SMEs Amidst the Pandemic and Reopening: Digital Edge and Transformation*

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Abstract

Using administrative universal business registration data as well as primary offline and online surveys of small businesses in China, we examine (i) whether digitization helps small and medium enterprises (SMEs) better cope with the COVID-19 pandemic, and (ii) whether the pandemic has spurred digital technology adoption. We document significant economic benefits of digitization in increasing SMEs' resilience against such a large shock, as seen through mitigated demand decline, sustainable cash flow, ability to quickly reopen, and positive outlook for growth. Post the January 2020 lockdown, firm entries exhibited a V-shaped pattern, with entries of e-commerce firms experiencing a less pronounced initial drop and a quicker rebound. Moreover, the pandemic has accelerated the digital transformation of existing firms and the aggregated industry in multiple dimensions (e.g., altering operation scope to include e-commerce, allowing remote work, and adopting electronic information systems). The effect persists at least one year after full reopening, offering suggestive evidence for the long-term impact of the pandemic and transitory mitigation policies.

Keywords: Small Businesses, COVID-19, Digital Economy, E-Commerce

JEL Codes: G30, L81, O14, H12

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1 Introduction

Small and medium enterprises (SMEs) are integral to the global economy.[1] During economic downturns, however, small businesses typically contract earlier and more severely than large firms (Davis et al., 1996). The COVID-19 pandemic is no exception, striking heavy blows to SMEs worldwide.[2] The relatively sparse literature has examined the role of clusters (e.g., Kranton and Minehart, 2000; Dai et al., 2021a) and policy interventions (e.g., Bartlett III and Morse, 2020; Chen et al., 2020) in helping SMEs cope with such external shocks. Yet, how digitization contributes to SMEs' resilience and how the pandemic shapes SMEs' digitization in the long run, especially in developing countries, has been rarely studied, despite the numerous media reports (e.g., TIME cover story by Wang, 2020; Economist, 2020; Kabir, 2021) on rising e-commerce, e-learning, telemedicine, digital banking, and work-from-home as immediate ramifications of the pandemic.

Our study is among the first attempts to bridge this knowledge gap. Specifically, we combine multiple rounds of primarily collected Enterprise Survey on Innovation and Entrepreneurship in China (ESIEC) and Online Survey of Micro-and-small Enterprises (OSOME) with administrative China business registration data. The comprehensive data coverage and large heterogeneity in Chinese SMEs allow us to directly document the benefits of e-commerce, one key aspect of digitization, on the performance of SMEs during and after the COVID-19 restrictions. Our multiple rounds of surveys, with their timing varying

[1]For example, in the United States, small businesses accounted for 44% of U.S. employment and 99% of firms (Bartlett III and Morse, 2020). According to a reported speech by the Chinese Vice Premier, in China, SMEs represent over 90% of all market entities, 80% of urban employment, 70% of technological patents, 60% of GDP, and 50% of tax revenues as of 2018. For details, please refer to `http://www.gov.cn/guowuyuan/2018-08/20/content_5315204.htm` and `http://www.xinhuanet.com/english/2018-10/19/c_137544504.htm`. In India and Singapore, SMEs also contributed to about 40% of value added in the manufacturing sector in 2012 (Allen et al., 2012) and 42% of the GDP in 2010 (Qian, 2010), respectively.

[2]Several recent studies conducted surveys of small businesses in the United States shortly after the onset of the pandemic and found massive closures, downsizing, layoffs (Bartik et al., 2020a; Bartlett III and Morse, 2020; Fairlie, 2020; Humphries et al., 2020; Dai et al., 2021b).

in relation to the national lockdown, as shown in Figure 1, also enable us to demonstrate both the instantaneous and persistent digital transformation of SMEs brought forth by the pandemic.[3]

Defining SMEs in China is challenging. Our dataset admits a rather general definition of SMEs including both privately-owned incorporated firms and self-employed businesses. Specifically, the business registration data covers the universe of registered enterprises in China, the majority of which are small businesses with very low registered capital. The ESIEC survey offers a representative and detailed sample of SMEs, including incorporated firms and registered self-employed businesses with few full-time employees. More than half of the respondents in ESIEC had fewer than ten employees. Besides registered businesses, the OSOME sample also includes unregistered self-employed businesses, which have long been neglected in previous research. The interviewed SMEs in the two surveys locate in both urban and rural areas of different city tiers across China, representing a wide coverage.

We first investigate whether digitizing business operations makes SMEs more resilient to the pandemic shock. Business digitization broadly encompasses technologies such as e-commerce, automation, AI, e-learning, and telemedicine. Our main proxy variable for digitization is e-commerce. The baseline ESIEC surveys conducted in 2017, 2018, and 2019 include a key question on the share of online sales, which is shown to be positively associated with an SME's cash flow level, market demand, working capital turnover, reopening status, and outlook for earnings observed in the phone interviews in 2020. Since e-commerce is only one dimension of digitization, our estimates likely represent a lower bound.

[3]At the time of the first round of phone interviews in February 2020, most provincial governments had allowed businesses to reopen (often with stringent conditions). After reining in COVID-19, authorities largely eased lockdown restrictions in April. As a result, most SMEs had reopened by the time of our second round of ESIEC surveys in May 2020. Besides, there have still been sporadic outbreaks and resultant local lockdowns in China since the nationwide reopening as shown in Figure 1, offering us more variations to examine the digital transformations based on quarterly OSOME surveys.

We then examine whether the pandemic has induced greater adoption of digital technologies, a question rarely studied in the literature in part due to data paucity.[4] We overcome the challenge by developing and applying a textual analysis and algorithm to the business operation scope, a text record embodied in the business registration database indicating what an enterprise is approved to conduct, to classify each registered firm's e-commerce adoption. The number of e-commerce firm entries at the city-industry-month level from 2015 to 2021 aggregated from the registration database is used as a key outcome variable for the extensive firm growth margin. We then employ an event study approach in relation to the timing of the nationwide lockdown to gauge the impact on the extensive growth margin. Compared with the same period prior to the pandemic, the year-on-year growth in firm entries has exhibited a V-shaped pattern since the lockdown in January 2020, with entries of e-commerce firms experiencing a less pronounced initial drop and a quicker rebound. Evidently, the COVID-19 restrictions have spurred more rapid growth in the entries of e-commerce firms compared with non-e-commerce firms.

Moreover, to analyze the intensive margin, we rely primarily on the business registration database and use the alteration of business operation scope related to e-commerce by existing firms as a proxy for incremental digitization. The same event study approach as for firm entries shows that among incumbent firms having altered business operation scope, the share of e-commerce adoption witnessed a marked growth in response to the COVID-19 shock, and the effect persisted at least one year after full reopening. In addition, using the multi-round quarterly OSOME surveys from 2020 to 2021, we find that SMEs, including

[4] A recent McKinsey Global Survey of executives at large firms suggests a affirmative answer. It shows that firm responses to COVID-19 have accelerated companies' adoption of digital technologies, and the digital changes are expected to be long-lasting and essential for recovery. Please refer to `https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/how-covid-19-has-pushed-companies-over-the-technology-tipping-point-and-transformed-business-forever` and `https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/the-covid-19-recovery-will-be-digital-a-plan-for-the-first-90-days`.

the unregistered ones, in regions exposed to sporadic local lockdowns (after the nationwide lockdown and reopening) are more likely to adopt online operation, online sales, remote work, and electronic information systems.

The Chinese setting offers several advantages in studying the digitization of SMEs amidst COVID-19 shocks. First, China is the largest e-commerce and FinTech market, with a massive number of SMEs varying in the extent of digitization.[5] Second, the lockdown was immediate and reasonably uniform across the nation, and so was the reopening, which rules out endogeneity concerns that the timing or size of the mitigation and reopening policies are correlated with the level of digitization.[6]

Our study contributes to the literature on SME resilience to shocks. The sparse literature on the resilience of firms to shocks focuses on how clusters help to increase firms' resilience to external shocks (Martin et al., 2013; Crespo et al., 2014; Kranton and Minehart, 2000) and how intervention policies help (e.g., Bartlett III and Morse, 2020; Chen et al., 2020). Several recent studies survey small businesses, mostly in developed countries, shortly after the onset of the pandemic (e.g., Bartik et al., 2020a; Bartlett III and Morse, 2020; Humphries et al., 2020; Fairlie, 2020).[7] These studies focus on impact heterogeneity (Chetty et al., 2020; Adams-Prassl et al., 2020), implications for business owners (Alekseev et al., 2020; Kim et

[5]Claessens et al. (2018), Frost et al. (2019), and Frost (2020) show an inverse relationship between the competitiveness of a country's financial sector and FinTech adoption. They find a higher adoption in emerging and developing economies where the population is more likely to be underserved by traditional banks financial systems.

[6]COVID-19 broke out in Wuhan in December 2019. Over January 2020, the infection spread to multiple other cities and the pandemic unfolded. The government took immediate actions to implement various mitigation policies. The coincidence of the Lunar New Year and the lockdown also implies that the policies were fully implemented, forcing people to stay in their hometowns, preventing them from resuming their jobs elsewhere, and limiting the spread of the virus.

[7]Bartik et al. (2020b) examine variations in shutdown rates in a survey of 5,800 U.S. businesses carried out between March 28 and April 4, 2020. Similarly, Fairlie (2020), Humphries et al. (2020), and Campello et al. (2020) also document business closures and mass layoffs early in the pandemic. Crane et al. (2020) investigate permanent shutdown rates in the US, and how these varied across different industries. Similar to Bartik et al. (2020b) who survey beliefs of the evolution the pandemic, Balla-Elliott et al. (2020) survey small business owners' expectations about their re-opening and future demand and the interaction of the two. They find that demand from consumers and downstream firms plays an important role.

al., 2020), and corporate hiring (Campello et al., 2020). More specifically in the Chinese context, Dai et al. (2021b) compare the efficacy of policies targeted at SMEs against the toll from the pandemic and lockdown.

We add to this body of work by analyzing how e-commerce adoption, an important dimension of digitization, enhances business resilience. Our findings are consistent with those in the literature. For example, Kwan et al. (2021) document that public U.S. banks with better IT originate more PPP loans and attracted more deposits during the pandemic. Several other studies similarly examine public firms and document how credit risk, financial flexibility, workplace flexibility, managerial ownership, executive entrenchment, financial policies, differential COVID-19 exposures, environmental and social policies affect firm resilience and outcomes such as stock returns (Acharya and Steffen, 2020; Albuquerque et al., 2020; Ramelli and Wagner, 2020; Ding et al., 2021; Fahlenbrach et al., 2021; Barry et al., 2021).

While the literature has identified managerial talent, financial flexibility, and governance as important drivers for resilience amidst the pandemic, we show several novel channels through which digitization enhances resilience. Given the immediate large negative impact on consumption associated with lockdowns (Chen et al., 2021), robust online consumption, as well as more timely payment and faster turnover of firm working capital, give enterprises with online operations a competitive advantage. Moreover, our surveys cover SMEs in all sectors and span pre-pandemic to post-reopening episodes, allowing us to examine the long-run impact of the pandemic on SME digitization across the board.

Our study also contributes to the emerging literature on FinTech adoption (e.g., Agarwal et al., 2020). According to the Plaid Report 2020, FinTech adoption has been accelerating amid the pandemic: 59% of Americans use more apps to manage money now than before COVID-19; 73% of surveyed people said they plan to continue managing most of their finances digitally; 80% of Americans say they favor contactless digital solutions.[8] Although FinTech deals decreased drastically during the first quarters of 2020 due to the lockdown, digital financial services will likely thrive as FinTechs are widely seen as natural remedies (CB Insights, 2020; Zachariadis et al., 2020). Recently, Fu and Mishra (2020) document that the COVID-19 pandemic and associated mitigation policies have led to sharp increases in daily downloads of FinTech APPs, whereas Tut (2020) finds a negative impact on the adoption of FinTech payment systems. Since e-commerce, a major variable of interest in our analysis, relies on online payment systems, our study is also related to the literature on FinTech adoption.

Broadly concerning technology adoption in response to shocks, through longitudinal interviews of musicians in the aftermath of Hurricane Katrina, Shklovski et al. (2010) find that disaster experience only had a temporary pick-up on computer-based communication and information technologies. Several other studies focus on network externality and coordination (e.g., Crouzet et al., 2019; Higgins, 2019), demographics (Carlin et al., 2017), and individual trusts (Rossi and Utkus, 2020) in FinTech adoption. Different from these studies, our paper focuses on SMEs rather than on consumers and households, examining whether the effect on digitization is lasting. Through combining surveys and other data sources, we also explore the underlying mechanisms, which are new to the literature.

We organize the remainder of the article as follows. Section 2 describes the data and survey design. Section 3 presents evidence of the digital edge of some SMEs amidst the COVID-19 outbreak and reopening. Section 4 discusses how the pandemic has accelerated the digital transformation of SMEs, with potential persistent effects. Section 5 concludes.

[8] Please refer to `https://plaid.com/documents/the-fintech-effect-spotlight-on-covid.pdf`.

2 Data and Survey Design

We assemble several large-scale data sets (including both primarily collected data and administrative data) concerning small and medium-sized enterprises in China and their digitization. The scale and coverage of the data, as well as the corresponding algorithm, mark one main contribution. Next, we introduce them one by one.

ESIEC data. ESIEC is an entrepreneur- and enterprise-specific joint field survey project led by the Center of Enterprise Research, Peking University, covering seven provinces.[9] ESIEC successfully interviewed nearly 10,000 private enterprise owners and self-employed entrepreneurs between 2017 and 2019, collecting high-quality and representative microdata on the entrepreneurs' backgrounds and business performances.

After the outbreak of the COVID-19 pandemic in China, the ESIEC team immediately conducted phone surveys with previously interviewed entrepreneurs in the baseline survey in February and May, and a new private firm sample in August 2020 (see Figure 1 for the timeline of the survey). The questionnaire mainly focused on the firm's reopening and operational status, challenges, responses, and prospects. The first two rounds of surveys in February and May 2020 tracked firms drawn from the 2017, 2018, and 2019 ESIEC surveys. We received 2,513 responses in the first round between February 11 and 16 and 2,508 responses (some respondents in Feb reportedly shut down their businesses in May) in the second round from May 18 to 24, 2020. Overall, the completion rate is about 50% for those with valid contact information.[10] As shown in Dai et al. (2021b), although the ESIEC

[9]The ESIEC sample covered Henan Province in 2017, six provinces in the 2018 baseline survey (Shanghai, Henan, Gansu, Guangdong, Zhejiang, and Liaoning), and Beijing in a supplementary study on high-tech firms in 2019. As of the writing of this manuscript, the ESIEC project alliance includes Peking University, Guangdong University of Foreign Studies, Harbin Institute of Technology at Shenzhen, Shanghai University of International Business and Economics, and Central University of Finance and Economics.

[10]In China, all the firms are required to provide contact information, including phone numbers, at the time of registration, which is subsequently updated if any changes occur.

sample is designed to be representative only in the chosen provinces, the distribution across one-digit industries ends up closely mirroring that in the China Economic Census of 2018. The distribution of firm size measured in employment and revenue also matches well with data at the national level, indicating the representativeness of our data.[11] Supplementary information can be matched with the baseline survey and the SAIC data.[12]

From August 14 to 21, 2020, the ESIEC team conducted another phone survey on a newly drawn sample of incorporated enterprises in the six baseline provinces from the 2018 in-person survey. One key difference from the first two rounds of phone surveys in February and May is that the August sample does not include self-employed businesses due to the lack of phone contact information. This third round received 2,272 responses, enabling us to examine various outcomes several months after the reopening. After dropping observations missing the main variable and those on firms that shut down before the pandemic outbreak, we still have 1,678, 1,715, and 1,521 observations for the three waves of the phone interview, respectively. In our analyses, we treat them as independent cross-sections.

By merging the ESIEC phone interview data in the first two rounds with the baseline surveys and the SAIC data, we are able to study whether firms with e-commerce activities prior to the shock performed better during and after the COVID restrictions in terms of reopening, recovery, and cash flow. The variable of interest is the share of online sales inferred from the field surveys in 2017-2019. The reopening status is a dummy variable defined based on the multi-rounds of telephone interviews. Table 1 contains the summary statistics of the key variables from the ESIEC survey used in our main analyses.

[11] For detailed information, please refer to Fig. 1 and 2 in Dai et al. (2021b).

[12] The original Chinese-language survey questionnaire in both English- and Spanish-language versions, as well as a technical note about the details of the survey process, can be found at `https://www.cgdev.org/blog/measuring-impact-coronavirus-global-smes-survey-instrument-chinese-english-and-spanish`.

SAIC registration data. The SAIC business registration database covers the universe of registered businesses in China. It contains information about location, sector, date of establishment, registered capital, business operation scope, ownership type, the list of shareholders and managers, and the alteration record for all the registered businesses. It has greater coverage of small, medium, and micro enterprises than other firm-level databases.[13] Since the SAIC registration data is up-to-date, we can analyze firm responses during the pandemic and after the reopening.[14] Besides, due to the lack of access to the most recent self-employed businesses in the registration database, our sample is limited to the registered incorporated enterprises. The other two survey datasets can help complement more detailed information on the self-employed.

The business registration database includes the "business operation scope" record, a mandatory, regulated, and standardized text record briefing what business operations an enterprise is approved to conduct.[15] We can therefore extract information from the records of entrant firms' business operation scope using natural language processing (NLP) tools to classify types of business. Specifically, we extract keywords associated with e-commerce sales from the "business operation scope" and create a binary variable about the status of e-commerce adoption. Then we calculate the total numbers of entrant firms at the city-industry-year-month level related and unrelated to e-commerce according to the binary variable. This outcome variable captures the extensive margin of SMEs' digital transformation

[13]In contrast, the commonly used Annual Survey of Industrial Firms (ASIF) in China, also known as China Industry Business Performance Database, covers manufacturing enterprises with annual sales over a threshold of 5 million RMB. It contains most large Chinese firms while leaving out SMEs in the manufacturing sector and all the firms in the service sector that make up the majority of Chinese firms. Besides, the National Bureau of Statistics in China has not released the most recent ASIF data, precluding studies on firm responses to the COVID-19 shock using the data.

[14]Dai et al. (2021a) have used the dataset to examine the role of clusters in businesses' buffering of the COVID-19 shock.

[15]For standards and rules of completing the business operation scope registration, please refer to `https://bj.jyfwyun.com/#/visitor/home`.

in terms of e-commerce. For a brief description of the NLP method, please refer to Appendix C for details. As a robustness check, We also use the four-digit industry codes in the firm registration data to classify SMEs into online and offline businesses in the wholesale and retail industries, in which online sales are clearly labeled. As an external validation, the algorithm can successfully predict the enterprises with online sales in the ESIEC sample as high as 87.5 percent.

Furthermore, we apply the same NLP classification to the records of incumbent firms' "alteration record of business operation scope" to construct a second dummy proxy for e-commerce adoption among incumbent firms that have changed the contents of the business operation scope.[16] A dummy variable for incumbent firms' adoption of e-commerce takes a value of one if the alteration entails changes from contents without any e-commerce keywords to words related to e-commerce, and zero otherwise.[17] Once again, the numbers of incumbents' alterations related and unrelated to e-commerce adoption, respectively, are aggregated at the city-industry-year-month level.

OSOME data. The quarterly OSOME survey is conducted by Peking University, Ant Group Research Institute, and MYBank, focusing on the small and micro businesses which are active users of Alipay.[18] Alipay reached 1.2 billion monthly users in 2019 and is the primary payment method for 90% of people in China's largest cities, along with WeChat

[16]There is a possibility that some firms, which actually adopted e-commerce, have failed to update the contents of the business operation in reflecting the change. The classification error, if any, will underestimate the actual degree of digitization found in this paper.

[17]That is, the dummy variable for an incumbent's adoption of e-commerce is 1 if and only if the binary e-commerce proxy from the NLP method is 0 for the pre-alteration business operation scope record and 1 for the after-alteration one.

[18]The active SME on the Alipay platform is defined as those that had transactions in at least three months, more than 90 transactions, and a total transaction turnover of more than 2,000 yuan RMB in the past twelve months.

Pay (Klein, 2020).[19] One key difference between the OSOME data from the ESIEC data lies in its inclusion of unregistered self-employed businesses.

The questionnaire mainly includes topics on business operation performance, COVID-19 recovery, digital adoption (online sales, remote work, and introduction of electronic information systems), challenges, and business outlook. The OSOME data provide a unique and up-to-date supplementary source for documenting the adoption of online sales and other digital technologies of SMEs over time, enabling us to validate whether the basic patterns identified from the ESIEC and SAIC data still hold for unregistered SMEs and in other types of digital adoption beyond e-commerce.

Table 2 shows the summary statistics of the OSOME data. The full sample covers six quarters spanning from the third quarter of 2020 to the fourth quarter of 2021. The sample respondents of the OSOME survey have been consistent in terms of their basic characteristics over the past six quarters, with the majority of sampled SMEs in the service industry (82.4%) and even distribution across different levels of cities. It also covers a larger share (38.7% in the full sample) of unregistered, self-employed businesses that have been neglected in previous research. Besides, nearly 33.3% of the business owners reported not hiring full-time employees, and 55.7% between one and ten employees. In the full sample, we mainly utilize online operations and sales as the outcome variables. Besides, a few more questions on digital transformation (remote work and electronic information systems) have been added to the questionnaire since the fourth quarter of 2020, enabling us to examine other forms of digitization besides e-commerce. Therefore, we also included a subsample excluding the third quarter of 2020.

[19] See also `http://www.xinhuanet.com/english/2019-10/01/c_138440413.htm` and `https://www.techinasia.com/wechat-cashless-china-data`.

3 A Digital Edge Among Small Businesses?

This section relies on the ESIEC data to investigate how digitization helps SMEs mitigate the systematic shock since the onset of the COVID-19 pandemic—the digital edge. The key variables of interest on firm performance include shrinking market order as a main challenge, cash flow condition, reopening status, and expectation for growth. We use the continuous ratio of online sales to total sales, *E-commerce ratio*, reported in the baseline survey in 2017, 2018, or 2019 as a measure of digitization when analyzing the February and May waves of the ESIEC survey; we then use the ratio in the first half of 2020 for the August wave rather than from the baseline because this round was based on a newly-drawn incorporated enterprises sample (following the same procedure of random sampling as in the samples from 2017, 2018, and 2019). Although we use the continuous measure in the regression, it is also helpful to describe the binary measure (*E-commerce ratio* > 0). As Table 1 shows, nearly 24.2% of SMEs in the ESIEC sample had adopted online sales. Yet, there is a variation in the adoption of online sales across industries and firm sizes, as demonstrated in Appendix Figure A.2. Larger enterprises are more likely to report online sales than their smaller counterparts. Overall, agricultural enterprises have a lower percentage of adoption than those in the service sector.

Table 3 presents results using Ordinary Linear Square (OLS) regressions. The results are also robust to Probit and Logit specifications but are not reported here. Panels A-D report the estimate for the key variable of interest, *E-commerce ratio*, on the four outcome variables. The controls include employment, year of establishment, a dummy for incorporated business, city-level COVID-19 confirmed cases, and city-level COVID-19 case growth in the past 30 days. Employment can be regarded as a proxy for the firm size. We also control for the city and one-digit industry fixed effects in the regressions, which are not reported in the table for clarity.

In the first regression (Column (1)), the three waves of data are pooled, and wave dummies are controlled. Columns (2)-(4) present separate regressions for each wave. The pooled and separate regression yield highly consistent results. Overall, having a higher fraction of online sales is associated with better subsequent firm performance.

Specifically, at the height of the lockdown, consumers turned almost entirely to online shopping. Even after the lockdown ended, there were still many restrictions in place, which limited people from shopping in physical retail stores. Because of the COVID restrictions, lack of market demand was persistently reported as a major challenge in the three waves of ESIEC survey (see also Dai et al., 2021b). Yet there is a sharp difference in the demand for online sales and offline sales. Figure 2 displays the national trends of year-on-year growth rate for online and offline retail sales from January 2016 to October 2021.[20] Within this period, the growth rate for online sales consistently exceeded that for offline sales. During the lockdown in early 2020, both online and offline sales saw a sharp decline. Yet the drop in growth rate was more pronounced for offline retail sales than for online sales. After the reopening, the growth rate is still negative for offline consumption.

After the spread of COVID-19 was reined in, online sales witnessed a more rapid V-shaped rebound than offline retail sales. By the end of 2020, the year-on-year growth rate for online sales exceeded 10 percent, while the growth rate for offline retail sales remained in the negative territory. Facing the more robust demand for online sales, e-commerce firms were naturally less likely to report demand decline as a main challenge than those without online sales, as revealed in Panel A of Table 3.

A firm's cash flow status hinges upon demands for their products or service as well as

[20]For data in 2021, we calculate the two-years average growth rate (geometric mean) to alleviate the influence of base effect.

turnover rates of working capital. Robust demand brings in more steady cash flow to e-commerce SMEs. Moreover, the digital payment systems used in major online platforms in China help solve the delayed payment problem plaguing traditional trade, ensuring a faster payment. E-commerce firms can immediately receive payment once customers verify their satisfaction with the delivery. The May wave of ESIEC 2020 survey includes questions on accounts receivable and payable. We use the May survey to test the impact of e-commerce on firm's financial situations. Column (1) of Table 4 shows that e-commerce helped firms maintain a relatively low level of accounts receivable, measured by the ratio to current assets.[21] SMEs with e-commerce had a 8.6% lower probability of having account receivable that was larger than half of the current assets than those without. Given that the average is 26.4% for the whole sample, it implies that digitization can help SMEs alleviate about one-third of cash flow issues during the pandemic and lockdown. We also find that e-commerce reduced the repayment period of accounts receivable and entrepreneurs' uncertainty towards it, as shown in Columns (2) and (3).

All three rounds of ESIEC phone surveys contain the cash flow question. The estimates in Panel B of Table 3 show that firms with online sales have reported better cash flow status in February, May, and August 2020, as measured by whether cash flow can sustain operation over a month.

Thanks to the combination of robust market demand and faster capital turnover associated with e-commerce, firms with a higher share of previous online sales exhibited a higher reopening rate than those without or lower share of online sales in February, May, and August 2020 (Panel C of Table 3). A firm with fully online sales is estimated to have a 6.0% higher probability of reopening on average than a counterpart with fully offline sales as of

[21] The "current assets" in the questionnaire is defined as the sum of inventories, accounts receivable, cash, and cash equivalents.

February 2020. Given that the average reopening rate in our February sample is 19.5%, it implies that the adoption of e-commerce can help improve firms' reopening rate by 31%. Not only did firms with more online sales have a higher reopening rate, but also they held a more optimistic outlook for future growth (Panel D of Table 3). These findings show that e-commerce provides firms an edge in coping with the pandemic.

As a robustness check, we further control for more firm-level pre-COVID characteristics and the owner's background information. A few variables gathered in the baseline survey, such as having innovation or new product, revenue, on-the-job training, government subsidies, and the firm's R&D investment prior to the pandemic, are included as additional firm-level controls. Besides, information about the owner's age, gender, working experience before starting the business, and education level are also controlled. The descriptive statistics for these variables can be found in Appendix Table B.1. Note that some variables are not included in the pooled sample and the August subsample because the related questions were not collected in the August wave phone interview. The results with the additional control variables are presented in Appendix Table B.2 and Table B.3, which remain consistent and robust.

4 Digital Transformation

Having observed the positive effect of digitization on improving the resilience of SMEs to the COVID-19 shocks, a natural question arises: Does the pandemic have a lasting impact on SMEs' digitization? We next answer this question by considering both the extensive and intensive margins of the SMEs' digital transformation based on the business scope texts in the SAIC registration database, as described in Section 2. The extensive margin focuses on the new firm entry, while the intensive margin examines whether incumbents have increasingly adopted digital technologies after the COVID restrictions were eased.

4.1 Identification Strategy

Similar to Fang et al. (2020), Chen et al. (2021), and Dai et al. (2021a), we use the Wuhan lockdown following the first outbreak of the COVID-19 in China as an exogenous shock to examine its impact on SMEs in a difference-in-differences framework. Since all SMEs are treated with the COVID-19 shock, the second difference is not in the cross section, but in the time series, with the "control group" being essentially firms in previous years who never experienced the COVID-19 shock. Specifically,

$$\ln(Y_{cjmy}) = \sum_m (\beta_m \times COVID_y \times Dummy_m) + FEs + f(y, c, j) + \varepsilon_{cjmy}, \tag{1}$$

where c indicates the city (prefecture) a firm is located in, j indicates the industry, m indexes the month(s) and y the year. We define m according to the Lunar calendar and set the month of Lunar New Year's Eve as $m = 0$ since it coincides with the nationwide lockdown policy.[22] This is important because the Lunar New Year is a traditional holiday in China when firms close their businesses and new firm registration or alteration is paused even before the pandemic. $COVID_y$ equals one for year 2020 and after (i.e., the treatment indicator), and zero otherwise. $Dummy_m$ is a dummy variable indicating the month gap between the month of observations and the Lunar New Year's Eve. We further control for the city, industry, month, and year fixed effects, and the corresponding two-way fixed effects except the interaction term between year and month. We also control the year trend of city-industry, $f(y, c, j)$. Standard errors are clustered at the city level. The sample period

[22] Wuhan lockdown was implemented in January 23, 2020, and other provinces in China took lockdown policies in the following days. The Lunar New Year's Eve was in January 24, 2020.

is January 2015 to April 2021. In sum, we compare the outcome variables in 2020-2021 to itself in the same matched lunar calendar period from 2015 to 2019 prior to the pandemic. Therefore, our data enable us to track and investigate the effect of the COVID shock.

As for the dependent variable, we first use the logarithm number of new entrants (plus one), $\ln(entry_{cjmy} + 1)$, as the outcome variable. As described in Section 2, we divide the entrant firms into two groups in several ways: (i) we apply our NLP classification based on firms' business operation scope to generate a binary variable on whether a firm has e-commerce operations for the whole sample; (ii) we use the online and offline firms in wholesale and retail sectors by the natural four-digit industry code. Then we aggregate the number of new entrants for the two groups, respectively. Next, we examine the intensive margin of digitization by exploiting the alteration records on business operation scope to quantify incumbent SMEs' digital transformation. We apply the same NLP tools as described in Section 2 and Appendix C to the alteration record and aggregate the number (plus one) related and unrelated to e-commerce adoption, respectively, into logarithm form $\ln(alteration_{cjmy} + 1)$ as another outcome variable.

We aggregate the data at the monthly level unless otherwise specified. Units without new entry or alteration are set to zero in our dataset. We aggregate the raw data at the city-industry level (unless otherwise specified) to alleviate the problem arising from having too many identical zero values. The set of coefficients β_m over time captures the dynamic impact of the COVID-19 outbreak and reopening on the outcome variables of interest. Since the outcome variable is in logarithmic form, the coefficient can be calculated to reveal the percentage change in outcomes driven by the shock.

Furthermore, we use a similar difference-in-differences specification among different industries to examine the heterogeneous effect of COVID-19 shock on both new entrants' and incumbents' adoption of e-commerce. Specially,

$$\ln(Y_{cmy}) = \beta \times (COVID_y \times After_m) + FEs + f(y, c) + \varepsilon_{cmy}, \tag{2}$$

where c, m, and y indexes the city, month, and the lunar year, respectively. We aggregate the data for each main industry at the city-year-month level. $After_m$ equals one for the months after each lunar New Year's Eve, and zero otherwise. The regression also controls for the city, month, and year fixed effects, the corresponding two-way fixed effects except the interaction term between year and month, and the year trend of city. Standard errors are clustered at the city level as well.

4.2 Empirical Result

We start by documenting several stylized facts. The COVID-19 pandemic had an enormous impact on small and micro businesses' entry in China. Using the aggregated number of newly registered entrants as the dependent variable in our specification (1), we plot the estimated coefficients β_m in Appendix Figure A.1(a). As shown in the figure, the start and beginning progression of the shock led to a huge decrease in new firm entries. In the first two months after the outbreak, the number of new entrants drops 72.6% and 32.0%, respectively, controlling for geographical differences and aggregate trends. After the pandemic was (temporarily) reined in and the economy reopened, firm creations had rebounded by the end of April. In the following ten months, the coefficients remain at the pre-crisis level.

Business activities of incumbents, measured by the number of alteration records on business operation scope, exhibits a similar V-shaped pattern as shown in Appendix Figure A.1(b). The patterns reveal that firms experienced initial drops of 67.2% and 26.6% in the first two months and rebounded quickly. After the reopening, the coefficients are slightly below the pre-crisis level, probably reflecting the fact that above-normal level of firms shut down during the lockdown.

Figure 3 displays the extensive margin of the COVID-19 on new firm entries for e-commerce and non-e-commerce groups classified by the NLP method. As shown in the figure, the number of new entries with e-commerce mode in all industries dropped less rapidly during the peak lockdown than their counterparts and recovered a bit faster thereafter. More importantly, the coefficients for e-commerce firms are significantly positive since the third month and kept a sustained gap with the non-e-commerce group. This implies a persistent effect that the COVID-19 pandemic has spurred the digital transformation of SME entries in China.

As a robustness check, we repeat the above excise by comparing the online and offline businesses in the wholesale and retail (W&R) sectors, which are clearly labeled by the four-digit industrial classification code at the time of registration.[23] Figure 4 shows that new online entrants in W&R industries were significantly less affected than their offline counterparts, and the online entrants kept growing for nearly half a year after the reopening, while the growth of traditional offline W&R was stagnant.

To examine the heterogeneous effect on new firm entries adopting e-commerce among different industries, we use specification (2) to estimate the heterogeneous impact and plot the coefficient estimate in Figure 5. It shows that the adoption of e-commerce by new entries in the W&R sectors increased by 12.9% in the year following the lockdown (on average), which is consistent with the estimates in Figure 4. More importantly, new entrants in other traditional industries also adopted more e-commerce, especially the newly registered enterprises in the agriculture and the manufacturing sectors, increasing by 19.1% and 22.7%, respectively.

[23]Similar to the textual analysis on business operation scope, the classification by industry code may also lead to underestimation, if anything, that goes against significant findings.

This embodies the trend that the COVID-19 pandemic has also significantly accelerated the transformation of SMEs in traditional industries to digitization. Besides, newly registered enterprises in the service sector have also accelerated the adoption of e-commerce after the lockdown, such as the resident services and the culture, sports, and entertainment services. New entrants in the information transmission, software, and information technology service industry didn't show a significant trend in adopting e-commerce. On the other hand, this effect does not exist in industries not directly related to e-commerce, such as mining and the production and supplies of electricity, heat, gas, and water. It is intuitive and can serve as a placebo test showing that the textual analysis algorithm and the identification strategy are reasonable. Therefore, the positive effect of the COVID-19 pandemic on the digital transformation of newly registered SMEs found above is not only limited to the W&R or the emerging digital sectors, but also includes the digitization of traditional industries as an important part.

Next, we examine the intensive margin of incumbent SMEs in digital transformation by using alteration records of business operation scope to construct subgroups. Figure 6 plots the estimated coefficients for this empirical design. Immediately after the COVID-19 outbreak, overall registration alteration dropped by 67.2 percent. By comparison, the alteration to e-commerce business declined by 55.2 percent, much less than other business operation scope changes. The effect on e-commerce transformation turned significantly positive in the second month, and the gap between alteration to e-commerce and the comparison further widened twelve months after the outbreak. The year-on-year growth for firms changing their operation scope to e-commerce was as high as 28.1 percent towards the end of the sample period, compared to negative growth for firms with other types of business scope alteration. This piece of evidence on intensive margin corroborates the persistent effect on the extensive margin.

Similarly, we also use specification (2) to analyze the industrial heterogeneity of incumbents' e-commerce transformation after the COVID-19 shock, and the results are shown in Figure 7. In the W&R industry, nearly 31.9% of incumbent enterprises changed their business operation scope from offline to (or added) online sales after the pandemic, which may have benefited from the existing warehouses, logistics, and purchase channels accumulated in their previous operations. In addition, incumbents in the agriculture sector, the manufacturing sector, and the service sector of culture, sports, and entertainment have also significantly accelerated their transformation to e-commerce, increasing by 15.2%, 22.3%, and 18.0%, respectively. Also, similar to Figure 5, in some industries that are not applicable to e-commerce, the incumbent enterprises have not made corresponding changes.

The above analyses focus on registered enterprises using the administrative business registration data. Yet nearly half of self-employed businesses are not registered in China (Kong et al., 2021). It is unclear whether the patterns observed from the registered enterprises still hold for self-employed businesses, especially the massive number of unregistered ones. The OSOME data enables us to check this out. The OSOME data includes not only registered incorporated companies (10.7%, as shown in Table 2) and registered self-employed (50.6%) but also unregistered businesses (38.7%) operating on the Alipay platform. Although the nationwide lockdown ended in April 2020, there have still been sporadic local lockdowns since then. We have manually gathered the local lockdown information at the city level and matched them with the quarterly OSOME survey. The OSOME questionnaire includes questions on online operation, remote work, and the adoption of various electronic information systems. Since the surveys cover at least six quarters, we can make use of the spatial and temporal variations in local lockdowns to evaluate the impact of COVID restrictions on digital transformation in multiple dimensions for small- and micro-enterprises, including those unregistered ones.

To this end, we follow a similar specification as before:

$$Y_{ijcq} = \beta \times (COVID_c \times After_q) + \mathbf{x}_i'\theta + \gamma_q + \zeta_c + \eta_j + \alpha_{cj} + \delta_{cy} + \mu_{iy} + \varepsilon_{icqj}, \qquad (3)$$

where the subscript indicates that a firm i in industry j located in city c was surveyed in quarter q of year y. The key explanatory variable of interest is a dummy variable ($COVID_c \times After_q$), which equals one if a business is located in a city that was subject to local lockdown prior to the survey, and zero otherwise. The control variables include firm age (i.e., established year), owner's age, owner's gender, business type (incorporation, registered self-employed, and unregistered self-employed), employment, and quarter revenue. The OLS regression also controls for the city, industry, quarter (wave), city × industry, city × year, and industry × year two-way fixed effects.[24]

Table 5 first reports the estimation results concerning online operation and sales.[25] The dependent variable in Column (1) is a dummy variable, indicating that a firm has online operations. The dependent variable in Column (2) is restricted to online operations only. The dependent variable in Column (3) is a dummy for online sales. Panel A includes the whole sample, while Panels B and C further restrict the analyses to new entry and incumbent subsamples, respectively. As shown in the table, exposure to local lockdowns is significantly associated with a subsequent higher probability of having online operations for the whole sample and incumbents. Compared with the average, the share of SMEs taking online operations has increased 5.2% for the whole sample and 6.5% for incumbents, especially

[24] The results are robust to the use of alternative fixed-effect Logit model.

[25] Online operation includes online advertisement, promotion, recommendation, design, etc.

those relying on both offline and online operations. In contrast, new entries rely more on pure online operations (37.8% more growth compared to the average level) and less on the combined offline and online operations.[26] Similarly, Column (3) shows that exposures to COVID-19 restrictions have accelerated the adoption of online sales (4.7% more growth compared to the average), and the impact concentrates on incumbent SMEs (5.8% more than the average).

Table 6 further reports the impact of exposures to lockdowns on adopting remote work and electronic information systems.[27] The specification is the same as in Table 5. These questions were not included in the questionnaire until the fourth quarter of 2020. As a result, We dropped the first wave of OSOME from the sample when conducting the empirical analyses. After a local lockdown, businesses, in particular incumbents, are more likely to adopt remote work mode. Given that only 15.3% of respondents have adopted remote work, exposures to local lockdowns explain nearly 16.3% of increase in the adoption of remote work for the whole sample. The magnitude is even more prominent when restricted to the incumbents (18.4%). Besides, incumbent businesses tend to adopt the electronic information system of sales. Compared to the average level, exposure to a lockdown leads to an 8.8% increase in the the adoption. However, we do not observe an association between exposures to COVID-19 restrictions and the introduction of electronic systems for newly established businesses. Overall, local lockdowns have induced small businesses to develop

[26] A potential concern is that this result reflects a survivorship bias, i.e., SMEs operating online are more likely to survive and respond to the survey. We dispel the concern by showing that there is not a systematic gap in transactions between survey respondents and all active SMEs on the Alipay platform using the same criteria as specified in footnote 18, within each industry and location.

[27] The remote work in the questionnaire includes working-from-home and flexible working hours. For self-employed without full-time staff, this question means whether they can manage and operate their businesses remotely. The electronic information system on management includes staff management, office automation (OA), and Cloud storage. None of these adoptions has been positively or negatively impacted by the lockdown during the research period.

online operations and adopt remote work modes.[28]

So far, our empirical analysis shows that the COVID-19 pandemic has a lasting positive effect on SMEs' digitization. The digital edge in Section 3 provides an aspect of the benefit of adopting digitization. Here we show some supplementary evidence on the cost side. As for the constraint to SMEs' adoption of digitization, we included a question in the OSOME survey in the second quarter of 2021 about the greatest difficulties they encountered in digital transformation or upgrading. We collected 11,225 observations in this wave and calculated the percent of respondents, as shown in Figure 8.[29] It turns out that the lack of time and energy to learn is the key to hinge digital adoption. Nearly 41.7% reported it is one of the main difficulties they faced. The cost of usage and maintenance (including the charge by the service provider) and the shortage of funds to introduce digital technology, equipment, and talents, are another two main difficulties, reported by 26.9% and 20.3% of interviewees, respectively.[30]

5 Conclusion

Using the ratio of previous online sales as a proxy for digitization in combination with multiple data sources, our paper shows that SMEs with greater digitization are more resilient to the pandemic shock. Firms with online sales had more robust market demand and faster turnover of working capital than those without online sales. Thereby they reported better

[28]We also show in the appendix that digitization in terms of online operation (Figure A.3) and electronic information system adoption (Figure A.4) vary across different industries and increases as employment size goes up.

[29]It is a multiple-choice question where SME owners can choose two options at most. We use 11,225 as the denominator to calculate the percent of respondents. We also calculate the percent of answers, using the total number of selected options as the denominator, and the result is naturally consistent.

[30]in the second quarter of the year 2021, the OSOME survey found that 31.3% of SMEs didn't need financing. Among those who got loans or credits, most of them (70.4%) used it as the liquidity to maintain operations and 40.0% to expand their businesses, which may include the digital adoption and upgrade.

cash flow situations and were more likely to reopen during and after the lockdown. They also held a more optimistic view of future growth.

Cognizant of these digital edges, both entrants and incumbents have increasingly embraced digitization and e-commerce during the outbreak and after the reopening. We find that after the lockdown in January 2020, firm entries have exhibited a V-shaped pattern, with new entries of e-commerce firms experiencing a shallower initial drop and a quicker rebound. The COVID-19 pandemic has also accelerated the adoption of digital technology in existing firms in various dimensions (captured by, e.g., the alteration of operation scope to include e-commerce activities, allowing remote work, and adoption of electronic information systems) with persistent effects, including those small unregistered self-employed businesses.

The rapid digitization of SMEs in China benefited from numerous supporting infrastructures, such as broadband connection, network services, digital payment platforms, and warehouses, which were already in place prior to the COVID-19 pandemic. Some other countries may lack the necessary infrastructure for the digital transformation seen in China in response to the COVID-19 shock. For example, only about 50 percent of Mexico's population had a bank account, compared to 80% in India prior to the COVID-19 shock, although its per capita GDP was four times of Mexico (Bandura and Ramanujam, 2021). Nevertheless, the pandemic may promote digital infrastructure development in these countries, which in turn transforms small businesses and braces them for future recessions and economic downturns.[31] Our study, therefore, constitutes an initial step towards understanding SMEs' resilience and the lasting transformative effect of the COVID-19 pandemic and similar systematic shocks. Besides, our main specification uses e-commerce as a proxy for digitization, likely underestimating the true degree of digitization. More researches on other aspects of digitization are

[31] Please refer to `https://www.reuters.com/article/us-latam-mercadolibre-payments-focus/latin-american-payment-giant-rises-amid-pandemic-with-an-eye-on-chinas-ant-idUSKBN2751FB` for recent progress in Latin American countries, including Mexico.

called for.

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Figures

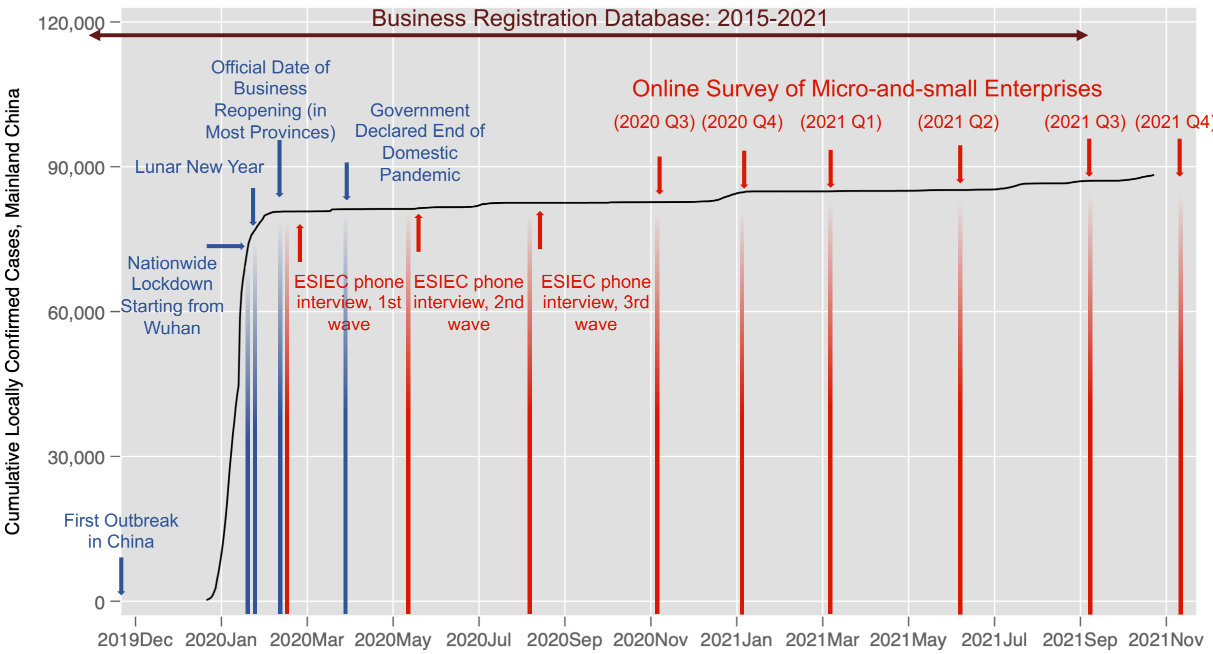


Figure 1: COVID-19 Outbreak, Reopening, Mitigation Policies, and Surveys

Data source: National Health Commission of China.
Please refer to `http://www.nhc.gov.cn/xcs/yqtb/list_gzbd.shtml`.

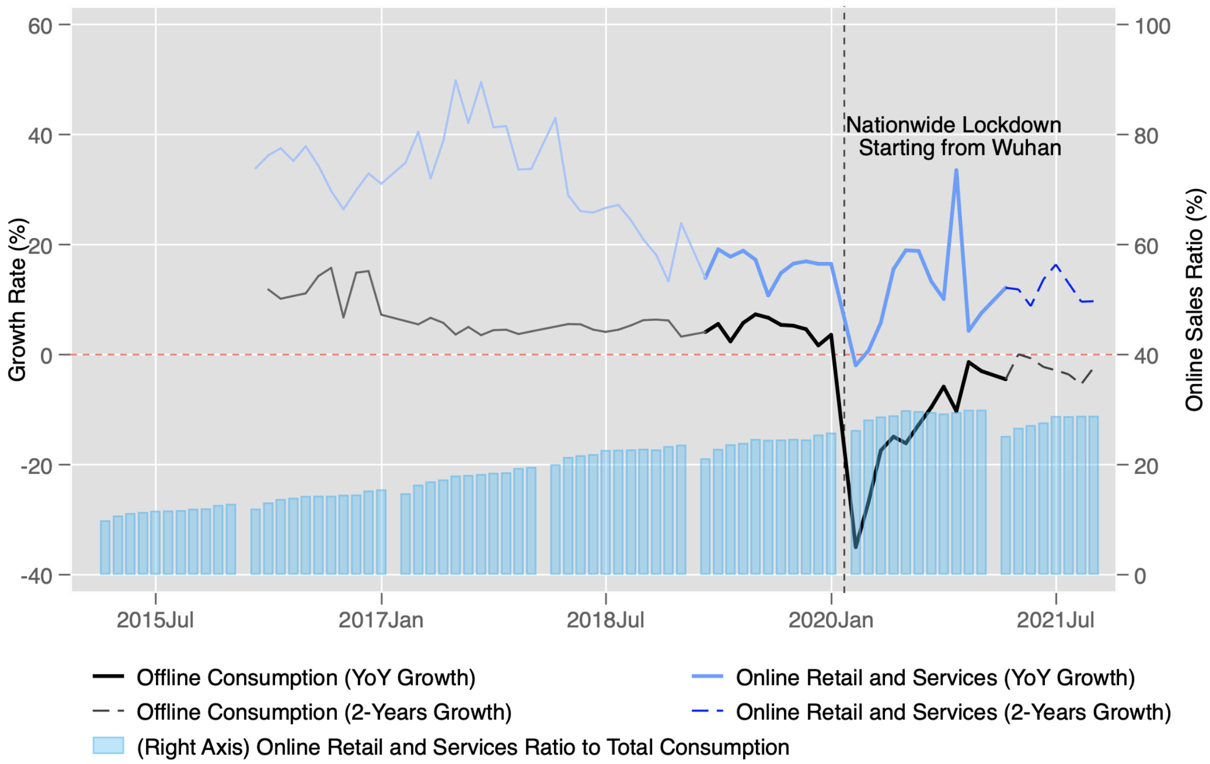


Figure 2: National Trend of Online and Offline Sales in China

Data source: National Bureau of Statistics of China.
Please refer to `https://data.stats.gov.cn/english/easyquery.htm?cn=A01` for the "Domestic Trade" indicator.

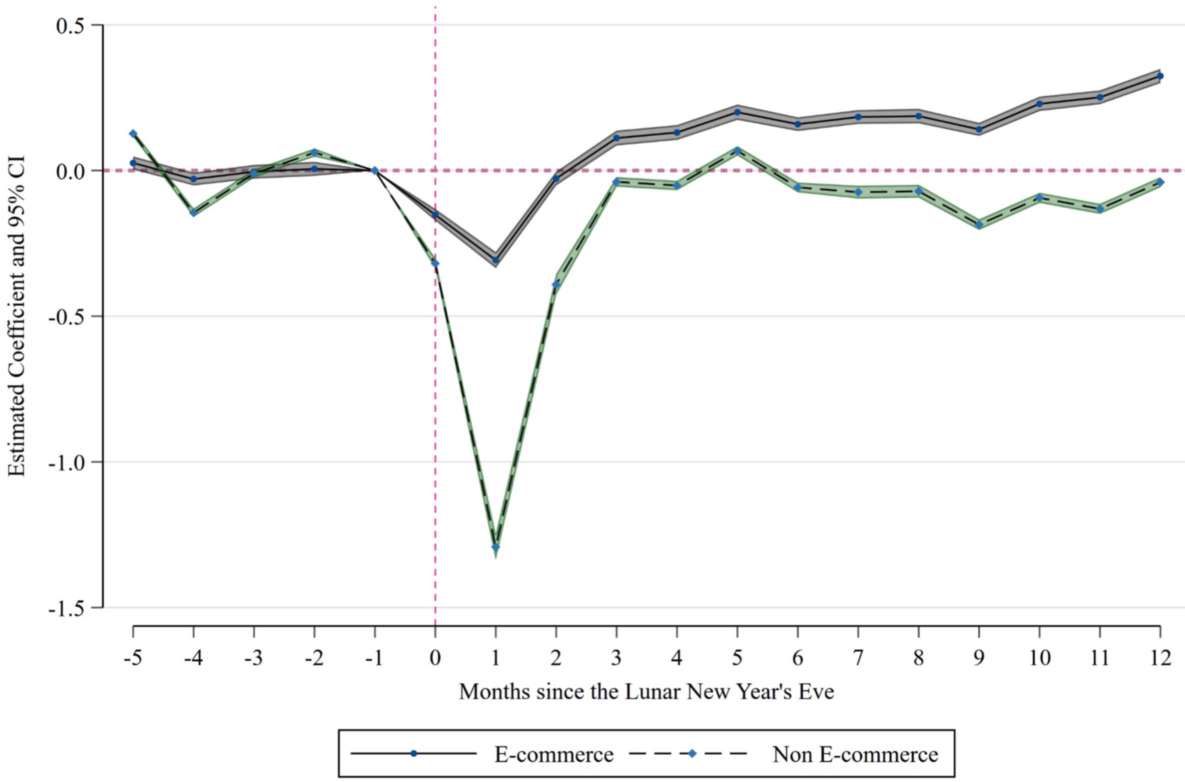


Figure 3: Event Study of COVID-19 Outbreak and Reopen on New Firm Entry for the Subgroups of E-commerce and Non E-Commerce

The dependent variable is the logarithm number of newly registered firms plus one. The X-axis label is the month(s) before (negative) or after (positive) each Lunar New Year's Eve. The shaded area shows the 95% confidence intervals. The e-commerce and non-e-commerce enterprises are divided by analyzing the keywords in the business operation scope text. The coefficient before one month (m = -1) is set as the baseline level. The coefficients before five more months and after twelve more months are included in the regression but omitted here. Monthly numbers of firm entries at the city level from 2015 to 2021 are included. All observations are at the city-industry-year-month level. Standard errors are clustered at the city level. The regression controls for the city, industry, month, and year fixed effects, the corresponding two-way fixed effects except the interaction term between year and month, and the year trend of city-industry.
Data source: SAIC registration database.

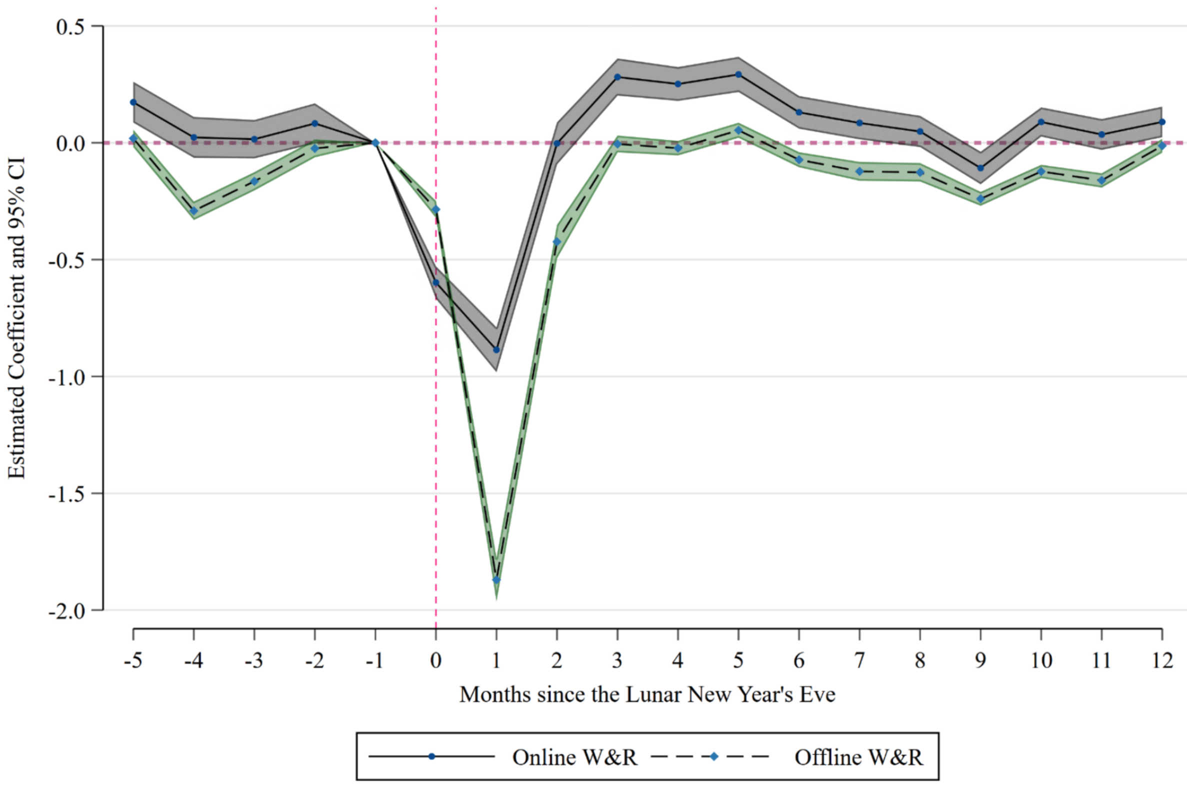


Figure 4: Event Study of COVID-19 Outbreak and Reopen on New Firm Entry for the Subgroups of E-commerce and Non E-Commerce, Wholesale and Retail Industries

The regression uses only the subsamples in wholesale and retail industries. The dependent variable is the logarithm number of newly registered firms plus one. The X-axis label is the month(s) before (negative) or after (positive) each Lunar New Year's Eve. The shaded area shows the 95% confidence intervals. The online and offline wholesale and retail enterprises are divided by four-digit industry code classification. The coefficient before one month (m = -1) is set as the baseline level. The coefficients before five more months and after twelve more months are included in the regression but omitted here. Monthly numbers of firm entries at the city level from 2015 to 2021 are included. All observations are at the city-industry-year-month level. Standard errors are clustered at the city level. The regression controls for the city, industry, month, and year fixed effects, the corresponding two-way fixed effects except the interaction term between year and month, and the year trend of city-industry.
Data source: SAIC registration database.

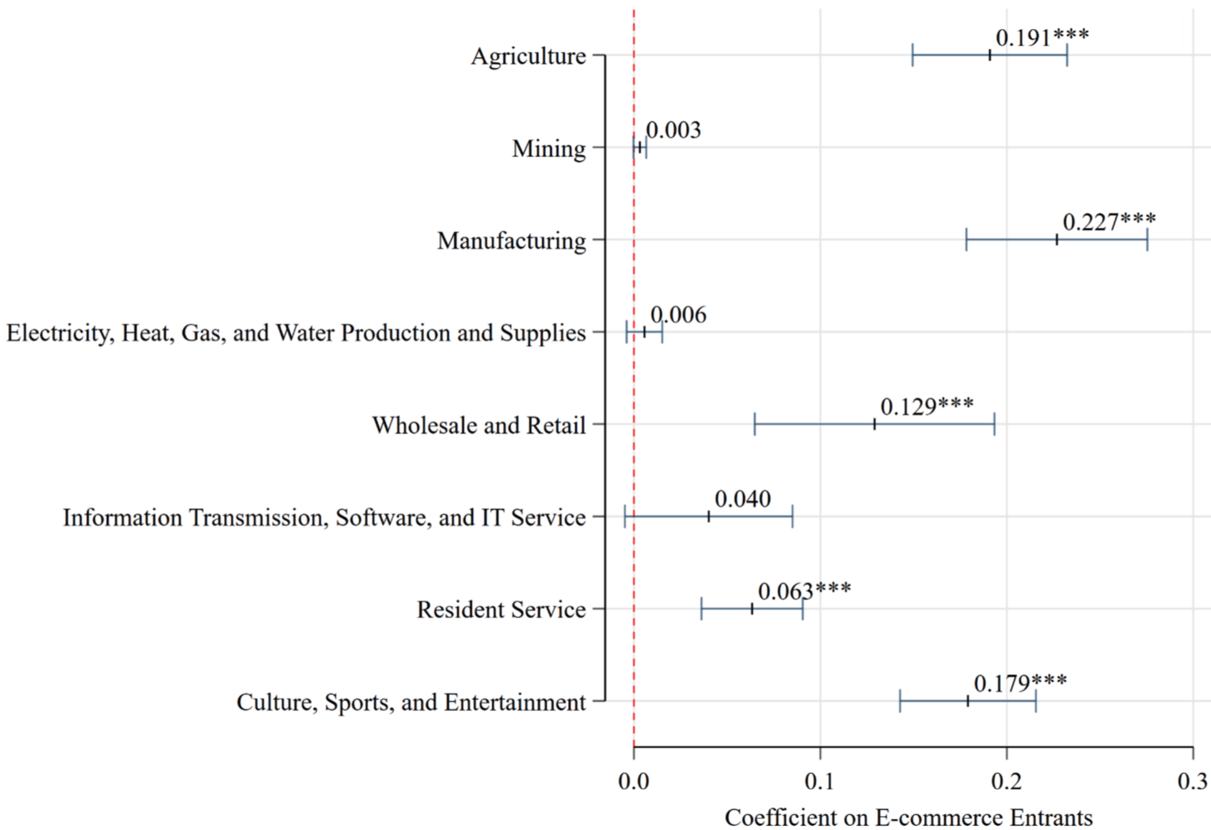


Figure 5: Heterogeneous Effect of COVID-19 Outbreak and Reopen on New Firm Entry for the E-commerce Subgroup, by Industry

The dependent variable is the logarithm number of newly registered firms adopting e-commerce (plus one), identified by analyzing the keywords in the business operation scope text. The figure plots the coefficient estimate and the confidence interval for each main industry. The label shows the estimated value and the significant level. Monthly numbers of firm entries at the city level from 2015 to 2021 are included. All observations for each industry are at the city-year-month level. Standard errors are clustered at the city level. The regression controls for the city, month, and year fixed effects, the corresponding two-way fixed effects except the interaction term between year and month, and the year trend of city.
Significance level: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.
Data source: SAIC registration database.

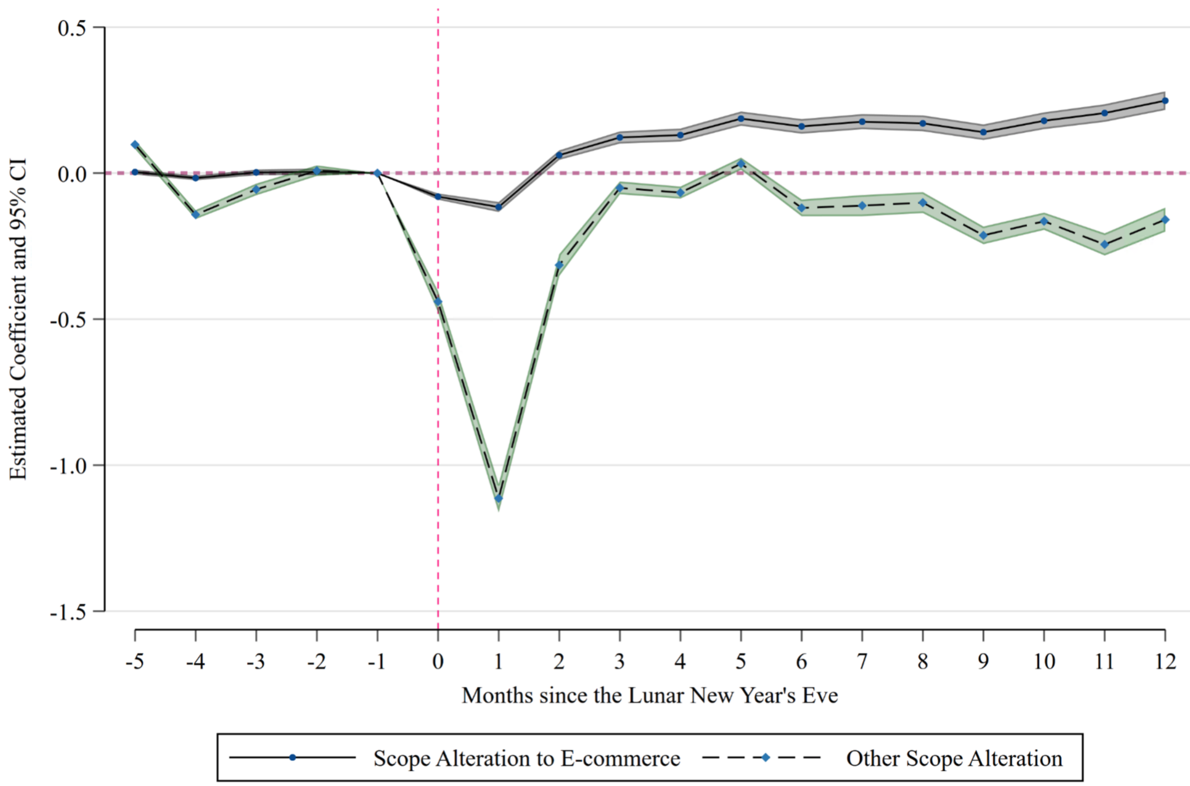


Figure 6: Event Study of COVID-19 Outbreak and Reopen on Incumbents' Business Operation Scope Alteration for the Subgroups of E-commerce Adoption and Others

The dependent variable is the logarithm number of business operation scope alterations plus one. The X-axis label is the month(s) before (negative) or after (positive) each Lunar New Year's Eve. The shaded area shows the 95% confidence intervals. The two groups are divided by analyzing the keywords in the business operation scope alteration record, where "Scope Alteration to E-commerce" are defined as changing from non-e-commerce to e-commerce business. The coefficient before one month (m = -1) is set as the baseline level. The coefficients before five more months and after twelve more months are included in the regression but omitted here. Monthly numbers of firm entries at the city level from 2015 to 2021 are included. All observations are at the city-industry-year-month level. Standard errors are clustered at the city level. The regression controls for the city, industry, month, year fixed effects, the corresponding two-way fixed effects except the interaction term between year and month, and the year trend of city-industry.
Data source: SAIC registration database.

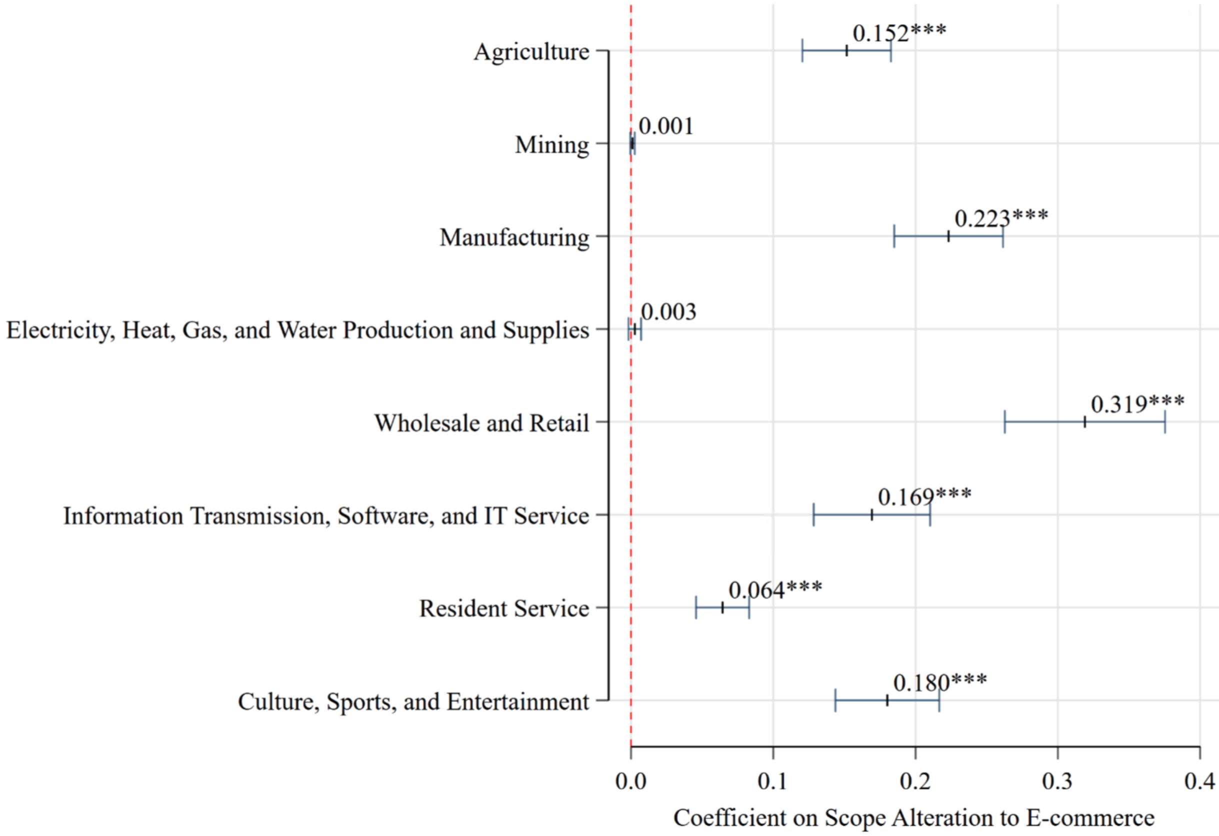


Figure 7: Heterogeneous Effect of COVID-19 Outbreak and Reopen on Incumbents' Business Operation Scope Alteration to E-commerce, by Industry

The dependent variable is the logarithm number of business operation scope alterations to e-commerce (plus one), identified by analyzing the keywords in the business operation scope alteration record, where "Scope Alteration to E-commerce" are defined as changing from non-e-commerce to e-commerce business. The figure plots the coefficient estimate and the confidence interval for each main industry. The label shows the estimated value and the significant level. Monthly numbers of firm entries at the city level from 2015 to 2021 are included. All observations for each industry are at the city-year-month level. Standard errors are clustered at the city level. The regression controls for the city, month, and year fixed effects, the corresponding two-way fixed effects except the interaction term between year and month, and the year trend of city.
Significance level: * $p<0.1$ ** $p<0.05$ *** $p<0.01$.
Data source: SAIC registration database.

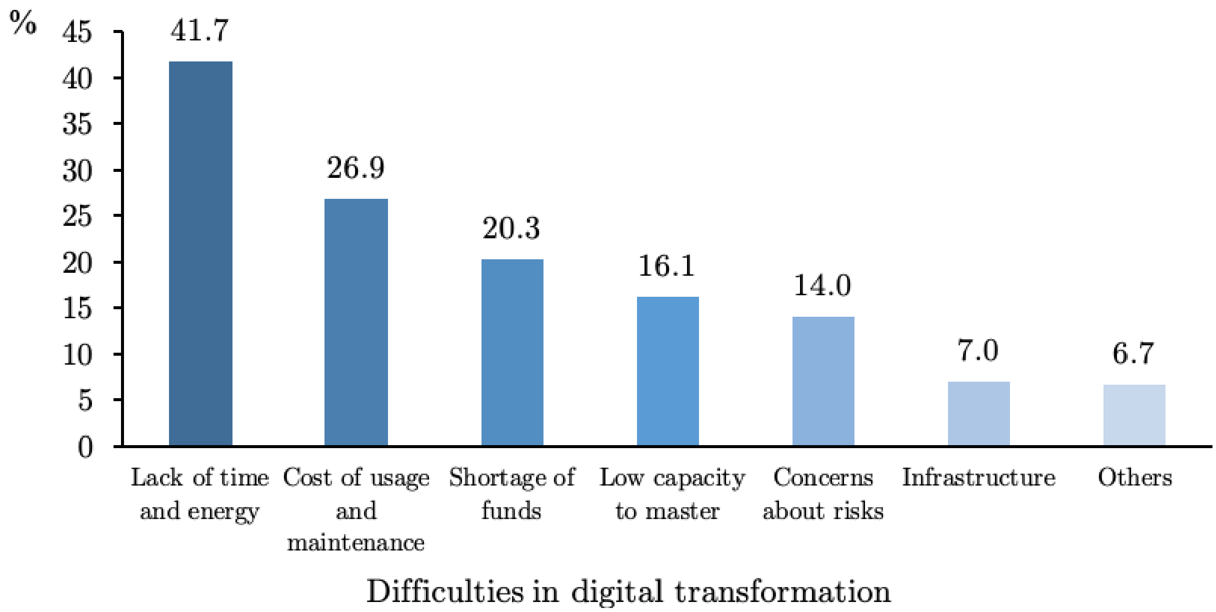


Figure 8: SME's Greatest Difficulties in Digital Transformation or Upgrading

The OSOME survey included this question only in the second quarter of 2021. 11,225 observations were collected in this wave. It is a multiple-choice question where SME owners can choose two options at most. We use 11,225 as the denominator to calculate the percentage of respondents. We also calculate the percentage of answers, using the total number of selected options as the denominator, and the result is naturally consistent.
Data source: OSOME.

Tables

Table 1: Summary Statistics of ESIEC Data

Variable	Pooled		February	May	August
	Mean	S.D.	Mean		
Panel A: Firm level					
Outcomes:					
Order decline as main challenge	0.181	0.385	0.502	0.022	0.007
Cashflow >1 month	0.696	0.460	0.636	0.779	0.669
Reopen status	0.653	0.476	0.195	0.861	0.924
Outlook for growth	0.292	0.455	0.080	0.450	0.359
Main independent variable:					
E-commerce ratio	0.122	0.286	0.069	0.172	0.123
(share of E-commerce ratio >0)	0.242	0.428	0.190	0.275	0.262
Controls:					
Firm age	4.674	2.362	5.299	5.254	3.331
Registered as self-employed	0.161	0.367	0.228	0.237	n.a.
Employment in 2019:					
0-10	0.568	0.495	0.551	0.618	0.529
11-50	0.340	0.474	0.359	0.286	0.380
51-100	0.050	0.219	0.058	0.043	0.051
>100	0.042	0.200	0.032	0.053	0.040
Industry:					
Agriculture	0.077	0.267	0.080	0.079	0.072
Construction and manufacturing	0.209	0.407	0.204	0.197	0.228
Residential service	0.347	0.476	0.393	0.419	0.214
Business service	0.367	0.482	0.323	0.306	0.486
Obs.	4,914		1,678	1,715	1,521
Panel B: City-wave level					
ln(confirmed COVID-19 cases)	3.035	1.389	2.994	2.985	3.156
ln(COVID-19 cases growth in 30 days)	0.102	0.228	0.089	0.089	0.137
Obs.	224		79	84	61

The main independent variable, *E-commerce ratio*, is the ratio of online sales to total sales reported in the baseline survey in 2017, 2018, or 2019, depending on the baseline survey year, for the February and May waves, and in the first half year of 2020 for the August wave. It ranges from 0 to 1. All samples in the August wave are incorporated.
Data source: ESIEC.

Table 2: Summary Statistics of OSOME Data

Variable	Full sample		Exclude 2020Q3	
	Mean	S.D.	Mean	S.D.
Main independent variable:				
COVID×After	0.069	0.251	0.088	0.283
(COVID)	0.190	0.392	0.191	0.393
Controls:				
Firm age	4.831	5.393	4.947	5.455
Owner's age	32.430	9.035	32.490	9.003
Female owner	0.173	0.378	0.172	0.378
Business type:				
Corporate enterprise	0.107	0.309	0.114	0.318
Self-employed, register	0.506	0.500	0.502	0.500
Self-employed, unregister	0.387	0.487	0.384	0.486
Industry:				
Agriculture	0.069	0.254	0.071	0.256
Construction and manufacturing	0.106	0.308	0.113	0.317
Service	0.824	0.381	0.816	0.387
Employment:				
0	0.333	0.471	0.335	0.472
1-4	0.453	0.498	0.445	0.497
5-7	0.104	0.305	0.103	0.305
8-19	0.068	0.251	0.072	0.258
>19	0.043	0.203	0.044	0.205
City tier:				
Tier 1	0.278	0.448	0.276	0.447
Tier 2	0.190	0.392	0.192	0.394
Tier 3	0.123	0.328	0.121	0.326
Tier 4	0.208	0.406	0.208	0.406
Tier 5	0.201	0.401	0.203	0.402
Obs.	84,316		65,036	

The main independent variable, *COVID* × *After*, equals one if a business is located in a city with localized lockdowns due to new COVID-19 confirmed cases and was surveyed in a quarter after the outbreak; zero otherwise. Variable *COVID* equals one if a business is located in a city with newly confirmed sporadic cases and subsequently localized lockdowns, and zero otherwise.
The employment scale is defined as the number of full-time employees receiving a fixed or regular wage in accordance with government regulations, excluding the business owners, operators, and interns. In the case of a family workshop or business, the spouses or other family members who don't receive wages are not counted as full-time employees. The owner's age is winsorized at 99.5% percentile.
For the city tier category by Yicai, please refer to `https://www.yicai.com/news/100648666.html`. For example, the 'First-tier' city category includes Beijing, Shanghai, Guangzhou, and Shenzhen; the 'Second-tier' city category, also defined as 'New First-tier' by Yicai, includes Chengdu, Dongguan, Foshan, Hangzhou, Hefei, Nanjing, Qingdao, Shenyang, Suzhou, Tianjin, Wuhan, Xi'an, Changsha, Zhengzhou, and Chongqing.
The full sample period covers from 2020Q3 to 2021Q4. There is also a subsample excluding 2020Q3 because the survey didn't include some variables in the third quarter of 2020.
Data source: OSOME.

Table 3: Baseline Regression of Digital Edge

	(1) Pooled	(2) February	(3) May	(4) August
Panel A:	Demand: order decline as main challenge			
E-commerce ratio	-0.028**	-0.114*	-0.020***	-0.013***
	(0.011)	(0.060)	(0.006)	(0.005)
adj. R-sq	0.374	0.072	0.018	-0.007
Panel B:	Cash flow >1 month			
E-commerce ratio	0.129***	0.099**	0.104***	0.204***
	(0.020)	(0.045)	(0.026)	(0.041)
adj. R-sq	0.050	0.088	0.030	0.018
Panel C:	Reopen status			
E-commerce ratio	0.078***	0.060	0.062***	0.106***
	(0.015)	(0.045)	(0.020)	(0.015)
adj. R-sq	0.501	0.097	0.035	0.022
Panel D:	Outlook for growth			
E-commerce ratio	0.103***	0.024	0.062*	0.201***
	(0.024)	(0.037)	(0.036)	(0.048)
adj. R-sq	0.139	0.008	0.080	0.042
Control	YES	YES	YES	YES
Wave dummy	YES	-	-	-
City FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Obs.	4,914	1,678	1,715	1,521

All regressions in the table use OLS estimation. The Probit model gives consistent results. Robust standard errors are reported in parentheses, and standard errors clustered at city level are also consistent. The independent variable, *E-commerce*, is the ratio of online sales to total sales reported in the baseline survey in 2017, 2018, or 2019, depending on the baseline survey year, for the February and May waves, and in the first half year of 2020 for the August wave. It ranges from 0 to 1.
The control variables include employment, established year, a dummy for corporate business, city-level COVID-19 confirmed case, and city-level COVID-19 case growth in 30 days. The regressions also control for the city and one-digit industry fixed effects.
Significance level: * p <0.1 ** p <0.05 *** p <0.01.
Data source: ESIEC.

Table 4: Short-term Digital Edge on Corporate Finance during the Early Reopening (May 2020)

	(1)	(2)	(3)	(4)
	Account receivable:			Account Payable:
	% Current Assets >50%	Repayment period:		% Current Assets >50%
		>60 days	Uncertainty	
E-commerce ratio	-0.086***	-0.091***	-0.089***	-0.072***
	(0.029)	(0.032)	(0.027)	(0.021)
Adj. R-sq	0.023	0.050	0.052	0.028
Mean of dependent variable	0.264	0.355	0.243	0.160
S.D. of dependent variable	0.441	0.479	0.429	0.367
Control	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Obs.	1,715			

All regressions in the table use OLS estimation. The Probit model gives consistent results. Robust standard errors are reported in parentheses, and standard errors clustered at city level are also consistent.
The independent variable, *E-commerce*, is the ratio of online sales to total sales reported in the baseline survey in 2017, 2018, or 2019, depending on the baseline survey year, for the February and May waves, and in the first half year of 2020 for the August wave. It ranges from 0 to 1.
The control variables include employment, established year, a dummy for corporate business, city-level COVID-19 confirmed case, and city-level COVID-19 case growth in 30 days. The regressions also control for the city and one-digit industry fixed effects.
Significance level: * $p<0.1$ ** $p<0.05$ *** $p<0.01$.
Data source: ESIEC.

Table 5: Impact of Local Lockdowns on Online Operation and Sales

	(1)	(2)	(3)
	Online operation		Online sales
	Any	Only online	
Panel A: All sample			
COVID × After	0.023**	0.011	0.018**
	(0.009)	(0.007)	(0.009)
Mean of dependent variable	0.441	0.110	0.383
S.D. of dependent variable	0.496	0.312	0.486
adj. R-sq	0.058	0.071	0.067
Obs.		84,316	
Panel B: Newly established subsample			
COVID × After	-0.022	0.065**	-0.027
	(0.039)	(0.029)	(0.045)
Mean of dependent variable	0.516	0.172	0.430
S.D. of dependent variable	0.500	0.378	0.495
adj. R-sq	0.000	0.050	0.026
Obs.		7,772	
Panel C: Incumbent subsample			
COVID × After	0.028***	0.007	0.022**
	(0.009)	(0.007)	(0.010)
Mean of dependent variable	0.433	0.103	0.378
S.D. of dependent variable	0.495	0.304	0.485
adj. R-sq	0.057	0.065	0.066
Obs.		76,544	
Control	YES	YES	YES
City, industry, & quarter (wave) FEs	YES	YES	YES
City × industry FE	YES	YES	YES
City × year FE	YES	YES	YES
Industry × year FE	YES	YES	YES

All regressions in the table use OLS estimation. The fixed-effect Logit model also gives consistent results. Standard errors in parentheses are clustered at the city level. The independent variable, *COVID* × *After*, equals one if a business is located in a city with localized lockdowns due to new COVID confirmed cases and was surveyed in a quarter after the outbreak; zero otherwise. The control variables include firm age, owner's age, owner's gender, business type (corporation and registration status), employment, and quarter revenue. The regression also controls for the city, industry, quarter (wave), city × industry, city × year, and industry × year fixed effects.
Significance level: * p <0.1 ** p <0.05 *** p <0.01.
Data source: OSOME.

Table 6: Impact of Local Lockdowns on the Adoption of Remote Work and Electronic Information Systems

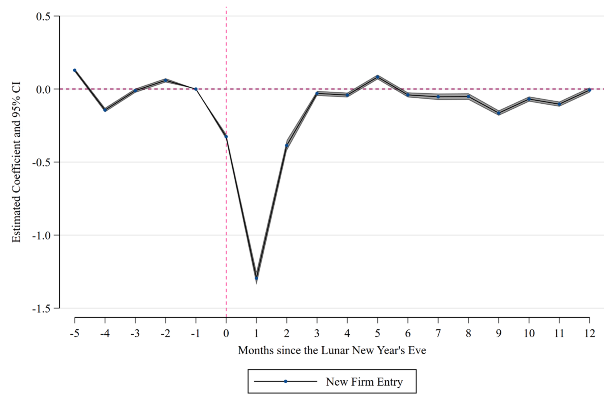
	(1)	(2)	(3)	(4)	(5)	(6)
	Remote work	Electronic information system				
		Sale	Finance	Payment	Management	Product
Panel A: All sample						
COVID × After	0.025*	0.011*	0.002	0.004	0.005	0.009
	(0.013)	(0.007)	(0.011)	(0.015)	(0.010)	(0.010)
Mean of dependent variable	0.153	0.146	0.145	0.264	0.233	0.088
S.D. of dependent variable	0.360	0.353	0.352	0.441	0.423	0.283
adj. R-sq	0.056	0.059	0.077	0.030	0.070	0.046
Obs.	65,036					
Panel B: Newly established subsample						
COVID × After	0.009	-0.036	-0.001	-0.018	-0.054	0.006
	(0.053)	(0.042)	(0.019)	(0.055)	(0.062)	(0.026)
Mean of dependent variable	0.166	0.134	0.139	0.219	0.235	0.079
S.D. of dependent variable	0.372	0.341	0.346	0.413	0.424	0.269
adj. R-sq	-0.088	-0.108	-0.058	-0.077	-0.074	-0.080
Obs.	5,918					
Panel C: Incumbent subsample						
COVID × After	0.028**	0.013**	0.004	0.005	0.009	0.009
	(0.012)	(0.007)	(0.012)	(0.017)	(0.010)	(0.010)
Mean of dependent variable	0.152	0.147	0.145	0.269	0.233	0.089
S.D. of dependent variable	0.359	0.354	0.352	0.443	0.423	0.285
adj. R-sq	0.055	0.062	0.079	0.027	0.072	0.045
Obs.	59,118					
Control	YES	YES	YES	YES	YES	YES
City, industry, & quarter (wave) FEs	YES	YES	YES	YES	YES	YES
City × industry FE	YES	YES	YES	YES	YES	YES
City × year FE	YES	YES	YES	YES	YES	YES
Industry × year FE	YES	YES	YES	YES	YES	YES

All regressions in the table use OLS estimation. The fixed-effect Logit model also gives consistent results. Standard errors in parentheses are clustered at the city level. The independent variable, *COVID × After*, equals one if a business is located in a city with localized lockdowns due to new COVID confirmed cases and was surveyed in a quarter after the outbreak; zero otherwise. The control variables include firm age, owner's age, owner's gender, business type (corporation and registration status), employment, and quarter revenue. The regression also controls for the city, industry, quarter (wave), city × industry, city × year, and industry × year fixed effects.

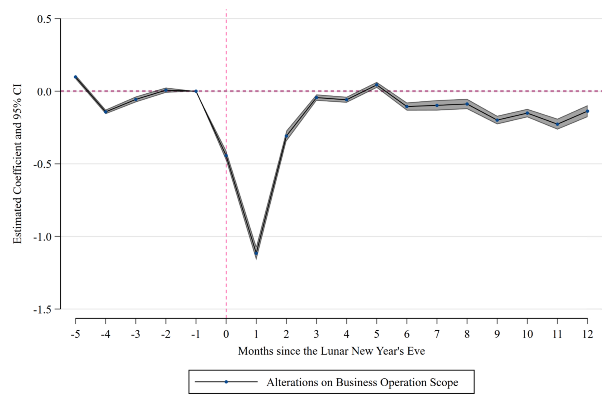
Significance level: * $p<0.1$ ** $p<0.05$ *** $p<0.01$.

Data source: OSOME.

Appendix A Figures



(a) New Firm Entry



(b) Alterations on Business Operation Scope

Figure A.1: New Firm Entry and Business Adjustment Throughout the COVID-19 Outbreak and Reopening

The dependent variable in Panel (a) is the logarithm of one plus the number of newly registered firms; the dependent variable in Panel (b) is the logarithm of one plus the number of alterations of business operation scope. The X-axis label is the month(s) before (negative) or after (positive) Lunar New Year's Eve in 2020. The shaded area indicates the 95% confidence intervals. The coefficient before one month (m = -1) is set as the baseline level. The coefficients before five more months and after fifteen more months are included in the regression but not displayed here. Monthly numbers of firm entries at the city level from 2015 to 2021 are included. All observations are at the city-industry-year-month level. Standard errors are clustered at the city level. The regression controls for the city, industry, month, and year fixed effects, the corresponding two-way fixed effects except the interaction term between year and month, and the year trend of city-industry.
Data source: SAIC registration database.

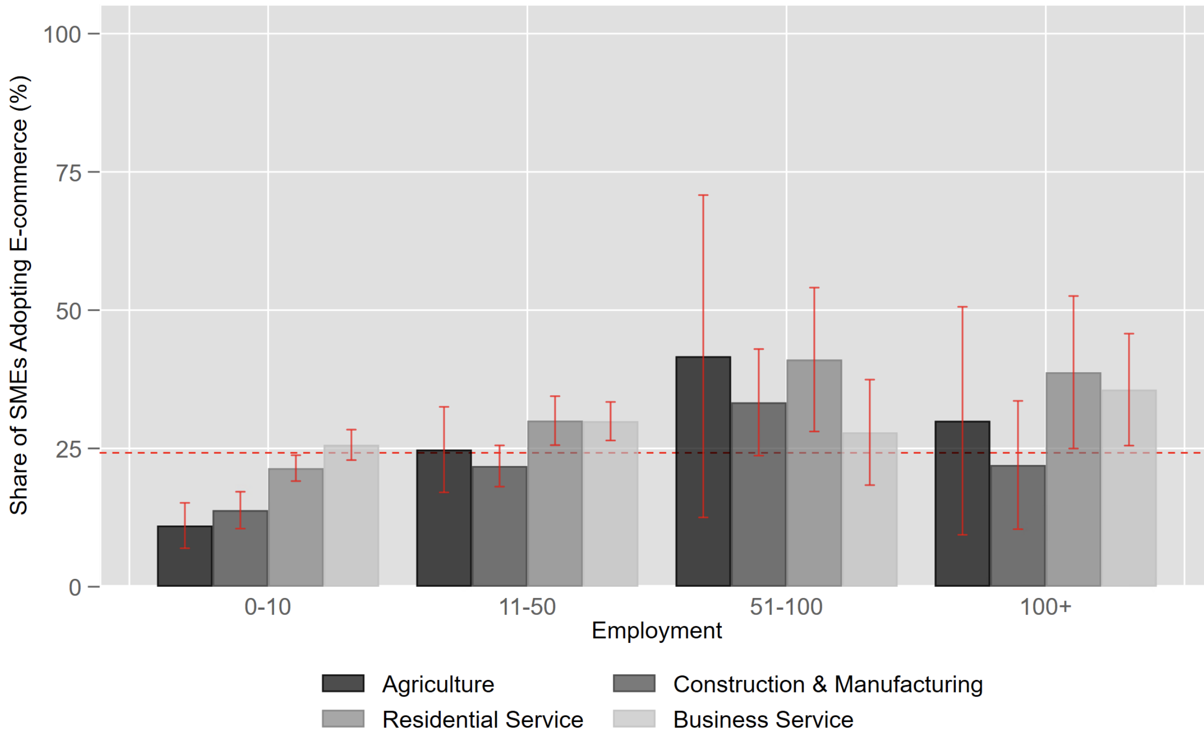


Figure A.2: Share of SMEs Adopting E-commerce in ESIEC, by Industry and Employment

Mean of the dummy variable (*E-commerce* > 0) is reported. The vertical line corresponding to the bar represents 95% confidence interval. The horizontal dash line shows the sample average.
Data source: ESIEC.

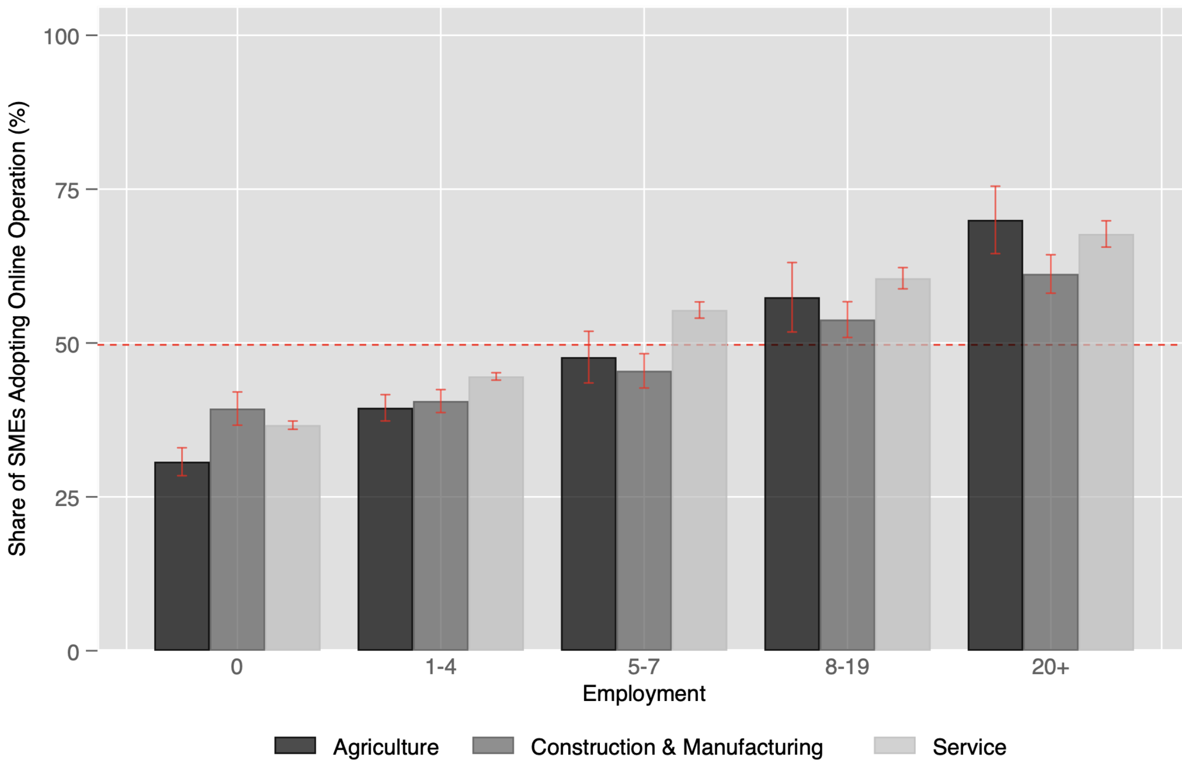


Figure A.3: Share of SMEs Adopting Online Operation in OSOME, by Industry and Employment

Mean of the dummy variable (*Online operation: Any*) is reported. The vertical line corresponding to the bar represents 95% confidence interval. The horizontal dash line shows the sample average. The full sample period covers from 2020Q3 to 2021Q4.
Data source: OSOME.

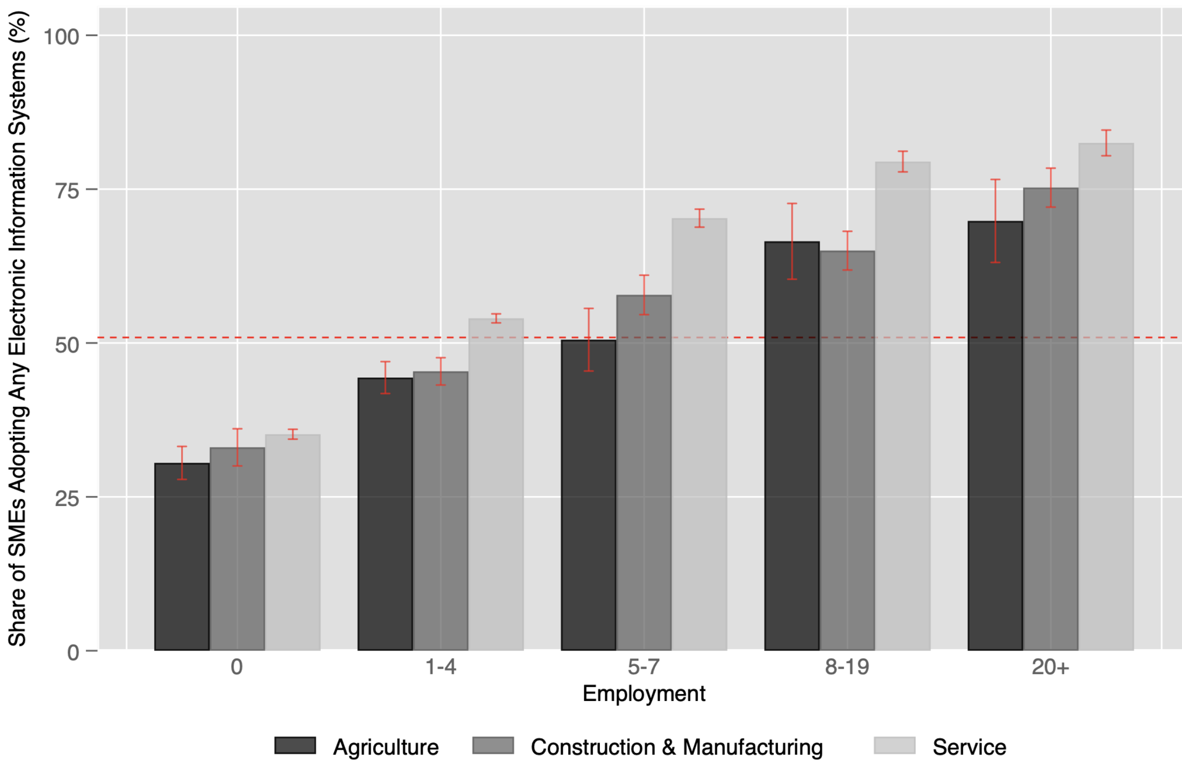


Figure A.4: Share of SMEs Adopting Any Electronic Information Systems in OSOME, by Industry and Employment

Mean of the dummy variable (*Electronic information system: Any*) is reported. The vertical line corresponding to the bar represents 95% confidence interval. The horizontal dash line shows the sample average. The subsample period covers from 2020Q4 to 2021Q4.
Data source: OSOME.

Appendix B Tables

Table B.1: Supplementary Summary Statistics of ESIEC Data

Variable	Pooled		February	May	August
	Mean	S.D.	Mean		
Owner's characteristics					
Age	38.950	9.745	38.890	39.020	n.a.
Female	0.243	0.429	0.270	0.273	0.169
Work year(s) before venture	4.247	6.411	3.001	3.094	7.266
Education level:					
No schooling	0.013	0.013	0.010	0.013	0.018
<= Senior high school	0.483	0.250	0.522	0.537	0.364
>= College	0.504	0.250	0.468	0.449	0.617
Firm's pre-COVID characteristics					
Innovation or new product	0.453	0.498	0.488	0.469	0.389
Revenue >1 million RMB	0.476	0.499	0.485	0.511	0.420
Job training	0.503	0.500	0.503	0.503	n.a.
Gov. subsidy	0.079	0.269	0.081	0.076	n.a.
R&D investment (log)	0.805	1.554	0.840	0.767	0.808
Obs.	4,365 (3,120)		1,541	1,579	1,245

Owner's age, on-the-job training, and government subsidy are not included in Columns (1) and (4) since these questions were not included in the August wave questionnaire. The total number of observations for these three variables is 3,120, and 4,365 for others.
We report three categories for the owner's education level. In regressions, we further control for a set of dummy variables for each education level: no schooling, elementary school, junior high school, regular senior high school, technical secondary school, junior technical college, undergraduate, master's degree, and doctor's degree, respectively.
Data source: ESIEC.

Table B.2: Regression of Digital Edge with Additional Control Variables

	(1) Pooled	(2) February	(3) May	(4) August
Panel A:	Demand: order decline as main challenge			
E-commerce ratio	-0.027**	-0.110*	-0.015**	-0.009*
	(0.013)	(0.064)	(0.006)	(0.005)
adj. R-sq	0.376	0.074	0.035	-0.010
Panel B:	Cash flow >1 month			
E-commerce ratio	0.090***	0.063	0.076***	0.171***
	(0.021)	(0.054)	(0.029)	(0.045)
adj. R-sq	0.060	0.099	0.022	0.044
Panel C:	Reopen status			
E-commerce ratio	0.061***	0.053	0.042**	0.096***
	(0.016)	(0.055)	(0.021)	(0.019)
adj. R-sq	0.506	0.104	0.041	0.018
Panel D:	Outlook for growth			
E-commerce ratio	0.067***	0.003	0.039	0.141***
	(0.026)	(0.038)	(0.038)	(0.054)
adj. R-sq	0.149	0.026	0.082	0.053
Control	YES	YES	YES	YES
Supplementary Control	YES	YES	YES	YES
Wave dummy	YES	-	-	-
City FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Obs.	4,365	1,541	1,579	1,245

All regressions in the table use OLS estimation. The Probit model gives consistent results. Robust standard errors are reported in parentheses, and standard errors clustered at city level are also consistent. The independent variable, *E-commerce*, is the ratio of online sales to total sales reported in the baseline survey in 2017, 2018, or 2019, depending on the baseline survey year, for the February and May waves, and in the first half year of 2020 for the August wave. It ranges from 0 to 1.

The control variables include employment, established year, a dummy for corporate business, city-level COVID-19 confirmed case, and city-level COVID-19 case growth in 30 days. The regressions also control for the city and one-digit industry fixed effects.

The supplementary control variables include owner's age, gender, work experience (measured by working year(s) before venture), education level, and other firm's pre-COVID characteristics: a dummy for innovation or new product, a dummy for revenue larger than one million RMB, a dummy for on-the-job training, a dummy for receiving subsidies for the government, and the R&D investment (in logarithm). Owner's age, on-the-job training, and government subsidy are not included in Columns (1) and (4) since these questions were not included in the August wave questionnaire.

Significance level: * p <0.1 ** p <0.05 *** p <0.01.

Data source: ESIEC.

Table B.3: Regression of Short-term Digital Edge on Corporate Finance during the Early Reopening (May 2020) with Additional Control Variables

	(1)	(2)	(3)	(4)
	Account receivable:			Account Payable:
	% Current Assets >50%	Repayment period:		% Current Assets >50%
		>60 days	Uncertainty	
E-commerce ratio	-0.062**	-0.089***	-0.067**	-0.083***
	(0.031)	(0.034)	(0.029)	(0.028)
Adj. R-sq	0.023	0.050	0.052	0.028
Mean of dependent variable	0.262	0.349	0.239	0.157
S.D. of dependent variable	0.440	0.477	0.427	0.364
Control	YES	YES	YES	YES
Supplementary Control	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Obs.	1,579			

All regressions in the table use OLS estimation. The Probit model gives consistent results. Robust standard errors are reported in parentheses, and standard errors clustered at city level are also consistent.
The independent variable, *E-commerce*, is the ratio of online sales to total sales reported in the baseline survey in 2017, 2018, or 2019, depending on the baseline survey year, for the February and May waves, and in the first half year of 2020 for the August wave. It ranges from 0 to 1.
The control variables include employment, established year, a dummy for corporate business, city-level COVID-19 confirmed case, and city-level COVID-19 case growth in 30 days. The regressions also control for the city and one-digit industry fixed effects.
The supplementary control variables include owner's age, gender, work experience (measured by working year(s) before venture), education level, and other firm's pre-COVID characteristics: a dummy for innovation or new product, a dummy for revenue larger than one million RMB, a dummy for on-the-job training, a dummy for receiving subsidies for the government, and the R&D investment (in logarithm).
Significance level: * $p<0.1$ ** $p<0.05$ *** $p<0.01$.
Data source: ESIEC.

Appendix C Text-based Digitization Metric

Based on the nature of business operation scope text in the SAIC registration data, we develop and apply the Chinese text segmentation tool and an NLP algorithm. The division in wholesale and retail sectors by industrial classification code provides us with a natural training set. For robustness, we also use the ESIEC baseline data as an external validation test set.

Firstly, we split the text into Chinese words using `jieba` ("stutter" in Chinese) package, which is widely used for Chinese text processing. The stop words set includes meaningless numbers and alphabet (mostly indicating order) and some regulated phrases in the business operation scope, such as the frequently-quoted phrase "Items subject to approval by law can only be carried out after approval by relevant departments." which doesn't provide helpful information. Next, we vectorize the segmented feature words and apply different NLP algorithms. We first calculate the word frequency and extract keywords that can classify the e-commerce and non-e-commerce firms. Then we apply the Decision Tree and Naive Bayes (with different specifications) models to the training set. It turns out that the model nodes largely overlap with the keywords we extract, and the classification is quite intuitive. Besides, the results in most models remain consistent, and the cross-validation gives a higher accuracy rate. Furthermore, we also use the ESIEC sample as an external validation to alleviate the concern of over-fitting. Our algorithm has an accuracy of 87.5% for the ESIEC sample reporting online sales in the baseline survey. Besides, if we relabel firms with an e-commerce sales ratio larger than 50% as "e-commerce", the accuracy rate is 90.0%.

To test the extensive margin of digital transformation of SMEs, we use the above NLP tool to classify each entrant's business operation into two groups with different levels of e-commerce adoption. As for the intensive margin of the incumbent firm's transformation, we further exploit the alteration record of business operation scope. It contains the pre-change and post-change text of the business operation scope, as well as the date. Therefore, we apply the NLP tool to texts both before and after the alteration. For each firm in the alteration record, we define a binary variable as one if it has changed from non-e-commerce to e-commerce. Then we aggregate it at the city-industry-month-year level to construct our dependent variable. We also construct the total number of firms' alterations on business operation scope as a placebo.