Small and Medium Enterprises Amidst the Pandemic and Reopening: Digital Edge and Transformation

Lin William Cong, Xiaohan Yang, and Xiaobo Zhang

Abstract

Using administrative universal firm registration data as well as primary offline and online surveys of small business owners in China, we examine (i) whether the digitization of business operations helps small and medium enterprises (SMEs) better cope with the pandemic shock, and (ii) if the pandemic has induced digital technology adoption. We identify 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. After the lockdown in January 2020, firm entries have exhibited a V-shaped pattern, with entries of e-commerce firms experiencing a less pronounced initial drop and a quicker rebound. The COVID-19 pandemic has also accelerated digital technology adoption of 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 system), and the effect persists after one year of full reopening.

Keywords: SMEs, COVID-19, Digital economy, E-commerce

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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 current COVID-19 pandemic is no exception, striking heavy blows to SMEs worldwide.[2] What then helps SMEs remain resilient to such shocks? In the relatively sparse literature on this topic, a few studies examine the role of clusters (Kranton and Minehart, 2000; Martin et al., 2013; Crespo et al., 2014; Dai et al., 2021a) and policy interventions (e.g., Bartlett III and Morse, 2020; Chen et al., 2020) in helping firms cope with external shocks . However, the contribution of digitization to SMEs' resilience against large economic shocks, especially in developing countries, is scarcely researched. Moreover, we understand little on the long-run impact of the pandemic on small businesses, especially concerning their digitization, despite the numerous media reports on rising e-commerce, e-learning, telemedicine, and work-from-home as immediate ramifications of the pandemic and temporary mitigation policies (e.g., TIME cover story by Wang (2020) and telemedicine in Bangladesh by Kabir (2021)).

Our study is among the first attempts to bridge this knowledge gap. Specifically, we combine (through primary data collection) multiple rounds of Enterprise Survey on Innovation and Entrepreneurship in China (ESIEC), Online Survey of Micro-and-small Enterprises (OSOME), and China business registration data. The comprehensive data coverage and large

[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).

heterogeneity in Chinese SMEs allow us to directly document the benefits of e-commerce and digitization on the performance of SMEs during and after the COVID-19 restrictions. Our multiple rounds of surveys, with their timing varying in relation to the lockdown as shown in Figure 1, also enable us to demonstrate both the short-term and persistent digital transformation of SMEs brought forth by the pandemic.[3]

The first challenge that we must overcome is defining SMEs in China. Because the business registration data covers the universe of registered enterprises in China, the majority of which are small businesses with very low registered capital, our dataset admits a rather general definition of SMEs with comprehensive coverage. Besides, the ESIEC survey offers a representative and detailed sample of SMEs, including incorporated firms and registered self-employees with few full-time employees. In fact, more than half of the respondents in ESIEC had fewer than ten employees. To supplement the above SME scope, we also include the OSOME sample. This sample covers a large share of self-employed businesses, especially the unregistered ones that have long been neglected in previous research. The interviewed SMEs locate in both urban and rural areas of different city tiers across China, with a significant share of them having adopted digital operations or systems. Overall, our data allow us to cover a wide range of definitions of SMEs.

We proceed to investigate whether the digitization of business operations helps SMEs better cope with the pandemic shock. Business digitization broadly encompasses technologies such as e-commerce, automation, AI, e-commerce, e-learning, and telemedicine. For example, the baseline ESIEC surveys conducted in 2017, 2018, and 2019 include a key question on

[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.

the share of online sales, which is shown to be positively associated with an SME's cash flow level, market demand, reopening status, and outlook for earnings observed in the phone interviews in 2020. If anything, our focus on the adoption of e-commerce, online operation, remote work, electronic information systems, etc., thereby underestimates the magnitude of digitization and its associated benefits for small businesses.

We further examine whether the pandemic has induced greater adoption of digital technologies. This is rarely studied in the literature in part due to data paucity.[4] We contribute by investigating whether the pandemic has accelerated digital adoption on both the extensive and intensive margins. We develop and apply a textual analysis and algorithm to the business operation scope, a text record indicating what an enterprise is approved to conduct, to classify each registered firm's e-commerce adoption. In this way, we use the number of e-commerce and non-e-commerce firm entries at the county-month level from 2015 to 2021 aggregated from the registration database as a key outcome variable. We then employ an event study approach in relation to the timing of nationwide lockdown to measure 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

[4] One exception is a report based on a recent McKinsey Global Survey of executives, which shows that firms responses to COVID-19 have accelerated companies' adoption of digital technologies, and the digital changes are expected to be long-lasting, which would continue playing an essential role in recovery. This survey focuses on large firms. 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`.

database and use the alteration of business operation scope (text record) in relation to e-commerce by existing firms as a proxy for incremental digitization. Adopting the same event study approach as for firm entries, we show that among incumbent firms which have altered business operation scope, the share of e-commerce adoption has witnessed a marked growth in response to the COVID-19 shock, and the effect persists at least one year after full reopening. In addition, using the multi-round quarterly OSOME surveys from 2020 to 2021, we find that SMEs in regions exposed to sporadic local lockdowns (after the nationwide lockdown and reopening), including the unregistered ones, are more likely to adopt online operation, online sales, remote work, and electronic information systems.

The Chinese setting offers several advantages in the aforementioned investigations. First, China is the largest e-commerce and FinTech market, with a massive number of SMEs varying in the extend of digitization.[5] Second, the lockdown was immediate and reasonably uniform across the nation, 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] Third, and perhaps more importantly, due to the early stringent mitigation policies, China was able to keep the initial infection rate low and reopen the economy by April 2020. The Chinese setting thus holds the advantage of having fully reopened the economy for more than a year. The insights from the Chinese setting may shed light on other countries with plans to reopen at the time of our writing, perhaps offering a glimpse into the post-pandemic world.

[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.

Our study contributes to the literature on SMEs, especially concerning their performance and adjustments throughout the pandemic. The literature on the resilience of firms to shocks is relatively sparse. Many are about 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 the heterogeneity of the impact (Chetty et al., 2020; Adams-Prassl et al., 2020), implications on business owners (Alekseev et al., 2020; Kim et al., 2020), and corporate hiring (Campello et al., 2020). More specifically in the Chinese context, studies, such as Dai et al. (2021b), compare the efficacy of policies targeted at SMEs, in addition to presenting how SMEs took a toll from COVID-19 pandemic and lockdown.

We add to this body of work by analyzing the differential impacts of the pandemic on firms at different levels of digitization, which offers a new perspective on the survival mechanisms of small businesses. In particular, we emphasize how digitization, such as e-commerce adoption, creates business resilience. Moreover, our surveys span pre-pandemic to post-reopening episodes which, once combined with the other datasets we collect, allow us to be among the first to document the longer-run post-reopening impact of the pandemic shock on SMEs.

Our study also adds to the emerging literature on FinTech adoption. According to

[7]Bartik et al. (2020b) examine variations in shutdown rates in a survey of 5800 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.

the Plaid Report 2020, FinTech adoption has been accelerating amid the global COVID-19 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. Our study not only provides rigorous empirical evidence to complement industry reports but also extends the discussion beyond FinTech to business digitization in general.

Broadly concerning technology adoption and digitization, 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., 2019), 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

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

the digital transformation of SMEs, with potential persistent effects. Section 5 concludes.

2 Data and Survey Design

We assemble several large-scale data sets (including both manually collected primary data and proprietary data from third parties) concerning small and medium-sized enterprises in China and their digitization. The scale and coverage of the data mark one main contribution. We first conduct a representative survey of Chinese entrepreneurs in seven provinces, the Enterprise Survey of Innovation and Entrepreneurship in China (ESIEC), which includes both multiple rounds of in-person surveys and three follow-on phone interviews in 2020, in order to provide first-hand information on the response and recovery during the COVID-19 pandemic. At the aggregated level, we also exploit the business registration database from the State Administration of Industry and Commerce (SAIC) in China. Finally, we conducted five rounds of Online Surveys of Micro-and-Small Enterprises (OSOME) to collect additional information from SMEs using Alipay, the platform of Alibaba from the third quarter of 2020 to the third quarter of 2021.

ESIEC survey 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 has successfully interviewed nearly 10,000 private enterprise owners and self-employed entrepreneurs since 2016, collecting high-quality and representative microdata on the entrepreneurs' background and business performances.

[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.

After the outbreak of the COVID-19 pandemic in China, the ESIEC team immediately conducted phone surveys (each an independent draw from 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. Supplementary information can be matched with the baseline survey and the SAIC data.[10]

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.[11] As shown in Dai et al. (2021b), although the ESIEC sample is designed to be representative only in the chosen provinces, the distribution across one-digit industries ends up 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 representativeness of our 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. 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.

[10]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`.

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

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

In our analyses, we treat them as independent cross-sections.

By merging the ESIEC phone interview data 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.

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] Because the SAIC registration data is up-to-date, we can analyze firm responses during the pandemic and after the reopening.[14]

The business registration database includes the "business operation scope" record, which is 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)

[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`.

tools we develop, in order to measure digitization.[16] In particular, since e-commerce is a salient indicator of digitization, we first utilize the NLP method to classify enterprises as e-commerce and non-e-commerce ones, creating a binary variable about the status of e-commerce adoption. Then we calculate the total numbers of entrant firms at the city-industry-month level related and unrelated to e-commerce (distinguished by the above binary variable), respectively. This outcome variable captures the extensive margin of SMEs' digital transformation. 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.

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 incumbent firms' e-commerce adoption. Specifically, the sample only includes firms that have changed the contents of the business operation scope.[17] A dummy variable for incumbent firms' adoption of e-commerce takes a value of one if the alteration entails changes from content without any e-commerce keywords to words related to e-commerce, and zero otherwise.[18] Once again, the numbers of incumbents' alterations related and unrelated to e-commerce adoption, respectively, are also aggregated at the city-year-month level.

[16] Specifically, we extract keywords associated with e-commerce sales and other types of digitization from the "business operation scope." We then develop and apply natural language processing (NLP) tools to classify registered firms in terms of their level of digitization. For a brief description on the NLP method, please refer to Appendix B. As a validation, our algorithm performs well in distinguishing online wholesale and retail firms from their offline counterparts. We also manually labeled training sets from ESIEC and OSOME, respectively, to conduct robustness tests. The method is more likely to underestimate rather than overestimate, if any, the extent of both new firm's digital transformation and incumbents' adoption since firms can try online sales on a small scale without registration.

[17] 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.

[18] 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.

OSOME surveys. 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, including small, incorporated enterprises, and both registered and unregistered self-employed businesses.[19] 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 Pay (Klein, 2020).[20]

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 benefits and costs of online sales as well as the adoption of other digital technologies over time, which potentially serve as corroborating evidence for the basic patterns we identify from the SAIC and ESIEC data.

Table 2 shows the summary statistics of the OSOME data. The full sample covers five quarters spanning from the third quarter of 2020 to the third quarter of 2021. The sample respondents of the OSOME survey have been consistent in terms of their basic characteristics over the past five quarters, with the majority of sampled SMEs in the service industry (82.6%) and even distribution across different levels of cities. It also covers a larger share (38.4% in the full sample) of unregistered, self-employed businesses that have been neglected in previous research. Besides, nearly 33.0% of the business owners reported not hiring full-time employees, and 55.9% between one and ten employees. In the full sample, we mainly utilize online operations and sales as the outcome variables. A few more questions on digital transformation (remote work and electronic information systems) have been added

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

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

to the questionnaire since the fourth quarter of 2020, enabling us to examine other forms of digitization besides e-commerce. The basic characteristics of the subsample excluding the third quarter in 2020 remain the same as those the whole sample.

3 A Digital Edge Among Small Businesses?

In this section, we rely 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 we analyze the February and May waves of ESIEC survey; we then use the (continuous) ratio in the first half of 2020 for the August wave because this round was based on a newly drawn 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 helpful to have some summary statistics on the corresponding dichotomous measure (*E-commerce ratio* $>$ *0*). As Table 1 shows, nearly 24.2% of SMEs in the ESIEC sample had adopted online sales. We further show in Appendix Figure A.2 that the digitization ratio varies across different industries and goes up as the scale of employment increases. The percentage of online sales is the lowest for agricultural businesses with fewer than ten employees (11.1%), implying the large potential benefit of digitization.

Table 3 presents results using Ordinary Linear Square (OLS) regressions, which are also robust under Probit and Logit specifications. Panels A-D report the estimate for the key variable of interest, the e-commerce ratio, on the four outcome variables. The controls include employment, year of establishment, a dummy for incorporated business, registered capital, city-level COVID-19 confirmed cases, and city-level COVID-19 case growth in the past 30 days. Employment and registered capital can be regarded as a proxy for firm size. We also control for the province and one-digit industry fixed effects in the regressions, although we omit them 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.[21] 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

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

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 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.[22] SMEs with e-commerce had a 9.8% lower probability of having account receivable that was larger than half of the current assets than those without. Given that the average is 21.7% for the whole sample, it implies that digitization can help SMEs alleviate cash flow issues during the pandemic and lockdown significantly. We also find that e-commerce reduced the repayment period of account 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 associ-

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

ated with e-commerce, firms with a greater share of online sales exhibited a higher reopening rate than those without or lower share of online sales (Panel C of Table 3). Firms with a higher share of online sales are more prone to reopen than others in February, May and August 2020. A firm with fully online sales is estimated to have a 7.4% higher probability of reopening on average than a counterpart with fully offline sales as of February 2020. Given that the average reopening rate in our February sample is 19.5%, it implies that the adoption of e-commerce can significantly help firms respond to the crisis. Not only did firms with online sales have 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.

4 Digital Transformation

Having observed the positive effect of digitization on improving the resilience of SMEs to the COVID-19 shocks, a more important question naturally arises: How does the pandemic transform SMEs after the mitigation policies are largely eased, especially in terms of firms' digitization? We next consider both the extensive and intensive margins of the SMEs' digital transformation, which are captured using SAIC registration data, as described in Section 2. The extensive margin focuses on the new firm entries, while the intensive margin examines whether the existing firms have increasingly adopted digital technologies after the pandemic.

4.1 Identification Strategy

Similar to Fang et al. (2020) and Dai et al. (2021a), we use the Wuhan lockdown following the very first widespread outbreak of the COVID-19 in China as an exogenous shock to examine the impact on SMEs in China 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,

$$\ln(Y_{imy}) = \sum_m (\beta_m \times COVID_y \times Dummy_m) + \alpha_i + \gamma_m + \theta_y + \eta_{iy} + \varepsilon_{imy}, \tag{1}$$

where i indicates the city (prefecture) a firm is located in, m indexes the month(s) and y the year. We define m according to the Lunar calendar and set the Lunar New Year's eve as $m = 0$ since it coincides with the nationwide lockdown policy.[23] This is important as the Lunar New Year is a traditional holiday when firms close their businesses and the new firm registration or alteration is suspended in the pre-COVID-19 era. $COVID_y$ 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 (α_i), month (γ_m), year (θ_y), and the city-year (η_{iy}) fixed effects. Standard errors are clustered at the city level. The sample period is January 2015 to April 2021. In sum, we compare the outcome variables in 2020 (and 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), $\ln(entry_{imy} + 1)$, 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; (ii) we use the online and offline firms in wholesale and retail sectors

[23] 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.

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 B to the alteration record and aggregate the number (plus one) related and unrelated to e-commerce adoption, respectively, into logarithm form $\ln(alteration_{imy} + 1)$ as another outcome variable.

The set of coefficients β_m ofver 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 interpreted as the percentage change in outcomes driven by the shock. 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 level (unless otherwise specified) to alleviate the problem arising from having too many identical 0 values. The β_m estimates help us gain insights from the evolution of groups with different levels of digitization.

4.2 Empirical Result

We start by documenting several stylized facts. First, 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 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 83.4% and 31.2%, respectively, controlling for geographical differences and aggregate trends. After the pandemic was (temporarily) reined in and the economy reopened, firm creations had fully rebounded by the end of April (the difference-in-differences estimate is statistically indistinguishable from zero). In the following ten months, the coefficients remain at the pre-crisis level.

There is also a similar V-shaped pattern on incumbent firms' business adjustment, measured by the number of alteration records on business operation scope, as shown in Appendix Figure A.1(b). The patterns reveal that firms experienced initial drops of -77.6% and -25.5% in the first two months and rebounded quickly. After the reopening, the coefficients are slightly below the pre-crisis level, probably reflecting that some firms shut down during the lockdown.

Next, we study 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 Figure 3 shows, 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 of 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 in spurring digital transformation of SME entries in China.

For robustness, we compare the online and offline wholesale and retail (W&R) sectors using the above specification. We split W&R firms naturally into online and offline based on the four-digit industrial classification code when they registered.[24] Figure 4 shows that online new 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.

Next, we examine the intensive margin of the digital transformation of incumbent SMEs.

[24] Similar to the textual analysis on business operation scope, the classification by industry code can lead to underestimation instead of overestimation, if any.

Specifically, we extract alteration records of business operation scope to construct subgroups. Firms with alteration from non-e-commerce to e-commerce form the "Scope Alteration to E-commerce" group and other firms with changes in business operation scope form a comparison group. To this end, we apply the same natural language tools as above to both the pre- and post-alteration texts in each record. The (logarithm after plus one) number of records by year-month-city is aggregated as the dependent variable in our specification. Figure 5 plots the estimated coefficients for this empirical design. As documented above, immediately after the COVID-19 outbreak, overall registration alteration dropped by 77.6 percent. By comparison, the alteration to e-commerce business declined by 53.8 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 82.8 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 corroborates the gap observed in new entries the persists from immediately after the end of the national lockdown to one year later.

The above analyses are based on the business registration data, yet nearly half of self-employed businesses are not registered in China (Kong et al., 2021). The OSOME survey includes not only registered incorporated companies (10.7%, as shown in Table 2) and registered self-employed (50.9%) but also unregistered businesses (38.4%) 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 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 five quarters, we can make use of the spatial and temporal variations in local lockdowns to evaluate the impact of COVID restrictions on digital transformation for small- and micro-enterprises, including those unregistered ones.

To this end, we further report the estimation results following a similar specification:

$$Y_{ijcq} = \beta \times (COVID_c \times After_q) + \alpha \times COVID_c + \mathbf{x}_i'\theta + \gamma_q + \zeta_{province} + \eta_j + \varepsilon_{icqj}, \quad (2)$$

where the subscript indicates that a firm i in industry j located in city c (of *province*) was surveyed in quarter q. 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 a dummy for COVID-impacted cities ($COVID_c$), business type (incorporation and registration status), employment, city tiers, and established year. The OLS regression also controls for the quarter, province, and industry fixed effects.[25]

Table 5 first reports the estimation results concerning online operation and sales. The dependent variable in Column (1) is a dummy variable, indicating that a firm has online operations. The dependent variable in Column (2) is one if an enterprise operates both online and offline, while in Column (3), it is restricted to pure online operations. The dependent variable in Column (4) is measured as the share of online sales in total sales quarterly. Panel A includes the whole sample, while Panels B and C further restrict the analyses to the new entry and incumbent subsamples, respectively. No matter which dependent variable is used, exposures to local lockdowns are significantly associated with subsequent higher probability of having online operation for the whole sample and incumbents. Compared with the average,

[25]The results are robust under Probit or Ordered Probit models as well.

the share of SMEs taking online operations has increased 7.4% for the whole sample and 7.6% for incumbents, especially those exclusively relying on online sales (16.4% increase for the full sample and 14.4% for incumbents, respectively). Although the association is positive for the new entries, it is only statistically significant in Column (1) (whether an enterprise has adopted an online operation or not).[26] Similarly, Column (4) shows that following COVID-19 restrictions has accelerated the adoption of online sales (10.3% growth to the average), and the impact concentrates on incumbent SMEs.

Table 6 further reports the impact of exposures to lockdowns on the adoption of remote work and electronic information systems. The specification is the same as in Table 5. The questions were not included in the questionnaire until the fourth quarter in 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 5.0% of respondents have adopted remote work, the impact of local lockdown explains a nearly 26.0% increase for the whole sample. The magnitude is even more prominent when restricted to the incumbents (30.6%). In contrast, the newly established businesses show a high tendency (11.7% compared to average) to adopt at least one of the electronic information systems (finance, payment, product, sale, and management), especially payment and product systems.[27] Compared to the average level of new entrants, the lockdown leads to a 21.9% increase in payment system adoption and 40.3% in product system adoption, respectively. However, we do not observe an association between exposures to COVID restrictions and the introduction of electronic systems for incumbents.

[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 19, within each industry and location.

[27] 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.

Overall, local lockdowns have induced small businesses to develop online operations and adopt remote work modes.[28]

5 Conclusion

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. We capture digitization using proxies such as the ratio of online sales and document that SMEs with greater digitization are more resilient to the pandemic shock. The COVID shock reshaped the pattern of consumer demand, which may last long after the COVID is over. Using primary surveys of small business owners in China, we show that firms with online sales had more robust market demand than those without online sales. Thereby they reported better cash flow situations and were more likely to reopen during and after the lockdown. They also held a more optimistic view on 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. Using administrative business registration data, 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.

[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 the scale of employment increases, while micro businesses in the agriculture sector have a share of 30.7% in adopting online operation and 30.5% in electronic information systems, respectively.

Our main specification using e-commerce as a measure of digitization likely underestimates the true degree of digitization. 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. This is partly due to the fact the inter-bank payment platform only connects to traditional bank accounts and fails to engage in fintech firms (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.[29] Our study, therefore, constitutes an initial step towards understanding firm resilience and the lasting transformative effect of the COVID-19 pandemic and similar systematic shocks.

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Figures

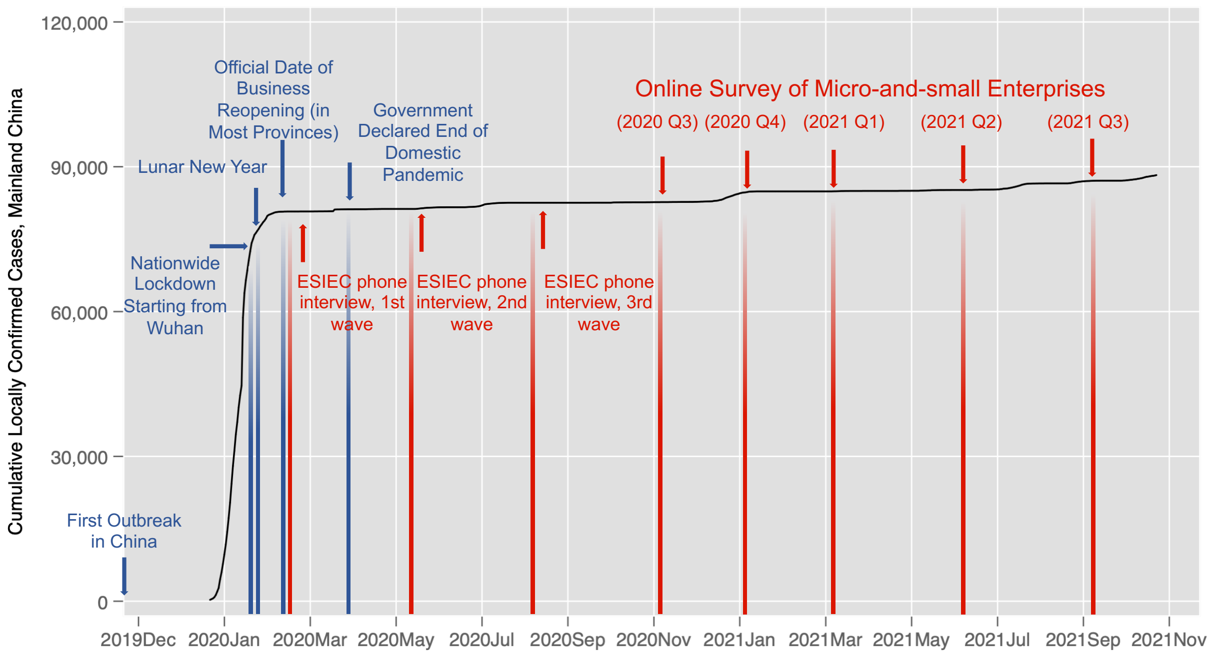


Figure 1: COVID-19 Outbreak, Reopening, Mitigation Policies, and Surveys

Data source: National Health Commission of China.

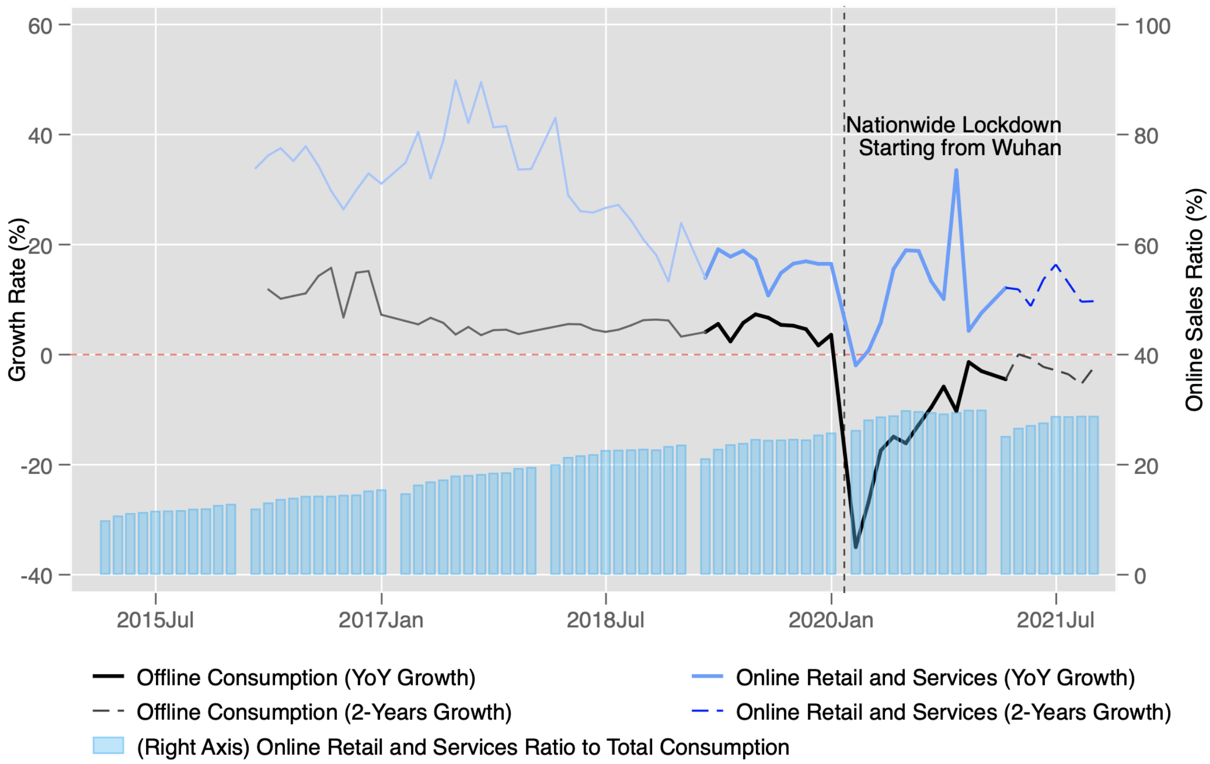


Figure 2: National Trend of Online and Offline Sales in China

Data source: National Bureau of Statistics of China.

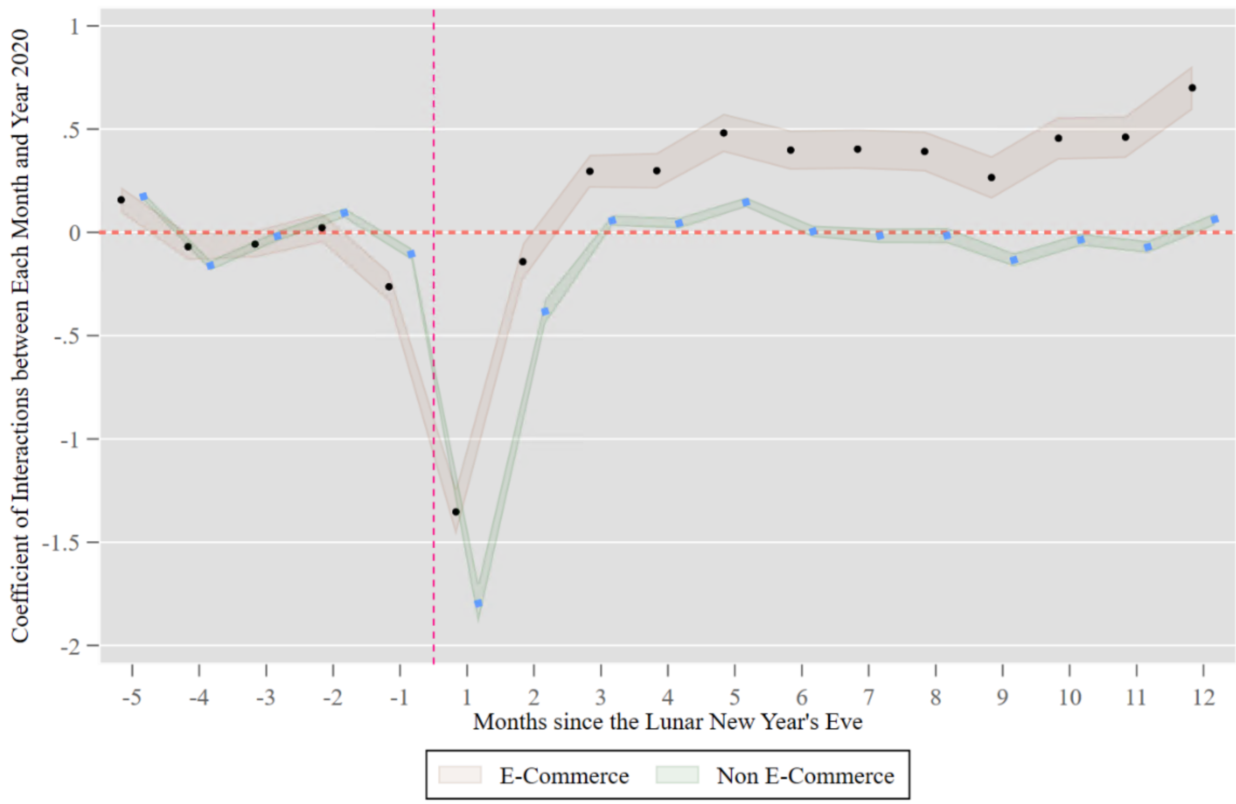


Figure 3: Event Study of COVID-19 Outbreak and Reopen on New Firm Entry, by E-commerce and Others

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 Spring Festival coefficient (m = 0) is omitted as the baseline level (zero as default). 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-(lunar) year-month level. Standard errors are clustered at the city level. The regression controls for the city, month, year, and city-year fixed effects.
Data source: SAIC registration database.

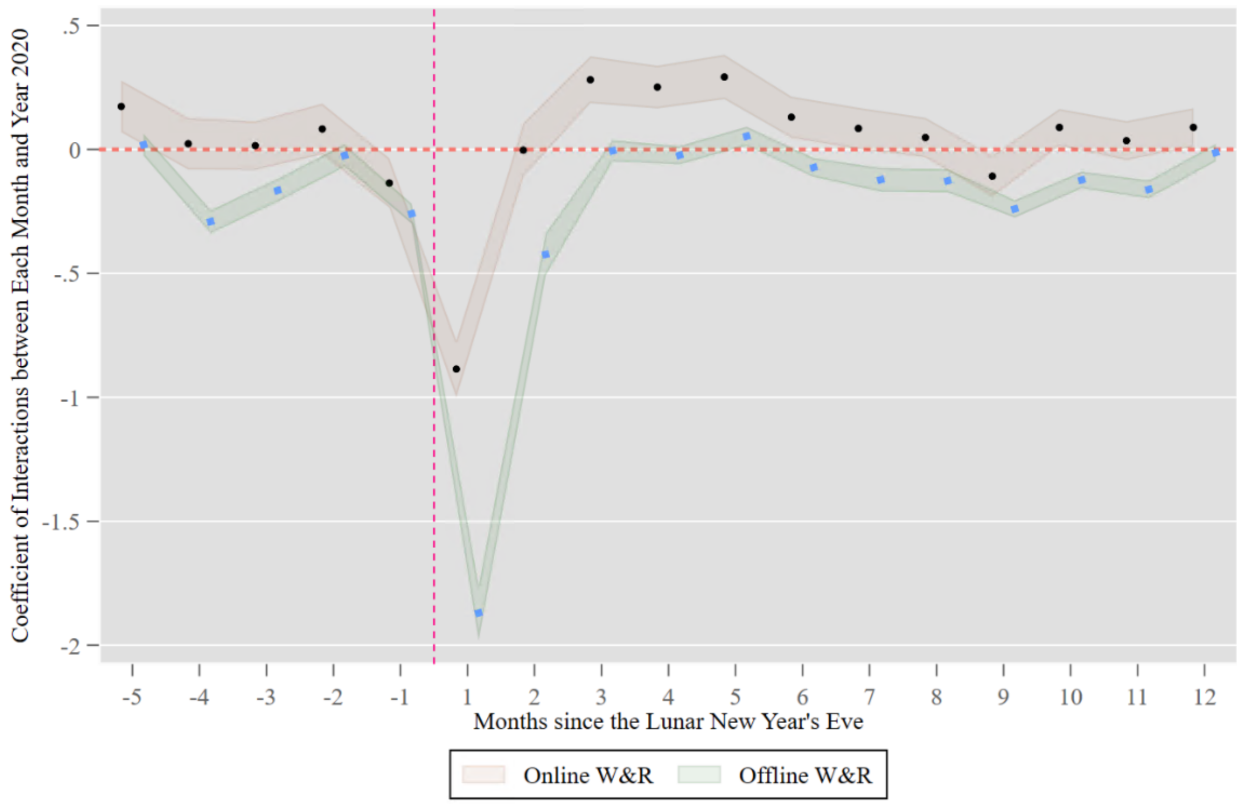


Figure 4: Event Study of COVID-19 Outbreak and Reopen on Wholesale and Retail New Firm Entry, by Online and Offline

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 wholesales and retail enterprises are divided by four-digit industry code classification. The Spring Festival coefficient (m = 0) is omitted as the baseline level (zero as default). 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-(lunar) year-month level. Standard errors are clustered at the city level. The regression controls for the city, month, year, and city-year fixed effects.
Data source: SAIC registration database.

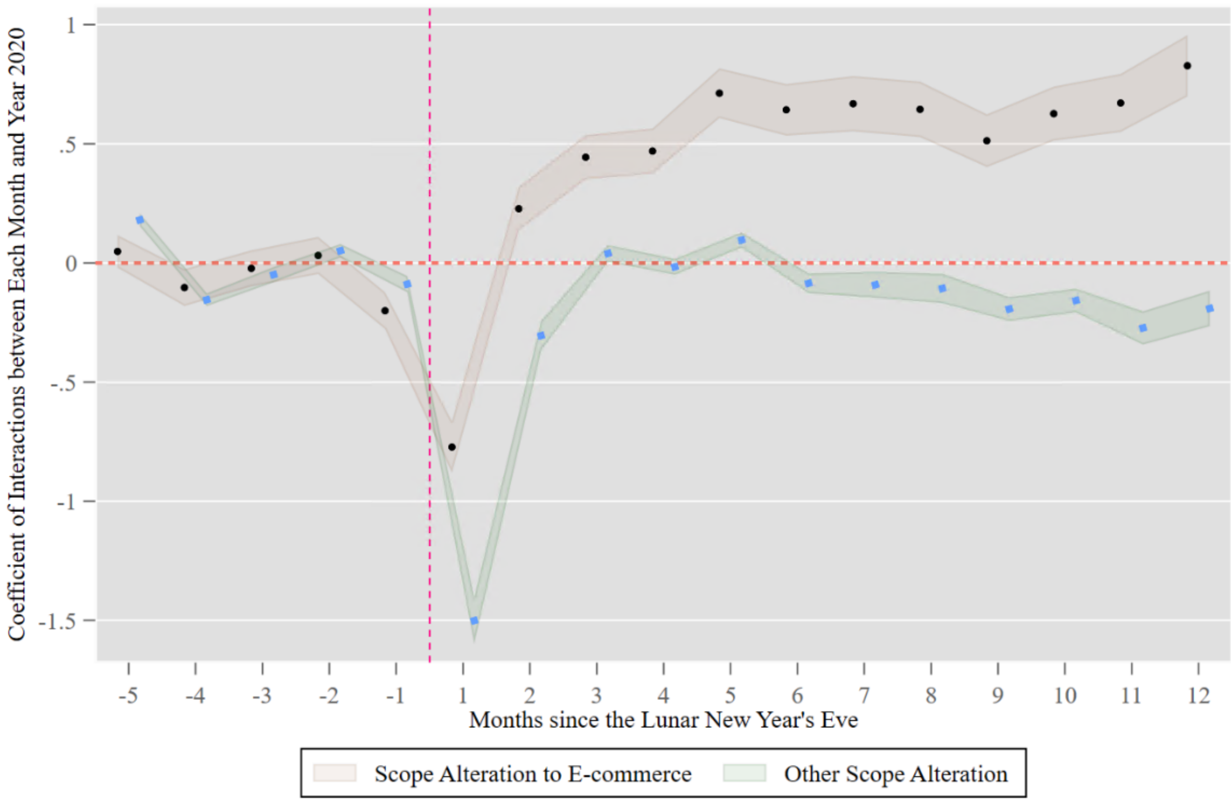


Figure 5: Event Study of COVID-19 Outbreak and Reopen on Business Operation Scope Alteration, by E-commerce Adoption and Others

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 Spring Festival coefficient ($m = 0$) is omitted as the baseline level (zero as default). 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-(lunar) year-month level. Standard errors are clustered at the city level. The regression controls for the city, month, year, and city-year fixed effects. Data source: SAIC registration database.

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	0.000
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. Panel A describes the basic industry distribution of the ESIEC sample surveyed in 2020. In regressions, we further control for more detailed one-digit industry fixed effect.
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	0.057	0.231	0.075	0.263
Controls:				
COVID	0.141	0.348	0.143	0.350
Firm age	4.834	5.399	4.977	5.477
Business type:				
Corporate enterprise	0.107	0.309	0.115	0.319
Self-employed, registered	0.509	0.500	0.504	0.500
Self-employed, unregistered	0.384	0.486	0.380	0.485
Industry:				
Agriculture	0.069	0.253	0.070	0.255
Construction and manufacturing	0.105	0.307	0.113	0.317
Service	0.826	0.379	0.816	0.387
Employment:				
0	0.330	0.470	0.332	0.471
1-4	0.454	0.498	0.446	0.497
5-7	0.105	0.307	0.106	0.308
8-19	0.066	0.248	0.070	0.256
>19	0.044	0.206	0.046	0.209
City tier:				
Tier #1	0.232	0.422	0.209	0.406
Tier #2	0.209	0.407	0.218	0.413
Tier #3	0.133	0.339	0.133	0.339
Tier #4	0.221	0.415	0.224	0.417
Tier #5	0.205	0.404	0.217	0.412
Obs.	68,581		47,452	

The main 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. Control 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.
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.
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	-0.030***	-0.099*	-0.020***	-0.014***
	(0.011)	(0.059)	(0.005)	-0.005
adj. R-sq	0.368	0.042	0.004	0.001
Panel B:	Cash flow >1 month			
E-commerce ratio	0.121***	0.093*	0.097***	0.199***
	(0.020)	(0.051)	(0.025)	(0.040)
adj. R-sq	0.037	0.039	0.016	0.013
Panel C:	Reopen status			
E-commerce ratio	0.078***	0.074	0.070***	0.103***
	(0.015)	(0.046)	(0.019)	(0.014)
adj. R-sq	0.497	0.072	0.026	0.024
Panel D:	Outlook for growth			
E-commerce ratio	0.094***	0.011	0.064*	0.182***
	(0.024)	(0.037)	(0.036)	(0.048)
adj. R-sq	0.133	0.007	0.047	0.039
Control	YES	YES	YES	YES
Wave dummy	YES	-	-	-
Province 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 also gives consistent results. Robust standard errors are reported in parentheses. 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, registered capital, city-level COVID-19 confirmed case, and city-level COVID-19 case growth in 30 days. The regressions also control for the province and one-digit industry fixed effects.
Significance level: * p<0.1 ** p<0.05 *** p<0.01.
Data source: ESIEC.

Table 4: Short-term Impact of Digital Transformation on Corporate Finance during the Early Reopening

	Dependent variables in May 2020:			
	Account Receivable:			Account Payable:
	(% Current Assets >50%)=1	Repayment period:		(% Current Assets >50%)=1
		(>60 days)=1	(Uncertainty)=1	
	(1)	(2)	(3)	(4)
E-commerce ratio	-0.098***	-0.103***	-0.095***	-0.068***
	(0.028)	(0.031)	(0.026)	(0.026)
Control	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Obs.	1,715	1,715	1,715	1,715
Adj. R-sq	0.020	0.042	0.025	0.017
Mean of dependent variable	0.217	0.362	0.242	0.266
S.D. of dependent variable	0.412	0.481	0.428	0.442

All regressions in the table use OLS estimation. The Probit model also gives consistent results. Robust standard errors are reported in parentheses. 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. The control variables include employment, established year, a dummy for corporate, registered capital, city-level COVID-19 confirmed case, and city-level COVID-19 case growth in 30 days. The regression also controls for the province 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)	(4)
	Online operation			Online sales ratio
	Any	Combine with offline	Only online	
Panel A: all sample				
COVID × After	0.033***	0.016*	0.018***	0.016***
	(0.008)	(0.008)	(0.006)	(0.004)
Mean of dependent variable	0.443	0.333	0.110	0.155
S.D. of dependent variable	0.497	0.471	0.313	0.228
adj. R-sq	0.063	0.062	0.052	0.057
Obs.	68,581			
Panel B: newly established subsample				
COVID × After	0.046*	0.005	0.041	0.018
	(0.025)	(0.027)	(0.026)	(0.015)
Mean of dependent variable	0.519	0.345	0.173	0.175
S.D. of dependent variable	0.500	0.476	0.379	0.247
adj. R-sq	0.029	0.068	0.053	0.027
Obs.	6,060			
Panel C: incumbent subsample				
COVID × After	0.033***	0.018**	0.015***	0.016***
	(0.008)	(0.008)	(0.006)	(0.004)
Mean of dependent variable	0.436	0.332	0.104	0.153
S.D. of dependent variable	0.496	0.471	0.305	0.226
adj. R-sq	0.064	0.062	0.048	0.061
Obs.	62,521			
Control	YES	YES	YES	YES
Quarter FE (wave dummy)	YES	YES	YES	YES
Province FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES

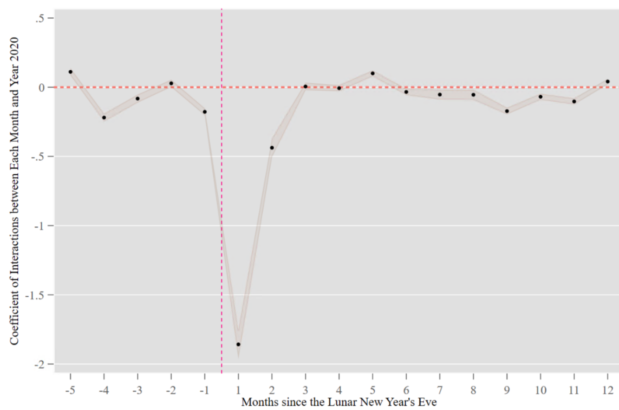
All regressions in the table use OLS estimation. The Probit or Ordered Probit model also give consistent results. Standard errors in parentheses are clustered at the city level. The independent variable, *COVID × After*, equals one if a business is located in a city with localized lockdowns due to new COVID confirmed cases and was surveyed in a quarter after the outbreak; zero otherwise. The control variables include a dummy for COVID-impacted cities, business type (corporation and registration status), employment, city tiers, and established year. The regression also controls for the quarter, province, and industry 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

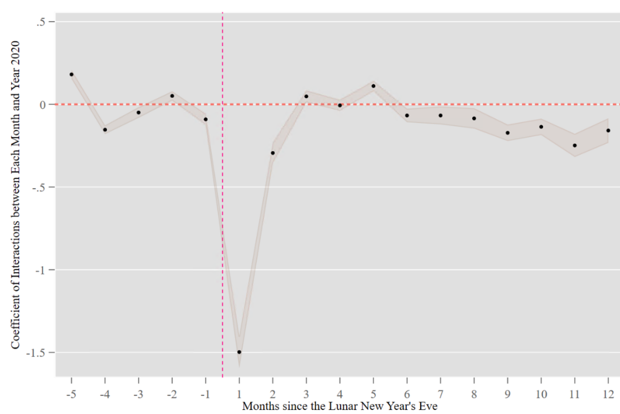
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Remote work	Electronic information system					
		Any	Finance	Payment	Product	Sale	Management
Panel A: all sample							
COVID × After	0.013***	0.004	-0.010*	0.007	-0.003	-0.011*	0.005
	(0.004)	(0.009)	(0.006)	(0.008)	(0.005)	(0.006)	(0.007)
Mean of dependent variable	0.050	0.509	0.150	0.274	0.091	0.151	0.244
S.D. of dependent variable	0.218	0.500	0.357	0.446	0.287	0.358	0.429
adj. R-sq	0.020	0.097	0.094	0.037	0.069	0.062	0.106
Obs.				47,452			
Panel B: newly established subsample							
COVID × After	-0.017	0.056*	0.031	0.051*	0.031**	0.020	0.017
	(0.014)	(0.032)	(0.019)	(0.028)	(0.015)	(0.019)	(0.032)
Mean of dependent variable	0.054	0.479	0.143	0.233	0.077	0.137	0.240
S.D. of dependent variable	0.225	0.500	0.350	0.423	0.266	0.344	0.427
adj. R-sq	0.029	0.080	0.077	0.032	0.049	0.030	0.074
Obs.				4,060			
Panel C: incumbent subsample							
COVID × After	0.015***	-0.001	-0.005	0.003	-0.005	-0.014**	0.004
	(0.004)	(0.009)	(0.006)	(0.009)	(0.005)	(0.006)	(0.007)
Mean of dependent variable	0.049	0.512	0.150	0.278	0.092	0.153	0.244
S.D. of dependent variable	0.217	0.500	0.357	0.448	0.289	0.360	0.429
adj. R-sq	0.020	0.098	0.096	0.036	0.071	0.065	0.109
Obs.				43,392			
Control	YES	YES	YES	YES	YES	YES	YES
Quarter FE (wave dummy)	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

All regressions in the table use OLS estimation. The Probit 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 a dummy for COVID-impacted cities, business type (corporation and registration status), employment, city tiers, and established year. The regression also controls for the quarter, province, and industry 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 Spring Festival coefficient (m = 0) is omitted as the baseline level (zero as default). 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-(lunar) year-month level. Standard errors are clustered at the city level. The regression controls for the city, month, year, and city-year fixed effects. Data source: SAIC registration database.

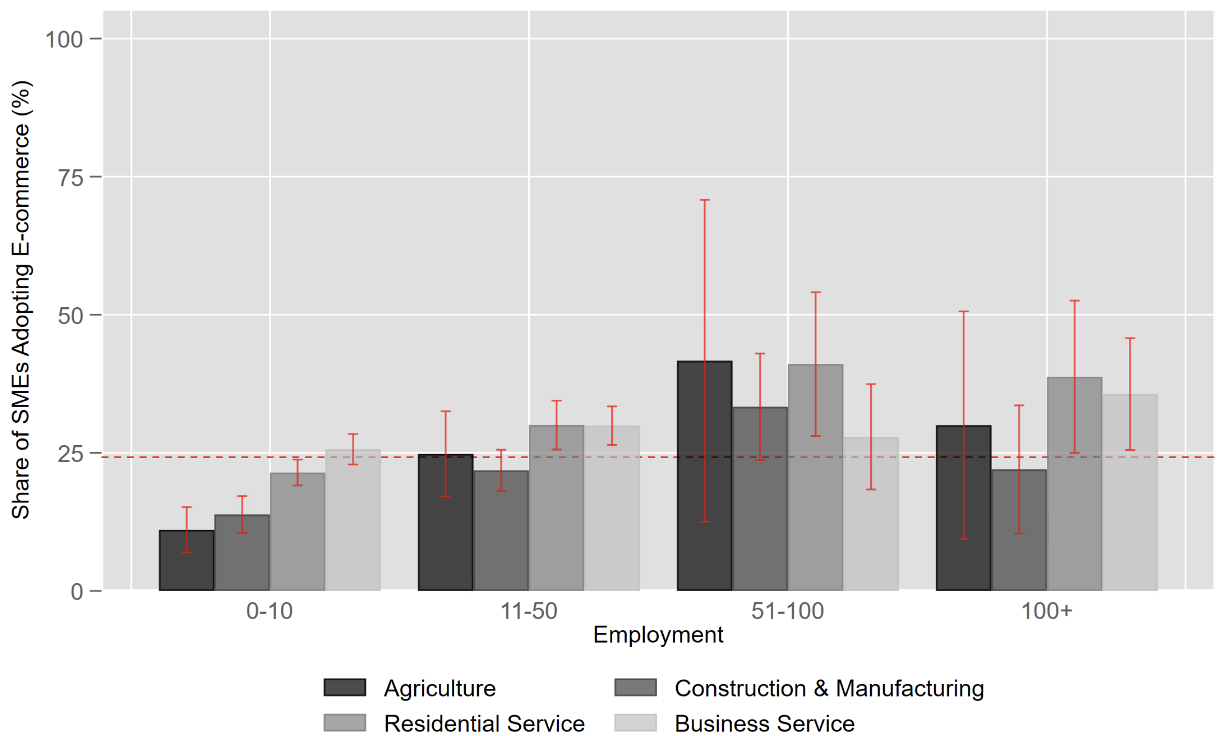


Figure A.2: Share of SMEs Adopting E-commerce in ESIEC, by Industry and Employment

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.

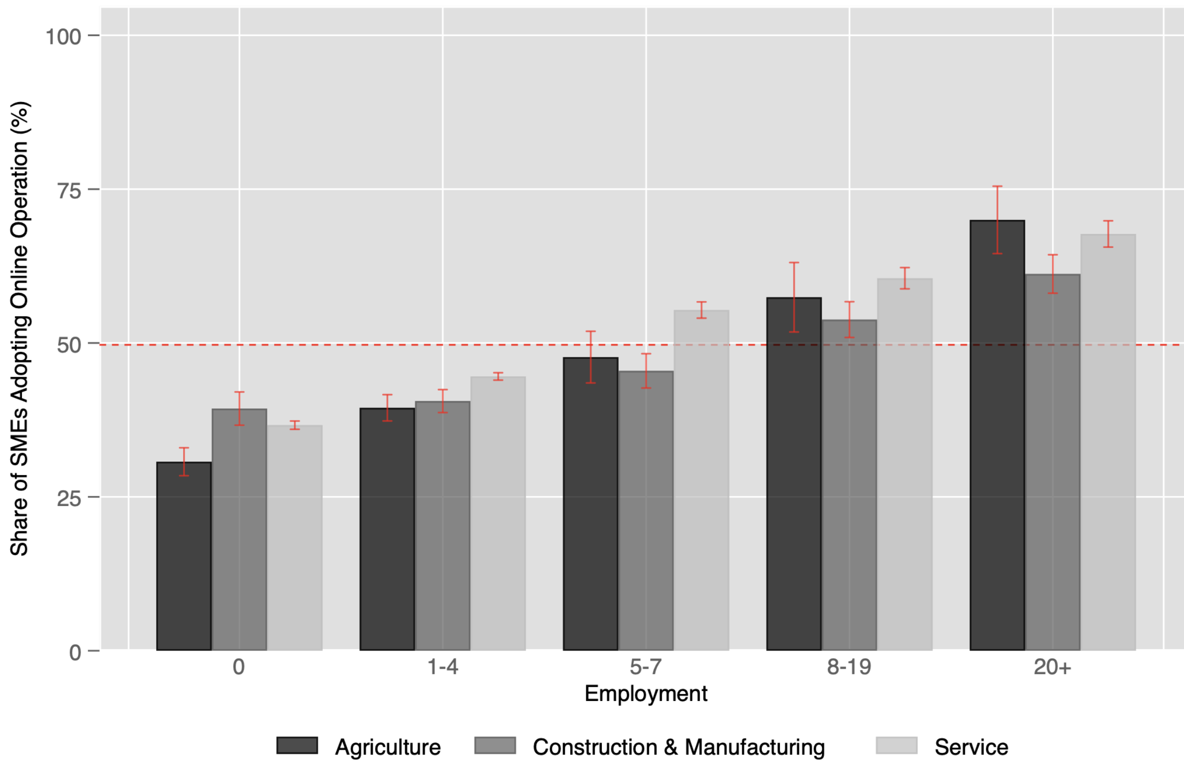


Figure A.3: Share of SMEs Adopting Online Operation in OSOME, by Industry and Employment

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 2021Q3.
Data source: OSOME.

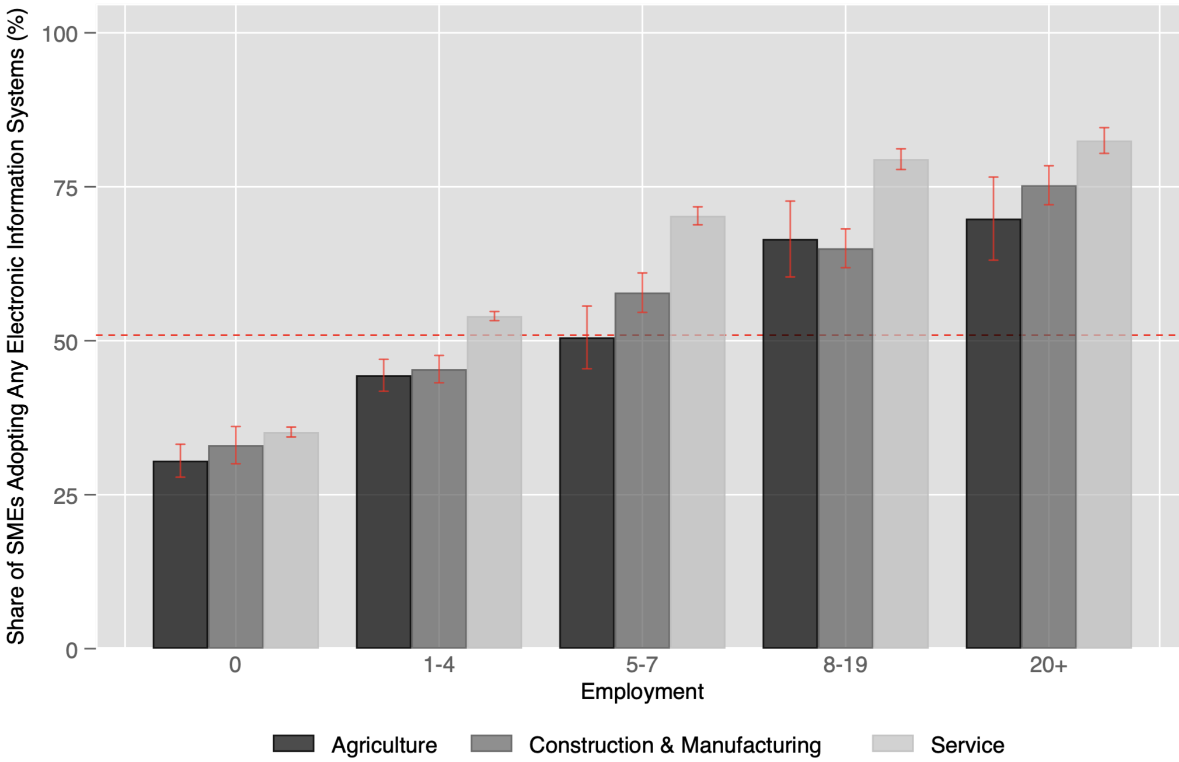


Figure A.4: Share of SMEs Adopting Any Electronic Information Systems in OSOME, by Industry and Employment

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 2021Q3.
Data source: OSOME.

Appendix B Natural Language Processing for Capturing the Level of E-Commerce Adoption and Digitization

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 provides us a natural training set. For robustness, we also manually labeled training sets from ESIEC and OSOME, respectively.

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. 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 a Decision Tree model to our labeled training set. It turns out that the model nodes largely overlap with the keywords we extract, and the classification is consistent. We also use the Naive Bayes text classification for robustness check, and the results remain consistent.

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-month-year level to construct our dependent variable. We also construct the total number of firms' alterations on business operation scope as a placebo.