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Early mover advantage in e-commerce platforms with low entry barriers: The role of customer relationship management capabilities

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ABSTRACT

This research investigates whether early mover advantage (EMA) exists among entrepreneurial e-tailers operating on third-party e-commerce platforms. Contrary to traditional wisdom, the current research hypothesizes that e-tailers may enjoy early mover advantages because of the consumer demand inertia amplified by the nature of the Internet and the system design characteristics of e-commerce platforms. We also argue that customer relationship management capabilities help enhance early mover advantages in an online setting. We employ panel data on 7309 e-tailers to perform analyses and find empirical evidence that strongly supports the abovementioned hypotheses.

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1. Introduction

The concept of early mover advantage (EMA) posits that early movers into a new marketplace may acquire certain advantages over subsequent entrants and thus achieve a strong competitive advantage in the form of high market share or returns [17,34]. Timing a new market entry or the adoption of technology, such as the Internet, is an important strategic choice for firms [17,28]. Although the strategic early entry of e-commerce firms has attracted research interest, the issue has yet to be fully explored in the literature.

The following main types of e-tailing business models enjoy different sources of EMAs: e-commerce platforms, independent stores, and e-tailers operating on third-party platforms. E-commerce platforms are online platforms that provide technological solutions to numerous small sellers. Examples of e-commerce platforms include Taobao, eBay, and Amazon. These firms enjoy EMAs from entry barriers resulting from network effects and advanced IT infrastructure [33]. Strong empirical evidence supports the existence of EMAs in this business model [33].

Independent stores are those that sell branded products through their stand-alone official websites. Examples of such stores include Walmart and Zappos. These firms enjoy EMAs from the entry barriers created by investment in IT infrastructure. They may also leverage prior brand reputation and organization capabilities to achieve EMAs because many of them are built upon their traditional offline businesses [30,48,52]. Mixed empirical evidence supports the existence of EMAs in this business model [40,42,43].

E-tailers operating on third-party platforms are largely ignored by the literature. In contrast to the two previous categories, which are represented by mostly large-sized organizations, e-tailers operating on third-party platforms are small- and medium-sized enterprises (SMEs). They do not seem to enjoy EMAs because third-party platforms feature extremely low entry barriers and hyper-competition [8]; specifically, these platforms require small upfront investments in technology because they provide readily available technological features, standard web store templates, and easy-to-use administration capabilities. The services offered by third-party platforms further minimize learning costs. The aggregation of e-tailers in a central location further reduces the switching costs of consumers. These characteristics do not seem to support the existence of EMAs. Prior research has also purposely excluded small- and medium-sized e-tailers from their samples [42].

However, studying the EMAs of e-tailers is important because (i) e-tailers represent a large market share when aggregated [60],

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(ii) platform-based sales have demonstrated a considerable increase as tens of thousands of entrepreneurial firms burgeon and wither on such platforms as Amazon and Taobao [60], and (iii) SMEs are lagged adopters of new technologies. Therefore, studying the EMAs of e-tailers can help such firms in timing their entry into online platforms. The current work intends to address this research gap.

Based on the literature on EMAs in low-entry-barrier industries [39], which underscores the importance of demand-side inertia as a potential source of EMAs, we argue that EMAs do exist for e-tailers operating on third-party platforms mainly because of demand-side factors that favor early movers, including Internet-enhanced prototypicality and product-specific reputational advantages [29], high-switching costs [29], and herding effects [25,4,7]. Although independent e-tailers also enjoy these sources of EMA to a certain extent, the nature of platform-based selling may strengthen such sources for participating e-tailers. For example, because independent e-tailers are scattered across the Internet, consumers cannot easily imitate the behaviors of other customers. In this case, herding behavior is minimized because of the invisibility of the sales of other stores. We further discuss the role of customer relationship management (CRM) capabilities in reinforcing demand-side factors, which lead to EMAs on the Internet.

To empirically investigate the existence of EMAs in third-party e-commerce platforms, we employ 38 weeks' worth of panel data on 7309 e-tailers operating on Taobao, one of the largest third-party e-commerce platforms in the world. This platform has an extremely low entry barrier and hosts millions of entrepreneurial e-tailers without significant physical presence. With this approach, we can control for the effect of entry barriers as a source of firm EMAs and focus on the essential demand-side sources of EMAs and on the role of CRM in moderating such advantages. The empirical analyses support our theoretical hypotheses. This research contributes to the literature by elaborating upon the sources of EMAs of e-tailers on third-party e-commerce platforms. Moreover, it extends the boundaries of both EMA and CRM theories and identifies the role of organizational CRM capabilities in creating and enhancing EMAs.

2. Theoretical background

2.1. EMA theory

The concept of first mover advantage was introduced to the industrial organization economics literature in the 1950s [17], and its development in management began through the work of Lieberman and Montgomery [34]. Since its development, the concept of first mover advantage has been expanded to the management literature and has been gradually employed interchangeably with EMA [17,34,57].

The EMA literature consists of three research streams [56]. The first stream examines the sources of EMA [35]. For example, Kerin et al. [29] summarize the important sources of EMA, namely, entry barriers created by economies of scale, preemption of key resources, technological expertise and experience, and behavioral demand-side factors such as shaping customer preference and becoming the "prototype" against which all later entrants are judged. In the second stream, EMA theory explores firm-level resources and capabilities that allow organizations to exploit EMAs [17,35]; such resources include technological capabilities [13,18], political resources [19], and social identity [5]. The third research stream investigates the relationship between environment and competitive advantage based on the order of market entry [56,38].

The Internet presents a special context for studying EMA because of its unique nature [33,58]. On the one hand, the Internet renders some sources of EMA, such as the achievement of technological leadership, the preemption of valuable resources (e.g., input factors and location), and the creation of customer switching costs, less relevant [34]. This condition is the result of the falling prices of hardware and software, the high imitability of online business models, the virtual space nature of Internet businesses, and the easiness of online switching for customers. On the other hand, the Internet offers new/enhanced sources of EMA. Varadarajan et al. [58] argue that Internet firms continue to enjoy significant EMAs derived from three sources: network effects (especially enjoyed by platform-based business models), technological innovation protected by patents, and non-contractual switching costs created by firms by leveraging the availability of customer data online and the ability to provide personalization tools.

Table 1 summarizes several empirical studies on EMAs in the e-commerce field. Researchers have tested the main effect of online entry order on various performance measures, including profitability, cost, revenue, and market share. Their samples include general Internet firms that consist of e-tailers [33,30], the e-tailing industry [42,43], and a subset of e-tailers and multi-channel retailers [48]. The EMAs of Internet firms are only confirmed in limited research [30,48], with strong support found for online businesses with network effects [33].

Several researchers have also examined the mediating effect of organizational capabilities, including patents (a measure of technological capability) [33], operational and advertising capabilities [52], and prior business models [48], on EMAs. The study of Lieberman [33] is the only study to examine the role of environmental characteristics (e.g., industry with network effects) on EMAs.

The review of the literature on EMAs online reveals the following. (1) Existing research has studied e-tailers as platforms or independent stores with stand-alone domain names but has yet to explore the EMAs of entrepreneurial e-tailers operating on third-party ecommerce platforms. (2) Existing research has not focused on the demand-side behavioral sources, which are important in creating EMAs among e-tailers on online platforms. (3) Existing research has not studied the role of CRM capabilities that can fortify the impact of such sources.

2.2. Customer relationship management (CRM) capabilities

This research emphasizes that the CRM capabilities of e-tailers reinforce EMAs because they function as comprehensive indicators of the ability of firms to strengthen the demand-side sources of EMA [54]. CRM capability is defined as a firm's capability of building and integrating the required resources, activities, and processes to manage customer relationships while simultaneously creating both firm and customer value [9,6]. CRM capabilities have proven to be profitable for companies [1,50]. CRM activities directly enhance customer relationship quality; consequently, these activities add to the non-contractual switching costs of customers [14,31,36,49] and help increase customer lifetime value for firms [51]. Customer attraction, conversion, and retention are the three major dimensions of CRM objectives [9,20,47,62].

Internet technologies produce new marketing tools and tactics to help firms attract, convert, and retain customers. Customer attraction refers to the ability of e-tailers to attract online traffic to their web stores operating on e-commerce platforms [42]. To attract and acquire new customers, e-tailers can utilize an array of online marketing tools such as banner advertisements, search engine marketing, social marketing, e-mail marketing, and affiliated marketing tools. Customer conversion refers to the ability of e-tailers to convert potential visitors into purchasers. Sticky

Table 1
An overview of empirical studies on EMAs online.

Sources	Industry	Sample size	Data (sample period)	Performance measure	Results for the main effect	Other results
Lieberman and Montgomery [33]	Internet	207 public Internet firms	Panel data (1999–2003)	Stock market capitalization; revenue; survival	Conditional	Advantages for early entrants in environments with network effects and for pioneers with patented innovations
Lee et al. [30]	Internet	103 Internet firms	Cross-sectional survey data (2001)	Composite measure of organizational performance	Confirmed	Early and late movers differ significantly in cumulative strategic capability building
Nikolaeva [42]	E-tailing	89 top e-tailers	Cross-sectional data (2000)	Web traffic	No	N/A
Nikolaeva [43]	E-tailing	460 e-tailers	Panel data (1994–2003)	Survival chances	Partly confirmed	EMAs diminish with time
Nikolaeva et al. [44]	E-tailing	418 e-tailers	Panel data (1994–2003)	Survival chances	No	N/A
Min and Wolfinbarger [40]	E-tailing	42 e-tailers	Panel data (1999–2000)	Marketing efficiency; profit margin; market share	No	N/A
Pentina et al. [48]	Multi-channel retailers	158 retailers	Panel data (1996–2006)	Net income; market share; gross margin; average inventory cost	Confirmed for inventory cost reduction only	In general, retailers with catalog selling experience or those that are large in size have EMAs, but bricks-and-mortar retailers have no EMAs
Shi [52]	E-tailing	8 retailers	Panel data (1999–2001)	Profitability	Partly confirmed	Only firms with prior superior operational capability stand to benefit from EMAs

features, such as personalization tools, online recommendation systems, and customer feedback information, can increase the frequency and duration of site visits and the average purchase volume of each visit; such features can also enhance the likelihood of converting visitors into purchasers [27,37]. Customer retention refers to the ability of e-tailers to retain customers by building relationships with them [53]. Customization, contact interactivity, care, community features, websites' ease of use, wide product variety, and creativity in user interface design are tactics used to enhance customer e-loyalty and retain existing customers [53]. These tactics all require firms to learn new skills and transform their CRM capabilities on the Internet [62].

The explosion of customer data as a result of the development of IT and the Internet has allowed firms to implement CRM on the basis of data analytics [46]. In addition to customer attraction and retention as two classical metrics of firm CRM capabilities [9,20,47], conversion rates are regarded as another important aspect of CRM that e-commerce firms can track, analyze, and manage using clickstream data [37,41]. Customer conversion is a fine-grained measure that bridges acquisition and retention in CRM; thus, it has been incorporated into the CRM objectives of firms, especially those with e-commerce channels [62].

3. Hypothesis development

Fig. 1 summarizes our conceptual model. We argue that EMAs are most likely generated by demand-side factors in e-commerce platforms that feature low entry barriers. The organizational CRM capabilities that would help strengthen the demand-side sources of EMA are likely to moderate the relationship between order of entry and online e-tailer performance.

3.1. Order of entry and e-tailer performance

Despite the pessimistic view about the EMAs of e-tailers operating on third-party e-commerce platforms [33,35], this research argues that EMAs do exist because of the three sources of behavioral EMAs: (i) prototypicality and product-specific reputational advantages [29], (ii) switching costs [29], and (iii) herding effects [25].

Prototypicality and product-specific reputational advantage [29] refers to the situation in which a firm establishes a reputation for its products as standard products in a new market. Such a reputation is an important source of EMA because consumers are likely to know little about the value of product attributes, store

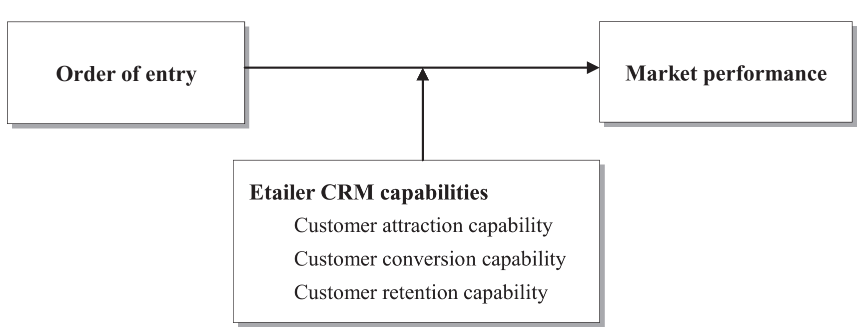

Fig. 1. Conceptual model.

service attributes, or their ideal combination during the early stages of online market evolution [24]. The same is especially true for e-commerce platforms because most sellers are SMEs without reputable product and store attributes. Online early movers thus have an opportunity to influence consumers' perceptions of the relative importance of their product and service attributes and establish service and product standards against which the offerings of later entrants can be compared. With regard to consumer products, the brand that a consumer uses first forms a very strong impression that shapes the subsequent consumption preferences of such consumers [35]. E-tailers also adapt their business strategies to effectively leverage the nature of the Internet to shape consumer preferences. On the one hand, they integrate the design and development and even coordinate the production of products as part of their active response to changes in customer preferences [59]. On the other hand, they enable the wide, rapid, and large-scale involvement of customers in new product development and promotion [45]. This strategy allows early movers to enjoy prototypicality and product-specific reputational advantages on a wide scale. Moreover, a common practice adopted by firms in the e-commerce industry is to move quickly and race to seize the market by shaping customer preferences and habits [28].

Switching costs help establish EMAs. Currently, the issue concerning whether online switching costs are higher than their offline counterparts remains controversial [33,58]. Buyers seem to exert minimal effort when switching to the offerings of late entrants, especially on an e-commerce platform, because all e-tailers are hosted on the same platform and share the same payment service. However, the uncertain nature of the Internet market may require frequent buyers to spend a significant amount of time and effort to assess the trustworthiness of late entrants. This situation results in high buyer switching costs. When purchasing from e-tailers, consumers cannot see or touch the products; thus, their knowledge about product–person fit [24] is likely to be very specific to a certain e-tailer and is not easily transferable to other e-tailers. This condition is particularly true for e-tailers operating in the long tail that is characterized by highly differentiated products [2,23]. Switching to other e-tailers may mean a significant loss of buyers' time and monetary investment in learning the particularities of products. Kerin et al. [29] suggest that if the products of early movers are satisfactory, consumers are inclined to remain loyal to familiar brands when faced with late entrant products to economize on searching costs.

The herding behaviors of online consumers further enhance the influence of an initial customer base and strengthen online EMAs. Herding refers to the situation in which late consumers follow the choices of previous customers when making purchasing decisions [25]; this behavior is favorable for early movers who exert great efforts to influence the preferences of early consumers in the market. On the Internet, e-tailers and online platforms can leverage the herding effect to enhance such influences. For example, many e-commerce platforms allow the sales track record of a product to be visible to prospective customers, offer recommendations to potential consumers based on "what other buyers have bought on the platform," present the reviews of previous buyers, and allow consumers to rank and browse stores according to their sales and reputation scores. These features provide signaling information that influences the decision making of late customers [63]. This condition leads to the concentration of online sales to early movers with a large initial customer base and high sales. Based on the abovementioned arguments, we generate the following hypothesis:

H1. *Early movers operating on third-party e-commerce platforms can achieve high market performance.*

3.2. Moderating effect of CRM capabilities

In line with the work of Suarez and Lanzolla [56], we argue that CRM capabilities interact with EMAs by enhancing the three EMA sources of firms: prototypicality and product-specific reputation, switching costs, and herding effects.

3.2.1. Customer attraction capability

Early moving e-tailers with high customer attraction capability can attract a large initial customer base to enhance their ability to build product prototypes by involving numerous customers. In this way, these firms enjoy a high product-specific reputation. These customers are also particularly valuable because they are early adopters of e-commerce who are willing to try new products and tolerate the risks that product innovations entail [29]. This customer quality is extremely important because a major difference between online and traditional product development is that online product development takes the experimental approach by allowing e-tailers to quickly obtain customer feedback on new products at minimal costs [28]. Early-moving retailers with high attraction capability are also able to enhance users' awareness of the unique characteristics of brands and reinforce customer relationships with such brands, thus increasing the non-contractual switching costs of customers. They are also able to attract a large number of customers, which form a large base for potential herding followers. These characteristics all help reinforce EMAs and enable such retailers to subsequently achieve higher performance than those retailers with low attraction capability.

To achieve the same level of performance when entering the market, late-moving e-tailers may need to establish a customer base that is larger than that of early movers because their customers are either those who are switching from early movers and are thus less loyal or those who are late adopters of technology and are thus not likely to take risks [29,54]. This approach puts late movers at a disadvantage in terms of leveraging customers to build product prototypes. The marketing expenses of late movers may also be higher than those of their counterparts because of the intensified online marketing competition. Thus, we propose the following hypothesis:

H2a. *Customer attraction capability strengthens the impact of early entry on the market performance of e-tailers.*

3.2.2. Customer conversion capability

Conversion capability can help reinforce EMA because of the following factors. (1) High conversion equates to large numbers of online buyers and buyer feedback, which can help e-tailers improve product design and build online reputations. (2) High conversion equates to a large number of buyers who have achieved a certain level of familiarity with the purchasing process, in which case the switching costs of such buyers increase. (3) Early-moving e-tailers with high conversion capability are likely to enjoy strong herding behavior because they can obtain a large number of buyers to send sales signals online [25].

On the contrary, late movers are at a disadvantage. To achieve the same level of performance as early movers, late movers must possess a strong conversion capability because their customers are not always loyal and are difficult to convert. Some late-moving e-tailers use frequent price promotions to boost conversion. Such an approach may boost sales volume in the short term, but it is detrimental to sales revenue (because of low prices) and profitability. Therefore, we propose the following:

H2b. *Customer conversion capability strengthens the impact of early entry on the market performance of e-tailers.*

3.2.3. Customer retention capability

Early movers with high retention capability can enjoy high product-specific reputations because retained customers are highly likely to broadcast positive word-of-mouth information online. They can benefit from switching costs as a result of their retained customers having high switching costs derived from loyalty programs and the learning curve; in addition, they can enjoy strong herding effects as a result of retained customers being repeat purchasers who also contribute to sending sales signals online [25].

By contrast, late movers are at a disadvantage. To achieve the same level of performance as early movers, late movers need to exert great efforts to cultivate retained customers because their customer base is not always loyal [29]. As mentioned previously, late-moving e-tailers may use price promotions to reactivate existing customers and convert them into retained customers. In this case, a high retention rate may contribute to sales volume; however, this is detrimental to sales revenue and profitability because of the low prices charged. Therefore, we propose the following:

H2c. *Customer retention capability strengthens the impact of early entry on the market performance of e-tailers.*

4. Methodology

4.1. Sample

A dataset of 7309 e-tailers provided by a third-party e-commerce platform in China (i.e., Taobao) is employed to test the conceptual model. Taobao is the largest Chinese e-commerce platform and enjoys an 80% market share. At the end of 2013, Taobao hosted approximately 8 million individual and SME sellers. The e-tailers on Taobao are mostly SMEs, a few of which have grown into large companies that have successfully attracted venture capitalist investments.

Taobao's business model differs from that of other similar platforms in North America such as eBay and Amazon. Whereas eBay and Amazon rely on sales commissions and direct sales as major revenue sources, Taobao relies on advertisements for revenue, and its platform services are free for e-tailers [11,15,32]. Taobao develops a wide array of marketing tools, arranges various types of marketing campaigns, and builds many affiliated websites to help e-tailers advertise and market themselves. Therefore, sellers on this platform do more than passive selling; they use the platform for advertising, promotion, sales, marketing, and branding. On this platform, a good proactive marketing capability is essential for competitive selling.

The data on 7309 e-tailers were retrieved weekly for 38 weeks, starting from the end of November 2010 and ending in early September 2011. The data collection yielded 261,909 observations. The sampling period is suitable for studying EMAs because the Taobao platform, which was established in 2003, was still a new, technology-enabled market for many firms and individuals during that period. In the first period, the e-tailers were randomly selected from two product categories, i.e., cosmetics and women's clothing, and then tracked throughout the 38-week period. The panel dataset is unbalanced because some sellers exited the market during the data collection period. This sampling approach helps alleviate potential survival bias.

These two industries are selected for the following reasons. (1) They are among the best-selling product categories. Many sellers have evolved from individual sellers to SMEs that have developed certain marketing and CRM capabilities. (2) Both industries host a variety of differentiated products. We know that the demand-side sources of EMA are stronger for differentiated products than for standard products [55]. (3) Customers in these product categories tend to buy repeatedly from a certain brand or e-tailer because they know, for example, that the clothes provide a good fit.[1] Thus, both industries enjoy high switching costs because of the nature of the products. (4) Both product categories have strong sociality, which makes online selling successful. The women's clothing industry is especially interesting. It is the top product category on Taobao and is extremely differentiated. This characteristic is seemingly counterintuitive because standard products are regarded to be more suitable for online selling than differentiated products. Women's clothing and cosmetics are fashion products, and fashion is an area in which interpersonal communications have been found to be highly important in the diffusion of information; with the Internet, such diffusion of information in the form of online conversations, reviews, and feedbacks has become relatively easy [21]. The difference between the women's clothing industry and the cosmetics industry is that the former is more heterogeneous and comprises more sellers and products compared with the latter.

4.2. Measurement

Order of entry is employed to measure EMA [16]. Two measures most widely employed in the literature are adopted in this study: (i) ranked order of market entry time of a firm and (ii) the extent of entry delay after the first mover's entry [39]. Using two alternative measures of order of entry facilitates the cross validation of results. Specifically, order of entry is measured by the ranked order of firm entry by the day this firm enters the market (RO) and by the logarithm of the number of days of delays after the entry of the first entrant, i.e., ln(DAYS).

Customer attraction (CA) is measured by the average number of pages viewed per day within 28 days at an e-tailer's store. Customer conversion (CC) is measured as the ratio of average daily purchasers to average daily unique visitors over 28 days. Customer retention (CR) is measured as the percentage of customers who made at least two transactions within the last 180 days. When measuring CA capability, advertisement investment could have been used as a proxy, but such data were not made available to us by the platform. Based on the available data, we believe that the number of page views is a good proxy for attraction capability for three reasons. (1) This e-metric is frequently used by the e-commerce industry to evaluate seller traffic attraction capability [22]. (2) This e-metric is an outcome-based measure and is thus a comprehensive reflection of the effectiveness of various methods used to improve customer attraction, including within and outside the focal platform. (3) The outcome-based measurement of CRM capabilities is also frequently used in the literature [47].

The market performance of an e-tailer is measured by its sales (SALES) within the past 28 days. When the sample is analyzed within each industry, sales becomes a performance metric equivalent to market share, which is the most significant variable related to entry timing [57]. As a result of the special nature of Internet selling, i.e., selling to a wide geographical area and obtaining quick feedback from consumers, small- and medium-sized e-tailers on the platform may experience volatile marketing performance caused by marketing campaigns or other uncertain events in very short periods [3]. Therefore, we adopt 28 days as the

[1] We acknowledge an anonymous reviewer for raising this point.

Table 2
Descriptive statistics of samples.

	Cosmetics (observations: 130,977)				Women's clothing (observations: 130,932)			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
ln(SALES)	4.228	2.666	0	12.287	3.613	2.726	0	13.803
RO (standardized)	0	1	−1.717	1.746	0	1	−1.729	1.735
ln(DAYS)	7.594	0.356	4.635	7.916	7.645	0.332	3.401	7.916
ln(CA)	3.444	2.294	−4.605	12.540	4.411	2.494	−4.605	14.155
CC	0.054	0.076	0	1	0.015	0.040	0	1
CR	0.201	0.192	0	1	0.102	0.134	0	1
Ln(TSALES)	8.704	0.140	8.294	8.752	8.704	0.140	8.294	8.752
OHV	0.723	0.444	0	1	0.647	0.478	0	1
OHP	0.208	0.278	0	1	0.035	0.130	0	1

interval in measuring the aforementioned CRM capabilities. In this manner, such disturbances caused by market uncertainties are settled.

In addition to entry timing and CRM capability, two firm-specific control variables related to the sales capability of firms are considered to capture the sources of e-tailer performance: orders in high volume (OHV) and orders in high price (OHP). OHV is measured as the percentage of orders in which more than one product was purchased. OHP is measured as the percentage of orders that are worth more than twice the average price of the products online.

A set of location dummy variables is added to capture the systematic differences in the performance of the e-tailers in different regions. Developed regions may generate high returns in e-tailing thanks to the support of a mature supply chain, delivery infrastructure, and high consumer e-commerce awareness. We employ 35 regional dummy variables, given that the e-tailers in our dataset are from 35 province-level regions. Those from abroad are categorized into one group. A set of monthly dummies is also added to capture any time-specific shocks that may affect the sales of all the e-tailers simultaneously.

Variables used to capture industry-specific effects are considered in the model as well. The sales growth of e-tailers may be partly attributed to the growth in the e-commerce industry resulting from external macroeconomic environments. We use the logarithm of the overall e-commerce sales on this platform (TSALES) to capture this effect as well as market competition. Given that Taobao enjoys a dominant position in China, its sales are representative of the industry or may at least reflect the trend of China's e-commerce industry. TSALES is measured on a yearly basis because of the unavailability of monthly or weekly data. We also attempt to add the number of online firms to account for the competitive effect that may erode e-tailer sales and EMA. However, this number is highly correlated with TSALES. Therefore, only *TSALES* is retained to capture both industry growth and competitive effects.

Table 2 reports the descriptive statistics of the main variables. On average, women's clothing stores experience higher customer attraction but lower customer conversion and retention compared with cosmetics stores. The *t*-tests show that these differences are significant.

5. Empirical results

This research uses the following random effect model to test our hypotheses. The random effect model is selected because the order of entry measured by entry timing is a time-invariant variable. In this case, the fixed effect model is not a feasible choice. The Breusch and Pagan Lagrangian multiplier (LM) test for random effects suggests the appropriateness of the random effect model as well.

$$\begin{aligned}\ln(\mathrm{SALES})_{i(t+1)} = {} & \beta_0 + \beta_1 \mathrm{OE}_i + \beta_2 \ln(\mathrm{CA})_{it} + \beta_3 \mathrm{CC}_{it} + \beta_4 \mathrm{CR}_{it} \\ & + \beta_5 \ln(\mathrm{CA})_{it} * \mathrm{OE}_i + \beta_6 \mathrm{CC}_{it} * \mathrm{OE}_i + \beta_7 \mathrm{CR}_{it} * \mathrm{OE}_i \\ & + \beta_8 \ln(\mathrm{TSALES})_{it} + \beta_9 \mathrm{OHP}_{it} + \beta_{10} \mathrm{OHV}_{it} \\ & + \beta_{11-45} \mathrm{Location}_{\mathrm{Dum}_i} + \beta_{46-55} \mathrm{Month}_{\mathrm{Dum}_{it}} + a_i \\ & + u_{it}\end{aligned}$$

In the model, i indexes the ith e-tailer, and t indexes the tth week. OE (order of entry) is measured using RO and ln(DAYS). RO is standardized to facilitate cross-industry comparison. SALES, CA, and TSALES are log-transformed to scale down their measurement units. The variables in the interaction items are mean-centered to alleviate potential multicollinearity. The analysis is implemented in Stata version 11. We execute each model within the two product categories and with the aggregate data. We present three models for each product category in a hierarchical manner: (i) with control variables only, (ii) with control and independent variables, and (iii) with all the variables, including the interactions. The results are shown in Table 3.

As predicted by H1, the main effects of entry order are negative and significant in all the models regardless of the OE measurements. The interaction effects of CRM capabilities and order of entry are also confirmed. The coefficients of OE*ln(CA), OE*CC, and OE*CR are negative and significant regardless of the OE measurements. Because the coefficients of OE are negative, the negative coefficients of OE*ln(CA), OE*CC, and OE*CR in all the models indicate that CA, CC, and CR enhance the EMA of e-tailers in both industries. This outcome can be effectively explained by calculating the marginal impact of the order of entry on the sales performance. For example, the partial differentiation of the model in (1) with respect to OE is $\partial \ln(\mathrm{SALES})/\partial \mathrm{OE} = -0.241 - 0.074{*}\ln(\mathrm{CA}) - 1.065{*}\mathrm{CC} - 0.261{*}\mathrm{CR}$. As CA, CC, and CR increase, the *disadvantage* brought by a high OE (i.e., latecomer) becomes relatively large. This result implies that the *advantage* of early movers is high.

The coefficients of the control variables are also reported in Table 3, except for the location and monthly dummy variables because they are too lengthy to display. The positive and significant coefficients of OHP and OHV indicate that the sales capability of e-tailers contributes to e-tailer performance as expected. The positive coefficient of ln(TSALES) suggests that the industry growth effect outweighs the competition effect and therefore generates a positive net impact on e-tailer performance.

The post-estimation procedure, namely, the Breusch and Pagan LM test for random effects [10], is employed to justify the model selection. The test suggests that the random effect panel data model performs better than the pooled OLS regression. As shown for all models in Table 3, the LM test scores are significant, thus indicating that the random effect model represents a good choice. Moreover, we include *vce*(*robust*) in the Stata command to determine the Huber and White estimator of variance [61,26],

Table 3
Statistical analysis of empirical models.

	OE = RO								
	Total			Cosmetics			Women's clothing		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln(TSALES)	0.409***	1.828***	1.804***	−0.088*	1.103***	1.086***	0.949***	2.664***	2.626***
	(0.040)	(0.037)	(0.037)	(0.057)	(0.052)	(0.052)	(0.057)	(0.051)	(0.051)
OHP	1.543***	0.689***	0.703***	1.405***	0.608***	0.615***	1.630***	0.718***	0.732***
	(0.008)	(0.007)	(0.007)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
OHV	0.076***	0.292***	0.278***	0.091***	0.229***	0.220***	0.210***	0.470***	0.455***
	(0.015)	(0.014)	(0.013)	(0.018)	(0.016)	(0.016)	(0.033)	(0.029)	(0.029)
H1									
OE		−0.257***	−0.241***		−0.281***	−0.272***		−0.139***	−0.126***
		(0.01)	(0.01)		(0.014)	(0.014)		(0.012)	(0.012)
ln(CA)		0.671***	0.682***		0.646***	0.654***		0.723***	0.730***
		(0.003)	(0.003)		(0.004)	(0.004)		(0.003)	(0.003)
CC		6.289***	6.743***		5.961***	6.254***		6.764***	8.239***
		(0.06)	(0.06)		(0.066)	(0.069)		(0.108)	(0.127)
CR		0.539***	0.570***		0.421***	0.447***		0.443***	0.436***
		(0.02)	(0.02)		(0.028)	(0.028)		(0.037)	(0.038)
H2a									
OE*ln(CA)			−0.074***			−0.040***			−0.106***
			(0.00)			(0.003)			(0.003)
H2b									
OE*CC			−1.065***			−0.776***			−2.333***
			(0.05)			(0.059)			(0.122)
H2c									
OE*CR			−0.261***			−0.211***			−0.229***
			(0.02)			(0.029)			(0.038)
Constant	0.053	−14.453***	−14.382***	4.345***	−7.931***	−7.882***	−4.626***	−22.017***	−21.841***
	(0.344)	(0.313)	(0.312)	(0.483)	(0.445)	(0.445)	(0.487)	(0.436)	(0.432)
Obs.	261,266	260,998	260,998	130,674	130,513	130,513	130,592	130,485	130,485
Breusch and Pagan Lagrangian multiplier test for random effects									
chi2(1)	1.40E+06	5.00E+05	4.90E+05	6.60E+05	2.70E+05	2.60E+05	7.20E+05	1.80E+05	1.80E+05
	OE = ln(DAYS)								
	Total			Cosmetics			Women's clothing		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
ln(TSALES)	0.409***	1.829***	1.813***	−0.088*	1.103***	1.092***	0.949***	2.664***	2.634***
	(0.040)	(0.037)	(0.037)	(0.057)	(0.052)	(0.052)	(0.057)	(0.051)	(0.051)
OHP	1.543***	0.690***	0.698***	1.405***	0.608***	0.612***	1.630***	0.719***	0.727***
	(0.008)	(0.007)	(0.007)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
OHV	0.076***	0.294***	0.284***	0.091***	0.231***	0.225***	0.210***	0.471***	0.457***
	(0.015)	(0.014)	(0.014)	(0.018)	(0.016)	(0.016)	(0.033)	(0.029)	(0.029)
H1									
OE		−0.704***	−0.500***		−0.715***	−0.629***		−0.461***	−0.153***
		(0.03)	(0.030)		(0.041)	(0.043)		(0.037)	(0.038)
ln(CA)		0.672***	0.678***		0.646***	0.651***		0.723***	0.726***
		(0.003)	(0.003)		(0.004)	(0.004)		(0.003)	(0.003)
CC		6.290***	6.720***		5.963***	6.244***		6.759***	8.596***
		(0.056)	(0.059)		(0.066)	(0.069)		(0.108)	(0.132)
CR		0.543***	0.574***		0.426***	0.458***		0.439***	0.432***
		(0.022)	(0.022)		(0.028)	(0.028)		(0.037)	(0.038)
H2a									
OE*ln(CA)			−0.153***			−0.078***			−0.225***
			(0.007)			(0.010)			(0.008)
H2b									
OE*CC			−3.842***			−2.511***			−12.139***
			(0.190)			(0.205)			(0.526)
H2c									
OE*CR			−0.791***			−0.617***			−0.725***
			(0.074)			(0.093)			(0.122)
Constant	0.053	−9.114***	−10.626***	4.345***	−2.522***	−3.142***	−4.626***	−18.492***	−20.708***
	(0.344)	(0.388)	(0.392)	(0.483)	(0.551)	(0.559)	(0.487)	(0.528)	(0.532)
Obs.	261,266	260,998	260,998	130,674	130,513	130,513	130,592	130,485	130,485
Breusch and Pagan Lagrangian multiplier test for random effects									
chi2(1)	1.40E+06	5.00E+05	5.00E+05	6.60E+05	2.70E+05	2.60E+05	7.20E+05	1.80E+05	1.80E+05

Note (1): The dependent variable is ln(SALES). The standard errors are enclosed in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. Location and monthly dummies are not reported for brevity.
Note (2): The chi2 statistics of the Breusch and Pagan Lagrangian multiplier test for random effects in all models are significant at the 1% level.

Table 4
Comparisons of group coefficients.

	OE = RO		OE = ln(DAYS)	
	Beta difference (cosmetics industry–women's clothing industry: models 6–9)	Z score	Beta difference (cosmetics industry–women's clothing industry: models 15–18)	Z score
OE	−0.146***	−7.918	−0.476***	−8.295
ln(CA)	−0.076***	−15.200	−0.075***	−15.000
CC	−1.985***	−13.734	−2.352***	−15.791
CR	0.011	0.233	0.026	0.551
OE*ln(CA)	0.066***	15.556	0.147***	11.479
OE*CC	1.557***	11.489	9.628***	17.054
OE*CR	0.018	0.377	0.108	0.704

Note: The beta difference is calculated with the coefficient of the cosmetics industry minus that of the women's clothing industry.
*** Statistical significance at 1% level.

which is used to address potential heteroscedasticity. The results remain highly consistent.

Product return in e-commerce sales is more frequent than that in offline sales and may thus affect the validity of our results. We do not have accurate returned sales data, but we can estimate it by multiplying the "number of returns during the last 28 days" with the "average value of customer orders." We then re-run the above regressions by including the return adjusted sales and obtain similar results. These results suggest that returned sales do not affect the validity of our results.

The differences in the main factors and their interactions are manifested when the regression coefficients for the cosmetics and women's clothing industries are compared. We follow Clogg et al. [12] in calculating the Z test statistics under the null hypothesis of equality of the two coefficients. The results in Table 4 suggest that the cosmetics industry experiences higher EMAs than the women's clothing industry but that its moderating effects of CC and CA are significantly weaker. The moderating effects of CR are stronger in the cosmetics industry than in the women's clothing industry, but their beta difference is not significant. The results may suggest that although the women's clothing industry is less likely to benefit from EMAs compared with the cosmetics industry, its EMA is likely to be more affected by CRM capability.

6. Discussion

6.1. Findings and research implications

This research investigates whether EMAs exist among e-tailers operating in third-party electronic marketplaces and determines the role of CRM capability in strengthening EMAs. All the hypotheses are confirmed. The results associated with the main EMA effects are more evident in the cosmetics industry (a relatively homogeneous industry) than in the women's clothing industry, whereas the results associated with CRM capabilities and their moderating effects are more evident in the women's clothing industry (a relatively heterogeneous industry) than in the cosmetics industry. This difference can be explained by the presence of a relatively small number of product lines and firms in a homogeneous market and by the widespread effect of the tactics used by e-tailers to encourage the herding behaviors of consumers.

This research offers several theoretical contributions. First, it contributes to EMA research in the e-commerce context [40]. We find empirical evidence that supports the presence of EMAs among e-tailers operating on third-party e-commerce platforms. The results of this work differ from those of Min and Wolfinbarger [40], Nikolaeva [42,43], and Nikolaeva et al. [44] but are consistent with those of Lieberman [33], Pentina et al. [48], and Shi [52], who suggest that EMAs exist on the Internet for certain groups of firms. The current work explores demand-side factors in explaining EMAs among e-tailers, thus complementing the research of Lieberman [33], which explains the EMAs of Internet firms from a network effect perspective.

Second, this research contributes to EMA theory by incorporating the boundary conditions of EMAs, i.e., CRM capabilities, through the argument that capabilities can enhance the demand-side factors of EMAs. By identifying organizational capabilities as indirect sources of EMA, this study responds to the call for a study on the relationship between organizational capability and EMAs [17,33]. Although previous research has investigated the role of prior organizational capability in generating EMAs [48], it has failed to explore cumulative capability building after entry. The role of cumulative capability building after entry is extremely important for firms in strengthening their EMAs, especially in a dynamic business environment such as the Internet [30].

The results of our study have several implications for managers. First, this research supports the existence of EMAs among e-tailers. With knowledge of such existence, early movers can gain confidence even with late movers being equipped with strong financial and reputable resources. Early movers should leverage their enhanced understanding of the Internet to explore their capabilities of reinforcing their EMAs. Second, understanding the moderating role of CRM capabilities is important because early-moving managers can purposely cultivate their CRM capabilities in the direction that strengthens EMAs by increasing customer non-contractual switching costs, strengthening prototypicality and product-specific reputational advantages, and influencing the herding behaviors of consumers. Third, managers should understand that EMAs and CRM capabilities are not equally important for all industries. In our research, EMAs are more prominent in the cosmetics industry than in the women's clothing industry, whereas CRM capabilities are more important in the women's clothing industry than in the cosmetics industry. Hence, in the decision-making process, e-tailers from different industries should assign different weights to entry timing decisions and CRM capability building strategies.

6.2. Research limitations and future research

Several factors might limit the generalizability of our findings. First, among the variety of firm capabilities, we only examine CRM capabilities. Such a choice is motivated by the fact that CRM is considered as one of the most important factors that complement the EMAs of e-tailers operating on platforms with extremely low entry barriers. The other capabilities of e-tailers, such as supply chain and internal management capabilities, are not studied.

Customer attraction, conversion, and retention may require the cooperation of special supply chains and operations management practices. Second, we examine only two industries that involve a relatively large number of female customers. Investigating other industries can extend the generalization of the results.

Third, one characteristic of the sample is that a majority of the e-tailers are SMEs and entrepreneurial firms without prior physical presence. This situation is not the result of purposive selection but is typical in the platform studied (see Dobbs et al. [15] for a comparison of the China and U.S. e-commerce markets). Although this characteristic of the sample helps us eliminate the influence of prior endowment on EMAs and focus on the demand-side sources of EMA, such characteristic should be considered when interpreting and extrapolating the results.

This research hints at a future research avenue for explicitly studying other sources of EMA on the Internet. For example, technological innovation and leadership can potentially contribute to EMAs because the assets purchased and deployed to implement technology can be used as entry barriers to deter late movers. More important, as CRM capabilities do not lend confidence to late movers when catching up with early movers, future research must identify alternative capabilities with strong enabling effects. Otherwise, late-moving entrepreneurial firms will remain at the bottom of the pyramid and be excluded from the center of gravity of e-commerce development.

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