



Can e-commerce platforms build the resilience of brick-and-mortar businesses to the COVID-19 shock? An empirical analysis in the Chinese retail industry

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Abstract

We proposed a research model that examined the differences between the contributions of large, third-party e-commerce platforms and self-operated e-commerce platforms to businesses' resilience to the COVID-19 shock. The difference-in-differences approach was employed to analyze a substantial sample of Chinese retailers. The study found that (1) under the baseline condition, the large, third-party e-commerce platforms built significant resilience for the brick-and-mortar businesses, (2) resource constraints induced by factor immobility weakened the contribution of large, third-party e-commerce platforms to the businesses' resilience in regions of severe shock, and (3) the physical retailers' self-operated EC platforms built resilience in regions of severe shock.

Keywords E-commerce · Brick-and-mortar business · COVID-19 · Digital resilience

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1 Introduction

As digital transformation continues to penetrate and galvanize a myriad of business segments, conventional brick-and-mortar businesses equipped with e-commerce (EC) platforms have gained increased momentum across the globe. In China, for example, nearly 80 percent of brick-and-mortar business enterprises have integrated their in-person business with a variety of EC channels [15], likewise, nearly two-thirds of American traditional retailing executives have described “building e-commerce capabilities” as a top priority [35]. Admittedly, this paradigmatic evolution has been largely attributed to the flexibility of EC. Search and discovery are more accessible for customers through EC platforms than through on-site shopping in terms of demand [13], reaching buyers through EC platforms and digital distribution entails fewer constraints for suppliers than doing so face-to-face [19]. Under this rationale, EC platforms are a crucial factor in brick-and-mortar businesses’ *resilience* to unprecedented shocks, such as the COVID-19 pandemic [46, 60]. With their higher flexibility in meeting supply and demand, EC platforms can enable brick-and-mortar businesses to avoid disruptions caused by shocks through shifting from in-person to online operations.¹

Importantly, resilience to exogenous shocks has piqued mounting interest in extant IS research. However, although a plethora of research has attempted to investigate this crisis-driven phenomenon by analyzing EC platforms’ contributions to brick-and-mortar businesses’ resilience, little attention has been given to the shocks per se. We conjecture that the underlying assumption that the shocks shut down brick-and-mortar businesses but have had few negative effects on the EC platforms may not fully depict the entire situation. In essence, we posit that the extant research has largely neglected to shed light on the shock-triggered unsuitability of some EC platforms in building resilience and whether the heterogeneity in the degree of shock across different regions can cause differences.

Due to the COVID-19 crisis, a new context has arisen through which we need to reconsider the points of focus when discussing how EC platforms contribute to brick-and-mortar businesses’ resilience to unprecedented shocks. Compared to the predictable, temporary, or industry-endogenous shocks mentioned in prior studies (e.g., [29, 31, 33]), the first wave of the COVID-19 pandemic simultaneously featured a sudden onset,² ongoing impact, and exogeneity. The sudden outbreak of the long-lasting pandemic induced a forced shift of mass consumers from in-person to online channels for the sake of continuing to purchase goods. Such a type of *customer channel migration*, summarized as *generally forced customer channel migration* in this study, implies that the shifted consumers felt more anxious than

¹ This is the definition of the resilience to shocks built by EC platforms for brick-and-mortar businesses—a shock-reactive performance of maintaining continuous operations under disruptions. In this study, this concept definitely differs from the type of capability enabled by strategies, which is widely used in the organization- and strategy-centered studies [4]. Instead, it measures the extent to which the strategy-enabled capability is realized during specific shocks.

² In this paper, the terms “COVID-19 shock” and “COVID-19 pandemic” are restricted to the first wave of the pandemic unless specified.

normal [53, 68] and expected a pandemic-driven income reduction [24]. In this case, consumers might tend to follow the crowd and to concentrate on the necessity and safety of their purchase [61, 66]. Thus, the structure of the shifted demand for online purchases might be characterized by homogenous preferences—most of the shifted consumers could only be matched and adopted by EC platforms with certain features [14]. Furthermore, sweeping social-distancing measures shaped a common supply-side environment, the so-called *factor immobility*.³ When people were asked to stay at home and most physical travel was restricted [20], the resource organization of both in-person and online-based businesses faced greater challenges in accessing their material resources [23, 36, 77]. In other words, EC platforms in regions under stricter pandemic prevention measures might also struggle with tighter constraints on accessing their production factors [25]. In general, the uniqueness of the pandemic-driven simultaneous changes in *demand structure* and *resource constraints* reminds us of the scant attention given to a shock-specific perspective. That is, the evaluation of brick-and-mortar businesses' resilience built by EC platforms should be restricted to the specific context rather than considered as measuring a generic capability.

To address the abovementioned paucity and illuminate how EC platforms can build brick-and-mortar businesses' resilience to unprecedented shocks, this study focuses on the different contributions of large, third-party EC platforms and physical enterprises' self-operated EC platforms in terms of their resilience to the COVID-19 shock.⁴ The study also endeavors to investigate heterogeneous resilience due to differences in the degree of regional shock. A research model was constructed in the new context of the COVID-19 pandemic, and hypotheses were formulated following the *structure-conduct-performance (S-C-P)* paradigm with the *resource-based view* [8, 17, 49, 59, 74]. Specifically, (1) given the baseline demand structure in the generally forced customer channel migration, only the exact-matched EC platforms with higher publicity and reliability could thrive by adopting the consumers shifting from offline to online. (2) In regions with more severe infection, although there were more consumers shifting from offline to online, EC platforms' operational performance of adopting the *excessive demand* was weakened by the stricter resource constraints caused by the intensified factor immobility.

By employing the difference-in-differences (DID) approach to analyze a substantial sample of Chinese listed retailers from the first quarter of 2019 to the first quarter of 2020, this study found that (1) basically, the large, third-party EC platforms helped brick-and-mortar businesses build the resilience of their selling and operations to the COVID-19 shock, while the adoption of the physical retailers' self-operated EC platforms made little difference; (2) the contribution of the large,

³ In this paper, unless noted, the term “factor immobility” denotes geographical factor immobility.

⁴ As a definition in this study, these two types of EC platforms can technically provide similar services or products to a single consumer. For example, the difference between a large EC platform and a physical enterprise's EC platform can denote the difference between Tmall.com and tianhong.cn but cannot represent the difference between Amazon.com and saksoff5th.com. In some parts of this paper (especially the empirical results section), we simply use “self-operated EC platforms” to denote “physical enterprises' self-operated EC platforms”.

third-party EC platforms to the resilience of the operations was weaker in regions of more severe shock; and (3) the physical retailers' self-operated EC platforms built resilience in regions of severe shock.

This study contributes to the research in two significant ways. First, in the context of the COVID-19 pandemic, the empirical findings add thorough knowledge to the evaluation of EC platforms' contribution to sustaining brick-and-mortar businesses. Particularly, they revealed this counterintuitive fact: Although the physical enterprises' self-operated EC platforms did not work under normal circumstances dominated by the aforementioned superstar effect, they could build resilience by supplementing the excessive demand in some regions where the large, third-party EC platforms faced tough resource constraints. Second, this study indicates the importance and feasibility of focusing on shock features rather than strategic advantages in discussing the extent to which EC platforms build resilience to shocks. Drawing on the S-C-P paradigm with the resource-based view, this study found that two shock-specific conditions must hold simultaneously for certain EC platforms to smoothly enable brick-and-mortar businesses' resilience: (1) The shocks make the brick-and-mortar businesses' shift to the EC platforms easier than normal, and (2) the shocks do not significantly restrict the EC platforms' operational capacity to adopt the shift.

2 Theoretical background

2.1 The COVID-19 shock: key features and implications

To address the specific environments derived from the COVID-19 shock, we should carefully analyze the uniqueness of the pandemic in terms of the sudden onset, ongoing impact, and exogeneity. The simultaneous existence of these features makes the COVID-19 shock distinct from the shocks mentioned in previous studies focusing on e-commerce's contribution to brick-and-mortar businesses' resilience. The sudden onset of the massive outbreak, as a result of the high infectivity of the coronavirus, implies that there was no predesigned plan for consumers and EC platforms to adjust to the pandemic [39]. This situation differs from that of predictable shocks, such as traffic jams or weather events (e.g., [33]). The ongoing impact represents the duration of the pandemic's impacts, which was a prediction mentioned by many experts [75]. This feature deviates from that of temporary shocks during which EC platforms only need to work as a set of temporary alternatives for consumers of brick-and-mortar businesses (e.g., [29]). The exogeneity of the shock stemmed from the nature of anti-COVID-19 measures—they were restrictions to the interpersonal transmissions themselves rather than to certain industries or organizations [20]; that is, the shock derived from the COVID-19 pandemic was common for every agent who had the same risk of infection. Therefore, the COVID-19 shock cannot be regarded as a shock only to brick-and-mortar businesses (e.g., [31]).

Taking the unusual features of the COVID-19 shock as a basis, we propose that EC platforms faced two environments that determined whether they could build resilience for brick-and-mortar businesses: *generally forced customer channel migration* on the demand side and *factor immobility* on the supply side.

2.1.1 Generally forced customer channel migration

In this study, the pandemic-forced shift of mass consumers from in-person to online channels in order to continue to purchase goods is summarized as *generally forced customer channel migration*. It deviated from the standard *customer channel migration* initiated based on individual cost-effectiveness analyses [7, 71]. In view of the ongoing impact and exogeneity of the COVID-19 shock, mass consumers had to tolerate either an increase in costs to continue purchasing in person or new costs induced by migrating to online purchasing [37, 61]. Simultaneously, they might have worries about income decline in the future [24, 63]. These two common troubles led to a common negative real income shock, which meant that the consumers' budgets for all goods shrank [61, 66]. Additionally, the sudden onset of the COVID-19 pandemic resulted in most consumers not having sufficient time and information to prepare for their migration, even if they were aware of the ongoing impact of the shock [38]. Thus, consumers might have felt more anxious than they would have in a channel migration over the long run because they had to consider more variables under more urgent conditions [53, 68].

2.1.2 Factor immobility

Factor immobility stems from the concept of *factor mobility*, which denotes to what extent the factors that support production can freely migrate or transfer to other regions [12, 41]. Factor immobility is used to describe how factor mobility is restricted when analyzing regional economic topics [70]. During the COVID-19 pandemic, exogeneity implies that many anti-infection measures focused on common travel restrictions and social distancing, and many people feared in-person interactions [65, 73]. Thus, the shock created factor immobility for both physical enterprises and EC platforms, as all the factor transfers requiring in-person connections became more expensive [23, 36, 77].

2.2 Superstar effect on demand structure

Studies on the effect of digital searches formulated the concept of the *superstar effect*: online searching can increase the proportion of purchases of frequently bought goods [58]. Researchers have suggested that the superstar effect can be explained by homogenous demand and search technology [14]. Online purchasing takes place in a network-based environment. In such an environment, low search costs enable everyone to access others' comments and recommendations. Thus, consumers with homogenous taste and demand can easily gather in the same online channel, and such gatherings can be self-reinforced through intensive communications in online communities [9, 56].

In addition to active gatherings, consumers' choice is shaped by search techniques. When shopping online, many consumers use search engines to search for

goods and search engines tend to recommend popular goods and channels to their users [28, 45]. Hence, online consumers, especially “newbies”, are led to gather on channels with high publicity.

2.3 Resource constraints on e-commerce operation

The well-established *resource-based view* argues that operational capacity affects firms’ capability to implement strategies and derive benefits from competition [10, 74]. Enabling EC operation requires external resources, such as an information system infrastructure [62], and internal resources, such as technological, human, and financial resources [69]. Although the required resources for EC operation vary with the external environments and features of the business, a lack of resources will always create barriers for EC operation [11]. For example, if an EC platform does not hire sufficient couriers, the goods cannot be delivered to customers on time; if an EC platform’s inventory resources are inadequate, some orders will need to be canceled since the goods cannot be provided as promised [79]. Thus, EC operation can be disrupted by *resource constraints*—if a core resource is insufficient, the whole system cannot operate efficiently [72].

2.4 From shock to resilience: The S-C-P paradigm with the resource-based view

To derive a shock-specific understanding of how effectively EC platforms build resilience for brick-and-mortar businesses, the *S-C-P* paradigm with the *resource-based view* was introduced to integrate theory construction in this paper. As an old framework in industrial organization analysis, the *S-C-P* paradigm contends that the performance (e.g., competitive advantages) derived by conduct (e.g., a strategy) is determined by how well the conduct fits the industry structure (e.g., demand structure in the industry) shaped by marketplace dynamics (e.g., shocks) [8, 17]; the resource-based view is sometimes inserted as an extension to the *S-C-P* paradigm [59, 74].

Many strategic management researchers have criticized the paradigm for misleading strategic decisions—the industry structure can only work to explain performance in static equilibrium, but strategies should be formed toward constantly changing environments [52, 59]. However, such a disadvantage in the context of strategic decisions coincidentally constitutes the advantage of employing the theory for our study. The interest of concern in this study boils down to evaluating the shock-specific resilience (i.e., a type of performance in a nearly static equilibrium) built by already existing EC platforms (i.e., given conducts). This exactly satisfies the necessary condition for the *S-C-P* paradigm with the resource-based view to make sense (c.f., [49]). As illustrated in Fig. 1, a shock-specific framework can be formulated with the following logic: (1) The demand structure shaped by the COVID-19 pandemic formed the baseline condition that enabled the suitable EC platforms to build resilience for brick-and-mortar businesses; (2) the pandemic-driven resource constraints in a region reversely affected the EC platforms’ operational capacity of building the resilience in the region.

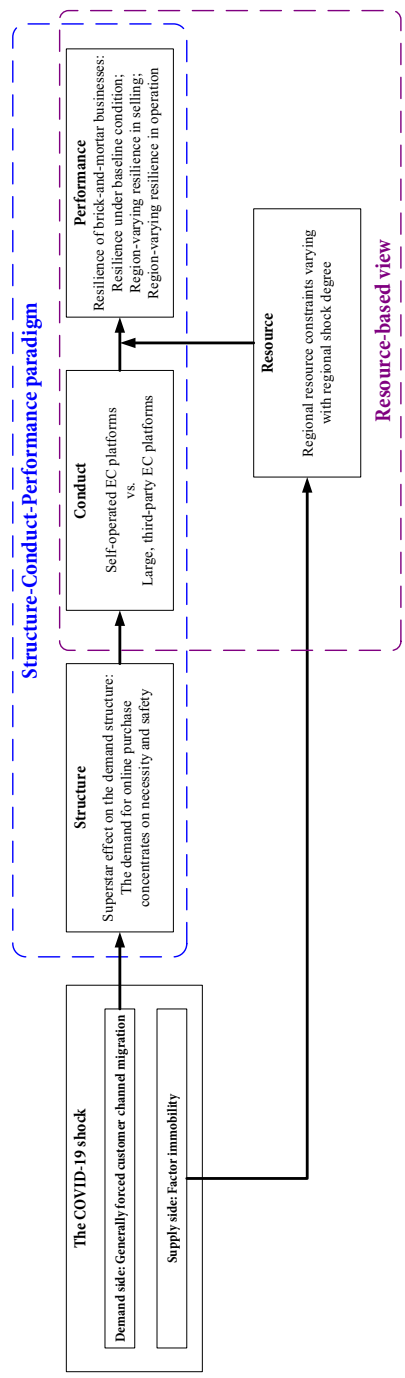


Fig. 1 The theoretical framework employed for this study

3 Hypothesis development

The COVID-19 shock on the demand side actually caused a type of superstar effect on the demand structure. As indicated above, generally forced customer channel migration implies that consumers of brick-and-mortar businesses face (1) a negative real income shock and (2) an anxiety-inducing decision environment when they consider shifting their demand to online purchasing. The former incentivized consumers to give up the demand for goods with high price elasticity (i.e., top-shelf goods) and preserve budgets for goods with low price elasticity (i.e., daily necessities) [50]; the latter led consumers to concentrate on safe and reliable purchasing to escape cognitive overload in a demanding environment [43]. Thus, the demand shifting from in-person to online channels was featured with a highly homogenous preference for the necessity and reliability of purchases. This created the condition for the superstar effect to exist—in view of the low costs of online searching and the search techniques, the shifted consumers with homogenous preferences would agree about the reliability of large, third-party EC platforms and crowd into these well-publicized channels [28, 56]. Therefore, most of the demand was more likely to be undertaken by large, third-party EC platforms, while the physical enterprises' self-operated EC platforms were more likely to be ignored.

In view of the S-C-P paradigm [8, 17], we propose that the extent to which EC platforms could build resilience (i.e., performance) for brick-and-mortar businesses corresponds to the extent to which the EC platforms (i.e., conduct) fit the pandemic-driven demand structure (i.e., structure). Hence, the following hypothesis was formulated for the baseline condition (i.e., the main effect under the condition of no variation in the regional shock degrees):

- H1 Under the baseline condition, large, third-party EC platforms built the resilience of brick-and-mortar businesses, while self-operated EC platforms made little difference to the resilience.

Within the COVID-19 context, the pandemic-driven environments on both the demand and supply sides spontaneously varied with the regional shock degree (i.e., the regional severity of the pandemic).⁵ Hence, for brick-and-mortar businesses operated in different regions,⁶ the resilience that EC platforms could build for these businesses might also vary with the degree of regional shock [47].

⁵ Usually, this concept is measured in the intensity of COVID-19 transmission, which is commensurable across regions with similar statistic systems [51]. It can correspond with the degree of people's awareness of the pandemic and the intensity of anti-infection measures, which are also commensurable across regions governed by similar institutions (e.g., a unitary system).

⁶ Specifically, in this research, brick-and-mortar businesses are supposed to be operated or rooted in a particular region when in-person transactions between suppliers and consumers of such businesses are made in the region. In this sense, the consumers of brick-and-mortar businesses operating in a region are local to the region; the operators of the businesses need to organize factors to produce goods in the region or obtain already-made goods from other regions; then, they need to deliver the goods to the local consumers. For example, the transactions of physical retail businesses operating in a province in China or a state in the U.S.A. are taking place in offline retail stores located in such a province or state.

On the one hand, regions facing a higher degree of shock might have higher intensity in generally forced customer channel migration than other regions. This result might be derived from two forces: (1) The more intensive transmissions in the regions could intensify consumers' fear of face-to-face purchasing such that a larger share of consumers would buy online to avoid risks; (2) the stricter anti-infection measures forced more consumers to shift from offline to online purchasing [61]. Regardless of the specific reason, such a demand-side environment implies that the scale of the shifted demand enlarged with the same demand structure. Hence, according to the same logic in the S-C-P paradigm, large, third-party EC platforms could work better in building resilience for disrupted brick-and-mortar businesses by adopting shifted demand on a larger scale.⁷

On the other hand, the higher shock degree in a region was not a piece of fully good news for EC platforms to build resilience in the region because the supply-side environment backfired. When the COVID-19 transmission in a region became severe, the travel restrictions that blocked the region from other regions tightened [20]. As a result, the factor immobility of the region intensified, and there were stricter resource constraints—the EC platforms' capacity to transfer their nonlocal resources to such a region contracted [25]. In this case, with reference to the resource-based view [11, 74], large, third-party EC platforms might work less effectively in building resilience for disrupted brick-and-mortar businesses because of their more stressful operation under stricter resource constraints. Such an implication is reflected in the “labor crunch” of couriers reported by *ChinaNews* [16] and Amazon's lack of workers reported by *The Telegraph* [26] in the regions of severe COVID-19 transmission.

Here, we introduced *excessive demand* to represent the shifted demand through which EC platforms can enable more transactions at the expense of suffering more in operation. Considering the demand-side and supply-side environments in regions with a higher degree of the COVID-19 shock, it is reasonable to summarize that (1) stricter factor immobility induced stricter regional resource constraints on the operations of large, third-party EC platforms, while (2) the higher intensity of generally forced customer channel migration induced higher regional excessive demand for large, third-party EC platforms to enable more transactions. Taken together, Hypotheses 2 and 3 were formulated as follows⁸:

⁷ As hypothesized above, only the large, third-party EC platforms are effective in building resilience, so the regional shock degree's impact on the resilience built by EC platforms only concerns the large, third-party EC platforms.

⁸ To some extent, we used the concept of the regional excessive demand as a byproduct of the existence of the regional resource constraints. If the COVID-19 shock had not caused changes in resource constraints, we could have deleted the term “excessive” and written that “as the demand in a region increased, the EC platforms' contribution to the resilience in the region strengthened”.

- H2 As the excessive demand in a region increased with the increased degree of shock, the contribution of large, third-party EC platforms to the resilience in the selling of the brick-and-mortar businesses rooted in the region increased.
- H3 As the resource constraint in a region became stricter with a higher degree of shock, the contribution of large, third-party EC platforms to the resilience in operations of the brick-and-mortar businesses rooted in the region weakened.⁹

Based on the hypotheses and the proposed theoretical background, the research model of this study is summarized in Fig. 2.

4 Data sources and identification framework

4.1 Data sources and variables

A sample of physical enterprises that focused on brick-and-mortar business before the COVID-19 pandemic, including both those who had participated in the different EC platforms and those who had not, was required for empirical analysis. Therefore, Chinese listed firms belonging to the China Securities Regulatory Commission (CSRC) wholesale and retail industry were employed as the units of measurement based on their accessibility and representativeness. These retailers operated mainly in physical stores and offered face-to-face services to customers before the pandemic. Compared with businesses in other industries, the retailers' businesses were homogeneous to some extent—their performances in selling and operation were commensurable and their features that may have confounded the issue of interest were also similar [18]. After eliminating firms that concentrated on wholesale and specialty stores, 260 qualified observations (obs.) of 52 retailers from the first quarter of 2019 (2019Q1) to the first quarter of 2020 (2020Q1) remained in the sample. The data for the core variables in the analysis were retrieved as follows.

In this study, we focus on the resilience restricted to a reactive performance toward specific shock environments. For this purpose, we did not involve the interval after the first quarter of 2020 in our sample. The specific environments illustrated in the theoretical background faded dramatically in China after the first quarter of 2020 [40].¹⁰ The starting point of our time span is set to avoid disturbances from events occurring before 2019; technically, the four periods before the shock are enough to test the assumptions in our identification design [3, 30].

⁹ These two hypotheses actually describe the moderating effects of the regional shock degree on EC platforms' impacts to two outcome variables. In the empirical section, this moderator is designated as a continuous variable.

¹⁰ The long-run dynamics of EC platforms' impacts on brick-and-mortar businesses represent an interesting and complicated topic. However, it is more likely a topic concerning the performance of purposeful EC adoption practices (e.g., responsiveness) rather than the reactive performance of given EC platforms [4].

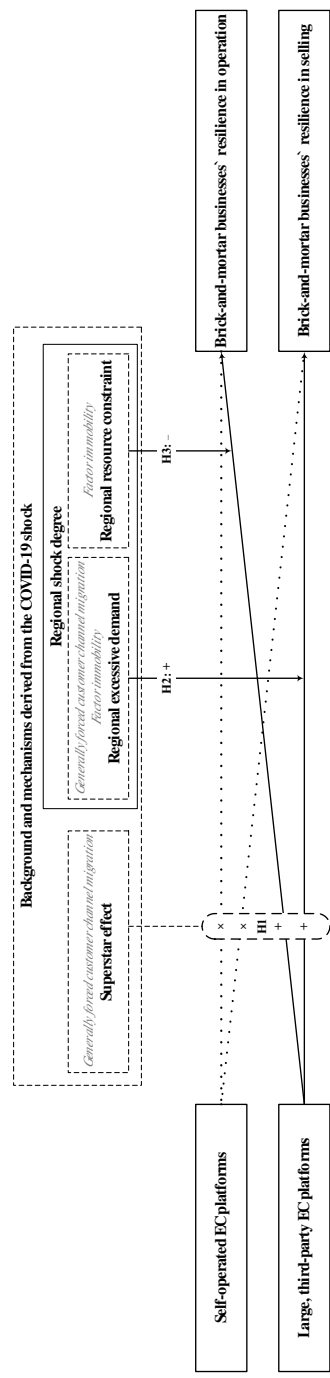


Fig. 2 The research model for empirical analysis

4.1.1 Performance in selling and operation

The micro-level data on the financial indices of retailers came from the WIND® Shanghai Security Exchange and Shenzhen Security Exchange Stock Database, which records the financial data of all Chinese listed firms from their regular reports. According to the theoretical foundation and hypotheses mentioned above, the basic financial indices of sample retailers, including sales growth (*SGro*) and inventory turnover (*IT*), were utilized in this study. Sales growth has frequently been used as a measurement of selling performance, while inventory turnover is usually regarded as a proxy of retailers' operation performance [11, 76].

4.1.2 Regional shock degree

Because this study also considered the impact of the regional heterogeneity of the COVID-19 shock on brick-and-mortar businesses' performance, regional variations in pandemic severity were required for the empirical analysis. Referring to relevant studies (e.g., [51]), the regional daily average newly confirmed cases in 2020Q1 were derived from the CSMAR® Novel Coronavirus Epidemic and Economic Research Database. For each sample retailer, the regional shock degree it faced (*Severity*) was computed as follows:

$$Severity_i = \frac{\sum_{r \in r(i)} w_r \times DailyNewConfirmedCases_r}{\sum_{r \in r(i)} w_r}, \quad (1)$$

where *DailyNewConfirmedCases_r* denotes the number of newly confirmed COVID-19 cases in region *r* per day over the first quarter of 2020 and *w_r* denotes a retailer's revenues generated from region *r* in 2019. For retailer *i*, the set of its main business areas, *r(i)*, is either the set of all regions in which the retailer generates more than 30% of its revenues generated in China or the set of all regions in which the retailer operates (i.e., the retailer generates no more than 30% of its total domestic revenues even in one of these regions) [21]. In the latter case, *w_r* is set as a constant parameter.

As illustrated above, the regional resource constraint of EC platforms and the regional excessive demand positively correspond with this single variable during the pandemic. For the hypothesis development to hold, there might be two concerns in terms of the measurement of the regional shock degree—such a volume measure was incommensurable across regions with different populations, and the intensity of the anti-infection measures was sometimes inconsistent with the severity of the COVID-19 pandemic. The former is easy to address. The number of new COVID-19 cases per capita or even per 100,000 people seems trivial in China. Actually, the attitudes that Chinese people and government have toward a pandemic were determined based on the volume measure (i.e., the number of new cases) instead of a ratio measure [78]. The latter—notwithstanding it is not a problem in this study—is slightly more complicated. Discussion about this issue will be reported in the robustness checks.

Table 1 Treatment statuses used in the empirical analysis

Variable	Treatment status = 1 (treated group)		Treatment status = 0 (control group)	
	Criteria	Num	Criteria	Num
<i>IsOwnEC</i>	The retailer had its self-operated EC platform before 2020	24	The retailer did not have its self-operated EC platform before 2020	28
<i>Is3rdEC</i>	The retailer participated in large, third-party EC platforms before 2020	17	The retailer did not participate in large, third-party EC platforms before 2020	35

4.1.3 Treatment status

To examine the hypotheses, the sample retailers were grouped depending on their participation in different EC channels and EC business models. The relevant information was reported in the annual reports and official websites of the sample retailers. Of the 52 retailers (260 obs.), 24 (120 obs.) had their own self-operated EC platforms, while 17 (85 obs.) participated in large, third-party EC platforms before 2020. Here, two indicator variables were formed, as shown in Table 1.

4.2 Identification principle

Empirically, this study aimed to assess how certain EC platforms contributed to brick-and-mortar businesses' resilience in selling and operation during the COVID-19 shock. According to the data, it is necessary to identify the difference in change in the sample retailers' business performance by examining the change in their overall performance. To achieve this goal, a DID framework was used, as shown in Fig. 3.

Several properties of the sample were employed in this study; thus, the resilience to the COVID-19 shock that certain EC platforms built for brick-and-mortar businesses was validly identified by the DID. First, the sample retailers' businesses were homogeneous to some extent.¹¹ In this case, their businesses' financial performance was commensurable and the average difference in the performance across different retailers made sense [18]. Second, the EC businesses only played a small part in the sample retailers' businesses before the pandemic, and this part focusing on regular customers may have not been significantly influenced by the shock [48]. Thus, the "change in the original EC businesses' contribution" shown in Fig. 2 was irrelevant. Finally, as verified in the next subsection, the pre-shock performance (i.e., selling and operation) of the brick-and-mortar businesses was parallel across the sample retailers with each pair of treatment statuses (e.g., *IsOwnEC* = 0 vs. *IsOwnEC* = 1)

¹¹ The sample retailers, such as Bailian Group and Wangfujing, were general retailers in a narrow industry (i.e., CSRC wholesale and retail industry), so their businesses could be generally regarded as providing comprehensive goods. The counterparts of these companies are firms, such as the Carrefour Group in Europe or AEON in Japan.

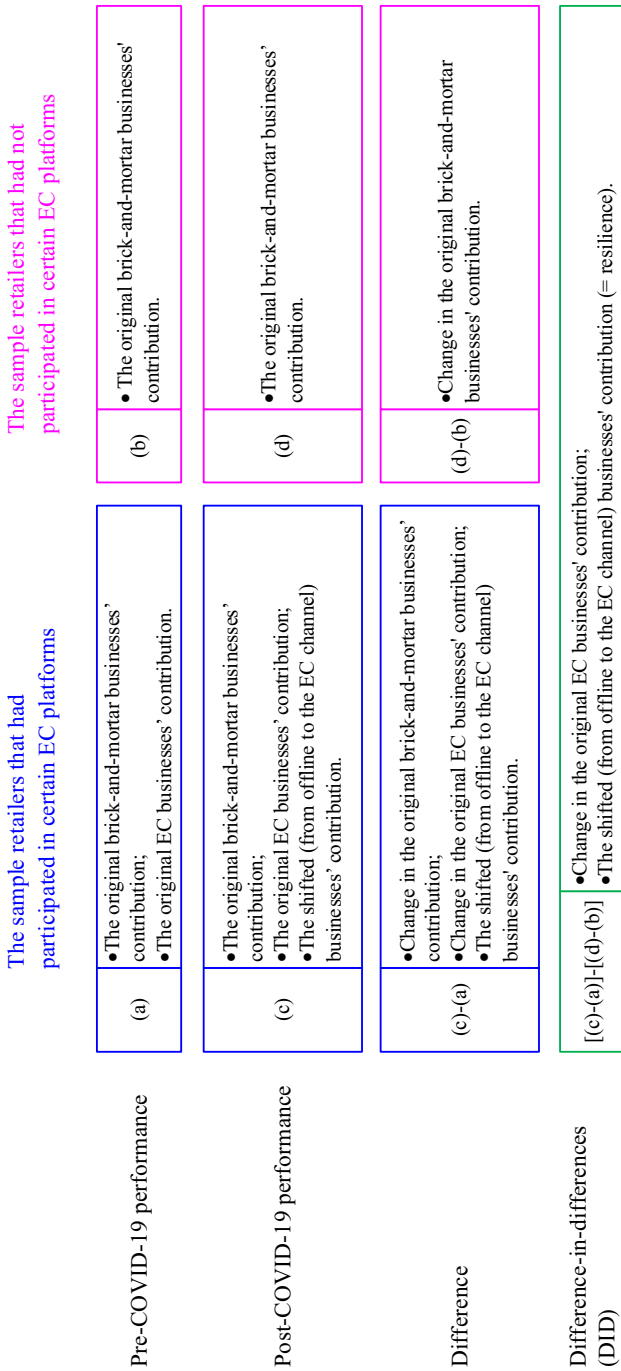


Fig. 3 Process for resilience identification using the sample

over periods. This confirmed that the “change in the original brick-and-mortar businesses’ contribution” mentioned in Fig. 3 was equal across the treatment statuses [2]. Thus, the DID exactly identified the businesses’ resilience, as illustrated in Fig. 4.

4.3 Econometric models

In econometrics, using Stata[®],¹² the abovementioned resilience (i.e., the DID) and relevant effects can be estimated by the following models:

$$Out_{it} = \alpha + \gamma_1 Post_t + \gamma_2 Severity_{it} + \pi(Placebo_{it} \times Post_t) + c_t + u_i + \varepsilon_{it} + \delta_1(IsOwnEC_{it} \times Post_t) + \delta_2(Is3rdEC_{it} \times Post_t). \quad (2)$$

$$Out_{it} = \alpha + \gamma_1 Post_t + \gamma_2 Severity_{it} + \pi(Placebo_{it} \times Post_t) + c_t + u_i + \varepsilon_{it} + \delta_1(IsOwnEC_{it} \times Post_t) + \delta_2(Is3rdEC_{it} \times Post_t) + \theta_1(IsOwnEC_{it} \times Post_t \times Severity_{it}) + \theta_2(Is3rdEC_{it} \times Post_t \times Severity_{it}), \quad (3)$$

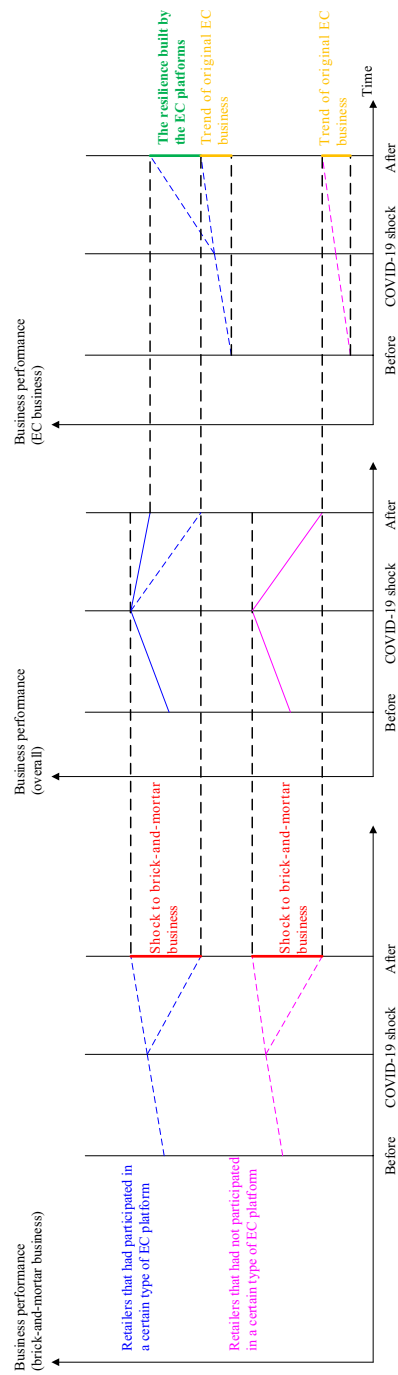
where Eq. (2) was the basic model of causal inference employed in this study. Out_{it} is a proxy for one of the outcome variables of retailer i in quarter t . As mentioned above, such variables include $SGro_{it}$ and IT_{it} , so two separate regressions must exist for each set of independent variables. $Post_t$ is an indicator variable that takes the value of 1 in 2020Q1. In the DID analysis, the coefficient of the interaction term between each treatment status and $Post_t$ (i.e., DID estimators δ_1 or δ_2) captured the difference in certain outcome before and after the COVID-19 pandemic between retailers that were and were not designated a treated unit (i.e., treatment effect). If participation in certain EC platforms indeed contributed to the resilience of the retailers’ brick-and-mortar business regarding selling or operation, the corresponding DID estimator was expected to be significantly positive.¹³

Equation (3) involves the regional degree of shock in Eq. (2) as a moderator of the DID estimators, while the moderating estimators θ_1 and θ_2 capture the treatment effects in terms of treatment states $IsOwnEC_{it}$ and $Is3rdEC_{it}$ as moderated by the regional degree of shock. If an increase in the regional shock degree at the margin led to an increase in the contribution of certain EC platforms to the retailers’ recovery in a certain financial index, the corresponding moderating estimator was expected to be significantly positive.

For other model specifications, γ_1 and γ_2 controlled for the common quarter-specific shocks to all retailers and the initial heterogeneity across retailers, respectively. Next, c_t represents the quarter fixed effects in addition to 2020Q1, and u_i represents the fixed effects at the firm level. Moreover, whether the supermarket business was

¹² Stata[®] is used for deriving all the empirical results in this study.

¹³ Note that the DID estimator did not elucidate which physical stores the consumers used before the COVID-19 pandemic.



Note: the vertical axes are drawn on the same scale, but the origins of them cannot be the same.

Fig. 4 A diagram of empirical identification of the resilience examined by this study

a retailers' main business drove a confounding problem in estimating the treatment effects; thus, a placebo term, $Placebo_{it} \times Post_t$, was involved in the models. The estimator of the coefficient of this term controlled for the difference in certain outcomes before and after the COVID-19 pandemic between retailers that focused and did not focus on the supermarket business.

Taking δ_1 as an example, the principle of identification is mathematically illustrated as follows.

The effect measured by δ_1 can be expressed as

$$[E(Outcome_{it}|IsOwnEC_i = 1, Post_t = 1, \dots) - E(Outcome_{it}|IsOwnEC_i = 1, Post_t = 0, \dots)] \\ - [E(Outcome_{it}|IsOwnEC_i = 0, Post_t = 1, \dots) - E(Outcome_{it}|IsOwnEC_i = 0, Post_t = 0, \dots)].$$

The value of this effect should be equal to the shock-reactive resilience of brick-and-mortar businesses built by the self-operated EC platforms (i.e., the "resilience built by the platforms" as mentioned in Fig. 4) [2]. Basically, this identification can make sense if the *parallel trends assumption* holds, namely,

$$E(Outcome_{it}|IsOwnEC_i = 1, Post_t = 0, \dots) - E(Outcome_{it}|IsOwnEC_i = 0, Post_t = 0, \dots) = 0,$$

or more strictly,

$$E(Outcome_{it=2019Q1}|IsOwnEC_i = 1, \dots) - E(Outcome_{it=2019Q1}|IsOwnEC_i = 0, \dots) \\ = E(Outcome_{it=2019Q2}|IsOwnEC_i = 1, \dots) - E(Outcome_{it=2019Q2}|IsOwnEC_i = 0, \dots) \\ = E(Outcome_{it=2019Q3}|IsOwnEC_i = 1, \dots) - E(Outcome_{it=2019Q3}|IsOwnEC_i = 0, \dots) \\ = E(Outcome_{it=2019Q4}|IsOwnEC_i = 1, \dots) - E(Outcome_{it=2019Q4}|IsOwnEC_i = 0, \dots) = 0.$$

As a well-established proposition in the DID approach, the parallel trends in an outcome between a pair of treatment statuses over a sufficiently long time span imply that the parallel trends should hold after the time span if there were no external interventions [2, 3]. Therefore, for the COVID-19 shock, if the assumption holds, the post-shock difference in an outcome between a pair of treatment statuses (e.g., $IsOwnEC = 0$ vs. $IsOwnEC = 1$) can be regarded as a shock-reactive difference driven by the intrinsic difference between the treatment statuses.

4.4 Validity of the identification assumptions

To validate the parallel trend assumption, a t -test was performed for each outcome variable between each treated and control group in each quarter of 2019. The results are shown in Table 2. The difference in each outcome variable between each treated and control group was trivial over the quarters before 2020 (i.e., the timing of treatment), indicating that the parallel trends hold.

In addition to the parallel trend assumption, the causal effects of the COVID-19 shock on the sample retailers' financial performance may have been disturbed by concurrent changes in some other factors. The sample retailers' participation in EC

Table 2 Parallel trend test for each pair of treated and control groups

Treatment status	Quarter	t-test for equality of means (difference with significance)	
		<i>SGro</i>	<i>IT</i>
<i>IsOwnEC</i>	2019Q1	2.652 (5.816)	2.123 (1.589)
	2019Q2	−0.918 (5.400)	1.429 (1.367)
	2019Q3	1.064 (6.410)	1.408 (1.342)
	2019Q4	6.046 (5.408)	2.689 (1.880)
<i>Is3rdEC</i>	2019Q1	1.316 (6.208)	2.683 (1.676)
	2019Q2	0.481 (5.726)	2.260 (1.433)
	2019Q3	−2.620 (6.788)	2.102 (1.411)
	2019Q4	1.483 (5.816)	2.461 (2.009)

Standard errors are in parentheses. All coefficients were insignificant at the $p < 0.10$ level

platforms was irrelevant to short-term factors with high volatility,¹⁴ but its links to firm-level and region-level characteristics in the long term may have confounded the causal inference in this study.¹⁵ Typically, the adoption of EC is regarded as conditioned by firm size and market expectations; these are proxies of *organizational readiness* for EC adoption [55]. At the regional level, factors such as economic size, EC infrastructure, and market potential have been considered important determinants of EC adoption [42, 55]. These factors may also have influenced the sample retailers' post-COVID-19 selling and operation.

To address this concern, we investigated whether each treatment status was related to some observable factors. By using each factor as a separate outcome variable and involving all treatment variables in Eq. (2), the DID estimators showed systematic differences in the trends of the observable factors. As shown in Table 3, the results of the balance test indicated no significant association between each observable factor and the treatment status from 2019Q1 to 2020Q1, since all the coefficients

¹⁴ In the sample retailers employed in this study, the adoption of EC was determined long before 2019.

¹⁵ For example, a firm's total assets at the end of a certain year always has inheritance from the firm's total assets in the past. Statistically, if the sample retailers' participation in EC platforms is related to the retailers' previous total assets, then the participation may have a link with the retailers' present total assets, which can cause a confounding problem.

Table 3 A balance test for some observable factors against the treatment statuses

Observable factors	<i>IsOwnEC</i>	<i>Is3rdEC</i>
<i>Firm-level factors</i>		
Total assets (in billion yuan)	−0.783 (0.977)	1.416 (1.521)
Total liabilities (in billion yuan)	−0.044 (0.570)	0.777 (0.819)
Price-book ratio	4.844 (6.782)	−9.604 (11.123)
<i>Regional-level factors</i>		
Growth rate of regional total retail sales of consumer goods	0.512 (1.279)	1.251 (1.283)
Quarterly regional delivery volume (in billion case)	−4.218 (2.674)	−1.980 (3.190)
Quarterly regional GDP (in trillion yuan)	−0.505 (0.306)	−0.300 (0.368)

Each column reports the coefficients of the interaction terms of the post dummy and each treatment variable from regressions using the observable factors as separate dependent variables. At the firm level, the dependent variables comprised proxies of firm size, which are total assets and total liabilities, and the price-book ratio, a proxy of market expectations. At the regional level, external factors related to market potential, EC infrastructure, and economic development were involved. National and industrial factors were excluded because they are fixed across firms. Standard errors are in parentheses. All coefficients were insignificant at the $p < 0.10$ level

of interest were insignificant. This finding provided evidence that the treatment variables were orthogonal to trends in other observable factors related to the outcomes, and it informally implied that the treatment variables should also not covary with unobservable factors that affect the outcomes [1].

In general, the validation of the parallel trend assumption and the result of the balance test suggest that the design of the empirical framework is supported, which indicates that the results of the DID analysis are unlikely to be confounded by preexisting trends and concurrent changes in other factors. Further robustness checks for the endogeneity of regional shock degree and placebo effects will be reported at the end of the empirical analysis.

5 Empirical results and analysis

5.1 Main impacts on performance

As derived with Eq. (2), the DID estimators of the COVID-19 shock's effect on the sample retailers with their self-operated EC platforms and those with large, third-party EC participation are shown in Table 4. Columns (1) and (2) report this main result with the outcome variables *SGro* and *IT*.

Table 4 Main impacts with and without heterogeneity on regional shock degrees

		Main impacts		Main impacts with heterogeneity	
		(1)	(2)	(3)	(4)
		<i>SGro</i>	<i>IT</i>	<i>SGro</i>	<i>IT</i>
<i>IsOwnEC</i> × <i>Post</i>		−2.264 (7.485)	1.077 (1.010)	−3.745 (7.981)	−0.256 (0.670)
<i>IsOwnEC</i> × <i>Post</i> × <i>Severity</i>				0.028*** (0.010)	0.028*** (0.001)
<i>Is3rdEC</i> × <i>Post</i>		16.245** (8.076)	1.866** (0.753)	15.461* (8.451)	1.555** (0.596)
<i>Is3rdEC</i> × <i>Post</i> × <i>Severity</i>				0.007 (0.014)	−0.003*** (0.001)
Common trend	<i>Post</i>	−43.776*** (6.416)	−3.258*** (0.916)	−42.622*** (6.871)	−0.079*** (0.015)
Region trend	<i>Severity</i>	−0.040*** (0.010)	−0.009 (0.007)	−0.060*** (0.008)	−0.000*** (0.000)
The placebo effect		Y	Y	Y	Y
Firm fixed effects		Y	Y	Y	Y
Quarter fixed effects		Y	Y	Y	Y
Observations		260	260	260	260
Adjusted R^2		0.584	0.317	0.584	0.544

*Significant at $p < 0.10$ level; **Significant at $p < 0.05$ level; ***Significant at $p < 0.01$ level. Standard errors in parentheses are clustered at firm level as a default setting for the short panel

As indicated in the results, the COVID-19 shock allowed the retailers that had participated in large, third-party EC platforms to perform better in selling and operation than the other retailers (Outcome: *SGro*, $\delta_2 = 16.245$, $p < 0.05$; Outcome: *IT*, $\delta_2 = 1.866$, $p < 0.05$), while no difference was found between the performance of retailers with their self-operated EC platforms and those without self-operated EC platforms. In other words, a superstar effect was visible in the resilience built by the EC platforms, such that Hypothesis 1 was supported. The demand that shifted from in-person to online channels tended to concentrate on necessity and reliability. Therefore, the large, third-party EC platforms with higher publicity and reliability carried the majority of such demand and built the brick-and-mortar businesses' resilience, while the self-operated EC platforms were ignored by the consumers.

Nevertheless, the resilience built by the large, third-party EC platforms could not cover all the losses derived from the shock. For each regression reported, the DID estimators were significantly smaller than the sum of the opposite common trend and regional trend; this implied that the large, third-party EC platforms could only undertake part of the original in-person business from before the COVID-19 outbreak. In other words, a great proportion of the demand for physical goods was given up or postponed.

5.2 Heterogeneity of the main impacts across regions

To further illustrate the mechanism of interest, a further analysis of the regional degree of shock was conducted. Utilizing Eq. (3), the moderating effects of the regional degree of shock on the main impacts were identified. Similarly, in Table 4, Columns (3) and (4) report the result.

The results showed that participation in large, third-party EC platforms could help retailers gain stronger recovery in selling as the regional shock degree increased, but this effect is insignificant (Outcome: *SGro*, $\delta_2 = 15.461$, $p < 0.10$; $\theta_2 = 0.007$, $p > 0.10$). Thus, Hypothesis 2 was marginally supported. These results also showed that the recovery in operation provided by participation in large, third-party EC platforms weakened when the regions were disrupted by the COVID-19 shock more severely (Outcome: *IT*, $\delta_2 = 1.555$, $p < 0.05$, $\theta_2 = -0.003$, $p < 0.01$). Thus, Hypothesis 3 was supported. When the degree of shock in a region grew, the large, third-party EC platforms could not smoothly reach their resources outside the region and allocate them to meet the boom of the shifted demand induced by the more severe shock. Consequently, such a regional resource constraint weakened the resilience that the large, third-party EC platforms built for the brick-and-mortar businesses.

A more interesting and counterintuitive result in terms of hypotheses 2 and 3 concerns the retailers' self-operated EC platforms. As shown in Table 4, the retailers' self-operated EC platforms became effective in helping retailers gain significant recovery in selling and operation as the regional shock degree increased (Outcome: *SGro*, $\theta_1 = 0.028$, $p < 0.01$; Outcome: *IT*, $\theta_1 = 0.028$, $p < 0.01$). Taking the results in terms of large, third-party EC platforms together, it is reasonable to derive the following explanation in the context of the COVID-19 pandemic. In regions with a higher shock degree, as large, third-party EC platforms suffered more from resource constraints, they had a harder time satisfying the even more excessive demand for substitutes for brick-and-mortar businesses. Under this condition, because of delivery delays or a lack of inventory, consumers in regions that originally preferred to purchase on large, third-party EC platforms could become unsatisfied such that some excessive demand might turn to physical retailers' self-operated EC platforms [6]. Coincidentally, since these self-operated platforms' resources were originally underused due to the superstar effect, they did not need to face stricter resource constraints. They still had the operational capacity to handle the demand that was not smoothly satisfied by large, third-party EC platforms. Hence, self-operated EC platforms were able to build resilience for brick-and-mortar businesses by playing an in-concept supplementary role [25]. Such a supplementary role was also supported by the empirical results, as the retailers' selling recovery derived from their participation in self-operated EC platforms was weaker than that derived from participation in large, third-party

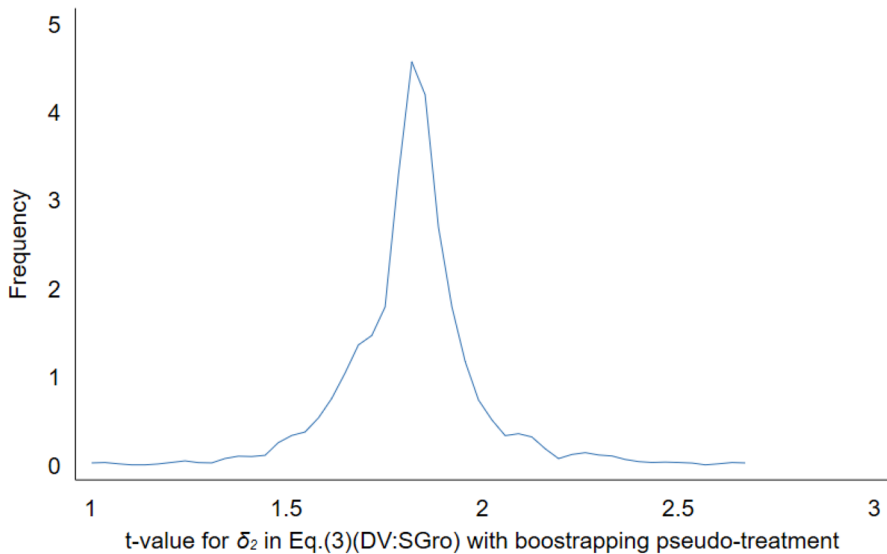


Fig. 5 The distributions of the bootstrap t -values that concern the effect of interest

EC platforms (Outcome: $SGro$, $\delta_2 - [\theta_1 \times \text{median}(Severity_{i,t=2020Q1})] = 15.239$, $p < 0.10$).¹⁶

5.3 Robustness checks

5.3.1 Further placebo test for the risky effect

Since the sample size was limited, a placebo test for the weakly significant effect (i.e., δ_2 in Eq. [3] using $SGro$ as the dependent variable) was performed by resetting the treated groups with the bootstrap method [44]. Specifically, a “false” treatment variable was constructed and randomly reassigned a value. By adding this false treatment variable to the original regression, the weakly significant effect was re-estimated. Through 500 repetitions of the above exercise, the effect size was re-evaluated with the distribution of the effect’s bootstrap t -values with a false treatment effect, as shown in Fig. 5.

The distribution of the bootstrap t -values for δ_2 in Eq. (3), which used $SGro$ as a dependent variable, was normally centered at approximately 1.821; this distribution supported the statistical power of the contribution of large, third-party EC platforms to brick-and-mortar businesses’ resilience in selling. The validity of the key findings was not significantly threatened by these results.

¹⁶ $\delta_2 - [\theta_1 \times \text{median}(Severity_{i,t=2020Q1})]$ measures the difference between the impact of participation in large, third-party EC platforms on the recovery in selling and the impact of participation in self-operated EC platforms on the recovery in selling given the median regional shock degree.

Table 5 Regressions of the moderator on the treatment statuses and observable confounders

Confounder	Severity
<i>IsOwnEC</i>	42.593 (56.520)
<i>Is3rdEC</i>	3.987 (58.910)
Growth rate of regional total retail sales of consumer goods in 2019Q4	10.223 (9.608)
Quarterly regional delivery volume in 2019Q4 (in billion cases)	− 1.781 (2.185)
Quarterly regional GDP in 2019Q4 (in trillion yuan)	13.902 (16.865)

To rule out replicated observations, the last three regressions were run at the regional level instead of the individual (retailer) level. The regressions focused only on the regional shock degree in 2020Q1 because there were no cases of COVID–19 reported before this period. Standard errors are in parentheses. All coefficients were insignificant at the $p < 0.10$ level

5.3.2 Endogeneity problem related to the moderator

Theoretically, as the coronavirus was by nature highly infectious, the moderator in Eq. (3) (i.e., the degree of regional shock) should be almost exogenous to the treatment statuses and to observable confounders that might threaten the balance assumption. To ensure this, the regressions of the moderator on the treatment statuses and observable confounders were run in turn. As expected, the results reported in Table 5 showed that the moderator did not covary with the treatment statuses and observable confounders, which relieves concerns of endogeneity regarding the moderator.

5.3.3 Inconsistence between the severity of the pandemic and anti-infection measures

In terms of the measurement of regional shock degree, there is a potential problem regarding the inconsistency between the severity of the COVID-19 pandemic and the intensity of anti-infection measures. Given the severity of the pandemic, governments in some regions implemented stricter restriction levels than those implemented by governments in other regions [57]. Under this condition, the regional shock degree employed in the empirical analysis may deviate from the conceptual relations mentioned in the hypotheses. To address this concern, the variable *Severity* was adjusted with the official restriction level by means of multiplication and

Table 6 Main impacts with heterogeneity on regional shock degrees adjusted by the restriction levels

		Adjustment: Multiplication		Adjustment: Exponentiation	
		(1)	(2)	(3)	(4)
		<i>SGro</i>	<i>IT</i>	<i>SGro</i>	<i>IT</i>
<i>IsOwnEC</i> × <i>Post</i>		− 3.755 (7.943)	− 0.199 (0.665)	− 4.014 (8.036)	− 0.474 (0.674)
<i>IsOwnEC</i> × <i>Post</i> × <i>Severity</i>		0.038*** (0.013)	0.038*** (0.001)	0.157*** (0.057)	0.163*** (0.005)
<i>Is3rdEC</i> × <i>Post</i>		15.474* (8.413)	1.537** (0.592)	15.435* (8.493)	1.562** (0.607)
<i>Is3rdEC</i> × <i>Post</i> × <i>Severity</i>		0.009 (0.018)	− 0.004*** (0.001)	0.043 (0.079)	− 0.017*** (0.006)
Common trend	<i>Post</i>	− 42.724*** (6.846)	− 2.468*** (0.717)	− 42.157*** (6.924)	− 2.201*** (0.720)
Region trend	<i>Severity</i>	− 0.081*** (0.011)	− 0.036*** (0.001)	− 0.343*** (0.049)	− 0.154*** (0.004)
The placebo effect		Y	Y	Y	Y
Firm fixed effects		Y	Y	Y	Y
Quarter fixed effects		Y	Y	Y	Y
Observations		260	260	260	260
Adjusted R^2		0.584	0.546	0.584	0.545

*Significant at $p < 0.10$ level; ** Significant at $p < 0.05$ level; *** Significant at $p < 0.01$ level. To control for the potential disturbance of heterogeneity and serial correlation, clustered robust standard errors were applied to the regressions as a default setting for short panel. Standard errors are in parentheses.

exponentiation.¹⁷ By taking these two into Eq. (3), the results shown in Table 6 indicated that the key effects and their significance basically remain unchanged.

Actually, in the context of the COVID-19 pandemic, the real intensity of anti-infection measures was usually more flexible than the official restriction level, but it was almost consistent with the severity of pandemics in regions with similar institutional systems [1, 22]. Hence, in view of the endogeneity of the official restriction level [22, 54], it is inefficient to employ the adjusted regional shock degree in this study. However, the results reported in Table 6 are still informative for extending the findings of this study to countries and regions other than China, where restriction-level-based adjustment is necessary.

¹⁷ Specifically, $DailyNewConfirmedCases_t$ in Eq. (1) was replaced by $DailyNewConfirmedCases_t \times \frac{Interval_t(1stlevel)}{Interval(1stquarter)}$ for

the multiplication adjustment and by $(DailyNewConfirmedCases_t)^{\frac{Interval_t(1stlevel)}{Interval(1stquarter)}}$ for the exponentiation adjustment, where $\frac{Interval_t(1stlevel)}{Interval(1stquarter)}$ denotes the ratio of the interval of keeping the 1st restriction level (i.e., the highest restriction level in Chinese legal systems) to the interval of the first quarter of 2020.

6 Discussion

6.1 Summary of the key findings

Based on the research model, DID analyses were conducted to reveal how EC platforms contributed to brick-and-mortar businesses' resilience to the COVID-19 shock. The following is a summary of the key findings on such resilience in the new context of generally forced customer channel migration and factor immobility induced by the COVID-19 shock:

- Under the baseline condition, facing the pandemic-driven demand structure featuring a superstar effect, the large, third-party EC platforms built significant resilience for brick-and-mortar businesses; they could better meet the shifted demand with a homogenous preference for necessity and reliability in the context of generally forced customer channel migration. Self-operated EC platforms could not build such resilience because the shifted consumers did not notice them.
- When the large, third-party EC platforms faced stricter resource constraints as the degree of shock in a region increased, the brick-and-mortar businesses' resilience in operations that was built by large, third-party EC platforms weakened. In such regions, factor immobility caused the large, third-party EC platforms to experience greater difficulty in allocating external resources to maintain efficient operation.
- In a region severely shocked by the COVID-19 pandemic, the physical retailers' self-operated EC platforms could also build significant resilience for brick-and-mortar businesses. Such EC platforms played a supplementary role in adopting the regional excessive demand that large, third-party EC platforms could not smoothly meet.

Although the fact that the physical retailers' self-operated EC platforms were not significantly disturbed by regional resource constraints seems slightly strange, it is logically reasonable in the S-C-P paradigm with the resource-based view. According to the baseline demand structure, the self-operated EC platforms should have been ineffective in certain regions if the large, third-party EC platforms had smoothly adopted the shifted demand in the region. However, such a result also implies that the self-operated EC platforms' operational capacity of adopting the shifted demand was preserved. When large, third-party EC platforms cannot fully adopt the demand due to stricter resource constraints, the preserved resources owned by the self-operated EC platforms could work. In fact, unlike many journalists' predictions that the pandemic is only good for giants, the reality—for example, in Germany—showed that smaller local retailers also profited from the pandemic [25], when large EC platforms like Amazon reached their capacity limits [26]. Similarly, in China, when the Alibaba-operating large EC platform Freshippo fought against the lack of inventory in main cities during the pandemic, the physical retailer YH's self-operated EC

platform became more popular in such cities and accounted for an unprecedented increase in revenues [27].

6.2 Contributions to research

This paper contributes to research in the field of e-commerce and digital resilience in two ways. First, this study revealed the shock-specific inadequacies of EC platforms in helping brick-and-mortar businesses continue to operate during the COVID-19 pandemic. Well-known intuition usually presumes the common advantages of EC platforms over brick-and-mortar businesses in dealing with shocks, including the COVID-19 shock (e.g., [60]). This study elucidated the demand structure shaped by the generally forced customer channel migration and the resource constraints derived from factor immobility during the pandemic. Within this new context, a certain type of EC platform could work smoothly in building brick-and-mortar businesses' resilience only if the EC platform exactly fitted the demand structure and was not significantly restricted by resource constraints.

Second, this study is one of the first to empirically employ the S-C-P paradigm with the resource-based view for digitalization-enabled resilience assessment. The findings suggested the necessity of switching from a strategy-centered view to a shock-specific perspective when evaluating EC platforms' contribution to building resilience for brick-and-mortar businesses. Prior researchers have believed in the flexibility of EC platforms; they have usually regarded shocks to brick-and-mortar businesses as shocks only to those businesses (e.g., [13, 19]). Such logic makes sense in some cases, but it is not refined in terms of the complexity of shocks. The findings of this study indicated that, if a shock does not make the shift of certain offline-based brick-and-mortar businesses to certain EC platforms easier, then such EC platforms cannot build resilience for the businesses. In this way, the shock-specific perspective may help researchers avoid overstating the advantages of EC platforms when facing shocks.

6.3 Managerial implications

This study emphasized that, if executives of EC platforms want to take over the demand on brick-and-mortar businesses that were disrupted by a shock, they must first ensure that the operation of their EC platforms is not significantly disrupted by the same shock. For example, many restaurants could not completely transfer their businesses online as their delivery capacities were overused [67]; the problematic resource constraints faced by large, third-party EC platforms in regions of intense COVID-19 transmission were also evident. In addition, smaller EC platforms should consider consumers' preferences and remind consumers that EC platforms have the ability to adopt consumer demand.

Furthermore, this study offered a lesson to policy-makers concerning EC and digital resilience. A digitalized business is much more flexible than a face-to-face business [32], but the possibility that a brick-and-mortar business can be operated on EC platforms does not mean that such a business can be totally digitalized or automated. A shock mainly to brick-and-mortar businesses can also disrupt the operation of EC

platforms Therefore, if policy-makers want to employ EC platforms—or, more generally, digital platforms—to build resilience to shocks, they should invest in digital infrastructures and empower brick-and-mortar businesses with options to digitalize more stages of their business processes.

Moreover, for physical enterprises aiming at maintaining resilience when facing shocks, the findings in this paper encourage them to keep their businesses relevant for their customers rather than consider whether they need to participate in certain EC platforms. The COVID-19 pandemic showcased this: a great part of the demand for offline luxury goods, which were truly easy to purchase online, was almost given up or postponed [61], while many consumers of fresh food still kept buying this daily necessity in person [34].

6.4 Limitations and further research

Although this study more completely identified how different EC platforms contributed to brick-and-mortar businesses' resilience to the COVID-19 shock, a number of limitations still exist, as well as gaps for future research. The lack of data is an obvious concern. With limited degrees of freedom, a deeper analysis of the heterogeneity of the effects cannot be fulfilled because the employment of more complex empirical models is infeasible. If the sample could be enlarged and more unlisted businesses could be incorporated into the analysis correctly, this problem would be mitigated.

Another limitation of this paper is its external validity. The sample of Chinese listed retailers was well defined to lend credibility to the empirical framework for analyzing the concerns of interest, but the induced scarcity in the variety of individuals weakened the implications of the findings. In the future, researchers should pay more attention to how different EC platforms build resilience for brick-and-mortar businesses by considering the shifts caused by each shock. For example, during the COVID-19 pandemic, the shock to supermarkets and bars, as well as the technical difficulties in digitalizing these businesses, was not the same [34]. If more evidence from different brick-and-mortar businesses can be obtained, the external validity of the conditions under which EC platforms can build resilience for brick-and-mortar businesses as proposed in this study could be better evaluated.

Regarding the uniqueness of the Chinese situation, the already-controlled fixed effects in the empirical analysis helped this study rule out disturbances from unobservable country-level factors. The inconsistency between the severity of the pandemic and anti-infection measures, which existed in many countries and regions, was also proven irrelevant to the key findings. Some outside-China evidence from previous studies (e.g., [25, 26]) is also provided to reinforce the findings in the empirical analysis. Nevertheless, empirical research based on worldwide evidence is still in demand to derive more specific findings and improve validity.

7 Conclusion

Drawing on a framework formed from the S-C-P paradigm with the resource-based view, we investigated the shock-specific environments shaped by the COVID-19 pandemic in this study. Based on the demand structure in the generally forced customer channel migration and the resource constraints derived from factor immobility, a research model was formulated: The demand structure formed the foundation that determined EC platforms' effectiveness in building resilience for brick-and-mortar businesses, while the resource constraints weakened the effectiveness in some regions. By employing a DID identification framework for the research model, we revealed the following findings. On the one hand, under the baseline condition, the large, third-party EC platforms helped build resilience for brick-and-mortar businesses toward the COVID-19 shock, while the self-operated EC platforms made little difference to the resilience. On the other hand, as the degree of shock in a region increased, the contribution of large, third-party EC platforms to the resilience in the operation of the brick-and-mortar businesses rooted in the region weakened, while the self-operated EC platforms' supplementary contribution strengthened.

The shock-specific perspective proposed in this study constitutes the starting point of a fruitful avenue for future research on how digitalization strategies empower brick-and-mortar businesses. Researchers can refine the shock-specific perspective by extending the S-C-P paradigm or replacing it with novel theoretical frames. Based on a more inclusive framework, it would be possible for us to review more shocks from the past to the future and clarify the ambiguity concerning the heterogeneous effectiveness of digitalization strategies in building the resilience of brick-and-mortar businesses. Furthermore, from the shock-specific resilience evaluation, the resilience-oriented strategic decision could be improved to be more suitable for scenario-based reality [64].

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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