costs c_i, and lastly, $q_i(c_i)$ is the output of firm i. F is the fixed costs of using AI each period for the firm.

Under this alternative revenue function, we predict that artificial intelligence (AI) will decrease the likelihood of firm exit for larger firms, while increasing the probability of exit by smaller firms.

Prediction 3. Artificial intelligence is associated with a decrease in firm exit by large firms and an increase in firm exit by smaller firms. This increase is greater in industries that are more affected by artificial intelligence.

3 Data and Identification Strategy

3.1 Data and Sample Construction

Our main data comes from the RESSET Enterprise Big Data Platform, whose original data source is the National Enterprise Credit Information Publicity System.[9] The RESSET

[9]More details about this system are available at: http://www.gsxt.gov.cn/index.html.

Platform collects the registration and cancellation information of all firms in China, covering approximately tens of millions of firms each year. According to the Company Law of the People's Republic of China, all firms must be registered in State Administration for Market Regulation.[10]

Our data provide information on the entry and exit of all firms in China from 2007 to 2018.[11] The data includes all non-listed and listed firms, including small and micro firms, and all industry sectors. The data includes firm name, location, registered capital, industry, business scope, established time, status (either surviving or exit), cancellation or revocation time, and exit reason. When firms alter their business information, they shall apply for alteration registration with the original firm registration organ. Registered firms can be traced back to as early as 1950 when the People's Republic of China was founded. Thus we can identify surviving firms in our sample period from their established and cancellation (or revocation) time. The data also includes firms' detailed equity financing information, such as investors, financing time, financing amount, and financing phase.

The National Enterprise Credit Information Publicity System uses Industrial Classification for National Economic Activities in China (GB/T 4754-2011) to assign each firm to an industry.[12] Hence, we use 89 distinct two-digit industry sections of Industrial Classification for National Economic Activities in China to compute the number of firm entry and exit.[13]

We construct the panel data of entry, exit, surviving number and even financing at the

[10]Chinese companies used to be registered in China's State Administration for Industry and Commerce, SAIC.

[11]We collect national data on unlicensed business cases from the China Industry and Commerce Administration Yearbook. Over the period from 2009 to 2016, unlicensed businesses that were investigated and prosecuted accounted for approximately 1.6% of the total number of firms, which indicates that the incidence of unlicensed business cases is relatively low and insignificant compared to firms with business licenses that are recorded in our sample. Furthermore, the average cost of illegal operations without a business license was RMB 3414.5 in 2013. However, under the *Regulations of the People's Republic of China on Company Registration and Administration (2005)*, a company with a registered capital of RMB 1000000 needs to pay RMB 1100 to obtain a business license in 2013. Therefore, the cost of obtaining a business license was lower than the potential penalty of conducting illegal operations without a business license in 2013.

[12]Source: http://www.stats.gov.cn/tjsj/tjbz/hyflbz/2011/.

[13]There are 96 two-digit industry sections in China. However, we drop the industry groups that are mainly nonprofit organizations, such as the Chinese Communist Party, National institutions, social groups, and international organizations.

industry-year level. We first identify each firm's industry, entry year, exit year, and financing information. We can use this firm level data and in addition, calculate entry and exit counts by entry year and industry at the industry-year level.

We complement these entry and exit data with the National Tax Survey Database (NTSD) from 2007 to 2016. NTSD data is collected by the State Administration of Taxation of China (SAT) and the Ministry of Finance of China (MOF). The data comprises an annual survey of approximately 500,000 firms distributed across all two-digit industries and all regions nationwide. The panel data include information on firms' performance such as sales and assets. We merge this dataset with our main dataset to calculate industry competition and size distribution across industries.

3.1.1 Firm Entry

Firm entry is defined as a new firm registration. Each firm is assigned as a two-digit industry section of the Industrial Classification for National Economic Activities in China. Legally establishing a new firm requires registration with the Chinese government. Chinese law clearly stipulates that a firm shall not engage in any business activity in its name unless it is registered with the company registration organization.[14] If a firm operates without registration, the registration authorities shall order it to cease its business activities, confiscate any illegal gains and impose a fine.[15] In addition, if a company fails to start the business after six months of its establishment without justifiable reasons, the company registration organization shall revoke its business license by law.[16] This means the firm has to start operating within six months after its establishment.

Firms must operate in accordance with the registered business scope, industry, and address, otherwise, it is illegal. Therefore, entrepreneurs generally prepare what they need to

[14] According to "Regulation of the People's Republic of China on the Administration of Company Registration" (2016 Revision), Chapter 1 General Provisions, Article 3.

[15] Implementing Rules for the Administrative Regulations of the People's Republic of China on the Registration of Enterprise Legal Persons (Revised in 2014), Supervision and Penalty Provisions, Article 63(1).

[16] According to Regulation of the People's Republic of China on the Administration of Company Registration (2016 Revision), Chapter X Legal Responsibilities, Article 67.

run their business before registering the company and start a business as soon as possible after registration. It is reasonable to regard the year of firm registration as the year of firm entry. In addition, the fines for not registering a business are significantly greater than the business registration fee.

We examine entry at the industry-year level with entry equal to the sum of newly-established firms based on the registered time in industry i in year t, using the two-digit industry classification of the National Economic Activities from China.

3.1.2 Firm Exit

Chinese law requires a firm shall go through the procedures for deregistration with the firm registration authority when it is declared bankrupt or terminates its business operations.[17] A firm must stop operating after deregistration, otherwise, its behavior is illegal. We treat firm deregistration year as the year of firm exit.

Besides exiting the market through self-deregistration, some firms may exit due to the revocation of the business license by the government. The main reason for being revoked by the government could be a violation of company law or company registration management regulations, such as failure to pass the annual inspection or tax evasion.[18]

We examine exit at both the firm, f, and industry level, i. $Exit_{f,i,t}$ equals 1 for a given firm if it is self-deregistered or its license is revoked. At the industry level, exit is calculated as the nationwide counts of the sum of deregistered and revoked firms based on the deregistration and revocation dates in industry i in year t. As we do for entry, we use a two-digit industry section of Industrial Classification for National Economic Activities to classify each industry.

We also define a specific type of exit, i.e., voluntary exit, which is determined by the owners because the data includes the firm's exit reasons. We classify voluntary exits accord-

[17] Administrative Regulations of the People's Republic of China on the Registration of Enterprise Legal Persons (Revised in 2016), Chapter VII Deregistration, Article 20.

[18] Implementing Rules for the Administrative Regulations of the People's Republic of China on the Registration of Enterprise Legal Persons (Revised in 2014), Supervision and Penalty Provisions, Article 63(9).

ing to their exit reasons. If a firm exit due to poor performance or business adjustment, we define the case as a voluntary exit. Thus, $Exitvol_{i,t}$ is calculated as the nationwide counts of the sum of voluntary exits in industry i, year t.

3.1.3 Summary Statistics

Table 1 presents summary statistics for firm entry, and exit at the industry-year level. Across all industries, the average number of entrants was 15,110 in 2007. It increases gradually with time and rises to 78,096 in 2018. Firm entry experiences a sharp increase after 2013. The total number of entrants in all 89 2-digit industries increased by only about 0.8 million in the first six years post-cloud computing, and increases by about 4 million in the following six years after cloud computing. The sharp upward trend in entry after 2013 is consistent with the rising trend in firm entry coinciding with the time when the cloud computing increase occurs.

The average number of exiting firms rose from 5,089 in 2007 to 27,120 in 2018. The average number of exiting firms decreased slightly from 2007 to 2011 but fluctuated slightly from 2011 to 2013. However, firm exits have seen a large increase after 2014. The total number of exits in all 89 2-digit industries decreased by about 0.07 million from 2007 to 2013 but increased sharply by about 1.8 million from 2014 to 2018 post-cloud computing.

Entrants can rent cloud resources and enter immediately. But it takes some time for entrants to occupy market share and crowd out incumbents. Thus, the impact of cloud computing on firm exit may lag, which may explain why it was 2014 rather than 2013 that saw a sharp increase in firm exit.

3.2 Estimation Strategy

We examine the effect of cloud computing on firm dynamics by exploiting the variation in the impact of cloud computing on different industries.

We set 2013 as the first year of the cloud computing technological shock for China, as in this year the Chinese government allowed the entry of foreign cloud computing companies in China.[19] We use 2013 as this year had nearly all the significant entrants and expansions into cloud computing in China, both new domestic and foreign entrants. Domestically, in 2013 Tencent Cloud was opened to the public one month after Ali Cloud announced its successful 5K testing in 2013. In addition, there were new independent cloud service providers that appeared in that year, including SpeedyCloud, UCloud, QingCloud, and QiniuYun. Lastly, this year saw the entry of many foreign technology firms into the Chinese market. Windows Azure announced that a Public Preview for the Windows Azure service would be available for sign-up starting June 6, 2013.[20] AWS, the biggest cloud computing firm worldwide, announced its entry into the Chinese market on December 2013.[21] IBM, following Amazon, also announced entry into the Chinese market on the same day.[22] Table A.1 shows the key events in the cloud computing industry in China.

2013 was also the year we identify for the beginning of the emergence of AI in China. According to the "China AI Development Report, (2018)"[23] from 2013 to 2015, China entered the preliminary stage of AI development, during which the significance of AI started to be recognized in China. In February 2013, the Chinese government took a significant step towards encouraging AI development by issuing a policy titled "Council Guidelines on Promoting the Healthy and Orderly Development of the Internet of Things". The post-2015 period saw rapid AI development in China, highlighted by the release of numerous AI policy documents. These AI-related policies included "Made in China 2025" issued by the State Council in 2015, Guidelines on Promoting the "Internet+" Action in 2015, and "Next Gen-

[19]We did not consider the emergence of AWS in 2006 as a shock event since Chinese companies were not able to utilize AWS in the US until 2013. The first challenge was latency. Since AWS data centers were located outside of China before 2013, accessing AWS services from China could lead to slow response times. Second, the Chinese government has been maintaining the Golden Shield Project, also called the "Great Firewall of China" (GFC) to block foreign websites, VPNs, emails, and other online resources deemed inappropriate or offensive by authorities since 1998. It means that companies that use foreign cloud services such as AWS and Azure in China may be exposed to the possibility of having their international IP addresses blocked.

[20]See: https://blogs.microsoft.com/2013/05/22/microsoft-announces-expansion-of-azure-in-asia/.

[21]See: https://aws.amazon.com/cn/2013/12/18/announcing-the-aws-china-beijing-region/.

[22]See: https://stockhouse.com/news/press-releases/2013/12/18/ibm-in-china.

[23]See pages 70-77, https://ChinaAIDevelopmentReport2018.pdf.

eration Artificial Intelligence Development Plan" issued by the State Council in 2017. In March 2016, the 13th Five-year Plan for Economic and Social Development of the People's Republic of China was released which emphasized making breakthroughs in AI and cloud computing.

Our sample period is thus from 2007 to 2018 to allow for both pre- and post-shock years. $Post_t$ is defined as a dummy variable, which equals one if year t is between 2013 and 2018, and zero if year t is between 2007 and 2012.

Our estimated specifications thus take the following form:

$$X_{i,t} = \alpha + \beta_{Cloud}(Post_t \times Cloud_i) + \gamma_i + \delta_t + \varepsilon_{i,t} \tag{3}$$

where i and t indicate industry and year, respectively. After our initial analysis examining the impact of the Cloud, we then include AI in additional specifications by including the term, $\beta_{AI}(Post_t \times AI_i)$. Industry i is defined as one of the 89 two-digit industry codes in the Industrial Classification for National Economic Activities. $X_{i,t}$ represents the log of the number of firms entering and exiting at the industry-year level, respectively. All dependent variables are winsorized at the 1% level.

We define the intensity of treatment following Ewens, Nanda, and Rhodes-Kropf (2018). $Cloud_i$ is defined as the proportion of the affected firms whose business scope description contains the keywords of "online," "web," "E-commerce," "Hosting," or "software" to all surviving firms in industry i in 2012, which can measure the influence of cloud computing. We define the magnitude of the usage of these words based on the business scope of all surviving firms in the two-digit industry in 2012 prior to the cloud computing sharp increase.

Specifically, we construct the variable $Cloud_i$ as follows. Firms have to operate in accordance with their registered business scope that has clearly defined the main products or services provided by the firms, otherwise, it is illegal behavior. We first look for the affected firms whose business scope contains the keywords of "online," "web," "E-commerce," "Hosting," or "software".[24] We then calculate $Cloud_i$ as the number of affected firms at the industry level as a percentage of all surviving firms in 2012. The higher the *Cloud* of industry i, the greater the impact of cloud computing on that industry.[25]

The top five industry-segments for *Cloud* are "Internet and related services," "Software and information technology services," "Science and technology promotion and application," "Entertainment," and "Telecommunications, Broadcasting." Nearly all of these industries provide products highly related to hardware, software, and services that are delivered over the web. Those industries with lower *Cloud* contain "Agriculture," "Forestry," "Hunting," "Fishing," "Mining," and "Oil and Gas Extraction." Most of these control industries provide tangible goods, such as "drugs," "vegetables," "fish," and "ore."

To investigate the potentially different impacts of cloud computing and AI, we follow a similar procedure as is used for the Cloud to classify the influence of AI on each industry based on the fact that different industries are affected differently by AI.

We use the same method of defining the influence of cloud computing above but changing the keywords to "AI," "intelligence," "algorithms," "machine learning," "deep learning," "automation," and "robots," which are obtained from Russell and Norvig (2009). Russell and Norvig (2009) delve into four definitions of AI, which differentiate AI on the basis of thinking vs. acting.[26] We extract the keywords "intelligence," "algorithms," "machine learning," and "deep learning" from the first dimension of the definitions of AI, which are concerned with thought processes and reasoning. We also extract the keywords "automation" and "robots" from the second dimension of the definition of AI, which relates to behavior.

[24]Following Ewens, Nanda, and Rhodes-Kropf (2018), we use the same keywords, including "online," "web," "E-commerce," and "Hosting." However, we add another keyword, "software," to our paper because Platforms-as-a-Services, one of the three main types of cloud computing, is regarded as a cloud platform where firms can build and run their own software applications, such as Google App Engine and OpenShift.

[25]Figure A.3 shows the comparison of cloud computing usage by industry between Singapore and China in 2018. The prevalence of cloud computing usage in Singapore surpasses that of China, indicating a more advanced stage of cloud computing development in Singapore. But the trend across industries is similar between the two countries, with Infocomm and Media, Education, and Business Services occupying the top positions in both countries.

[26]The definitions of AI are organized into four categories, that is: thinking humanly, thinking rationally, acting humanly, and acting rationally.

We also add another key "AI."[27]

We also define the influence of AI based on all surviving firms in 2012 prior to the sharp increase in cloud computing given that computer cloud infrastructure is also key to the use of AI. AI_i is defined as the proportion of the affected firms whose business scope description contains the keywords of "AI," "intelligence," "algorithms," "machine learning," "deep learning," "automation," or "robots" to all surviving firms in industry i in 2012.

We find that most industries with higher AI, but lower cloud computing, are manufacturing sectors due to the great benefits of automation in production by substituting directly for workers, especially in routine manual-related occupations, similar to the findings in Acemoglu and Restrepo (2020).

Throughout our specifications, we also include industry fixed effects γ_i, capturing all the time-invariant characteristics for each industry. δ_t is the year fixed effects, controlling for nationwide shocks in a particular year likely to have affected all industries in a similar manner. We cluster the standard errors at the industry level.

4 Empirical Findings on Firm Dynamics for the Cloud

4.1 Firm Entry

4.1.1 Difference-in-Differences Estimates for Firm Entry

We test whether industries that are more dependent on cloud computing experience a higher increase in entry after the sharp increase in cloud computing (*Prediction 1* of our model). The DID estimates with log(Entry) as the dependent variables from equation (3) are shown in column (1) of Table 2. The regression results reveal a positive and statistically significant correlation between cloud computing and firm entry at the industry-year level. Column (1) shows that cloud computing is positively related to firm entry in industries that are more dependent on cloud computing. The coefficient suggests that a 1% increase in exposure to

[27] There is no keyword overlap between cloud computing and AI.

cloud computing is associated with a 0.90% ($= exp(0.897 * 0.01) - 1$) increase in the number of firms entering the market. Relative to the average entry rate in 2012 (0.51%), the average entry rate increases by approximately 1.75 times (= 0.90%/0.51%) post-cloud computing for a 1% increase in exposure to cloud computing.

Based on the difference in Cloud between the bottom and top quartile industries (0.202), industries in the top quartile of cloud computing exposure experienced a 19.87% ($= exp(0.897 * 0.20) - 1$) increase in the number of entrants post-cloud computing, compared to the industries in the bottom quartile. Relative to the average entry rate for industries in the top quartile of cloud computing exposure in 2012 (6.84%), the average entry rate for the top quartile increases by 2.95 times post-cloud computing.

According to Cohn, Liu, and Wardlaw (2022), log-linear regression estimates may be biased and inconsistent due to heteroskedastic model error. To ensure that the estimates are unbiased and consistent, we reestimate the impact using a Poisson regression with count data as the dependent variable in column (2).

The coefficient estimate in Poisson regression is close to the linear regression result and statistically significant at the 1% level, suggesting bias is not an issue in this setting. Compared to industries in the bottom quartile of cloud computing exposure, the industry in the top quartile is expected to have a 24.35% ($= exp(1.079 * 0.202) - 1$) increase in the expected count of entrants post-cloud computing. Relative to the average entry rate for industries in the top quartile of cloud computing exposure in 2012, the average entry rate for the top quartile increases by 3.62 times post-cloud computing.

4.1.2 Yearly Estimates for Firm Entry

We turn next to examine the year-wise effect of cloud computing on firm entry by conducting an event study:

$$X_{i,t} = \alpha + \sum_{k \geq -6, k \neq -1}^{5} \beta_k (D_{2013+k} \times Cloud_i) + \gamma_i + \varepsilon_{i,t} \tag{4}$$

where i and t indicate industry and year, respectively. $X_{i,t}$ represents the natural log of firm entry at the industry-year level. All dependent variables are winsorized at 1%.

D_{2013+k} jointly represent a window of periods around the sharp increase in cloud computing. D_{2013+k} is a series of dummies indicating whether t-2013=k, with k=-6, -5, -4, -3, -2, 0, 1, 2, 3, 4, 5. The omitted time category is k=-1 to avoid collinearity. The coefficients β_k measure the annual increases in entry post-cloud computing relative to the year before the sharp increase in cloud computing. Standard errors are clustered at the industry level.

Figure 1a shows the yearly coefficients with log(Entry) as the dependent variable. We find that none of the pre-treatment indicators shows any statistical power. Coefficients β, however, become statistically significant at the 5% level right after the increase in cloud computing. The coefficients remain strong and significant after 2013.

Taken together, these results show that the differences in log(Entry) across different industries affected by cloud computing begin to diverge with the cloud computing increase. These results are consistent with the prediction that the differential effects on firm entry across different industries are related to the increase in cloud computing.

4.2 Firm Exit

4.2.1 Firm-Level Analysis for Firm Exit

We test for the changes in firm exit after the sharp increase in cloud computing using a DID estimator. Estimates in Panel A, Table 3 are consistent with the conclusion that exits increase sharply post-cloud computing.

The detailed firm-level data in the RESSET Enterprise Data allows us to examine exit at the firm level given that our dataset tracks the birth, survival, and death of each firm. This analysis at the firm level helps to alleviate reverse causality concerns as a firm's exit decision will not reversely affect the development of cloud computing.

These specifications take the form:

$$Exit_{f,t} = \alpha + \beta_{Cloud}(Post_t \times Cloud_i) + \theta_f + \delta_t + \varepsilon_{f,t} \tag{5}$$

where f and t indicate firm and year, respectively. $Exit_{f,t}$ equals zero if firm i survived through year t and equals one if firm i exited that year. The outcome is set to missing in the years after death.

We include θ_f, firm fixed effects and δ_t, year fixed effects. To address possible concerns about within-firm auto-correlation, standard errors are clustered by firm.

Firm-level estimate confirms that cloud computing is associated with firm exit. Regression that controls for the differential influence of cloud computing confirms that in industries more affected by cloud computing, firms are more likely to exit after 2013 as shown in column (1) of Panel A, Table 3.

The coefficient in column (1) suggests that post-cloud computing, for a 1% increase in exposure to cloud computing, the exit probability increases by approximately 1.30% (= 0.025%/1.90%) relative to the average exit probability in 2012 (1.90%), where 2012 is the year prior to the introduction of cloud computing in China. Relative to the exit probability for industries in the top quartile of cloud computing exposure in 2012, the exit probability in the top quartile increases by 23.96% post-cloud computing.

To account for potential regional factors, we use region-year fixed effects instead of relying solely on year fixed effects in the model. The results are similar as shown in column (1) of Appendix Table A.2. The results remain positive and significant, as shown in column (2) of Appendix Table A.2.

4.2.2 Industry-Level Analysis for Firm Exit

Column (2) of Panel A, Table 3 shows the result of OLS regression from equation (3) by using log(Exit) at the industry-year level as the dependent variables. We include industry and year fixed effects. Regression that controls for the differential industry exposure to cloud computing shows that cloud computing has a positive relation with firm exit as shown in column (2) of Panel A, Table 3. The result in column (2) is significant at the 1% levels.

Relative to the average exit rate of 6.57% in 2012, the exit rate increases by approximately 11.83% corresponding to a 1% increase in exposure to cloud computing. Furthermore, industries in the top quartile of cloud computing exposure experience a 16.92% (calculated as $= exp(0.77 * 0.20) - 1$) increase in the number of firm exits post-cloud computing, compared to industries in the bottom quartile. Given that the average exit rate for industries in the top quartile was 10.30% in 2012, the exit rate for the top quartile industry increases by a multiple of 1.67 times post-cloud computing.

Column (3) of Panel A, Table 3 estimates Poisson regression using the number of firm exits as the outcome variable. The coefficient in column (3) confirms that cloud computing is positively related to firm exit in industries more affected by cloud computing, with a significance level of 5%.

4.2.3 Yearly Estimates for Firm Exit

We also examine how the annual exit rates are related to cloud computing. Figure 1b shows that the coefficients β are mostly close to zero without any statistical power in the pre-period. These annual rates, however, diverge for the treated industries after 2014. Annual rates remain stronger and significant after 2014, a year following the sharp increase in cloud computing. These results imply that it takes about one year for inefficient incumbents to exit. Figure 1b demonstrates that the timing of the increases in firm exits is consistent with the sharp increase in cloud computing.

4.2.4 Voluntary Exit

We now redefine exit to a narrower measure, focusing only on voluntary exit. Some firms exit involuntarily because they violate the company law or company registration management regulations, such as by evading taxes or engaging in business activities beyond their approved registered business scope. These involuntary exits are driven by the government, not by the entrepreneurs' own choices.

Because cloud computing increases the productivity cut-off and reduces business profits, some firms with negative business profits may voluntarily exit. The data reported by the National Enterprise Credit Information Publicity System includes firm exit reasons. Voluntary exit is defined as the case where the exit reasons include poor performance and business adjustment.

Columns (4)-(6) in Table 3 shows the results for the relation of cloud computing with voluntary exit. Column (4) in Table 3 shows the firm-level estimates with voluntary exit (Exitvol) as the dependent variable from equation (5). $Exitvol_{f,t}$ equals one if firm i exited voluntarily that year and equals zero if firm i survived through year t. The outcome is set to missing in the years after death. The result at the firm level confirms that cloud computing is positively associated with firm voluntary exits as shown in column (4). Columns (5) and (6) show similar results at the industry level where we sum up the number of exits. We estimate both OLS and Poisson models at the industry level.

We controlled for regional factors by using region-year fixed effects instead of year fixed effects in our model. The result on voluntary exit is consistent in column (3) of Appendix Table A.2. Furthermore, replacing industry fixed effects with firm fixed effects did not change the positive and significant results, as shown in column (4) of Appendix Table A.2.

Column (5) in Table 3 also shows the estimate with log(Exitvol) as the dependent variables from equation (3). log(Exitvol) is calculated by logging the counts of voluntary exits at the industry-year level. Relative to the industry in the bottom quartile, the industry in the top quartile experienced a 36.93% increase in the number of firms exiting voluntarily post-cloud computing.

We also reestimate the Poisson regression using the number of voluntary exits as the outcome variable. As shown in column (6) of Table 3, the result confirms that cloud computing is associated with firm voluntary exit.

Furthermore, the positive relation of cloud computing with voluntary exits in columns (5) and (6) are larger than the positive relation of cloud computing with firm exits in columns (2) and (3). These estimates show that firm voluntary exit is mainly responsible for the positive relation with cloud computing. Specifically, markets become more competitive post-cloud computing (as will be demonstrated subsequently). Consequently, incumbents find it more difficult to maintain positive profits in the more competitive market and therefore decide to exit due to poor performance.

4.3 Prices for Cloud Computing and Firm Dynamics

To accurately assess the impact of prices for cloud computing on firm dynamics, we collect prices at the end of each year from Alibaba Cloud, the largest provider in China. Alibaba Cloud started to provide cloud services to the public in July 2011, so we collected prices from 2011. To collect historical prices, we used the Internet Archive[28], and historical news.

However, the cloud servers provided by Alibaba Cloud were highly configured and expensive before 2013. For example, the minimum configuration of cloud servers is 2 core vCPU/ 1.5G Memory / 150 G Disk Storage / 5M DataTransfer, whose price is 499 RMB/month. The price of Alibaba Cloud did not change until 2013. Alibaba Cloud started to reduce its price and provide low-configuration cloud servers for entrepreneurs after 2013 following the entry of foreign and domestic cloud computing providers.

Alibaba Cloud provides three basic products: computing, databases, and storage. We focus on the ECS (Elastic Compute Service) price, which provides virtual cloud servers and pooled IT resources. Alibaba Cloud offers many different configurations of ECS products in terms of the power of the processor (vCPU), memory, the amount of disk storage allocated and network performance. We use the basic ECS product which is configured with 1 core vCPU/ 1G Memory / 40 G Disk Storage / 1MB DataTransfer. We collect data for only "reserved" instances that provide a capacity reservation when used in a specific availability

[28]It is also called the WayBack Machine. It is used to pull posted prices from web pages that were archived in prior periods.

zone.[29] The ECS product is priced in terms of RMB per month.

The price trend of Alibaba Cloud is shown in Appendix Figure A.4. The prices of Alibaba Cloud were decreasing from 2012 to 2018. The prices of Alibaba Cloud experienced a steep decline from 2013 to 2014, likely due to the entry of domestic and international cloud providers, such as Tencent Cloud and AWS.

To study the impact of prices for cloud computing on firm dynamics, we estimate the following regression:

$$X_{i,t} = \alpha + \beta_1(Price_t \times Post_t \times Cloud_i) + \beta_2(Price_t \times Cloud_i) + \gamma_i + \delta_t + \varepsilon_{i,t} \tag{6}$$

where $Price_t$ is defined as the price of Alibaba Cloud, which is configured with 1 core vCPU/ 1G Memory / 40 G Disk Storage / 1TB DataTransfer (unit: 100RMB/Month). Since the prices of Alibaba Cloud were unchanged before 2013, we use the price of Alibaba Cloud in 2012 to measure the price of Alibaba Cloud from 2007 to 2011.

$Post_t \times Cloud_i$ is collinear with $Price_t \times Cloud_i$, and $Price_t \times Post_t$ is collinear with the year fixed effects. Hence, $Post_t \times Cloud_i$ and $Price_t \times Cloud_i$ are omitted in the regressions.

The results are shown in Table 4. Column (1) shows the heterogeneous impact of the prices of cloud computing on firm entry by using OLS regressions from equation (6). It shows that the impact of cloud computing on firm entry is more pronounced when the price of cloud computing is lower. The result shown in column (2) is consistent when we use Poisson regression. Both estimates are statistically significant.

Columns (3) and (4) show the heterogeneous impact of prices for cloud computing on firm exit using OLS and Poisson regressions, respectively. Both results again show that the impact of cloud computing on firm exit is more pronounced when the price for cloud computing is lower. Although the estimate in OLS regression is not statistically significant, the estimate in Poisson regression is statistically significant at the 1% level.

[29] Reserved instances provide a significant discount (up to 79%) compared to on-demand instances. Alibaba Cloud often offers discounted reserved ECS packages for promotions.

5 Differences between Cloud Computing and AI

5.1 Differences in Exit between Cloud Computing and AI

We now examine whether there are differences in the effect of cloud computing and artificial intelligence on firm exit. Cloud computing is predicted to increase firm exits by decreasing adjustment costs. However, AI could increase a firm's fixed costs, given the substantial amounts of data and computational power required to train AI models. According to Babina, Fedyk, He, and Hodson (2020), firms investing in artificial intelligence (henceforth, AI) experience faster growth and AI tends to benefit larger firms given the high use of data used in AI. Thus we might expect that, unlike cloud computing, AI may actually decrease exits of larger firms.

To study the potential differences in the impact of cloud computing and AI on firm exit, we estimate the DID regression including a term for AI in addition to cloud computing. We estimate:

$$Exit_{f,t} = \alpha + \beta_{AI}(Post_t \times AI_i) + \beta_{Cloud}(Post_t \times Cloud_i) + \theta_f + \delta_t + \varepsilon_{f,t} \tag{7}$$

where $Cloud_i$ is a measurement of the influence of cloud computing and AI_i is a measurement of the influence of AI. We also include firm fixed effects and year fixed effects.

Column (1) of Table 5 shows the result at the firm level. It confirms that cloud computing has a positive and statistically significant relation with firm exit after considering the potential confounding effects of AI. However, the regressions that control for the differential industry exposure to AI reveal a negative correlation between AI and firm exit as firm exits decreases subsequent to the increased use of cloud computing in industries that are more impacted by AI.

The results for OLS regressions and Poisson regressions are also shown in columns (2) and (3) of Table 5, respectively. Both estimates in columns (2) and (3) confirm that cloud computing increases firm exit, but AI decreases firm exit.

We hypothesize that cloud computing and AI are used by different sizes of firms. Cloud computing is an incredibly cost-effective solution for small firms and allows them to enjoy the same IT resources as larger firms without the need for costly upfront hardware investments. However, given lower fixed costs, there will be more churn with more exit as well as entry and that these would be more pronounced among smaller firms.

However, Babina, Fedyk, He, and Hodson (2020) find that the positive effects of AI on firm growth are concentrated among larger firms. Therefore, we examine whether AI reduces the tendency for larger firms to exit. We hypothesize given the evidence from Babina, Fedyk, He, and Hodson (2020) that AI is more beneficial to larger firms because using AI requires large amounts of data to use effectively. It also requires significant firm resources to develop.

We divide the sample into two subsamples using the median of registered capital by industries for all surviving firms in 2007. The results at the firm level are shown in columns (4)-(5) of Table 5. Columns (4) and (5) show the results for the small and big firm subsamples, respectively. The impacts of cloud computing on exit for firms of different sizes are positive, with the positive impact of cloud computing on firm exit being larger among smaller firms.

However, the effects of AI on exit for firms of different sizes are quite different. In industries more affected by AI, we find that larger firms are *less* likely to exit as shown in column (5) of Table 5. Smaller firms in industries more impacted by AI are more likely to be crowded out of the market due to stronger competition from larger firms as shown in column (4). Hence, the positive benefits (lower exit rates) of AI are concentrated among larger firms.

Furthermore, to study whether the differences in the coefficients of Post_AI (or, Post_Cloud) between small and large firms are statistically significant, we examine the following regression:

$$Exit_{f,t} = \alpha + \beta_{\Delta AI}(Size_f \times Post_t \times AI_i) + \beta_{\Delta Cloud}(Size_f \times Post_t \times Cloud_i)$$
$$+\beta_{AI}(Post_t \times AI_i) + \beta_{Cloud}(Post_t \times Cloud_i) + \beta_1(Size_f \times Post_t) + \theta_f + \delta_t + \varepsilon_{f,t} \quad (8)$$

where $Size_f$ equals one if firm f is in a small subsample and zero if firm f is in a big subsample. $\beta_{\Delta AI}$ ($\beta_{\Delta Cloud}$) measures the different effects of AI (cloud computing) between small and big subsamples.

The estimates of $\beta_{\Delta AI}$ and $\beta_{\Delta Cloud}$ are shown in Table 5. Both estimates are positive and statistically significant at the 1% level. The results confirm that AI reduces exit for larger firms while cloud computing is associated with increased exit for both large and small firms.

We also examine the difference in voluntary exit between cloud computing and AI. Column (1) in Table 6 shows the estimates using full sample. The results show that increased cloud computing is associated with an increase in voluntary exits while increased AI is associated with a decrease in voluntary exits. Both estimates are statistically significant at the 1% level.

We further divide the sample into two subsamples based on the median of the registered capital by industries for all surviving firms in 2007. Column (2) uses small subsamples. The estimates show that both cloud computing and AI increase firm voluntary exits. Column (3) uses large subsamples. The relation of cloud computing with voluntary exits is still positive and statistically significant. However, the relation of AI with voluntary exits is negative and statistically significant.

In sum, the estimates of cloud computing and AI on voluntary exits are similar to estimates on firm exits. Cloud computing is positively related to voluntary exit for firms of different sizes. In contrast, larger firms get positive benefits from AI and have lower exit rates, though smaller firms in industries more affected by AI are more likely to exit voluntarily.

5.2 M&A Differences between Cloud Computing and AI

We also examine the differences in M&A between Cloud Computing and AI. Although the database does not directly record M&A information for companies, it encompasses information on shareholder changes for each firm. During a M&A transaction, a new company acquires stock rights from the incumbent shareholders of the firm, which may include companies or individuals.[30] We classify a transaction as a M&A when a firm transfers its stock rights from its original shareholders to a different company.

Table 7 reports the firm-level results of cloud computing and AI on M&A for firms of different sizes. We regress an indicator for whether the firm is merged in a given year. The variable *M&A* equals one if a given firm is merged in a given year and to zero if it continues to operate. The result in column (1) using full-sample shows that cloud computing and AI are strongly associated with increases in M&A.

The full sample is also split into two subsamples based on the median of registered capital by industries for all surviving firms in 2007, as shown in columns (2) and (3). Overall we find that for cloud computing, both large and small firms are likely to merge, while for firms exposed to AI, large firms are likely to be merger targets, while small firms are less likely. Large firms, owing to their likelihood of possessing substantial data, become more appealing within industries impacted by AI. Therefore, large firms are more likely to be merged by other firms in AI affected industries.

6 Industry Concentration and Size Distribution

6.1 Industry Concentration

We now study differences in changes in industry concentration after the increased adoption of cloud computing and AI. We use the information on firms' sales and assets from the

[30] We exclude transactions when the stock rights are transferred from companies or individuals to other individuals. Additionally, We exclude cases involving the transfer of stock rights from a parent company to its subsidiary, as well as from a subsidiary to its parent company.

NTSD dataset to calculate traditional measures of concentration. We use HHI to measure industry concentration, where HHI is the Herfindahl-Hirschman Index and is calculated by squaring the market share percentage of each firm competing in a market and then summing the resulting numbers.

The first column in Table 8 shows the estimates of the different effects of cloud computing and AI on industry concentration by using firms' sales to calculate the market percentage. The results show that industry concentration goes down post-cloud but goes up post-AI. Economically, the results show that a one-standard-deviation increase in exposure to cloud computing post-cloud will lead to a 0.11-standard-deviation decrease in HHI while a one-standard-deviation increase in exposure to AI will lead to a 0.07-standard-deviation increase in HHI. Both estimates of cloud computing and AI are statistically significant at the 1% and 5% levels, respectively.

The second column in Table 8 shows that our estimates are robust to how we measure HHI. Using firms' assets to calculate HHI, increasing the exposure to cloud computing by one standard-deviation (SD) would decrease the HHI by 0.15 SD while increasing the exposure to AI by 1 SD would increase the HHI by 0.08 SD. Both estimates are also statistically significant at the 1% and 5% levels, respectively.

These results in Table 8 imply that cloud computing is associated with decreases in industry concentration while AI is associated with increases in industry concentration.

6.2 Size Distribution across Industries

We now examine the changes in the size distribution of surviving firms across industries. We use the information on sales and assets of firms from the NTSD dataset to measure firms' size. Table 9 reports the results examining the central tendency and dispersion of size distribution post-cloud computing.

Columns (1) and (2) show the estimates using median and mean sales as dependent variables. These estimates show that cloud computing is associated with a decrease in the average size of cloud affected industries. At the same time, AI has no impact on the average size of AI affected industries. Both estimates of cloud computing are statistically significant.

The coefficient in column 2 implies that a one-standard-deviation increase in exposure to cloud computing would lead to a 34.36-standard-deviation reduction in average sale. Relative to the average sale of industries in the top quartile of cloud computing exposure in 2012 (here 132.83 million RMB), their average sale decreased by 16.09% post-cloud computing.

Columns (3)-(4) show that our estimates are robust to how we measure firm size. Using firms' assets to calculate the median and mean size, the coefficients in columns (3) and (4) confirm that cloud computing increases the proportion of small firms in cloud affected industries while AI has no impact on the size composition within industries. The average asset of industries in the top quartile of cloud computing exposure decreases by 19.08% post-cloud computing relative to their average asset in 2012 (here 347.75 million RMB). Both estimates of cloud computing in columns (3) and (4) are statistically significant.

We then examine the impact of cloud computing and AI on size concentration as measured by the coefficient of variation. Column (5) shows that the coefficient of variation of the size of all firms by industries declines by 0.140 (s.e.=0.044) post-cloud computing. The average size dispersion of industries in the top quartile of cloud computing exposure declines by 7.94% post-cloud computing relative to the mean coefficient of variation in 2012 (here 0.36).

Column (6) shows the same pattern, using assets to measure size dispersion. The estimate indicates that, relative to the mean coefficient of variation in 2012 (here 0.32), the size concentration of industries in the top quartile of cloud computing exposure increases by 10.23% post-cloud computing. Both estimates in columns (5) and (6) are statistically significant at the 1% level. In addition, columns (5) and (6) also show that AI has no impact on size dispersion since the coefficients of Post_AI are not significant.

In sum, the estimates in Table 9 imply that cloud computing increases the ratio of smaller firms inside the cloud affected industries. In contrast, AI has no impact on size composition.

7 Equity Financing Decisions

7.1 Firm Level Evidence on Equity Financing Decisions

We now examine differences in the use of equity financing post increases in cloud computing. It is generally recognized that new technologies can cause adaptation by financial intermediaries (Chandler 1965; Laeven, Levine, and Michalopoulos 2015). Ewens, Nanda, and Rhodes-Kropf (2018) show that technological shocks to the cost of starting new businesses have led to changes in the investment strategy of venture capitalists, particularly in the early-stage financing of software and service-oriented startup ventures.

Due to data limitations, we only focus on equity financing, not debt financing. It is reasonable to focus on equity financing decisions since equity financing is more likely to be used for new technologies. Risk-averse creditors care more about whether the borrowers can pay the principal and interest on time, so they prefer to lend to older and large firms with stable cash flows(Berger and Udell 1998). However, equity investors, especially venture investors, may follow the development of new technologies because shareholders can share the potential returns of the technology firms' substantial growth.

Table 10 shows the results examining equity financing decisions. First, we examine equity financing at the firm level. We estimate the DID estimator with *fin* as the dependent variable, where *fin* is an indicator of whether a given firm is financed in a given year. The outcome is set to missing if a firm exits that year.

The firm-level results examining equity financing decisions are shown in column (1) of Panel A, Table 10. It shows that cloud computing is associated with an increase in the probability of being equity-financed for firms in industries more affected by cloud computing. AI is also associated with an increase in the probability of being equity-financed for firms in AI-affected industries. Both estimates are statistically significant at the 1% level. The estimates imply that a one-standard-deviation increase in exposure to cloud computing (AI) will lead to a 4.3-standard-deviation (8.15-standard-deviation) increase in the probability of being equity-financed.

Next, in order to exploit the relation of cloud computing with the financing decisions of venture capitalists (VCs), we examine venture capital financing by itself.[31] In column (1) of Panel B, we find smaller but still significant effects of cloud computing and AI when we only use the venture capital financing data. The results show that both cloud computing and AI are associated with an increase in the probability of being VC equity-financed for firms. A one-standard-deviation increase in exposure to cloud computing (AI) will increase the probability of being VC equity-financed by 2.24 SD (1.58).

7.2 Industry Level Evidence on Equity Financing Decisions

We also estimate the DID model at the industry-year level, using alternative measures of equity financing. Column (2) f Panel A, Table 10 use the natural log of the number of equity-financed firms in a given industry in a given year (log(FNumber). The estimates using OLS regression show that increased cloud computing is associated with increases in the number of equity-financed firms in industries more affected by cloud computing.

However, the coefficient of AI is not significant at the industry-year level. We examine and find that the insignificant effects of AI on the number of equity-financed firms can be attributed to the concentration of equity financing in a more limited number of industries (see Appendix A.5(a)) instead of being spread out across industries.

Column (3) estimates Poisson regression using the number of equity-financed firms as the dependent variable. The estimate is close to the estimate in OLS regression. Both estimates of cloud computing in columns (2) and (3) are statistically significant at the 1% level.

Column (4) use the proportion of equity-financed firms to all surviving firms in a given industry in a given year, expressed in percentage % (FRatio). The result shows that increased cloud computing is associated with increases in the proportion of firms being equity-financed in cloud-affected industries. In addition, the coefficient of AI is also positive and significant.,

[31] We remove equity financing that is not venture capital financing, such as private placement and refinancing after listing.

implying that increased AI is associated with increases in the proportion of firms being equity-financed in AI-affected industries[32].

Column (5) of Panel A uses the natural log of the equity financing amount in a given industry in a given year (log(FAmount)). Note not all firms have this variable reported thus the observations are smaller. The estimate also shows that increased cloud computing is associated with increases in the amount of financing in cloud-affected industries. Since the financing amount is concentrated in a limited number of industries (see Appedix A.5(a)), the results for AI are insignificant.

The estimates are robust to using measures of VC financing, as shown in Panel B, Table 10. Column (2) shows that increased cloud computing is associated with an increase in the number of VC-financed firms in affected industries while the estimate of AI is not significant. Column (3) shows that both increased cloud computing and increased AI are associated with increases in the ratio of VC-financed firms to all surviving firms in cloud-affected and AI-affected industries, separately. Column (5) also finds that the amount of VC financing in affected industries goes up post-cloud computing.

8 Robustness Tests

8.1 Alternative Measures

8.1.1 Alternative Measures of the Influence of Cloud Computing

We also simply assign each of the 89 two-digit industry sections to the "treated" or "control" group according to Ewens, Nanda, and Rhodes-Kropf (2018). Unlike $Cloud_i$, which is a continuous measurement of the influence of cloud computing on a given industry, $Treat_i$ is a dummy variable.

First, we also focus on firms that survived in 2012. Second, we cut the texts of all business

[32] Appedix A.5(b) shows that, unlike the number of equity-financed firms, the concentration of the proportion of firms being equity-financed across industries is smaller. This is why the estimate of AI in this regression is significant.

scope into words after excluding a list of common words and conjunctions, such as "the," "like," "about," "and," "department," "material," "plan," "product," "service," "management," "company," and "firm." These excluded words appear commonly in all industries and have no specific meaning. Third, we aggregate and rank the words at the industry level. If the top 100 words in the industry contain "online," "web," "E-commerce," "Hosting," or "software," we assign it to the "treated" industry, otherwise, it is assigned to the "control" industry.

Appendix Table A.3 shows the treated and control industry sections in China. The 17 industry segments classified as treated are "Computer and Electronic Product Manufacturing," "Instrument Manufacturing," "Wholesale Trade," "Internet and related services," "Software and information technology services," and "Professional, Scientific, and Technical Services."[33] Nearly all of these industries provide products highly related to hardware, software, and services that are delivered over the web.

We estimate the treatment effects by substituting the interaction term between Post and Cloud with the interaction term between Post and Treat in equation 3. All estimates shown in Appendix Table A.4 are still positive and significant using industry-year and firm regressions providing further support for our baseline estimates.

8.1.2 Alternative Measures of Industry Classifications

We also use several alternative measures of industry classifications to check the robustness of our results. We redefine the influence of *Cloud* by using more detailed cells (417 three-digit industry cells). Our estimates are still significant and positive, providing further support for our baseline estimates (see Table A.6).

In addition, we use alternative outcome variables as additional robustness tests. The annual ratios of firm entry and exit to the surviving firms in the previous year are used as

[33] The remaining categories are "Postal Service," "Telecommunications, Broadcasting," "Capital markets services," "Other Financial Activities," "Scientific Research and Development Services," "Professional and Technical Services," "Science and technology promotion and application," "News and Publishing Industries," "Broadcasting, Motion Picture and Sound Recording Industries," "Arts," "Entertainment."

the dependent variables to control for the potential impact of the number of surviving firms. The estimated effects are still positive and statistically significant (see Table A.7).

8.2 Other Potential Confounding Policies

The first policy we examine is the Registered Capital Registration System Reform which started in China in March 2014. This reform no longer requires a minimum amount of registered capital to set up a company in China. Suppose industries with higher average registered capital before the reform are less exposed to the reform for registered capital since the average registered capital for those industries far exceeds the minimum amount of registered capital. Based on this case, we control for the interaction term between the average registered capital and post dummies. We calculate the log of the average registered capital (CAP) inside each industry by using the surviving firms in 2012, rather than 2013 to avoid the potential impact of increased cloud computing. Since the registered capital registration system reform began in 2014, we use $Post2014$, a dummy variable, to indicate if year t is between 2014 and 2018. The main results still have a significant and positive effect, with a slight change in magnitude as shown in Panel A of Table A.5.

Second, we examine the mass entrepreneurship and innovation campaign by China since 2015. This campaign was aimed to promote innovation and boost entrepreneurship-driven employment. Since the policy was advanced to promote entrepreneurship for all industries equally, the impact of this policy may be absorbed by including year fixed effects. Empirically, we also reestimate the baseline DID model between 2011 and 2014. Our previous results on firm entry remain robust as shown in columns (1)-(2) of Panel B, Table A.5. The results on firm exit are not significant because the impact of cloud computing on exit is not significant until after 2014, as evidenced by figure 1b. We thus conclude that our results are not primarily driven by the mass entrepreneurship and innovation campaign police.

The third policy we examine is the Strategic Emerging Industries (SEI) policy launched in 2012. Seven strategic emerging industries (SEI) were identified and received increased financial support from the government. This additional support may increase the competitive advantage for incumbents and hinder free competition. It suggests that the SEI policy may have a negative relation with entry and exit. Nevertheless, we find that the estimated relations with cloud computing are not affected by the SEI policy when we control for the interaction term between the SEI-related industries and post dummies as shown in Panel C of Table A.5.

8.3 Placebo Tests

To check whether the results are influenced by potential omitted variables, we conduct two permutation tests. We first construct a placebo test by randomly assigning the treatment variables to two-digit industries, $Treat_{Random}$. We replace the true treatment dummies, $Post * Treat$, with the randomly generated interaction term, $Post * Treat_{Random}$. In order to mitigate the impact of rare events and increase the power of the test, the placebo tests are repeated 500 times.

Figure A.6(a) shows the result for firm entry. Only 3.41% of the estimated coefficients of $Post * Treat_{Random}$ are larger than the actual estimated coefficient in Column (1) of Table A.4. Figure A.6(b) shows the result for firm exit. Only 2.20% of the estimated coefficients of $Post * Treat_{Random}$ are larger than the actual estimated coefficient in Column (2) of Table A.4.

Second, we randomly assign the value of $Post$ and estimate the treatment effect by replacing the true treatment dummies, $Post * Treat$, with the randomly generated interaction term, $Post_{Random} * Treat$. Figure A.6(c) and A.6(d) show the results for firm entry and exit, respectively. The probabilities that the coefficients from the placebo test are greater than the actual estimates are both 0.20% in Figure A.6(c) and A.6(d).

Taken together, the results in Figure A.6 support that our baseline results are not driven by random variables.

Lastly, there may be a concern that the increase in firm entry and exit after the sharp increase in cloud computing may be due to the adaption in the investment strategy of investors after technological shocks, instead of the adoption of cloud infrastructure. Ewens, Nanda, and Rhodes-Kropf (2018) find that VCs have invested in more startups after technological shocks to the cost of starting new businesses, which may lead to an increase in firm entry. To address this potential channel, we exclude firms from our sample that have previously obtained equity or VC financing. The exclusion of these subsamples did not materially impact our estimates, so we conclude that our results are not primarily driven by the changes in the investment strategy.

9 Conclusions

This paper examines the relation between cloud infrastructure and industry dynamics in China, focusing on the sharp increase in cloud computing in China that began in 2013. We examine whether cloud computing is associated with increased entry by new firms and increased exit by existing incumbent firms as entry costs and entry barriers are predicted to decrease for new firms causing less efficient existing firms to exit. We also contrast the impact of cloud computing with AI.

We find that the increase in cloud computing is associated with increases in firm entry and exit. Our results are consistent with cloud computing lowering the upfront fixed costs and variable costs for entrants and thereby raising the relative competitiveness of entrants using cloud computing versus incumbents without cloud computing. We find that the increase in exits post-cloud computing is mainly arising from voluntary exits, including operation failures and business adjustments.

In contrast, we find different tendencies for exit when we examine industries and firms that are more influenced by artificial intelligence (AI). Larger firms in industries impacted more by AI are less likely to exit. These results are consistent with AI being more effective when used by larger firms who are more likely to produce more data which is key in the use of AI.

We also find that cloud computing is associated with increases in the probability of being merged for both small and large firms, In contrast, the adoption of artificial intelligence (AI) only shows a positive association with merger probabilities for large firms. These results are consistent with larger firms being more effective with the use of AI. We also show that industry concentration and the average and median firm size decrease post-cloud computing. Post-AI, industry concentration increases. These results are again consistent with smaller firms benefiting from cloud computing while larger firms benefit from AI.

We also find that financing patterns change between cloud computing and AI. At the firm level, there is a higher probability of equity financing for both cloud computing and AI. However, comparing these technologies at the industry level, we find cloud computing, but not AI, is associated with increased equity and VC financing.

To conclude, our study shows that cloud computing is associated with increased industry churn and decreased concentration while AI is associated with increased concentration and decreased industry churn as exit decreases. Our results do not address the performance and efficiency consequences of cloud computing or AI due to data limitations. We also acknowledge that our study can not estimate the elasticity of productivity with the usage of cloud computing or AI. However, the results for AI suggest that larger firms benefit from its use through a decreased tendency to exit. Our results raise additional questions for further research on how different new technologies affect the productivity and performance of firms.

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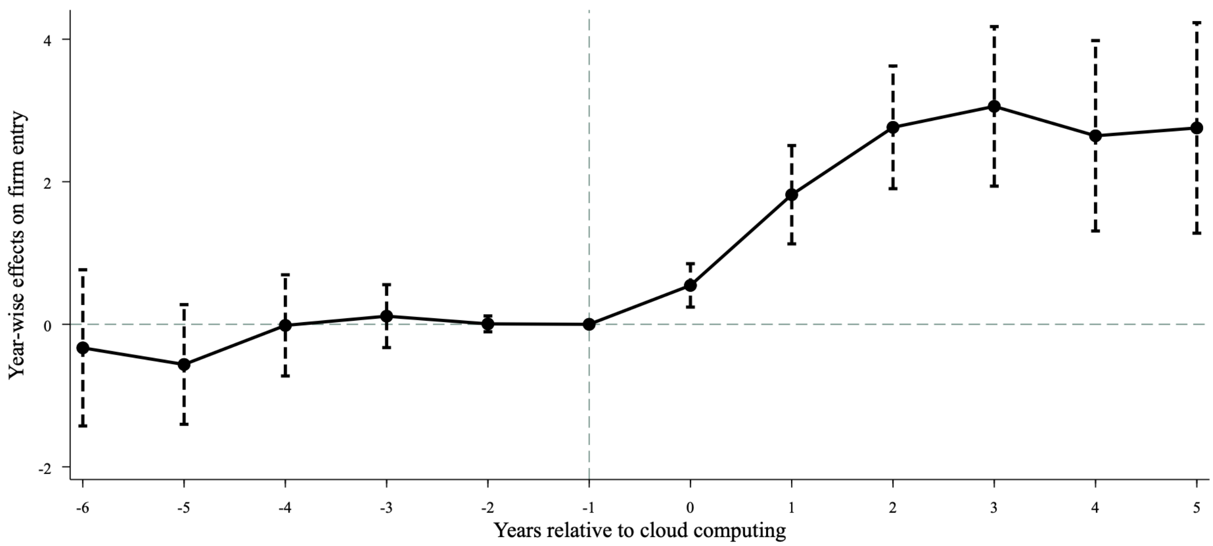
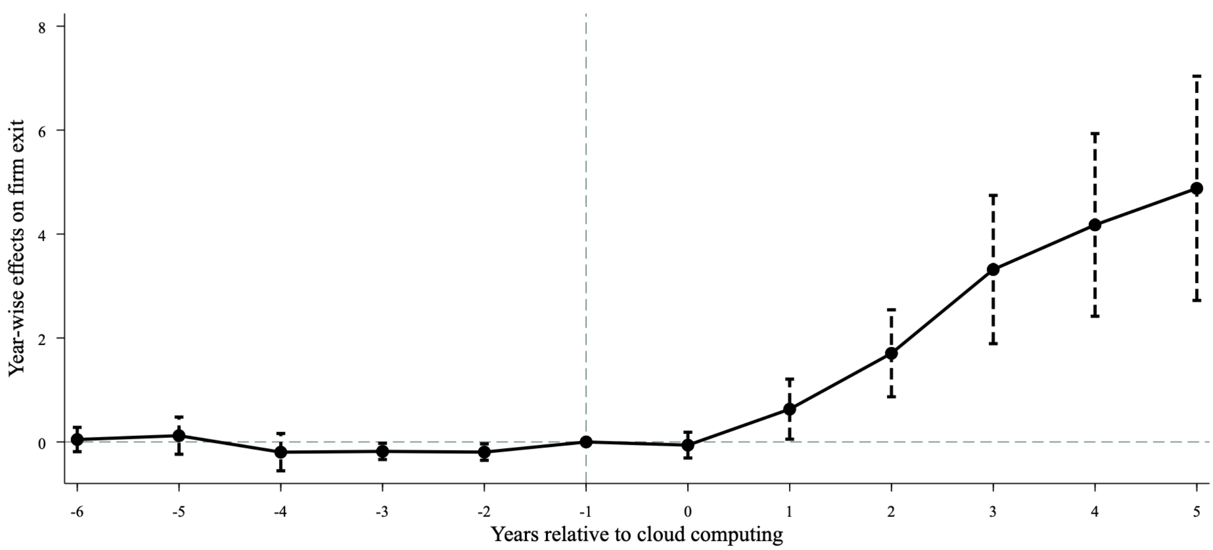
Figure 1: Event Study Results for Firm Entry and Exit

This figure reports the yearly coefficients of cloud computing on firm entry and exit as obtained from estimating Equation 4. Year $t = 0$ signifies the current year of 2013. We use 2012 as the reference point. Error bars mark the 95% confidence intervals. Standard errors are clustered at the industry level. The vertical axis represents the coefficients β_k from Equation 4. β_k measures the annual rates of cloud computing across different industries relative to the year before the sharp increase in cloud computing. Figure (a) shows the dynamics effects on firm entry. Figure (b) shows the dynamics effects on firm exit.



(a) Entry



(b) Exit

Table 1: The Summary Statistics of RESSET Enterprise Data

This table presents the summary statistics for firm entry, and exit each year at the industry-year level. We use 89 distinct two-digit industries from Industrial Classification for National Economic Activities in China (GB/T4754-2011) to calculate the number of firm entrants, and exits each year.

Variables	Year	Obs.	Sum	Mean	S.D.	Min	Median	Max
Entry	2007	89	1,344,781	15,110	40,776	30	5,716	338,768
	2008	89	1,388,593	15,602	41,730	24	5,490	342,808
	2009	89	1,658,437	18,634	50,226	25	5,971	406,113
	2010	89	1,926,881	21,650	59,588	13	6,717	481,746
	2011	89	2,157,704	24,244	69,261	22	6,775	551,714
	2012	89	2,178,399	24,476	68,596	23	7,403	525,963
	2013	89	2,903,496	32,624	89,290	10	8,533	637,360
	2014	89	3,970,724	44,615	125,475	22	11,023	914,897
	2015	89	4,715,903	52,988	147,494	27	14,133	981,634
	2016	89	5,865,994	65,910	186,115	6	16,984	1,276,617
	2017	89	6,355,054	71,405	209,801	0	15,182	1,560,322
	2018	89	6,950,561	78,096	229,569	0	14,626	1,647,073
Exit	2007	89	452,911	5,089	16,096	8	1,722	137,283
	2008	89	433,699	4,873	14,877	14	1,604	125,252
	2009	89	386,128	4,339	13,621	8	1,420	114,529
	2010	89	381,475	4,286	13,041	4	1,291	108,940
	2011	89	388,199	4,362	13,367	5	1,223	110,788
	2012	89	419,776	4,717	14,646	5	1,319	120,880
	2013	89	383,956	4,314	13,545	5	1,188	112,053
	2014	89	592,186	6,654	20,586	8	1,881	155,773
	2015	89	802,119	9,013	26,891	12	2,898	186,019
	2016	89	1,330,118	14,945	43,502	19	4,639	312,958
	2017	89	1,755,829	19,728	58,437	22	5,587	434,467
	2018	89	2,413,663	27,120	81,521	24	5,844	597,871

Table 2: Baseline Estimation Results: Cloud Computing and Firm Entry

This table reports the panel regression results examining firm entry and cloud computing from equation (3). The sample covers the period 2007 through 2018. We use the cloud computing increase in 2013 as the beginning year of technological shock. Column (1) shows the result of OLS regression while column (2) shows the result of Poisson regression. The dependent variable is log(Entry) and Entry. log(Entry) is calculated by logging Entry, where Entry is the nationwide count of the sum of newly-established firms in a given industry in a given year. We use 89 distinct two-digit industries from Industrial Classification for National Economic Activities in China (GB/T4754-2011) to calculate the number of firms entering each year. Cloud is defined as the proportion of the affected firms whose descriptions of the business scope contain the keywords of "online," "web," "E-commerce," "Hosting," or "software" to all surviving firms in a given industry in 2012, which can measure the influence of cloud computing. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. All regressions control for year fixed effects and industry fixed effects. Robust standard errors reported in parentheses are clustered at the industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

LEVEL	Industry-Year	
MODEL	OLS	Poisson
VARIABLES	log(Entry)	Entry
	(1)	(2)
Post_Cloud	0.897**	1.079***
	(0.419)	(0.216)
Constant	8.392***	12.046***
	(0.058)	(0.019)
Observations	1,066	1,068
R-squared	0.385	
Year FE	Yes	Yes
Industry FE	Yes	Yes

Table 3: Baseline Estimation Results: Cloud Computing and Firm Exit

This table reports the panel regression results examining firm exit and cloud computing. The sample covers the period 2007 through 2018. We use the cloud computing increase in 2013 as the beginning year of technological shock. Columns (1)-(3) report the results for firm exits, including all types of firm exits. Columns (4)-(6) reports the results limited to voluntary exits, which are classified as the cases where a firm exits due to poor performance or business adjustment, according to their exit reasons. Columns (1) and (4) are obtained from estimating equation (5) at the firm level. Columns (2) and (5) show the results of OLS regression from equation (3) at the industry-year level. Columns (3) and (6) show the results of Poisson regression at the industry-year level. The dependent variables are Exit, Exitvol, log(Exit), and log(Exitvol). Exit equals one if a given firm exits in a given year and zero if it is operating. Exitvol equals one if a given firm exits voluntarily in a given year and zero if it is operating. We multiply coefficients for the Exit and Exitvol regressions by 1000. log(Exit) and log(Exitvol) are calculated by logging the counts of firm exits and voluntary exits in a given industry in a given year, respectively. The variable of main interest is Post_Cloud. Cloud is a measurement of the influence of cloud computing. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. We use 89 distinct two-digit industries from Industrial Classification for National Economic Activities in China (GB/T4754-2011). Regressions in columns (1) and (4) control for year fixed effects and firm fixed effects. Regressions in columns (2)-(3) , (5)-(6) control for year fixed effects and industry fixed effects. Standard errors reported in parentheses are clustered at the firm level in columns (1) and (4). Standard errors reported in parentheses are clustered at the industry level in columns (2)-(3) and (5)-(6). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

LEVEL	Exit			Voluntary Exit		
LEVEL	Firm	Industry-Year		Firm	Industry-Year	
MODEL	OLS	OLS	Poisson	OLS	OLS	Poisson
VARIABLES	Exit	log(Exit)	Exit	Exitvol	log(Exitvol)	Exitvol
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Cloud	24.801***	0.774***	0.475**	4.562***	1.556*	3.331**
	(0.178)	(0.187)	(0.238)	(0.066)	(0.811)	(1.397)
Constant	-28.627***	7.238***	10.768***	1.809***	0.868***	7.056***
	(0.037)	(0.037)	(0.018)	(0.005)	(0.080)	(0.165)
Observations	224,037,419	1,068	1,068	189,298,377	1,068	1,068
R-squared	0.325	0.758		0.175	0.887	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	No	Yes	No	No
Industry FE	No	Yes	Yes	No	Yes	Yes

Table 4: Prices for Cloud Computing and Firm Dynamics

This table examines the prices of cloud computing and the changes in firm dynamics at the industry-year level from equation (6). The sample covers the period 2007 through 2018. Columns (1) and (3) are OLS regressions and columns (2) and (4) are Poisson regressions. The dependent variables in OLS regressions are log(Entry) and log(Exit). The dependent variables in Poisson regressions are Entry, and Exit. Entry, and Exit are defined as the counts of entrants, and exits at the industry-year level. log(Entry), and log(Exit) are calculated by logging Entry, and Exit. Price is defined as the annual price of Alibaba Cloud. Cloud is a measurement of the influence of cloud computing. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. All columns control for year fixed effects and industry fixed effects. Standard errors reported in parentheses are clustered at the industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

LEVEL	Industry-Year			
MODEL	OLS	Poisson	OLS	Poisson
VARIABLES	log(Entry)	Entry	log(Exit)	Exit
	(1)	(2)	(3)	(4)
Price_Post_Cloud	-0.231*	-0.433**	-0.092	-0.792***
	(0.129)	(0.219)	(0.113)	(0.197)
Price_Cloud	-1.019**	-1.139***	-0.811***	-0.682***
	(0.393)	(0.198)	(0.157)	(0.185)
Constant	8.883***	12.261***	7.527***	10.884***
	(0.029)	(0.023)	(0.011)	(0.016)
Observations	1,066	1,068	1,068	1,068
R-squared	0.383		0.758	
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table 5: Differences in Firm Exit between Cloud Computing and AI

This table examines the differences in firm exit between cloud computing and AI. Column (1) reports the full-sample result of OLS regression at the firm-year level. Columns (2) and (3) report the full-sample result of OLS regression and Poisson regression at the industry-year level, respectively. In columns (4)-(5) we analyze firm-level data to study the different impacts of AI and cloud computing on firm exits of different sizes. We divide the sample into two subsamples based on the median of the registered capital by industries for all surviving firms in 2007. Column (4) reports the result for a small-size subsample while column (5) reports the result for a big-size subsample. $\beta_{\Delta Cloud}$ is the difference in the coefficients of Post_Cloud between small-size and big-size subsamples. $\beta_{\Delta AI}$ is the difference in the coefficients of Post_AI between small-size and big-size subsamples. Exit is defined as the count of exits at the industry-year level. log(Exit) are calculated by logging Exit. Exit equals one if a given firm exits in a given year and to zero if it is operating. We multiply coefficients for the Exit regressions by 1000 in the firm-level regressions. AI is a measurement of the influence of artificial intelligence. Cloud is a measurement of the influence of cloud computing. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. Columns (2)-(3) control for year fixed effects and industry fixed effects while columns (1), (4) and (5) control for year fixed effects and firm fixed effects. Standard errors reported in parentheses are clustered at the industry level in columns (2)-(3), and firm level in columns (1), (4)-(5), respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

LEVEL	Firm	Industry-Year		Firm	
MODEL	OLS	OLS	Poisson	OLS	
SIZE	Full	Full	Full	Small	Big
VARIABLES	Exit	log(Exit)	Exit	Exit	Exit
	(1)	(2)	(3)	(4)	(5)
Post_Cloud	30.053***	0.829***	0.977***	31.129***	19.966***
	(0.298)	(0.144)	(0.332)	(0.429)	(0.389)
Post_AI	-36.421***	-0.534	-2.969*	42.985***	-128.204***
	(1.178)	(1.136)	(1.798)	(1.748)	(1.509)
Constant	26.643***	7.443***	10.783***	29.009***	25.218***
	(0.015)	(0.010)	(0.024)	(0.022)	(0.020)
Observations	217,805,372	1,068	1,068	108,654,971	109,150,401
R-squared	0.263	0.758		0.255	0.273
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	No	Yes	Yes
Industry FE	No	Yes	Yes	No	No
			$\beta_{\Delta Cloud}$	5.011***	
				(0.602)	
			$\beta_{\Delta AI}$	180.335***	
				(2.394)	

Table 6: Differences in Voluntary Exit between Cloud Computing and AI

This table examines the differences in voluntary exit between cloud computing and AI. Voluntary exit is classified as the cases where a firm exits due to poor performance or business adjustment, according to its exit reasons. Column (1) reports the full-sample result of OLS regression at the firm-year level. We divide the sample into two subsamples based on the median of the registered capital by industries for all surviving firms in 2007. Column (2) reports the result for a small-size subsample while column (3) reports the result for a big-size subsample. Exitvol equals one if a given firm exits voluntarily in a given year and to zero if it is operating. We multiply coefficients for the Exitvol regressions by 1000 in the firm-level regressions. Cloud is a measurement of the influence of cloud computing. AI is a measurement of the influence of artificial intelligence. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. All columns control for year fixed effects and firm fixed effects. Standard errors reported in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

LEVEL	Firm		
MODEL	OLS		
SIZE	Full	Small	Big
VARIABLES	Exitvol	Exitvol	Exitvol
	(1)	(2)	(3)
Post_Cloud	4.743***	4.711***	4.044***
	(0.097)	(0.142)	(0.123)
Post_AI	-0.995***	10.142***	-15.345***
	(0.368)	(0.555)	(0.461)
Constant	1.815***	1.835***	1.922***
	(0.005)	(0.007)	(0.006)
Observations	189,298,377	90,577,975	98,720,402
R-squared	0.175	0.160	0.192
Year FE	Yes	Yes	Yes
Firm FE	Yes	No	No
Industry FE	No	Yes	Yes

Table 7: Differences in M&A between Cloud Computing and AI

This table examines the differences in M&A for firms of different sizes between cloud computing and AI. All columns show the results of OLS regression at the firm-year level, with M&A as the dependent variable. M&A equals one if a given firm is merged in a given year and to zero if it is operating. Column (1) reports the full-sample result. The full sample is split into two subsamples based on the median of registered capital by industries for all surviving firms in 2007, as shown in columns (2) and (3). We multiply coefficients for the M&A regressions by 1000 in the firm-level regressions. Cloud is a measurement of the influence of cloud computing. AI is a measurement of the influence of artificial intelligence. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. All columns control for year fixed effects and firm fixed effects. Standard errors reported in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

LEVEL	Firm		
MODEL	OLS		
SIZE	Full	Small	Big
VARIABLES	M&A	M&A	M&A
	(1)	(2)	(3)
Post_Cloud	1.426***	0.770***	4.184***
	(0.085)	(0.055)	(0.186)
Post_AI	4.287***	-0.086	7.127***
	(0.332)	(0.201)	(0.690)
Constant	2.209***	0.617***	3.659***
	(0.005)	(0.003)	(0.011)
Observations	210,561,233	104,767,826	105,793,407
R-squared	0.204	0.221	0.200
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table 8: Cloud Computing vs. AI and Industry Concentration

This table examines cloud computing and HHI at the industry-year level from equation (3). We use firm performance information from the National Tax Survey Database (NTSD). The data is collected jointly by the State Administration of Taxation of China and the Ministry of Finance of China employing a stratified random sampling method. The data comprises an annual survey of approximately 500,000 firms from a wide spectrum of industries and regions nationwide. NTSD data covers the period 2007 through 2016. We use HHI to measure industry competition. HHI is Herfindahl-Hirschman Index and calculated by squaring the market share percentage of each firm competing in a market and then summing the resulting numbers. We use sales and asset to calculate the market share percentage, separately. Column (1) shows the result on HHI calculated by using firm sales while column (2) shows the result on HHI calculated by using firm asset. We use 89 distinct two-digit industries from Industrial Classification for National Economic Activities in China (GB/T4754-2011). The variables of main interest is Post_Cloud and Post_AI. Cloud is a measurement of the influence of cloud computing. AI is a measurement of the influence of AI. Post equals one if the given years are in 2013-2016, and zero in 2007-2012. All columns control for year fixed effects and industry fixed effects. Standard errors reported in parentheses are clustered at the industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

LEVEL	Industry-Year	
MODEL	OLS	
VARIABLES	HHI(Sales)	HHI(Asset)
	(1)	(2)
Post_Cloud	-710.758***	-1,306.561***
	(198.285)	(477.820)
Post_AI	1,877.489**	2,980.986**
	(722.938)	(1,460.566)
Constant	366.837***	549.620***
	(56.374)	(94.883)
Observations	886	886
R-squared	0.025	0.024
Year FE	Yes	Yes
Industry FE	Yes	Yes

Table 9: Cloud vs. AI and Size Distribution inside Industries

This table estimates changes in the size distribution of firms Post-cloud computing using equation (3). All columns show the result of OLS regression. We use firm performance information from the National Tax Survey Database (NTSD). The data is collected jointly by the State Administration of Taxation of China and the Ministry of Finance of China employing a stratified random sampling method. The data comprises an annual survey of approximately 500,000 firms from a wide spectrum of industries and regions nationwide. NTSD data covers the period 2007 through 2016. Columns (1)-(4) report the change in the central tendency of the size distribution, while columns (5)-(6) examine changes in the degree of dispersion of size distribution inside a certain industry. We use firm sales and assets to measure firm size (unit: 1,000,000 RMB). We use the median, mean, and CV of size distribution in a given industry in a given year as the dependent variables. CV is calculated as dividing the standard deviation by the mean to measure the degree of dispersion on the unit mean. We use 89 distinct two-digit industries from Industrial Classification for National Economic Activities in China (GB/T4754-2011). The variables of main interest are Post_Cloud and Post_AI. Cloud is a measurement of the influence of cloud computing. AI is a measurement of the influence of AI. Post equals one if the given years are in 2013-2016, and zero in 2007-2012. All columns control for year fixed effects and industry fixed effects. Standard errors reported in parentheses are clustered at the industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

MODEL	OLS					
	Central tendency				Degree of dispersion	
VARIABLES	Sale_Median	Sale_Mean	Asset_Median	Asset_Mean	Sales_CV	Asset_CV
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Cloud	-38.424***	-104.240***	-152.383**	-323.583***	-0.140***	-0.162***
	(12.556)	(33.834)	(76.334)	(79.164)	(0.044)	(0.045)
Post_AI	-16.801	47.438	-518.763	-715.328	0.055	0.014
	(59.378)	(157.173)	(461.372)	(539.734)	(0.214)	(0.229)
Constant	21.439***	100.647***	65.480***	212.676***	0.413***	0.407***
	(1.909)	(4.727)	(23.651)	(24.989)	(0.007)	(0.008)
Observations	886	886	886	886	886	885
R-squared	0.134	0.329	0.050	0.267	0.066	0.161
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Cloud Computing vs. AI and Equity Financing

This table examines changes in equity financing Post increases in cloud computing. Panel A reports the results for all types of equity financing decisions, while Panel B reports the results limited to venture capital equity financing decisions. In column (1), *fin* is an indicator of whether a given firm is financed in a given year. We multiply coefficients for column (1) regressions by 1000. Columns (2), (4) and (5) show the results of OLS regression while column (3) shows the result of Poisson regression. FNumber is the number of equity-financed firms in a given industry in a given year. log(FNumber) is the natural log of FNumber. FRatio is the proportion of the number of equity-financed firms to all surviving firms in a given industry in a given year, expressed in percentage %. FAmount is the natural log of the equity financing amount in a given industry in a given year. The observations of financing amounts are less than the full sample size for the reason that half of the financing amounts are not disclosed at random. The variable of main interest is Post_Cloud and Post_AI. Cloud is a measurement of the influence of cloud computing. AI is a measurement of the influence of AI. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. We use 89 distinct two-digit industries from Industrial Classification for National Economic Activities in China (GB/T4754-2011). column (1) control for year fixed effects and firm fixed effects while columns (2)-(5) control for year fixed effects and industry fixed effects. Standard errors reported in parentheses are clustered at the firm level in columns (1), and firm level in columns (2)-(5), respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. The Results for All Types of Equity Financing Decisions

LEVEL	Firm	Industry-Year			
MODEL	OLS	OLS	Poisson	OLS	OLS
VARIABLES	fin	log(FNumber)	Fnumber	FRatio	log(FAmount)
	(1)	(2)	(3)	(4)	(5)
Post_Cloud	0.618***	1.302***	1.964***	0.143**	2.521***
	(0.035)	(0.311)	(0.667)	(0.058)	(0.909)
Post_AI	5.150***	-0.009	-3.426	0.354*	0.129
	(0.168)	(1.694)	(3.118)	(0.205)	(3.990)
Constant	0.224***	1.357***	6.339***	0.011***	11.420***
	(0.003)	(0.077)	(0.089)	(0.004)	(0.271)
Observations	302,118,752	980	1,068	1,068	846
R-squared	0.363	0.785		0.406	0.321
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	No	No	No
Industry FE	No	Yes	Yes	Yes	Yes

Panel B. The Results for VC Equity Financing Decisions

LEVEL	Firm	Industry-Year			
MODEL	OLS	OLS	Poisson	OLS	OLS
VARIABLES	fin	log(FNumber)	FNumber	FRatio	log(FAmount)
	(1)	(2)	(3)	(4)	(5)
Post_Cloud	0.279***	1.975***	2.581***	0.125***	3.895***
	(0.027)	(0.405)	(0.845)	(0.039)	(1.121)
Post_AI	0.865***	0.450	-4.681	0.215	1.419
	(0.126)	(1.983)	(3.867)	(0.149)	(5.179)
Constant	0.224***	1.069***	6.152***	0.007***	9.519***
	(0.002)	(0.081)	(0.135)	(0.002)	(0.239)
Observations	302,118,631	923	1,056	1,068	700
R-squared	0.388	0.602		0.348	0.167
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	No	No	No
Industry FE	No	Yes	Yes	Yes	Yes

Appendix A Tables and Figures

Table A.1: Events Covering the Development of Cloud Computing in China

This table shows the important events regarding the development of cloud computing in China.

Time	**Event**
2009-2011	**The budding period of cloud computing**
Sep 2009	Ali Cloud was established.
Jul 2011	Ali Cloud opened the cloud computing resources to the public.
2013-after	**The sharp increase period of cloud computing**
Jan 2013	Ali Cloud merged with Wanwang and transferred all users on Wanwang to Ali Cloud.
Jan 2013	Baidu Personal Cloud also reached 30 million registered users.
May 2013	SpeedyCloud was opened to the public.
Jun 2013	Microsoft Azure announced its entry into the Chinese market.
Jul 2013	All the operations and transactions of Alibaba Group are carried out on Ali Cloud.
Jul 2013	QingCloud was opened to the public.
Aug 2013	Ali Cloud successfully provided 5K cloud computing service capabilities.
Sep 2013	Tencent Cloud was opened to the public.
Nov 2013	UCloud received 10 million dollar financing from VC.
Dec 2013	AWS announced its entry into the Chinese market.
Dec 2013	IBM announced its entry into the Chinese market.
2014-after	A constant price war began.

Figure A.1: An Overview of Cloud Computing

The figure presents an overview of cloud computing. It describes how cloud computing connects users with providers and what types of services cloud computing provides.

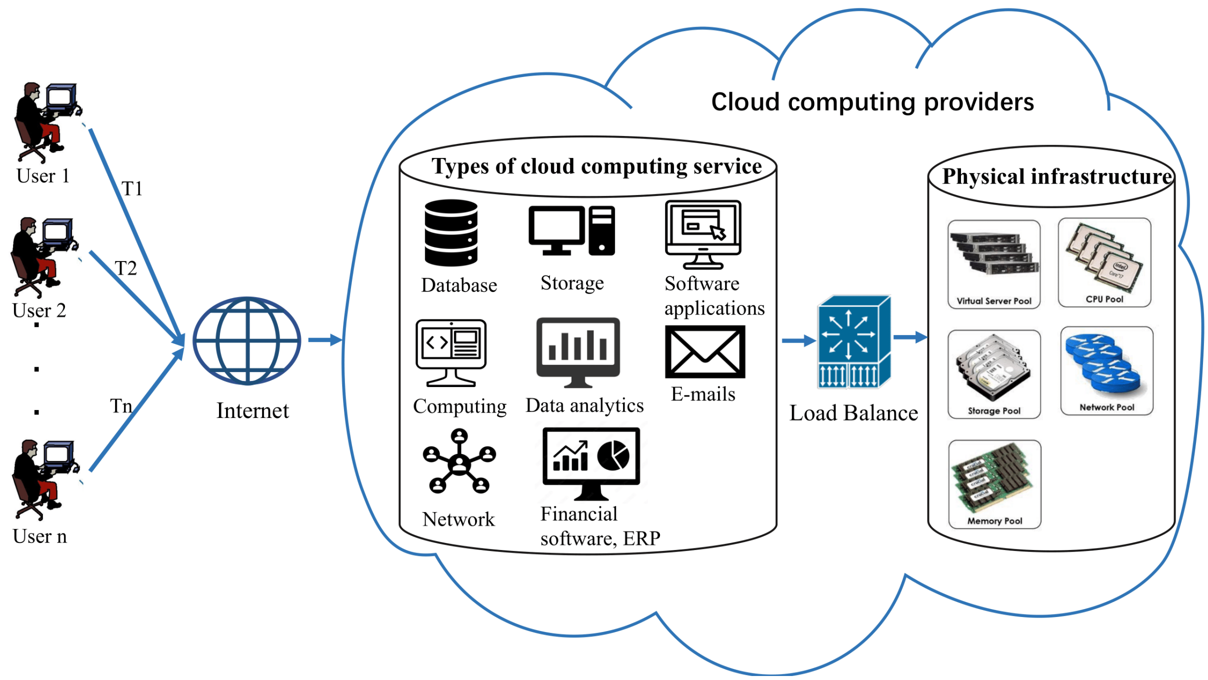


Figure A.2: Company Deregistration Process

This figure shows the detailed process for the company to deregister its business license.

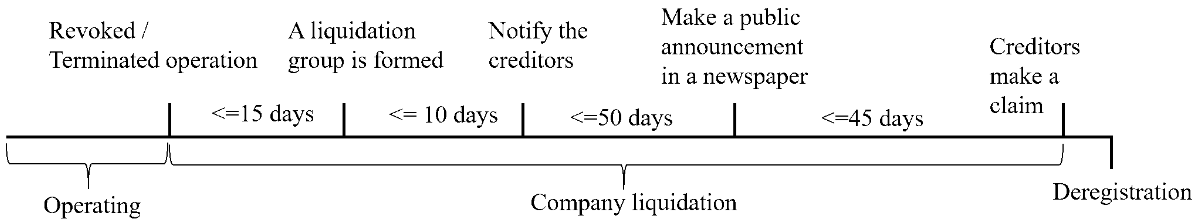


Figure A.3: Cloud Computing Usage in Singapore and China by Industry

This figure presents the comparison of cloud computing usage by industry between Singapore and China in 2018. We collect the usage of cloud computing services by industry in Singapore from *ANNUAL SURVEY ON INFOCOMM USAGE BY ENTERPRISES FOR 2018*, which is conducted by the Research and Statistics Unit of the Infocomm Development Authority of Singapore. The survey report did not reveal the result concerning the usage of cloud computing services by industries until 2018. To compare this with China's industry exposure to cloud computing, we employ data from the surviving firms in 2018 to determine the cloud computing measurement in China. The unit is %. Business Services Industries include enterprises from the following segments: Real Estate; Professional Services; Scientific and Technical Activities; Environmental Services; Security; Other Administrative and Support Services; Employment Activities; Travel Agencies. Other Goods and Service Industries include personal and household services not elsewhere classified such as hairdressing shops, beauty salons, and spas, repair and maintenance of motor vehicles, activities of other membership organizations (Churches, country clubs, charity organizations).

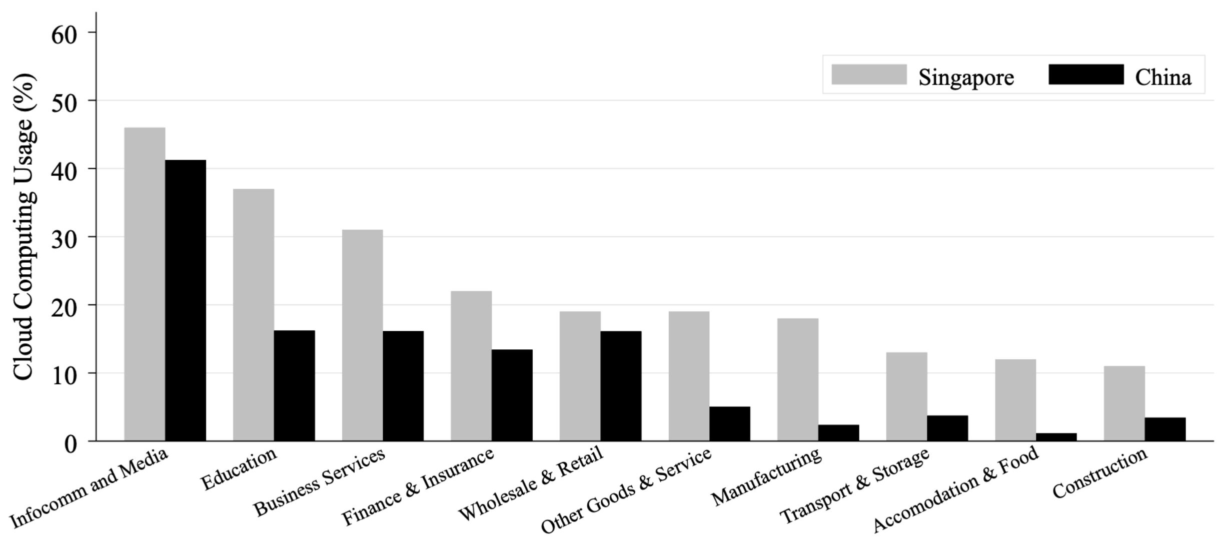


Figure A.4: Price Trend of Alibaba Cloud 2012-2018

This figure presents the annual price of Alibaba Cloud with different configurations in 2012-2018. We have collected the prices of two configurations of products in terms of vCPU and memory. The price unit is RMB/month.

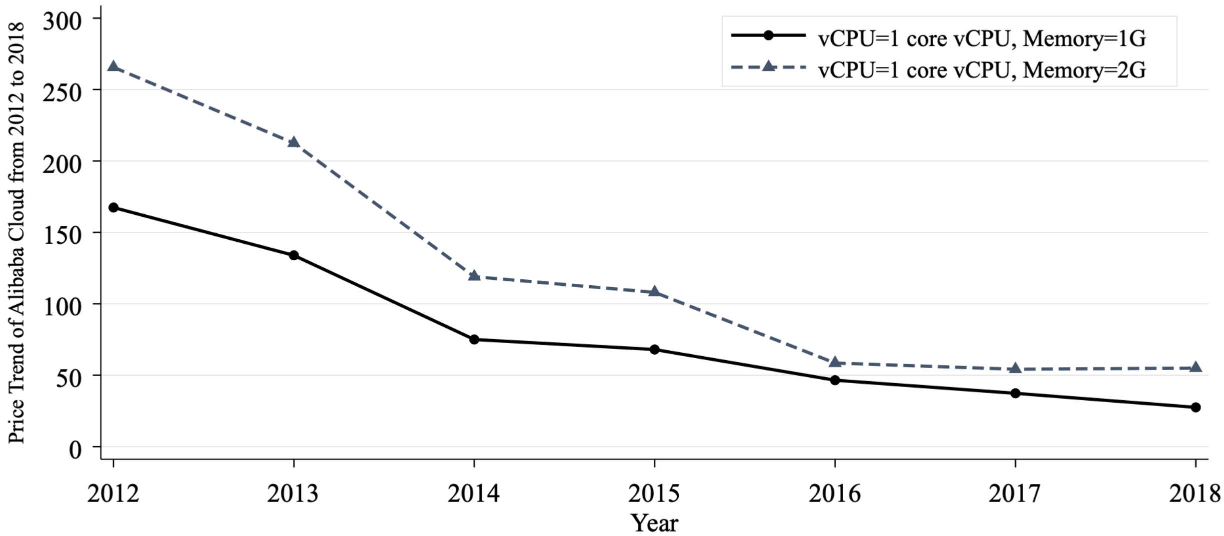
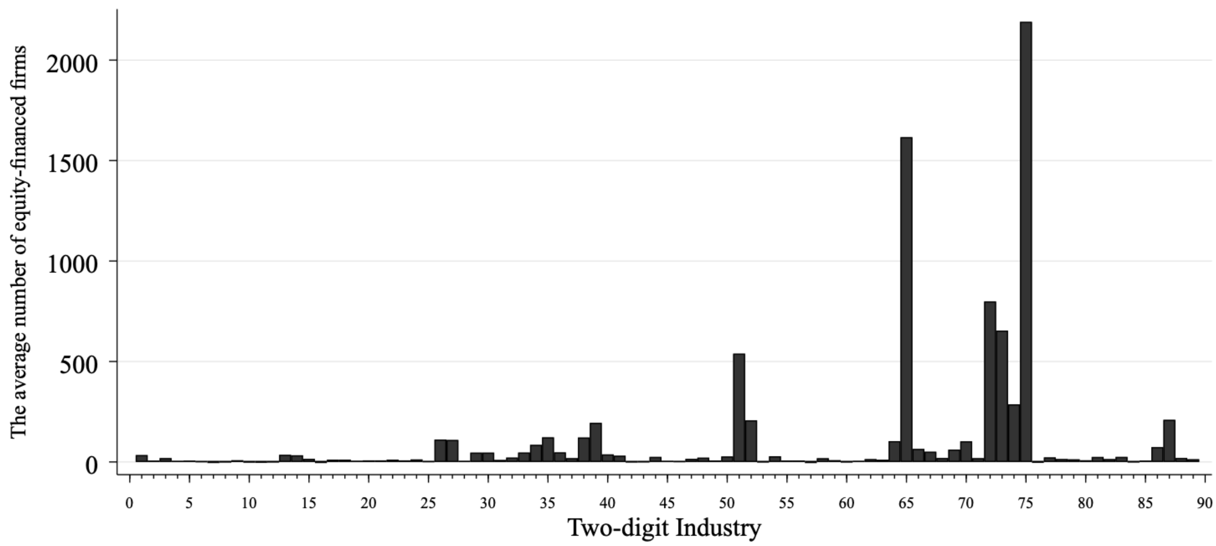
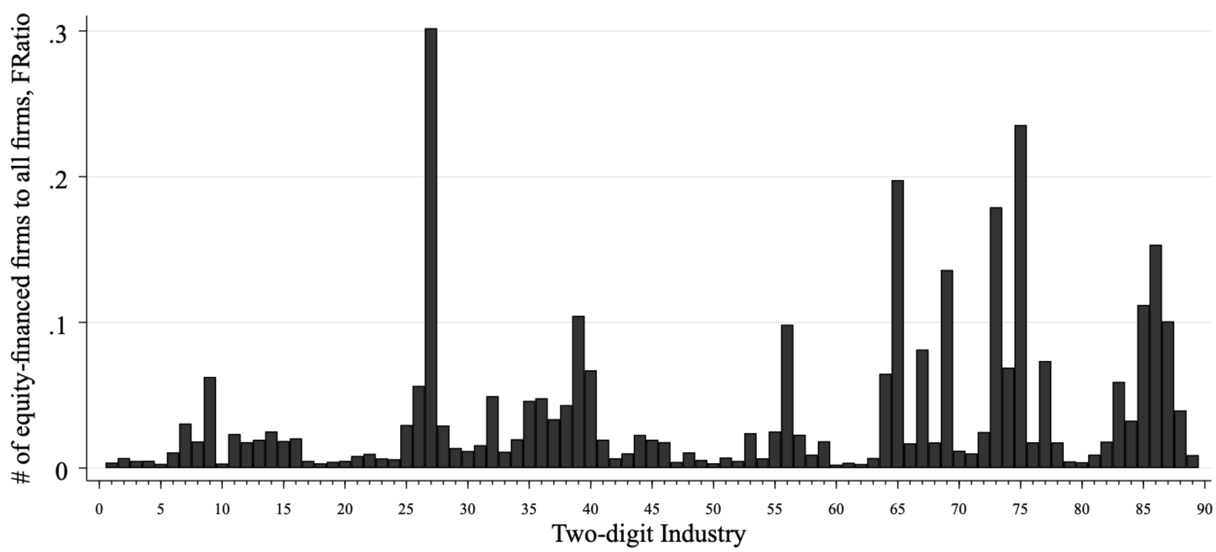


Figure A.5: Equity Financing Distribution across Industries

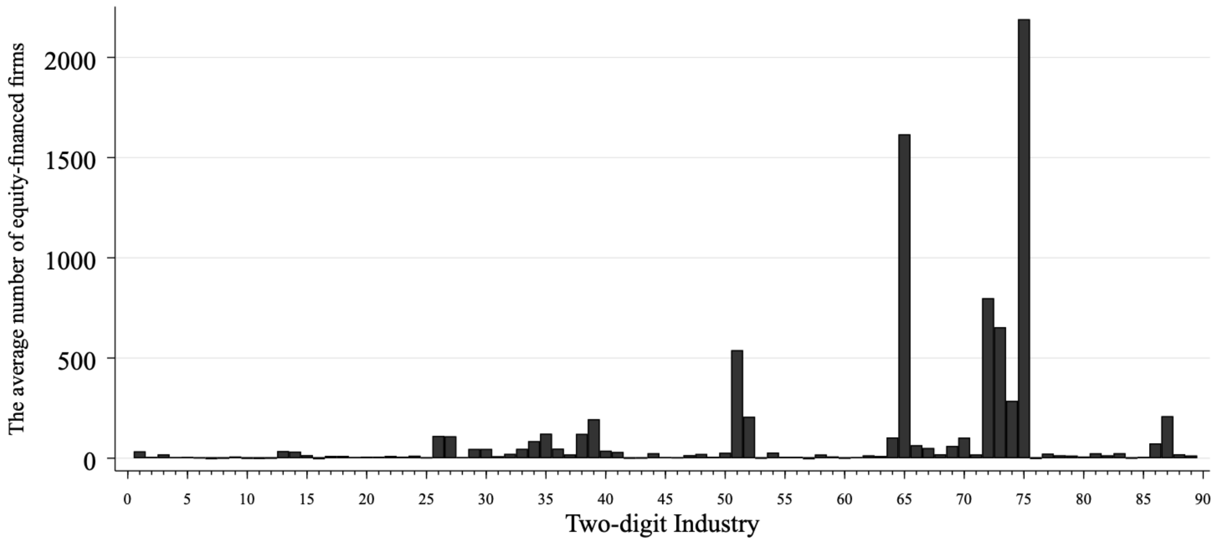
This figure presents the average equity-financing distribution across industries. Figure (a) represents the average number of equity-financed firms (FNumber) across industries from 2007 to 2018. Figure (b) represents the average proportion of the number of equity-financed firms to all surviving firms (FRatio) across industries from 2007 to 2018. Figure (c) represents the average equity financing amount (FAmount) across industries from 2007 to 2018.



(a) FNumber



(b) FRatio


The average number of equity-financed firms
2000
1500
1000
500
0
0
5
10
15
20
25
30
35
40
45
50
55
60
65
70
75
80
85
90
Two-digit Industry

(c) FAmout

Table A.2: Alternative Tests: Cloud Computing and Firm Exit

This table reports the panel regression results examining firm exit and cloud computing at the firm level. The dependent variable is Exit and Exitvol. Exit equals one if a given firm exits in a given year and zero if it is operating. Exitvol equals one if a given firm exits voluntarily in a given year and zero if it is operating. We multiply coefficients for the Exit and Exitvol regressions by 1000. The variable of main interest is Post_Cloud. Cloud is a measurement of the influence of cloud computing. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. We use 89 distinct two-digit industries from Industrial Classification for National Economic Activities in China (GB/T4754-2011). We use 31 different provinces to measure the region-level variable. Regressions in columns (1) and (3) control for firm fixed effects and region-year fixed effects. Regressions in columns (2) and (4) control for industry fixed effects and region-year fixed effects. Standard errors reported in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

MODEL	OLS			
LEVEL	Firm			
VARIABLES	Exit	Exit	Exitvol	Exitvol
	(1)	(2)	(3)	(4)
post_Cloud	20.536***	3.785***	1.817***	0.124***
	(0.164)	(0.146)	(0.048)	(0.026)
Constant	27.198***	30.156***	1.621***	1.729***
	(0.010)	(0.013)	(0.003)	(0.003)
Observations	320,433,704	320,433,704	311,164,372	311,164,372
R-squared	0.270	0.014	0.186	0.019
Firm FE	Yes	No	Yes	No
Region-Year FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes

Table A.3: Treated vs. Control Industries in China

Panel A. Treated Industries

Code	Industry Name
39	Computer and Electronic Product Manufacturing
40	Instrument Manufacturing
51	Wholesale Trade
60	Postal Service
63	Telecommunications, Broadcasting
64	Internet and related services
65	Software and information technology services
67	Capital markets services
69	Other Financial Activities
72	Professional, Scientific, and Technical Services
73	Scientific Research and Development Services
74	Professional and Technical Services
75	Science and technology promotion and application
85	News and Publishing Industries
86	Broadcasting, Motion Picture and Sound Recording Industries
87	Arts
89	Entertainment

Panel B. Control Industries

Code	Industry Name
1	Agriculture
2	Forestry
3	Hunting
4	Fishing
5	Support Activities for Agriculture, Forestry, Fishing and Hunting
6	Mining
7	Oil and Gas Extraction
8	Ferrous Metal Ore Mining
9	Nonferrous Metal Ore Mining
10	Nonmetallic Mineral Ore Mining
11	Support Activities for Extraction

12	All Other Mining
13	Farm Product Milling
14	Food Manufacturing
15	Wine, Beverage and Tea Manufacturing
16	Tobacco Product Manufacturing
17	Textile Mills
18	Apparel Manufacturing
19	Leather and Allied Product Manufacturing
20	Wood Product Manufacturing
21	Furniture Manufacturing
22	Paper Manufacturing
23	Printing and Related Support Activities
24	Miscellaneous Manufacturing
25	Petroleum and Coal Products Manufacturing
26	Chemical Manufacturing
27	Pharmaceutical and Medicine Manufacturing
28	Chemical Fibers Manufacturing
29	Plastics and Rubber Products Manufacturing
30	Nonmetallic Mineral Product Manufacturing
31	Ferrous Metal Manufacturing
32	Nonferrous Metal Manufacturing
33	Fabricated Metal Product Manufacturing
34	General Purpose Machinery Manufacturing
35	Special Purpose Machinery Manufacturing
36	Motor Vehicle Manufacturing
37	Transportation Equipment Manufacturing
38	Electrical Equipment, Appliance, and Component Manufacturing
41	Other Manufacturing
42	Waste Management and Remediation Services
43	Repair and Maintenance
44	Electricity and Heat Generation, Transmission and Distribution
45	Natural Gas Generation and Distribution
46	Water Generation and Distribution
47	Construction of Buildings
48	Civil Engineering Construction
49	Building Equipment Contractors

50	Building Finishing Contractors and Other Contractors
52	Retail Trade
53	Rail Transportation
54	Road Transportation
55	Water Transportation
56	Air Transportation
57	Pipeline Transportation
58	Handling and Transportation Arrangement
59	Warehousing and Storage
61	Accommodation
62	Food Services and Drinking Places
66	Monetary and financial services
68	Insurance
70	Real Estate
71	Rental and Leasing Services
76	Water Conservancy Management
77	Environment and Conservation
78	Public Facilities Management
79	Resident Services
80	Automotive, Electronic Equipment and Household Goods Repair and Maintenance
81	Other Services
82	Educational Services
83	Health Care
84	Social Assistance
88	Sports

Table A.4: Robustness Tests: Treatment Effects of Cloud Computing

This table reports the panel regression results examining the treatment effects of cloud computing on firm dynamics. Columns (1)-(2) show the results at the firm level. Columns (3)-(5) show the results at the industry-year level. The dependent variable is Exit, Exitvol, log(Entry), log(Exit) and log(Exitvol).Exit equals one if a given firm exits in a given year and zero if it is operating. Exitvol equals one if a given firm exits voluntarily in a given year and zero if it is operating. log(Entry), log(Exit) and log(Exitvol) is calculated by logging the number of entrants, exits and voluntary exits in a given industry and year, respectively. We use 89 distinct two-digit industries from Industrial Classification for National Economic Activities in China (GB/T4754-2011) to calculate the number of firms entering each year. Treat equals one if the industry is treated group as we define in table A.3, otherwise equals zero. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. Regressions in columns (1)-(2) control for year fixed effects and firm fixed effects. Regressions in columns (3)-(5) control for year fixed effects and industry fixed effects. Standard errors reported in parentheses are clustered at the firm level, and industry level in columns (1)-(2), and (3)-(5), respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

MODEL	OLS				
LEVEL	Firm		Industry-Year		
VARIABLES	Exit	Exitvol	log(Entry)	log(Exit)	log(Exitvol)
	(1)	(2)	(3)	(4)	(5)
Post_Treat	9.196***	1.682***	0.303*	0.233**	0.519**
	(0.044)	(0.012)	(0.179)	(0.105)	(0.243)
Constant	-28.735***	-0.496***	8.392***	7.238***	0.868***
	(0.037)	(0.005)	(0.058)	(0.038)	(0.080)
Observations	320,433,704	311,164,372	1,066	1,068	1,068
R-squared	0.325	0.174	0.383	0.756	0.886
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No	No
Industry FE	No	No	Yes	Yes	Yes

Table A.5: Robustness Tests: Other Potential Confounding Policies

This table reports the robustness tests examining other policies in China. Panel A reports the robustness tests controlling for the Reform for the Registered Capital Registration System in China. Under the registration system reform, a minimum amount of registered capital for establishing an enterprise in China is no longer required. We control for the interaction term between the average registered capital (CAP) and pre-post dummies (Post2014). We calculate the log of the average registered capital (CAP) in a given industry by using the surviving firms in 2012, rather than 2013 to avoid the potential impact of the sharp increase in cloud computing. Since the registered capital registration system reform began in 2014, we use $Post2014$, a dummy variable, to indicate if a given year is between 2014 to 2018. Panel B reports the robustness tests controlling for the Mass Entrepreneurship, Mass Innovation Policy in China. The Mass Entrepreneurship, Mass Innovation Policy has been implemented since 2015. We re-estimate the baseline DID model between 2011 and 2014. Panel C reports the robustness tests controlling for China's "Strategic Emerging Industries (SEI)" policy launched in 2012. We identify a two-digit industry is SEI-related by the SEI list obtained from China's National Bureau of Statistics (NBS). If the two-digit industry contains SEI-related four-digit industries, SEI equals one, otherwise equals zero. Post_SEI captures the impact of SEI policy on firm dynamics. Cloud is a measurement of the influence of cloud computing. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. Columns (1) and (3) are the results of OLS regressions while columns (2) and (4) are the results of Poisson regressions. All regressions control for year fixed effects and industry fixed effects. Standard errors reported in parentheses are clustered at the industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Robustness Tests: the Reform for the Registered Capital Registration System

LEVEL	Industry-Year			
MODEL	OLS	Poisson	OLS	Poisson
VARIABLES	log(Entry)	Entry	log(Exit)	Exit
	(1)	(2)	(3)	(4)
Post_Cloud	0.732*	1.079***	0.805***	0.488*
	(0.431)	(0.218)	(0.181)	(0.259)
Post2014_CAP	-0.165**	0.001	0.031	0.073
	(0.064)	(0.042)	(0.051)	(0.087)
Constant	8.392***	12.042***	7.238***	10.413***
	(0.058)	(0.203)	(0.037)	(0.424)
Observations	1,066	1,068	1,068	1,068
R-squared	0.407		0.759	
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Panel B. Robustness Tests: the Mass Entrepreneurship, Mass Innovation Policy

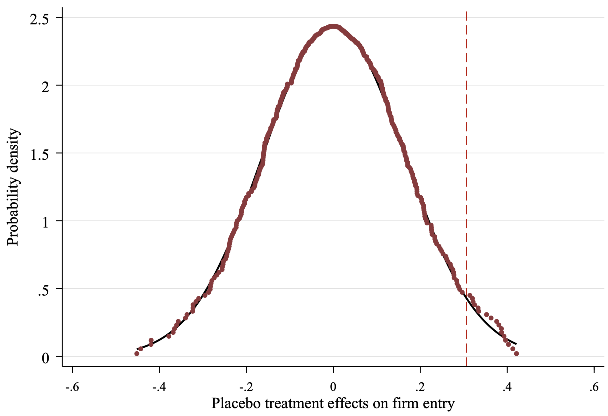
LEVEL	Industry-Year			
MODEL	OLS	Poisson	OLS	Poisson
VARIABLES	log(Entry)	Entry	log(Exit)	Exit
	(1)	(2)	(3)	(4)
Post_Cloud	0.411***	0.343***	0.149	-0.306
	(0.125)	(0.131)	(0.153)	(0.199)
Constant	8.576***	11.772***	7.011***	9.991***
	(0.022)	(0.008)	(0.015)	(0.010)
Observations	356	356	356	356
R-squared	0.513		0.354	
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Panel C. Robustness Tests: the Strategic Emerging Industries (SEI) Policy

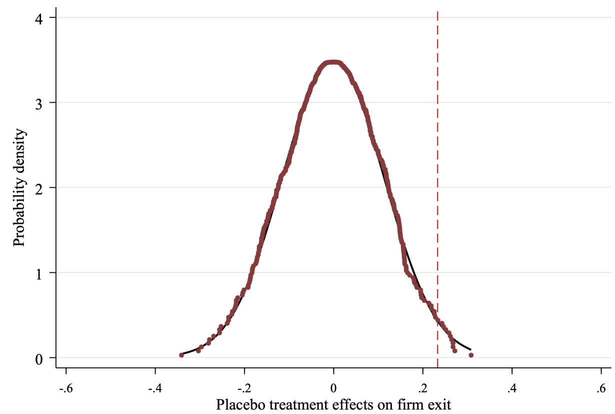
LEVEL	Industry-Year			
MODEL	OLS	Poisson	OLS	Poisson
VARIABLES	log(Entry)	Entry	log(Exit)	Exit
	(1)	(2)	(3)	(4)
Post_Cloud	0.969**	1.043***	0.796***	0.417***
	(0.415)	(0.233)	(0.190)	(0.155)
Post2012_SEI	-0.282**	0.051	-0.088	0.078
	(0.131)	(0.122)	(0.085)	(0.060)
Constant	8.392***	12.030***	7.238***	10.748***
	(0.058)	(0.042)	(0.037)	(0.021)
Observations	1,066	1,068	1,068	1,068
R-squared	0.400		0.759	
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Figure A.6: Probability Density Functions of Placebo Estimates

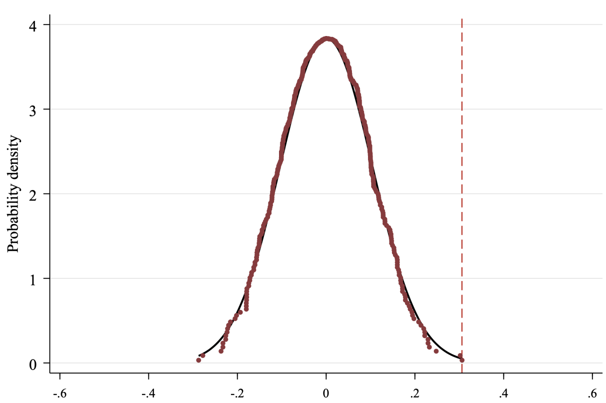
These figures plot four empirical distributions of the placebo effects for firm entry and exit at the industry-year level. For each figure, the probability distribution function is constructed from 500 placebo estimates of β using OLS regression with the interaction term between Post and Treat as the independent variable. Figures (a) and (b) show the placebo estimates for firm entry and exit constructed by randomly assigning affected industry groups, respectively. Figures (c) and (d) show the placebo estimates for firm entry and exit constructed by randomly assigning affected years, respectively. The horizontal lines show the placebo treatment effect estimates β. The vertical lines show the probability density of β. The dashed lines show the estimates from the actual treatment variables using the true treatment dummies, $Post * Treat$.



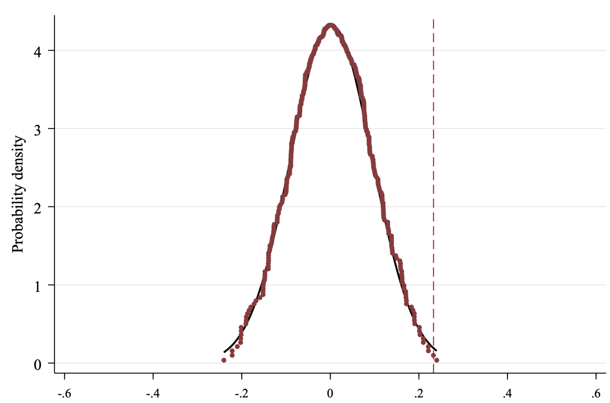
(a) Using $Post * (Treat)_{Random}$ on Firm Entry



(b) Using $Post * (Treat)_{Random}$ on Firm Exit



(c) Using $(Post)_{Random} * Treat$ on Firm Entry



(d) Using $(Post)_{Random} * Treat$ on Firm Exit

Table A.6: Robustness: Alternative Measures of Industry Classifications

This table reports the results of robustness tests using alternative measures of industry classifications. We redefine the influence of *Cloud*, using 417 three-digit industry cells rather than 89 two-digit industry cells from Industrial Classification for National Economic Activities in China (GB/T4754-2011). Columns (1) and (3) show the results using OLS regressions while Columns (1) and (3) show the results using Poisson regressions. Cloud is a measurement of the influence of cloud computing. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. All regressions control for year fixed effects and industry fixed effects. Standard errors reported in parentheses are clustered at the industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

LEVEL	Industry-Year			
MODEL	OLS	Poisson	OLS	Poisson
VARIABLES	log(Entry)	Entry	log(Exit)	Exit
	(1)	(2)	(3)	(4)
Post_Cloud	0.834**	0.960***	0.957***	0.290**
	(0.371)	(0.357)	(0.356)	(0.147)
Constant	6.395***	10.666***	5.355***	9.290***
	(0.033)	(0.032)	(0.024)	(0.013)
Observations	4,949	5,004	4,948	5,004
R-squared	0.112		0.617	
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table A.7: Robustness Tests: Alternative Measures of Dependent Variables

This table reports the results of robustness tests using alternative measures of our dependent variables. We use 89 two-digit industries from Industrial Classification for National Economic Activities in China (GB/T4754-2011). The dependent variables are Entry_ratio and Exit_ratio. Entry_ratio and Exit_ratio are calculated by dividing the number of firms entering and exiting in a given year by the total number of surviving firms in the previous year in a given industry, respectively. Entry_ratio and Exit_ratio are expressed in percentages (%). Cloud is a measurement of the influence of cloud computing. Treat equals one if the industry is treated group as we define in table A.3, otherwise equals zero. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. All regressions control for year fixed effects and industry fixed effects. Standard errors reported in parentheses are clustered at the industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

LEVEL	Industry-Year			
MODEL	OLS			
VARIABLES	Entry_ratio	Entry_ratio	Exit_ratio	Exit_ratio
	(1)	(2)	(3)	(4)
Post_Cloud	9.827**		0.937**	
	(4.532)		(0.427)	
Post_Treat		3.039*		0.010
		(1.792)		(0.124)
Constant	11.155***	11.175***	2.648***	2.677***
	(0.143)	(0.171)	(0.023)	(0.023)
Observations	1,068	1,068	1,068	1,068
R-squared	0.123	0.118	0.697	0.693
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Appendix B Background of Cloud Computing Development in China

In China, cloud computing first appeared in 2009, when Ali Cloud was established in September 2009. However, Ali Cloud only developed cloud computing for Alibaba's internal infrastructure and did not open these services up to developers outside Alibaba until 2011. It was its e-commerce business that forced Alibaba to develop cloud computing.

As one of the world's largest retailers and e-commerce companies, Alibaba naturally faced fast-developing and large-volume business data processing problems. For example, Double 11 in 2013, the largest and most popular annual shopping festival in China, had a total turnover of 35.019 billion and 188 million transactions in a single day. In addition, according to data from Alibaba, it reached 1 billion transaction volume just after 6 minutes and 7 seconds at 0:00 in the morning and reached 2 billion at 0:13:22. Therefore, Alibaba had to build sufficient internal infrastructure to support the skyrocketing business volume in a short time.

It turned out to be a great waste for Alibaba to leave these computing resources unused during the low peak period of business volume. Rather, Alibaba decided to open these computing resources to developers outside to make full use of its computing resources in July 2011.

Nevertheless, cloud computing did not attract great attention in China until 2013 given it was an immature technology and unclear business model. Tencent CEO Ma Huateng stated that "cloud computing will only come in the era of Avatar," and Baidu CEO Li Yanhong famously claimed that "cloud computing is just old wine in a new bottle" in 2010.

However, the cloud market eventually enjoyed a rapid increase starting around 2013. First, there was a breakthrough in cloud computing technology. In August 2013, Ali Cloud independently developed the large-scale distributed computing operating system Apsara and became the first firm in the world to provide 5K cloud computing service capabilities. In addition, Alibaba internally substituted all IBM servers, Oracle Databases or EMC saving equipment with Ali Cloud after July 2013. All the operations and transactions of Alibaba Group were then carried out on Ali Cloud.

Second, more and more companies began to understand the huge market demand for cloud computing in China and entered it almost at the same time. For example, in 2013 Tencent Cloud was subsequently opened to the public one month after Ali Cloud announced its successful 5K testing and became the second largest cloud computing firm in China a few years later. Relying on its enormous customer databases, Baidu Personal Cloud also reached 30 million registered users on January 18, 2013. In addition, a proliferation of independent cloud service providers also appeared in this period, including UCloud, QingCloud and QiniuYun.

In addition, this period saw the entry of many foreign tech giants into the Chinese market. AWS, the biggest cloud computing firm worldwide, announced its entry into the Chinese market in 2013. IBM and Microsoft Azure, following Amazon, also announced to enter the Chinese market on December 2013.

Third, many investors saw the potential of cloud computing in the application market and invested much capital. Many cloud computing entrants, such as UCloud and SpeedyCloud, received tens of millions of dollars from equity investors in 2013.

Finally, cloud computing companies experienced rapid growth in the number of customers. Ali Cloud merged with Wanwang and transferred all users on Wanwang to Ali Cloud in January 2013, which helped Ali Cloud to have about 200 thousand enterprise users directly instead of expanding its customers one by one.

Lastly, according to IDC China, the public cloud market size in China was about 4.76 billion yuan in 2013, with a growth rate of 36%, higher than the global growth rate (29.7%). Ali Cloud had six times more web-facing computers than it did a year ago, reaching a total of 17,934 in September 2013. Only the cloud computing giant Amazon has more web-facing computers than Ali Cloud worldwide. Similarly, the number of hostnames increased from 91,553 to 389,171 in Ali Cloud and the active sites increased from 23,596 to 150,089.

Since 2013, competition between tech giants and independent cloud solution services has increased. Ali Cloud first launched six price cuts in 2014 and the highest drop was 61%. Other cloud computing companies, like Tencent cloud and Jinshan cloud, also reacted and announced a new round of price reductions.

In addition, Ali Cloud received a 6 billion yuan strategic investment from Alibaba and announced direct competition with AWS in 2015. Just two months later, Tencent subsequently decided to invest 10 billion in the next five years to develop Tencent Cloud and thus catch up with Ali Cloud. Following Alibaba and Tencent, Baidu also announced investing 10 billion into Baidu Cloud in 2016.

Overall, the intensified competition in the cloud computing industry has pushed cloud computing providers to advance at an increasingly rapid speed to surpass the competitors. All of these factors contributed to cloud computing in China experiencing rapid growth since 2013.

Although the market size of cloud computing in China is smaller than that in the US, the growth rate of cloud computing in China is much higher than that worldwide. First, China has the greatest Internet users worldwide (591 million at the end of June 2013). Chinese increasingly rely on mobile phones for electronic payments, shopping, and communication.

The increasing amounts of Internet users promote the digitization of society and require firms to build up their own web-facing computers to conduct online transactions. Hence, firms need more powerful computing capacity and web-facing technology to process big data and deal with digital business, which constitutes the customer base for the development of cloud computing. Therefore, cloud computing service providers emerged to meet the need for outsourcing computing powers, IT hardware and software.

Second, software and hardware technologies that support the construction of computing platforms have gradually matured, including the construction of ultra-large-scale data centers, high-speed interconnection networks, as well as computing resource virtualization (Hypervisor) and Software Defined Network (SDN). These technologies eventually constitute the technical foundation for the development of cloud computing.

Finally, the Chinese government has formulated a series of policies to push the domestic development of cloud computing services as part of a wider digital transformation effort. In August 2013, State Council issued the "Several Opinions of the State Council on Promoting Information Consumption and Boosting Domestic Demand," which required the governments at all levels shall include the information infrastructure (e.g., internet data center and other cloud computing) in the urban and rural construction and land use planning as well as provide necessary political and financial support.

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