# 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 industry in multiple dimensions (e.g., altering operation scope to include e-commerce, allowing remote work, and adopting electronic information systems). The effect persists more than one year after reopening, offering suggestive evidence for the long-term impact of the pandemic and supposedly transitory mitigation policies.

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**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 and Morse, 2021; Chen et al., 2020a) 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, are understudied, despite numerous media reports (e.g., the TIME magazine 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 to bridge this knowledge gap. 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 universal business registration data from the State Administration for Industry and Commerce of the People's Republic of China (SAIC). The comprehensive data coverage and large heterogeneity in Chinese SMEs allow us to directly document the benefits of e-commerce, a 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 in relation to the national lockdown, as shown in Figure 1, also enable us to demonstrate both the immediate and persistent digital transformation of SMEs the pandemic brings forth.[3]

Defining SMEs in China is challenging. Our dataset admits a rather general definition in-

[1]For example, in the United States, small businesses accounted for 44% of U.S. employment and 99% of firms (Bartlett and Morse, 2021). 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 (see, e.g., `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 approximately 40% of the 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 and Morse, 2021; Fairlie, 2020; Humphries et al., 2020).

[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.

cluding both privately-owned incorporated firms and self-employed businesses. Specifically, SAIC covers the universe of registered enterprises in China, the majority of which are small businesses with low registered capital. ESIEC surveys a representative sample of SMEs, including incorporated firms and registered self-employed businesses, with more than half of the respondents having fewer than ten employees. Besides registered businesses, OSOME also includes unregistered self-employed businesses long neglected in previous research. Importantly, the SMEs interviewed in the two surveys are located in both urban and rural areas of different city tiers across China.

We first investigate whether digitizing business operations make SMEs more resilient to shocks such as the pandemic. Business digitization broadly encompasses technologies such as e-commerce, automation, AI, and e-learning, with e-commerce serving as the main proxy for digitization in our setting. 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 baseline estimates likely constitute a lower bound.

We then examine whether the pandemic has induced greater adoption of digital technologies for SMEs, a question rarely studied in the literature in part due to data paucity.[4] We overcome the challenge by developing a textual analysis algorithm to apply to business operation scope, a written record embodied in SAIC indicating what activities an enterprise is approved to conduct, effectively classifying each registered firm's e-commerce adoption status. We employ an event study approach exploiting the timing of the nationwide lockdown to gauge its impact on the extensive growth margin, the number of e-commerce firm entries at the city-industry-month level aggregated from SAIC. Compared with the pre-pandemic period, 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.

For 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

[4]A McKinsey Global Survey of executives at large firms 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 (Baig et al., 2020; McKinsey, 2020). Our study expands on SME.

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. Moreover, using the multi-round quarterly OSOME surveys from 2020 to 2021, we find that SMEs—including the unregistered ones—in regions exposed to sporadic local lockdowns (after the nationwide 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. Several recent studies survey small businesses, mostly in developed countries, immediately after the onset of the pandemic (e.g., Bartik et al., 2020a; Bartlett and Morse, 2021; 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 al., 2020), and corporate hiring (Campello et al., 2020). Adding to how intervention policies help (e.g., Bartlett and Morse, 2021; Chen et al., 2020a), Dai et al. (2021b) investigate the efficacy of policies targeted at SMEs while Chen et al. (2020b) show that local economic stimulus policies for small businesses actually benefited larger firms more both in the Chinese context.

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 studies examining how basic IT, credit risk, financial flexibility, workplace flexibility, executive entrenchment, financial policies, differential COVID-19 exposures, ESG policies affect

[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 underserved by traditional financial institutions.

[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 action 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 (March 28-April 4, 2020) of U.S. businesses. Balla-Elliott et al. (2020) similarly survey small business owners' expectations about their reopening and future demand. Fairlie (2020), Humphries et al. (2020), and Campello et al. (2020) 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.

firm resilience and outcomes such as stock returns (Kwan et al., 2021; Acharya and Steffen, 2020; Albuquerque et al., 2020; Ramelli and Wagner, 2020; Ding et al., 2021; Fahlenbrach et al., 2021; Barry et al., 2021). Recently, Gaspar et al. (2022) use text-based measurement of firm digitization to quantify the size of the digital economy and also test the impact of digitization on firm resilience. They almost all analyze public U.S. firms (some in particular sectors) shortly after the onset of the pandemic, whereas we cover all registered firms in China in all sectors, especially private SMEs, and examine both the onset of the pandemic and reopening to understand how the pandemic spurs long-term digitization.[8] While the literature has identified managerial talent, financial flexibility, and governance as important drivers for resilience amidst the pandemic, we show several novel digitization channels: Given the immediate consumption reduction associated with lockdowns (Chen et al., 2021), robust online consumption, as well as more timely payment and faster turnover of firm working capital, gives enterprises with online operations a competitive advantage.

Our study also contributes to the emerging literature on FinTech adoption (e.g., Agarwal et al., 2020), which has been accelerating amid the pandemic (Plaid, 2020).[9] Although FinTech deals decreased drastically during the first quarters of 2020 due to the lockdown, digital financial services likely thrive as FinTechs are widely seen as natural remedies (CB Insights, 2020; Zachariadis et al., 2020). Recently, Fu and Mishra (2021) document that the pandemic has led to sharp increases in FinTech APP downloads whereas Tut (2020) finds a negative impact on the adoption of FinTech payments. 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. Broadly concerning technology adoption in response to shocks, Shklovski et al. (2010) find that Hurricane Katrina experience only had a temporary pick-up on digital communication and IT. Different from these studies, our paper focuses on SMEs rather than on consumers and households, and exmaines persistent effects of digitization such as e-commerce adoption and novel mechanisms. We thus complement Gao et al. (2023) which finds that digital training by the British government helps SMEs to increase revenue the resilience, in the context of a developing economy.

[8]We also avoid the critique on using public firms that the stock market is divorced from the pain of a pandemic economy because the SMEs that suffer the most are not listed (Thorbecke, 2020).

[9]The Plaid report reveals that 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.

# 2 Data and Survey Design

We assemble several large-scale data sets (both manually collected primary data and administrative data) with comprehensive coverage of SMEs in China and their digitization.

**ESIEC data.** ESIEC is an entrepreneur- and enterprise-specific joint field survey project led by the Center of Enterprise Research, Peking University, in total covering seven provinces.[10] ESIEC successfully interviewed nearly 10,000 private enterprise owners and self-employed entrepreneurs between 2017 and 2019, collecting high-quality microdata on the entrepreneurs' backgrounds and business performances, which is representative (e.g., Dai et al., 2021b).

After the outbreak of COVID-19 in China, the ESIEC team immediately conducted multiple phone surveys with previously interviewed entrepreneurs in the baseline survey (see Figure 1). The questionnaire mainly focused on the firm's reopening and operational status, challenges, responses, and prospects. The first two rounds of phone surveys tracked firms drawn from pre-pandemic surveys. 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 for cooperated enterprises (Appendix C contains more details). 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.

**SAIC business registration data.** The dataset covers the universe of registered businesses in China, containing 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. Appendix C explains its

[10] 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 2022, the ESIEC project alliance included 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.

greater coverage of incorporated small, medium, and micro enterprises than other databases. Because SAIC is up-to-date, we can analyze firm responses during the pandemic and after the reopening. While SAIC is limited to the registered enterprises, the other surveys complement with detailed information on self-employments.

SAIC includes "business operation scope" record, a mandatory and standardized text record briefing what business operations an enterprise is approved to conduct.[11] We therefore extract information from the records of entrant firms' business operation scope using natural language processing (NLP, described in Appendix D) 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 in terms of e-commerce. As a validation, the algorithm successfully predicts as high as 87.5 percent of the enterprises with online sales in the ESIEC sample.

We further 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 their business operation scope.[12] A dummy variable for incumbent firms' e-commerce adoption takes a value of one if the alteration entails changes from no e-commerce keywords to having words related to e-commerce, and zero otherwise. 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.[13] 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

[11]For rules of the operation scope registration, see `https://bj.jyfwyun.com/#/visitor/home`.

[12]Some firms, which actually adopt e-commerce, may fail to update the contents of the business operation. Such classification error, if any, only causes underestimation of the actual degree of digitization.

[13]Active SMEs on the Alipay platform are 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. Alipay reached 1.2 billion monthly users in 2019 and is the primary payment method for 90% of people in China, along with WeChat Pay (Klein, 2020). See also `http://www.xinhuanet.com/english/2019-10/01/c_138440413.htm` and `https://www.techinasia.com/wechat-cashless-china-data`.

recovery, digital adoption (online sales, remote work, and introduction of electronic information systems), challenges, and business outlook. OSOME provides 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 ESIEC and SAIC still hold for unregistered SMEs and in other types of digital adoption beyond e-commerce. Table 2 shows the summary statistics of OSOME (Appendix C contains more detailed discussions). 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.

# 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 firm-level 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. Although we use the continuous measure in the regression, it is also helpful to check the binary specification (*E-commerce ratio* $> 0$). As Table 1 shows, nearly 24.2% of SMEs in the ESIEC sample had adopted online sales. We also check the robustness of this alternative measure in Appendix E.

Table 3 presents results using OLS regressions, which are robust under Probit and Logit specifications (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 firm size. We also control for the city and one-digit industry fixed effects in the regressions, which are not displayed in the table for clearer presentation.

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 yields 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. The resulting lack of market demand was persistently reported as a major challenge in the three waves of the ESIEC survey (see also Dai et al., 2021b). Yet there is a sharp difference in the national trends of year-on-year growth rate for online and offline retail sales (driven by differential demands) from January 2016 to October 2021, as shown in Figure 2.[14] 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 outbreak of COVID-19 was reined in, online sales witnessed a more rapid V-shaped rebound than offline retail sales. By the end of 2020, its year-on-year growth rate exceeded 10 percent, while the growth rate for offline retail sales remained negative 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 faster payment. E-commerce firms can immediately receive payment once customers verify their satisfaction with the delivery. The May wave of the ESIEC 2020 survey includes questions on accounts receivable and payable. We use the May survey to test the impact of e-commerce on a firm's financial situation. 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.[15] SMEs with e-commerce had an 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

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

[15]"Current assets" is defined as the sum of inventories, accounts receivable, cash, and cash equivalents.

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). 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 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.[16]

Furthermore, we use the ESIEC survey in August 2020 to document the role of the production network in affecting firm performance amidst the pandemic. The survey asked respondents whether the key suppliers and customers pre-pandemic were local or not. In Panel A (B) of Appendix Table B.5, we have added a dummy variable indicating whether having local suppliers (customers) or not and its interaction term with the e-commerce ratio variable. SMEs with local suppliers were less likely to report demand decline as a main challenge and had better cash flow status than those without local suppliers (customers). More importantly, as shown in the interaction terms, having local suppliers (customers) acts as a substitute for e-commerce. The role of e-commerce in maintaining demand and cash flow is more pronounced for SMEs without local suppliers (customers). While the pandemic and mitigation policies disrupted production supply chains, e-commerce can mitigate this disruption, making small businesses, particularly those without local suppliers and customers,

[16]For robustness, we further control for more firm-level pre-COVID characteristics and the owner's background information (e.g., owner's age, gender, prior working experience, and education). 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. Appendix Table B.1 contains the descriptive statistics. 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. Appendix Tables B.2 and B.3 demonstrate the robustness of our findings under additional control variables.

more resilient.

We also conduct more analyses to examine the importance of online experience or financial capacity in the adoption of e-commerce. Pre-existing e-commerce business owners had accumulated online business experience, such as online sales and e-payment, enabling them to better cope with the COVID-19 shock. As shown in Appendix Table B.6 using ESIEC phone survey data in May 2020, SMEs with pre-COVID e-commerce experience were more likely to adopt online sales and purchases as well as the mode of remote work during the first wave of nationwide lockdown. They also experienced less degree of disruption in production.

The quarterly OSOME data has also tracked the major challenges facing SMEs. As Appendix Table B.7 shows, high operating costs and weak demand were consistently the two main challenges for SMEs. Concerns about loan repayment and uncertainty grew significantly as the COVID restrictions persisted. E-commerce can help SMEs to cope with these challenges by mitigating the demand decline and sustaining cash flow.

Besides, as shown in Table 4 that having e-commerce before the pandemic helped SMEs maintain more stable cash flow and robust demand, here we conducted more analyses on the cost side using the incumbent subsample (established before 2020 to avoid the COVID impact on entry selection) of the OSOME data. Since 2020Q4, the OSOME survey asked SMEs about their main cost challenges in the questionnaire, including rent, raw material, labor, COVID prevention, and marketing cost. Overall, rental and raw material costs are the primary concerns for SMEs. Table 5 presents the regression results on major operating cost challenges based on the OSOME data. The key variable of interest is the interaction term between the mode of online operation with the COVID shock. A dummy variable for financial need is included as a control variable. It is apparent from the table that online-operating incumbents reported lower cost pressures in rent, raw material, and COVID prevention. The nature of sales on demand in e-commerce can greatly reduce the inventory cost, as shown in Dai and Zhang (2015). The more flexible mode of production in e-commerce can reduce the prevention cost, since workers don't need frequent face-to-face interaction. Therefore, e-commerce can also mitigate the cash flow problem by reducing the main operating costs. Yet, e-commerce SMEs have relatively higher costs on labor and marketing, since they have to hire people with basic internet skills and pay promotion fees on e-commerce platforms. Notably, these two types of costs are not among the top challenges facing SMEs.

# 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 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 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, $j$ stands for 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.[17] 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 the 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, the corresponding two-way fixed effects except for the interaction term between year and month, and the year trend of city-industry, $f(y, c, j)$. 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 2020-2021 to those in the same

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

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 four-digit industry codes. 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 algorithms as described in Section 2 and Appendix D 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 entries or alterations 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 $\beta_m$ 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 reveals the percentage change in outcomes driven by the shock.

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

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

where $c$, $m$, and $y$ index the city, month, and 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 for the interaction term between year and month, and the year trend. Standard errors are again clustered at the city level.

As a robustness check, we also repeat the previous analyses by using a continuous pandemic variable. We have gathered the growth rate of confirmed cases (including asymptomatic cases) at the city level from public official sources for the period January-March, 2020 (the outbreak). This is indicated by $COVID'_c$ (infection rate). We define a dummy variable $After_m = 1$ for 2020 Lunar New Year and after, otherwise the value is 0. The specification is shown in Equation (3), where the definition of the index is the same as in Equation (1).

$$\ln(Y_{cjmy}) = \beta_m \times COVID'_c \times After_m + FEs + f(y, c, j) + \varepsilon_{cjmy}. \tag{3}$$

## 4.2 Empirical Results

**Baseline analysis.** We start with 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 $\beta_m$ in Appendix Figure A.1(a). As shown in the figure, the pandemic outbreak led to a huge decrease in new firm entries. In the first two months after the outbreak, the number of new entrants dropped 72.6% and 32.0%, respectively, controlling for geographical differences and aggregate trends. After the pandemic was initially 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, exhibit 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, likely reflecting a gradual recovery from the lockdown and the heightened market uncertainty.

Figure 3 displays the extensive margin of 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 of the pandemic on the digital transformation of SME entries in China. For robustness check, we repeat the above excise by comparing online and offline businesses in the wholesale and retail (W&R) sectors, which are clearly indicated by the four-digit industrial classification code at the time of registration. Appendix Figure A.6 shows that the results remain.

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 4. 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 A.6. More importantly, new entrants in two traditional industries, the agriculture and the manufacturing sectors, have increased the adoption of e-commerce by 19.1% and 22.7%, respectively. Besides, newly registered enterprises in the service sector, such as the resident services and the culture, sports, and entertainment services, have also accelerated the adoption of e-commerce after the lockdown. New entrants in the information transmission, software, and information technology service industry also witnessed a growth in e-commerce adoption, but the effect is not statistically significant. By comparison, this effect does not exist in industries not directly related to e-commerce, such as mining and the production and supply of electricity, heat, gas, and water. The finding for these industries 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 traditional agricultural and manufacturing industries.

Next, we examine the intensive margin of incumbent SMEs in digital transformation using alteration records of business operation scope to construct subgroups. Figure 5 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 the 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 complements the documented persistent effect on the extensive margin in revealing the further digitization brought forth by the pandemic.

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 6. 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 4, in some industries that are not applicable to e-commerce, the incumbent enterprises have not made corresponding changes.

Table 6 shows the regression results based on Equation (3) using a continuous pandemic variable. The greater the growth of COVID cases in a particular city, the more subsequent new local entries in e-commerce-related business in the intermediate and long term (Column 1 below), and the more switches in business operation scopes among enterprises established before 2019 from non-e-commerce to e-commerce (Column 3). In contrast, the effect for non-e-commerce entries (Column 2) and other business operation switches (Column 4) is negative, consistent with the patterns shown in Figures 3 and 5, indicating that the pandemic affected non-e-commerce ventures more adversely in cities with higher infection rates. We also include the analogous industrial heterogeneous effects for extensive margin and intensive margin in Appendix Figure A.5, which are consistent with Figures 4 and 6 based on Equation (2).

There is also a significant and massive firm dynamic of exit. In our data, the exit information is much less frequently updated than the entry information in the registration data. Due to the lag in the reporting of firm exit, it doesn't make sense to conduct similar analyses at the monthly level as for firm entries. Instead, we conduct the analysis on exit at the annual level. In Table 7, Columns 1 and 2 compare the exits of enterprises before and after 2020 (without monthly variation), showing that the effect of the pandemic on the exit of e-commerce enterprises is smaller than that of non-e-commerce firms. Columns 3 and 4 repeat the exercise in the first two columns by using the growth in accumulative COVID cases as an alternative measure of the pandemic shock, and the results are robust.

It should be noted that the pandemic exacerbates firm exit. This is likely due to a combination of factors. On the one hand, the pandemic has caused disruptions in the supply chain, suffocating firm survival. On the other hand, the spurring entry of new e-commerce enterprises and the transformation of incumbent enterprises into e-commerce have intensified competition, leading to more exits in terms of firm dynamics. Despite the negative effect on firm exit, the effect is less severe for e-commerce firms than for non-e-commerce firms.

**Heterogeneity.** Besides heterogeneous effects across industries, we also explore heterogeneity across firm characteristics. Due to very limited information on firm characteristics in the business registration data, we mainly compare state-owned enterprises (SOEs) and non-SOEs. In a nutshell, the effects of the pandemic and reopening are more pronounced for non-SOEs than SOEs, as shown in Appendix Table B.10.

We have also conducted more analyses on regional heterogeneity by the degree of industrial clustering. The measure of industrial clusters was first developed by Long and Zhang (2011) and subsequently extended by Ruan and Zhang (2015). This industrial cluster index is constructed based on the proximity matrix of the production space, while taking into account factors such as correlation and concentration.[18] Using this measure, Dai et al. (2021a) show that firms in industrial clusters were more resilient to the pandemic shock. Following the same spirit, we interacted the cluster index (in logarithm) with the key variable of interest ($COVID \times After$) in regressions and the results are shown in Table 8. On the extensive margin, as shown in Column 1, regions with a higher degree of industrial clusters witnessed more new e-commerce firm entries than lower clustering regions when facing the pandemic shock. The effect is the opposite for non-e-commerce entries (Column 2). As indicated in Columns 3-4, the findings on the intensive margin are the same. In the face of the pandemic shock, incumbent firms in clusters experienced a more rapid transformation into e-commerce in their operation.

In addition, following Zhang and Tan (2007) and Hsieh and Klenow (2009), we have constructed a financial inefficiency index, which is measured by the variation in the marginal product of capital.[19] In this paper, we compute the standard deviation of the logarithm of the value added/total asset ratio at the city-industry level from the China Economic Census 2008. Once again, we mainly report the interaction term of ($COVID \times After$) and the financial inefficiency index in Table 9. As shown in the table, in areas of high financial inefficiency, new entries into non-e-commerce have significantly decreased in the

[18]The intuition behind this is that the proximity in the production space reflects the common factors in technology, inputs, know-how, and markets among different industries, while previous correlation indices have focused mainly on concentration at the regional or industry level but cannot fully reflect the interrelationships among enterprises, which are actually more important in industrial clusters.

[19]For a production function with constant returns to scale, the marginal product of capital is proportional to the average product of capital. Therefore, the variation in the log(marginal product of capital) = variation in the log(average product of capital).

event of COVID shock (Column 2), so do switches in business operations by incumbent firms (Column 4, potentially due to the fact that more enterprises fail to survive). By comparison, as indicated in Column 1, regions with lower financial efficiency have witnessed more e-commerce-related entries, suggesting that digitization helps firms cope with financial inefficiency against the pandemic shock. Similarly, on the intensive margin, we also observe that in the areas of high financial inefficiency, a greater number of firms have switched to e-commerce-related business operations, as demonstrated in Column 4.

We also used the city-level index of digital finance in 2015 to check the heterogeneous impact of digital finance. The index was produced by a research team from the Institute of Digital Finance at Peking University and Ant Group, involving coverage breadth, usage depth, and digitization level (Guo et al., 2020). The result in Panel B of Table 9 shows that there was more e-commerce adoption by new entrants and incumbents in areas with better digital financial inclusion.

## 4.3 Extension: Findings from OSOME Survey

The above analyses focus on registered enterprises using the administrative business registration data. Yet nearly half of the self-employed businesses are not registered in China (Kong et al., 2021). It is unclear whether the patterns observed from the registered incorporated enterprises still hold for self-employed businesses, especially the massive number of unregistered ones. The OSOME data enable us to check this out. The OSOME survey 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:

$$Y_{ijcq} = \beta \times (COVID_c \times After_q) + \mathbf{x}_i'\theta + \gamma_q + \zeta_c + \eta_j + \alpha_{cj} + \delta_{cy} + \mu_{iy} + \varepsilon_{icqj}, \tag{4}$$

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 quarterly revenue. The OLS regression also controls for the city, industry, quarter (wave), city × industry, city × year, and industry × year two-way fixed effects.[20]

Table 10 first reports the estimation results concerning online operations (e.g., online advertisement, promotion, recommendation, design, etc.) 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 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 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.[21] 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 11 further reports the impact of exposure to lockdowns on the adoption of remote

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

[21] 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 13, within each industry and location.

work and electronic information systems.[22] The specification is the same as in Table 10. 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 the 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 adoption. However, we do not observe an association between exposure to COVID-19 restrictions and the introduction of electronic systems for newly established businesses. Overall, local lockdowns have induced small businesses to develop online operations and adopt remote work modes.[23] We also conduct more heterogeneous analyses by the firm (registration type, industry, size, and financial needs) and entrepreneurial characteristics (gender, age, and education level) in Appendix Table B.12. Overall, the effect is more pronounced for firms larger in size and firms owned by female, young, colleague-educated entrepreneurs.

To evaluate the economic efficiency of using online operations to overcome constraints on face-to-face interactions, we apply the Propensity Score Matching (PSM) method to match the samples of online operations (pure online and online-offline hybrid) with samples of purely offline operations. Overall, as shown in Panel A of Appendix Table 12, SMEs in areas affected by the pandemic had significantly worse revenue, profits, cash flow (Columns 1-3), and recovery relative to the same quarter in 2019 (for incumbent firms only, Column 4 in Panel C). SMEs who adopted online operations figured much better in revenues and cash flow, but the coefficient for profit is significantly negative, indicating the e-commerce business is extremely competitive with a thin profit margin. Yet, the positive coefficient for the interaction term between online operation and exposure to lockdowns indicates that adopting online business under the impetus of the pandemic has overall improved the operational

[22] 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.

[23] 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.

performance and efficiency of small and micro-enterprises. Using profit as a measure of efficiency, the effect of using online operations to offset the impact of the pandemic is not significant in the subsample of newly-entered businesses in the surveyed quarter, but highly significant for the incumbent firms.

We further conducted more heterogeneity analyses along several dimensions, including business type, industry, scale, city tier, and gender. Table 13 reports the estimates for the interaction terms between COVID restrictions and online operations (to save space, standard errors are omitted) using the same PSM specification as in the above table. In terms of registration type, the efficiency improvement for the corporate enterprises which adopted online operations is higher than for self-employed businesses. When comparing the three major sectors, though insignificant, we found that SMEs with online operations in the service sector exhibited an increase in profit, while those in the agricultural sector suffered in profit. There are several explanations, such as the online demand for agricultural products being subject to transportation timeliness constraints. It may also be because the digitization of the agricultural industry requires larger economies of scale, which are not yet available. It is a future question to test which effect dominates.

In terms of firm size measured in employment, online operations improve the economic efficiency of enterprises with more than 20 full-time employees, while the effect is not significant for smaller-scale businesses. Across city tiers, the effect is significantly positive for more developed cities, yet insignificant for less developed areas. Interestingly, female entrepreneurs have enjoyed a significantly greater efficiency improvement by adopting online operations, while the effect on their male counterparts is negligible.

Finally, the digital edge does not come free. 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 7.[24] The lack of time and energy to learn is the key obstacle to 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,

[24]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 percent of answers, using the total number of selected options as the denominator, and the result is naturally consistent.

reported by 26.9% and 20.3% of interviewees, respectively.[25] For more detailed discussions, please refer to Appendix G.

# 5 Conclusion

SMEs are integral to the global economy and play an important role in China.[26] Using e-commerce proxies for digitization and combining multiple data sources, we document in China that SMEs with greater digitization had more robust market demand and faster turnover of working capital, and were thus more resilient to the pandemic shock: They reported better cash flow situations, were more likely to reopen during and after the lockdown, and held more optimistic views of future growth. Likely 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 firm entries have exhibited a V-shaped pattern post the initial lock-down, with new entries of e-commerce firms experiencing a shallower initial drop and a quicker rebound. The pandemic has also accelerated digitization in existing firms (e.g., alteration of operation scope to include e-commerce activities, allowing remote work, and adopting electronic information systems) with persistent effects.

The observed digital transformation is consistent with the intuition of optimizing resource allocation under constraints (the pandemic). First, given the SME owners' limited cognitive bandwidth, learning digital technologies is difficult during normal times but the pandemic and the lockdown provided more time and opportunity (often out of necessity) to adopt new technologies. Meanwhile, the rising online demand from consumers increased the benefit of adopting digital technologies, making investments in digital technologies more beneficial for many firms, especially in areas with less developed financial markets (where SMEs face more financial constraints). At the macroeconomic level, industrial clustering and mass adoption of digital technologies create synergy and network effects, and lower the average adoption cost, rendering the pandemic essentially a "big push" for new technologies, which would have cost the government a lot more under normal circumstances.

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

[26] As an additional example, the OSOME survey from Q4 2021 reveals that 76.7% of the SMEs in the sample are self-employed or have a small number of employees (between 0-4 full-time employees), creating an average of about 4.3 jobs excluding the owners themselves based on estimates in Appendix Table B.13. In China, there are more than 50 million active self-employed businesses and the percentage of workers with part-time jobs in self-employed businesses is much higher than those in incorporated enterprises.

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.[27] Our study, therefore, constitutes an initial step toward understanding SMEs' resilience and the transformative effect of digitization in response to systematic shocks. Besides, using e-commerce as a proxy likely underestimates the true degree of digitization; other aspects of digitization constitute interesting future research.

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# Figures

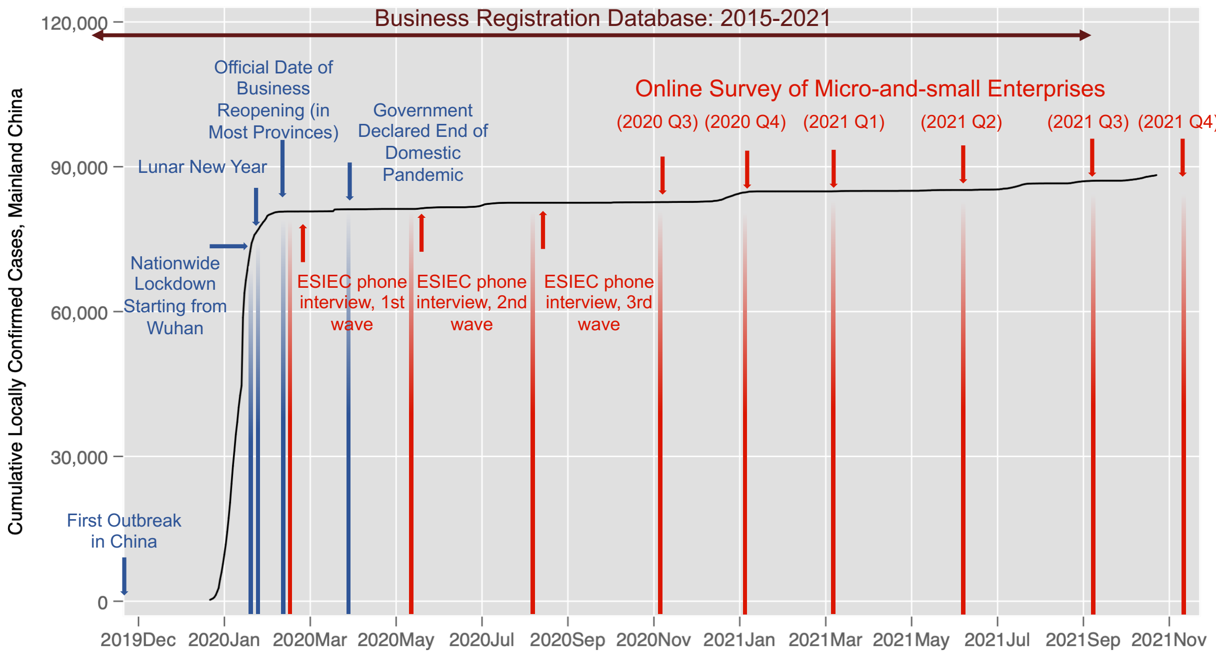



**Figure 1: COVID-19 Outbreak, Reopening, Mitigation Policies, and Surveys**

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

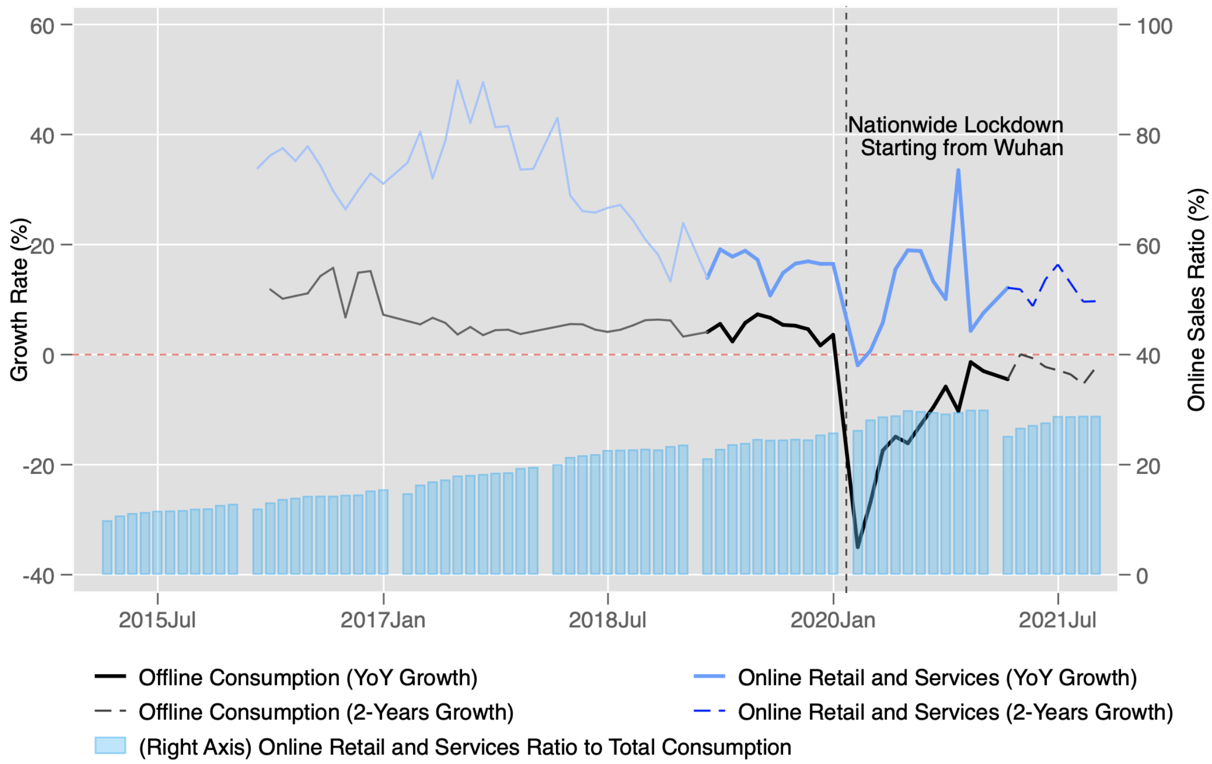



**Figure 2: National Trend of Online and Offline Sales in China**

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.

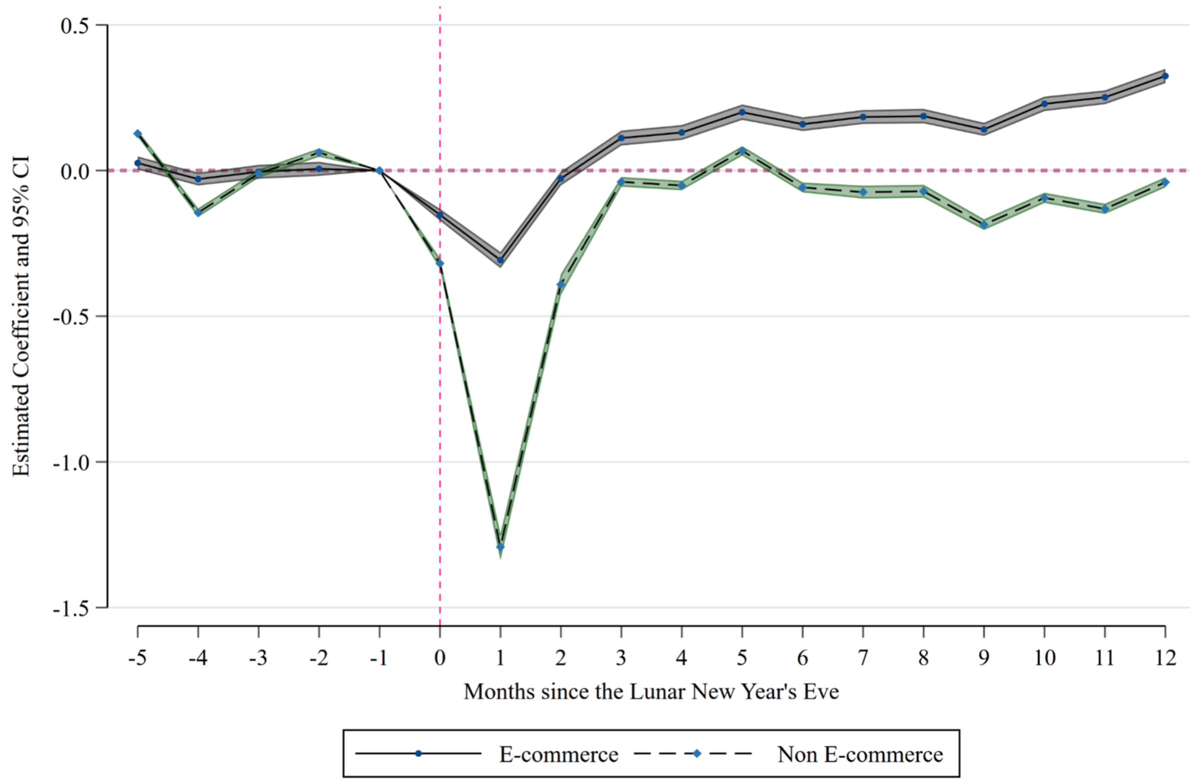



**Figure 3: Event Study of COVID-19 Outbreak and Reopen on New Firm Entry for the Subgroups of E-commerce and Non E-Commerce**

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 for the interaction term between year and month, and the year trend of city-industry.
Data source: SAIC registration database.

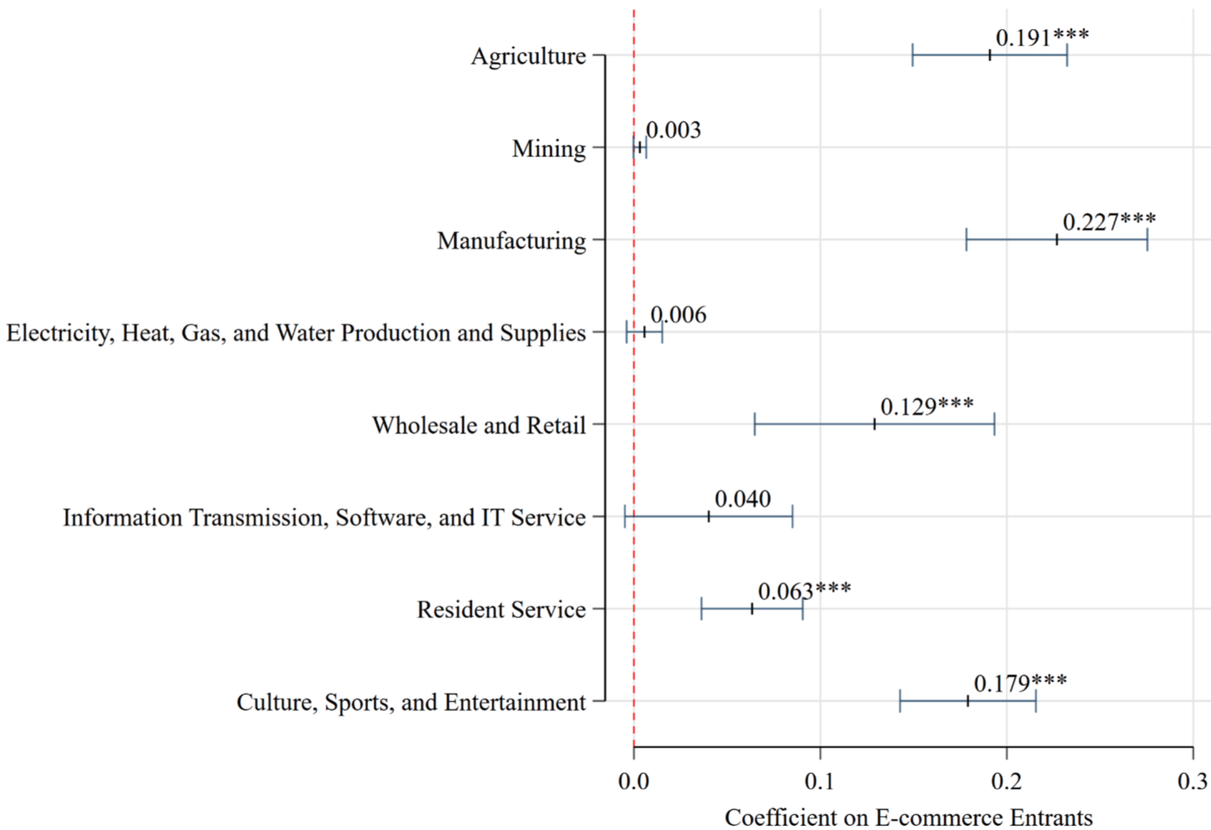



**Figure 4: Heterogeneous Effect of COVID-19 Outbreak and Reopen on New Firm Entry for the E-commerce Subgroup, by Industry**

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 for the interaction term between year and month, and the year trend of the city.
Significance level: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.
Data source: SAIC registration database.

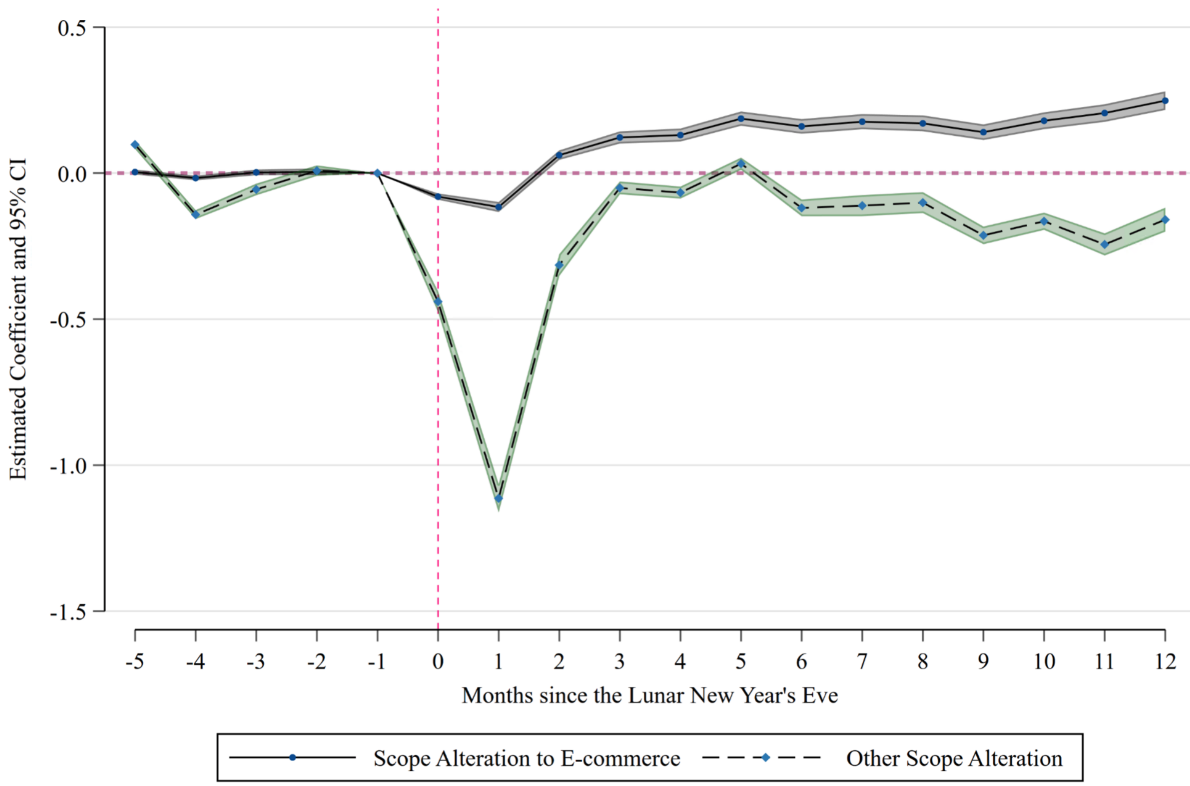



**Figure 5: Event Study of COVID-19 Outbreak and Reopen on Incumbents' Business Operation Scope Alteration for the Subgroups of E-commerce Adoption and Others**

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.

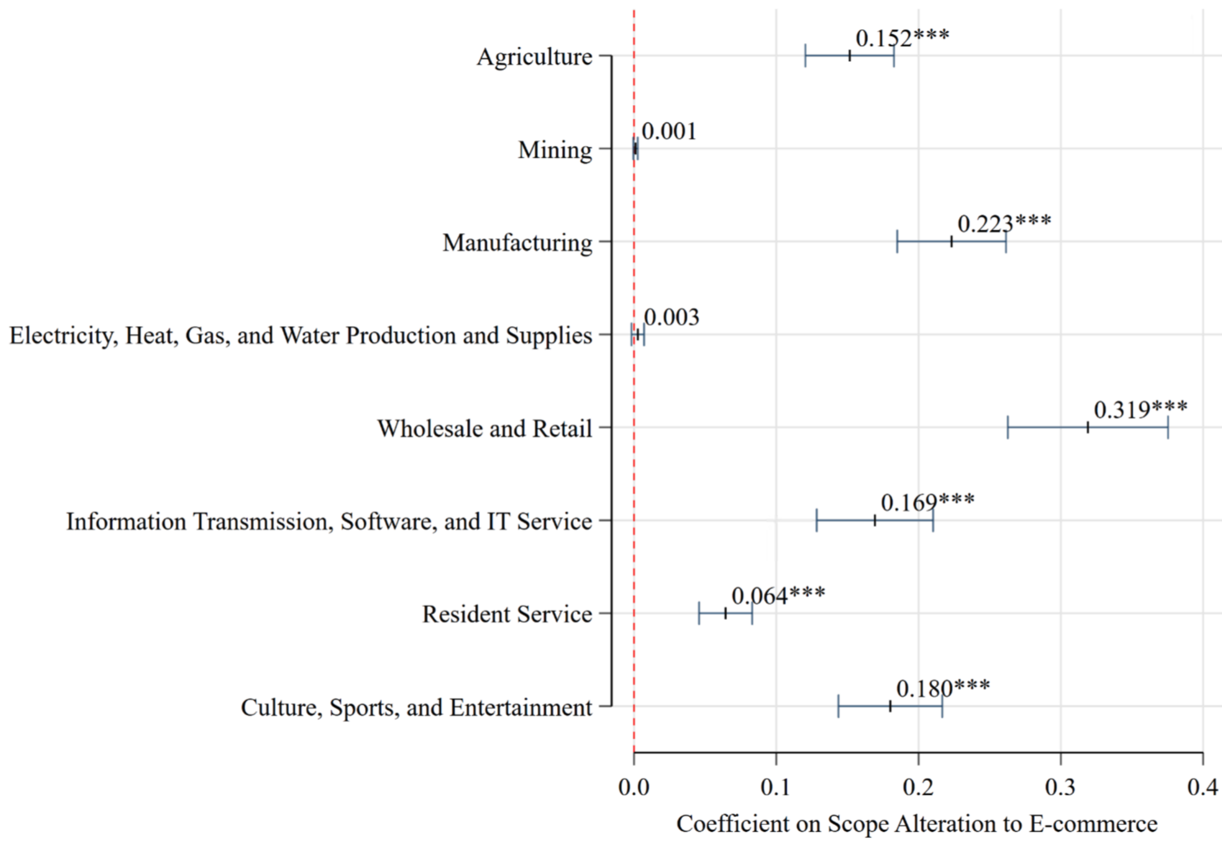



**Figure 6: Heterogeneous Effect of COVID-19 Outbreak and Reopen on Incumbents' Business Operation Scope Alteration to E-commerce, by Industry**

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 for the interaction term between year and month, and the year trend of the city.
Significance level: * $p$ <0.1 ** $p$ <0.05 *** $p$ <0.01.
Data source: SAIC registration database.

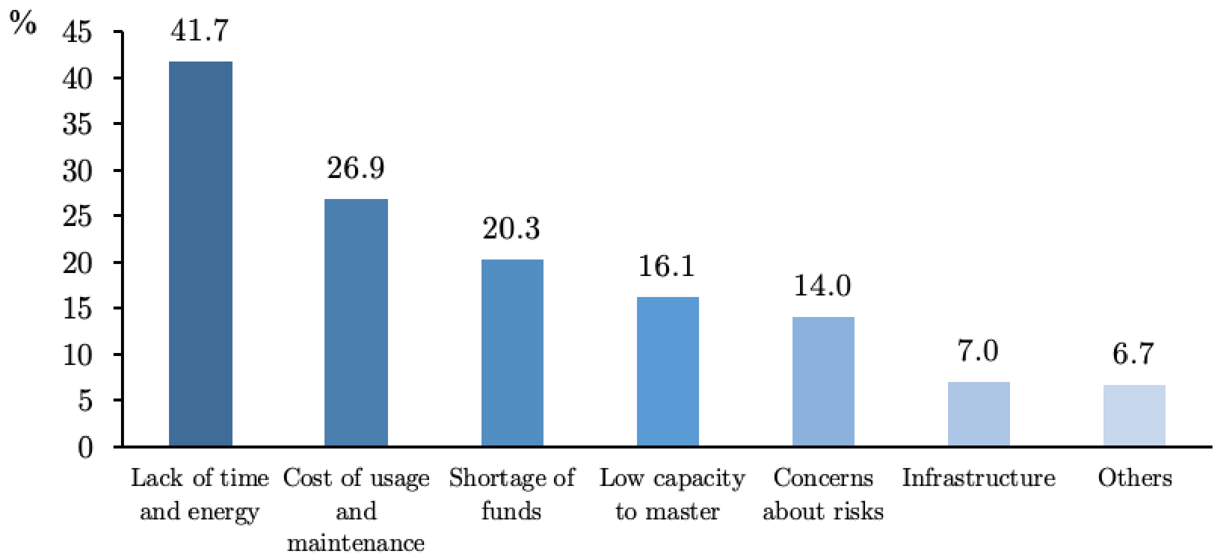



**Figure 7: SME's Greatest Difficulties in Digital Transformation or Upgrading**

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* $\times$ *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 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 the 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 cases, 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 the city level are also consistent. All regressions use samples from the 2020 May wave survey.
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. It ranges from 0 to 1.
The control variables include employment, established year, a dummy for corporate business, city-level COVID-19 confirmed cases, 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: Regression of Online Operation during the Pandemic on SMEs' Cost Pressures**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Operating cost challenge: | | | | |
| | Rent | Raw material | Labor | Prevention | Marketing |
| (COVID × After) × Online operation | -0.016 | -0.055*** | 0.043** | -0.001 | 0.004 |
| | (0.017) | (0.021) | (0.018) | (0.015) | (0.014) |
| Online operation | -0.097*** | -0.032*** | 0.015** | -0.014*** | 0.138*** |
| | (0.006) | (0.007) | (0.006) | (0.004) | (0.004) |
| COVID × After | 0.026 | 0.022 | -0.037 | 0.058** | -0.000 |
| | (0.019) | (0.022) | (0.025) | (0.022) | (0.009) |
| Financing needs | 0.046*** | -0.056*** | 0.062*** | 0.014*** | 0.016*** |
| | (0.008) | (0.007) | (0.007) | (0.004) | (0.005) |
| adj. R-sq | 0.056 | 0.016 | 0.028 | -0.007 | 0.053 |
| Obs. (Incumbents reporting cost challenge) | | | 26,007 | | |
| Control | YES | YES | YES | YES | YES |
| City, industry, & quarter (wave) FEs | YES | YES | YES | YES | YES |
| City × industry FE | YES | YES | YES | YES | YES |
| City × year FE | YES | YES | YES | YES | YES |
| Industry × year FE | 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 of interest includes online operation, *COVID* × *After*, and their interaction term. 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: Regression on Entry and Incumbent's Transformation for the Subgroups of E-commerce and Non E-commerce**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ln(Number of entry + 1) | | ln(Number of incumbents' alteration + 1) | |
| | E-commerce | Non e-commerce | Alteration to e-commerce | Other scope alteration |
| COVID′ (Infection Rate) × After | 0.451*** | -0.339*** | 0.449** | -0.192* |
| | (0.120) | (0.095) | (0.132) | (0.097) |
| Adj. R-sq | 0.797 | 0.875 | 0.585 | 0.852 |
| FEs | YES | YES | YES | YES |
| Obs. | 738,000 | | | |

The dependent variable is the logarithm number of newly registered firms plus one in Columns (1)-(2) and the logarithm number of business operation scope alterations plus one in Columns(3)-(4). The two groups, e-commerce and non e-commerce, are divided by textual analyzing the keywords in the business operation scope and the alteration record. *COVID′* (Infection Rate) indicates the growth rate of confirmed cases (including asymptomatic cases) at the city level from public official sources for 2020 Jan-March. $After = 1$ indicates 2020 Lunar New Year and after, otherwise the value is 0. 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, and the year trend of city-industry.
Significance level: * $p$ <0.1 ** $p$ <0.05 *** $p$ <0.01.
Data source: SAIC registration database.

**Table 7: Regression of on Exit Dynamics for the Subgroups of E-commerce and Non E-commerce**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ln(Number of exit + 1) | | | |
| | E-commerce | Non e-commerce | E-commerce | Non e-commerce |
| COVID × After | 0.598*** | 0.810*** | | |
| | (0.020) | (0.016) | | |
| COVID′ (Infection Rate) × After | | | 0.560*** | 1.722*** |
| | | | (0.110) | (0.368) |
| Adj. R-sq | 0.704 | 0.880 | 0.955 | 0.865 |
| FEs | YES | YES | YES | YES |
| Obs. | 47,880 | | | |

The dependent variable is the logarithm number of exit firms (plus one). The two groups, e-commerce and non e-commerce, are divided by textual analyzing the keywords in the business operation scope and the alteration record. Columns (1) and (2) use the dummy variable for the COVID shock. Columns (3) and (4) use the growth in accumulative COVID cases as an alternative measure of the pandemic shock. All observations are at the city-industry-year level because the exit information is much less frequently updated than the entry information in the registration data due to the lag in the reporting of firm exit. Standard errors are clustered at the city level. The regression controls for the city, industry, and year fixed effects.
Significance level: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.
Data source: SAIC registration database.

**Table 8: Regression of Industrial Clusters on Entry and Incumbent's Transformation for the Subgroups of E-commerce and Non E-commerce**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ln(Number of entry + 1) | | ln(Number of incumbents' alteration + 1) | |
| | E-commerce | Non e-commerce | Alteration to e-commerce | Other scope alteration |
| (COVID × After) × ln(Cluster Index) | 0.039*** | -0.104*** | 0.078*** | -0.163** |
| | (0.015) | (0.009) | (0.018) | (0.015) |
| Adj. R-sq | 0.828 | 0.893 | 0.664 | 0.876 |
| FEs | YES | YES | YES | YES |
| Obs. | 738,000 | | | |

The dependent variable is the logarithm number of newly registered firms plus one in Columns (1)-(2) and the logarithm number of business operation scope alterations plus one in Columns(3)-(4). The two groups, e-commerce and non e-commerce, are divided by textual analyzing the keywords in the business operation scope and the alteration record. The *ln(Cluster Index)* is the logarithmic pre-pandemic cluster index constructed based on the proximity matrix of the production space, while taking into account factors such as correlation and concentration as in Long and Zhang (2011) and Ruan and Zhang (2015). 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, and the year trend of city-industry.
Significance level: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.
Data source: SAIC registration database.

**Table 9: Regression of Financial Capacities on Entry and Incumbent's Transformation for the Subgroups of E-commerce and Non E-commerce**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ln(Number of entry + 1) | | ln(Number of incumbents' alteration + 1) | |
| | E-commerce | Non e-commerce | Alteration to e-commerce | Other scope alteration |
| *Panel A:* | | | | |
| (COVID × After) × Financial Inefficiency | 0.083*** | -0.143*** | 0.099*** | -0.180*** |
| | -0.022 | -0.017 | -0.026 | -0.022 |
| Adj. R-sq | 0.839 | 0.894 | 0.680 | 0.880 |
| Obs. | | | 653,500 | |
| *Panel B:* | | | | |
| (COVID × After) × Digital Financial Inclusion | 0.003*** | -0.004*** | 0.004*** | -0.006*** |
| | (0.022) | (0.017) | (0.026) | (0.022) |
| Adj. R-sq | 0.828 | 0.893 | 0.664 | 0.876 |
| Obs. | | | 738,000 | |
| FEs | YES | YES | YES | YES |

The dependent variable is the logarithm number of newly registered firms plus one in Columns (1)-(2) and the logarithm number of business operation scope alterations plus one in Columns(3)-(4). The two groups, e-commerce and non e-commerce, are divided by textual analyzing the keywords in the business operation scope and the alteration record. The financial inefficiency index in Panel A is the standard deviation of logarithm of the value added/total asset ratio at the city-industry level from China Economic Census 2008. Some observations are dropped since the China Economic Census 2008 didn't cover some areas and some sectors such as agriculture. The digital financial inclusion index in Panel B is the city-level index of digital finance in 2015 produced by a research team from the Institute of Digital Finance at Peking University and Ant Group. 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, and the year trend of city-industry.
Significance level: * $p<0.1$ ** $p<0.05$ *** $p<0.01$.
Data source: SAIC registration database, China Economic Census 2008, Peking University Digital Financial Inclusion Index of China.

**Table 10: 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 quarterly 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 11: 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 quarterly 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 12: Regression of Online Operation during the Pandemic on SMEs' Efficiency using Propensity Score Matching**

| | Revenue | Profit | Cashflow | Recover |
|---|---|---|---|---|
| *Panel A: All sample* | | | | |
| (COVID × After) × Online operation | 1.149 | 1.000* | 0.112* | n.a. |
| | (1.008) | (0.531) | (0.060) | |
| Online operation | 1.615*** | -0.243* | 0.191*** | |
| | (0.199) | (0.129) | (0.017) | |
| COVID × After | -1.432* | -2.192*** | -0.125** | |
| | (0.785) | (0.482) | (0.062) | |
| adj. R-sq | 0.201 | 0.010 | 0.017 | |
| Matched Obs. | | 63,532 | | |
| *Panel B: Newly established subsample* | | | | |
| (COVID × After) × Online operation | 0.546 | -1.849 | 0.073 | n.a. |
| | (2.850) | (1.561) | (0.282) | |
| Online operation | 1.174** | -0.352 | 0.140*** | |
| | (0.502) | (0.357) | (0.049) | |
| COVID × After | 0.725 | -2.710** | -0.209 | |
| | (2.024) | (1.279) | (0.175) | |
| adj. R-sq | 0.047 | -0.074 | -0.058 | |
| Matched Obs. | | 7,170 | | |
| *Panel C: Incumbent subsample* | | | | |
| (COVID × After) × Online operation | 1.649* | 1.812*** | 0.179** | 2.738 |
| | (0.996) | (0.572) | (0.073) | (1.774) |
| Online operation | 1.947*** | -0.305** | 0.213*** | 2.229*** |
| | (0.239) | (0.140) | (0.020) | (0.370) |
| COVID × After | -0.943 | -2.335*** | -0.157** | -3.372*** |
| | (0.671) | (0.517) | (0.075) | (1.056) |
| adj. R-sq | 0.212 | 0.007 | 0.014 | 0.028 |
| Matched Obs. | | 48,430 | | |
| Control | YES | YES | YES | YES |
| City, industry, & quarter FEs | YES | YES | YES | YES |
| City × industry FE | YES | YES | YES | YES |
| City × year FE | YES | YES | YES | YES |
| Industry × year FE | YES | YES | YES | YES |

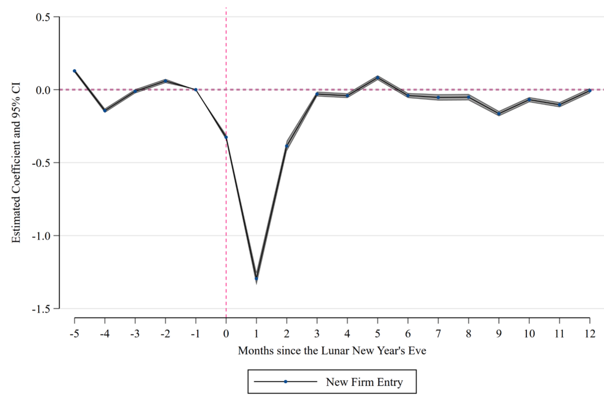
The table uses propensity score matching method on SMEs' basic characteristics to construct the matched sample for each panel, including business type, industry, employment, firm age, owner's age and gender, city tier, and survey quarter. Using nearest neighbors matching, Radius matching, or Kernel matching doesn't change the result.
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 of interest includes online operation, *COVID × After*, and their interaction term. 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 13: Coefficients of Heterogeneity Regressions using Propensity Score Matching**

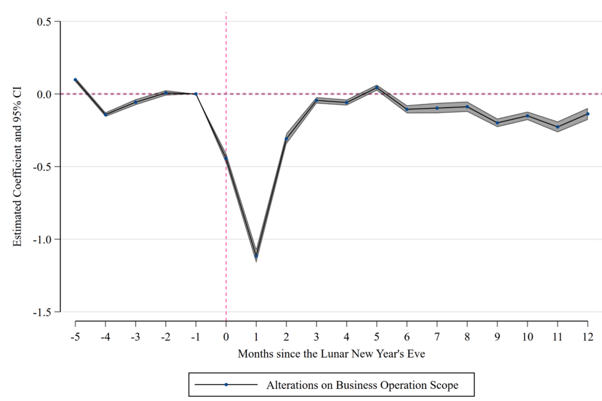
| | Coefficient of *(COVID × After) × Online operation* on *Profit* |
|---|---|
| *Business type:* | |
| Corporate enterprise | 4.373*** |
| Self-employed, registered | -0.304 |
| Self-employed, unregistered | 1.550* |
| *Industry:* | |
| Agriculture | -1.467 |
| Construction and manufacturing | -1.002 |
| Service | 1.001 |
| *Employment:* | |
| 0-19 | 0.749 |
| 20+ | 5.517** |
| *City tier:* | |
| Tier 1 | 1.200* |
| Tier 2 | 3.108** |
| Tier 3 | -0.325 |
| Tier 4 | -0.558 |
| Tier 5 | -0.706 |
| *Gender:* | |
| Female | 3.291*** |
| Male | 0.985 |

The table reports the estimates for the interaction terms between COVID restrictions and online operations, *(COVID × After) × Online operation*, and significance levels. To save space, standard errors are omitted. The table uses propensity score matching method on SMEs' basic characteristics to construct the matched sample for each panel, including business type, industry, employment, firm age, owner's age and gender, city tier, and survey quarter. Using nearest neighbors matching, Radius matching, or Kernel matching doesn't change the result.
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 of interest includes *Online operation*, *COVID × After*, and their interaction term. 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 the corresponding interacted fixed effects.
Significance level: * $p$ <0.1 ** $p$ <0.05 *** $p$ <0.01.
Data source: OSOME.

# Appendix A Appendix 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 interval. 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 for the interaction term between year and month, and the year trend of city-industry.
Data source: SAIC registration database.

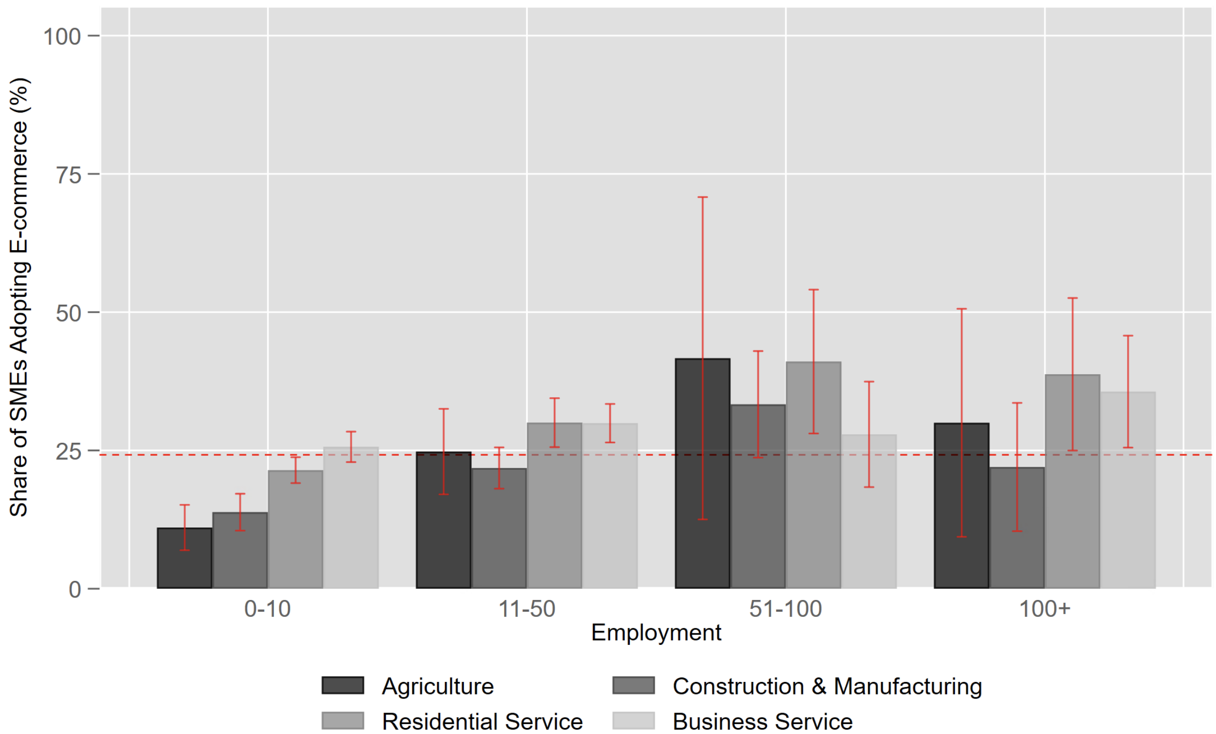



**Figure A.2: Share of SMEs Adopting E-commerce in ESIEC, by Industry and Employment**

The 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.

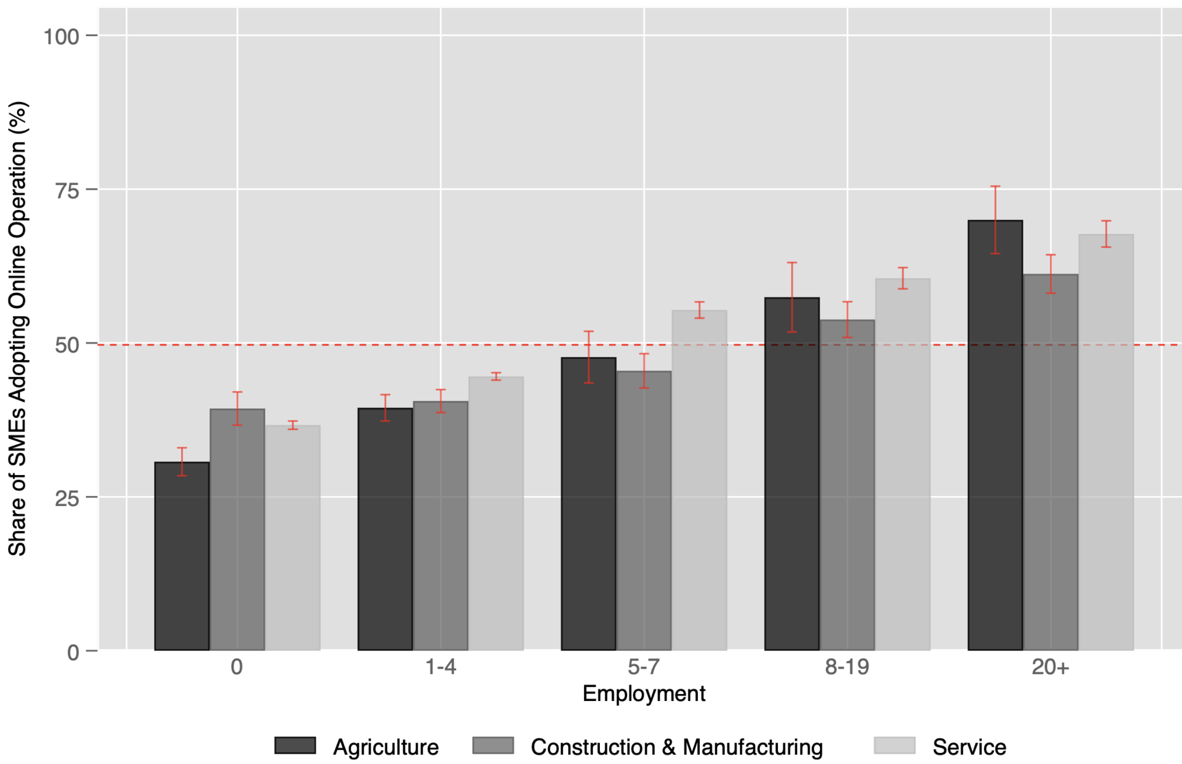



**Figure A.3: Share of SMEs Adopting Online Operation in OSOME, by Industry and Employment**

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.

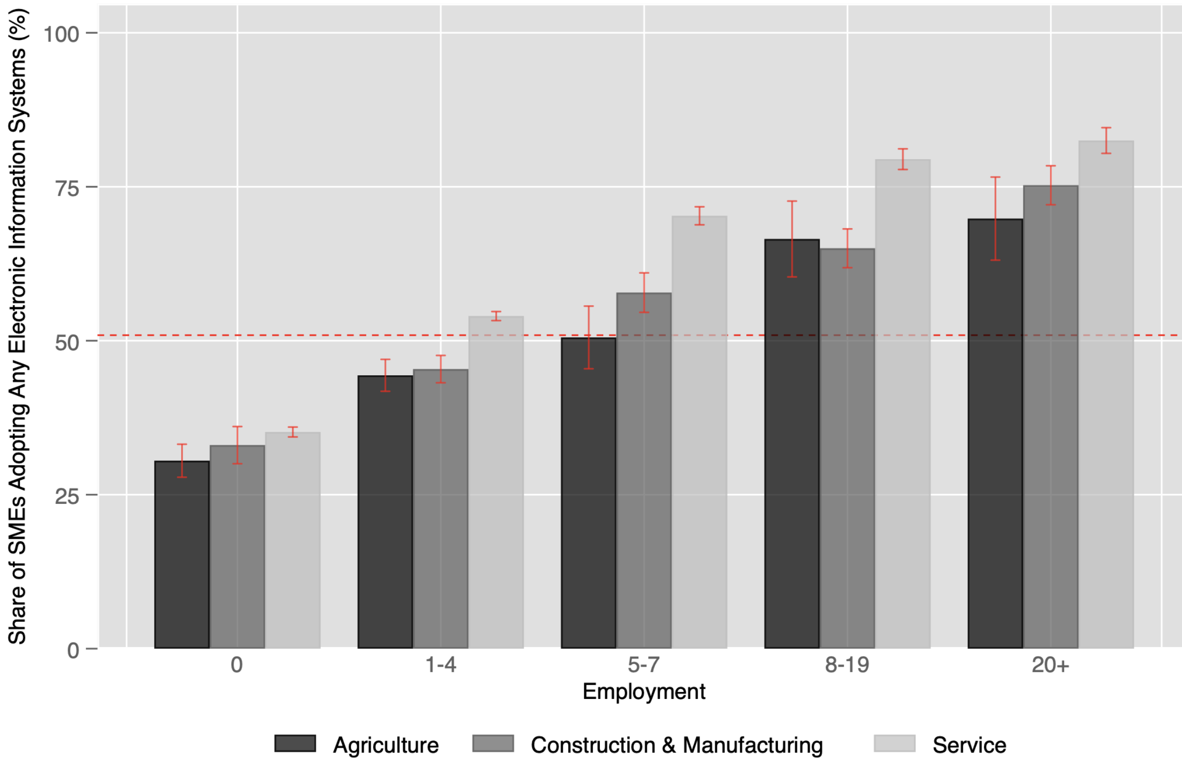
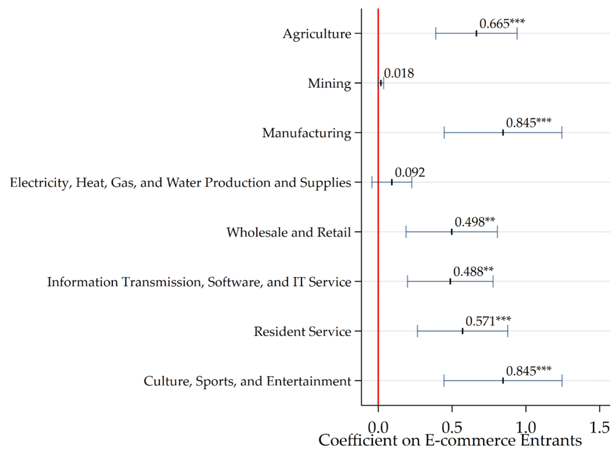
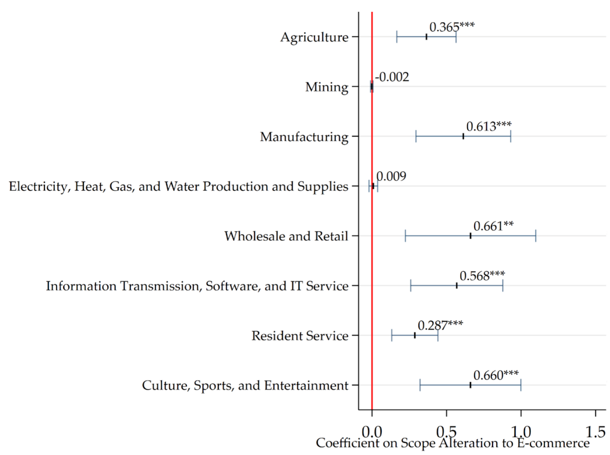



**Figure A.4: Share of SMEs Adopting Any Electronic Information Systems in OSOME, by Industry and Employment**

The 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.




(a) New Firm Entry




(b) Alterations on Business Operation Scope

**Figure A.5: Heterogeneous Effect of COVID-19 Outbreak and Reopen on Entry and Incumbents' Transformation to E-commerce, by Industry**

The dependent variable in Panel (a) is the logarithm of one plus the number of newly registered firms (plus one); the dependent variable in Panel (b) is the logarithm of one plus the number of alterations of business operation scope (plus one), identified by textual analyzing the keywords in the business operation scope text and the alteration record. The figure plots the coefficient estimate of $COVID \times After$ and the confidence interval for each main industry, where $COVID$ indicates the growth rate of confirmed cases at the city level from public official sources for 2020 Jan-March, and $After = 1$ indicates 2020 Lunar New Year and after, otherwise the value is 0. The label shows the estimated value and the significant level. 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 for the interaction term between year and month, and the year trend of the city.
Significance level: * $p$ <0.1 ** $p$ <0.05 *** $p$ <0.01.
Data source: SAIC registration database.

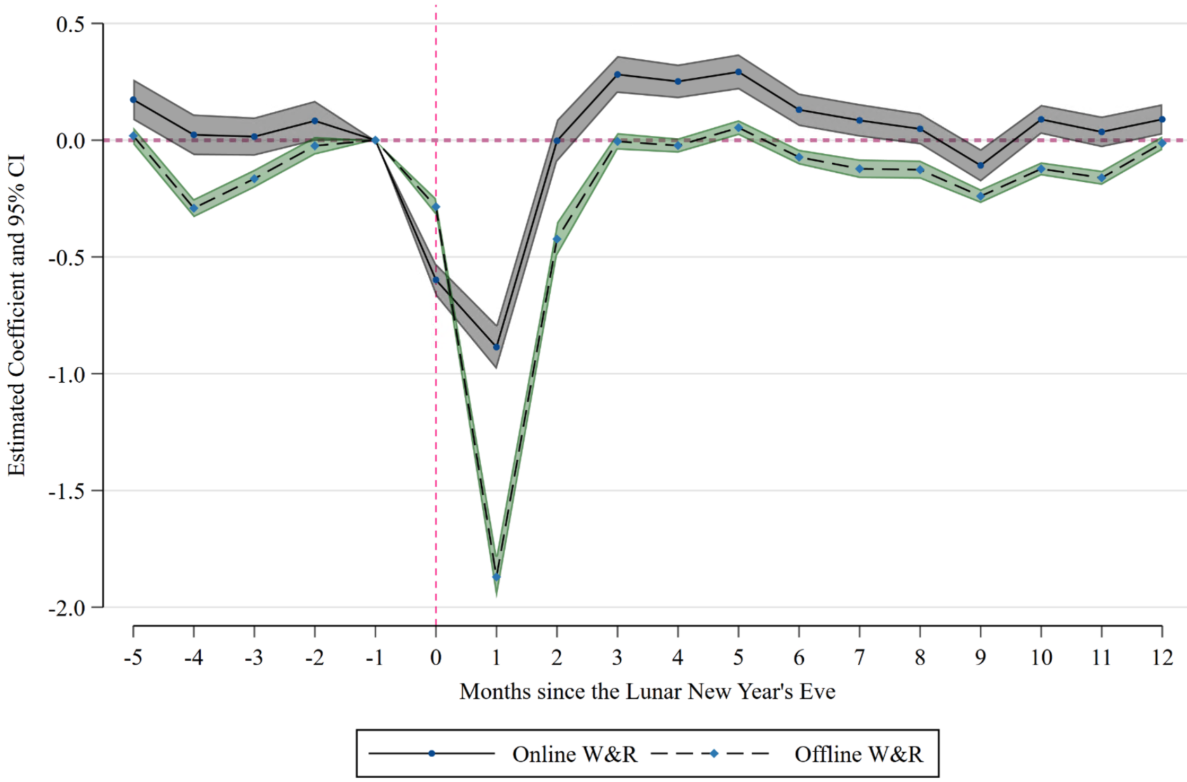



**Figure A.6: Event Study of COVID-19 Outbreak and Reopen on New Firm Entry for the Subgroups of E-commerce and Non E-Commerce, Wholesale and Retail Industries**

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 for the interaction term between year and month, and the year trend of city-industry.
Similar to the textual analysis of business operation scope, the classification by industry code may also lead to underestimation, if anything, that goes against significant findings. This figure 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.
Data source: SAIC registration database.

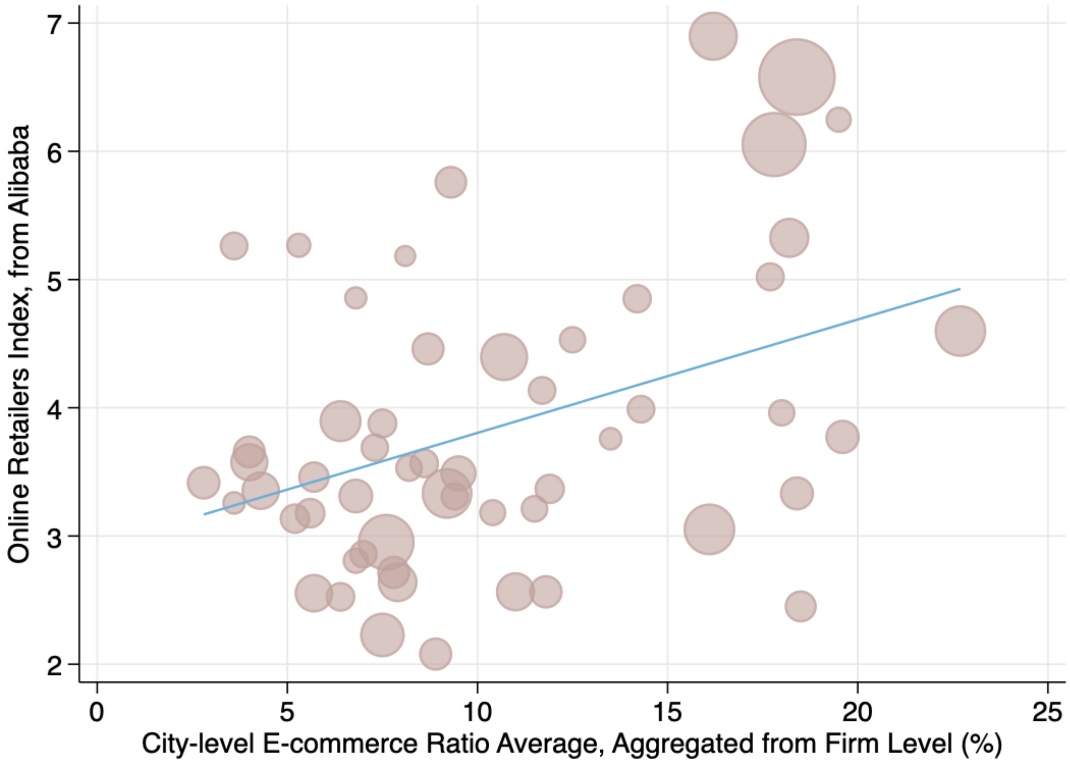



**Figure A.7: City-level E-commerce Ratio Average Aggregated from ESIEC and Alibaba E-commerce Index**

The X-axis is the city-level e-commerce average aggregated from firm-level *E-commerce*, which 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. The size of each bubble represents the sample size in each city. The Y-axis is the city-level Online Retailers Index from Alibaba in 2018.
Data source: ESIEC, Alibaba Research.

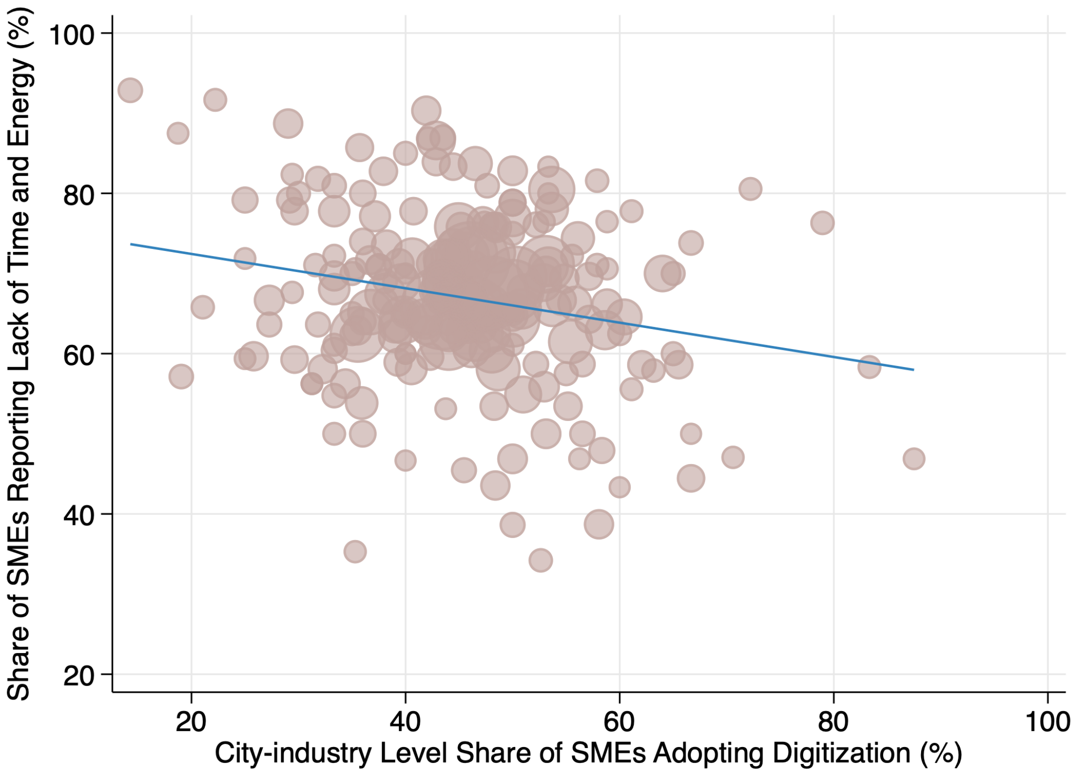



**Figure A.8: City-level Digitization and SMEs' Report on "Lack of Time and Energy to Learn"**

The X-axis is the city-industry level share of SMEs adopting digitization, including online operation, e-commerce, remote work, and electronic information systems. The Y-axis is the share of SMEs reporting a "lack of time and energy to learn (digital tools)" at each city-industry cell. The size of each bubble represents the sample size in each city-industry cell.
Data source: OSOME.

# Appendix B Tables for Additional Results

**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 the 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 cases, 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 the 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 the 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.
The control variables include employment, established year, a dummy for corporate business, city-level COVID-19 confirmed cases, 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 the 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.

**Table B.4: Regression of Digital Edge with Logarithm E-commerce Ratio**

| | (1) Pooled | (2) February | (3) May | (4) August |
|---|---|---|---|---|
| *Panel A:* | Demand: order decline as main challenge | | | |
| log(1 + E-commerce ratio) | -0.037** | -0.148 | -0.018* | -0.017* |
| | (0.019) | (0.091) | (0.011) | (0.009) |
| adj. R-sq | 0.378 | 0.087 | 0.114 | -0.036 |
| *Panel B:* | Cash flow >1 month | | | |
| log(1 + E-commerce ratio) | 0.130*** | 0.084 | 0.122*** | 0.200*** |
| | (0.031) | (0.077) | (0.044) | (0.069) |
| adj. R-sq | 0.067 | 0.103 | 0.030 | 0.062 |
| *Panel C:* | Reopen status | | | |
| log(1 + E-commerce ratio) | 0.082*** | 0.027 | 0.056* | 0.154*** |
| | (0.023) | (0.078) | (0.033) | (0.032) |
| adj. R-sq | 0.511 | 0.112 | 0.041 | 0.033 |
| *Panel D:* | Outlook for growth | | | |
| log(1 + E-commerce ratio) | 0.087** | 0.002 | 0.030 | 0.183** |
| | (0.037) | (0.057) | (0.057) | (0.078) |
| adj. R-sq | 0.155 | 0.009 | 0.091 | 0.065 |
| 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 uses the logarithm form of firm-level *E-commerce*, which 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.
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 B.5: Regression of Supply Chains and E-commerce Adoption on SMEs' Resilience (August 2020)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Demand: order decline as main challenge | Cash flow >1 month | Reopen status | Outlook for growth |
| *Panel A: Supplier* | | | | |
| Local suppliers | -0.013** | 0.087** | 0.015 | 0.099* |
| | (0.005) | (0.033) | (0.020) | (0.034) |
| E-commerce ratio | -0.025** | 0.207*** | 0.102*** | 0.114 |
| | (0.010) | (0.066) | (0.030) | (0.075) |
| Local suppliers × E-commerce ratio | 0.029** | -0.159* | 0.011 | 0.012 |
| | (0.012) | (0.096) | (0.039) | (0.109) |
| adj. R-sq | -0.033 | 0.066 | 0.031 | 0.072 |
| *Panel B: Customer* | | | | |
| Local customers | -0.004 | 0.124*** | 0.031 | 0.063* |
| | (0.008) | (0.034) | (0.022) | (0.034) |
| E-commerce ratio | -0.017 | 0.296*** | 0.136*** | 0.125 |
| | (0.011) | (0.076) | (0.031) | (0.090) |
| Local customers × E-commerce ratio | 0.008 | -0.255*** | -0.047 | -0.013 |
| | (0.011) | (0.098) | (0.041) | (0.114) |
| adj. R-sq | -0.037 | 0.072 | 0.033 | 0.066 |
| Control | YES | YES | YES | YES |
| Supplementary Control | YES | YES | YES | YES |
| City FE | YES | YES | YES | YES |
| Industry FE | YES | YES | YES | YES |
| Obs. | 1,245 | | | |

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. All regressions use samples in August 2020 wave survey. The *Local suppliers* is a dummy variable indicating whether the firm had any local key suppliers before the pandemic. The *Local customers* is a dummy variable indicating whether the firm had any local key customers before the pandemic.

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, education level, and other firm-level pre-COVID characteristics: dummy variables for innovation or new product, revenue larger than one million RMB, on-the-job training, and 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.

**Table B.6: Regression on SMEs' Adjustment during the Lockdown in Jan-Apr 2020**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Adjustment during the lockdown in Jan-Apr 2020: | | | |
| | Online sales and purchase | Remote work | Production reduction or suspension | New equipment |
| E-commerce ratio | 0.601*** | 0.093** | -0.044* | -0.044* |
| | (0.033) | (0.040) | (0.025) | (0.025) |
| adj. R-sq | 0.477 | 0.141 | 0.080 | 0.080 |
| Control | YES | YES | YES | YES |
| Supplementary Control | YES | YES | YES | YES |
| City FE | YES | YES | YES | YES |
| Industry FE | YES | YES | YES | YES |
| Obs. | 1,671 | | | |

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.
The control variables include employment, established year, a dummy for corporate business, city-level COVID-19 confirmed case, city-level COVID-19 case growth in 30 days, and supplementary controls above. The regression further control for a series of dummy variables indicating whether SMEs had tax support, financial support, rent or cost reduction, and social security subsidies. 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 B.7: SMEs' Primary Source of Business Operating Pressures**

| | Percent of Answers: | | | | | |
|---|---|---|---|---|---|---|
| | 2020Q3 | 2020Q4 | 2021Q1 | 2021Q2 | 2021Q3 | 2021Q4 |
| Operating costs escalation | 30.9 | 33.0 | 36.6 | 33.2 | 31.9 | 32.9 |
| Weak market demand | 40.5 | 39.3 | 32.3 | 32.5 | 30.8 | 30.9 |
| Loan repayment | 12.1 | 11.0 | 13.8 | 15.2 | 14.8 | 13.9 |
| Uncertainty in policies | 11.3 | 11.1 | 11.9 | 12.0 | 15.4 | 15.1 |
| Taxation and fee | 2.5 | 2.0 | 3.2 | 3.5 | 3.6 | 3.7 |
| Other | 2.7 | 3.7 | 2.3 | 3.5 | 3.5 | 3.5 |

It is a multiple-choice question where SME owners can choose two options at most. The table calculate the percentage of answers. We also calculate the percentage of respondents, and the result is naturally consist. Data source: OSOME.

**Table B.8: Regression of Digital Edge for Tradable and Non-tradable Sectors**

| | (1) Demand: order decline as main challenge | (2) Cash flow >1 month | (3) Reopen status | (4) Outlook for growth |
|---|---|---|---|---|
| *Panel A: Tradable sector* | | | | |
| E-commerce ratio | -0.055** | 0.017 | 0.078** | 0.008 |
| | (0.028) | (0.052) | (0.032) | (0.051) |
| adj. R-sq | 0.462 | 0.083 | 0.542 | 0.188 |
| Obs. | | 1,247 | | |
| *Panel B: Non-tradable sector* | | | | |
| E-commerce ratio | -0.018 | 0.111*** | 0.059*** | 0.078** |
| | (0.015) | (0.025) | (0.020) | (0.031) |
| adj. R-sq | 0.341 | 0.066 | 0.502 | 0.143 |
| Obs. | | 3,010 | | |
| Control | YES | YES | YES | YES |
| Supplementary Control | YES | YES | YES | YES |
| Wave dummy | YES | YES | YES | YES |
| City FE | YES | YES | YES | YES |
| Industry FE | YES | YES | YES | YES |

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 tradable and non-tradable sectors are classified by the definition of OECD. 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, city-level COVID-19 case growth in 30 days, and supplementary controls above. The regression further control for a series of dummy variables indicating whether SMEs had tax support, financial support, rent or cost reduction, and social security subsidies. 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 B.9: Short-term Digital Edge on Corporate Finance during the Early Reopening (May 2020) for Tradable and Non-tradable Sectors**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Account receivable: | | | Account Payable: |
| | % Current Assets >50% | Repayment period: | | % Current Assets >50% |
| | | >60 days | Uncertainty | |
| *Panel A: Tradable sector* | | | | |
| E-commerce ratio | -0.079* | -0.169** | 0.019 | -0.034 |
| | (0.046) | (0.066) | (0.063) | (0.061) |
| adj. R-sq | 0.072 | 0.141 | 0.262 | 0.136 |
| Obs. | 484 | | | |
| *Panel B: Non-tradable sector* | | | | |
| E-commerce ratio | -0.065* | -0.068* | -0.064** | -0.058 |
| | (0.036) | (0.040) | (0.032) | (0.039) |
| adj. R-sq | 0.099 | 0.111 | 0.211 | 0.118 |
| Obs. | 1,183 | | | |
| Control | YES | YES | YES | YES |
| Supplementary Control | YES | YES | YES | YES |
| City FE | YES | YES | YES | YES |
| Industry FE | YES | YES | YES | YES |

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 tradable and non-tradable sectors are classified by the definition of OECD. 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 business, city-level COVID-19 confirmed case, city-level COVID-19 case growth in 30 days, and supplementary controls above. The regression further control for a series of dummy variables indicating whether SMEs had tax support, financial support, rent or cost reduction, and social security subsidies. 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 B.10: Regression on SOEs and non-SOEs Entry for the Subgroups of E-commerce and Non E-commerce**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ln(Number of entry + 1), SOE | | ln(Number of entry + 1), non SOE | |
| | E-commerce | Non e-commerce | E-commerce | Non e-commerce |
| COVID × After | 0.048** | 0.006 | 0.461*** | 0.088 |
| | (0.020) | (0.085) | (0.149) | (0.063) |
| Adj. R-sq | 0.045 | 0.220 | 0.811 | 0.907 |
| FEs | YES | YES | YES | YES |
| Obs. | 738,000 | | | |

The dependent variable is the logarithm number of newly registered firms plus one. SOEs and non-SOEs are based on the registered enterprise type. The two groups, e-commerce and non e-commerce, are divided by textual analyzing the keywords in the business operation scope and the alteration record. *COVID′* (Infection Rate) indicates the growth rate of confirmed cases (including asymptomatic cases) at the city level from public official sources for 2020 Jan-March. *After = 1* indicates 2020 Lunar New Year and after, otherwise the value is 0. 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, and the year trend of city-industry.
Significance level: * $p$ <0.1 ** $p$ <0.05 *** $p$ <0.01.
Data source: SAIC registration database.

**Table B.11: Primary difficulty for SMEs in digital transformation or upgrading**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Difficulties in digital transformation | | | |
| *Panel A: Subjective constraints* | Subjective: all | Lack of time and energy | Low capacity to master | Concerns about risks |
| Digital adoption | -0.061*** | -0.123*** | -0.019*** | 0.064*** |
| | (0.009) | (0.009) | (0.007) | (0.007) |
| Employment >20 | 0.058* | -0.102*** | 0.053* | 0.080*** |
| | (0.035) | (0.036) | (0.031) | (0.029) |
| adj. R-sq | 0.021 | 0.033 | 0.016 | 0.013 |
| *Panel B: External constraints* | External: all | Cost | Shortage of fund | Infrastructure |
| Digital adoption | 0.111*** | 0.016* | 0.086*** | 0.034*** |
| | (0.010) | (0.009) | (0.008) | (0.006) |
| Employment >20 | 0.018 | -0.013 | -0.008 | 0.034* |
| | (0.036) | (0.036) | (0.028) | (0.018) |
| adj. R-sq | 0.048 | 0.021 | 0.030 | 0.006 |
| Control | YES | YES | YES | YES |
| City FE | YES | YES | YES | YES |
| Industry FE | YES | YES | YES | YES |
| City-industry FE | YES | YES | YES | YES |
| Obs. | 11,225 | | | |

The OSOME survey included this question only in the second quarter. All regressions in the table use OLS estimation. The fixed-effect Logit model also gives consistent results. The *Digital adoption* includes online operation or sales, remote work, and electronic information systems. Standard errors in parentheses are clustered at the city level. 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, and city × industry fixed effects.
Significance level: * $p$ <0.1 ** $p$ <0.05 *** $p$ <0.01.
Data source: OSOME.

**Table B.12: Coefficients of Heterogeneity Regressions on Digital Adoption during the Pandemic**

| | (1) | (2) | (3) |
|---|---|---|---|
| | Coefficient of $COVID \times After$ on: | | |
| | Online operation | Online sales | Remote work |
| ***Panel A: Firm*** | | | |
| *Business type:* | | | |
| Corporate enterprise | 0.032 | 0.007 | -0.005 |
| Self-employed, register | 0.027* | 0.020 | 0.008 |
| Self-employed, unregister | 0.004 | 0.008 | 0.018 |
| *Industry:* | | | |
| Agriculture | 0.024 | 0.017 | -0.007 |
| Construction and manufacturing | 0.039 | 0.032 | 0.019 |
| Service | 0.020* | 0.014 | 0.010 |
| *Employment:* | | | |
| 0-19 | 0.015 | 0.010 | 0.009 |
| 20+ | 0.117* | 0.116** | 0.025 |
| *Financing needs:* | | | |
| Yes | -0.004 | -0.005 | 0.005 |
| No | 0.026** | 0.021 | 0.016 |
| ***Panel B: Entrepreneur*** | | | |
| *Gender:* | | | |
| Female | 0.076*** | 0.073*** | 0.034* |
| Male | 0.009 | 0.002 | 0.019** |
| *Age:* | | | |
| 18-35 | 0.023** | 0.017 | 0.014* |
| 36-60 | 0.008 | 0.006 | -0.008 |
| 61+ | n.a. | n.a. | n.a. |
| *Education:* | | | |
| No schooling | 0.157 | -0.018 | 0.087 |
| <= Senior high school | 0.002 | -0.008 | 0.002 |
| >= College | 0.037*** | 0.037*** | 0.016 |

The table reports the estimates for the interaction terms *($COVID \times After$)* and significance levels. To save space, standard errors are omitted. 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, $COVID \times After$, 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 B.13: SMEs' Job Creation Estimation**

| | Job creation (excluding business owners) | | % no full-time employee | % 1-4 full-time employees |
|---|---|---|---|---|
| | average | median | | |
| *Full sample* | 4.3 | 2.0 | 35.0% | 43.9% |
| *by Business type:* | | | | |
| Self-employed, unregister | 2.8 | 1.0 | 47.4% | 38.4% |
| Self-employed, register | 3.6 | 2.0 | 30.5% | 51.4% |
| Corporate enterprise | 13.1 | 5.0 | 10.5% | 31.8% |

Samples in the 2021Q4 survey are included.
Data source: OSOME.

# Appendix C Supplementary Description on Data

**ESIEC phone following survey in 2020.** After the outbreak of the COVID-19 pandemic in China, the ESIEC team immediately conducted multiple phone surveys with previously interviewed entrepreneurs in the baseline survey (Figure 1 for the timeline of the surveys). The questionnaire mainly focused on the firm's reopening and operational status, challenges, responses, and prospects. The first two rounds of phone surveys tracked firms drawn from the 2017, 2018, and 2019 ESIEC surveys, and received 2,513 responses (February 11-16, 2020) and 2,508 responses (May 18-24, 2020, with some respondents from Feb reportedly shut down their businesses in May), respectively. Overall, the completion rate is about 50% for those with valid contact information. 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 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.[28] Supplementary information can be matched with the baseline survey and the SAIC data.[29]

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.

**SAIC business registration data.** This dataset has greater coverage of small, medium, and micro enterprises than other firm-level databases. In contrast, the commonly used Annual Survey of Industrial Firms (ASIF) in China, also known as the China Industry

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

[29]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`.

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. Besides, since SAIC is up-to-date, we can analyze firm responses during the pandemic and after the reopening. Dai et al. (2021a) have used the dataset to examine the role of clusters in businesses' buffering of the COVID-19 shock.

**OSOME data.** The full sample we use 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 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.

# Appendix D 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 for external validation.

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 include 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 algorithms 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 algorithms 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.

# Appendix E Firm-level E-commerce Ratio Measurement

We use the firm-level 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. Although we use the continuous measure in the regression, it is also helpful to check the binary specification (*E-commerce ratio* $> 0$). As Table 1 shows, nearly 24.2% of SMEs in the ESIEC sample had adopted online sales. Yet, the adoption of online sales across industries and firm sizes varies, 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. For robustness, we add more tests.

First, we add Appendix Table B.4 by using log (1+ E-commerce ratio). It is apparent from the table that the results are robust. We also check that our results are robust to using the Poisson pseudo maximum likelihood, but decided not to report the results to save space.

Besides, it is definitely possible to aggregate the E-commerce ratio at the city level, and then compare that with the information in the official statistical yearbook too. we have added some discussions to compare the city-level online sales ratio calculated from our survey data with official statistics. According to the *China Retail Industry Development Report* by the Ministry of Commerce in 2018, the proportion of national online retail sales to the total retail sales of consumer goods was 18.4%, which is higher than the 12.2% (arithmetic average) in the descriptive statistics in Table 1. The reason for the discrepancy is that the retail statistics only account for final consumption, while intermediate goods sold by enterprises through online channels in the supply chain are not included. In general, the wholesale sales of intermediate goods rely more on offline channels.[30]

The city-level measurement for online retails, especially in official statistics yearbooks, is not available. Yet we collected the city-level Alibaba e-commerce index as a proxy to double-check the representativeness of our E-commerce ratio measurement from the survey data. Specifically, this index is based on massive transaction data from the Taobao and Tmall platforms. It summarizes the transaction information of each region of the country on

[30]Please refer to `http://tjj.sz.gov.cn/ztzl/zt/tjzshb/qytjzsdb/pflsyzscyyhxftj/content/post_10038677.html`.

its e-commerce platform each year and calculates the index by standardizing and weighting according to the weight criteria, including online shopping index, e-commerce retailers index, logistics index, etc. Taobao and Tmall, the two major e-commerce platforms operated by Alibaba in China, have a dominant market share in the country's e-commerce market. Therefore, the index can reflect the regional heterogeneity of e-commerce penetration to some extent. Here we use the city-level e-commerce retailers index in 2018 with the city-level average aggregated from the E-commerce ratio variable in our baseline survey. The below figure shows that our survey data is highly correlated to the online retailers index.

# Appendix F Tradable Versus Nontradable Sectors

Using the definitions by OECD, we first classify tradables and non-tradables. Tradable sectors are defined by a selection of the 10 industries defined in the SNA 2008. They include agriculture (A), industry (BCDE), information and communication (J), financial and insurance activities (K), and other services (RSTU). Non-tradable sectors are composed of construction, distributive trade, repairs, transport, accommodation, food services activities (GHI), real estate activities (L), business services (MN), and public administration (OPQ).[31]

We then show Appendix Table B.8 to examine the subsample of the Tradable and non-tradable sectors. Note that in order to pencil out a few confounding factors, such as local government-specific fiscal and financial subsidies by the E-commerce platform, we further control for a series of dummy variables indicating whether SMEs had tax support, financial support, rent or cost reduction, and social security subsidies, respectively. Unfortunately, the data on platform subsidies are not available. We find that e-commerce plays a greater role in the tradable sector to mitigate demand decline, while its role in sustaining cash flow is more pronounced in non-tradable sectors. Similarly, for Table 4, we distinguish tradable and non-tradable sectors, using the ESIEC following survey in May 2020 with the corresponding pre-pandemic information from the baseline survey data. The results are reported in Appendix Table B.9, showing that e-commerce played a positive role in SMEs' financial turnover for both tradable and non-tradable sectors. E-commerce helped firms maintain a relatively lower level of accounts receivable, measured by the ratio to current assets, and a shorter repayment period, especially for the tradable sectors, while it also significantly reduced the repayment period uncertainty for non-tradable sectors. After controlling for the subsidies, the effect of e-commerce on accounts payable is still negative but not significant.

Furthermore, we also add more discussions on potential spillover effects in the adoption of digitization within a city. The owners of SMEs are super busy and often do not have time to learn new digital technologies. However, after observing peers adopting new digital technology, they are more likely to follow suit, as shown in Figure A.8 based on the OSOME survey. This is the classical mechanism highlighted in the literature on clusters (Marshal, 1920).

[31]Please refer to `https://www.oecd-ilibrary.org/sites/9789264293137-5-en/index.html?itemId=/content/component/9789264293137-5-en`.

## Appendix G Constraints Driving Digital Adoption

We conduct more heterogeneity analyses. First, we divide SMEs into two groups, those who have adopted digital technologies and those having not. It is likely those who have never adopted digital technology face different constraints from those who have adopted some technologies and would like to further update the technologies. Second, we classify the sample by firm size. The adoption of digital technologies has a fixed cost. Larger companies can hire IT professionals to work on the task, while micro and small enterprise owners must figure this out by themselves, further taxing their already busy time. Appendix Table B.11 reports the regression results. As shown in Columns 2 and 3 of Panel A, those who have not yet introduced digital business methods such as e-commerce consider subjective attitudes to be the main obstacle, particularly due to a lack of time and energy for learning or fear of low capacity to master. In contrast, those who have already taken up digital operations are more concerned about risks (Column 4 of Panel A). In addition, external factors such as costs, funds, and infrastructure also hinder their digital technology upgrading and transformation, as shown in all columns of Panel B.

Firm size is also highly correlated with the reported challenges of digital transformation. Larger SMEs are less concerned about the difficulty of "lack of time and energy for learning." SMEs with a certain scale can dedicate personnel in charge of new technology applications, while their smaller counterparts do not have such luxury. The larger firms are also more concerned about risks, lack of infrastructure, and the inability to master relevant technologies.

We also investigate heterogeneity in the adoption of digital technologies between new entries and incumbents. Tables 10 and 11 show that incumbent firms are relatively more likely to take advantage of digital transformation. In Appendix Table B.12, we explore more heterogeneity by firm characteristics, such as registration type, industry code, firm size, and financial needs, as well as entrepreneurial features, including gender, age, and education. As shown in Panel A, in response to the COVID restrictions, registered self-employed and SMEs in the service sectors are significantly more likely to adopt online operations. Larger SMEs (with 20 or more full-time employees) are more likely to adopt online operations and sales, consistent with the previous results. Businesses lacking financing needs during the surveyed quarter were more likely to switch to online operations. In terms of entrepreneurial characteristics, female entrepreneurs were more likely than males to adopt e-commerce and other digital operations; young people exhibited a higher rate of adopting online operations and remote work; and business owners with college degrees or above had a higher likelihood of adopting online operations and sales.