Journal of Business Research xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Journal of Business Research

Early-mover advantages at cross-border business-to-business e-commerce portals

Ziliang Deng, Zeyu Wang *

School of Business, Renmin University of China, Beijing 100872, China

ARTICLE INFO

Article history:
Received 3 March 2015
Received in revised form 23 May 2016
Accepted 24 May 2016
Available online xxxx

Keywords:
Business-to-business (B2B)
Early-mover advantages
e-Commerce
Export
International entrepreneurship
Third-party portal

ABSTRACT

The Internet enables enterprises to sell their products via cross-border business-to-business (B2B) e-commerce portals. However, researchers know little about the early-mover advantages for such third-party platforms. The rapid, convenient, and wide market access offered by these platforms may allow early-mover exporters to enjoy advantages over late movers in terms of learning effects and switching costs. We hypothesize that early-mover advantages may diminish beyond a critical length of tenure because of the free-riding costs, resolution of technological or market uncertainty, as well as the incumbent inertia of early movers. We also argue that product price and diversity will pose different boundary conditions on how early-mover advantages are manifested. Using web search and mining methods, we collect data on approximately 300,000 B2B export transactions conducted by nearly 4000 firms in 2007–2014 through online portals. Employing panel data models, we find strong evidence supporting our hypotheses.

© 2016 Elsevier Inc. All rights reserved.

1. Introduction

The Internet has become an important accelerator for global trade (Gabrielsson & Gabrielsson, 2011; Petersen, Welch, & Liesch, 2002). The number of third-party cross-border business-to-business (B2B) e-commerce portals and transaction intermediaries is increasing, and enormous enterprises start their international venturing on such platforms. For example, Alibaba.com offers hundreds of millions of wholesale products to buyers located in more than 190 countries every year (Alibaba.com, 2015).

E-commerce platforms pose limited entry barriers to newcomers, given that many of the platforms do not charge admission fees but merely charge reasonable commission fees based on the value of online transactions (Chen, Seong, & Woetzel, 2014). Several platforms provide enabling services, such as free training courses for newcomers on online sales techniques, standard web store templates, and convenient technological features (Wang, Cavusoglu, & Deng, 2016). With the facilitation measures, e-commerce portals have accommodated a full spectrum of firms, ranging from massive small- and medium-sized enterprises (SMEs) to large players. Newcomers may easily enter the marketplace with low entry barriers and replicate the business model of the early movers (Makadok, 1998); thus, SMEs may encounter difficulty in possessing early-mover advantages (EMA) in cross-border B2B portals. In particular, cross-border B2B portals attract potential entrants and buyers from every corner of the world to participate in the global online trade, extremely intensifying the already hypercompetitive environment. These special features of cross-border B2B portals have shaken the foundation of conventional EMA and rendered the potential EMA unprecedentedly transient and easily obsolete.

People may express skepticism toward the EMA at such emerging, important and special portals. In particular, this subject raises several questions: Are early entrants at such platforms capable of enjoying their early entry? If an EMA exists, how long can it persist? Can any competitive strategy help prolong the EMA?

However, the extant EMA literature, originating from the seminal work of Lieberman and Montgomery (1988), has not explicitly answered these new questions. Some studies have focused on variations in the EMA of brick-and-mortar firms in the Internet environment (Min & Wolfinbarger, 2005), whereas others have examined the EMA of e-commerce portals per se (Mellahi & Johnson, 2000). The study of Wang et al. (2016) is the first in the literature investigating the EMA of etailers on a domestic third-party e-commerce portal. It has found evidence of EMA but has neglected the potentially fleeting nature of EMA on such a platform, and therefore does not examine the sustainability of EMA in a time horizon. As firms are entering an era of global connectivity unprecedentedly enabled by cross-border e-commerce, a study on the EMA of firms at *third-party cross-border e-commerce portals* has become necessary for researchers and practitioners to truly comprehend the new dynamism of EMA. Therefore with panel data collected from a cross-border B2B e-commerce portal, we re-examine the classic EMA logic (Lieberman & Montgomery, 1988), as well as incorporating

* Corresponding author at: School of Business, Renmin University of China, Haidian, Beijing 100872, China.
E-mail addresses: ziliang.deng@ruc.edu.cn (Z. Deng), wangzeyu@ruc.edu.cn (Z. Wang).

http://dx.doi.org/10.1016/j.jbusres.2016.05.015
0148-2963/© 2016 Elsevier Inc. All rights reserved.

two moderating effects of competitive strategies, namely, product price and diversity (Porter, 1980, pp. 34–46).

2. Theory

2.1. Early-mover advantages related to the Internet

Lieberman and Montgomery (1988) suggest that first-mover advantages primarily arise from three sources, namely, (a) technological leadership (i.e., learning curve and R&D), (b) preemption of resources (i.e., key input factors and locations), and (c) switching costs and buyer choice under uncertainty. At the same time, first movers have to incur disadvantages arising from four sources as time elapses, namely, (a) free-rider effects, (b) resolution of technological or market uncertainty, (c) shifts in technology or customer needs, and (d) incumbent inertia (Lieberman & Montgomery, 1988). The term "first-mover advantages" has gradually been employed interchangeably with EMA (Makadok, 1998). Recent research has incorporated the market environment and firm capabilities as factors that moderate EMA (Suarez & Lanzolla, 2007; Wang et al., 2016). It has also examined the mediating role of switching cost in determining EMA (Gómez & Maícas, 2011).

The Internet presents a special context for studying EMA due to its unique nature (Varadarajan, Yadav, & Shankar, 2008). First, EMA resulting from R&D could be hampered because business models and processes are highly transparent and imitable online (Porter, 2001). Second, the preemption argument is undermined by the fact that the costs of opening up and maintaining a virtual shop have decreased rapidly as hardware, electronic devices are becoming increasingly affordable (Sheth & Sharma, 2005). Empirical studies on etailer EMA generate mixed evidence. Some studies find no evidence of EMA among etailers (Min & Wolfinbarger, 2005; Nikolaeva, 2007), whereas other studies show that EMA can be achieved in a market by firms with significant network effects (Lieberman & Montgomery, 1998) and by larger retailers (Pentina, Pelton, & Hasty, 2009).

Three types of business models are associated with the Internet, each of which may exhibit their EMA differently (Wang et al., 2016). First, e-commerce portals per se such as eBay enjoy EMA from network effect and pioneering infrastructure construction (Mellahi & Johnson, 2000). Second, independent stores such as online Wal-Mart leverage their EMA with prior brand loyalty and huge investment in physical facilities. Third, an increasing number of etailers have been doing businesses in third-party e-commerce portals such as eBay. The extent to which the etailers exhibit their EMA has been challenged by the extremely low entry barriers and the buyer loyalties in such portals (Wang et al., 2016). Scant extant studies on EMA in the third-party e-commerce portals employ survey data from a limited scope of sellers, which cannot reflect the overall landscape of B2B transactions (Pentina et al., 2009). The literature has also neglected the contingency conditions under which EMA may be sustained for a long period.

2.2. EMA at cross-border B2B e-commerce portals

Among the various sources of EMA articulated in the seminal work of Lieberman and Montgomery (1988), *learning curve* and *switching costs* remain valid in cross-border B2B portals. As early movers grow older, three sources of early-mover disadvantages stated in the paper of Lieberman and Montgomery (1988) will play a dominant role, namely, *free-rider effect*, *resolution of technological or market uncertainty*, and *incumbent inertia*.

EMA at cross-border B2B portals originates from two major sources, with supplier *learning curve* as the most important factor in knowledge accumulation and innovation via B2B relationships (Biggemann & Buttle, 2012; Kim, Basu, Naidu, & Cavusgil, 2011). Cross-border B2B sellers may easily meet internationally diversified demand using far-reaching B2B platforms (Partanen, Möller, Westerlund, Rajala, & Rajala, 2008) and may obtain access to the customer data stored by the portals through external sources (Kim et al., 2011). The longer a B2B seller stays at the portal, the better it will understand its buyers (Chen et al., 2014). In addition, a B2B seller can then improve its sales and marketing techniques, develop the most desirable products, and promote sales performance (Petersen et al., 2002; Porter, 2001). Moreover, early entrants will be able to accumulate significant operational knowledge using these novel platforms (Grewal & Tansuhaj, 2001). These export sales experience and capability will reinforce the effectiveness of adopting the virtual export channels, forming a virtuous cycle between learning and exporting (Morgan-Thomas & Bridgewater, 2004). Using the cross-border B2B platform, this learning effect will be amplified by the exposure to an extremely wide buyer base. The great variety of demand around the globe will push the early entrants to effectively tailor their products and rapidly accumulate abundant international experience (Reuber & Fischer, 1997).

An early entrant can enhance its reputation and associated non-contractual *switching cost* for buyers (Gómez & Maícas, 2011). Such switching cost still prevails for B2B scenarios, although the cost may be lower compared with brick-and-mortar businesses (Porter, 2001). The early stages of a product launch provide early movers with an opportunity to influence buyers' perceptions of the relative importance of attributes (Kerin, Varadarajan, & Peterson, 1992; Porter, 2001). Through its marketing and active product co-development efforts, an early mover may be able to establish the perceptual structure of the market to its advantage, and become the prototype against which all late entrants' offerings are compared (Gómez & Maícas, 2011). Although cross-border B2B platforms have extremely low entry barriers for potential entrants, the latecomers to such platforms will still encounter difficulty in rapidly overcoming the high barriers constructed by the early entrants in terms of reputation and market memory (Barnett, Feng, & Luo, 2013). In a cross-border B2B context, opportunistic behavior is common due to information imperfection caused by the general lack of in-depth face-to-face communication and on-site quality control (Daniels, Radebaugh, & Sullivan, 2011, pp. 470–473). Compared with the individual customers at business-to-customer portals, wholesale buyers at B2B portals can hardly afford the large risks of switching to an unreliable supplier. Under the uncertainty of cross-border B2B, buyers will be rationally loyal to the early suppliers that have delivered their orders satisfactorily (Balabanis, Reynolds, & Simintiras, 2006; Srinivasan, Anderson, & Ponnavolu, 2002).

However, the marginal benefit of early entry will start to diminish after a certain period. As B2B portals provide standardized and professional virtual trading rooms for sellers and buyers, the entry barrier to online exporting has been lowered to a minimum level (Chang, Jackson, & Grove, 2003). The costs of international advertising, information searches, and transactions at cross-border B2B platforms are substantially lower than the costs in the conventional brick-and-mortar export marketing mode (Clarke & Flaherty, 2003; Petersen et al., 2002). As new competitors emerge and the market becomes saturated, the early-mover disadvantages of incumbent sellers will counterbalance the effects of EMA, with a relatively quicker pace compared with brick-and-mortar markets (Porter, 2001).

Late movers may be able to take a *free ride* on the first movers' efforts to educate customers, create the market, and nurture talents. When early movers initially enter the market, they need to heavily invest in market research and advertisements to identify what potential buyers want and how to draw buyers' attention to the new products and purchasing channel (Carlton & Chevalier, 2001). These education costs may be relatively high in cross-border B2B marketplaces because foreign wholesale buyers tend to prefer transactions with conventional offline approaches (Quelch & Klein, 1996). These foreign wholesale buyers might not even know they could have purchased foreign products through online channels. In effecting cross-border B2B transactions, early movers also need to engage extra resources in cultivating professionals (Guasch & Weiss, 1980) with profound expertise in export, foreign language, and information technology (Morgan-Thomas

& Bridgewater, 2004). However, late entrants may circumvent these education costs and take a free ride on the early entrants (Lieberman & Montgomery, 1988).

Second, late movers may take advantage of the successful products introduced by the early movers, imitate them using reverse engineering, and thus *resolve technological and market uncertainty* (Lieberman & Montgomery, 1988). Developing new products for foreign customers is risky for early movers in international markets. A market entrant will usually enjoy a higher return rate through innovation only when a technological development is already well established (Åstebro & Michela, 2005; Cefis & Marsili, 2006). Given that exporters face international buyers with a considerably wider spectrum of preferences, innovative activities that have been tested at home labs will not be necessarily appropriate for overseas clients and may even generate unfavorable consequences (Deng, Guo, Zhang, & Wang, 2014). In reality, exporters are inclined to adopt a home replication strategy and produce goods that do not always suit foreign customers (Peng, 2009). Late movers on cross-border B2B platforms may easily observe the particular products that are favored by overseas customers and focus their production and marketing efforts on these proven and less risky products; in the process, they circumvent costly trial and error processes and secure a decent cash flow (Lieberman, 1987).

Early movers that are locked in to the fixed assets associated with specific products in cross-border B2B portals tend to suffer from *incumbent inertia* and encounter difficulty in upgrading their old production lines for new market trends (Lieberman & Montgomery, 1988). As the technology and taste of overseas buyers evolve over time, exported products need to be upgraded with newer models and functionalities (Sinkovics, Jean, Roath, & Cavusgil, 2011). Nonetheless, cross-border B2B e-commerce portals substantially expand the geographic coverage of early-mover wholesalers and push them to scale up their fixed asset investments and other resource commitments to match their global orders. These commitments naturally induce severe structural inertia (Hannan & Freeman, 1989), rendering the early exporters' deep entrenchment in the old routines (Sapienza, Autio, George, & Zahra, 2006). Consequently, these early exporters will be unable to rapidly adjust their resource allocations to fully accommodate the external shocks in technologies and buyer preferences (Tushman & O'Reilly, 1996); at the same time, their previous core capabilities could soon become rigidities (Leonard-Barton, 1992). Any attempt to radically change core organizational forms may also increase the risks of exit (Sapienza et al., 2006), thus engendering a major dilemma for early-mover cross-border firms (Christensen, 1997). However, new entrants lack these liabilities arising from existing product lines and structural inertia. They may design their products for the latest trend from day one and adapt to market changes more easily than early entrants (Robinson, Fornell, & Sullivan, 1992). They may take full advantage of the inflexibility of the early movers and transcend the achievements of these early movers, particularly in industries with a conservative attitude toward new product launches such as consumer products (Hultink, Hart, Robben, & Griffin, 2000).

Hypothesis 1. (H1): *Early-mover advantages at cross-border B2B portals exist at the initial post-entry stages but diminish after a certain critical time, so that an inverted U-shape relationship emerges between firm tenure and performance.*

2.3. Product price and EMA

Product positioning driven by cost leadership exerts an amplifying effect on the increase of EMA. The *learning curve* will be more prominent for firms selling cheap products with a low cost structure. A significant long-tail effect exists in online markets, and products sold online tend to be relatively homogeneous within the same product category (Anderson, 2004). The degree of homogeneity may be substantially aggravated in the international marketplace because many more sellers operate across the world (Sheth & Sharma, 2005). On B2B portals, price comparison between global suppliers has become extremely convenient, consequently shifting the sellers' competition focus toward price to obtain more direct and quicker attention from the buyers on the Internet (Porter, 2001). Thus, a price leadership strategy exerts a strong effect on attracting customer attention and helping e-commerce firms obtain large orders (Carlton & Chevalier, 2001). Learning by producing a large number of products may allow sellers to rapidly accumulate experience with international marketing and frugal innovation (Hatch & Mowery, 1998). Therefore, EMA will be strengthened by a low-price product strategy.

The *switching cost* is high for buyers if they are dependent on and satisfied with the competitive cost structure of products offered by low-price early entrants (Balabanis et al., 2006). In the cross-border B2B market, early overseas buyers who are dependent on cheap inputs tend to build a low-cost corporate culture (Newbert & Tornikoski, 2013). These early buyers save on financial resources, and may spend these savings on increasing their marketing efforts through, for example, channel development and advertisements. Once the organizational structure and business routines of buyers have become highly dependent on the low-cost structure of their input purchases through cross-border B2B portals, switching to more expensive sellers becomes difficult for the early buyers (Pfeffer & Salancik, 1978). In particular, for products with relatively low technology content such as standardized industrial components, the entire supply chain adopts a low-cost strategy, and buyers who rely on cheap inputs will build their own low-price reputation to attract downstream customers (Zeng & Williamson, 2007). The branding image will be self-reinforced once such a position is established, and switching to high-cost purchases will be difficult for such downstream buyers (Balabanis et al., 2006).

However, low price also exerts an amplifying effect on the decline of EMA on those cross-border B2B platforms with a low entry barrier and a large number of sellers. First, taking a *free ride* on the early entrants who are selling cheap products is easier. Other things being equal, selling cheap products generates thin profit margins (Lawton, 1999). Early entrants who want to sell cheap products must inevitably invest in cultivating the market and the talent pool and demonstrate to potential buyers the process of conducting online transactions with overseas suppliers. These sunk costs will eventually be translated into product costs, and therefore render the price leadership of the early entrants unsustainable (Coeurderoy & Durand, 2004). By contrast, late entrants need to make little or no investment in persuading potential buyers to use this B2B purchase mode. Their lean cost structure may generate a competitive advantage over the early entrants (Coeurderoy & Durand, 2004).

Second, the cost-saving effects of imitating successful products and *resolving technological and market uncertainty* are even more tremendous for producers who offer low-price products. Imitation is always more cost effective and less risky than innovation in most sectors (Lieberman & Montgomery, 1988). Early entrants have to incur high trial and error costs, which sometimes pose an unbearable or fatal burden for firms selling low-price products and earning relatively thin profit margins. However, the transparency of information in the B2B marketplace may allow late entrants to identify and subsequently imitate the bestselling products when the market prospects of the successful products become clearer (Makadok, 1998). Without high experimental costs, the low-cost follower entrants can offer very similar products with more competitive prices, thus hedging their own cost risks and eroding the EMA of early entrants (Mansfield, 1981).

Finally, *incumbent inertia* caused by the fixed investment in assets specific to the cheap products will be detrimental to firms that adopt a low-price strategy. These investments in machines, equipment, or R&D have been specifically adjusted for the low-cost culture of the organization. Readjusting these investments for new technologies or buyer needs necessitates extra inputs in machine upgrading, new component

Please cite this article as: Deng, Z., & Wang, Z., Early-mover advantages at cross-border business-to-business e-commerce portals, *Journal of Business Research* (2016), http://dx.doi.org/10.1016/j.jbusres.2016.05.015

ARTICLE IN PRESS

repurchase, and worker training, among others (Tushman & O'Reilly, 1996). This process will pose a formidable financial challenge for low-cost firms (Hughes, Martin, Morgan, & Robson, 2010). Even if these low-cost firms manage to upgrade their current products, they have to spread the extra adjustment cost to the new products; consequently, this approach will prevent them from selling at a competitive price, which they are previously known for in the global B2B market (Newbert & Tornikoski, 2013).

Hypothesis 2. (H2): *Price leadership will amplify the inverted U-shape effect of EMA. In other words, low-price firms will enjoy a faster emergence of EMA but experience a faster decline of EMA.*

2.4. Product diversity and EMA

The product diversity of firms also exerts an amplifying effect on the rise of EMA. First, a stronger cross-product *learning curve* arises for firms offering diversified products (Tanriverdi & Lee, 2008). As cross-border B2B platforms host a large number of sellers who provide very similar products within each category, the competition for each individual product is intensified (Palumbo & Herbig, 1998). Nonetheless, firms may hedge these competitive risks by adopting a product diversification strategy (Peterson, Balasubramanian, & Bronnenberg, 1997) and exploiting cross-product learning effects (Sridhar, Bezawada, & Trivedi, 2012). If a firm's product obtains positive market responses, then the firm has an opportunity to scrutinize the forces driving the success of this product and clone the good practice for its other products (Robinson et al., 1992). Similarly, if one of the products experiences a sales setback due to poor web design or inferior product quality, the firm can detect this problem and avoid the occurrence of similar problems in the other products (Datar, Jordan, Kekre, Rajiv, & Srinivasan, 1996).

The *switching cost* is high for buyers who rely on sellers to offer a diversified product, as the buyers become deeply caught up in the network advantage offered by multi-product firms (Tanriverdi & Lee, 2008). In virtual online B2B marketplaces, firms offering differentiated products are more likely than single-product providers to be able to match with downstream buyers (Gabrielsson & Gabrielsson, 2011). Building trust between buyers and sellers on the Internet is a lengthy and risky process (Urban, Sultan, & Qualls, 2000). Thus, when considering the purchase of different but related products, overseas buyers will tend to browse the product catalogue and buy products from sellers with whom they already trade than initiate a new supply chain relationship with an unfamiliar seller. Moreover, sellers with a broad portfolio of products are more able to introduce innovative designs and functions to their existing products and to tailor products to the upgraded demand of sellers (Quelch & Klein, 1996; Tanriverdi & Lee, 2008). This capacity of the sellers will weaken the desire of overseas buyers to switch to new sellers, given the buyers' familiarity and compatibility with the existing technologies embedded in the seller's original products (Gómez & Maícas, 2011).

Product diversification also exerts an amplifying effect on the decline of EMA. *Free riding* multi-product firms will generate substantial cost savings for the late movers. Multi-product early movers need to spend even more exploratory resources than single-product early movers in educating overseas buyers and training personnel (Lim, Lee, & Tan, 2001). Multi-product late movers may enjoy greater free-riding benefits and competitive advantages by avoiding the payment of the costs of creating multiple markets (Lim et al., 2001).

The cost savings in imitating successful products and *resolving technological and market uncertainty* are even more significant for multi-product early movers compared with single-product firms (Barnett & Freeman, 2001). Multi-product firms may conduct market research by searching the historical data on transactions at cross-border B2B portals to identify the bestselling products. Engaging in reverse engineering or slightly altering these multiple successful products allows the late entrants to effectively circumvent the trial and error risks with an even greater magnitude. As cross-border B2B portals accommodate sellers worldwide and maintaining buyer loyalty by constantly offering customized products and a variety of choices is relatively difficult, early movers with successful products will be vulnerable to considerable risks of imitation (Srinivasan et al., 2002).

Incumbent inertia associated with the fixed investment and organizational routine for multiple products is detrimental to early movers. Early movers invest tremendous amounts of resources into the fixed assets for creating and producing multiple products (Barnett & Freeman, 2001), but the high operational uncertainties and organizational inertia signify that these early movers will be more conservative in upgrading their product lines than those early movers producing a single product (Tushman & O'Reilly, 1996). Instead, early movers are more likely to be locked in to the extant market and associated technologies because the replication of the extant products can warrant stable financial income (Christensen, 1997; Leonard-Barton, 1992).

Hypothesis 3. (H3): *Product diversity will amplify the inverted U-shape effect of EMA. In other words, multi-product firms will enjoy a faster emergence of EMA but experience a faster decline of EMA.*

Fig. 1 summarizes the theoretical framework.

3. Method

3.1. Sample

The sample for the study is obtained from a typical cross-border B2B portal, that is, DHgate (http://www.dhgate.com/). This website provides a gateway for online wholesale transactions between small- and medium-sized manufacturers and overseas buyers, but it does not accommodate domestic B2B transactions. This portal was founded in 2004, although most of its sellers started exporting in 2007. In 2013, transactions of 30 million types of products were made on this portal and exported to 227 countries and regions, and the value of its online transactions was ranked No. 1 in Asia and No. 6 in the world (DHgate, 2014). Compared with other third-party cross-border B2B portals that are pure information portals (e.g., Alibaba.com), DHgate not only serves as an information platform but also enables immediate online transactions in association with major international payment methods such as Visa, MasterCard, and Western Union. Products sold at DHgate are organized and coded within a three-layer hierarchy (i.e., "sector", "category", and "product"), as shown in Fig. 2. Opening up an online shop at DHgate is free, and the portal only charges fees based on the value of each transaction. Therefore, the portal poses almost no entry barrier to new entrants. To provide a full disclosure of the reputation of each seller, the website reports detailed information on every product-level transaction record of every seller, including product name, number of transactions, price, and transaction date.

To avoid potential product bias (Pentina et al., 2009), we selected eight sectors of consumer products and eight sectors of industrial intermediate products from DHgate. We collected all historical export

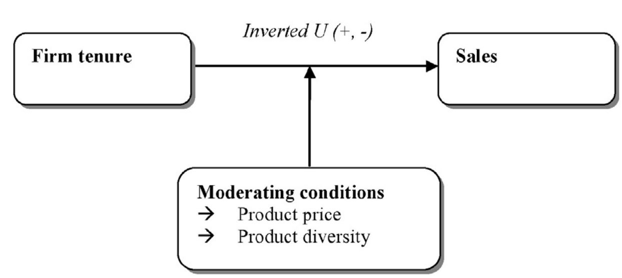

Fig. 1. Theoretical framework.

Please cite this article as: Deng, Z., & Wang, Z., Early-mover advantages at cross-border business-to-business e-commerce portals, *Journal of Business Research* (2016), http://dx.doi.org/10.1016/j.jbusres.2016.05.015

ARTICLE IN PRESS

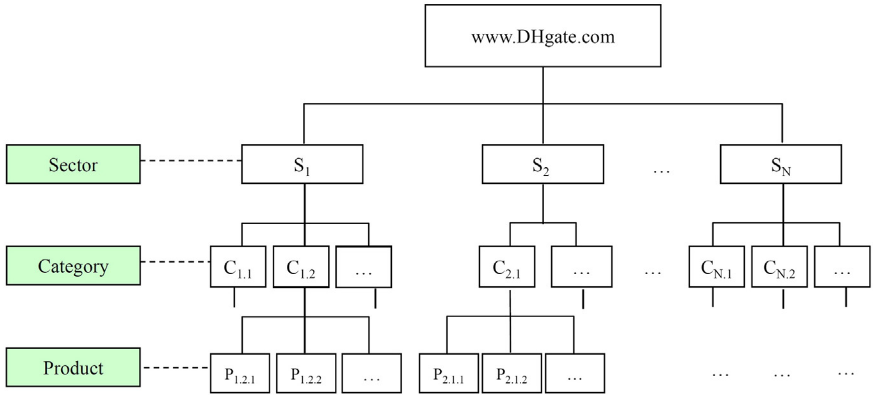

Fig. 2. Product hierarchy.

transaction data of all firms from these 16 sectors through web search and mining techniques (Chakrabarti, 2003). The data contained 297,846 B2B export transactions conducted by 3969 sellers in 84 months between June 2007 and May 2014. We aggregated the raw data into monthly data. As small- and medium-sized etailers experience volatile daily or weekly performance caused by marketing campaigns or other uncertain events (Ashworth, Schmidt, Pioch, & Hallsworth, 2006), a one-month interval helps smooth out such disturbances (Wang et al., 2016). The data structure of the sample is summarized in Table 1.

3.2. Variables

3.2.1. Dependent variable

In the EMA literature, the widely adopted dependent variables of firm performance include sales, profits, and market share (Pentina et al., 2009; VanderWerf & Mahon, 1997). As many firms in the sample sell products in more than one category or even in more than one sector, classifying each firm into a certain "market" and calculating its "market share" are inappropriate. Moreover, market share may not fully capture the benefits of early entry (Gómez & Maícas, 2011; Lieberman & Montgomery, 1998; VanderWerf & Mahon, 1997). In the text mining process, we can only obtain data about sales value (in US dollars); thus, we use the logarithm of *sales* in each month as the dependent variable.

3.2.2. Explanatory variables

We use *tenure* (the number of months) of a firm at the e-commerce portal as the main independent variable (Barnett et al., 2013). It is calculated by deducting the foundation month from the current month at each time point of observation. Given that our data record entry timing since the inception of the portal, this variable can precisely measure the earliness of each firm entering the market. The longer a firm stays at the portal, the larger value *tenure* will have. For example Firm A and Firm B enter the portal in July 2010 and July 2011, respectively. Their *tenure* values will be 24 and 12 months in July 2012, and they will be 25 and 13 months in August 2012, respectively. Therefore the early-mover status is fully captured by *tenure* in this panel dataset. If EMA exists, then a positive relationship should emerge between tenure and firm performance. To allow for a potential curvilinear relationship between tenure and sales, we also include a quadratic term of *tenure* and divide it by 1000 to reduce its scale to a lower level (Hannan & Freeman, 1989, pp. 271–309). We expect a negative sign for this term.

As for control variables, we use the average product *price* weighted by the number of product by each firm sold in each month to measure the aggregate price of the firm. We also include *diversity* measured by the degree of product differentiation (the lowest level in the product hierarchy shown in Fig. 2) of each firm in each month (Robinson et al., 1992).

We also include the number of all historical *transactions* conducted by the current month at DHgate for the focal firm. The lack of a solid foundation for building trust between sellers and buyers in the virtual international marketplace may prompt buyers to rely on the transaction volume of a seller to make a judgment on its track record and reliability (Urban et al., 2000). Moreover, some firms switch from brick-and-mortar channels to electronic channels, and they may divert a major cohort of buyers within a short period (Gabrielsson & Gabrielsson, 2011). The inclusion of transaction volume may help control for such disturbances.

Similarly, DHgate provides online the average *review* score for buyer satisfaction, which ranges from 0 to 1. This variable is also included to control for potential variation caused by seller reputation (Ludwig et al., 2013). Online buyers put more trust in peer buyers than in advertisements; furthermore, their evaluations may effectively influence future sales (Ludwig et al., 2013).

We include three dummy variables (i.e., summer, fall, and winter) to control for seasonal differences. For customer products such as clothing, the seasonal fluctuation of demand induces significant volatility in sales (Lam, Vandenbosch, Hulland, & Pearce, 2001), and this factor must be considered. We include 15 product sector dummy variables, given that various sectors host different numbers of sellers and degrees of market concentration. We also add 30 region dummy variables. Different regions in China are endowed with different resources; moreover, local governments have implemented liberalization at different paces, thereby forming sub-national variations in institutional quality and attractiveness to firm operations (Ma, Delios, & Lau, 2013). Table 2 reports the descriptive statistics and correlation coefficients.

Table 1
Product categories covered in the sample.

Consumer products (no. of firms)	Industrial products (no. of firms)
Baby & kids clothing (1)	Active components (169)
Breast care & treatment (1)	Electronic accessories & supplies (335)
Fashion dresses (1,077)	Industrial supplies (354)
Hats, scarves & gloves (1)	Office & school supplies (676)
Lower garments (249)	Optoelectronic displays (71)
Suits (643)	Packing & shipping (251)
Underwear (404)	Passive components (68)
Upper garments (761)	Retail & services (414)
Total (3,137)	Total (2,338)

Note: Firms may be double counted across sectors, as firms have variations in sector classification over time.

4. Results

Based on the aforementioned empirical design, we employ a generalized least square panel data model with fixed effects. The first column (Model 1) in Table 3 reports the regression results of the baseline model. Seller *tenure* measured by month has a significantly positive

Please cite this article as: Deng, Z., & Wang, Z., Early-mover advantages at cross-border business-to-business e-commerce portals, *Journal of Business Research* (2016), http://dx.doi.org/10.1016/j.jbusres.2016.05.015

ARTICLE IN PRESS

Table 2
Descriptive statistics and correlation coefficients.

	Mean	S.D.	Min	Max	1	2	3	4	5
1. ln(sales)	5.981	2.134	0	13.258	1				
2. *Tenure*	24.572	17.544	0	83	−0.042	1			
3. *Price*	736.394	1,216.593	0.165	4,533	0.686	−0.098	1		
4. *Diversity*	3.273	6.386	1	176	0.307	0.062	−0.065	1	
5. *Transaction*	1,999.101	4,441.417	1	60,215	0.103	0.200	−0.065	0.276	1
6. *Review*	0.977	0.115	0	1	−0.023	0.088	−0.070	0.043	0.053

Note: All correlation coefficients are significant at 1% level.

Table 3
Regression results, whole sample.

Model	1	2	3	4	5
Sample	Full	Low price	High price	Low diversity	High diversity
Tenure	0.019*** (0.002)	0.028*** (0.003)	0.011*** (0.002)	0.008*** (0.002)	0.016*** (0.003)
Z-statistic for low/high coefficient comparison		[4.814]***		[2.057]**	
Tenure^2	−0.190*** (0.029)	−0.361*** (0.044)	−0.089** (0.036)	−0.123*** (0.037)	−0.211*** (0.041)
Z-statistic for low/high coefficient comparison		[4.790]***		[1.593]*	
Turning point (month)	50.000	39.030	60.191	34.021	37.498
Price	4.80e − 04*** (1.21e − 05)	0.048*** (0.003)	3.86e − 04*** (1.09e − 05)	4.92e − 04*** (1.30e − 05)	3.79e − 04*** (2.77e − 05)
Diversity	0.112*** (0.002)	0.101*** (0.002)	0.123*** (0.002)	0.208*** (0.005)	0.071*** (0.001)
Transaction	−0.003*** (4.26e − 04)	−0.003*** (4.76e − 04)	−0.002** (0.001)	−0.003*** (0.001)	−0.001*** (4.34e − 04)
Review	13.505* (6.932)	−14.762 (11.023)	29.832*** (8.122)	9.243 (8.164)	22.659** (10.383)
Quarter dummies	Included	Included	Included	Included	Included
Sector dummies	Included	Included	Included	Included	Included
Province dummies	Included	Included	Included	Included	Included
R^2	0.228	0.227	0.251	0.181	0.284
F value	330.99	215.91	186.10	160.44	139.940
No. of firms	3969	1763	2685	3897	1280
No. of firm-month observations	28,645	14,281	14,364	19,916	8729

Note: (1) Dependent variable is ln(sales). (2) t-statistics is reported in the parentheses. (3) z-statistics is reported in square brackets.
* Denotes significance at the 10% level.
** Denotes significance at the 5% level.
*** Denotes significance at the 1% level.

coefficient, suggesting the existence of EMA. Moreover, the quadratic term of *tenure* has a significantly negative coefficient, suggesting that EMA will diminish after a certain period. Therefore, Hypothesis 1 is fully supported. After deriving the partial differentiation of ln(*sales*) with respect to *tenure*, we calculate that the turning point will be $(0.019 / (2 \times 0.190)) \times 1000 = 50$ (months). For the entire sample, the early entrants will start to observe a diminishing effect of seller tenure on sales after 50 months of online operation. The main control variables, including *price*, *diversity*, and *review*, all have significantly positive coefficients.

In testing the moderating effects, the literature employs either multiplication or sample division. We follow the intuitive practice of Lamin and Livanis (2013) and adopt the sample division approach to obtain several statistical and conceptual advantages. First, multiplying a moderator with *tenure* and *tenure*^{2} will yield extremely high correlation coefficients (above 0.8) among the moderator and the two interaction terms, that is, moderator × *tenure* and moderator × *tenure*^{2}. This approach will induce severe multicollinearity and render the estimated coefficients unstable and unreliable (Gujarati, 2004, p. 344, 350). Sample division may avoid this problem. Second, pooling the entire sample and collectively running regressions implicitly assume that the observed variations in the control variables are the same for all firms, which is not necessarily true in reality (Lamin & Livanis, 2013). We will justify this aspect in later analysis. Third, dividing the sample by price and diversity will track the potentially dynamic membership of firms across different months, and therefore, may identify the effects of such membership on firm performance.[1]

[1] We thank an anonymous reviewer for suggesting this point.

To test the moderating effects of product price, we use the median value of product price to dichotomize the full sample into "low-price" and "high-price" subsamples. Chow test ($F = 1430.606$) has justified the sample division (Chow, 1960). We subsequently run the same regression model for each of the two subsamples, and by comparing the coefficients of *tenure* and *tenure*^{2}, we will be able to identify the moderating effect. The results are shown in Models 2 and 3 in Table 3. Both groups exhibit a similar pattern in terms of the inverted U shape for EMA, confirming H1 again, but the magnitudes (absolute value) of the coefficients of *tenure* and *tenure*^{2} in the low-price group are larger than those of the coefficients in the high-price group. To determine whether this difference is statistically significant, we calculate the Z-statistic for both *tenure* and *tenure*^{2}. The Z-statistics (4.814 and 4.790) reject the null hypothesis of the coefficients being equal, at the 1% level (Clogg, Petkova, & Haritou, 1995), confirming H2, that is, a significant moderating effect of product price exists on the EMA for cross-border B2B sales.

The difference of the coefficients of the control variables between Models 2 and 3 suggests the necessity of using separate subsamples to test the moderating effect of product price. Note we keep *price* as a control variable to control for the differentiated effects of *price* and thus remove potential sample selection bias caused by the group division with *price*. The coefficient of *review* in "high price" group is significantly positive, whereas that in "low price" group is insignificant. This result implies the "low price" buyers pursue cost leadership more than product quality and reputation.

Fig. 3 illustrates the difference between these two groups. The early movers selling cheaper products will clearly enjoy a faster emergence in this virtual international market, but this EMA will also diminish more rapidly. The turning point will occur at roughly 39 months for the

Please cite this article as: Deng, Z., & Wang, Z., Early-mover advantages at cross-border business-to-business e-commerce portals, *Journal of Business Research* (2016), http://dx.doi.org/10.1016/j.jbusres.2016.05.015

ARTICLE IN PRESS

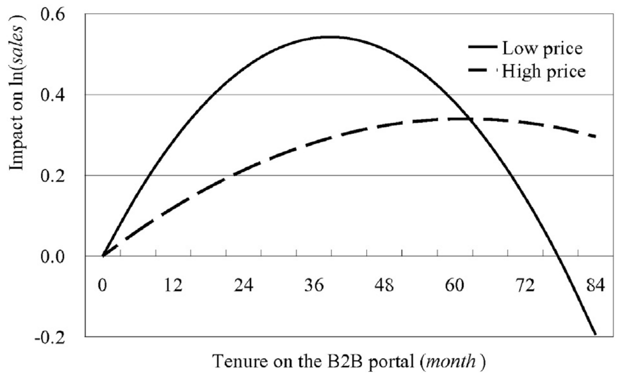

Fig. 3. EMA of firms, with low and high prices.

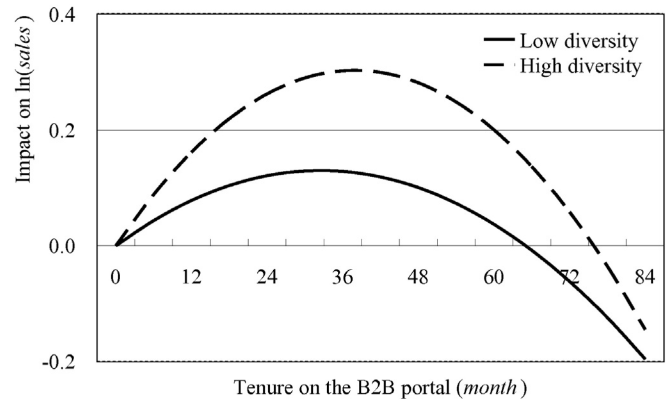

Fig. 4. EMA of firms, with low and high diversities.

low-price group, but considerably earlier than that for the high-price group, at 60 months.

Furthermore, we test product diversity as an additional boundary condition. We select "category" as the product classification level to define if a firm is adopting a focus strategy or not (Porter, 1980, pp. 34–46). The lowest level of classification shown in Fig. 2 exhibits only a trivial product difference, and thus cannot actually reflect the degree of product diversification. Accordingly, we use a higher level product classification, denoted by "category" in Fig. 2, to divide the sample. If a firm sells products in only one category, it will be in the "low diversity" subsample; otherwise, it will be in the "high diversity" subsample. For example, suppose that Firm A sells three different products in the "integrated circuits" category and four different products in the "sensors" category, whereas Firm B sells two different products in the "diode" category. In our group division, Firm A will be in the "high diversity" group because it sells products of two categories, whereas Firm B will be in the "low diversity" group because it sells only one category. However, the control variable *diversity* will still take the values of 7 and 2 for Firm A and Firm B, respectively, in the regression model.

The regression results are reported in Models 4 and 5 in Table 3. As predicted by H3, the absolute values of the coefficients of *tenure* and $tenure^2$ in the high diversity group are significantly higher than those in the low diversity group. Therefore, the speed with which the EMA declines to zero is greater in the high diversity group, although the turning (highest) point of EMA comes later. Similar to Figs. 3, 4 shows a clear difference between the subsamples. Note we keep *diversity* as a control variable to control for the differentiated effects of diversity and thus to remove potential sample selection bias caused by the group division with *diversity*. The high diversity group will exhibit a faster emergence of EMA, but this EMA will start to diminish at a greater rate after 37 months. The low diversity group will have a relatively flatter inverted U shape for the EMA effect. Both turning points in the split groups are smaller than that in the overall model. That is caused by the large number of control and dummy variables (Lamin & Livanis, 2013). After splitting the sample, the coefficients of the control and dummy variables in "low diversity" group are rather different from those in the "high diversity" group. Therefore the portion of variance in the dependent variable to be explained by *tenure* and $tenure^2$ in Model 4 is different from that in Model 5.

We run several robustness tests to justify the validity of the results. External shocks to the reliability of the empirical results may emerge due to the seasonal volatility in sales, particularly during Christmas (Lam et al., 2001). Therefore, we keep spring and fall seasons only and once again run all of the regressions. Highly consistent results are obtained (Table 4), thus supporting all of the hypotheses.

We also use the mean instead of the median value of product price as the threshold to divide the entire sample into "low price" and "high price" groups. The coefficient difference between Models 1 and 2 in Table 5 remains as significant as that between Models 2 and 3 in Table 3, hence supporting H2. We select "product" (i.e., the lowest level in Fig. 2) as the product classification level to define if a firm is adopting a focus strategy or not. *Diversity* in Model 3 of Table 5 is omitted because of the single unit value of *diversity*. The coefficient difference between Models 3 and 4 in Table 5 remains as salient as that between Models 4 and 5 in Table 3, thus supporting H3.

5. Discussion and conclusion

The number of firms using cross-border B2B e-commerce portals has tremendously increased (Chen et al., 2014); however, the extant literature has paid little attention to the EMA of these firms. To address this research gap, we have proposed a theoretical framework that argues for the existence and the curvilinear nature of this EMA. Moreover, we hypothesize the amplifying effects of product price and diversity on the dynamic nature of the EMA.

The empirical study justifies the existence of EMA on the Internet and echoes the findings from conventional non-Internet markets (Lieberman & Montgomery, 1988; VanderWerf & Mahon, 1997). However, the sustainability of EMA on cross-border B2B portals is substantially weaker compared with the non-Internet markets (Makadok, 1998). After three to five years, early-mover disadvantages will counterbalance the EMA. After six to seven years, such disadvantages will even completely negate the EMA. This study is the first in the EMA literature to explicitly illustrate the rapidly fleeting nature and extremely low sustainability of EMA, exemplified by the firms on global B2B portals. Furthermore, in contrast to the extant EMA literature, this study examines how firm strategies on product pricing and diversification can prolong the EMA.

The current study extends EMA theory and opens up avenues for future research. First, it extends the conventional wisdom regarding EMA and identifies the dynamic nature of EMA (inverted U shape) in a cross-border context. The extant literature has ignored the existence of EMA with respect to sellers on third-party B2B platforms. The low entry barriers for such platforms signify that the competition tends to be very intense. Cross-border platforms push this fierce competition to a new level because they create a borderless marketplace for sellers and produce a hypercompetitive environment for every participant. Such a fundamental alteration of the competitive scene will accelerate the rise and fall of EMA, which necessitates research on the full life cycle of firms on such platforms. Our findings regarding the temporary nature of EMA on cross-border B2B portals remind the research community to rethink the conventional paradigm employed for brick-and-mortar transactions, which features the relatively slow emergence of new entrants.

The study also contributes to the EMA literature by examining two boundary conditions. We determine the vital importance for a seller to decide strategically on the product prices and portfolio to introduce online. Examining the alternative moderating effects of other factors, such as web design, international diversity of buyers, geographic and

Please cite this article as: Deng, Z., & Wang, Z., Early-mover advantages at cross-border business-to-business e-commerce portals, *Journal of Business Research* (2016), http://dx.doi.org/10.1016/j.jbusres.2016.05.015

Table 4
Robustness test, subsample with spring and fall only.

Model	1	2	3	4	5
Sample	Full	Low price	High price	Low diversity	High diversity
Tenure	0.029*** (0.003)	0.043*** (0.005)	0.017*** (0.004)	0.009** (0.004)	0.038*** (0.004)
Z-statistic for low/high coefficient comparison		[4.301]***		[4.815]***	
Tenure^2	−0.239*** (0.046)	−0.408*** (0.073)	−0.115* (0.060)	−0.082* (0.060)	−0.379*** (0.066)
Z-statistic for low/high coefficient comparison		[3.106]***		[3.276]***	
Turning point (month)	60.748	52.595	73.027	54.640	49.695
Price	0.001*** (2.69e − 05)	0.045*** (0.006)	4.53e − 04*** (2.52e − 05)	0.001*** (3.06e − 05)	3.79e − 04*** (5.99e − 05)
Diversity	0.101*** (0.002)	0.104*** (0.003)	0.088*** (0.003)	0.208*** (0.008)	0.064*** (0.002)
Transaction	−0.002*** (0.001)	−0.003*** (0.001)	−0.002 (0.001)	−0.003** (0.002)	−0.001** (0.001)
Review	−7.359 (12.630)	−19.583 (18.384)	−4.987 (18.486)	−19.497 (16.499)	−28.883** (17.932)
Quarter dummies	Included	Included	Included	Included	Included
Sector dummies	Included	Included	Included	Included	Included
Province dummies	Included	Included	Included	Included	Included
R^2	0.243	0.265	0.239	0.182	0.308
F-value	136.17	121.36	62.01	55.43	63.44
No. of firms	2947	1320	1987	2757	952
No. of firm-month observations	11,452	5700	5752	7770	3682

Note: (1) Dependent variable is ln(sales). (2) t-statistics is reported in the parentheses. (3) z-statistics is reported in square brackets.
* Denotes significance at the 10% level.
** Denotes significance at the 5% level.
*** Denotes significance at the 1% level.

Table 5
Robustness test, whole sample
(price mean and product diversity as sample division points, respectively).

Model	1	2	3	4
Sample	Low price	High price	Low diversity	High diversity
Tenure	0.022*** (0.002)	0.006** (0.003)	0.007*** (0.003)	0.014*** (0.002)
Z-statistic for low/high coefficient comparison	[4.057]***		[2.051]**	
Tenure^2	−0.226*** (0.033)	−0.042* (0.035)	−0.074* (0.042)	−0.176*** (0.034)
Z-statistic for low/high coefficient comparison	[2.927]***		[1.875]*	
Turning point (month)	47.918	74.406	48.688	40.861
Price	0.005*** (2.41e − 04)	1.90e − 04*** (1.27e − 05)	4.99e − 04*** (1.44e − 05)	4.15e − 04*** (1.95e − 05)
Diversity	0.108*** (0.002)	0.115*** (0.003)	Omitted	0.080*** (0.001)
Transaction	−0.003*** (4.36e − 04)	−0.001 (0.001)	−0.004*** (0.002)	−0.002*** (3.62e − 04)
Review	−2.477 (9.226)	49.640 (14.986)	13.193 (8.796)	14.363* (8.731)
Quarter dummies	Included	Included	Included	Included
Sector dummies	Included	Included	Included	Included
Province dummies	Included	Included	Included	Included
R^2	0.222	0.206	0.100	0.280
F value	229.12	114.11	60.02	213.04
No. of firms	2708	1638	3768	1952
No. of firm-month observations	20,410	8235	15,174	13,471

Note: (1) Dependent variable is ln(sales). (2) t-statistics is reported in the parentheses. (3) z-statistics is reported in square brackets.
* Denotes significance at the 10% level.
** Denotes significance at the 5% level.
*** Denotes significance at the 1% level.

institutional distances between sellers and buyers, and web ranking of products, presents an interesting direction for future research (Sheth & Sharma, 2005).

This study also adds to the international entrepreneurship literature, in that its findings suggest that B2B e-commerce portals constantly offer windows of opportunity for nascent latecomers to venture into the international markets. Easy-entry electronic intermediaries fundamentally differ from conventional export management companies, as they have substantially reduced information search costs and transaction costs and exponentially expanded international visibility (Porter, 2001; Wang et al., 2016). The international expansion trajectory of new ventures on B2B e-commerce portals involves more opportunities and challenges than those encountered by conventional businesses (Sheth & Sharma, 2005). This study calls for re-examining, in an e-commerce era, how earliness and speed of firm internationalization affect firm performance, which however has been investigated mainly in a brick-and-mortar context (e.g. Sapienza et al., 2006).

This research has rich managerial implications. First, it indicates the inclusiveness of online cross-border B2B portals for both early and late entrants. As the evolution of the market changes the requirements for success, windows of opportunity open for new entrants with different features (Robinson et al., 1992). Second, EMA does exist, thereby leaving early entrants several years to learn from the market, to accumulate financial resources, and to develop marketing capabilities before this EMA declines (Sapienza et al., 2006; Wang et al., 2016), rather than simply exploit the benefits of earliness per se. Third, firms need to strategically extend their EMA effects by switching between different strategic groups (Porter, 1980, pp. 129–41). They may migrate from one group to another strategically, as illustrated in Fig. 4. A firm may be present as a low-diversity seller in the early stage, but it may become a high-diversity seller in the later stage, extending its EMA effects. Similarly, firms may start out as a low price seller but to survive, they may become niche, high price sellers, thus avoiding the crowded low price group.[2]

Admittedly, this study has limitations that might constrain the generalizability of the findings. We collect data on the surviving firms in an

[2] We thank an anonymous reviewer for suggesting this point.

ARTICLE IN PRESS

ex post manner. Therefore we cannot track firms that have stopped using the portal, thus inducing a survivor bias (VanderWerf & Mahon, 1997). The available data hinder our identification of companies that have brick-and-mortar marketing channels; therefore, we cannot control for the potential interaction between these channels and B2B e-commerce channels (Brynjolfsson & Smith, 2000; Carlton & Chevalier, 2001). Data constraint prevents us from further pinning down the potential difference in the detailed mechanisms of EMA for consumer products and industrial products. Finally, the special features of B2B suppliers and buyers in emerging markets need to be incorporated for potentially insightful findings (Biggemann & Fam, 2011). We will leave these aspects for future research.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (grant numbers 71202149, 71372157, 71232011). Authors are grateful to comments from the audience at AIB 2015 (Bengaluru) and AIB China 2015 (Tianjin).

References

Alibaba.com (2015). About Alibaba.com. http://activities.alibaba.com/alibaba/following-about-alibaba.php?spm=a2700.7224109.a271py.9.KanJTr/ (Accessed 19.10.2015)

Anderson, C. (2004). The long tail forget squeezing revenue from a few megahits at the top of the charts. The future of entertainment is in the millions of niche markets at the shallow end of the bitstream. *Wired-San Francisco*, *12*(10), 170–177.

Ashworth, C. J., Schmidt, R.Ä., Pioch, E. A., & Hallsworth, A. (2006). An approach to sustainable 'fashion' e-retail: A five-stage evolutionary strategy for 'clicks-and-mortar' and 'pure-play' enterprises. *Journal of Retailing and Consumer Services*, *13*, 289–299.

Åstebro, T., & Michela, J. L. (2005). Predictors of the survival of innovations. *Journal of Product Innovation Management*, *22*(4), 322–335.

Balabanis, G., Reynolds, N., & Simintiras, A. (2006). Bases of e-store loyalty: Perceived switching barriers and satisfaction. *Journal of Business Research*, *59*(2), 214–224.

Barnett, W. P., & Freeman, J. (2001). Too much of a good thing? Product proliferation and organizational failure. *Organization Science*, *12*(5), 539–558.

Barnett, W. P., Feng, M., & Luo, X. (2013). Social identity, market memory, and first-mover advantage. *Industrial and Corporate Change*, *22*(3), 585–615.

Biggemann, S., & Buttle, F. (2012). Intrinsic value of business-to-business relationships: An empirical taxonomy. *Journal of Business Research*, *65*(8), 1132–1138.

Biggemann, S., & Fam, K. -S. (2011). Business marketing in bric countries. *Industrial Marketing Management*, *40*(1), 5–7.

Brynjolfsson, E., & Smith, M. D. (2000). Frictionless commerce? A comparison of Internet and conventional retailers. *Management Science*, *46*(4), 563–585.

Carlton, D. W., & Chevalier, J. A. (2001). Free riding and sales strategies for the internet. *Journal of Industrial Economics*, *49*(4), 441–461.

Cefis, E., & Marsili, O. (2006). Survivor: The role of innovation in firms' survival. *Research Policy*, *35*(5), 626–641.

Chakrabarti, S. (2003). *Mining the web: Discovering knowledge from hypertext data*. Burlington, MA: Morgan Kaufmann Publishers.

Chang, K. -C., Jackson, J., & Grove, V. (2003). E-commerce and corporate strategy: An executive perspective. *Information Management*, *40*(7), 663–675.

Chen, Y., Seong, J., & Woetzel, J. (2014). China's rising Internet wave: Wired companies. *The McKinsey Quarterly*, *2014*(4), 68–77.

Chow, G. C. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica*, *28*(3), 591–605.

Christensen, C. (1997). *The innovator's dilemma*. Boston, MA: Harvard Business School Press.

Clarke, I., III, & Flaherty, T. B. (2003). Web-based B2B portals. *Industrial Marketing Management*, *32*(1), 15–23.

Clogg, C. C., Petkova, E., & Haritou, A. (1995). Statistical methods for comparing regression coefficients between models. *American Journal of Sociology*, *100*(5), 1261–1293.

Coeurderoy, R., & Durand, R. (2004). Leveraging the advantage of early entry: Proprietary technologies versus cost leadership. *Journal of Business Research*, *57*(6), 583–590.

Daniels, J. D., Radebaugh, L. H., & Sullivan, D. P. (2011). *International business: Environments and operations* (13th ed.). Pearson Education.

Datar, S., Jordan, C., Kekre, S., Rajiv, S., & Srinivasan, K. (1996). New product development structures: The effect of customer overload on post-concept time to market. *Journal of Product Innovation Management*, *13*(4), 325–333.

Deng, Z., Guo, H., Zhang, W., & Wang, C. (2014). Innovation and survival of exporters: A contingency perspective. *International Business Review*, *23*(2), 396–406.

DHgate (2014). About us. http://www.dhgate.com/about/about_us.html#hp1501-about-brand/ (Accessed 30.09.2014)

Gabrielsson, M., & Gabrielsson, P. (2011). Internet-based sales channel strategies of born global firms. *International Business Review*, *20*(1), 88–99.

Gómez, J., & Maícas, J. P. (2011). Do switching costs mediate the relationship between entry timing and performance? *Strategic Management Journal*, *32*(12), 1251–1269.

Grewal, R., & Tansuhaj, P. (2001). Building organizational capabilities for managing economic crisis: The role of market orientation and strategic flexibility. *Journal of Marketing*, *65*(2), 67–80.

Guasch, J. L., & Weiss, A. (1980). Adverse selection by markets and the advantage of being late. *Quarterly Journal of Economics*, *94*(3), 14.

Gujarati, D. N. (2004). *Basic econometrics* (4th ed.). Columbus, Ohio: McGraw Hill.

Hannan, M. T., & Freeman, J. (1989). *Organizational ecology*. Cambridge, MA: Harvard University Press.

Hatch, N. W., & Mowery, D. C. (1998). Process innovation and learning by doing in semiconductor manufacturing. *Management Science*, *44*(11), 1461–1477.

Hughes, M., Martin, S. L., Morgan, R. E., & Robson, M. J. (2010). Realizing product-market advantage in high-technology international new ventures: The mediating role of ambidextrous innovation. *Journal of International Marketing*, *18*(4), 1–21.

Hultink, E. J., Hart, S., Robben, H. S. J., & Griffin, A. (2000). Launch decisions and new product success: An empirical comparison of consumer and industrial products. *Journal of Product Innovation Management*, *17*(1), 5–23.

Kerin, R. A., Varadarajan, P. R., & Peterson, R. A. (1992). First mover advantage: A synthesis, conceptual framework, and research propositions. *Journal of Marketing*, *56*(1), 33–52.

Kim, D., Basu, C., Naidu, G. M., & Cavusgil, E. (2011). The innovativeness of born-globals and customer orientation: Learning from Indian born-globals. *Journal of Business Research*, *64*(8), 879–886.

Lam, S. Y., Vandenbosch, M., Hulland, J., & Pearce, M. (2001). Evaluating promotions in shopping environments: Decomposing sales response into attraction, conversion, and spending effects. *Marketing Science*, *20*(2), 194–215.

Lamin, A., & Livanis, G. (2013). Agglomeration, catch-up and the liability of foreignness in emerging economies. *Journal of International Business Studies*, *44*(6), 579–606.

Lawton, T. C. (1999). The limits of price leadership: Needs-based positioning strategy and the long-term competitiveness of Europe's low fare airlines. *Long Range Planning*, *32*(6), 573–586.

Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal*, *13*, 15.

Lieberman, M. B. (1987). The learning curve, diffusion, and competitive strategy. *Strategic Management Journal*, *8*(5), 12.

Lieberman, M. B., & Montgomery, D. B. (1988). First-mover advantage. *Strategic Management Journal*, *9*, 41–58.

Lieberman, M. B., & Montgomery, D. B. (1998). First mover advantages: Retrospective and link with the resource based view. *Strategic Management Journal*, *19*(12), 1111–1125.

Lim, G. H., Lee, K. S., & Tan, S. J. (2001). Gray marketing as an alternative market penetration strategy for entrepreneurs: Conceptual model and case evidence. *Journal of Business Venturing*, *16*(4), 405–427.

Ludwig, S., de Ruyter, K., Friedman, M., Brüggen, E. C., Wetzels, M., & Pfann, G. (2013). More than words: The influence of affective content and linguistic style matches in online reviews on conversion rates. *Journal of Marketing*, *77*(1), 87–103.

Ma, X., Delios, A., & Lau, C. -M. (2013). Beijing or Shanghai? The strategic location choice of large MNEs' host-country headquarters in China. *Journal of International Business Studies*, *44*(9), 953–961.

Makadok, R. (1998). Can first-mover and early-mover advantages be sustained in an industry with low barriers to entry/imitation? *Strategic Management Journal*, *19*(7), 683–696.

Mansfield, E. M. S. (1981). Imitation costs and patents: An empirical study. *The Economic Journal*, *91*(364), 12.

Mellahi, K., & Johnson, M. (2000). Does it pay to be a first mover in e.Commerce? The case of Amazon.Com. *Management Decision*, *38*(7), 445–452.

Min, S., & Wolfinbarger, M. (2005). Market share, profit margin, and marketing efficiency of early movers, bricks and clicks, and specialists in e-commerce. *Journal of Business Research*, *58*, 1030–1039.

Morgan-Thomas, A., & Bridgewater, S. (2004). Internet and exporting: Determinants of success in virtual export channels. *International Marketing Review*, *21*(4/5), 393–408.

Newbert, S. L., & Tornikoski, E. T. (2013). Resource acquisition in the emergence phase: Considering the effects of embeddedness and resource dependence. *Entrepreneurship: Theory and Practice*, *37*(2), 249–280.

Nikolaeva, R. (2007). The dynamic nature of survival determinants in e-commerce. *Journal of the Academy of Marketing Science*, *35*(4), 560–571.

Palumbo, F., & Herbig, P. (1998). International marketing tool: The Internet. *Industrial Management & Data Systems*, *98*(6), 253–261.

Partanen, J., Möller, K., Westerlund, M., Rajala, R., & Rajala, A. (2008). Social capital in the growth of science-and-technology-based SMEs. *Industrial Marketing Management*, *37*(5), 513–522.

Peng, M. W. (2009). *Global strategy* (2nd ed.). Cincinnati: South-Western Cengage Learning.

Pentina, I., Pelton, L. E., & Hasty, R. W. (2009). Performance implications of online entry timing by store-based retailers: A longitudinal investigation. *Journal of Retailing*, *85*(2), 177–193.

Petersen, B., Welch, L. S., & Liesch, P. W. (2002). The Internet and foreign market expansion by firms. *Management International Review*, *42*(2), 207–221.

Peterson, R. A., Balasubramanian, S., & Bronnenberg, B. (1997). Exploring the implications of the internet for consumer marketing. *Journal of the Academy of Marketing Science*, *25*(4), 329–346.

Pfeffer, J., & Salancik, G. R. (1978). *The external control of organizations: A resource dependence perspective*. New York: Harper and Row.

Porter, M. E. (1980). *Competitive stratey: Techniques for analyzing industries and competitors*. New York: Free Press.

Porter, M. E. (2001). Strategy and the Internet. *Harvard Business Review*, *79*(3), 62–78.

Quelch, J. A., & Klein, L. R. (1996). The internet and international marketing. *Sloan Management Review*, *37*(3), 60–75.

Please cite this article as: Deng, Z., & Wang, Z., Early-mover advantages at cross-border business-to-business e-commerce portals, *Journal of Business Research* (2016), http://dx.doi.org/10.1016/j.jbusres.2016.05.015

ARTICLE IN PRESS

Reuber, A. R., & Fischer, E. (1997). The influence of the management team's international experience on the internationalization behaviors of smes. *Journal of International Business Studies*, *28*(4), 807–825.

Robinson, W. T., Fornell, C., & Sullivan, M. (1992). Are market pioneers intrinsically stronger than later entrants? *Strategic Management Journal*, *13*(8), 609–624.

Sapienza, H. J., Autio, E., George, G., & Zahra, S. A. (2006). A capabilities perspective on the effects of early internationalization on firm survival and growth. *Academy of Management Review*, *31*(4), 914–933.

Sheth, J. N., & Sharma, A. (2005). International e-marketing: Opportunities and issues. *International Marketing Review*, *22*(6), 611–622.

Sinkovics, R. R., Jean, R. -J. B., Roath, A. S., & Cavusgil, S. T. (2011). Does IT integration really enhance supplier responsiveness in global supply chains? *Management International Review*, *51*(2), 193–212.

Sridhar, K., Bezawada, R., & Trivedi, M. (2012). Investigating the drivers of consumer cross-category learning for new products using multiple data sets. *Marketing Science*, *31*(4), 668–688.

Srinivasan, S. S., Anderson, R., & Ponnavolu, K. (2002). Customer loyalty in e-commerce: An exploration of its antecedents and consequences. *Journal of Retailing*, *78*(1), 41–50.

Suarez, F., & Lanzolla, G. (2007). The role of environmental dynamics in building a first mover advantage theory. *Academy of Management Review*, *32*(2), 377–392.

Tanriverdi, H., & Lee, C. H. (2008). Within-industry diversification and firm performance in the presence of network externalities: Evidence from the software industry. *Academy of Management Journal*, *51*(2), 381–397.

Tushman, M. L., & O'Reilly, C. A. (1996). Ambidextrous organizations: Managing evolutionary and revolutionary change. *California Management Review*, *38*(4), 8–30.

Urban, G. L., Sultan, F., & Qualls, W. J. (2000). Placing trust at the center of your Internet strategy. *Sloan Management Review*, *42*(1), 39–48.

VanderWerf, P. A., & Mahon, J. F. (1997). Meta-analysis of the impact of research methods on findings of first-mover advantage. *Management Science*, *43*(11), 1510–1519.

Varadarajan, R., Yadav, M. S., & Shankar, V. (2008). First-mover advantage in an internet-enabled market environment: Conceptual framework and propositions. *Journal of the Academy of Marketing Science*, *36*(3), 293–308.

Wang, S., Cavusoglu, H., & Deng, Z. (2016). Early mover advantage in e-commerce platforms with low entry barriers: The role of customer relationship management capabilities. *Information Management*, *53*(2), 197–206.

Zeng, M., & Williamson, P. J. (2007). *Dragons at your door: How Chinese cost innovation is disrupting global competition*. Boston, MA: Harvard Business School Press.

Please cite this article as: Deng, Z., & Wang, Z., Early-mover advantages at cross-border business-to-business e-commerce portals, *Journal of Business Research* (2016), http://dx.doi.org/10.1016/j.jbusres.2016.05.015