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Small and Medium Enterprises 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 (including unregistered self-employments) 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. After the January 2020 lockdown, firm entries exhibited a V-shaped pattern, with entries of e-commerce firms experiencing a less pronounced immediate 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, and it is more pronounced for certain sectors, firms in industrial clusters, and areas with more digital inclusion but less financial efficiency, constituting initial evidence for the long-term impact of the pandemic and the supposedly transitory mitigation policies.

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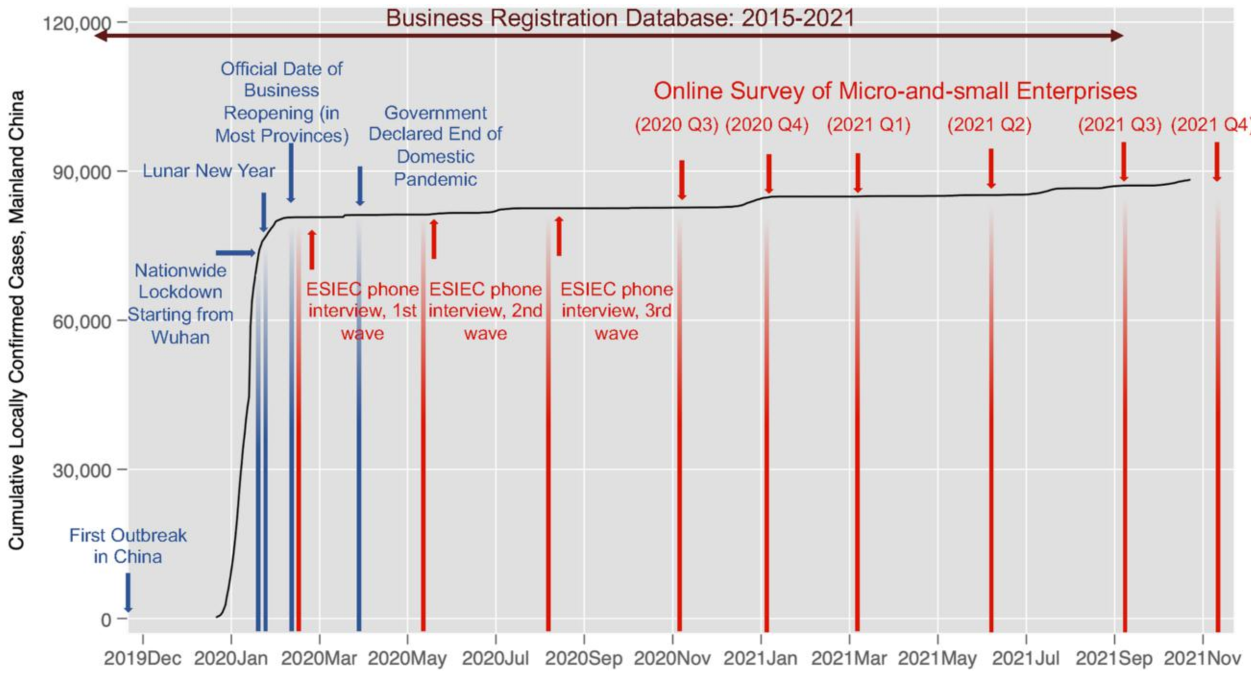
1. Introduction

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 coronavirus disease 2019 (COVID-19) pandemic is no exception, striking heavy blows to SMEs worldwide.[2] Some literature has examined the role of industrial clusters (e.g., Kranton and Minehart 2000, Dai et al. 2021a) and policy interventions (e.g., Bartlett and Morse 2021, Chen et al. 2022) in helping SMEs cope with such external shocks. However, how digitization contributes to SMEs' resilience and how the pandemic shapes SMEs' digitization in the long run, especially in developing countries, are understudied because of a paucity of data, despite numerous media reports (e.g., The Economist 2020, the *TIME* magazine cover story by Wang 2020, Kabir 2021) on rising e-commerce, e-learning, telemedicine, digital banking, and work from home as immediate ramifications of the pandemic.

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 digitization on the performance of SMEs (including unregistered self-employment) during and after the COVID-19 restrictions. Our multiple rounds of surveys, with varying timing relative to the national lockdown (see Figure 1), also enable us to demonstrate

Figure 1. (Color online) COVID-19 Outbreak, Reopening, Mitigation Policies, and Surveys



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

for the first time both the immediate and persistent digital transformation of SMEs that the pandemic brings forth, which exhibits rich heterogeneity hitherto not discussed in the literature. Given the lack of a consensus definition of business digitization and data limitations, we focus on e-commerce as the main proxy of digitization. We also examine other major aspects of digitization, such as online operation, remote work, and information technology (IT) systems. Because we cannot cover all dimensions of digitization, our baseline estimates likely constitute a lower bound.

We first investigate whether digitizing business operations makes SMEs more resilient to shocks, such as the pandemic. 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. Although it is not surprising that prior digitization makes SMEs more resilient during the pandemic and that previous studies take this as a given, our contribution lies in systematically verifying it, quantifying its extent, and highlighting the underlying mechanisms and heterogeneous responses.

We then examine whether the pandemic has induced greater adoption of digital technologies for SMEs.[3] We develop a textual analysis algorithm to apply to business operation scope, a written record embodied in the business registration data set indicating what activities an enterprise is approved to conduct, effectively classifying each registered firm's e-commerce adoption status. We then employ an event study approach exploiting the timing of the nationwide lockdown to gauge its impact on the extensive growth margin (i.e., the number of e-commerce firm entries at the city-industry-year-month level aggregated from the business registration data). Compared with the prepandemic 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 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. The industrial heterogeneity further demonstrates the synergy that digitization brings in traditional sectors at both extensive and intensive margins. At the macro level, industrial clustering and financial development also matter for the adoption of digital technologies. Moreover, using the multiround 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.

Note that the Chinese setting offers several advantages in studying SMEs' digitization amidst the pandemic. First, China is the largest e-commerce and fintech market, with a massive number of SMEs varying in the extent of digitization as well as in many other dimensions.[4] Second, the lockdown was immediate and reasonably uniform across the nation, and so was the reopening, ruling out endogeneity concerns that the timing and size of the mitigation and reopening policies are correlated with the level of digitization. These advantages also enable us to discuss the heterogeneous spurring effects on firm digitization. Specifically, the effects are more pronounced for wholesale and retail (W&R), manufacturing, and agriculture sectors; industries more prone to allow working from home; firms in industrial clusters and areas with better digital financial inclusion; and nonstate-owned enterprises (non-SOEs). Regions traditionally with lower financial efficiency also accelerated digitization after the pandemic, indicating potential opportunities to close the efficiency gap or even leapfrog other regions in terms of SMEs' resilience and technology adoption. These heterogeneities likely have implications for redistribution and allocative efficiency in the long run.

Our study contributes to the literature on SMEs' resilience to shocks. Several recent studies surveyed small businesses, mostly in developed countries and immediately after the onset of the pandemic (e.g., Bartik et al. 2020, Bartlett and Morse 2021), focusing on heterogeneous impacts (Adams-Prassl et al. 2020, Chetty et al. 2020), implications for business owners (Kim et al. 2020, Alekseev et al. 2023), and business closures and corporate layoffs/hiring (Campello et al. 2020, Fairlie 2020, Humphries et al. 2020). Adding to how intervention policies help (e.g., Bartlett and Morse 2021, Chen et al. 2022), Dai et al. (2021b) investigate the efficacy of policies targeted at SMEs, whereas Chen et al. (2020) show that local economic stimulus for small businesses benefited larger firms more in China.

We add to this body of work by analyzing an important new dimension on how digitization, especially e-commerce adoption, 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, and Environmental, social, and corporate governance policies affect firms' resilience and outcomes, such as stock returns (Acharya and Steffen 2020, Albuquerque et al. 2020, Ramelli and Wagner 2020, Ding et al. 2021, Fahlenbrach et al. 2021, Kwan et al. 2021, Barry et al. 2022). Recently, Gaspar et al. (2022) use text-based measurement of firm digitization to quantify the size of the digital economy and analyze how digitization relates to firms' resilience. They almost all analyze public U.S. firms (in particular sectors) shortly after the onset of the pandemic, whereas we cover all registered firms and a large sample of unregistered ones in China in all sectors, especially private SMEs. We also examine both the onset of the pandemic and reopening to understand how the pandemic spurs persistent digitization.[5] Although the literature has identified managerial talent, financial flexibility, and governance as important drivers for resilience amidst the pandemic, we show that several novel channels related to digitization (e.g., robust online consumption, more timely digital payment, and faster turnover of firms' working capital) give enterprises with online operations competitive advantages and document rich heterogeneity in firms' digital transformation spurred by the pandemic. In particular, the firm characteristics and regional heterogeneities are important factors in shaping the digital transformation.

Our study also contributes to the emerging literature on fintech adoption (e.g., Agarwal et al. 2020), which has been accelerating amid the pandemic.[6] Although fintech deals decreased drastically during the first quarters of 2020 because of 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) documented that the pandemic has led to sharp increases in fintech app downloads, whereas Tut (2023) finds a negative impact on the adoption of fintech payments. Several other studies focus on network externality and coordination (e.g., Higgins 2019, Crouzet et al. 2023), demographics (Carlin et al. 2017), and individual trusts (Rossi and Utkus 2020) in fintech adoption. The broader literature on technology adoption in response to shocks only documents temporary pickup on digital communication and IT (e.g., Shklovski et al. 2010). Our paper studies SMEs rather than consumers or households, and it examines persistent effects and changes related to digitization. The work by Gao et al. (2023), which finds that public digital training increases SMEs' resilience, complements our study but in the context of a developed economy. We are also among the first to document that such effects persist, whereas previous studies mainly examine the contemporaneous responses.

2. Data and Survey Design

We now describe our large-scale data sets with comprehensive coverage of SMEs in China and their digitization. More details can be found in Online Appendix C.

2.1. ESIEC Data

ESIEC is an entrepreneur- and enterprise-specific field survey project led by Peking University covering six provinces in total. ESIEC has successfully interviewed nearly 10,000 private enterprise owners and self-employed entrepreneurs between 2017 and 2019, collecting high-quality microdata on the entrepreneur's background and business performance. It is representative nationwide in terms of industry or firm size distributions, as discussed in Online Appendix C, based on the public descriptive statistics from the China Economic Census 2018. After the outbreak of COVID-19 in China, the ESIEC team immediately conducted multiple phone surveys (see Figure 1), focusing on firms' responses to the shock. The first two rounds tracked firms interviewed in prepandemic surveys. In August, the ESIEC team conducted another phone survey on a newly drawn sample of incorporated enterprises with additional questions on their pre–COVID-19 performance. One should treat them as independent cross-sectional data sets.

By merging the ESIEC phone interview data with the baseline surveys and the registration data set, we can study whether firms with e-commerce activities prior to the shock performed better during and after COVID-19 restrictions in terms of reopening, recovery, and cash flow. The variable of interest is the firm-level ratio of online sales inferred from the field surveys in 2017–2019, as discussed in Online Appendix D. Additionaly, Table 1 contains summary statistics of the key variables from the ESIEC survey used in our main analyses.

2.2. SAIC Business Registration Data

The data set 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. Online Appendix C explains its greater coverage of incorporated small, medium, and microenterprises than other databases.

Table 1. Summary Statistics of ESIEC Data

	Pooled		February	May	August
Variable	Mean	S.D.	Mean		
Panel A: Firm level					
Outcomes					
Order decline as main challenge	0.181	0.385	0.502	0.022	0.007
Cash flow > 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	0.286	0.452	0.080	0.422	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.
Prepandemic employment					
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 services	0.347	0.476	0.393	0.419	0.214
Business services	0.367	0.482	0.323	0.306	0.486
Observations	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
Observations	224		79	84	61

Source. ESIEC.
Notes. 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 zero to one. All samples in the August wave are incorporated. n.a., not applicable; S.D., standard deviation.

Because SAIC is up to date, we can analyze firm responses during the pandemic and after the reopening. Although our analyses based on SAIC are limited to registered enterprises, the other surveys complement detailed information on self-employed businesses.

The data set includes the "business operation scope" record, a mandatory and standardized text record briefing what business operations an enterprise is approved to conduct. We, therefore, extract information from the records of entrant firms' business operation scope using natural language processing (NLP) (described in Online Appendix E) tools to classify the types of business, with the labeled training set from ESIEC data. We further apply the same NLP classification to the records of incumbent firms' "alteration record of business operation scope" to identify incumbent firms that have changed business operation scope. In this way, we construct two aggregated measurements on both the extensive margin (entrants' e-commerce adoption) and the intensive margin (incumbents' transformation from non–e-commerce to e-commerce).

2.3. OSOME Data

The online OSOME survey is conducted on the most widely used e-payment platform Alipay, focusing on active small and microbusiness users.[7] One key difference lies in its inclusion of unregistered self-employed businesses, covering a larger share (38.7% in the full sample as in Table 2) that has long been neglected in previous research. The questionnaire mainly includes topics on business operation performance, COVID-19 recovery, more aspects of digital adoption (online sales, remote work, and adoption of electronic information systems), and business challenges. OSOME provides a unique and novel information source regarding the digital transformation of SMEs over time, enabling us to extend the basic findings to unregistered SMEs and other types of digital adoption beyond e-commerce. We discuss more details, including the sample representativeness, in Section 4.3 and Online Appendix C, which show that the firm size in OSOME is comparable with the national average by registration type.

Table 2. Summary Statistics of OSOME Data

	Full sample		Exclude 2020Q3	
Variable	Mean	S.D.	Mean	S.D.
Main independent variable				
COVID × After	0.069	0.254	0.088	0.283
(*COVID*)	0.190	0.392	0.191	0.393
Controls				
Firm age	6.258	5.390	6.214	5.470
Owner's age	32.539	9.240	32.538	9.183
Female owner	0.173	0.378	0.172	0.377
Business type				
Corporate enterprise	0.107	0.309	0.113	0.317
Self-employed, register	0.506	0.500	0.502	0.500
Self-employed, unregister	0.387	0.487	0.385	0.486
Industry				
Agriculture	0.069	0.254	0.071	0.257
Construction and manufacturing	0.106	0.308	0.114	0.317
Service	0.824	0.381	0.815	0.388
Employment				
0	0.333	0.471	0.335	0.472
1–4	0.453	0.498	0.446	0.497
5–7	0.104	0.305	0.104	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	0.201	0.401	0.203	0.402
Tier 2	0.190	0.392	0.191	0.393
Tier 3	0.278	0.448	0.277	0.447
Tier 4	0.208	0.406	0.208	0.406
Tier 5	0.123	0.328	0.121	0.327
Observations	84,330		65,049	

Source. OSOME.
Notes. The main independent variable, *COVID × After*, equals one if a business is located in a city with localized lockdowns because of new COVID-19 confirmed cases and was surveyed in a quarter after the outbreak; it is 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 do not 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. The full sample period covers from 3rd quarter of 2020 (202Q3) to 4th quarter of 2020 (2021Q4). There is also a subsample excluding 2020Q3 because the survey did not include some variables in the third quarter of 2020. S.D., standard deviation.

3. A Digital Edge Among Small Businesses?

This section primarily relies on the ESIEC data to investigate how digitization helps SMEs mitigate the systematic shock because 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 prior to COVID-19, *e-commerce ratio*, reported in the baseline survey or interviewees' recall in the August wave. As Table 1 shows, nearly 24.2% of SMEs in the ESIEC sample had adopted online sales. We also check the robustness of this measure and the alternative forms in Online Appendix D.

3.1. Baseline Results

Table 3 presents results using ordinary least squares (OLS) regressions, which are robust under Probit specification. The controls include employment (a proxy for firm size), year of establishment, a dummy for incorporated business, city-level COVID-19 confirmed

Table 3. Baseline Regression of Short-Term Digital Edge

Outcome	(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)
Adjusted R^2	0.374	0.072	0.016	−0.007
Panel B: Cash flow > 1 month				
E-commerce ratio	0.129***	0.099*	0.104***	0.204***
	(0.020)	(0.051)	(0.026)	(0.041)
Adjusted R^2	0.050	0.087	0.029	0.018
Panel C: Reopen status				
E-commerce ratio	0.078***	0.060	0.062***	0.106***
	(0.015)	(0.053)	(0.020)	(0.015)
Adjusted R^2	0.501	0.102	0.036	0.022
Panel D: Outlook for growth				
E-commerce ratio	0.117***	0.024	0.086**	0.201***
	(0.024)	(0.037)	(0.036)	(0.048)
Adjusted R^2	0.129	0.020	0.083	0.042
Control	Yes	Yes	Yes	Yes
Wave dummy	Yes	—	—	—
City FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	4,914	1,678	1,715	1,521

Source. ESIEC.
Notes. 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 zero to one. 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 (FEs). Asterisks indicate significance levels.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

cases, and city-level COVID-19 case growth in the past 30 days. We also control for the city and one-digit industry fixed effects in the regressions. In column (1), the three waves of data are pooled, and wave dummies are controlled. Columns (2)–(4) present separate regressions for each wave, which yield highly consistent results.

Overall, a higher fraction of online sales is associated with better subsequent firm performance. Specifically, 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. The estimates in panel B of Table 3 show that firms with online sales have also reported better cash flow status in February, May, and August 2020 as measured by whether cash flow can sustain operation over a month. To be more specific, we use the May wave 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 (8.6%) of accounts receivable. Given that the average is 26.4% for the whole sample, it implies that digitization can help SMEs alleviate about one third of cash flow issues during the pandemic. E-commerce also reduced the repayment period of accounts receivable and entrepreneurs' uncertainty toward it, as shown in columns (2) and (3).

Thanks to the combination of more 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 online sales or with a lower share of online sales in May and August 2020 (panel C of Table 3). Not only did firms with more online sales have a higher reopening rate, but they also held a more optimistic outlook for future growth (panel D of Table 3). These findings show that e-commerce provides SMEs an edge in coping with the pandemic.[8]

3.2. Economic Mechanism

To understand the underlying mechanism, we use the offline ESIEC and online OSOME to analyze potential

Table 4. Short-Term Digital Edge on Corporate Finance During the Early Reopening (May 2020)

	(1)	(2)	(3)	(4)
	Accounts receivable			Accounts payable
		Repayment period		
Outcome	% Current assets > 50%	>60 days	Uncertainty	% Current assets > 50%
E-commerce ratio	−0.086***	−0.091***	−0.089***	−0.072***
	(0.029)	(0.032)	(0.027)	(0.021)
Adjusted R^2	0.023	0.050	0.053	0.029
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
Observations	1,715			

Source. ESIEC.
Notes. 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 zero to one. 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 (FEs). Asterisks indicate significance levels. S.D., standard deviation.
$^{***}p < 0.01$.

channels and find that production networks and previous online experience contribute to SMEs' digital edge. We present detailed empirical patterns in Online Appendix F and summarize them here. The role of e-commerce in maintaining demand and cash flow is more pronounced for SMEs without local suppliers or customers. Although the lockdown disrupted production supply chains, e-commerce can mitigate the negative effect, making small businesses with distant customers or suppliers that are not subject to local shocks more resilient. Moreover, pre-existing e-commerce business owners had accumulated online business experience, enabling them to adopt more digital technologies and better cope with the shock. We also compare the tradable and nontradable sectors.

4. Digital Transformation

After observing the positive effects of digitization on the resilience of SMEs during the pandemic, we investigate if the pandemic has a lasting impact on SMEs' digitization. We first consider both the extensive margin (new firm entry) and the intensive margin (incumbents' adoption of digital technologies) of the SMEs' digital transformation based on the business operation scope texts from SAIC data.

4.1. Identification Strategy

Similar to Fang et al. (2020), Chen et al. (2021), and Dai et al. (2021a), we first use the nationwide lockdown following the initial COVID-19 outbreak from Wuhan as an exogenous shock to examine its impact on SMEs in a difference-in-differences framework. 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) where a firm is located, j stands for the industry, m indexes the month(s), and y is the year. We define m according to the lunar calendar and set the month of Lunar New Year's Eve as $m = 0$ because it coincides with the nationwide lockdown; the Lunar New Year is a traditional holiday in China when firms close their businesses, and new firms' registration or incumbents' alteration is paused even before the pandemic.[9] $COVID_y$ 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, where positive (negative) values represent the month(s) after (before) the Lunar New Year's Eve in each year. 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.

As for the dependent variables, on the extensive margin, we use the logarithm number of new entrants (plus one because of a few zero values) with e-commerce operations as the first outcome variable, just as described in Section 2 and Online Appendix E. Next, we examine the intensive margin of digitization by exploiting the alteration records on business operation scope to quantify incumbent SMEs' (established before 2019) digital transformation. We apply the same NLP algorithms to the alteration record and label these changes related and unrelated to e-commerce adoption, respectively. Only alterations from non–e-commerce to e-commerce are labeled as adoption. We then aggregate it at the city-industry-year-month level (unless otherwise specified) to alleviate the issue of identical zero values (no new entries or alterations). The set of coefficients β_m over time captures the dynamic impact of the COVID-19 outbreak and reopening on the outcome variables of interest. Because 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 to examine the industrial heterogeneous effect of the COVID-19 shock on both new entrants' and incumbents' adoption of e-commerce across sectors. 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-month-year level. $After_m$ equals one for the months after each Lunar New Year's Eve and zero otherwise. The regression also controls for the corresponding fixed effects and cluster standard errors at the city level.

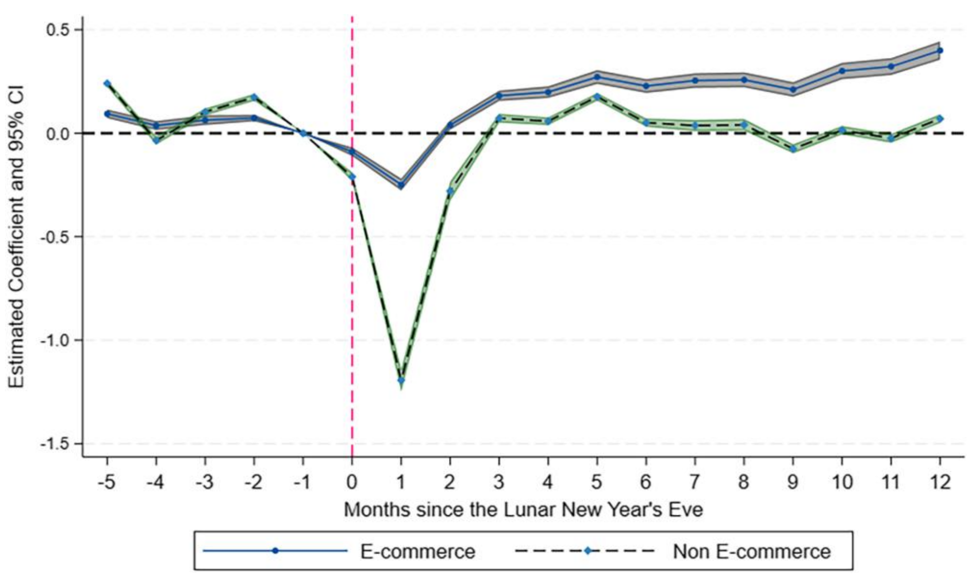
More importantly, we repeat the previous analyses of Equation (1) using a continuous pandemic variable. We gather the growth rate of confirmed cases (including asymptomatic cases) at the city level from public official sources to construct the specification as follows:

$$\begin{aligned}\ln(Y_{cjmy}) = {} & \gamma \times COVID'_c \times (COVID \times After)_{ym} \\ & + \beta \times (COVID \times After)_{ym} + FEs + f(y,c,j) \\ & + \varepsilon_{cjmy},\end{aligned} \tag{3}$$

where $COVID'_c$ indicates the city-level growth rate of confirmed cases for the period January to March 2020 (the outbreak). The dummy variable $(COVID \times After)_{ym}$ equals one for the 2020 Lunar New Year and after; otherwise, the value is zero. The other definitions of the index and the regression settings are the same as in Equation (1).

Moreover, we interact the $(COVID \times After)_{ym}$ term with regional variables on industrial clustering or financial development to explore the heterogeneous effect of SMEs' digital transformation in an analogous specification to Equation (3). The added term, $Index_c \times (COVID \times After)_{ym}$, can capture the heterogeneous response of SMEs

Figure 2. (Color online) Event Study of the COVID-19 Outbreak and Reopen on New Firm Entry for the Subgroups of E-Commerce and Non–E-Commerce



Source. SAIC registration database.
Notes. The dependent variable is the logarithm number of newly registered firms plus one. The x-axis label is the months before (negative) or after (positive) each Lunar New Year's Eve. The shaded area shows the 95% confidence intervals (95% CIs). 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 5 more months and after 12 more months are included in the regression but omitted in the figure. 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.

Management Science, 2024, vol. 70, no. 7, pp. 4564–4582, © 2024 INFORMS

among regions or industries on adopting e-commerce, as in Equation (4):

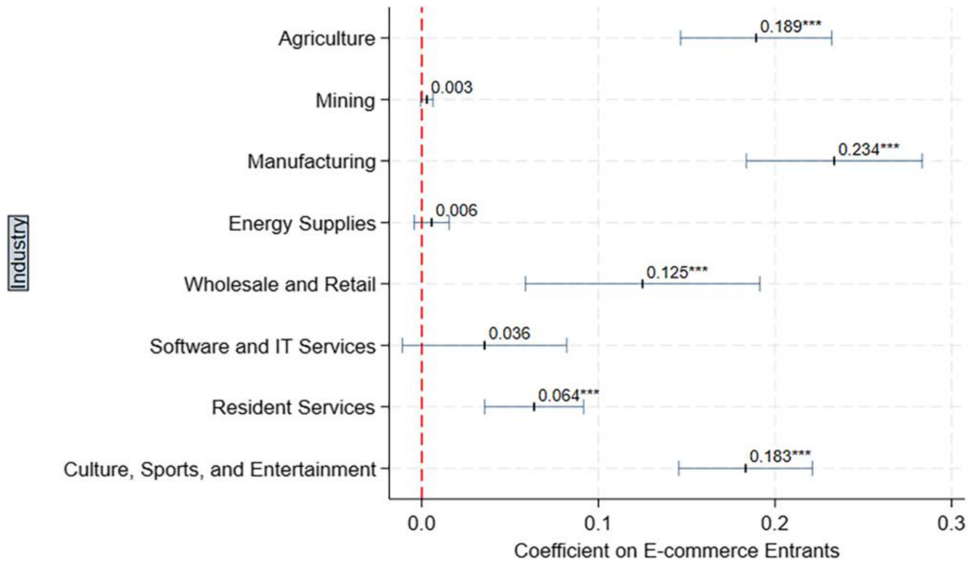
$$\ln(Y_{cjmy}) = \gamma \times Index_c \times (COVID \times After)_{ym} + \beta \times (COVID \times After)_{ym} + FEs + f(y, c, j) + \varepsilon_{cjmy}. \tag{4}$$

4.2. Empirical Results

4.2.1. Baseline Analysis. Figure 2 first displays the extensive margin of COVID-19 on new firm entries for e-commerce and non–e-commerce groups classified by our NLP algorithm. Using the number of new entrants as the dependent variable in Equation (1), we plot the estimated coefficients β_m for e-commerce and non–e-commerce entries, respectively. As shown in the figure, the number of new entries with e-commerce in all industries dropped less rapidly during the peak lockdown than their non–e-commerce counterparts and recovered a bit faster thereafter. More importantly, the coefficients for e-commerce entries have been significantly positive since the third month and kept a sustained gap with the non–e-commerce group for at least 12 months. This implies a persistent effect of the pandemic on the digital transformation of SME entries in China.[10]

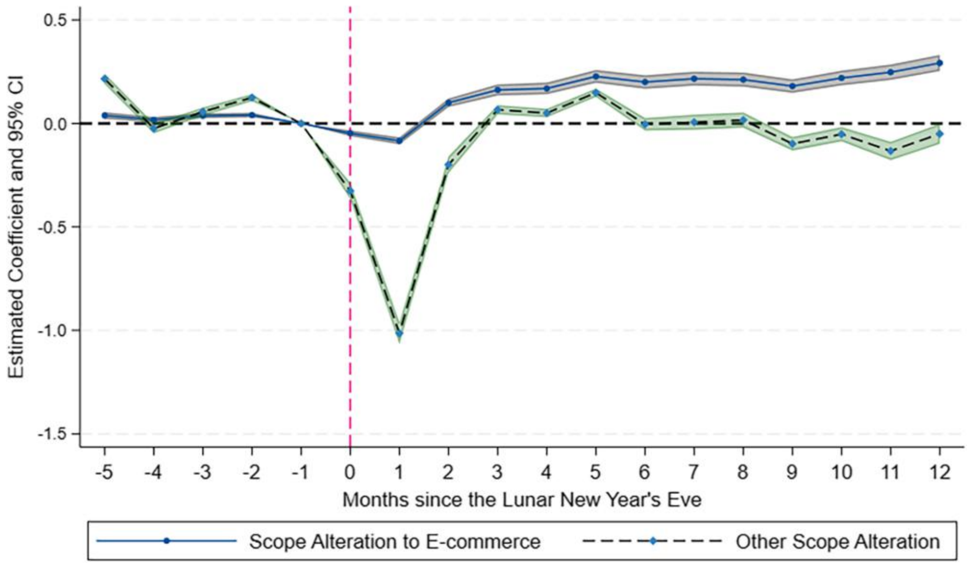
To examine the heterogeneous effect on new firm entries adopting e-commerce among different industries, we use specification (2) to estimate the heterogeneous impact and plot the coefficient estimate in Figure 3. It shows that the adoption of e-commerce by new entries in the W&R sectors increased on average by nearly 12.5% in the year following the lockdown, which is consistent with the estimates in Online Appendix Figure A.1. More importantly, new entrants in two traditional industries, the agriculture and manufacturing sectors, have increased the adoption of e-commerce by approximately 18.9% and 23.4%, respectively. Additionally, 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 IT services industry also witnessed a growth in e-commerce adoption, although not statistically significant. By comparison, this effect does not exist in industries not directly related to e-commerce, such as mining and energy supply. The findings 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 is not only limited to the W&R or the emerging digital sectors but also includes traditional

Figure 3. (Color online) Heterogeneous Effect of the COVID-19 Outbreak and Reopen on New Firm Entry for the E-Commerce Subgroup by Industry



Source. SAIC registration database.
Notes. 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 labels show 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: $p < 0.01$.

Figure 4. (Color online) Event Study of the COVID-19 Outbreak and Reopen on Incumbents' Business Operation Scope Alteration for the Subgroups of E-Commerce Adoption and Others



Source. SAIC registration database.
Notes. The dependent variable is the logarithm number of business operation scope alterations plus one. The *x*-axis label is the months before (negative) or after (positive) each Lunar New Year's Eve. The shaded areas show the 95% confidence intervals (95% CIs). The two groups are divided by analyzing the keywords in the business operation scope alteration record, where "scope alteration to e-commerce" is 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 5 more months and after 12 more months are included in the regression but omitted in the figure. Monthly numbers of firm entries at the city level from 2015 to 2021 are included. All observations are at the city-industry-year-month level. Standard errors are clustered at the city level. The regression controls for the city, industry, month, and year fixed effects; the corresponding two-way fixed effects except the interaction term between year and month; and the year trend of city-industry.

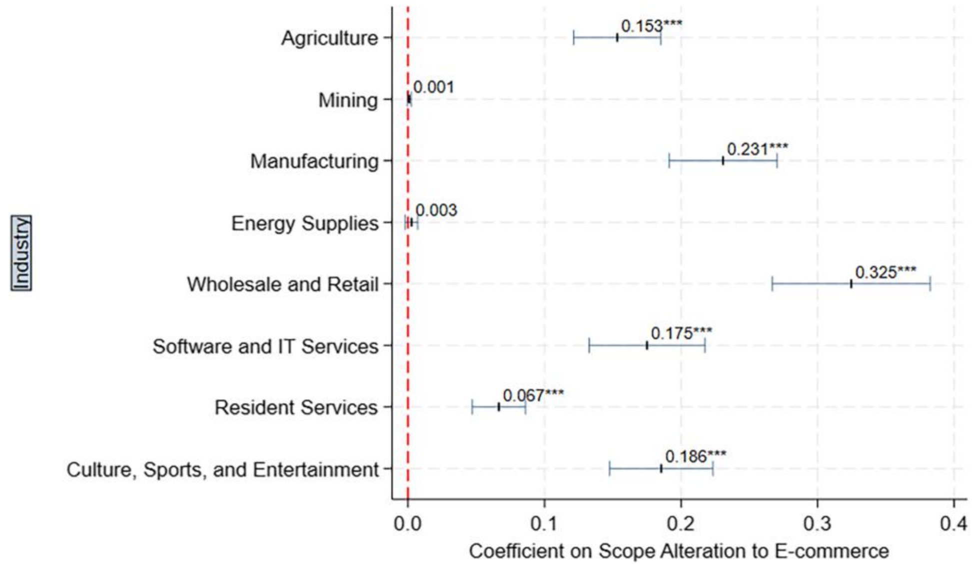
agricultural and manufacturing industries. The finding contributes to the debate as to whether the traditional sectors are left behind in digital transformation.

Next, we examine the intensive margin of incumbent SMEs established before 2019 in digital transformation using alteration records of business operation scope to construct subgroups. Figure 4 plots the estimated coefficients for this empirical design. Immediately after the COVID-19 outbreak, overall registration alteration dropped significantly. By comparison, the alteration to e-commerce business declined much less than other business operation scope changes. The effect of the pandemic 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 12 months after the outbreak. The year-on-year growth for firms changing their operation scope to e-commerce was as high as 29.2% toward the end of the sample period compared with 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 5. In the W&R industry, nearly 32.5% of incumbent enterprises changed their business operation scope from offline (or added) to 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 approximately 15.3%, 23.1%, and 18.6%, respectively. Also, similar to Figure 3, in some industries that are not applicable to e-commerce, the incumbent enterprises have not made corresponding changes.

Table 5 shows the regression results based on Equation (3) using a continuous pandemic variable. We find that the greater the growth of COVID-19 cases in a particular city, the more subsequent new local entries there are in e-commerce–related business in the intermediate and long term (column (1)) and the more switches there are in business operation scopes from non–e-commerce to e-commerce among enterprises established before 2019 (column (3)). In contrast, the effect for non–e-commerce entries (column (2)) and other business operation switches (column (4)) is negative, consistent with

Figure 5. (Color online) Heterogeneous Effect of the COVID-19 Outbreak and Reopen on Incumbents' Business Operation Scope Alteration to E-Commerce by Industry



Source. SAIC registration database.
Notes. 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" is 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 labels show 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: $p < 0.01$.

the patterns shown in Figures 2 and 4, 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 Online Appendix Figure A.2, which are consistent with Figures 3 and 5 based on Equation (2). Moreover, in Online Appendix G, we show that the pandemic exacerbates firm exit, but the effect on e-commerce enterprises is significantly less severe than that of non–e-commerce firms. Finally, to complement our definition of digitization, we collect the industry-level work-from-home index by Dingel and Neiman (2020) to extend the empirical analysis that defines work from

Table 5. 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*)	
Outcome	E-commerce	Non–e-commerce	Alteration to e-commerce	Other scope alteration
COVID′ (Infection Rate) × *After*	0.152*	−0.297***	0.285***	−0.434***
	(0.089)	(0.055)	(0.097)	(0.091)
Adjusted R^2	0.828	0.893	0.664	0.876
FEs	Yes	Yes	Yes	Yes
Observations	738,000			

Source. SAIC registration database.
Notes. The dependent variable is the logarithm number of newly registered firms plus one in columns (1) and (2) and the logarithm number of business operation scope alterations plus one in columns (3) and (4). The two groups, e-commerce and non–e-commerce, are divided by textually 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 January to March 2020. *After* = 1 indicates the 2020 Lunar New Year and after; otherwise, the value is zero. 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 (FEs); the corresponding two-way FEs; and the year trend of city-industry. Asterisks indicate significance levels.
*$p < 0.1$; ***$p < 0.01$.

home as digitization. As also shown in Online Appendix G, COVID-19 has spurred more incumbents to adopt e-commerce, especially in industries that allow more jobs to be done at home.

4.2.2. Heterogeneity Analyses. We further analyze regional heterogeneity using the degree of industrial clustering and financial inefficiency. The heterogeneity in digital transformation not only informs us of the differential impact of the pandemic on firms but also has implications for redistribution and allocative efficiency in the long run. Specifically, we first use the industrial cluster index (Long and Zhang 2011, Ruan and Zhang 2015) constructed based on the production proximity matrix incorporating correlation and concentration.[11] Firms in industrial clusters are known to be more resilient to the pandemic shock (Dai et al. 2021a), and we complement this by interacting the cluster index in 2015 (in logarithm) with the key variable of interest ($COVID \times After$) in Equation (4). The results are shown in panel A of Table 6. On the extensive margin, as 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) and (4), on the intensive margin, incumbent firms in clusters experienced a more rapid transformation into e-commerce operations as well. The result remains robust when we use the index in 2019, the year right before the outbreak (panel B of Table 6).[12]

In addition, finance matters to SMEs' digitization. Following Zhang and Tan (2007) and Hsieh and Klenow (2009), we construct a financial inefficiency index, which is measured by the variation in the marginal product of capital.[13] 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, the most updated and accessible wave with microlevel financial information as used in Dai et al. (2021a), to get a predetermined variable before the e-commerce boom. Once again, we mainly report the interaction term of ($COVID \times After$) and the financial inefficiency index in Table 7. As shown in panel A, in areas of high financial inefficiency, new entries into non–e-commerce significantly decreased right after the COVID-19 outbreak (column (2)) as do business switches unrelated to e-commerce by incumbent firms (column (4)), potentially because of the fact that more enterprises fail to survive. By comparison, as indicated in column (1), regions with high financial inefficiency 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

Table 6. 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*)	
Outcome	E-commerce	Non–e-commerce	Alteration to e-commerce	Other scope alteration
		Panel A		
($COVID \times After$) × ln(*Cluster Index 2015*)	0.039***	−0.104***	0.078***	−0.163**
	(0.015)	(0.009)	(0.018)	(0.015)
Adjusted R^2	0.828	0.893	0.664	0.876
Observations			738,000	
		Panel B		
($COVID \times After$) × ln(*Cluster Index 2019*)	0.043***	−0.112***	0.085***	−0.177***
	(0.016)	(0.009)	(0.018)	(0.016)
Adjusted R^2	0.828	0.893	0.664	0.876
Observations			738,000	
FEs	Yes	Yes	Yes	Yes

Source. SAIC registration database.
Notes. The dependent variable is the logarithm number of newly registered firms plus one in columns (1) and (2) and the logarithm number of business operation scope alterations plus one in columns (3) and (4). The two groups, e-commerce and non–e-commerce, are divided by textually analyzing the keywords in the business operation scope and the alteration record. The ln(*Cluster Index*) is the logarithmic prepandemic cluster index in 2015 in panel A and 2019 in panel B 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 (FEs); the corresponding two-way FEs; and the year trend of city-industry. Asterisks indicate significance levels.
$^{**}p < 0.05$; $^{***}p < 0.01$.

Table 7. 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)	
Outcome	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)
Adjusted R^2	0.839	0.894	0.680	0.880
Observations			653,500	
		Panel B		
(COVID × After) × Digital Financial Inclusion 2015	0.003***	−0.004***	0.004***	−0.006***
	(0.001)	(0.000)	(0.001)	(0.001)
Adjusted R^2	0.828	0.893	0.664	0.876
Observations			738,000	
		Panel C		
(COVID × After) × Digital Financial Inclusion 2019	0.002**	−0.003***	0.002***	−0.004***
	(0.001)	(0.000)	(0.001)	(0.001)
Adjusted R^2	0.828	0.892	0.664	0.876
Observations			738,000	
FEs	Yes	Yes	Yes	Yes

Source. SAIC registration database, the China Economic Census 2008, and the Peking University Digital Financial Inclusion Index of China.

Notes. The dependent variable is the logarithm number of newly registered firms plus one in columns (1) and (2) and the logarithm number of business operation scope alterations plus one in columns (3) and (4). The two groups, e-commerce and non–e-commerce, are divided by textually analyzing the keywords in the business operation scope and the alteration record. The financial inefficiency index in panel A is the standard deviation of the logarithm of the value added/total asset ratio at the city-industry level from the China Economic Census 2008. Some observations are dropped because the China Economic Census 2008 did not cover some areas and some sectors, such as agriculture. The digital financial inclusion index is the city-level indices of digital finance in 2015 in panel B and 2019 in panel C produced by a research team from the Institute of Digital Finance at Peking University and the 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 (FEs); the corresponding two-way FEs; and the year trend of city-industry. Asterisks indicate significance levels.

$^{**}p < 0.05$; $^{***}p < 0.01$.

of high financial inefficiency, a greater number of firms have switched to e-commerce–related business operations, as demonstrated in column (4). Furthermore, using the pre–COVID-19 city-level index of digital finance inclusion in 2015 and 2019 (Guo et al. 2020), we further document greater e-commerce adoption by new entrants and incumbents in areas with better digital financial inclusion (panels B and C of Table 7)—an indication of potential opportunities to close the efficiency gap or even leapfrog other regions in terms of SMEs' resilience and technology adoption.[14]

We also explore the major firm-level factors behind the take-up of digital technologies, as detailed in Online Appendix I. Nevertheless, SMEs in the service sectors and of large scale are significantly more prone to adopt online businesses.

4.3. Self-Employed Businesses: Findings from the OSOME Survey

The 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). The OSOME data enable us to examine digitization and its interaction with the pandemic for unregistered self-employed businesses for the first time. In addition, the OSOME survey covers several vital aspects of digitization beyond e-commerce (e.g., online operations, remote work, and IT systems).

Although the nationwide lockdown ended in April 2020, sporadic local lockdowns ensued. We manually collected information concerning local lockdowns at the city level and matched them with the quarterly OSOME survey. Because the surveys cover at least six quarters, we make use of the spatial and temporal variations in local lockdowns to evaluate the impact of COVID-19 restrictions on digital transformation in multiple dimensions for small and microenterprises, including the unregistered ones. We follow a similar specification as before:

$$Y_{ijcq} = \beta \times (COVID_c \times After_q) + \mathbf{x}_i'\theta + FEs + \varepsilon_{icqj}, \quad (5)$$

where the subscript indicates that a firm i in industry j located in city c was surveyed in year-quarter q. The key

Table 8. Impact of Local Lockdowns on Online Operation and Sales

	(1)	(2)	(3)
	Online operation		
Outcome	Any	Only online	Online sales
Panel A: All sample			
COVID × *After*	0.023**	0.010	0.017*
	(0.009)	(0.008)	(0.009)
Mean of dependent variable	0.441	0.110	0.383
S.D. of dependent variable	0.496	0.312	0.486
Adjusted R^2	0.054	0.066	0.063
Observations		84,330	
Panel B: Newly established subsample			
COVID × *After*	−0.028	0.062**	−0.026
	(0.043)	(0.030)	(0.050)
Mean of dependent variable	0.516	0.172	0.430
S.D. of dependent variable	0.500	0.378	0.495
Adjusted R^2	−0.059	−0.005	−0.034
Observations		7,774	
Panel C: Incumbent subsample			
COVID × *After*	0.027***	0.006	0.022**
	(0.009)	(0.007)	(0.009)
Mean of dependent variable	0.433	0.103	0.378
S.D. of dependent variable	0.495	0.304	0.485
Adjusted R^2	0.052	0.059	0.061
Observations		76,556	
Control	Yes	Yes	Yes
City, industry, and quarter (wave) FEs	Yes	Yes	Yes
City × industry FE	Yes	Yes	Yes
City × year FE	Yes	Yes	Yes
Industry × year FE	Yes	Yes	Yes

Source. OSOME.
Notes. 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 because of new COVID-19 confirmed cases and was surveyed in a quarter after the outbreak; it is 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 (FEs). Asterisks indicate significance levels. S.D., standard deviation.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

explanatory variable is ($COVID_c \times After_q$), 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, owner's age and gender, business type (incorporation, registered self-employed, or unregistered self-employed), employment, and quarterly revenue. The regression also controls for the corresponding fixed effects.

Table 8 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 of Table 8 includes the whole sample, whereas panels B and C of Table 8 further restrict the analyses to new entry and incumbent subsamples, respectively. As shown in the table, exposure to local lockdowns is significantly correlated 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 6.2% for incumbents, especially those relying on both offline and online operations. In contrast, new entries rely more on pure online operations (36.0% more growth compared with the average level).[15] Similarly, column (3) shows that exposure to COVID-19 restrictions has accelerated the adoption of online sales (4.4% more growth compared with the average), and the impact concentrates on incumbent SMEs.

Table 9. Impact of Local Lockdowns on the Adoption of Remote Work and Electronic Information Systems

	(1)	(2)	(3)	(4)	(5)	(6)
		Electronic information system				
Outcome	Remote work	Sale	Finance	Payment	Management	Product
Panel A: All sample						
COVID × *After*	0.020*	0.013**	0.004	0.007	0.004	0.007
	(0.012)	(0.007)	(0.010)	(0.014)	(0.009)	(0.009)
Mean of dependent variable	0.137	0.146	0.145	0.264	0.233	0.088
S.D. of dependent variable	0.344	0.353	0.352	0.441	0.423	0.283
Adjusted R^2	0.045	0.058	0.076	0.028	0.068	0.042
Observations	65,049					
Panel B: Newly established subsample						
COVID × *After*	0.007	−0.023	0.006	−0.016	−0.046	0.015
	(0.046)	(0.042)	(0.020)	(0.049)	(0.058)	(0.027)
Mean of dependent variable	0.147	0.134	0.139	0.219	0.235	0.079
S.D. of dependent variable	0.354	0.341	0.346	0.413	0.424	0.269
Adjusted R^2	−0.110	−0.141	−0.081	−0.096	−0.092	−0.088
Observations	5,921					
Panel C: Incumbent subsample						
COVID × *After*	0.022*	0.014**	0.005	0.006	0.007	0.006
	(0.012)	(0.007)	(0.011)	(0.015)	(0.009)	(0.009)
Mean of dependent variable	0.136	0.147	0.145	0.269	0.233	0.089
S.D. of dependent variable	0.343	0.354	0.352	0.443	0.423	0.285
Adjusted R^2	0.044	0.061	0.078	0.026	0.070	0.042
Observations	59,128					
Control	Yes	Yes	Yes	Yes	Yes	Yes
City, industry, and 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

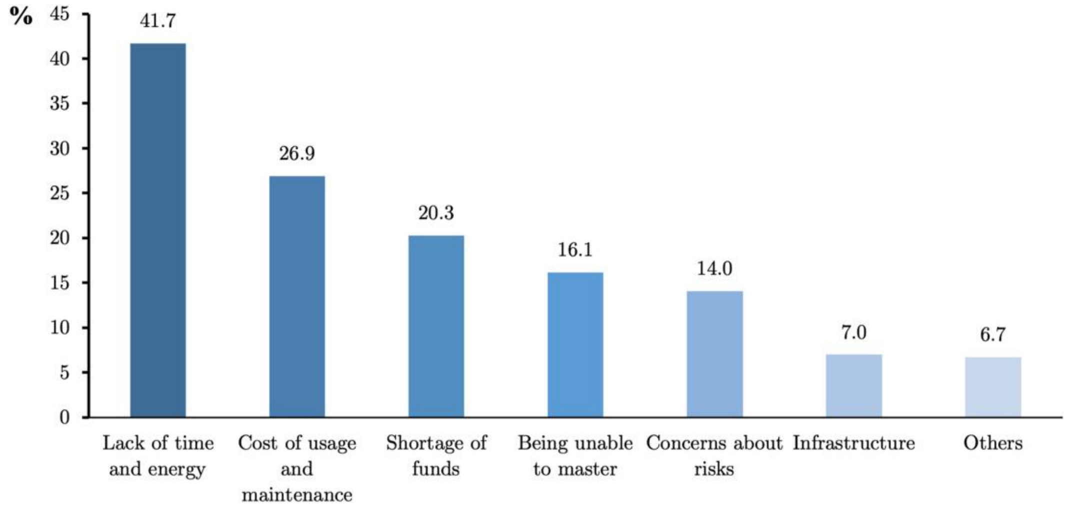
Source. OSOME.
Notes. All regressions in the table use OLS estimation. The fixed-effect Logit model also gives consistent results. Standard errors in parentheses are clustered at the city level. The independent variable, *COVID* × *After*, equals one if a business is located in a city with localized lockdowns because of new COVID-19 confirmed cases and was surveyed in a quarter after the outbreak; it is 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 (FEs). Asterisks indicate significance levels. S.D., standard deviation.
*$p < 0.1$; **$p < 0.05$.

Table 9 further reports the impact of exposure to lockdowns on the adoption of remote work and electronic information systems.[16] These questions were not included in the questionnaire until the fourth quarter of 2020, so we dropped the first wave of OSOME from the sample in Table 9. After a local lockdown, businesses, in particular incumbents, are more likely to adopt remote work. Given that only 13.7% of respondents have adopted remote work, exposures to local lockdowns explain nearly 14.6% of the increase in the adoption of remote work for the sample. The magnitude is even bigger when restricted to the incumbents (16.2%). Additionally, incumbent businesses tend to adopt the electronic information system of sales. Compared with the average level, exposure to a lockdown leads to an 9.5% increase in adoption. However, exposure to COVID-19 restrictions is not associated with the introduction of electronic systems for newly established businesses. Overall, local lockdowns have induced small businesses to develop online operations and adopt remote work.[17]

We further evaluate SMEs' performance under the impetus of the pandemic in Online Appendix H. SMEs adopting online operations fared better in revenues, but the immediate impact on profit is insignificant, especially for smaller firms (fewer than 20 full-time employees) and new entrants, likely because of the intense competition and the relatively low profit margin in e-commerce. This analysis enriches the literature that firm characteristics, such as firm size, matter to the benefit of investing in and adopting virtual technologies.

Finally, the digital edge does not come free. Concerning the constraint or cost to SMEs' adoption of digitization, we included a multiple-choice question in the OSOME survey in the second quarter of 2021 about the

Figure 6. (Color online) SME's Greatest Difficulties in Digital Transformation or Upgrading



Source. OSOME.
Notes. The OSOME survey included this question only in the second quarter of 2021. In total, 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.

greatest difficulties they encountered in digital transformation or upgrading. As shown in Figure 6, the lack of time and energy to learn is the key obstacle to digital adoption. Nearly 41.7% reported that it is one of the main difficulties they faced. The cost of usage and maintenance (including service charges) and the shortage of funds are two other main difficulties. We include detailed discussions in Online Appendix I.

5. Conclusion

SMEs are integral to the global economy and play an important role in the Chinese economy as well.[18] Using proxies for digitization, such as e-commerce adoption, from multiple data sources, we document how SMEs in China with greater digitization had more robust market demand and faster turnover of working capital, and thus, they were more resilient to the pandemic shock. They reported better cash flows, were more likely to reopen after the lockdown, and held more optimistic views of future growth. More importantly, 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 after the initial lockdown, 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 effects persisting for over one year, well beyond the immediate aftermath of the COVID-19 outbreak that extant studies have documented. The effects are more pronounced for W&R, manufacturing, service, and agriculture sectors; firms in industrial clusters; and areas with better financial inclusion but lower efficiency.

The observed digital transformation is consistent with rational resource allocation under constraints. Given the SME owners' limited cognitive bandwidth, 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 digitization. Individual SME owners, therefore, have strong incentives to invest in digital technologies, especially for mitigating financial constraints in areas with less developed financial markets. At the macro 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 (Murphy et al. 1989), which would have cost the government a lot more under normal circumstances. Moreover, our finding on increased entrepreneurship in businesses adopting digital technologies corroborates a long-run reallocation (Barrero et al. 2020), which warrants future studies.

Finally, 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. Many countries may lack the necessary infrastructure and comprehensive ecosystems or platforms for the digital transformation seen in China in response to the

COVID-19 shock. For example, only about 50% of Mexico's population had a bank account compared with 80% in India prior to the COVID-19 shock, although its per capita gross domestic product (GDP) was four times that of Mexico (Bandura and Ramanujam 2021). Nevertheless, some anecdotal evidence suggests that the pandemic may have spurred digital infrastructure development in these countries.[19] Various forms of digitization in other (developing) countries constitute interesting future research.

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Endnotes

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 45% of the GDP in 2012 (Yoshino and Taghizadeh-Hesary 2018), 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, and layoffs (Bartik et al. 2020, Fairlie 2020, Humphries et al. 2020, Bartlett and Morse 2021, Bloom et al. 2021).

3 A McKinsey Global Survey of executives at large firms shows that firm responses to COVID-19 have accelerated companies' adoption of digital technologies, which is expected to be long lasting and essential for recovery (Baig et al. 2020, McKinsey & Company 2020). Our study studies SMEs instead.

4 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.

5 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).

6 Plaid (2020) 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, and 80% of Americans say they favor contactless digital solutions.

7 Active SMEs on the Alipay platform are defined as those that had transactions in at least 3 months, more than 90 transactions, and a total volume of more than 2,000 yuan Renminbi (nearly 270 U.S. dollars) in the past 12 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. Note that active Alipay users are not restricted to the ones conducting e-commerce business. Alipay confirmed that our respondent sample is representative of active users in terms of transaction volume. The Alipay user base also overlaps with the Chinese population ages 16–59 (Bian et al. 2023). For further robustness, we control for registration type and other measurements of the SME's size.

8 For robustness, we further control for more firm-level pre–COVID-19 characteristics and the owner's background information gathered in the baseline survey. Online Appendix Table B.1 presents the descriptive statistics. Note that some variables are not included because the questions were not collected in the August wave. Online Appendix Tables B.2 and B.3 demonstrate the results under additional control variables. The OSOME survey also tracked that high operating costs and weak demand were consistently major challenges (Online Appendix F).

9 The Wuhan lockdown was implemented on January 23, 2020, and other provinces followed suit in the following days. The Lunar New Year's Eve was on January 24, 2020.

10 We report stylized patterns of business registration and exit in Online Appendix G. For robustness, we repeat the exercise by comparing online and offline businesses in W&R sectors (clearly indicated by the four-digit industrial classification code), and we find consistent results (Online Appendix Figure A.1).

11 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, whereas 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.

12 The indices of regional heterogeneity cannot be endogenous to the pandemic or digitization, so they have to be predetermined. In spite of China's fast-paced development, it is path dependent, and there is information in the previous state variables of the system. Therefore, we calculate the industrial cluster index and the digital financial inclusion index in 2015, the starting year of our sample

period, to get a predetermined variable. For robustness, we also use the indices constructed in 2019 right before the pandemic. The indices display a path-dependent trend throughout the period.

[13] With constant returns to scale, the marginal product of capital is proportional to the average product of capital (i.e., the variation in log(*marginal product of capital*) = variation in log(*average product of capital*)). The rationality lies in that in an ideal world with perfect financial markets, the marginal product of capital should be equal across firms and regions.

[14] We also find that digital transformation because of the pandemic and reopening is more pronounced for non-SOEs than SOEs (Online Appendix Table B.4) based on SAIC data.

[15] Survivorship bias is a potential concern. SMEs operating online are more likely to survive and respond to the survey. We dispel the concern by ruling out any systematic gap in transactions between survey respondents and all active SMEs on Alipay using the criteria in footnote 7 within each industry and location.

[16] Remote work in the questionnaire includes working from home and flexible working hours. For self-employed, this question means whether they can manage and operate businesses remotely. The electronic information system on management includes staff management, office automation, and cloud storage.

[17] Online Appendix Table B.5 contains more heterogeneous analyses by firm-level (registration type, industry, size, and financial needs) and entrepreneurial characteristics (gender, age, and education level). Overall, the effect is more pronounced for larger firms and firms owned by female, young, college-educated entrepreneurs.

[18] As an additional example, the OSOME survey from the fourth quarter of 2021 reveals that 76.7% of the SMEs in the sample are self-employed or have a small number of employees (between zero and four full-time employees), creating an average of about 4.3 jobs excluding the owners themselves based on the estimation in Online Appendix Table B.6. 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.

[19] Refer to https://www.reuters.com/article/us-latam-mercadolibre-payments-focus/latin-american-payment-giant-rises-amid-pandemic-with-an-eye-on-chinas-ant-idUSKBN2751FB for recent progress in Latin American countries, including Mexico. These developments are against the backdrop of the global convergence toward the superapp models pioneered by Chinese BigTech firms (Bian et al. 2023).

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