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THE IMPACT OF CLOUD COMPUTING AND AI ON INDUSTRY DYNAMICS AND CONCENTRATION

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ABSTRACT

We examine the rise of cloud computing and AI in China and their impacts on industry dynamics after the shock to the cost of Internet-based computing power and services. We find that cloud computing is associated with an increase in firm entry, exit and the likelihood of M&A in industries that depend more on cloud infrastructure. Conversely, AI adoption has no impact on entry but reduces the likelihood of exit and M&A. Firm size plays a crucial role in these dynamics: cloud computing increases exit rates across all firms, while larger firms benefit from AI, experiencing reduced exit rates. Cloud computing decreases industry concentration but AI increases concentration. On the financing side, firms exposed to cloud computing increase equity and venture capital financing, while only large firms increase equity financing when exposed to AI.

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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) demonstrate 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. New firms can capture the rents, and incumbents that don't adopt the new technologies may be forced to exit.[3] However, technological change does 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 U.S. over the last 30 years. In addition, computers, artificial intelligence (AI), 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 the adoption of new information technologies is related to industry dynamics, concentration, and equity financing. Although the ultimate goal of applying new technologies is to enhance economic efficiency, the economic mechanisms through which different technologies exert their impact may vary. We primarily focus on two different but related new technologies: cloud computing and AI. Both cloud computing and AI use Internet-based computing power, and users of both technologies frequently purchase large-scale Internet-based computing services/power from large computing external companies.

While both technologies involve the intensive use of Internet-based computing power and services, there are differences in their costs of implementation by firms of different sizes. Cloud computing, a novel computing paradigm, offers on-demand access to various com-

[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); 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.

puting resources like servers, storage, computing power, and software applications, all on a pay-as-you-go basis via the Internet. This model of cloud computing centralizes IT infrastructure, enabling the distribution of IT resources among a wide user base, which significantly enhances resource utilization and reduces costs. 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. Furthermore, the variable costs associated with cloud computing are typically lower than those of comparable on-premises infrastructures due to the economies of scale leveraged by cloud providers and the cost savings for firms (e.g., hardware maintenance costs, licensing costs, and unplanned downtime costs). In sum, cloud computing democratizes access to IT infrastructure, offering particular advantages to smaller firms that might otherwise struggle to establish comprehensive on-premises IT infrastructure.

In contrast, AI is machines' ability to perform tasks typically associated with human intelligence, such as learning and problem-solving.[4] AI is a technology that requires more sophistication and more extensive amounts of data in addition to computing resources purchased over the Internet. In the case of AI, large firms may disproportionally have access to the data required to effectively implement it and increase the training efficiency of their AI models. The effective use of AI may also require more sophisticated data scientists to train and customize a firm's AI model. Thus, we predict that large firms may have a scale advantage in the implementation of AI as they have more extensive data to train the AI model and may have sufficient scale to afford to hire more sophisticated data scientists.

We study the effect of these new technologies after a large-scale shock that decreased the cost of Internet-based computing power and services. In 2013, there was a sharp decrease in the cost of computing services purchased over the Internet.[5] In this year, there was a wave of large-scale internet computing providers entering the Chinese cloud computing market after

[4]The definition is sourced from Wikipedia.

[5]We distinguish between these computing services provider firms, also called cloud computing firms, that provide computing power over the internet and users of cloud computing and AI.

the Chinese government relaxed entry restrictions on foreign firms. These entrants included Amazon Web Services (AWS), Microsoft Azure and IBM in 2013. While we examine only one large cost shock, it was an exogenous one that we show persisted as the cost of internet-provided computing services decreased sharply and remained low since this time. This cost shock impacted *both* the current and potential users of cloud software and AI as it reduced the cost of purchased Internet-based computing services for both technologies. Thus, we use this single exogenous shock to study both technologies as both technologies use purchased Internet-based computing power, analogous to two different technologies that use oil.

We view this as an exogenous shock that impacted all firms that use cloud computing and AI. Why is this an exogenous shock and why does it impact costs for both technologies? Previously, foreign computing service firms had restrictions on their ability to enter China. Chinese laws require foreign computing service companies to store data locally and to operate through domestic companies and were allowed to enter with a partner starting in 2013.[6] The influx of computing service companies into China in 2013 led to a sharp decrease in the cost of Internet-based computing power and services as documented in Appendix Figure A.2.

In this paper, we empirically test the prediction that this large drop in the cost of purchased Internet-based computing power and services will affect firms using cloud computing and AI differently. We predict that small firms that wish to use cloud software offered over the Internet will benefit and be more likely to enter new markets after this large drop in the price of Internet-based computing services. We thus predict more entry and more competition by small firms in industries that use cloud computing software as their minimum efficient scale will drop. In contrast, we predict large firms using AI will disproportionally benefit relative to small firms from the drop in the cost of computing power as large firms can more cheaply implement using the extensive data that they have and can hire the more expensive data scientists to efficiently use this technology. Thus, for industries that have more firms that are more extensive users of AI we predict less competition and less entry by

[6] A more detailed description of the background of computing service providers offering computing power over the Internet in China is in Appendix Table A.1.

small or new firms after the drop in computing power costs given less data availability for small and new firms.

We test these basic predictions using a large and comprehensive firm registration and cancellation database from China, reported by the National Enterprise Credit Information Publicity System and collected by the RESSET Enterprise Big Data Platform. The data covers all non-listed and listed firms, including small and micro firms, and identifies 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 and sales, which allows us to calculate industry concentration measures and the firm size distribution across industries.

China is a good laboratory for analyzing 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 reached 133.4 billion RMB in 2019 and has become the world's second-largest cloud computing market.[7] 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.[8] 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.

Following Ewens, Nanda, and Rhodes-Kropf (2018), 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. We use a different set of keywords to measure the exposure to AI, which are obtained from Russell and Norvig (2009).

We begin our analysis by comparing how cloud computing and AI impacted firm entry,

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

[8]Details can be seen in the "China AI Development Report, 2018," available at https://ChinaAIDevelopmentReport2018.pdf.

exit, and M&A. Our results show that entry, exit, and the likelihood of being merged increase for industries that have more firms that are more extensive users of cloud computing post-shock. 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 contrast, AI has no impact on firm entry, but it is negatively associated with firm exit and becoming an acquisition target.

We next examine differences in the likelihood of exit and being merged between cloud computing and AI across different firm sizes. We find that cloud computing increases firm exit for both small and large firms, with a more pronounced impact on smaller firms. However, AI decreases the likelihood of firm exit for medium and large firms but increases it for small firms. The evidence is consistent with firms needing sufficient data and resources to use AI, which increases large firms' likelihood of survival. The results for AI are consistent with Babina, Fedyk, He, and Hodson (2020), which show the benefits of AI for the growth of large firms.

Our results also show that the positive relationship between cloud computing and the likelihood of being merged is monotonically increasing with the firm size, indicating that larger firms in industries that are heavy users of cloud computing are more likely to exit through a merger following the cost shock. Conversely, the negative relationship between AI and becoming an acquisition target becomes stronger among large firms. This is consistent with AI being beneficial to large firms and increasing their survival rate.

Furthermore, our results show that industry concentration is decreasing with cloud computing usage while industry concentration is increasing with AI usage. 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 post-shock. At the same time, AI has no impact on the overall size distribution of firms.

On the firm financing side, we examine how cloud computing and AI are associated with firms' external financing activities. We find that there is a higher probability of receiving equity financing for both cloud computing and AI. These results also hold when we examine venture capital equity financing. The positive impact of cloud computing on equity financing is significant among medium and large firms. In contrast, the positive impact of AI is exclusively pronounced in large firms. These findings suggest that equity investors are more willing to invest in larger firms that significantly use AI.

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 while AI usage has no impact on firm entry and decreases firm 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 and digital platform, can decrease firm entry. Hobijn and Jovanovic (2001), Samaniego (2010) and Kassem (2018) find that technological change increases firm exits, while Bessen (2020) finds that technological change can increase the productivity of top incumbents and thus improve their survival rate. Our results for cloud computing are consistent with the first set of findings, while those for AI are consistent with the latter. Our findings suggest that the distinct effects of technologies on industry dynamics are influenced by their impact on cost structures, including both fixed and variable costs. Our findings reveal that one technology may not be comparable to other technologies, and the impact of different technologies on the economy varies.

Our findings are also consistent with the previous studies that 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 transacted in the public market, so cloud computing raises the likelihood of exit for incumbents. However, our results for AI are different. Certain critical AI technologies or applications are privately held, making them more advantageous to large incumbents. We find the exit probability is reduced for incumbents in industries that use significant AI.

Our paper is also related to the recent active literature examining the long-term trend of industry concentration. Some studies highlight rising industry concentration in the US (Autor, Dorn, Katz, Patterson, and Van Reenen 2020; Covarrubias, Gutiérrez, and Philippon 2020; Kwon, Ma, and Zimmermann 2024). Our study shows that as two new technologies, cloud computing and AI can both affect industry concentration, but their impacts are different. Specifically, cloud computing is more beneficial to small firms, and thus may reduce industry concentration. However, large firms using AI have cost and scale advantages, and thus AI may increase industry concentration. Our findings further reveal how technology affects industry concentration.

We also add to the growing literature on the economic effects of emerging technologies, such as AI, robotics, big data, and cloud computing (see, e.g., Brynjolfsson and McAfee 2017; Graetz and Michaels 2018; Ewens, Nanda, and Rhodes-Kropf 2018; Acemoglu and Restrepo 2019; Farboodi, Mihet, Philippon, and Veldkamp 2019; Acemoglu and Restrepo 2020; Babina, Fedyk, He, and Hodson 2020). Our study examines the potential effect of two different emerging technologies on industry dynamics, studying both entry and exit as well as industry concentration, and the financing patterns of firms inside industries.

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, exit, and M&A are related to both cloud computing and AI. Section 5 explores how industry concentration and the size distribution of firms change. Section 6 investigates how firm financing changes. Section 7 describes robustness tests. Section 8 concludes.

2 Theoretical Framework

We first discuss the economics of cloud computing and AI and then develop hypotheses that we examine. For both technologies, we consider a profit function for firms using cloud computing or AI as: $Profit = R(q) - F_T - C_T(q)$, where *R(q)* is a firm's revenue, F_T = fixed costs for a firm using technology T, and $C_T(q)$ are the variable costs, with the subscript T indicating the technology the firm is using, either cloud computing (CC) or AI.

2.1 How Cloud Computing Affects Firms' 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 costs, F_{CC}, which include the costs of buying and maintaining computers and software to variable computing services, $C_{CC}(q)$, acquired over broadband networks from large-scale computing centers. These variable costs scale with size proportionally. Thus, cloud computing decreases the upfront fixed cost of ICT adoption, F_{CC} (see Bayrak, Conley, and Wilkie 2011; DeStefano, Kneller, and Timmis 2020).

Second, the variable costs for using cloud computing, $C_{CC}(q)$, 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 variable cost per year per firm using cloud computing, $C_{CC}(q)$, is much lower than before.[9]

2.2 How AI Affects Firms' Costs

The term "artificial intelligence" means a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments. AI also serves as a prediction technology, which is key for firms making decisions in uncertain situations.

The AI cost function may be written as $C(AI) = F_{AI} + C_{AI}(q)$ with $C_{AI}(q) = C_d + C_h$, where C_d are data acquisition costs and C_h are human resource costs. Both of these may involve some quasi-fixed costs and data costs that may be decreasing with size.

Specifically, C_d can be written as $C_d = D_f + D_v + D_s + D_p$ where: D_f = Fixed costs for data acquisition, D_v = Variable costs for data acquisition (which may be firm-size dependent), D_s = Data storage costs, D_p = Data processing costs. Specifically, D_v can be written as $D_v = U_v * q * S^{\alpha}$ with S = firm size with $\alpha < 1, U_v$ = Base unit variable cost per data point or record, q = Quantity of data acquired.

The cost of human AI specialists, C_h, can be written as $C_h = (W_a * N_a) + (W_d * N_d) + T$ where W_a = Average annual salary for AI specialists, N_a = Number of AI specialists, W_d = Average annual salary for data scientists, N_d = Number of data scientists, T = Training costs. These all may be significant for AI, and may involve scale economies unlike firms that just use cloud software over the internet.

[9] A survey conducted by the International Data Corporation (IDC), detailed in the IDC White Paper "Fostering Business and Organizational Transformation to Generate Business Value with Amazon Web Services," interviewed 27 organizations worldwide that use AWS. The survey revealed a 31% reduction in annual IT infrastructure costs when using AWS compared to on-premise environments. Compared to AWS fees, these IT infrastructure costs included power, facilities, licensing, and hardware costs. Furthermore, the annual average number of unplanned outages per firm decreased from 7 without AWS to 1.9 with AWS, thus leading to a 94% decrease in costs of lost productivity. Additionally, IDC found that cloud computing lowered time costs for IT staff by automating tasks, including patch automation, automated scaling, and monitoring.

For firms using AI, the fixed costs, F_{AI}, may be large as AI increases upfront fixed costs due to the need for specialized computational power, the recruitment of AI specialists, and extensive data acquisition and preprocessing.[10] Implementing AI systems typically involves a substantial initial investment in technology, software, hardware, and skilled personnel. This can be considered a fixed cost. While some fixed costs are associated with the initial implementation, ongoing maintenance, and updates to AI systems may also contribute to fixed costs.

The labor costs to build an AI-focused team, C_h, are also substantial. In the U.S., the average base salary for a data scientist (W_d) is \$123,039 per year, while a machine learning engineer (W_a) typically earns around \$161,138 annually.[11]

Concurrently, AI technologies can automate routine and repetitive tasks, reducing the need for human labor in specific areas, and potentially lowering variable costs related to wages and benefits. Additionally, AI has the capacity to enhance operational efficiency, leading to a reduction in variable costs associated with energy, materials, and other resources necessary for production or service delivery.

Lastly, and perhaps most importantly, the degree to which firms benefit from AI largely hinges on the amount of data the firms own (Fedyk 2016; Jones and Tonetti 2020). The marginal cost of AI deployment will diminish as data input rises and its efficiency improves. Specifically, large firms have more data, which helps them reduce the marginal costs for data acquisition and become more productive. Productive firms grow more and produce more data, which then improves their efficiency (Farboodi, Mihet, Philippon, and Veldkamp 2019). In addition, more data input improves the accuracy of AI models significantly. Overall, as AI systems handle larger volumes of tasks, firms may achieve economies of scale, ultimately resulting in a decrease in average costs per unit of output.

[10] As firms require substantial computing resources to train AI models, the shock to the cost of Internet-based computing power and services can initially lower the unit cost. However, when considering the large amounts of computing power and services needed, as well as additional expenses such as hiring AI experts, the total fixed cost of using AI ultimately increases rather than decreases.

[11] Salary information from Indeed (the information is obtained on July 15, 2024).

2.3 Hypothesis Development

We draw on Melitz and Ottaviano (2008) to provide a conceptual framework from which we generate specific predictions concerning firm entry and exit, which we will subsequently test empirically. To study the impact of technological changes on firm entry and exit, we consider the underlying model of Melitz and Ottaviano (2008) in which firms maximize expected profits when considering entry and exit decisions.

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. Therefore, a firm's decision to enter or exit a market is influenced by the interplay between the upfront fixed cost and its variable cost.

The impact of new technologies on firm entry and exit depends on their effects on both fixed and variable costs. Our paper begins with an analysis of technologies that reduce fixed costs and variable costs, particularly focusing on cloud computing. To elucidate the underlying mechanisms, we also investigate technologies that increase fixed costs while simultaneously offering economies of scale through costs that are decreasing with firm size, like AI. By testing implications from the previous cost functions we presented and the theoretical framework derived from Melitz and Ottaviano (2008), we aim to predict the potential effects of cloud computing and AI on firm entry and exit, respectively. Subsequently, we will empirically validate these predictions.

2.3.1 Hypothesis about Cloud Computing

Cloud computing not only reduces fixed entry costs but also marginal variable costs. 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 and variable costs are $C(q)$ before cloud computing. After the sharp increase in cloud computing, fixed costs drop to $\mathrm{F}_{CC} = \mu F$ and variable costs drop to $\mathrm{C}_{CC}(q) = \tau C_{CC}(q)$ where $\mu, \tau < 1$.

As a result of these cost savings, potential entrants are likely to use cloud services following the emergence of cloud computing. In contrast, incumbent firms face a decision: to transition to cloud computing or to maintain their current IT infrastructure. This choice hinges on a trade-off between the expected benefits of adopting cloud computing and the related transferring costs. Specifically, if incumbents decide to transition to cloud computing, they must decommission their existing IT infrastructure, which includes server rooms, hardware, and software. They must also transfer data from their pre-built servers to cloud platforms, potentially lay off some IT staff, and provide training for the remaining employees to adapt to the cloud platform. Hence, if the transferring costs are deemed too high, incumbent firms may be less likely to transition to cloud computing[12].

There is only one type of firm indexed by $\{(F, C(q)\}$ before cloud computing. However, there are two types of firms indexed by $\{(F, C(q), (\mu F, \tau C(q)\}$ post-cloud computing, where the former is the incumbents entering before cloud computing and the latter is the entrants using cloud computing. 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.

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

[12] With the emergence of cloud computing, incumbents with lower transfer costs are likely to migrate to cloud service platforms. Following this migration, their variable costs, denoted as τc, become equivalent to those of potential entrants. However, this migration incurs an additional one-time transition cost denoted by f_T. To streamline our analysis, we strategically exclude these transitioning incumbents. This exclusion is rationalized by the fact that their post-migration expected profit function aligns with that of potential entrants, as both share identical variable costs. Consequently, their absence does not exert a significant influence on the predictions derived from our framework.

with no fixed costs for cloud computing:[13]

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

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 (1), 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, due to the variable cost reductions associated with cloud computing, entrants require a lower minimum productivity level to achieve zero profit compared to incumbents who haven't transferred the technology. The difference in the required minimum productivity between entrants and incumbents increases as the variable cost reduction from cloud computing becomes more pronounced. 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 (μF) 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

[13] Cloud computing shifts IT resource costs from fixed costs, such as purchasing and maintaining computers and software, to variable computing services acquired over broadband networks.

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 sustain positive profits in a more competitive market with lower market prices. Furthermore, incumbents might be burdened with ongoing obligations for principal and interest repayments, stemming from substantial loans acquired from financial institutions for the initial establishment of their on-premise IT infrastructures. 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.

2.3.2 Hypothesis about AI

We also examine an additional type of new information technology: AI. If the use of AI 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 due to the substantial amounts of data, specialized computational power and the recruitment of AI specialists required to train AI models. However, 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:

$$[p_i(c_{AIi}(q_i)) - C_{AIi}(q_i)]\, q_i(c_{AI,i}) - F_{AI} \tag{2}$$

with $c_{AI,i}(q_i)$ 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_{AI} is the fixed cost of using AI each period for the firm, including fixed costs of data acquisition (D_f), data storage (D_s), data processing (D_p), and human resources (C_h).

Based on this alternative revenue function, the impact of AI on firm entry hinges on its dual effects on both the fixed costs F_{AI} and the variable cost $c_i(q_i)$, with the latter dependent on the scale of the firm. When firms adopt AI, they face increased fixed costs, which could initially lower their expected profits. However, the marginal costs decrease in size post-AI, thereby potentially increasing their profitability through economies of scale. Thus, the net effect on expected profits for new entrants depends on the interplay between these opposing forces: the rise in fixed costs and the decline in variable costs. If the increase in fixed costs surpasses the reductions in variable costs experienced by average-sized firms, AI is likely to decrease firm entry. In contrast, if the reduction in variable costs due to AI adoption outweighs the increase in fixed costs, AI could encourage more entrants to enter the market. Consequently, the overall impact of AI on firm entry remains ambiguous and requires empirical investigation.

Under this alternative revenue function (2), AI increases fixed costs while having economies of scale. This interaction defines a critical cut-off size, making the point where the savings on variable costs from increased size offset the increased fixed costs associated with AI adoption. The expected revenue for firms exceeding the cut-off size increases post-AI, thus AI increases the relative competitiveness of those firms. Conversely, for firms below the cut-off size, the increase in fixed costs might be disproportionately large relative to the benefits of reduced variable costs. Consequently, AI reduces their expected profits and undermines their relative competitiveness. Therefore, we predict that AI will decrease the exit probability for larger firms while increasing the exit probability for smaller firms.

Prediction 3. AI 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 AI.

3 Estimation Strategy and Data

3.1 Estimation Strategy

We examine the different effects of cloud computing and AI on firm dynamics by exploiting the variation in the impact of cloud computing and AI on different industries after the large-scale cost shock experienced by both technologies in 2013.

3.1.1 Why only one shock for both technologies?

We set 2013 as the first year of the Internet-based computing power and services technological shock for China. While we have just one shock, this shock affected both firms using cloud computing and AI as it lowered the cost of purchased computing power and services for firms using either cloud computing or AI (like an oil shock for all using firms). While there is only one shock lowering computing costs for both technologies, we predict different effects on firms in industries that are heavy users of cloud computing versus in industries where AI is more likely to be used. The previous section discussed how we predict different effects for firms using these two different technologies. Appendix Figure A.2 shows a sharp and persistent decline in the annual price of Alibaba Cloud services since 2013.

This significant cost drop in computing power and services was propelled by two key developments: the Chinese government's decision to permit foreign internet computing service companies to operate within the country, and a notable breakthrough in the costs of providing computing services over the internet.[14]

First, this year was marked by a surge in entrants and expansions into China's purchased computing services sector (generically called cloud services), encompassing both domestic and foreign purchased computing service providers as shown in Appendix Table A.1. On the domestic front, 2013 saw the emergence of new independent computing service providers, including Tencent Cloud, SpeedyCloud, UCloud, QingCloud, and QiniuYun. Concurrently, numerous foreign computing service companies entered the Chinese market when the Chinese government relaxed regulations allowing their entry.[15] For instance, Windows Azure announced the availability of a Public Preview for its service, commencing on June 6, 2013.[16] In December of the same year, AWS, a global leader in cloud computing, announced its entry into the Chinese market.[17] IBM, another major player, followed suit with a similar announcement on the same day.[18]

Second, the cost of Internet-based computing services decreased sharply and remained lower since 2013, driven by significant breakthroughs in computing technology and intense competition among cloud computing providers. Specifically, in August of that year, Alibaba Cloud achieved a milestone by independently developing Apsara, a large-scale distributed computing operating system. This innovation positioned Alibaba Cloud as the world's first firm to offer 5K cloud computing service capabilities. Key events in China's cloud computing

[14]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" to block foreign websites, VPNs, 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.

[15]Chinese laws require foreign cloud service companies to store data locally and to operate through domestic companies. So foreign cloud service providers like Microsoft Azure have had to find local partners. Microsoft Azure operates in China through a unique partnership with 21Vianet, which is a domestic internet data center services provider in China. Azure was the first multinational organization to make public cloud services available in China. AWS and IBM followed Azure's entry model by partnering with Chinese companies.

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

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

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

industry are summarized in Table A.1. A persistent price war in Internet-based computing services has ensued since 2013, after the entry of all of these new technology providers.

Why does the cost shock impact both cloud computing and AI? First, the influx of numerous computing service companies into the Chinese market in 2013 significantly accelerated the development of cloud computing technology in China, leading to a sharp decrease in the cost of computing power and services. This reduction primarily benefits firms that rely heavily on online or web-based operations, as they can transition their operations to cloud platforms instead of maintaining on-premise environments.

Second, AI development requires powerful computing services in addition to extensive amounts of data for training, reasoning, and prediction. Cloud computing provides AI with nearly unlimited computing power at lower costs. Consequently, the big drop in computing power and service costs has been a key driver of the rapid growth of AI.

Additionally, 2013 was a key year for Chinese policy development. The Chinese government has developed a series of policies to promote the development of cloud computing and AI since 2013. For cloud computing, in February 2013, the Ministry of Industry and Information Technology issued the "Top-Level Design Guidelines for Cloud-based Public Platform for E-Government" to guide the government on utilizing cloud computing. 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 encourage small and medium-sized enterprises to use cloud computing. For AI, the Chinese government took a significant step toward encouraging AI development by issuing a policy titled "Council Guidelines on Promoting the Healthy and Orderly Development of the Internet of Things" in February 2013.

3.1.2 Difference-in-Differences

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. Following Cohn, Liu, and Wardlaw (2022), we use Poisson regression, using count data as the dependent variable, in our primary table.[19]

Our estimated specifications take the following forms:

$$log(E(X_{i,t})) = \alpha + \beta_{Cloud}(Post_t \times Cloud_i) + \beta_{AI}(Post_t \times AI_i) + M_{i,2007} \times \delta_t + \gamma_i + \delta_t \quad (3)$$

$$log(E(X_{i,t})) = \alpha + \beta_{Cloud}(Post_t \times Cloud_i) + \beta_{AI}(Post_t \times AI_i) + M_{i,t-1} + \gamma_i + \delta_t \quad (4)$$

where i and t indicate industry and year, respectively. 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 number of firms entering and exiting at the industry-year level, respectively. All dependent variables are winsorized at the 1% level.[20]

In equation 3, $M_{i,2007} \times \delta_t$ are time-invariant industry characteristics interacted with year fixed effects. First, entrepreneurs may prefer to enter industries with higher profit margins (Siegfried and Evans 1994; Ilmakunnas and Topi 1999). Consequently, we include industry ROA, calculated by dividing net income by total assets, as a control variable. Second, higher Property, Plant, and Equipment (PP&E) investment typically denotes more entry barriers (Ericson and Pakes 1995), so we incorporate the ratio of fixed asset investment to total assets as a control variable. Additionally, following Ilmakunnas and Topi (1999), industry size is positively related to subsequent firm entry and exit. Thus, we also include the logarithm of average total assets in 2007 as a control variable. These industry characteristics are obtained from the National Tax Survey Database.

In equation 4, we adjust for the previous year's industry characteristics as an alternative specification. Given that the National Tax Survey database covers the period from 2007 to 2016, the sample used in equation 4 spans from 2008 to 2017.

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 na-

[19] Given in most specifications we have very few zero values, we also reestimate the impact using log-linear regression in the Appendix.

[20] Our results remain robust across various levels of winsorization.

tionwide shocks in a particular year likely to have affected all industries in a similar manner. In this and all subsequent analyses, the *Cloud* and *AI* variables are standardized to have a mean of zero and a standard deviation of one, facilitating clearer economic interpretation. Finally, we cluster the standard errors at the industry 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.[21] An industry with higher $Cloud_i$ has a greater concentration of heavy users 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 large-scale cost shock.

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".[22] We then calculate $Cloud_i$ as the number of affected firms at the industry level as a percentage of all surviving firms in 2012.[23]

The top five industries 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.

[21]The concordance relationships between Cloud keywords and their corresponding Chinese translations are shown in Panel A, Appendix A.2.

[22]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 software applications, such as Google App Engine and OpenShift.

[23]Figure A.5 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.

Thus, firms in these industries with higher *Cloud* are more exposed to the cost shock of Internet-based computing services. In contrast, industries with lower *Cloud* include "Agriculture," "Forestry," "Hunting," "Fishing," "Mining," and "Oil and Gas Extraction." Most of these control industries provide tangible goods, such as "vegetables," "fish," and "ore."

To investigate the potentially disparate effects of cloud computing and AI, we follow a similar procedure as used for the Cloud to classify the influence of AI on each 2-digit industry. This classification is based on the varying likelihood of AI adoption across different industries.

We classify a firm as an AI-affected firm if its business description has at least one of the following keywords: *AI, intelligence, artificial intelligence, algorithms, machine learning, deep learning, neural networks, face recognition, computer vision, natural language processing, or automation.* Russell and Norvig (2009) delve into four definitions of AI, which differentiate AI on the basis of thinking vs. acting.[24] We extract the keywords "intelligence," "algorithms," "machine learning," "deep learning," "neural networks," "face recognition," "computer vision," and "natural language processing" from the first dimension of the definitions of AI, which are concerned with thought processes and reasoning. We also extract the keywords "automation" from the second dimension of the definition of AI, which relates to behavior. We also add other keywords "AI," and "artificial intelligence."[25] Additionally, there is no keyword overlap between cloud computing and AI.

We also define the influence of AI based on all surviving firms in 2012 prior to the large-scale cost shock. AI_i is defined as the proportion of the affected firms whose business scope description contains AI-related keywords to all surviving firms in industry i in 2012.

We find that most industries with higher AI adoption levels (higher AI) but lower cloud computing adoption levels (lower *Cloud*) 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). Fur-

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

[25]The concordance relationships between AI keywords and their corresponding Chinese translations are shown in Panel B, Appendix A.2.

thermore, the correlation coefficient between cloud computing and AI measures is 0.391, indicating a positive but relatively weak association between the two technologies across industries.

Appendix Figure A.3 illustrates the impact of cloud computing across various 1-digit industry sectors, and Appendix Figure A.4 provides a similar analysis of the influence of AI technologies. "Information Transmission, Software, and Information Technology Services (Information)" and "Scientific Research and Technical Services (Research)" sectors exhibit the strongest exposure to both cloud computing and AI. However, the "Sports & Entertainment" sector ranks third for the influence of cloud computing, whereas the "Construction" sector takes the third position in terms of AI's impact.[26] Moreover, the figures highlight that the "Manufacturing" and "Utilities" sectors are markedly influenced by AI, contrasting with their limited exposure to cloud computing.

3.2 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.[27] The RESSET 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.[28]

Our data provide information on the entry and exit of all firms in China from 2007 to 2018. The data includes all non-listed and listed firms, including small and micro firms,

[26]Cloud platforms provide robust Content Delivery Networks (CDNs) that ensure high-quality, low-latency streaming for live sports and entertainment content. This efficiency in data transmission, provided by cloud computing, is crucial for seamless broadcasting. In contrast, while AI can enhance aspects like personalized recommendations, the core function of broadcasting relies on stable data delivery rather than AI. Consequently, firms in the "Sports & Entertainment" sector prioritize cloud computing for its essential benefits in content delivery, with AI being less critical and less utilized.

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

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

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 1949 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 detailed equity financing information for firms, such as investors, financing time, financing amount, and financing phase.

The National Enterprise Credit Information Publicity System uses the Industrial Classification for National Economic Activities in China (GB/T 4754-2011) to assign each firm to an industry.[29] 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.[30]

We construct the panel data of entry, exit, surviving number and even financing at the 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 either entry or exit year and industry at the industry-year level.

We complement our 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). NTSD data also uses the Industrial Classification for National Economic Activities in China (GB/T 4754-2011) to assign each firm to an industry.[31] The data comprises an annual survey of approximately 500,000 firms distributed across all two-digit industries and all regions nationwide. It includes both publicly listed and

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

[30]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.

[31]NTSD data before 2011 use the Industrial Classification for National Economic Activities in China in 2002 (GB/T 4754-2002). To ensure consistency and comparability across the entire dataset, we have updated the pre-2011 industry classifications from the 2002 codes to the 2011 codes. This adjustment was executed using a detailed concordance table between GB/T 4754-2002 and GB/T 4754-2011.

private firms, covering large firms as well as small and medium-sized firms. The panel data provides detailed information on firm performance such as sales and assets. We merge this dataset with our main dataset based on two-digit industry codes and then calculate industry competition and size distribution across industries.

3.2.1 Firm Entry

Firm entry is defined as a new firm registration.[32] Each firm is assigned to 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.[33] 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.[34] 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.[35] 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 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.

We examine entry at the industry-year level with entry equal to the sum of newly-

[32]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.

[33]According to Chapter 1 General Provisions, Article 3 of "Regulation of the People's Republic of China on the Administration of Company Registration" (2016 Revision), Chinese law stipulates that a firm shall not engage in any business activity in its name unless it is registered with the company registration organization.

[34]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).

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

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.

3.2.2 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.[36] 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.[37]

We examine exit at both the firm, f, and industry level, i. $Exit_{f,t}$ equals 1 for a given firm f if it is self-deregistered or its license is revoked. At the industry level, $Exit_{i,t}$ 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.

3.2.3 Summary Statistics

Table 1 presents summary statistics for entry and exit at the industry-year level. Across all industries, the average number of entrants was 15,110 in 2007. Entry rates increased gradually with time and rose to 78,096 in 2018. Firm entry experienced 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 before the large-scale cost shock and increased by about

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

[37]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).

4 million in the subsequent six years following the cost shock. The sharp upward trend in entry after 2013 is consistent with costs of entry decreasing with the large-scale cost shock of Internet-based computing power and services in 2013.

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. The rise in exit rates post-2013 is less pronounced than that of entry rates, which could be potentially attributable to the negative effects of AI on firm exit during this period.

4 Empirical Findings on Firm Entry, Exit and M&A

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 or AI experience a higher increase in entry following large-scale cost shock. The DID estimates with the count of firm entry as the dependent variables using Poisson regression are shown in Table 2.

All columns control for year fixed effects and industry fixed effects. Column (2) also controls for a set of time-invariant industry characteristics in 2007 interacted with the year fixed effects. Column (3) also controls for industry characteristics in the previous year.

The regression results reveal a positive and statistically significant correlation between cloud computing and firm entry at the industry-year level (*Prediction 1* of our paper), while AI shows no significant influence on firm entry. In terms of magnitude, all else being equal, a one-standard-deviation increase in the influence of cloud computing is associated with a 13–25% increase in the expected number of firm entry.[38] Appendix Table A.3 shows that

[38] Column (1) indicates that all else being equal, a one-standard-deviation increase in the influence of cloud computing is associated with a 13% ($= exp(0.122) - 1$) increase in the expected number of firm entry.

the results from the OLS regression are consistent with those from the Poisson regression.[39]

4.1.2 Yearly Estimates for Firm Entry

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

$$\begin{aligned} log(E(X_{i,t})) = \alpha + \sum_{k \geq -6, k \neq -1}^{5} \left[\beta_{Cloud,k}(D_{2013+k} \times Cloud_i) + \beta_{AI,k}(D_{2013+k} \times AI_i)\right] \\ + M_{i,2007} \times \delta_t + \gamma_i + \delta_t \end{aligned} \tag{5}$$

where i and t indicate industry and year, respectively. $X_{i,t}$ represents the counts of firms entering and exiting at the industry-year level. All dependent variables are winsorized at 1%. *Cloud* and *AI* are the measurements of the influence of cloud computing and AI, standardized to have a mean of zero and a standard deviation of one.

D_{2013+k} jointly represents a window of periods around the cost shock in 2013. 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 $\beta_{Cloud,k}$ and $\beta_{AI,k}$ measure the annual increases in entry caused by cloud computing and AI post-shock, respectively, relative to the year 2012. Standard errors are clustered at the industry level.

Figure 1a shows the yearly coefficients of cloud computing with Entry as the dependent variable. We find that none of the pre-treatment indicators shows any statistical power. Coefficients $\beta_{Cloud,k}$, however, become statistically significant at the 5% level after the sharp decrease in the cost of Internet-based computing power and services. The coefficients remain strong and significant after 2013.

[39] One potential concern is that the observed increase in entry, impacted by cloud computing, may be primarily due to the expansion of subsidiaries in various locations rather than the emergence of new firms, as cloud computing could also reduce coordination costs. To address this concern, we focus only on newcomers based on their ownership network. Specifically, we classify an entrant as a newcomer if its shareholders are not limited to one firm. Appendix Table A.4 presents the impacts of cloud computing on newcomers. The coefficients are close to the coefficient on firm entry and remain positive and statistically significant. The positive results suggest that cloud computing increases firm entry by reducing fixed entry costs and variable costs.

Figure 1b shows that there are no significant pre-treatment indicators pre-shock. Since AI has no statistically significant impact on firm entry, as shown in Table 2, the coefficients $\beta_{AI,k}$ do not become significant post-shock.

Taken together, these results show that the differences in entry across various industries affected by cloud computing begin to diverge following the large-scale cost shock of Internet-based computing services. These results are consistent with the prediction that the differential effects on firm entry across different industries are related to cloud computing rather than AI.

4.2 Firm Exit

4.2.1 Firm-Level Analysis for Firm Exit

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 shock to the cost of Internet-based computing power and services.

These specifications take the forms:

$$Exit_{f,t} = \alpha + \beta_{Cloud}(Post_t \times Cloud_i) + \beta_{AI}(Post_t \times AI_i) + M_{i,2007} \times \delta_t + \theta_f + \delta_t + \varepsilon_{f,t} \quad (6)$$

$$Exit_{f,t} = \alpha + \beta_{Cloud}(Post_t \times Cloud_i) + \beta_{AI}(Post_t \times AI_i) + M_{i,t-1} + \theta_f + \delta_t + \varepsilon_{f,t} \quad (7)$$

where f and t indicate firm and year, respectively. $Exit_{f,t}$ equals zero if firm f survived through year t and equals one if firm f exited that year. The outcome is set to missing in the years after death. *Cloud* and *AI* are the measurements of the influence of cloud computing and AI, standardized to have a mean of zero and a standard deviation of one. $M_{i,2007} \times \delta_t$ represent time-invariant industry characteristics that interact with year fixed effects, including ROA, PP&E investment, and the logarithm of the average total assets for 2007. $M_{i,t-1}$ are the time-variant industry characteristics from the previous year, $t-1$. We also 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 estimates examining firm exit are shown in columns (1)-(3) of Table 3. The relation between firm exit and cloud computing is significant and positive. Interestingly, we find that the regressions that control for the differential industry exposure to AI reveal a negative correlation between AI and firm exit. All estimates at the firm level are statistically significant.

Economically, when all controls are included, a one-standard-deviation increase in the influence of cloud computing leads to a 13-16% increase in the exit probability, compared to the mean exit probability prior to the cost shock. However, a one-standard-deviation increase in the influence of AI corresponds to a 6-7% decrease in the exit probability, relative to the mean exit probability before the cost shock.

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.6. Furthermore, the results remain unchanged and significant, as shown in columns (2) and (3) of Appendix Table A.6, after controlling for industry fixed effects and region-year fixed effects, or alternatively, industry-region fixed effects and region-year fixed effects.

We also redefine exit to a narrower measure, focusing only on voluntary exit.[40] Voluntary exit is defined as the case where the exit reasons include poor performance and business adjustment according to exit reasons. Appendix Table A.7 also shows that cloud computing also increases voluntary exit while AI decreases voluntary exit.

[40]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.

4.2.2 Industry-Level Analysis for Firm Exit

The last three columns in Table 3 show the results of Poisson regression by using the count of firm exit as the dependent variables at the industry-year level.

We include industry and year fixed effects in columns (4). Regression that controls for the differential industry exposure to cloud computing shows that cloud computing has a positive relation with firm exit. The estimate is statistically significant. The coefficient for AI is negative, though statistically insignificant.

We also control for a set of time-invariant industry characteristics in 2007 that interacted with the year fixed effects, as shown in column (5). Both the magnitude and significance of the coefficient for cloud computing increase, while the coefficient of AI remains negative and insignificant.

We subsequently adjust our model to account for time-variant industry characteristics from the prior year. Results shown in column (6) remain unchanged. In terms of economic magnitude, a one-standard-deviation increase in the influence of cloud computing is associated with approximately $10\%(= exp(0.092) - 1)$ increase in the expected number of firm exit as shown in column (6). Online Appendix Table A.5 shows that the OLS regression estimates are consistent with the Poisson regression estimates at the industry-year level.

4.2.3 Yearly Estimates for Firm Exit

We also examine how the annual exit rates are related to cloud computing and AI using equation 5. Figure 2a shows that the coefficients $\beta_{Cloud,k}$ are mostly close to zero without any statistical power in the pre-period. These annual rates, however, diverge for the affected industries and remain stronger and significant post-shock. Figure 2a demonstrates that the timing of the increases in firm exits caused by cloud computing is consistent with the large-scale cost shock of Internet-based computing services.

Figure 2b also shows that the annual exit rates of AI are near zero and lack statistical significance during the pre-period. However, the coefficients $\beta_{AI,k}$ become negative and statistically significant following 2013. Figure 2b confirms that the timing of the decrease in firm exit caused by AI coincides with the cost shock.

4.2.4 Differences in Exit Across Different Sizes

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 computing power and services 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 these would be more pronounced among smaller firms.

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

We divide the sample into three subsamples using the terciles of registered capital by 2-digit industries for all surviving firms in 2007. The results at the firm level are shown in Table 4. In columns (1) - (3), we control for both firm and year fixed effects and analyze the different impacts separately for each tercile subsample. The impacts of cloud computing on exit for firms of different sizes are positive, with the positive impact being larger among smaller firms. All estimates are statistically significant.

However, the effects of AI on exit for firms of different sizes are quite different. In industries where AI is more likely to be used, we find that larger firms in the medium and large size terciles are *less* likely to exit as shown in columns (1)-(3) of Table 4. Smaller firms in the smallest size tercile are more likely to be crowded out of the market due to intensified competition from larger firms post-shock. All estimates are statistically significant. Hence, the positive benefits (lower exit rates) of AI are concentrated among larger firms.[41]

[41]Since the cost shock is at the industry-year level, we also cluster standard errors by industry-year to address potential cross-sectional correlations among firms within the same industry and year. The results at

To examine whether the differences in the coefficients of Post_Cloud (or, Post_AI) are statistically significant between adjacent terciles, we use interaction terms, $\beta_{\Delta Cloud}$ or $\beta_{\Delta AI}$, to capture the differential effects by interacting the main independent variables with a binary group indicator denoting firm size (where the smaller subsample equals 1).

The estimates of $\beta_{\Delta Cloud}$ and $\beta_{\Delta AI}$ are shown in the final eight rows of Table 4. The differences in the coefficients of Post_Cloud are positive and statistically significant across the groups, indicating that the relationship between cloud computing and firm exit is monotonically decreasing in firm's initial size. These differences of AI are also positive and statistically significant between adjacent terciles, indicating an incremental beneficial impact of AI on survival rates of medium relative to large firms. Conversely, for firms in the smallest size category, AI is associated with a decreased likelihood of survival.

We also control for a set of time-invariant industry characteristics interacted with year fixed effects and the results are shown in columns (4)-(6). The estimates are consistent with those in columns (1)-(3) albeit with a modest reduction in most of the magnitude. The differences in coefficients of cloud computing and AI between adjacent terciles are still positive and significant. When all controls are included, a one-standard-deviation increase in the influence of cloud computing is associated with an 18% increase in the exit probability for small firms, 14% for medium-sized firms, and 12% for large firms, relative to their pre-shock mean exit probability.

Conversely, the impact of AI diverges significantly. A one-standard-deviation increase in the influence of AI leads to a 1% increase in the exit probability for small firms, relative to their pre-shock mean exit probability. However, a one-standard-deviation increase in the influence of AI leads to a 5% reduction in exit probability for medium-sized firms and a substantial 22% decrease for large firms, compared to their pre-shock averages.

Appendix Table A.8 also shows the impacts of cloud computing and AI on voluntary exit across firm sizes. Cloud computing is positively related to voluntary exit for firms of

the firm level remain statistically significant.

different sizes, with a more pronounced effect on smaller firms. In contrast, medium-sized and large firms get positive benefits from AI and have lower voluntary exit rates, though small firms in industries more affected by AI are more likely to exit voluntarily.

4.3 M&A Differences between Cloud Computing and AI

We also examine the differences in the effects on becoming an acquisition target between cloud computing and AI following the large-scale cost shock. Although the database does not directly record M&A information for companies, it encompasses information on shareholder changes for each firm. During an M&A transaction, a new company acquires stock rights from the incumbent shareholders of the firm, which may include companies or individuals.[42] We classify a transaction as an M&A when a firm transfers its stock rights from its original shareholders to a different company.

Table 5 reports the firm-level results of cloud computing and AI on whether a firm is merged post-shock. We regress an indicator for whether the firm is merged in a given year on cloud computing and AI. We first estimate the different impacts of cloud computing and AI on the likelihood of being merged using the full sample as shown in column (1) of Table 5. It controls for firm and year fixed effects and interactions between time-invariant industry characteristics and year fixed effects. The estimates show that cloud computing is strongly associated with increases in the likelihood of being merged while AI is associated with decreases in this likelihood. These different impacts of cloud computing and AI on the likelihood of being merged are similar to the impacts on exit as shown in Table 3. Both estimates are statistically significant. These results are consistent with M&A serving as a distinct exit mechanism, enabling the reallocation of assets to more efficient incumbents and facilitating firm exit.

We also divide the full sample into three subsamples based on the terciles of registered

[42] 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.

capital for surviving firms in 2007 and the results are shown in columns (2)-(4) of Table 5.[43] Overall we find that the relationship between cloud computing and being merged probability is monotonically increasing in the firm size. This pattern diverges from the trend observed in exit likelihood, where the association between cloud computing and exit likelihood is monotonically decreasing in the firm size. These findings indicate that for larger firms, M&A activities serve as the primary exit mechanism, in contrast to smaller firms. Smaller firms, characterized by fewer valuable assets, tend to exit the market directly.

In contrast, the coefficients of Post_AI in columns (2)-(4) are negative and statistically significant for all size terciles, with a more pronounced negative impact of AI on larger firms. Consequently, larger firms exhibit a higher survival rate caused by AI compared to their smaller and medium-sized counterparts post-shock. These results are consistent with AI being beneficial to larger firms given greater data and computational resources.

4.4 Cost Structure

We then discuss the empirical evidence on changes in fixed costs caused by cloud computing and AI after a large-scale shock that decreased the cost of Internet-based computing power and services. We estimate the following model at the firm level:

$$Fixed\_Income_{f,t} = \beta_0 + \beta_{cloud}\ Cloud_{f,t} + \beta_{AI}\ AI_{f,t}\gamma_0\ Control_{f,t} + \theta_f + \delta_t + \varepsilon_{f,t} \tag{8}$$

where f, and t represent firm, and year, respectively. $Fixed\_Income$ represents the ratio of total fixed assets to operating income. $Control_{f,t}$ include firm size (Size), measured by the natural logarithm of total assets at the end of the year; firm age (lnAge), measured by the natural logarithm of the number of years the firm has been listed; leverage ratio (Lev), measured by the ratio of total liabilities to total assets at the end of the year; firm equity concentration (Top1), measured by the shareholding ratio of the largest shareholder; return on assets (ROA), measured by dividing the firm's net income by its total assets at the end of the year; the growth rate of operating income (SaleGrowth), measured as the growth rate

[43] The results stay statistically significant when clustering standard errors by industry-year.

of operating income from year $t-1$ to t; and Tobin's Q (TobinQ), measured by dividing the firm's total market value by its total asset value.

To examine this question, we use all A-listed firms in China from 2007 to 2023, as they provide detailed sales and cost information.[44] After excluding financial firms, we use textual analysis of their annual reports to determine when a firm uses cloud computing or AI.

We first extract sentences from the annual reports containing cloud- or AI-related keywords. Cloud-related keywords include: *cloud computing, public cloud, private cloud, hybrid cloud, government cloud, personal cloud, enterprise cloud, AliCloud, Tencent Cloud, IaaS, PaaS, SaaS*. AI-related keywords include: *AI, intelligence, artificial intelligence, algorithms, machine learning, deep learning, neural networks, face recognition, computer vision, natural language processing, automation.*

These sentences are then manually verified to ensure they indicate the actual usage of the technologies. Sentences that describe technological development background or mention technological policies in China are excluded. The first year a given firm's annual report mentions the use of cloud computing or AI is marked as the initial year of adoption of that technology. We assume continued use in subsequent years and assign an indicator value of one for cloud computing or AI use ($Cloud_{f,t}$ or $AI_{f,t}$). We include firm fixed effects (θ_f) and year fixed effects (δ_t). Standard errors are clustered by firm.

The results are shown in Table 6. In column (1), we include firm fixed effects and year fixed effects. Column (2) adds control variables. In both columns, the coefficient of $Cloud_{f,t}$ is negative and statistically significant, suggesting that the adoption of cloud computing leads to lower fixed costs. Conversely, the coefficient of $AI_{f,t}$ is positive and statistically significant, indicating that AI use leads to higher fixed costs for firms.

[44] We use all A-listed firms in China instead of the NTSD dataset because we can determine whether a given firm uses cloud computing or AI in a given year based on their annual reports.

5 Industry Concentration and Size Distribution

5.1 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 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 three columns in Table 7 show the estimates of the different effects of cloud computing and AI on industry concentration by using firms' assets to calculate the market percentage. All columns control for industry and year fixed effect. Additionally, column (2) also controls for time-invariant industry characteristics interacted with year fixed effects. Column (3) controls for time-variant industry characteristics in the previous year.

The results show that industry concentration goes down after the increased adoption of cloud computing but goes up after the increased adoption of AI. Economically, when all controls are included, a one-standard-deviation increase in the influence of cloud computing leads to a 22-35% decrease in industry concentration, compared to their mean value before the cost shock. In contrast, a one-standard-deviation increase in the influence of AI leads to an 11-19% increase in industry concentration, compared to their mean value before the cost shock. All estimates of cloud computing and AI are statistically significant.

The final three columns in Table 7 show that our estimates are robust to how we measure HHI. Using firms' sales to calculate HHI, industry concentration decreases by approximately 19-28% per one-standard-deviation increase in the influence of cloud computing post-shock while industry concentration increases by about 10-14% per one-standard-deviation increase in the influence of AI post-shock, relative to the mean value before the cost shock. All estimates are also statistically significant.

In sum, these results in Table 7 imply that cloud computing is associated with decreases in industry concentration while AI is associated with increases in industry concentration.

5.2 Size Distribution across Industries

We now examine the changes in the size distribution of surviving firms across industries. We use the information on assets and sales of firms from the NTSD dataset to measure firms' size. Table 8 reports the results examining the central tendency and dispersion of size distribution after the increased adoption of cloud computing and AI.

Columns (1) and (2) show the estimates using median and mean firm assets as dependent variables. All columns control for industry and year fixed effects as well as the time-invariant industry characteristics interacted with time fixed effects.

These estimates show that cloud computing is associated with a decrease in the average firm size in industries where cloud computing is more likely to be used. Economically, a one-standard-deviation increase in the influence of cloud computing leads to a 16% decrease in the mean firm asset value, compared to the pre-shock average value (here 259.51 million RMB). Both estimates of the coefficients on cloud computing are statistically significant. At the same time, AI has no impact on the average size of firms in industries where AI is more likely to be used.

Columns (3)-(4) show that our estimates are robust to how we measure firm size. Using firms' sales 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 industries that are heavy users of cloud computing while AI has no impact on the size composition within industries where AI is more likely to be used. The average sale decreases by 14% per one-standard-deviation increase in the influence of cloud computing post-shock relative to their pre-shock average sale (here 106.31 million RMB). The estimates of cloud computing in columns (3)-(4) are statistically significant.

We then examine the impact of cloud computing and AI on size dispersion of firms as measured by the coefficient of variation. Column (5) shows that a one-standard-deviation increase in the influence of cloud computing leads to a 6% decrease in the coefficient of variation of the asset size of all firms by industries, compared to the mean coefficient of variation pre-shock (here 0.37).

Column (6) shows the same pattern, using sales to measure size dispersion. The estimate indicates that, relative to the mean coefficient of variation pre-shock (here 0.39), the size concentration increases by 5% per one-standard-deviation increase in the influence of cloud computing. Both estimates in columns (5) and (6) are statistically significant. However, columns (5) and (6) show that AI has no impact on size dispersion given the coefficients of Post_AI are not significant.

In sum, the estimates in Table 8 imply that cloud computing increases the ratio of smaller firms inside industries where cloud computing is more likely to be used. In contrast, AI has no impact on the size composition.

6 Equity Financing Decisions

6.1 Firm Level Evidence on Equity Financing Decisions

We now examine how cloud computing and AI affect equity financing differently after the cost shock. It is generally recognized that new technologies can cause adaptation by financial intermediaries (see, e.g., 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 9 shows the results examining equity financing decisions 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. In column (1), we include only firm and year fixed effects. In column (2), we also include time-invariant industry characteristics interacted with year fixed effects. In column (3), we change to include time-variant industry characteristics in the previous year.[45]

As shown in columns (1)-(3) of Table 9, cloud computing is associated with a significant and economically meaningful increase in the probability of being equity-financed for firms in industries more affected by cloud computing. Specifically, a one-standard-deviation increase in the influence of cloud computing results in a 47-51% increment in the probability of firms getting equity financing, compared to the average probability of equity financing.

AI also significantly contributes to an increase in the likelihood of firms being equity-financed in industries that are heavy users of AI. A one-standard-deviation increase in the influence of AI leads to an additional 21-29% growth in the probability of being equity-financed for firms relative to the average probability of equity financing. While significant, the magnitudes are only about one half as large as those for cloud computing - consistent with small firms that are the most likely entrants in industries with more usage of cloud computing needing more external finance. Larger firms who are the more likely adopters of AI have more existing internal cashflows.

Next, to exploit the relation of both cloud computing and AI with the financing decisions of venture capitalists (VCs), we examine venture capital financing by itself.[46] The results on VC equity financing are shown in columns (4)-(6) of Table 9. 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

[45]To address cross-sectional correlation, we also cluster standard errors by industry-year. The results continue to be statistically significant.

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

in the probability of being VC equity-financed for firms following the large-scale cost shock. These results are consistent with cloud computing firms needing more external finance from specialist VC funds.

6.2 Differences in Equity Financing Across Different Sizes

We further explore the disparate impacts of cloud computing and AI on the equity financing decisions, separately for each tercile of firm size, as shown in Table 10. We split the full sample into three based on the terciles of registered capital by 2-digit industries for all surviving firms in 2007.

Columns (1)-(3) in Panel A, Table 10 control for both year and firm fixed effects. In medium-sized (Tercile 2) and large firms (Tercile 3), cloud computing is associated with a significant increase in equity financing. Conversely, the impact of AI demonstrates a significant positive effect only in large firms (Tercile 3), also significant at the 1% level. This disparity suggests that cloud computing has a broader positive impact on equity financing across medium and large firms, while AI tends to provide financial benefits primarily to the largest firms. For smaller firms (Tercile 1), the impact of both technologies on equity financing is not significant. The insignificant coefficients in Tercile 1 can be attributed to the higher reliance on internal funds over external equity financing among these smaller firms in China. Given their relatively limited scale, they might be deemed less attractive to external investors.

We also control for the interaction between time-invariant industry characteristics and year fixed effect, as shown in columns (4)-(6) of Panel A, Table 10. The results remain robust. To determine if the impact of AI and cloud computing (captured by Post_AI and Post_Cloud) differ significantly between size groups, we introduce interaction terms, $\beta_{\Delta Cloud}$ and $\beta_{\Delta AI}$, which combine the main independent variables with a binary size indicator (1 for smaller firms). The interaction terms are presented in the final eight rows of Panel A, Table 10. These results show negative and statistically significant coefficients ($\beta_{\Delta Cloud}$ and $\beta_{\Delta AI}$)

between medium and large firms, indicating that the likelihood of getting equity financing increases as firms grow in size after the increased adoption of cloud computing and AI.

Turning to VC financing measures in Panel B of Table 10, the findings remain consistent. The positive effects of both cloud computing and AI on the likelihood of getting VC financing for large firms are still significant, while their impacts for small and medium firms are not significant.[47]

7 Robustness Tests

7.1 Alternative Measures

7.1.1 Alternative Measures of the Influence of Cloud Computing and AI

To ensure our findings are robust and not skewed by measurement noise, we also categorize continuous measurements of the influence of cloud computing (*Cloud*) and AI (*AI*) into quartile dummy variables.

We re-estimate the results by substituting continuous measurements of *Cloud* and *AI* with the quartile dummy variables *CloudQuartile* and *AIQuartile*. All estimates shown in Appendix Table A.9 are still consistent using industry-year and firm regressions providing further support for our baseline estimates.

7.1.2 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 computing and AI by using more detailed cells (417 three-digit industry cells) from the Industrial Classification for National Economic Activities in China (GB/T4754-2011). Our estimates are still significant and positive, providing further support for our baseline estimates (see Table A.10).

[47] The insignificant impact on small and medium firms may be attributed to the increased presence of state-owned funds in the venture capital market since 2014. This shift coincided with the introduction of a pilot reform of state-owned capital investment companies by the State-Owned Assets Supervision and Administration Commission of the State Council (SASAC). State-backed funds generally prefer lower-risk investment, often choosing to invest in larger, well-capitalized firms over smaller ones.

7.1.3 Alternative Measures of Outcome Variables

Moreover, alternative outcome variables are employed as additional robustness checks. Specifically, the annual ratios of firm entry and exit to the surviving firms in the previous year are used as 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 Panel A of Table A.11). We also use the year-over-year percentage changes in the number of firms entering and exiting an industry as dependent variables. The results are again robust (see Panel B of Table A.11).

7.2 Other Potential Confounding Policies

To ensure robustness, we control for 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 impact of the cost shock. 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 are still unchanged, with a slight change in magnitude as shown in Panel A of Table A.12.

Second, we examine China's mass entrepreneurship and innovation campaign since 2015. This campaign was aimed to promote innovation and boost entrepreneurship-driven employment. Since the policy was advanced to encourage 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. The results on firm entry and exit remain robust as shown in Panel B, Table A.12. 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 SEI-related industries were identified and received increased financial support from the government. This additional support may increase the competitive advantage for incumbents and hinder free competition. The SEI policy may impact entry and exit. Nevertheless, we find that the estimated relations with both cloud computing and AI 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.12.

7.3 Other Potential Confounding Channels

The effect of cloud computing technology resembles that of leasing, as leasing reduces entry barriers by providing additional external financing for fixed costs. This financial support can encourage more entrepreneurs to enter capital-intensive sectors (Li and Xu 2023). To isolate the impact of leasing on firm dynamics, we construct industry-year-level operating lease and finance lease variables from the National Tax Survey Database and incorporate these variables into the baseline model. Our findings indicate that the results of cloud computing and AI remain unchanged after controlling for leasing, as shown in Table A.13.

8 Conclusions

This paper examines the relation between the adoption of new information technologies and industry dynamics in China, focusing on two new technologies: cloud computing and AI. While the ultimate objective of adopting new technologies is to improve economic efficiency and allow entry, the economic mechanisms by which different technologies exert their impact may vary. We focus on cloud computing and AI as these two technologies have a distinct impact on firm cost structures. Specifically, cloud computing reduces both upfront fixed costs and variable costs, whereas AI increases firm fixed costs but provides benefits from economies of scale.

First, we investigate the different impacts of cloud computing and AI on firm entry, exit and M&A. We find that the increased cloud computing is associated with increases in firm entry, exit, and the likelihood of being merged. 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 using cloud computing. We find that the increased exit rates following increases in cloud computing mainly arise from voluntary exits, including operation failure and business adjustments.

In contrast, we find different effects on entry, exit and the likelihood of being merged when we examine industries and firms that are larger users of AI. AI has no impact on firm entry but increased AI is associated with decreases in firm exit and the likelihood of being merged post-shock.

Second, we compare differences in exit and M&A between cloud computing and AI across different firm sizes. The heterogeneous results in the likelihood of exit and being merged show that cloud computing has a broader impact on the likelihood of exit and being merged for all firms. In contrast, larger firms in industries where AI is more likely to be used are less likely to exit and be merged. These results are consistent with AI being more effective when used by larger firms who are more likely to have more extensive business data which is key in the use of AI. Thus, larger firms experience increased survival rates following increased AI adoption.

Third, we provide empirical evidence that cloud computing and AI have different impacts on cost structure. The adoption of cloud computing leads to lower fixed costs by converting fixed costs into variable costs. Conversely, AI adoption results in higher fixed costs.

Fourth, we find different effects on industry concentration. In industries where cloud computing is more likely to be used, industry concentration and the average and median firm size decrease as entry by small firms increases. However, in industries that are heavy users of AI, industry concentration increases as large firms are less likely to exit while small firms face an increased likelihood of exiting. AI, which increases fixed costs, may be a factor in the rise in corporate concentration, as shown in Kwon, Ma, and Zimmermann (2024).

We also find that financing patterns differ 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 across different sizes of firms, we find that cloud computing is associated with an increased probability of equity financing for medium and large firms. Conversely, AI is associated with an increased probability of equity financing only for large firms.

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 for large firms. 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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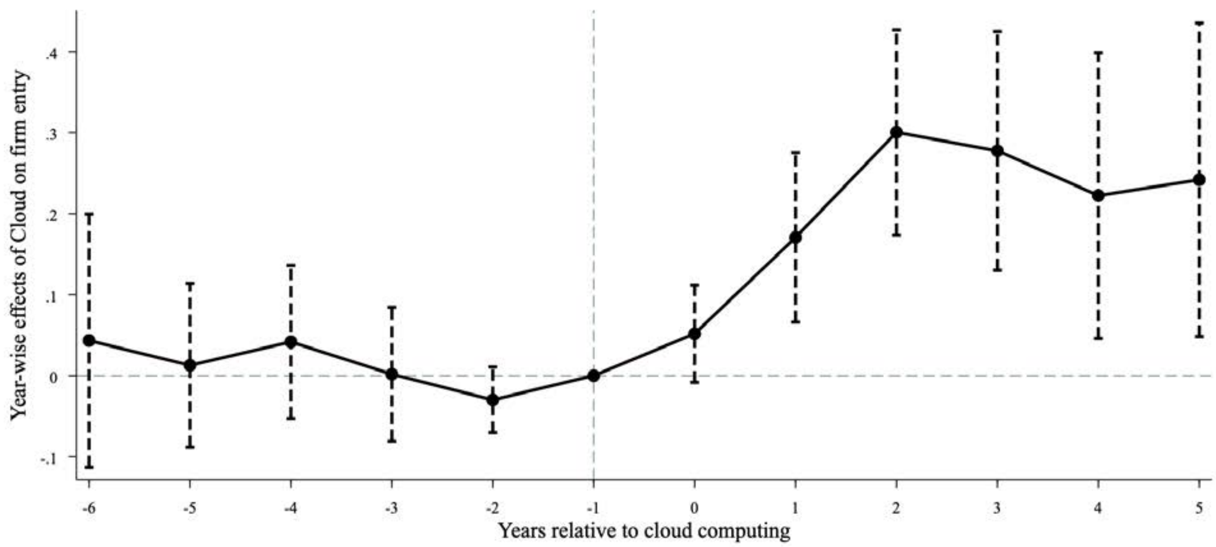
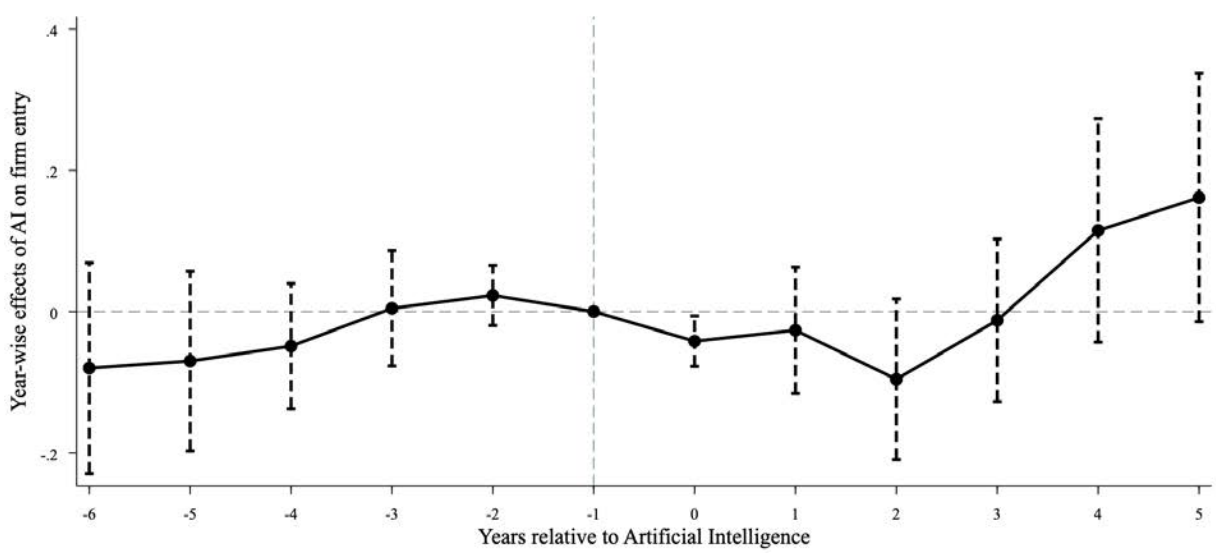
Figure 1: Event Study Results for Firm Entry

This figure reports the yearly coefficients of cloud computing and AI on firm entry as obtained from estimating Equation 5. Year $t = 0$ signifies the current year of 2013. We use 2012 as the reference point. Error bars mark the 95% confidence intervals. Cloud and AI are standardized to mean zero and standard deviation of one. Standard errors are clustered at the industry level. The vertical axis represents the coefficients $\beta_{Cloud,k}$ and $\beta_{AI,k}$ from Equation 5, respectively. $\beta_{Cloud,k}$ and $\beta_{AI,k}$ measure the annual rates of cloud computing and AI across different industries relative to the year 2012, respectively. Figure (a) shows the dynamic effects of cloud computing on firm entry. Figure (b) shows the dynamic effects of AI on firm entry.



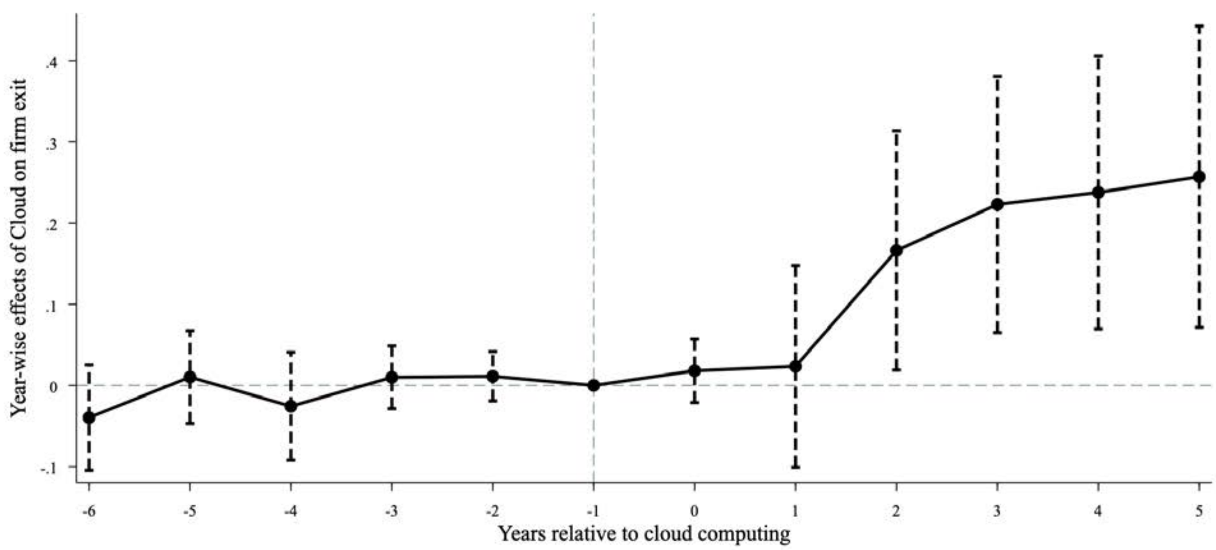
(a) Cloud Computing



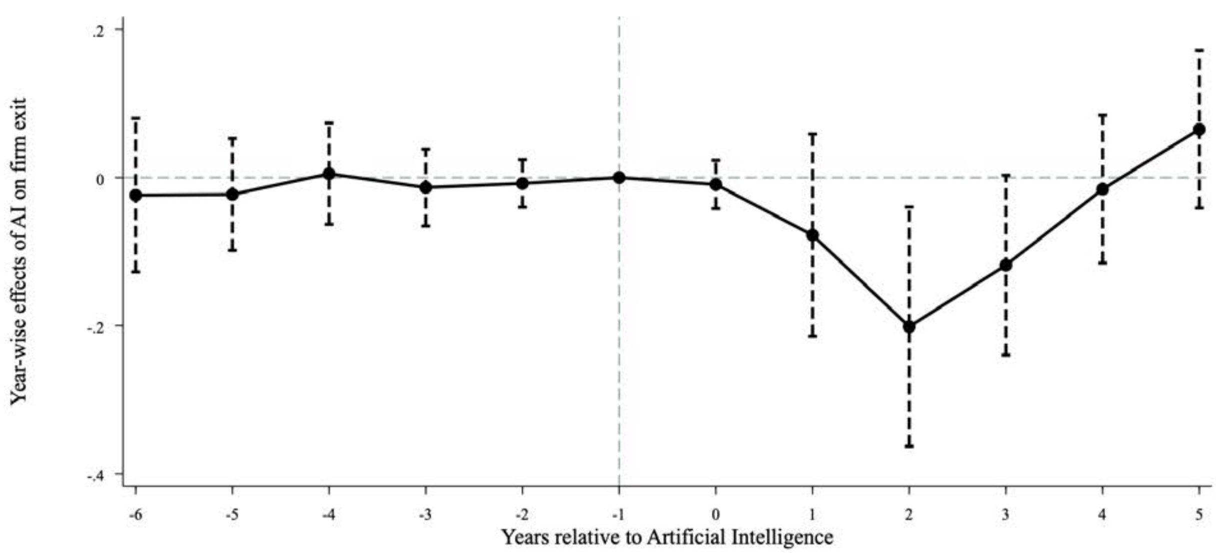
(b) AI

Figure 2: Event Study Results for Firm Exit

This figure reports the yearly coefficients of cloud computing and AI on firm exit as obtained from estimating Equation 5. Year $t = 0$ signifies the current year of 2013. We use 2012 as the reference point. Error bars mark the 95% confidence intervals. Cloud and AI are standardized to mean zero and standard deviation of one. Standard errors are clustered at the industry level. The vertical axis represents the coefficients $\beta_{Cloud,k}$ and $\beta_{AI,k}$ from Equation 5, respectively. $\beta_{Cloud,k}$ and $\beta_{AI,k}$ measure the annual rates of cloud computing and AI across different industries relative to the year 2012, respectively. Figure (a) shows the dynamic effects of cloud computing on firm exit. Figure (b) shows the dynamic effects of AI on firm exit.



(a) Cloud Computing



(b) AI

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 the Industrial Classification for National Economic Activities in China (GB/T4754-2011) to calculate the number of firms entering and exiting 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 vs. AI and Firm Entry

This table reports the panel regression results examining the differential impact of cloud computing and AI on firm entry from equations (3) and (4) using Poisson regressions. The sample covers the period 2007 through 2018. We use the sharply decreased cost of Internet-based computing services in 2013 as the beginning year of cost shock. The dependent variable is 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 the Industrial Classification for National Economic Activities in China (GB/T4754-2011) to calculate the number of firms entering each year. Cloud and AI are measurements of the influence of cloud computing and AI, respectively, at the industry level. Cloud and AI are standardized to mean zero and standard deviation of one. 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. Column (2) also controls for time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Column (3) also controls for the previous year's industry characteristics. 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	Poisson		
VARIABLES	Entry	Entry	Entry
	(1)	(2)	(3)
Post_Cloud	0.122*	0.220**	0.142**
	(0.065)	(0.093)	(0.055)
Post_AI	0.061	0.064	0.013
	(0.071)	(0.075)	(0.062)
L.ROA			1.974
			(2.145)
L.PPEAsset			-2.893
			(8.349)
L.lnAsset			0.009
			(0.097)
Observations	1,068	1,056	886
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Control×Year FE	No	Yes	No

Table 3: Baseline Estimation Results: Cloud Computing vs. AI and Firm Exit

This table reports the panel regression results examining the differential impact of cloud computing and AI on firm exit. Columns (1)-(3) report the results of OLS regression at the firm-year level. Columns (4)-(6) report the results of Poisson regression. The sample covers the period 2007 through 2018. We use the sharply decreased cost of Internet-based computing services in 2013 as the beginning year of cost shock. In columns (1)-(3), the dependent variable Exit equals one if a given firm exits in a given year and zero if it is operating. We multiply coefficients for the Exit regressions by 1000 in the firm-level regressions. In columns (4)-(6), the dependent variable Exit is the nationwide count of firm exits in a given industry in a given year. Cloud and AI are measurements of the influence of cloud computing and AI, respectively. Cloud and AI are standardized to mean zero and standard deviation of one. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. Columns (1)-(3) control for year fixed effects and firm fixed effects. Columns (4)-(6) control for year fixed effects and industry fixed effects. Columns (2) and (5) also control for time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Columns (3) and (6) also control for the previous year's industry characteristics. Standard errors reported in parentheses are clustered at the firm level in columns (1)-(3), and at the industry level in columns (4)-(6). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

LEVEL	Firm			Industry-Year		
MODEL	OLS			Poisson		
VARIABLES	Exit	Exit	Exit	Exit	Exit	Exit
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Cloud	4.522***	3.918***	2.981***	0.110**	0.209***	0.092*
	(0.038)	(0.039)	(0.039)	(0.054)	(0.073)	(0.052)
Post_AI	-1.522***	-1.462***	-1.767***	-0.040	-0.018	-0.080
	(0.035)	(0.035)	(0.035)	(0.072)	(0.055)	(0.057)
L.ROA			-66.124***			5.176**
			(2.249)			(2.187)
L.PPEAsset			561.375***			-17.795
			(4.680)			(12.456)
L.lnAsset			-4.135***			-0.136
			(0.064)			(0.122)
Observations	217,805,372	217,700,173	173,072,439	1,068	1,056	886
R-squared	0.263	0.263	0.270			
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No	No
Industry FE	No	No	No	Yes	Yes	Yes
Control×Year FE	No	Yes	No	No	Yes	No

Table 4: Cloud Computing vs. AI and Firm Exit Across Different Sizes

This table examines the different impacts of AI and cloud computing on firm exits of different sizes. Firms in each 2-digit industry sector are divided into terciles based on the registered capital in 2007. The dependent variable Exit equals one if a given firm exits in a given year and zero if it is operating. We multiply coefficients for the Exit regressions by 1000 in the firm-level regressions. Cloud and AI are measurements of the influence of cloud computing and AI, respectively. Cloud and AI are standardized to mean zero and standard deviation of one. 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. Columns (4)-(6) also control for the time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. $\beta_{\Delta Cloud,Tercile1-Tercile2}$ and $\beta_{\Delta AI,Tercile1-Tercile2}$ denote the differences in the coefficients of Post_Cloud and Post_AI between Tercile 1 and Tercile 2, respectively. $\beta_{\Delta Cloud,Tercile2-Tercile3}$ and $\beta_{\Delta AI,Tercile2-Tercile3}$ denote the differences in the coefficients of Post_Cloud and Post_AI between Tercile 2 and Tercile 3, respectively. 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	Tercile 1	Tercile 2	Tercile 3	Tercile 1	Tercile 2	Tercile 3
VARIABLES	Exit	Exit	Exit	Exit	Exit	Exit
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Cloud	6.171***	4.006***	2.219***	5.355***	3.775***	1.534***
	(0.065)	(0.077)	(0.054)	(0.066)	(0.079)	(0.058)
Post_AI	0.752***	-1.073***	-3.998***	0.305***	-1.326***	-2.856***
	(0.059)	(0.073)	(0.049)	(0.061)	(0.075)	(0.049)
Observations	80,621,249	57,439,083	79,745,040	80,594,789	57,410,632	79,694,752
R-squared	0.252	0.265	0.276	0.253	0.265	0.276
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Control×Year	No	No	No	Yes	Yes	Yes
$\beta_{\Delta Cloud,Tercile1-Tercile2}$	2.165***			1.580***		
	(0.101)			(0.103)		
$\beta_{\Delta AI,Tercile1-Tercile2}$	1.825***			1.631***		
	(0.094)			(0.096)		
$\beta_{\Delta Cloud,Tercile2-Tercile3}$		1.787***			2.241***	
		(0.094)			(0.098)	
$\beta_{\Delta AI,Tercile2-Tercile3}$		2.926***			1.530***	
		(0.088)			(0.089)	

Table 5: M&A between Cloud Computing and AI

This table examines the different impacts of cloud computing and AI on the likelihood of being merged. The dependent variable M&A equals one if a given firm is merged in a given year and zero if it is operating. Column (1) reports the full-sample result. The full sample is split into three subsamples based on the tercile of registered capital by 2-digit industries for all surviving firms in 2007, as shown in columns (2)-(4). We multiply coefficients for the M&A regressions by 1000 in the firm-level regressions. Cloud and AI are measurements of the influence of cloud computing and AI, respectively, standardized to mean zero and standard deviation of one. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. All columns control for year fixed effects, firm fixed effects, and interactions between time-invariant industry characteristics and year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. $\beta_{\Delta Cloud,Tercile1-Tercile2}$ and $\beta_{\Delta AI,Tercile1-Tercile2}$ denote the differences in the coefficients of Post_Cloud and Post_AI between Tercile 1 and Tercile 2, respectively. Similarly, $\beta_{\Delta Cloud,Tercile2-Tercile3}$ and $\beta_{\Delta AI,Tercile2-Tercile3}$ denote the differences in these coefficients between Tercile 2 and Tercile 3, respectively. 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	Tercile 1	Tercile 2	Tercile 3
VARIABLES	M&A	M&A	M&A	M&A
	(1)	(2)	(3)	(4)
Post_Cloud	0.239***	0.068***	0.103***	0.562***
	(0.011)	(0.007)	(0.015)	(0.031)
Post_AI	-0.100***	-0.064***	-0.046***	-0.311***
	(0.011)	(0.006)	(0.015)	(0.029)
Observations	210,458,505	77,565,528	55,355,207	77,537,770
R-squared	0.204	0.221	0.216	0.198
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Control×Year	Yes	Yes	Yes	Yes
$\beta_{\Delta Cloud,Tercile1-Tercile2}$		-0.036***		
		(0.017)		
$\beta_{\Delta AI,Tercile1-Tercile2}$		-0.018		
		(0.017)		
$\beta_{\Delta Cloud,Tercile2-Tercile3}$			-0.459***	
			(0.035)	
$\beta_{\Delta AI,Tercile2-Tercile3}$			0.264***	
			(0.033)	

Table 6: Cloud vs. AI and Fixed Costs

This table estimates changes in the fixed costs of firms after adopting cloud computing and AI. All columns show the result of OLS regression. The sample comprises all publicly listed firms in China, excluding financial firms, from 2007 to 2023. The dependent variable $Fixed\_Income$ represents the ratio of total fixed assets to operating income. $Cloud_{f,t}$ takes the value of 1 when firm f uses cloud computing at year t, and 0 otherwise. $AI_{f,t}$ takes the value of 1 when firm f uses AI at year t, and 0 otherwise. $Control_{f,t}$ include firm size (Size), firm age (lnAge), leverage ratio (Lev), firm equity concentration (Top1), return on assets (ROA), the growth rate of operating income from year $t-1$ to t (SaleGrowth), and Tobin's Q (TobinQ). All columns control for firm fixed effects and year fixed effects. Columns (2) also include for control variables. Standard errors reported in parentheses are clustered at the industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

LEVEL	Firm	
MODEL	OLS	
VARIABLES	Fixed_Income	Fixed_Income
	(1)	(2)
Cloud	-0.030*	-0.044***
	(0.017)	(0.017)
AI	0.034*	0.032*
	(0.017)	(0.017)
Size		0.008
		(0.013)
lnAge		0.050***
		(0.014)
Lev		0.013
		(0.043)
Top1		0.000
		(0.001)
ROA		-1.173***
		(0.068)
SaleGrowth		-0.001**
		(0.000)
TobinQA		-0.006
		(0.004)
Observations	43,736	43,736
R-squared	0.709	0.722
Year FE	Yes	Yes
Firm FE	Yes	Yes

Table 7: Cloud Computing vs. AI and Industry Concentration

This table examines the different impacts of cloud computing and AI on industry concentration at the industry-year level from equations (3) and (4). 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 concentration. 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. We use sales and assets to calculate the market share percentage, separately. Columns (1)-(3) show the result of HHI calculated by using firm assets while columns (4)-(6) show the result of HHI calculated by using firm sales. We use 89 distinct two-digit industries from the Industrial Classification for National Economic Activities in China (GB/T4754-2011). The variables of main interest are Post_Cloud and Post_AI. Cloud and AI are measurements of the influence of cloud computing and AI, respectively, standardized to mean zero and standard deviation of one. 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. Columns (2) and (5) also control for time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Columns (3) and (6) also control for the previous year's industry characteristics. 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(Asset)	HHI(Asset)	HHI(Asset)	HHI(Sales)	HHI(Sales)	HHI(Sales)
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Cloud	-180.253**	-200.352**	-125.755**	-99.436***	-111.330***	-75.986***
	(83.000)	(88.176)	(56.332)	(32.327)	(36.753)	(22.862)
Post_AI	89.607*	109.843**	63.216**	53.451**	53.917**	40.025**
	(46.328)	(48.828)	(31.699)	(23.651)	(25.919)	(18.783)
Observations	886	880	797	886	880	797
R-squared	0.027	0.140	0.014	0.030	0.233	0.023
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
L.Control	No	No	Yes	No	No	Yes
Control×Year FE	No	Yes	No	No	Yes	No

Table 8: Cloud vs. AI and Size Distribution inside Industries

This table estimates how cloud computing and AI impactthe size distribution of firms post-shock using equation (4). All columns show the result of OLS regression. We use firm performance information from the National Tax Survey Database (NTSD). 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 assets and sales to measure the 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 the Industrial Classification for National Economic Activities in China (GB/T4754-2011). The variables of main interest are Post_Cloud and Post_AI. Cloud and AI are measurements of the influence of cloud computing and AI, respectively. Cloud and AI are standardized to mean zero and standard deviation of one. 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. All columns also control for time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. 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	Asset_Median	Asset_Mean	Sale_Median	Sale_Mean	Asset_CV	Sales_CV
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Cloud	-20.077*	-42.652**	-5.724***	-14.655***	-0.022***	-0.019***
	(11.994)	(16.513)	(1.892)	(4.583)	(0.006)	(0.006)
Post_AI	-33.266	-58.366**	-1.651	-3.611	-0.005	-0.004
	(25.130)	(25.465)	(1.880)	(4.932)	(0.006)	(0.005)
Observations	880	880	880	880	879	880
R-squared	0.187	0.572	0.197	0.463	0.301	0.331
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Control×Year	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Cloud Computing vs. AI and Equity Financing

This table examines the impacts of cloud computing and AI on equity financing post-shock. Columns (1)-(3) report the results for all types of equity financing decisions, while columns (4)-(6) report the results limited to venture capital equity financing decisions. The dependent variable *fin* is an indicator of whether a given firm is financed in a given year in columns (1)-(3) while *fin* is an indicator of whether a given firm is financed from VC investors in a given year in columns (4)-(6). We multiply coefficients by 1000. The variables of main interest are Post_Cloud and Post_AI. Cloud and AI are measurements of the influence of cloud computing and AI, respectively. Cloud and AI are standardized to mean zero and standard deviation of one. 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. Columns (2) and (5) also control for time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Columns (3) and (6) also control for the previous year's industry characteristics. 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					
	All Types of Equity Financing			VC Equity Financing		
VARIABLES	fin	fin	fin	fin	fin	fin
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Cloud	0.220***	0.224***	0.242***	0.131***	0.133***	0.146***
	(0.010)	(0.010)	(0.011)	(0.009)	(0.009)	(0.009)
Post_AI	0.138***	0.100***	0.133***	0.041***	0.026***	0.045***
	(0.008)	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)
Observations	210,558,437	210,455,710	168,116,308	210,558,437	210,455,710	168,116,308
R-squared	0.361	0.361	0.389	0.369	0.369	0.398
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Control×Year FE	No	Yes	No	No	Yes	No
L.ControlVar	No	No	Yes	No	No	Yes

Table 10: Heterogeneous Relationship in Equity Financing by Firm Size

This table examines the differences in equity financing decisions between cloud computing and AI for each tercile of firm size. We divide the sample into three subsamples based on the tercile of the registered capital by 2-digit industries for all surviving firms in 2007. 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. The dependent variable *fin* is an indicator of whether a given firm is financed in a given year. All the coefficients are multiplied by 1000. The variables of main interest are Post_Cloud and Post_AI. Cloud and AI are measurements of the influence of cloud computing and AI, respectively, standardized to mean zero and standard deviation of one. 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. Columns (4)-(6) also control for the interactions between time-invariant industry characteristics and year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. $\beta_{\Delta Cloud,Tercile1-Tercile2}$ and $\beta_{\Delta AI,Tercile1-Tercile2}$ denote the differences in the coefficients of Post_Cloud and Post_AI between Tercile 1 and Tercile 2, respectively. Similarly, $\beta_{\Delta Cloud,Tercile2-Tercile3}$ and $\beta_{\Delta AI,Tercile2-Tercile3}$ denote the differences in these coefficients between Tercile 2 and Tercile 3, respectively. Standard errors reported in parentheses are clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Heterogeneous Relationship in All Types of Equity Financing

LEVEL	Firm					
MODEL	OLS					
SIZE	Tercile 1	Tercile 2	Tercile 3	Tercile 1	Tercile 2	Tercile 3
VARIABLES	fin	fin	fin	fin	fin	fin
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Cloud	0.003	0.013*	0.670***	0.003	0.015**	0.680***
	(0.003)	(0.007)	(0.030)	(0.003)	(0.007)	(0.031)
Post_AI	-0.002	0.004	0.354***	-0.001	0.003	0.244***
	(0.001)	(0.006)	(0.024)	(0.001)	(0.006)	(0.025)
Observations	77,591,351	55,382,310	77,584,776	77,565,160	55,354,579	77,535,971
R-squared	0.394	0.401	0.356	0.394	0.401	0.356
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Control×Year	No	No	No	Yes	Yes	Yes
$\beta_{\Delta Cloud,Tercile1-Tercile2}$	-0.010			-0.012		
	(0.008)			(0.008)		
$\beta_{\Delta AI,Tercile1-Tercile2}$	-0.006			-0.004		
	(0.006)			(0.006)		
$\beta_{\Delta Cloud,Tercile2-Tercile3}$		-0.656***			-0.665***	
		(0.031)			(0.032)	
$\beta_{\Delta AI,Tercile2-Tercile3}$		-0.350***			-0.242***	
		(0.025)			(0.025)	

Panel B. Heterogeneous Relationship in VC Equity Financing

LEVEL	Firm					
MODEL	OLS					
SIZE	Tercile 1	Tercile 2	Tercile 3	Tercile 1	Tercile 2	Tercile 3
VARIABLES	fin	fin	fin	fin	fin	fin
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Cloud	0.002	0.006	0.400***	0.001	0.007	0.406***
	(0.003)	(0.007)	(0.025)	(0.003)	(0.007)	(0.026)
Post_AI	-0.001	0.004	0.094***	-0.001	0.003	0.051**
	(0.001)	(0.006)	(0.020)	(0.001)	(0.006)	(0.020)
Observations	77,591,351	55,382,310	77,584,776	77,565,160	55,354,579	77,535,971
R-squared	0.394	0.403	0.364	0.394	0.403	0.364
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Control×Year	No	No	No	Yes	Yes	Yes
$\beta_{\Delta Cloud,Tercile1-Tercile2}$	-0.004			-0.006		
	(0.008)			(0.008)		
$\beta_{\Delta AI,Tercile1-Tercile2}$	-0.005			-0.004		
	(0.006)			(0.006)		
$\beta_{\Delta Cloud,Tercile2-Tercile3}$		-0.394***			-0.399***	
		(0.026)			(0.027)	
$\beta_{\Delta AI,Tercile2-Tercile3}$		-0.091***			-0.048**	
		(0.020)			(0.021)	

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. Chinese laws require foreign cloud service companies to store data locally and to operate through domestic companies. So foreign cloud service providers like Microsoft Azure have had to find local partners. Microsoft Azure operates in China through a unique partnership with 21Vianet, which is a domestic internet data center services provider in China. Azure was the first multinational organization to make public cloud services available in China. AWS and IBM followed Azure's entry model by partnering with Chinese companies.

Time	**Event**
Jan 2013	Alibaba Cloud merged with Wanwang and transferred all users on Wanwang to Alibaba 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 Alibaba Cloud.
Jul 2013	QingCloud was opened to the public.
Aug 2013	Alibaba 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.

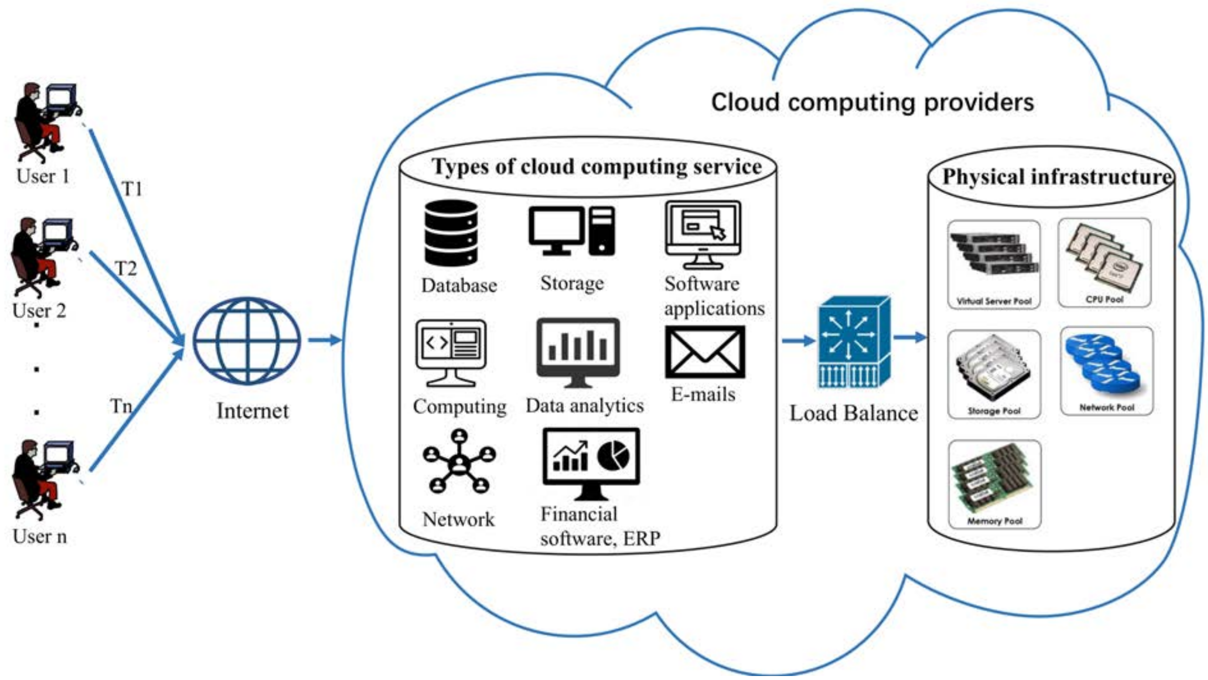


Figure A.2: Price Trend of Alibaba Cloud 2012-2018

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.

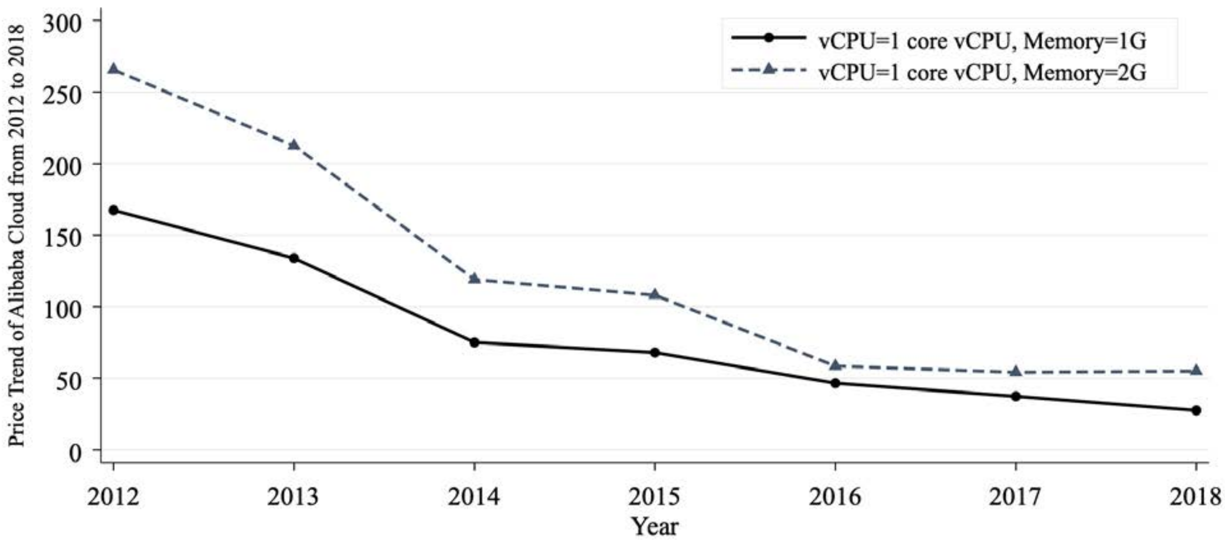


Table A.2: English-Chinese Keyword Concordance for Cloud Computing and AI Variables

This table presents the concordance relationships between selected English keywords and their corresponding Chinese translations as used in our paper. Panel A provides the English-Chinese keyword concordance for the *Cloud* variable, while Panel B provides the English-Chinese concordance for the *AI* variable.

Panel A. English-Chinese Keyword Concordance for Cloud Computing

Cloud Keywords	Chinese
online	网络、互联网、上网、因特网、网上、联网、在线
web	网页、网站
E-commerce	电子商务
Hosting	托管
software	软件、软硬件

Panel B. English-Chinese Keyword Concordance for AI

AI Keywords	Chinese
AI	AI
intelligence	智能
artificial intelligence	人工智能
algorithms	算法
machine learning	机器学习、监督学习、无监督学习、半监督学习
deep learning	深度学习
neural networks	神经网络、学习网络
face recognition	人脸识别、面部识别、脸部识别、面孔识别
computer vision	计算机视觉、电脑视觉
natural language processing	自然语言处理、NLP
automation	自动化

Figure A.3: The Influence of Cloud Computing by 1-digit Industry Sector

This figure presents the measurement of the influence of cloud computing at the one-digit industry level. For each sector based on 1-digit industry codes from the Industrial Classification for National Economic Activities in China (GB/T4754-2011), we compute 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 2012 by 1-digit industry sector. .

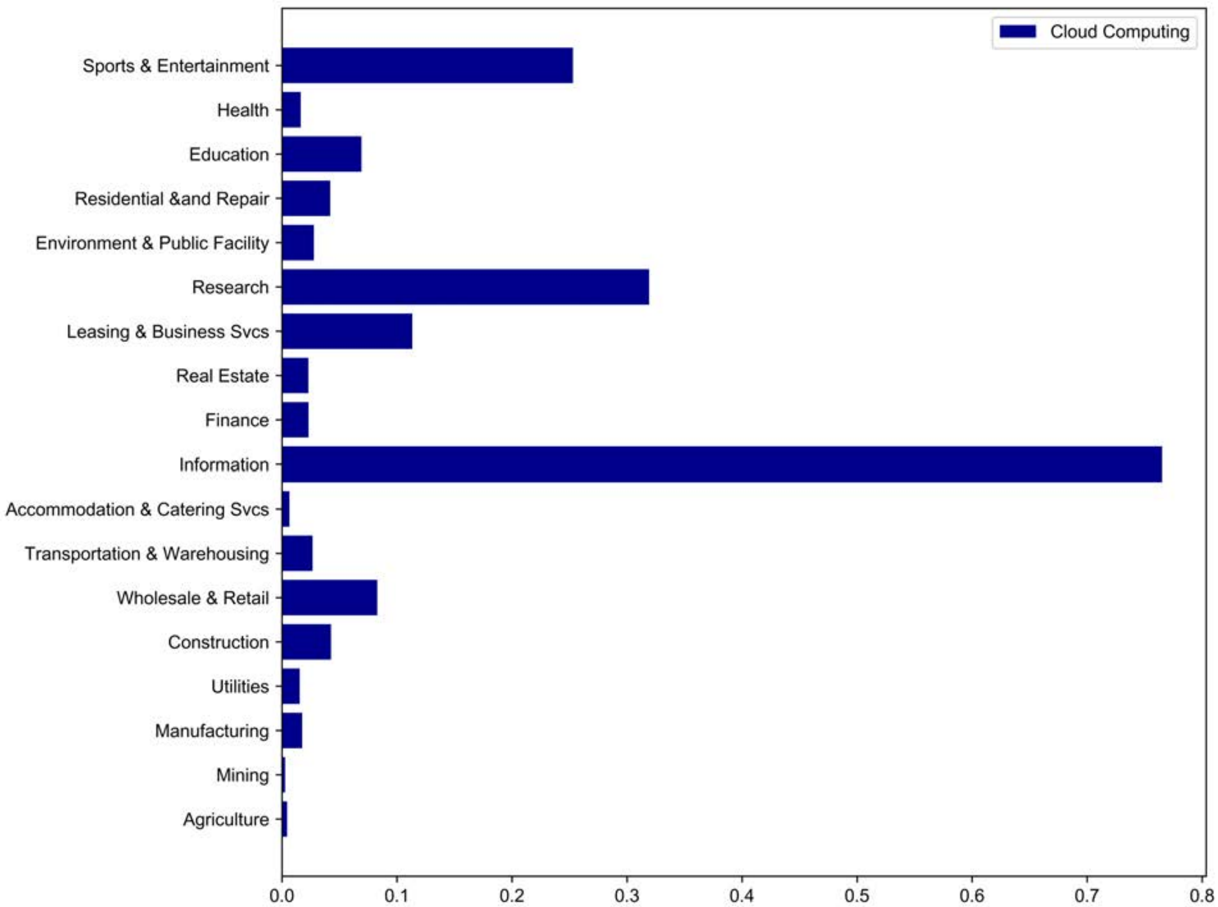


Figure A.4: The Influence of AI by 1-digit Industry Sector

This figure presents the measurement of the influence of AI at the one-digit industry level. For each sector based on 1-digit industry codes from the Industrial Classification for National Economic Activities in China (GB/T4754-2011), we compute the proportion of the affected firms whose business scope description contains the keywords of "AI," "intelligence," "artificial intelligence," "algorithms," "machine learning," "deep learning," "neural networks," "face recognition," "computer vision," "natural language processing," or "automation" to all surviving firms in 2012 by 1-digit industry sector. .

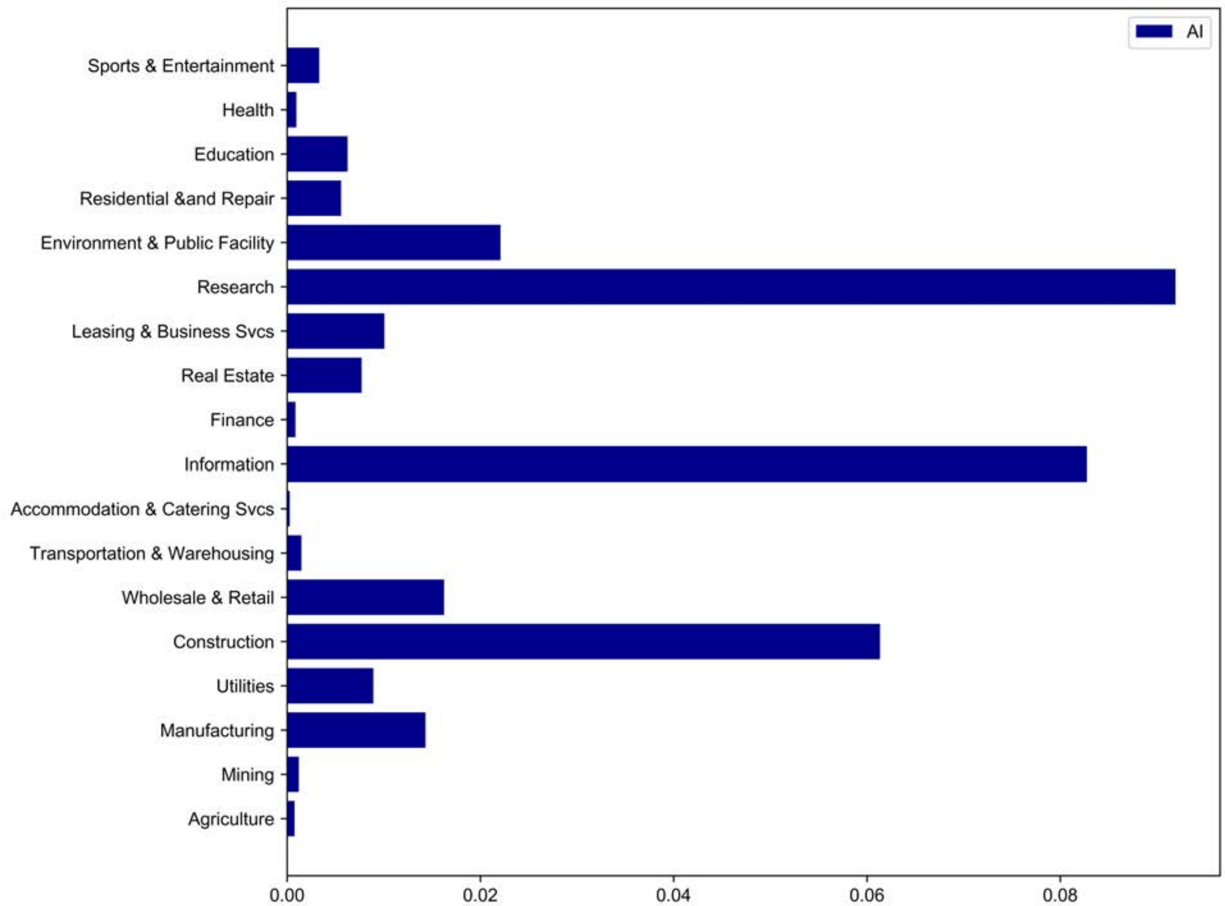


Figure A.5: Cloud Computing Usage in Singapore and China by Industry

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 results 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, and activities of other membership organizations (Churches, country clubs, charity organizations).

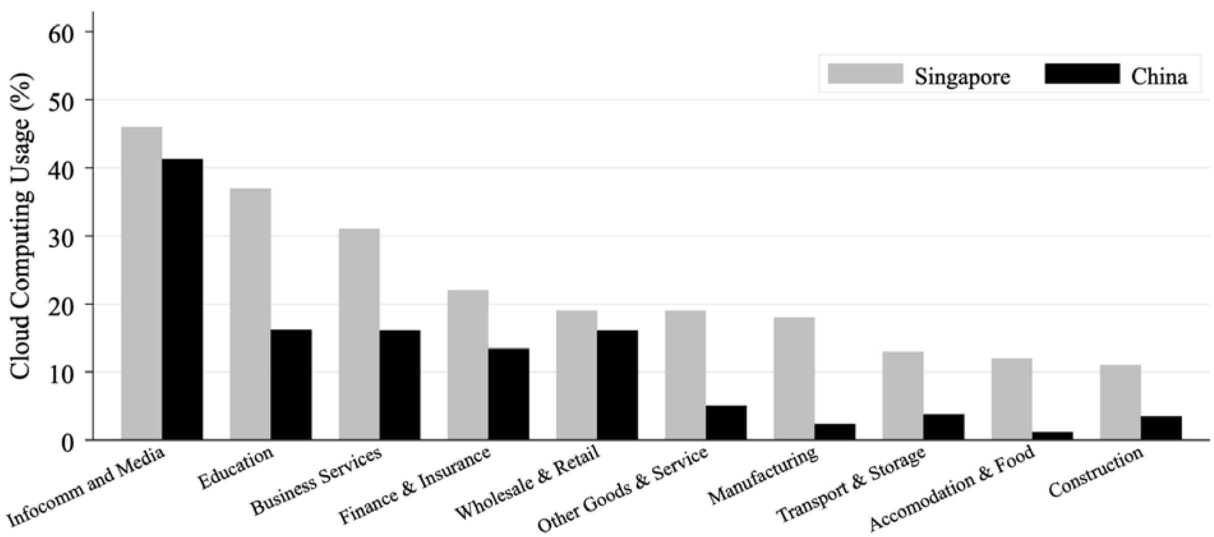


Table A.3: Cloud Computing vs. AI and Firm Entry

This table reports the panel regression results examining the differential impact of cloud computing and AI on firm entry using OLS regression. The sample covers the period 2007 through 2018. We use the sharply decreased cost of Internet-based computing services in 2013 as the beginning year of cost shock. The dependent variable is log(Entry), where log(Entry) is the logarithm of the count of the sum of newly-established firms in a given industry in a given year. We use 89 distinct two-digit industries from the Industrial Classification for National Economic Activities in China (GB/T4754-2011) to calculate the number of firms entering each year. Cloud is a measurement of the influence of cloud computing at the industry level. AI is a measurement of the influence of artificial intelligence at the industry level. Cloud and AI are standardized to mean zero and standard deviation of one. 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. Column (2) also controls for time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Column (3) also controls for the previous year's industry characteristics. 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		
VARIABLES	log(Entry)	log(Entry)	log(Entry)
	(1)	(2)	(3)
Post_Cloud	0.100*	0.140***	0.077*
	(0.056)	(0.045)	(0.044)
Post_AI	0.083	0.111**	0.060
	(0.060)	(0.051)	(0.044)
L.ROA			12.441***
			(2.282)
L.PPEAsset			0.258
			(3.198)
L.lnAsset			-0.095
			(0.067)
Observations	1,066	1,054	885
R-squared	0.390	0.546	0.493
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Control×Year FE	No	Yes	No

Table A.4: Cloud Computing and Newcomers

This table reports the panel regression results examining firm newcomers and cloud computing. The sample covers the period 2007 through 2018. Columns (1)-(3) show the results of Poisson regression while columns (4)-(6) show the results of OLS regression. The dependent variables are Newcomer and log(Newcomer). log(Newcomer) is calculated by logging Newcomer, where Newcomer is the nationwide count of the sum of newcomer entrants whose shareholders are not limited to one firm in a given industry in a given year. Cloud and AI are measurements of the influence of cloud computing and AI, respectively. Cloud and AI are standardized to mean zero and standard deviation of one. 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. Columns (2) and (5) also control for time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Columns (3) and (6) also control for the previous year's industry characteristics. 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	Poisson			OLS		
VARIABLES	Newcomer	Newcomer	Newcomer	log(Newcomer)	log(Newcomer)	log(Newcomer)
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Cloud	0.134**	0.239**	0.154***	0.112**	0.149***	0.091**
	(0.068)	(0.106)	(0.059)	(0.049)	(0.044)	(0.038)
Post_AI	0.046	0.037	0.000	0.082	0.100*	0.058
	(0.076)	(0.081)	(0.068)	(0.060)	(0.052)	(0.045)
L.ROA			1.418			11.636***
			(2.097)			(2.421)
L.PPEAsset			-4.188			-0.172
			(8.905)			(2.872)
L.lnAsset			-0.014			-0.099
			(0.110)			(0.072)
Observations	1,068	1,056	886	1,066	1,054	885
R-squared				0.431	0.552	0.519
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Control×Year FE	No	Yes	No	No	Yes	No

Table A.5: Cloud Computing vs. AI and Firm Exit

This table reports the panel regression results examining the differential impact of cloud computing and AI on firm exit post-shock using OLS regression. The sample covers the period 2007 through 2018. The dependent variable is log(Exit), where log(Exit) is the logarithm of the count of the sum of firms exiting in a given industry in a given year. We use 89 distinct two-digit industries from the Industrial Classification for National Economic Activities in China (GB/T4754-2011) to calculate the number of firms exiting each year. Cloud and AI are measurements of the influence of cloud computing and AI, respectively. Cloud and AI are standardized to mean zero and standard deviation of one. 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. Column (2) also controls for time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Column (3) also controls for the previous year's industry characteristics. 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		
VARIABLES	log(Exit)	log(Exit)	log(Exit)
	(1)	(2)	(3)
Post_Cloud	0.117***	0.139***	0.078***
	(0.022)	(0.030)	(0.022)
Post_AI	-0.011	0.007	-0.023
	(0.038)	(0.035)	(0.029)
L.ROA			4.189***
			(1.210)
L.PPEAsset			-1.134
			(3.108)
L.lnAsset			-0.101*
			(0.051)
Observations	1,068	1,056	886
R-squared	0.758	0.802	0.759
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Control×Year FE	No	Yes	No

Table A.6: Alternative Fixed Effects: Cloud Computing vs. AI and Firm Exit

This table reports the panel regression results examining the impact of cloud computing and AI on firm exit at the firm level. The dependent variable is Exit. Exit equals one if a given firm exits in a given year and zero if it is operating. We multiply coefficients for the Exit regressions by 1000. Cloud and AI are the measurements of the influence of cloud computing and AI, respectively, which are standardized to mean zero and standard deviation of one. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. We use 89 distinct two-digit industries from the Industrial Classification for National Economic Activities in China (GB/T4754-2011). We use 31 different provinces to measure the region-level variable. All columns control for the time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Column (1) also controls for firm fixed effects and region-year fixed effects. Column (2) controls for industry fixed effects and region-year fixed effects. Column (3) controls for industry-region 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.

LEVEL	Firm		
MODEL	OLS		
VARIABLES	Exit	Exit	Exit
	(1)	(2)	(3)
Post_Cloud	3.573***	1.174***	1.133***
	(0.040)	(0.036)	(0.036)
Post_AI	-0.902***	-1.929***	-1.764***
	(0.036)	(0.033)	(0.033)
Observations	217,700,173	223,931,594	223,931,593
R-squared	0.272	0.015	0.016
Firm FE	Yes	No	No
Region-Year FE	Yes	Yes	Yes
Industry FE	No	Yes	No
Industry-Region FE	No	No	Yes
Control×Year FE	Yes	Yes	Yes

Table A.7: Cloud Computing vs. AI and Voluntary Exit

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. All columns report the results of OLS regression at the firm-year level. The sample covers the period 2007 through 2018. We use the sharply decreased cost of Internet-based computing services in 2013 as the beginning year of cost shock. 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 and AI are the measurements of the influence of cloud computing and AI, respectively. Cloud and AI are standardized to mean zero and standard deviation of one. 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. Column (2) also controls for time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Column (3) also controls for the previous year's industry characteristics. 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		
VARIABLES	Exitvol	Exitvol	Exitvol
	(1)	(2)	(3)
Post_Cloud	0.677***	0.439***	0.411***
	(0.011)	(0.012)	(0.011)
Post_AI	-0.120***	-0.138***	-0.180***
	(0.010)	(0.010)	(0.010)
Observations	210,969,145	210,866,258	168,384,816
R-squared	0.175	0.175	0.170
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Control×Year FE	No	Yes	No
L.Control	No	No	Yes

Table A.8: Cloud Computing vs. AI and Voluntary Exit Across Different Sizes

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. The dependent variable Exitvol equals one if a given firm exits voluntarily in a given year and to zero if it is operating. Firms in each 2-digit industry sector are divided into terciles based on the registered capital in 2007. We multiply coefficients by 1000 in the firm-level regressions. Cloud and AI are the measurements of the influence of cloud computing and AI, respectively. Cloud and AI are standardized to mean zero and standard deviation of one. 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. Columns (4)-(6) also control for the time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. $\beta_{\Delta Cloud,Tercile1-Tercile2}$ and $\beta_{\Delta AI,Tercile1-Tercile2}$ denote the differences in the coefficients of Post_Cloud and Post_AI between Tercile 1 and Tercile 2, respectively. $\beta_{\Delta Cloud,Tercile2-Tercile3}$ and $\beta_{\Delta AI,Tercile2-Tercile3}$ denote the differences in the coefficients of Post_Cloud and Post_AI between Tercile 2 and Tercile 3, respectively. 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	Tercile 1	Tercile 2	Tercile 3	Tercile 1	Tercile 2	Tercile 3
VARIABLES	Exitvol	Exitvol	Exitvol	Exitvol	Exitvol	Exitvol
	(1)	(2)	(3)	(4)	(5)	(6)
Post_Cloud	0.745***	0.825***	0.409***	0.484***	0.631***	0.175***
	(0.019)	(0.023)	(0.015)	(0.019)	(0.024)	(0.017)
Post_AI	0.216***	-0.229***	-0.365***	0.168***	-0.315***	-0.271***
	(0.016)	(0.021)	(0.013)	(0.017)	(0.021)	(0.014)
Observations	77,757,109	55,494,407	77,717,629	77,730,906	55,466,635	77,668,717
R-squared	0.159	0.171	0.200	0.160	0.172	0.200
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Control×Year	No	No	No	Yes	Yes	Yes
$\beta_{\Delta Cloud,Tercile1-Tercile2}$	-0.080***			-0.147***		
	(0.030)			(0.031)		
$\beta_{\Delta AI,Tercile1-Tercile2}$	0.445***			0.483***		
	(0.026)			(0.027)		
$\beta_{\Delta Cloud,Tercile2-Tercile3}$		0.416***			0.456***	
		(0.028)			(0.029)	
$\beta_{\Delta AI,Tercile2-Tercile3}$		0.136***			-0.044*	
		(0.024)			(0.025)	

Table A.9: Robustness Tests: Using Quartile Dummy Variables for Cloud Computing and AI

This table reports the panel regression results examining the treatment effects of cloud computing and AI on firm dynamics. We use category variables to define the influence of cloud computing and AI on each 2-digit industry. We substitute continuous measurements of Cloud and AI with the quartile dummy variables, CloudQuartile and AIQuartile. These quartile dummy variables, CloudQuartile and AIQuartile, assign scores of 4, 3, 2, and 1 to observations falling within the top, third, second, and lowest quartiles of cloud and AI exposure, respectively. Columns (1)-(2) show the results of firm entry at the industry-year level using Poisson regression. Columns (3)-(4) show the results of firm exit at the firm-year level using OLS regression. The dependent variables are Entry and Exit. Entry is the number of entrants in a given industry and year. Exit equals one if a given firm exits in a given year and zero if it is operating. We multiply coefficients for the Exit regressions by 1000. We use 89 distinct two-digit industries from the Industrial Classification for National Economic Activities in China (GB/T4754-2011). 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 industry fixed effects. Regressions in columns (3)-(4) control for year fixed effects and firm fixed effects. Columns (2) and (4) also control for the time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Standard errors reported in parentheses are clustered at the industry level, and firm level in columns (1)-(2), and (3)-(4), respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

MODEL	Poisson		OLS	
LEVEL	Industry-Year		Firm	
VARIABLES	Entry	Entry	Exit	Exit
	(1)	(2)	(3)	(4)
Post_CloudQuartile	0.138**	0.173**	5.714***	3.176***
	(0.066)	(0.076)	(0.032)	(0.037)
Post_AIQuartile	-0.127	-0.096	-2.684***	-3.447***
	(0.112)	(0.098)	(0.034)	(0.036)
Observations	1,068	1,056	217,805,372	217,700,173
R-squared			0.263	0.263
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Industry FE	Yes	Yes	No	No
Control×Year FE	No	Yes	No	Yes

Table A.10: 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 computing and AI, using 417 three-digit industry cells rather than 89 two-digit industry cells from the Industrial Classification for National Economic Activities in China (GB/T4754-2011). Cloud and AI are the measurements of the influence of cloud computing and AI, respectively, which are standardized to mean zero and standard deviation of one. Columns (1)-(2) show the results of firm entry at the industry-year level using Poisson regression. Columns (3)-(4) show the results of firm exit at the firm-year level using OLS regression. The dependent variables are Entry and Exit. Entry is the number of entrants in a given industry and year. Exit equals one if a given firm exits in a given year and zero if it is operating. We multiply coefficients for the Exit regressions by 1000. 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 industry fixed effects. Regressions in columns (3)-(4) control for year fixed effects and firm fixed effects. Columns (2) and (4) also control for the time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Standard errors reported in parentheses are clustered at the industry level, and firm level in columns (1)-(2), and (3)-(4), respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

MODEL	Poisson		OLS	
LEVEL	Industry-Year		Firm	
VARIABLES	Entry	Entry	Exit	Exit
	(1)	(2)	(3)	(4)
Post_Cloud	0.111*	0.107	4.913***	4.749***
	(0.064)	(0.068)	(0.038)	(0.039)
Post_AI	0.023	0.020	-2.232***	-2.825***
	(0.056)	(0.058)	(0.033)	(0.034)
Observations	5,000	4,498	217,805,019	211,856,926
R-squared			0.263	0.263
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Industry FE	Yes	Yes	No	No
Control×Year FE	No	Yes	No	Yes

Table A.11: 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 the Industrial Classification for National Economic Activities in China (GB/T4754-2011). In panel A, 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. In panel B, the dependent variables are PctChangeEntry and PctChangeExit. PctChangeEntry and PctChangeExit are calculated as the percentage change in entry and exit from the previous year, respectively. All outcome variables are expressed in percentages (%). Columns (1)-(2), (3)-(4) show the results of firm entry and exit at the industry-year level using OLS regression, respectively. Cloud and AI are the measurements of the influence of cloud computing and AI, respectively, which are standardized to mean zero and standard deviation of one. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. Regressions in all columns control for year fixed effects and industry fixed effects. Regressions in columns (2) and (4) also control for the time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Standard errors reported in parentheses are clustered at the industry level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Firm Entry and Exit Relative to Surviving Firms.

LEVEL	Industry-Year			
MODEL	OLS			
VARIABLES	Entry_ratio		Exit_ratio	
	(1)	(2)	(3)	(4)
Post_Cloud	1.163*	1.489***	0.194*	0.211*
	(0.595)	(0.479)	(0.112)	(0.114)
Post_AI	0.722	0.851	-0.151**	-0.098
	(0.585)	(0.514)	(0.066)	(0.059)
Observations	1,068	1,056	1,068	1,056
R-squared	0.128	0.257	0.700	0.735
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Control×Year FE	No	Yes	No	Yes

Panel B. Yearly Percentage Change in Entry and Exit Rates.

LEVEL	Industry-Year			
MODEL	OLS			
VARIABLES	PctChangeEntry		PctChangeExit	
	(1)	(2)	(3)	(4)
Post_Cloud	3.971***	4.113***	4.972***	5.674***
	(0.934)	(1.136)	(0.541)	(0.851)
Post_AI	0.408	1.038	-1.330*	-0.766
	(1.239)	(1.408)	(0.711)	(0.775)
Observations	1,067	1,055	1,068	1,056
R-squared	0.177	0.221	0.487	0.523
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Control×Year FE	No	Yes	No	Yes

Table A.12: 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 of the Registered Capital Registration System in China. 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 that 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. Cloud and AI are the measurements of the influence of cloud computing and AI, respectively, which are standardized to mean zero and standard deviation of one. Post equals one if the given years are in 2013-2018, and zero in 2007-2012. Columns (2) and (4) also control for the time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Standard errors reported in parentheses are clustered at the industry level, and firm level in columns (1)-(2), and (3)-(4), respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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

MODEL	Poisson		OLS	
LEVEL	Industry-Year		Firm	
VARIABLES	Entry	Entry	Exit	Exit
	(1)	(2)	(3)	(4)
Post_Cloud	0.126**	0.218**	4.563***	4.024***
	(0.063)	(0.086)	(0.038)	(0.039)
Post_AI	0.063	0.074	-1.547***	-1.021***
	(0.070)	(0.069)	(0.035)	(0.035)
Post2014_CAP	0.066	0.053	0.836***	4.315***
	(0.083)	(0.065)	(0.028)	(0.041)
Observations	1,068	1,056	217,805,372	217,700,173
R-squared			0.263	0.263
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Industry FE	Yes	Yes	No	No
Control×Year FE	No	Yes	No	Yes

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

MODEL	Poisson		OLS	
LEVEL	Industry-Year		Firm	
VARIABLES	Entry	Entry	Exit	Exit
	(1)	(2)	(3)	(4)
Post_Cloud	0.080***	0.123***	2.216***	1.471***
	(0.029)	(0.040)	(0.043)	(0.044)
Post_AI	-0.040	-0.035	-0.590***	-0.585***
	(0.034)	(0.031)	(0.041)	(0.042)
Observations	356	352	61,082,581	61,049,344
R-squared			0.384	0.384
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Industry FE	Yes	Yes	No	No
Control×Year FE	No	Yes	No	Yes

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

MODEL	Poisson		OLS	
LEVEL	Industry-Year		Firm	
VARIABLES	Entry	Entry	Exit	Exit
	(1)	(2)	(3)	(4)
Post_Cloud	0.110*	0.201**	4.587***	3.783***
	(0.062)	(0.081)	(0.038)	(0.039)
Post_AI	0.055	0.062	-1.393***	-1.541***
	(0.070)	(0.066)	(0.035)	(0.035)
Post2012_SEI	0.163	0.187	-2.120***	2.301***
	(0.186)	(0.138)	(0.050)	(0.059)
Observations	1,068	1,056	217,805,372	217,700,173
R-squared			0.263	0.263
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Industry FE	Yes	Yes	No	No
Control×Year FE	No	Yes	No	Yes

Table A.13: Confounding Impacts of Leasing

This table reports the robustness tests examining the potential confounding effects of leasing on firm dynamics. We utilize operating lease and finance lease data from the National Tax Survey Database (NTSD). $FinLease2012$ is defined as the average ratio of finance leases to total assets at the industry level in 2012. Similarly, $OpeLease2012$ is defined as the average ratio of operating leases to total assets at the industry level in 2012. Columns (1) and (3) control for time-invariant operating leases and finance leases, interacting these variables with year fixed effects. Columns (2) and (4) control for the previous year's finance lease variables. We do not include controls for the previous year's operating leases due to incomplete coverage of operating lease data across all years in the database. Cloud and AI are the measurements of the influence of cloud computing and AI, respectively, which are standardized to mean zero and standard deviation of one. Columns (1)-(2) show the results of firm entry at the industry-year level using Poisson regression. Columns (3)-(4) show the results of firm exit at the firm-year level using OLS regression. The dependent variables are Entry and Exit. Entry is the number of entrants in a given industry and year. Exit equals one if a given firm exits in a given year and zero if it is operating. We multiply coefficients for the Exit regressions by 1000. 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 industry fixed effects. Regressions in columns (3)-(4) control for year fixed effects and firm fixed effects. All columns also control for the time-invariant industry characteristics interacted with year fixed effects, including ROA, Property, Plant, and Equipment investment, and the logarithm of the average total asset in 2007. Standard errors reported in parentheses are clustered at the industry level, and firm level in columns (1)-(2), and (3)-(4), respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

MODEL	Poisson		OLS	
LEVEL	Industry-Year		Firm	
VARIABLES	Entry	Entry	Exit	Exit
	(1)	(2)	(3)	(4)
Post_Cloud	0.184**	0.148***	3.306***	2.223***
	(0.086)	(0.045)	(0.043)	(0.042)
Post_AI	0.105*	0.002	-1.098***	-1.805***
	(0.055)	(0.055)	(0.035)	(0.038)
Observations	1,068	1,056	217,805,372	217,700,173
R-squared			0.263	0.263
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Industry FE	Yes	Yes	No	No
Control×Year FE	Yes	Yes	Yes	Yes
FinLease2012×Year FE	Yes	No	Yes	No
OpeLease2012×Year FE	Yes	No	Yes	No
L.FinLease	No	Yes	No	Yes

Appendix B Background of Cloud Computing Development in China

In China, cloud computing first appeared in 2009, when Alibaba Cloud was established in September 2009. However, Alibaba 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, Alibaba 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 Alibaba Cloud after July 2013. All the operations and transactions of Alibaba Group were then carried out on Alibaba 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 Alibaba 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 in 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. Alibaba Cloud merged with Wanwang and transferred all users on Wanwang to Alibaba Cloud in January 2013, which helped Alibaba 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%). Alibaba 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 Alibaba Cloud worldwide. Similarly, the number of hostnames increased from 91,553 to 389,171 in Alibaba 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. Alibaba 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, Alibaba 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 Alibaba 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, the State Council issued the "Several Opinions of the State Council on Promoting Information Consumption and Boosting Domestic Demand," which required that 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.