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Strategic entrepreneurship's dynamic tensions: Converging (diverging) effects of experience and networks on market entry timing and entrant performance

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ABSTRACT

In this paper, we return to the roots of strategic entrepreneurship research by examining the dynamic tension between opportunity-seeking and advantage-seeking activities and by testing key resources that affect both activities. More specifically, we identify the empirical manifestations of the two activities—market entry timing decisions and entrant performance—and examine the degree to which the type of resources (in particular, experience and networks) that enable firms to enter a new market space early converge with (or diverge from) the type of resources that enhance entrant performance. Through analysis of 78 new market spaces and the associated 6544 entrant games in the U.S. console video game industry between 1995 and 2012, we find that while some resources—particularly relevant experience—have convergent impacts on entry timing and entrant performance, the impacts of other resources—first-order and second-order embeddedness—on these two outcomes diverge. We demonstrate that this tension in terms of resource impact on the two aspects of strategic entrepreneurship persists as the markets evolve.

Executive summary

Highly competitive and dynamic environments have become increasingly common and introduce multiple challenges, such as uncertainty and ambiguity, for firms seeking to create value and wealth. In the face of such environments, strategic entrepreneurship (SE)—the pursuit of superior performance via simultaneous opportunity-seeking and advantage-seeking activities—has been proposed as a potentially viable means for promoting and sustaining firms' competitive advantage (Hitt et al., 2011; Hitt et al., 2001). The belief is that entrepreneurial opportunities arise from a competitive landscape that is characterized by discontinuities and rapid change (Schumpeter, 1934), and SE is particularly valuable for enabling firms to explore the changing landscape and exploit opportunities created by uncertainties and discontinuities (Hitt et al., 2017; Ireland et al., 2003).

In this paper, we extend this pioneering SE research by: (1) challenging its fundamental assumption that opportunity- and advantage-seeking activities are necessarily synergistic; (2) building theoretical arguments as to which resources have convergent (versus divergent) effects on both activities; and (3) adding to SE's empirical foundation by examining the effects of key resource drivers on two well-recognized, related strategic outcomes—market entry and entrant performance. To do so, we ground our theory

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development and empirical analysis in the context of the U.S. console video game industry, where new market spaces constantly emerge around hit games and the imperative for SE is strong among game publishers. Our results show that in this context, a firm's relevant video game production experience and its production networks represent two key resources that affect entry timing decisions and entrant performance. To wit, a firm's prior experience that is relevant to a new market space enables early product entry into that space, and convergently, also enhances entrant game performance; but the impacts of its first- and second-order network ties have divergent effects on entry timing versus entrant performance.

Our theory and findings thus enrich the conceptual framework around SE developed by Hitt and colleagues (Hitt et al., 2001; Ireland et al., 2003; Hitt et al., 2017) by specifying convergent and divergent drivers of opportunity- and advantage-seeking activities. We also help advance the literature on the entry timing-performance relationship by examining temporal shifts in that relationship, while introducing a novel method that helps account for the potential endogeneity issue of entry timing in estimating entrant performance. Practically, our study suggests that entrepreneurs and managers need to anticipate the convergent and divergent influences of their resources, particularly as the market evolves, and accordingly optimally configure resources in order to survive and thrive in competitive and dynamic environments (Zhao et al., 2017; Zhao et al., 2018).

1. Introduction

Strategic entrepreneurship (SE) refers to firms' pursuit of superior performance via opportunity-seeking activities of "entrepreneurship" and advantage-seeking activities associated with "strategic management" (Ireland et al., 2003). The entrepreneurship aspect of SE highlights the importance of exposure and alertness to emerging opportunities, whereas the strategic management side emphasizes the role of deep knowledge and strong expertise for exploiting those opportunities. The prospect of SE to integrate harmoniously the opportunity-seeking and advantage-seeking activities is particularly valuable for firms to adapt to shifting competitive landscape and maintain long-term sustainability (Hitt et al., 2011; Hitt et al., 2001).

While the SE concept and SE framework are intuitive appealing, they are theoretically under-developed and only partially tested (Simsek et al., 2017). It remains unclear what constitute opportunity- and advantage-seeking activities and what are their empirical manifestations. It is also largely unknown the extent to which these two activities can be successfully combined and integrated, whether and how firms can be meaningfully arrayed along these dimensions, and what are the specific mechanisms through which the two activities either coalesce or diverge. In this paper, we return to the roots of SE by examining whether and how firms in a new market space can integrate opportunity-seeking and advantage-seeking activities. In particular, we examine SE in the context of the U.S. console video game industry, a dynamic and entrepreneurial context where new market spaces frequently emerge and evolve around hit games (i.e., games that pioneered certain combination of game features and achieved significant market success and critical acclaim). These new market spaces represent a competitive landscape that is constantly changing and present potential entrants with valuable entrepreneurial opportunities. Indeed, new product releases in these emerging market spaces have been considered a typical form of strategic entrepreneurship (Kuratko and Audretsch, 2013).

In this case, firms' opportunity-seeking activities are manifested in their market entry decisions (i.e., the timing of entering a new market space created by a hit game), and the effectiveness of their advantage-seeking activities is reflected in the performance of their entrant products (Covin and Miles, 1999; Kuratko and Audretsch, 2009). Our goal in this paper is then to theoretically predict and empirically investigate the various drivers of market entry timing decisions and entrant performance, and the degree to which these drivers are aligned and synchronized in shaping the two outcomes. Specifically, we focus on two types of resources—experience and networks—that prior research has alluded to as important factors influencing strategic entrepreneurship (Ireland et al., 2003). Our contextual analysis of the empirical setting verified the importance of these resources in shaping firms' ability to identify and exploit new market opportunities. In developing our arguments, we articulate and elaborate on the mechanisms through which the two types of resources respectively shape firms' market entry timing decisions and entrant performance. Based on this, we formulate a set of hypotheses that help elucidate the degree to which the drivers of market entry timing decisions and entrant performance converge or diverge. On top of this, SE implies a long-term view of value creation and capture that results from simultaneously engaging in opportunity- and advantage-seeking activities over time, yet such temporal questions have not been adequately addressed. Accordingly, we also examine the shifting influence of the various drivers on both outcomes as the new markets evolve.

To test our hypotheses, we drew on two primary data sources widely used in video game research—MobyGames and NPD—and built a database of 6544 console-based video games that entered new market spaces formed around 78 exemplary hit games in the U.S. market between 1995 and 2012. We recently examined how conformity (or differentiation) of followers entering such new market spaces influenced performance via audience evaluations (see Zhao et al., 2018). In our current study, we built on that paper and augmented data used in that earlier study with market entry, prior experience and network information. Statistical analysis of this updated database revealed an interesting tension in SE in the video game industry: there is a mismatch between the type of resources that enable early entry into a new product market space and those that contribute to better entrant performance. Specifically, while for some resources (e.g., relevant experience) we observe convergent impacts on entry timing and performance, for other resources (e.g., first-order and second-order embeddedness) their effects on these two outcomes diverge. As such, entry and performance require different configurations of resources. We also find that this tension persists as the new markets evolve. Our findings thus suggest that while the initial conceptualization of SE assumes a harmonious and simultaneous pursuit of opportunity-seeking and advantage-seeking activities, the kind of resources these two aspects of SE require are not perfectly aligned. We discuss the implications of these findings for research on strategic entrepreneurship and market entry, as well as practical implications for entrepreneurs and managers.

2. Theoretical background: Strategic entrepreneurship's dynamic tension

The concept of SE originated in early 2000 and attracted immediate attention among strategy and entrepreneurship scholars given its goal of integrating strategic management and entrepreneurship research and its practical relevance (Hitt et al., 2011; Hitt et al., 2001). According to the original definition, firms engaging in SE simultaneously enact both opportunity- and advantage-seeking activities in an attempt to gain and sustain competitive advantage under highly dynamic and uncertain environments (Hitt et al., 2001; Ketchen et al., 2007). As such, opportunity recognition and exploitation are at the heart of SE, and it can be used to improve competitive positioning and transform firms, their markets, and industries as new opportunities emerge (Ireland et al., 2003).

Both opportunity-seeking and advantage-seeking activities are necessary for value creation and capture, yet neither alone is sufficient. Firms that lack the ability to identify entrepreneurial opportunities are unlikely to sense market changes in a timely manner and thus fail to explore emerging and sometimes fleeting market demands. Conversely, firms that identify valuable opportunities but are incapable of exploiting them to develop a competitive advantage do not ultimately realize their value creation and capture potential. Sustainable competitive advantage is achieved only when firms have a resource portfolio capable of combining and integrating timely opportunity-seeking with effective advantage-seeking activities.

However, building such a resource portfolio is difficult, since most firms have finite resources, meaning that trade-offs often must be made regarding the amount of resources allocated to exploiting current competitive advantages and those allocated to exploring for emerging opportunities (Hitt et al., 2011). Excelling along both dimensions is inherently challenging because the two dimensions may require different types of resources and capabilities and many firms are unbalanced in their resource endowment for fulfilling both functions (Kuratko and Audretsch, 2013). An emerging stream of work suggest that firms engage resource orchestration—actions taken to structure the firm's resource portfolio, bundle resources into capabilities, and leverage the capabilities to create value for customers—in order to strategically manage its resources and capabilities to identify new opportunities while exploiting those opportunity to achieve competitive advantage (Hitt et al., 2011; Sirmon et al., 2011). Even among this emerging stream of studies, few have attempted to make an explicit distinction between opportunity-seeking and advantage-seeking activities and link them directly to the types of resources being orchestrated (Simsek et al., 2017). In addition, these studies have not examined how the tensions between the strategic and entrepreneurial side are resolved over time and in changing markets, i.e., SE's *dynamic tension*, and there is scant empirical evidence regarding the underlying mechanisms driving both activities. As such, we have limited understanding of what those mechanisms are and the extent to which they converge or diverge.

Despite this lack of knowledge, prior conceptual work on SE has been built around the importance of resources as the driving force that shapes how this dynamic tension unfolds. SE researchers, relying on wider studies in strategy and entrepreneurship, have alluded to two types of resources that are particularly relevant in shaping firms' entrepreneurial and strategic actions: experience and networks (Ireland et al., 2003). Both experience and networks shape opportunity-seeking activities by influencing how firms identify and sort through market signals to sense and capture emerging market demands. They also affect advantage-seeking activities by channeling deep knowledge and strong expertise that are essential for successfully exploiting the market opportunity and fulfilling consumer expectations. To further verify the relevance of the two types of resources, we next contextualize SE in the U.S. video game industry and argue that the opportunity-seeking and advantage-seeking activities are manifested respectively in firms' market entry timing decisions and their entrant performance. Based on archival data on the industry context and our first-hand interviews with industry insiders,[1] we highlight the importance of firm experience and networks in shaping both outcomes. Grounded on this contextual discussion, we then develop our theoretical predictions and elaborate on the underlying mechanisms, focusing our attention on the degree to which the impacts of resources on the two outcomes converge or diverge and how these impacts change as the markets evolve.

3. Setting: U.S. console video game industry and new product market spaces formed around hit games

Our research setting—the U.S. console video game industry—is a useful venue for theorizing and testing the dynamic tension of SE for three reasons. First, the industry is known for its competitive and dynamic market environment (Robert, 2012). The competitive and dynamic nature of the industry is driven by a confluence of factors: Hardware technology evolves rapidly and new versions of console platforms (e.g., PlayStation, Xbox 360, etc.) appear about every five years. This technological advancement is often accompanied by key video game releases and sparks rapid growth in the software business. While some consumers (i.e., gamers) remain loyal to certain types of games, in most cases consumer tastes change quickly and they tend to chase creativity and novelty in their gaming experience; this leads to a growing demand for video game quality and differentiation (Loguidice and Barton, 2009). Both the technological advancement and higher consumer expectations entail significantly larger investment in video game production. The increasing budget coupled with highly fleeting and hard-to-predict consumer taste means that engaging SE is a strong imperative, and identifying the most lucrative market space to enter (i.e., opportunity-seeking) and producing the most appealing games (i.e., advantage-seeking) present a constant stress for firms, in this case video game publishers (Roberto and Carioggia, 2004).

Second, even though the industry is dynamic and evolving, firms engaging SE can resolve market uncertainty and adapt to rapid market change by entering markets defined by industry exemplars (Strang, 2010). While creating exemplars is highly rewarding, it is

[1] Through our personal connections, we were able to reach and interview 20 industry participants. Our interviewees included founders and top executives of some major video game publishers and developers, as well as important figures involved in game design and development (e.g., production team lead, senior game designers etc.).

also a highly costly and uncertain pursuit. In this case, following industry exemplars and capitalizing on the market opportunities formed around those exemplars often times constitute the most appealing strategy for many industry players (Zhao et al., 2018). In the context of the console video game market, industry exemplars are manifested in the release of 'hit games', i.e., those games that generate significant sales after release and attract wide acclaims among critics and gamers (Zhao et al., 2018). These hits receive a great deal of "buzz"; they are frequently discussed in game reviews, at conventions, and in online forums. The key features that make the hits distinctive are surfaced and debated, which in turn significantly influence subsequent game design (Arsenault, 2009). For example, in the case of *Resident Evil*, game critics and gamers highly praised its novel combination of action, puzzle-solving, survival and horror. The specific feature combination introduced by the hit game also becomes popularized and helps delineate the boundary of the new market space that is being formed around the hit game. In this case, the hit games and associated new market spaces present potential entrants with valuable opportunities for SE. Seizing the opportunity by entering the new market spaces and capturing the emerging market demand by releasing a successful entrant is core to maintaining competitive advantage.

Third, a video game publisher's prior experience in producing similar type of games as the hit game may affect whether the publisher can quickly release a game in the new market space and whether the new entrant will succeed. Indeed, publishers tend to rely on past experience to identify and evaluate new game concepts (Roberto and Carioggia, 2004). Experience plays a critical role in this industry because traditional market research does not work well and consumer testing normally are not as valuable as it is in other industries. Publishers also need to constantly monitor the progress of game development before releasing it to the market and be able to kill unpromising projects at any point of the development process in order to avoid further escalation of commitment. They refer to their past experience in making such critical decisions. Speaking of the importance of experience, one top executive of a video game publisher we interviewed stated: "We do market analysis, we also use formal procedures to forecast market trend, but none of those are perfect. Our own experience is an indispensable asset. We rely on our prior experience and knowledge to identify good concepts and decide whether to fund a new idea."

Beyond experience, a publisher's network connections also affect its ability to identify and exploit emerging market opportunities. In the console video game industry, a publisher's network is constituted by its co-production relationships with video game developers. Game developers develop new game concepts and then try to persuade publishers that their ideas have merits. These game developers typically lack financial resources, sales and marketing capabilities, and project management skills. By collaborating with publishers, they are able to overcome these challenges and bring promising game ideas into fruition. Conversely, publishers may solicit game ideas from developers. They will choose the most promising ideas and provide financing and technical assistance to support game development. Either way, publishers and developers collaborate on video game production. With the complexity of game technology increasing over the years and research and development costs escalating dramatically, such collaborative effort between publishers and developers becomes even more crucial for successful game development and release.

Over time, different game publishers build unique sets of network connections. The structure of a hypothetical co-production network in the console video game industry is illustrated in Fig. 1. In this figure, the focal publisher is tied with several developers (first-order ties), and each developer has co-production relationships with a few other publishers (second-order ties). The information and resources channeled through these first- and second-order ties may have significant impacts on both market entry timing decisions and entrant performance of the focal publisher.

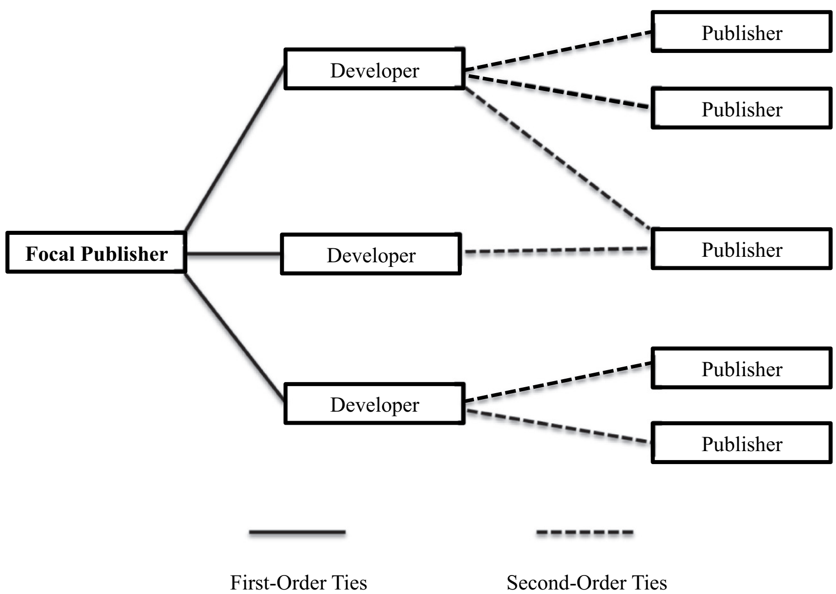

Fig. 1. A hypothetical co-production network in the console video game industry.

4. Hypothesis development

4.1. The role of experience

4.1.1. Experience and entry timing

As suggested by the SE literature and our contextual discussion of the console video game industry, the relevance of prior product development experience affects why firms differ with regard to opportunity identification and thus their varied entry timing decisions. Relevant experience is defined as a publisher's prior experience in producing games that share core features with hit games. Specifically, the relevant product development experience may shape entry timing through two mechanisms.

First, firms with more relevant experiences are better positioned to learn and understand technological developments in the new product market space early (Ahuja and Lampert, 2001; Cohen and Levinthal, 1990). Indeed, experience with a certain type of game leads to enhanced absorptive capacity and increased competence with that game. Greater competence in turn fosters increased awareness and understanding of related opportunities (Bakker and Shepherd, 2017; Ucbasaran et al., 2009). Consistent with this argument, past research has suggested that firms tend to discover opportunities related to the information that they already possess. Each firm's idiosyncratic prior experience creates a “knowledge corridor” that allows the firm to recognize certain opportunities, but not others (Shane, 2000).

Second, relevant experience affects entry timing through its influence on the speed of decision making. Specifically, firms with more experience tied to the new market space are likely to spend less time gathering information, because they already have a stock of knowledge on which to draw (Forbes, 2005). They are also likely to more quickly analyze information and put them into new product development because they have an organizing framework in place that facilitate the storage, comprehension, extrapolation, and application of new information in ways that those lacking that prior information cannot replicate (Forbes, 2005).

Supporting these arguments, Klepper and Simons (2000) found that firms with more past relevant experience producing radios entered the television industry earlier. Similarly, other studies have suggested that firms with more experience producing related products were more likely to enter new market spaces such as the diagnostic imaging markets (Mitchell, 1989).

As new market spaces evolve, the effects of these two mechanisms and hence the role of experience in enabling early entry is reduced. This is because more observable information regarding consumer demand and product specifications becomes available with an increasing number of new entrants, and as such the cognitive schemas regarding new market spaces becomes more developed and widely understood and market uncertainty decreases accordingly. This increase in information in the market place will render the prior relevant experience less important. Following these arguments, we predict:

Hypothesis 1a. (H1a). Relevant experience is positively associated with early market entry.

Hypothesis 1b. (H1b). The positive impact of relevant experience on early market entry will decrease as the new market evolves.

4.1.2. Experience and entrant performance

Prior relevant experience does not just affect entry timing, it also affects entrant performance. When a new market space emerges, firms with more relevant experiences contribute to better performance since they have better-matched expertise with the nascent market demand. As the market evolves, the impact of relevant experience on entrant performance may shift. With the market space getting increasingly crowded with new offerings, consumers' expectations keep rising and there is an increasing demand on product quality. Meanwhile, increasing rivalry coupled with consumer preference for novelty and creativity will impose a stronger pressure for new entrants to differentiate. In this case, overly relying on prior relevant experience may become a liability. The increased ease of learning and problem solving in specific domains will make experimentation of new products less attractive and potentially less rewarding. Greater levels of relevant experience can also lead to greater reliance on heuristics (Ucbasaran et al., 2006). As a firm develops a repertoire of deep knowledge to draw on, they may develop heuristic principles or decision-making shortcuts (Ucbasaran et al., 2009). This can lead to various biases (e.g., becoming constrained by the familiar; attempts to repeat previously successful “recipes” in changed circumstances) and dampen firms' aspiration and ability to think beyond the past (Wright et al., 1997). The reduction in experimentation and novelty may in turn limit firms' capacity for innovative and valuable product offerings. Summarizing preceding arguments, we predict:

Hypothesis 2. (H2). Relevant experience enhances entrant performance as a new market space emerges, but its positive impact decreases as the new market evolves.

4.2. The role of networks

4.2.1. Networks and entry timing

In addition to experience, firms' networks have also been suggested to influence the identification and exploitation of entrepreneurial opportunities (Stuart and Sorenson, 2007), and thus have a significant impact on entry timing and entrant performance. The video game co-production network (as shown in Fig. 1) is a typical two-mode network, with two parties—publishers and developers—connected through ties formed by their collaborative relationships in co-producing games. For two-mode networks like ours, structural embeddedness reflects the relational quality of interactor exchanges and the architecture of network ties (Zukin and DiMaggio, 1990); it captures the degree to which a focal firm (in our case, the publisher) concentrate its exchanges with a few partners (i.e., game developers) rather than spreading out its exchanges in small parcels among many partners (Uzzi, 1996). Structural embeddedness thus affects the amount, depth, and diversity of various types of resources (e.g., information, knowledge, trust, capital) that firms accrue through their participation in networks (Granovetter, 1985).

Structural embeddedness may affect entry timing through two mechanisms. First, networks have been widely regarded as the "plumbing" of the market, i.e. the channel or conduits through which important market information flows (Burt, 2000; Podolny, 2001). Firms with low structural embeddedness are more likely to be aware of new market opportunities early through their more extensive and diverse network connections and thus better positioned to seize these opportunities. This is because loose-knit and diverse networks compared with more embedded networks are more likely to enable firms to obtain non-redundant information and have a greater exposure to emerging market demand (Uzzi, 1997). Second, more extensive and diverse network connections also enable entry through uncertainty reduction. When a new market space emerges, future technological trajectories and product design remain largely unknown. Firms with a broader and more diverse network are better able to gather and synthesize information, gain better knowledge regarding the new market, and thus navigate such uncertainty and complexity more effectively (Lee, 2007).

As the market evolves, both the lack of information and market uncertainty become resolved with the increasing number of entrants. In this case, the benefits associated with less embedded networks in terms of information advantage and exploratory capacity may then decrease. Accordingly, we propose:

Hypothesis 3a. (H3a). Low structural embeddedness is positively associated with early market entry.

Hypothesis 3b. (H3b). The positive effect of low structural embeddedness on early market entry decreases as the new market evolves.

4.2.2. Networks and entrant performance

Firms that maintain a more embedded network of partners are better equipped to develop and launch high quality products. This is because highly embedded network ties foster trust between co-production partners (Larson, 1992; Uzzi, 1997). When trust between co-production partners is high, that will enhance the flow of high-quality information between the partners and make it easier to understand and meet the particular needs of both parties. They are also more willing to share private resources, and better able to match their competencies (Uzzi, 1999). In addition, a more embedded network helps enhance entrant performance via its positive impact on research and development (R&D) capacity and rate of innovation (Ahuja, 2000). All of these help promote value creation in the product development process and enhance the quality of product offerings.

The impact of structural embeddedness on entrant performance may change over the course of a new market's evolution. While more embedded network ties help enhance product quality when the new market first emerges, the same high embeddedness may become a liability over time. With increasing consumer demand for novelty and product differentiation, highly embedded firms may risk losing access to potentially important resources and private information held by other firms and isolating themselves from new insights and opportunities for product experimentation and differentiation (Uzzi, 1997; Zaheer et al., 2010). Indeed, past studies have found that highly embedded firms may suffer a decreased ability to adapt to environmental changes (Portes and Sensenbrenner, 1993; Uzzi, 1996). Summarizing preceding arguments, we propose:

Hypothesis 4a. (H4a). High structural embeddedness is positively associated with entrant performance.

Hypothesis 4b. (H4b). The positive effect of high structural embeddedness on entrant performance decreases as the new market evolves.

5. Method

5.1. The identification of hit games and associated new market spaces

In order to identify hit games and the associated new market spaces formed around the hit games, we drew upon the empirical approach used by Zhao et al. (2018) and relied on two primary data sources that have been widely used in previous video game research: NPD and MobyGames.[2] We started by compiling all standalone video games from NPD that were released in the U.S. market for any console (home or handheld) platform between 1995 and 2012 (in total, 15,578 games). We narrowed this initial sample to 12,214 games after excluding game compilations and bundles, non-standard editions (e.g., Game of the Year edition), expansion packs and add-ons, consistent with past research on the game industry (Mollick, 2012). We then matched this sample with data from MobyGames, and further excluded 3190 games that miss MobyGames information (e.g., game features), resulting 9024 games.

We next used two key criteria to systematically identify hit games among our sample of 9024 games. First, market performance is a typical yardstick for gauging industry exemplars. Accordingly, we narrowed the candidate pool down to those games with at least one standard deviation above the average total sales of the 9024 games. Second, hit games are also expected to be widely broadcast as being successful and innovative by key industry gatekeepers (in this case game critics), with the potential of triggering extensive

[2] NPD is a major data source on video game sales, and MobyGames is a widely used data source with important game demographic information such as publishers, developers, release date, game features, and critics' ratings. Both data sources have been validated by previous research (e.g., Corts and Lederman, 2009; Zhao et al., 2018).

interest among consumers and opening up new market spaces for potential entrants. Based on this, we further narrowed down the candidate list to keep only those games that appeared on at least one of the five "greatest games" charts: Electronic Game Monthly (top 200 games), G4TV (top 100 games), Game Informer (top 100 games), GameRankings (top 100 games), and IGN (top 100 games). The two criteria helped yield 163 potential hit games. Both criteria are consistent with previous scholarly work on defining and identifying industry exemplars in the video game industry (Zhao et al., 2018). Indeed, most of the 163 games gained substantial market reception and garnered (multiple) important annual awards upon and after formal release.

We then needed to determine the new market spaces that these hit games helped to open up. In cultural industries like video games and movies, market spaces and their boundaries are typically delineated by product features like genres. To identify these market-defining product features of the hit games, we collected text data (e.g., the critics' reviews, basic game descriptions, and detailed award information) associated with each of the 163 games from three major gamer websites (MobyGames, IGN, GameSpot) and Wikipedia. In these texts, games are compared on standard dimensions, such as gameplay, sound and graphics, storyline. More importantly, premium new features of the games are discussed and highlighted. Two authors independently scrutinized the texts and identified the core features of each game that were celebrated; all other game features were considered peripheral features. The celebrated core features were based on well-known descriptors in the industry of game attributes, such as the game's genre (e.g., "Action," "Horror"), its technical features (e.g., "1st-person perspective," "3-D"), and its action sequence (e.g., "Real Time," "Turn Based").

The initial independent coding by the two authors reached substantial agreement (kappa = 0.92). The two authors then had an open and intensive discussion to resolve any remaining disagreement. When there were debates between the two authors, the third author and a veteran industry insider were consulted, both equipped with extensive knowledge about the video game industry. Of the 163 games, 85 shared identical core features with an earlier hit game and were thus considered renewals, leaving 78 unique hit games and accordingly 78 new market spaces. Indeed, the 78 hit games were widely regarded as the greatest games of their time, attracted substantial gamer interest, and significantly influenced and inspired subsequent game design. Table 1 shows some sample hit games and their core features which define new market spaces.

New entrants into a market were then defined and identified as games released after a hit game and shared its core features. Thus, new market spaces are constituted by members that share common core characteristics but might differ with respect to peripheral features. While it is impossible to individually verify each entrant's strategic intention to follow a hit game and enter a new market space, the fact that it shares the core features with the hit game qualifies the entrant as a member of the new market space and thus a credible member of consumers' choice set. Since these new market spaces may have varied life cycles, we did not impose an a priori time window in tracing new entrants, but left the entry pattern to be naturally borne out of our data. After applying these criteria, we ended up with 6544 games that entered the 78 new market spaces.

5.2. Dependent variables

We have two key dependent variables: *timing of entry into a new market space* and *entrant performance*. Timing of entry into a new market space is measured by the number of six-month periods from the start of a new market space. For example, if a game enters two years after the start, the timing of entry is four. The six-month window for modeling entry timing is reasonable given most publishers did not release games monthly and given the lead development time required before a game's release. In our empirical analysis, instead of taking the timing of entry directly as a dependent variable, we cast it in a discrete-time survival analysis framework. In other words, the dependent variable, *market entry*, is a binary entry decision of a publisher for each six-month period from the start of a new market space. To test our hypotheses on entry timing, we compute the change in expected timing of entry from the survival models due to an increase in the key independent variables. *Entrant performance* was measured by inflation adjusted, lifetime dollar sales (logged) per game that enters a new market space.

5.3. Independent variables

We have three key independent variables, respectively capturing a game publisher's relevant experience, networks, as well as a variable tracking a market space's evolution—time since the start of a new market space. In particular, *relevant experience* was measured by the sum of all games released by a focal publisher with the core features of a new market space over the last three years. A publisher's networks were constructed based on its co-production relationships with game developers, as recorded on MobyGames. We operationalized the structure of a publisher's networks by two measures: first- and second-order embeddedness. These network characteristics have been regarded as important factors influencing information and resource access of a focal actor, which may strongly shape the actor's market entry timing decision and entrant performance. *First-order embeddedness* refers to the degree to which a publisher's games were developed by a small, concentrated (versus large and diverse) set of directly tied developers. It was calculated by summing the squared proportion of work done for the publisher by each of these developers; that is, $\Sigma_{i \in G_j} P_{ij}^2$, where G_j is the set of unique game developers who worked for publisher j in the past three years, and P_{ij} is the proportion of work done for publisher j by developer i. This measure approaches one as the publisher's relationships with developers become more embedded. *Second-order embeddedness* refers to the degree to which a publisher's developer partners maintain a small, embedded (versus large and diverse) set of partners themselves. For each developer i in G_j, we identified the set of publishers for whom developer i worked in the past three years, W_i. Then, we summed the squared proportion of developer i's work done for each of the publishers in W_i; that is, $Q_i = \Sigma_{w \in W_i} D_{wi}^2$, where D_{wi} is the proportion of developer i's work done for publisher w. Next, the second-order embeddedness for publisher j was computed by taking the average of Q_i; that is, $\Sigma_{i \in G_j} Q_i/|G_j|$, where $|G_j|$ is the number of developers in G_j. Again, if the

Table 1
Examples of hit games, new market spaces, and entrants.

Hit game	Publisher	Developer	Release date	Core features of the hit games that define new market spaces	Sample new entrant games
Final Fantasy IX	Square Enix	Square	November 13, 2000	Role-Playing(RPG), AnimeManga, MedievalFantasy, Real-Time, Turn-based	Final Fantasy X-2 Knights in the Nightmare
Grand Theft Auto 3	Rockstar Games	DMA Design	October 22, 2001	Action, RacingDriving, Shooter	The Getaway True Crime: Streets of LA
Super Mario Galaxy	Nintendo	Nintendo EAD Tokyo	November 12, 2007	Action, Puzzle-Solving, Sci-FiFuturistic, Platform	G-Force Portal 2
Mass Effect	Microsoft Game Studios	Bioware	November 20, 2007	Action, Role-Playing(RPG), Sci-FiFuturistic, Shooter	Fallout 3 Deus Ex: Human Revolution

focal publisher maintains one indirect tie, $Q_i = 1$, whereas with a more diverse set of arms-length, indirect contacts, it approaches zero.

To model the changing influence of experience and networks on a publisher's entry timing and entrant performance in a new market space requires a variable that captures the temporal dynamic of the market's evolution. Accordingly, we created a measure *time since the start of a new market space* to capture the temporal evolution of a new market space. Consistent with the survival model we used for the entry analysis, we computed time since the start of a new market space by counting the number (logged) of time periods (per 6 months) since the hit game release. As time passes, the market transitions from less known to better known phases, with increasing level of crowding and competition. Empirically, we interacted this temporal dynamic variable with the experience and network variables, and tested how the effects of these variables change as a new market space evolves.

5.4. Control variables

A set of market- and publisher-level control variables were included in both entry and performance models. Several of these control variables were also employed in models of performance examined in Zhao et al. (2018). First, we controlled for possible renewal of consumer interest during a new market's evolution. As discussed above, 85 out of our original 163 hit games shared core features with an earlier hit game and therefore were considered as renewal games of the same market space. For each of the remaining 78 market spaces, we then coded *market renewals* by counting the number of renewal games since its initiation. Market renewals either attract or deter further entry into the focal market, but may help enhance entrants' sales due to the renewed consumer interest.

Different market spaces might be partially overlapping each other. For instance, suppose hit game A's core features are “Action, Sci-Fi, Shooter” and a new market space is defined by this unique feature combination. After A's release, another hit game B is released with core features “Action, Sci-Fi.” In this case, we consider B's core features as a subset of A's. Similarly, if a later hit game C has core features “Action, Sci-Fi, Shooter, Horror,” we consider C's core features as a superset of A's. We therefore created two variables—*subset markets* and *superset markets*—by counting respectively the number of subsequent hit games whose core features are a subset and superset of those of the focal hit game. Broader markets (subset markets), via contagion, might stimulate new entrants in the focal market, whereas narrower markets (superset markets) within a focal market might steal potential new entrants due to its more targeted and unique identity.

We included the total *number of prior entrant games* (logged) in a market space and *prior entrant game success* (average dollar sales of all prior entrant games, logged), which may affect the focal publisher's entry timing decision as well as its product's sales. In addition, we controlled for the potential influence of seasonality by a *Christmas* dummy to indicate whether firms launched their games within a time frame that included Christmas. Given that we have 78 new market spaces with varying dynamics, in all models of entry and performance we also included *market* and *year fixed effects*.

At the publisher level, to capture the potential locational advantage of a publisher, we created a dummy variable *Japan branch* to indicate whether the publisher had a sister branch located in Japan. Given that some hit games were initially released in the Japanese market, a publisher with a Japan branch might better sense the new opportunity and more likely enter a new market than a publisher with only U.S. operations. We controlled for *publisher age*, measured by number of months since the founding of a publisher. A publisher's general experience reflects its breadth and diversity of expertise in producing and releasing different types of games, which may affect entry timing and entrant performance. As such, we controlled for *publisher general experience* by counting the number of unique features of all games it published in the past three years. We also considered controlling for *publisher size* by counting the publisher's number of unique workers (logged) who were involved in game production in the past three years. However, this size variable was dropped because of its high correlation with the general experience measure.

Different publishers may also have gained varied levels of reputation through their historical releases of well-received games, which in turn shape their new market entry timing decisions and entrant performance. One key element of a publisher's reputation is built around important awards its games garner, which recognize and uphold its creative and technical excellence. Accordingly, to measure a publisher's *reputation* we collected game-of-the-year (GotY) award data from 41 awarding institutions from 1980 to 2012.[3] For each game a publisher released in the past three years, we then calculated the proportion of institutions which conferred the GotY award to the game. Proportion was used instead of a simple count because the number of awarding institutions in a given year changed over time. We aggregated the proportion values over all games the publisher released in the past three years as the reputation measure. This award-based measure is consistent with the definition of reputation as a summary evaluation scale based on historical performance or awards.

We also controlled for whether a publisher released the focal hit game by a dummy variable *hit publisher*, because hit publisher may have some leverage in releasing a new game into the market launched by its own hit game. A publisher may also pace its game releases in the same market carefully. To account for this, we created two variables —*number of past entries* and *time since last entrant game release* (in months) by the focal publisher—to capture this pacing effect on the publisher's next entry timing into the same market.

Additional performance analysis controls. In estimating an entrant game's market performance, we included some additional publisher- and game-level controls. We included *publisher fixed effects* to control for unobserved publisher level strategies and to focus our analyses on game level variation. Previous research on categories has suggested that feature spanning has a significant impact on

[3] For a complete list of the awarding institutions, please see http://en.wikipedia.org/wiki/List_of_Game_of_the_Year_awards.

product performance. Accordingly, we included a variable *feature spanning* which counts the total number of features a game spans. We also included a dummy variable indicating whether a game was a *sequel* or not. In addition, we controlled for the rating of each video game by the Entertainment Software Rating Board (ESRB)—*ESRB rating*—whose aim is to aid consumers in determining a game's content and suitability. One more dummy variable—*licensed game*—was included to indicate whether a game is a licensed game based on pre-existing creations or not. We also controlled for *platform age*, which was measured by the number of months (logged) since the initial release of the focal game's console platform. In addition to platform age, we included *platform fixed effects* to control for any unobserved, time-invariant platform level heterogeneity. In light of the seasonality of performance and the importance of launch month in the industry, we included *release month fixed effects*.[4]

5.5. Estimation strategy

We modeled entry timing using a discrete-time survival analysis with multiple events in order to assess the impact of a game publisher's experience and networks on the likelihood of its entry into a new market space and trace how this impact changes as the market evolves. We used a logit hazard function with linear baseline hazard and allowed for market and year fixed effects so as to account for unobserved heterogeneity.[5] Given that the logged game performance followed a normal distribution in our data, we estimated performance using a linear regression model.

In our performance models, we faced a potential endogeneity issue of entry timing. That is, a publisher's decision to enter a new market space in a given period may be correlated with any unobserved shocks to consumers' demand for games in the new market and in that period. To address this, we included an unobserved shock to entry in the entry timing model and allowed it and the error term of the performance model to follow a bivariate normal distribution. We then jointly estimated the two models using the maximum simulated likelihood estimation with clustered standard errors at the publisher level. We provide an elaborated discussion of the estimation in the Appendix (see Appendix A.1–A.3). The estimated correlation between the two error terms was very close to zero, indicating that the market sales of a new entrant game did not seem to be significantly affected by unobserved factors that drove the publisher's initial decision to enter a market.

6. Results

6.1. Findings on market entry timing

Table 2 reports the descriptive statistics and correlation matrix of variables in entry timing models. A formal diagnostic using the variance inflation factor (VIF) revealed no multicollinearity concerns in entry timing analysis (mean VIF = 1.98; max VIF = 4.39).

Table 3 shows results of the survival analysis models estimating a publisher's timing decision to enter a new market space. In order to directly link the estimation results to our hypotheses, we report the change in expected time to enter (measured in the number of six-month periods) due to a one-unit change in each covariate.[6] A positive (negative) value indicates that the covariate increases (decreases) the expected time to enter, or equivalently, the covariate is negatively (positively) associated with early market entry.

Model 1 is the baseline model that contains controls only. Our results show that having more superset markets enables early entry into the focal market. Market renewals, despite the potential of triggering further interest, decrease the likelihood of early entry. Number of prior entrant games decreases the likelihood of early entry. Finally, the Christmas season is positively associated with early market entry.

At the publisher level, the Japan branch dummy is positively associated with early market entry, but publisher age is negatively associated with early market entry. Both publisher general experience and reputation enable early market entry. The same publisher that released the focal hit game—hit publisher—is more likely to release a new entrant game early than a normal publisher. In addition, a publisher is more likely to release another entrant game early if it has more past entries (i.e., number of past entries increases), but delay its new entry as time passes since its last entry in the same market.

In Model 2, we introduce time since the start of a new market space to track the evolution of a market. We see that the time since the start of a new market space is positively associated with early market entry. In Model 3, we examine the main effect of relevant experience. Consistent with H1a, we find relevant experience has a negative impact on expected time to enter, indicating that it is positively associated with early market entry. In Model 4, we add the interaction of relevant experience with time since the start of a new market space. Consistent with H1b, the positive effect of relevant experience on early market entry decreases overtime, meaning that as the market becomes better known, the importance of relevant experience in facilitating early entry decreases.

In Models 5 and 6 we include the two measures of a publisher's network structure—first- and second-order embeddedness—which

[4] This means that the Christmas dummy included in entry models was omitted in the performance models.

[5] We conducted several robustness checks, which included changing the specification of the hazard function (such as linear and quadratic baseline hazard), allowing for a publisher-level random effect (in addition to market- and year-fixed effects), and allowing for time-varying effects for all covariates (to account for the potential violation of the proportional hazard assumption). None of these changed our main results.

[6] In Table A.1 of the Appendix, we report the parameter estimates of the survival analysis models, i.e., the effects of covariates on the hazard function. The expected time to enter is computed using the estimated hazard function. The standard errors are obtained by simulating parameter vectors from the estimated variance covariance matrix and computing the variance of the expected time to enter across the simulated parameter vectors. For a detailed discussion of how we computed the expected time to enter, please refer to the Appendix A.4.

Table 2
Descriptive statistics and correlation matrix of key variables in entry models.

		Mean	S.D.	1	2	3	4	5	6	7	8
1	Market entry	0.041	0.199	1							
2	Subset markets	0.898	1.869	0.17	1						
3	Superset markets	0.611	0.999	−0.07	−0.12	1					
4	Market renewals	0.820	1.905	0.12	0.41	−0.04	1				
5	Number of prior entrant games	2.906	1.886	0.18	0.65	−0.16	0.50	1			
6	Prior entrant game success	13.807	5.259	0.05	0.18	−0.01	0.17	0.57	1		
7	Christmas season	0.502	0.500	0.01	−0.01	0.00	−0.01	−0.02	−0.04	1	
8	Japan branch	0.329	0.470	0.07	0.00	0.00	0.00	−0.01	−0.01	0.00	1
9	Publisher age	208.625	117.361	0.08	0.01	0.02	0.01	0.04	0.03	0.00	0.42
10	Publisher general experience	2.540	0.721	0.19	0.00	0.01	0.00	0.00	0.01	0.00	0.22
11	Publisher reputation	0.029	0.120	0.11	0.00	0.00	0.00	0.01	0.01	0.00	0.19
12	Hit publisher	0.011	0.104	0.11	−0.01	−0.01	0.00	0.00	0.00	0.00	0.12
13	Number of past entries	0.474	1.705	0.39	0.38	−0.09	0.29	0.37	0.10	−0.01	0.11
14	Time since last entrant game release	4.111	14.117	0.05	0.21	−0.04	0.16	0.29	0.11	−0.01	0.06
15	Time since the start of new market	2.403	0.731	0.00	0.29	0.31	0.24	0.59	0.50	−0.04	−0.02
16	Relevant experience	0.169	0.493	0.48	0.31	−0.11	0.22	0.33	0.09	0.00	0.10
17	First-order embeddedness	0.521	0.363	−0.16	0.00	−0.01	0.00	0.00	−0.01	−0.01	−0.14
18	Second-order embeddedness	0.753	0.198	0.03	0.02	0.01	0.00	0.02	0.01	0.00	0.05
19	Time since the start of new market × Relevant experience	0.020	0.337	0.06	0.22	−0.04	0.18	0.16	0.02	0.00	0.02
20	Time since the start of new market × First-order embeddedness	0.000	0.265	−0.02	0.01	0.02	0.01	0.03	0.03	−0.01	−0.04
21	Time since the start of new market × Second-order embeddedness	0.008	0.143	−0.01	0.01	0.01	0.01	0.03	0.02	0.00	−0.02

	9	10	11	12	13	14	15	16	17	18	19	20
1												
2												
3												
4												
5												
6												
7												
8												
9	1											
10	0.33	1										
11	0.18	0.28	1									
12	0.10	0.13	0.25	1								
13	0.17	0.28	0.17	0.16	1							
14	0.14	0.16	0.08	0.06	0.27	1						
15	0.06	0.00	0.01	−0.01	0.18	0.20	1					
16	0.15	0.33	0.17	0.19	0.75	0.14	0.05	1				
17	−0.28	−0.85	−0.24	−0.10	−0.24	−0.15	0.00	−0.29	1			
18	0.02	0.14	0.09	0.04	0.05	0.02	0.06	0.04	−0.09	1		
19	0.07	0.07	0.02	−0.03	0.52	0.06	0.14	0.22	−0.06	0.01	1	
20	−0.05	−0.04	−0.02	0.00	−0.16	−0.09	0.04	−0.06	0.02	0.00	−0.27	1
21	0.01	−0.01	0.01	0.00	0.03	0.00	0.03	0.00	0.00	0.00	0.04	−0.08

$N = 137{,}412$; $|rho| > 0.005$ statistically significant at $p < 0.05$.

Table 3
Survival analysis models of market entry timing: Impact on expected time to enter.

DV: Expected time to enter (in # six-month periods)	(1)	(2)	(3)	(4)	(5)	(6)
Subset markets	0.086**	0.097**	0.035**	0.025**	0.025**	0.028**
	(0.010)	(0.022)	(0.004)	(0.002)	(0.001)	(0.001)
Superset markets	−0.451**	−0.380**	−0.199**	−0.165**	−0.215**	−0.217**
	(0.071)	(0.085)	(0.059)	(0.034)	(0.035)	(0.021)
Market renewals	0.117**	0.120*	0.060**	0.055**	0.050**	0.053**
	(0.013)	(0.026)	(0.006)	(0.003)	(0.002)	(0.001)
Number of prior entrant games	0.002**	0.040**	0.096**	0.083*	0.122**	0.124**
	(0.000)	(0.013)	(0.033)	(0.041)	(0.024)	(0.009)
Prior entrant game success	−0.006+	−0.004**	−0.007**	−0.007**	−0.003**	−0.003**
	(0.006)	(0.001)	(0.003)	(0.001)	(0.000)	(0.000)
Christmas season	−0.088**	−0.077**	−0.079	−0.073**	−0.034**	−0.035**
	(0.029)	(0.021)	(0.068)	(0.021)	(0.002)	(0.001)
Japan branch	−0.307**	−0.317*	−0.319*	−0.284**	−0.222**	−0.230**
	(0.031)	(0.145)	(0.161)	(0.049)	(0.045)	(0.008)
Publisher age	0.001**	0.001	0.001**	0.001**	0.000**	0.000**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Publisher general experience	−1.770**	−1.731**	−0.937**	−0.882**	−1.156**	−1.144**
	(0.085)	(0.092)	(0.113)	(0.097)	(0.149)	(0.143)
Publisher reputation	−0.539**	−0.577**	−0.490**	−0.481**	−0.326**	−0.311**
	(0.103)	(0.049)	(0.074)	(0.041)	(0.026)	(0.019)
Hit publisher	−1.563**	−1.616**	−0.848**	−1.040	−0.788	−0.794**
	(0.381)	(0.345)	(0.218)	(1.126)	(0.664)	(0.105)
Number of past entries	−0.274**	−0.277**	−0.024**	−0.046**	−0.049**	−0.052**
	(0.026)	(0.024)	(0.004)	(0.003)	(0.003)	(0.001)
Time since last entrant game release	0.010**	0.010**	0.003**	0.003**	0.003**	0.003**
	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Time since the start of new market		−0.161**	−0.210**	−0.253**	−0.652**	−0.725**
		(0.035)	(0.037)	(0.048)	(0.055)	(0.028)
Relevant experience			−1.486**	−1.383**	−1.368**	−1.399**
			(0.093)	(0.208)	(0.189)	(0.095)
Time since the start of new market × Relevant experience				0.149**	0.184**	0.146**
				(0.031)	(0.031)	(0.011)
First-order embeddedness					0.120**	0.118**
					(0.022)	(0.011)
Second-order embeddedness					−0.477**	−0.486**
					(0.027)	(0.015)
Time since the start of new market × First-order embeddedness						−0.176**
						(0.028)
Time since the start of new market × Second-order embeddedness						−0.001**
						(0.000)
N	282,825	282,825	282,825	282,825	137,412	137,412
Log likelihood	−24,376.721	−24,372.735	−23,633.661	−23,622.516	−21,406.324	−21,395.308

Two-tailed tests. Standard errors in parentheses (clustered at the publisher level).
Market and year fixed effects included in all models.
Sample size (N) corresponds to the total number of (market, publisher, time period) observations. Sample size is smaller for models (5) and (6) because the first- and second-order embeddedness are not defined for publishers with no games released in the past three years.
Significance levels: $+p < 0.10$, $*p < 0.05$, $**p < 0.01$.

Table 4
The size of the impact of the three resources on market entry timing: Change in expected time to enter (in # six-month periods) due to a one standard deviation increase in firm resource.

	Early periods	Late periods
Relevant experience	−0.475	−0.384
First-order embeddedness	0.112	0.038
Second-order embeddedness	−0.053	−0.056

capture the focal publisher's access to expertise and information from its partners, as well as the interaction terms with time since the start of a new market space. Our results show that, early in a market, first-order embeddedness has a positive, significant effect, indicating that embedded network ties with directly connected developers delay entry more than extensive and diverse ties (consistent with H3a). As the market evolves, however, there is an increasingly negative impact of embedded ties on expected time to

Table 5
Descriptive statistics and correlation matrix of key variables in performance models.

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1	Dollar sales	14.717	1.612	1									
2	Subset markets	2.839	2.794	0.06	1								
3	Superset markets	0.206	0.491	0.00	−0.13	1							
4	Market renewals	2.717	4.078	0.04	0.18	−0.11	1						
5	Number of prior entrant games	4.944	1.668	−0.01	0.65	−0.22	0.54	1					
6	Prior entrant game success	15.261	2.847	0.01	0.18	0.07	0.13	0.55	1				
7	Japan branch	0.468	0.499	0.10	−0.04	0.05	0.01	−0.04	−0.02	1			
8	Publisher age	258.013	97.911	0.21	0.14	0.01	0.04	0.12	0.05	0.40	1		
9	Publisher general experience	3.279	0.477	0.23	0.11	0.01	0.12	0.13	0.05	0.21	0.40	1	
10	Publisher reputation	0.095	0.199	0.24	0.03	0.01	0.06	0.03	0.02	0.23	0.17	0.19	1
11	Hit publisher	0.057	0.232	0.16	−0.13	0.04	−0.08	−0.15	−0.03	0.18	0.13	0.09	0.29
12	Number of past entries	5.109	5.418	0.17	0.51	−0.14	0.52	0.62	0.18	0.11	0.26	0.39	0.18
13	Time since last entrant game release	6.471	10.999	−0.03	0.02	0.14	−0.06	0.05	0.11	0.01	0.09	0.03	0.02
14	Feature spanning	5.055	1.738	−0.02	−0.04	0.20	−0.32	−0.21	−0.02	−0.01	0.10	−0.01	−0.01
15	Sequel	0.294	0.456	0.17	0.00	0.11	−0.14	−0.07	0.04	0.15	0.10	0.04	0.15
16	Licensed game	0.403	0.491	0.02	0.05	−0.13	0.25	0.16	0.01	−0.17	−0.02	0.08	−0.08
17	Platform age	3.460	0.785	−0.09	0.09	0.08	−0.03	0.07	0.07	−0.04	0.01	−0.03	0.00
18	Time since the start of new market	2.459	0.657	−0.02	0.47	0.17	0.32	0.69	0.47	−0.02	0.19	0.12	0.05
19	Relevant experience	1.789	1.258	0.21	0.31	−0.25	0.45	0.48	0.09	0.08	0.17	0.42	0.14
20	First-order embeddedness	0.200	0.234	−0.22	−0.10	−0.02	−0.12	−0.11	−0.05	−0.11	−0.34	−0.81	−0.18
21	Second-order embeddedness	0.772	0.112	0.01	0.02	0.03	0.02	−0.01	−0.02	0.18	−0.01	0.17	0.19
22	Time since the start of new market × Relevant experience	0.101	0.770	0.05	0.07	−0.13	0.17	−0.05	−0.16	−0.01	0.04	0.00	0.04
23	Time since the start of new market × First-order embeddedness	−0.011	0.170	−0.03	0.01	0.04	−0.01	0.08	0.10	−0.04	−0.04	0.00	0.02
24	Time since the start of new market × Second-order embeddedness	0.003	0.075	0.00	0.02	0.07	0.04	0.07	0.07	−0.05	−0.01	0.00	0.04

	11	12	13	14	15	16	17	18	19	20	21	22	23
1													
2													
3													
4													
5													
6													
7													
8													
9													
10													
11	1												
12	0.00	1											

(continued on next page)

Table 5 (*continued*)

	11	12	13	14	15	16	17	18	19	20	21	22	23
13	0.03	−0.10	1										
14	0.00	−0.19	0.11	1									
15	0.15	0.03	0.02	−0.01	1								
16	−0.11	0.13	−0.05	0.07	−0.52	1							
17	−0.02	0.05	0.06	0.07	0.04	0.00	1						
18	−0.05	0.50	0.23	0.04	0.04	0.04	0.18	1					
19	−0.01	0.71	−0.24	−0.29	−0.01	0.22	−0.04	0.12	1				
20	−0.07	−0.31	−0.02	0.02	0.01	−0.12	0.05	−0.07	−0.37	1			
21	0.10	0.14	0.03	−0.04	0.10	−0.16	0.02	0.04	0.05	−0.03	1		
22	−0.03	0.33	−0.22	−0.06	−0.02	0.03	−0.04	−0.11	0.10	0.01	0.01	1	
23	0.01	0.12	0.02	0.02	−0.01	0.01	0.06	0.10	0.01	−0.10	−0.03	−0.39	1
24	0.01	0.12	0.01	0.01	0.01	0.00	0.05	0.08	0.00	−0.04	−0.03	0.03	0.01

N = 11,664; |rho| > 0.018 statistically significant at $p < 0.05$.

enter (consistent with H3b). In contrast, second-order embeddedness has a negative effect initially and the negative effect grows larger as the market evolves, suggesting that more focused and precise information channeled through developers from other publishers enables the focal publisher's early entry.

Based on Model 6 of Table 3, we quantify the size of the impacts of the three resources by increasing each resource by one standard deviation and examining its effect on entry timing. To see how the effect changes over time, we computed the change in early periods and the change in late periods. We use the median value of time since the start of a new market space (i.e., 12 six-month periods, or 6 years) to split time periods into early and late periods. The changes in the expected time to enter corresponding to one standard deviation increase in relevant experience, first-order and second-order embeddedness are reported in Table 4. It is apparent that among the resources, relevant experience seems to play a more prominent role in influencing entry timing than first- and second-order embeddedness.

6.2. Findings on entrant performance

Table 5 reports the descriptive statistics and correlation matrix of variables included in performance models. A formal diagnosis with VIF again detected no multicollinearity concerns (mean VIF = 2.24; max VIF = 7.37). The average, inflation-adjusted, aggregate sales of an entrant game translate into about $2.5 million.

Results of the performance analyses are reported in Table 6. We followed the same sequence of entering control and key independent variables as in entry timing models. In the baseline model 1, we observe that the number of subset markets increases an entrant game's sales, whereas the number of superset markets decreases sales. The number of market renewals, while deters further entry, enhances the entrants' market performance (also see Shamsie et al., 2009). The number of prior entrant games decreases performance, but average success of prior entrants increases performance. In addition, the Japan branch dummy and publisher age is negatively associated with performance. Publisher general experience and reputation are positively associated with performance. The same publisher that released the focal hit game is associated with better performance of a new entrant game. In addition, a publisher more likely earns larger sales from a new entrant game as the number of its prior entries increases and as time passes since its last entry in the same market. At the game level, being a sequel or a licensed game and having more features significantly increase market sales, while being released on an older console decreases sales (see Zhao et al., 2018 for additional details).

We introduce the time since the start of a new market space to track a market's evolution in Model 2. Its coefficient is significant and positive, indicating that on average sales per new entrant increase as the market evolves. In Models 3 and 4, we add relevant experience and its interaction with the time since the start of a new market. As predicted by H2, the effect of relevant experience on entrant performance is positive in the early stage of a new market's evolution, and this positive effect decreases over the course of the market's evolution. In Models 5 and 6, we include first- and second-order embeddedness and their interactions with time since the start of a new market. Consistent with H4a and H4b, first-order embeddedness has a positive impact on entrant sales early in a market, but the positive impact declines later. Second-order embeddedness, in contrast, has a negative effect on average, and this effect becomes more negative as the market evolves. This suggests that fresher, more creative and less redundant ideas gathered from less embedded second-order ties are more important for enhancing product quality and enabling differentiation, especially in later stages of market evolution.

Based on Model 6 of Table 6, we quantify the effect size on entrant performance across the three resources, following a similar procedure as we did for entry timing analysis. Results are reported in Table 7. In contrast to what we saw with market entry, compared with relevant experience, first- and second-order embeddedness play a more prominent role in influencing entrant performance.

6.3. Indirect and total effects of resources on entrant performance

While our hypotheses and main analyses focused on the direct impacts of resources on the two empirical manifestations of SE—entry timing and entrant performance—the empirical strategy we design allows us to compute the indirect effects of resources on performance via a change in entry timing. As discussed earlier, in terms of direct effects we find that some resources (e.g., low first-order embeddedness) enable early entry, but lower performance. To assess the total effects of resources on performance, we computed the indirect and total effects of the three resources. We used a similar approach as above to simulate the change in expected time to enter due to a one standard deviation increase in a resource. We then used the change in entry timing and the average values of independent variables in the outcome model to assess the indirect effects of resources on performance via the change in entry timing.

The results are presented in Table 8. The first column reports the change in expected (logged) entry timing across the three resources. Consistent with our analysis of the effect size above, relevant experience and second-order embeddedness decrease the expected time to enter (i.e., enable early entry), whereas first-order embeddedness increases the expected time to enter (i.e., hinder early entry). For example, a one standard deviation increase in relevant experience decreases the expected time to enter a new market by 0.092 (in logged scale); this translates into 0.85 periods (equivalent to about 5 months).

The indirect effects are presented in the second column. Given that the direct effect of entry lag (i.e., time since the start of a new market) on entrant performance is positive, earlier entry due to an increase in relevant experience and second-order embeddedness has a negative indirect effect on performance. In contrast, first-order embeddedness has a positive indirect effect on performance due to a delay in entry. Combined with the direct effects we discussed earlier (also shown in the third column), the total effects (in the fourth column) show that first-order embeddedness positively affects entrant performance, and relevant experience and second-order

Table 6
Linear regression models of entrant performance.

DV: Market sales of entrant games	(1)	(2)	(3)	(4)	(5)	(6)
Subset markets	0.020**	0.016**	0.008**	0.012**	0.021**	0.019**
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.000)
Superset markets	−0.144**	−0.185**	−0.165+	−0.181**	−0.202**	−0.200**
	(0.005)	(0.033)	(0.091)	(0.032)	(0.029)	(0.003)
Market renewals	0.002**	0.000	−0.008**	−0.005**	0.006**	0.007**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Number of prior entrant games	−0.211*	−0.289**	−0.292**	−0.294**	−0.316**	−0.317**
	(0.013)	(0.017)	(0.071)	(0.055)	(0.048)	(0.010)
Prior entrant game success	0.041**	0.042**	0.041**	0.040**	0.043**	0.043**
	(0.001)	(0.002)	(0.006)	(0.002)	(0.002)	(0.000)
Japan branch	−0.312**	−0.259**	−0.142**	−0.130**	2.432**	2.432**
	(0.010)	(0.018)	(0.045)	(0.018)	(0.093)	(0.024)
Publisher age	−0.002**	−0.002**	−0.002**	−0.002**	−0.003**	−0.003**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Publisher general experience	0.000**	0.000**	0.089**	0.093**	0.071**	0.067**
	(0.000)	(0.000)	(0.005)	(0.001)	(0.001)	(0.002)
Publisher reputation	0.065**	0.049**	0.107**	0.155**	0.099**	0.098**
	(0.010)	(0.016)	(0.033)	(0.034)	(0.001)	(0.004)
Hit publisher	0.330**	0.331**	0.489**	0.484**	0.316**	0.308**
	(0.003)	(0.022)	(0.056)	(0.020)	(0.021)	(0.002)
Number of past entries	0.038**	0.038**	0.032**	0.039**	0.033**	0.035**
	(0.001)	(0.003)	(0.006)	(0.004)	(0.003)	(0.001)
Time since last entrant game release	0.002**	0.002**	0.002**	0.001**	0.003**	0.003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Feature spanning	0.009**	0.008**	0.009**	0.010**	0.009**	0.009**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sequel	0.526**	0.525**	0.517**	0.516**	0.508**	0.509**
	(0.008)	(0.051)	(0.142)	(0.050)	(0.050)	(0.006)
Licensed game	0.323**	0.323**	0.308*	0.308**	0.311**	0.310**
	(0.005)	(0.047)	(0.137)	(0.048)	(0.044)	(0.005)
Platform age	−0.166*	−0.173**	−0.167	−0.171**	−0.153**	−0.152**
	(0.010)	(0.047)	(0.157)	(0.051)	(0.051)	(0.006)
Time since the start of new market		0.271**	0.284**	0.237**	0.363**	0.365**
		(0.029)	(0.102)	(0.025)	(0.020)	(0.010)
Relevant experience			0.348**	0.333**	0.069**	0.064**
			(0.105)	(0.064)	(0.005)	(0.005)
Time since the start of new market × Relevant experience				−0.059**	−0.049**	−0.028**
				(0.001)	(0.011)	(0.003)
First-order embeddedness					0.265**	0.274**
					(0.037)	(0.008)
Second-order embeddedness					−0.288**	−0.284**
					(0.032)	(0.016)
Time since the start of new market × First-order embeddedness						−0.058**
						(0.004)
Time since the start of new market × Second-order embeddedness						−0.308**
						(0.043)
Constant	11.271**	10.963**	9.220**	9.305**	9.343**	9.297**
	(0.096)	(0.209)	(0.603)	(0.351)	(0.371)	(0.092)
SD(ν_{mit}^{g})	1.103**	1.103**	1.165**	1.164**	1.102**	1.102**
	(0.000)	(0.003)	(0.048)	(0.212)	(0.003)	(0.000)
Correlation	0.010**	−0.014**	0.621**	0.618**	−0.012**	−0.007**
	(0.001)	(0.001)	(0.084)	(0.084)	(0.001)	(0.001)
N	12,029	12,029	12,029	12,029	11,664	11,664

Two-tailed tests. Standard errors in parentheses (clustered at the publisher level).
Market, publisher, platform, ESRB rating dummies, release year and release month fixed effects included in all models.
Sample size (N) corresponds to the total number of entries into new market spaces. Sample size is smaller for models (5) and (6) because the first- and second-order embeddedness are not defined for publishers with no games released in the past three years.
SD(ν_{mit}^{g}) measures the standard deviation of the error term, and Correlation is the correlation between the error and the unobserved shock to entry in the survival model.
Significance levels: $+p < 0.10$, $*p < 0.05$, $**p < 0.01$.

Table 7
The size of the impact of the three resources on entrant performance: Change in entrant performance (in US $) due to a one standard deviation increase in firm resource.

	Early periods	Late periods
Relevant experience	$92,072.89	$57,126.76
First-order embeddedness	$273,283.60	$214,296.39
Second-order embeddedness	$ − 58,133.55	$ − 195,203.07

Table 8
Indirect, direct and total effects of resources on entrant performance.

	Change in expected (logged) time to enter	Indirect effect on performance	Direct effect on performance	Total effect on performance
Relevant experience	− 0.092	− 0.032	0.032	− 0.001
First-order embeddedness	0.021	0.007	0.100	0.107
Second-order embeddedness	− 0.010	− 0.003	− 0.056	− 0.059

Change in expected time to enter is measured in terms of logged time, because we measure the time effect on entrant performance using logged time since the start of a new market space.

embeddedness negatively affect entrant performance. For relevant experience, a positive direct effect is dominated by a larger negative indirect effect. However, the total effect is very small for relevant experience. We find that networks have a larger total effect than relevant experience, positive for first-order and negative for second-order embeddedness.

Taken together, these findings suggest that a tension indeed exists in SE. That is, while some resources have convergent impacts on both entry timing and entrant performance, the impacts of other resources on these two outcomes may diverge. Specifically, we observe that relevant experience on average enables early entry, and at the same time it enhances game performance directly. In contradistinction, we see divergent effects for both first-order and second-order embeddedness. While higher first-order embeddedness on average delays entry, it has a positive impact on game performance in terms of both direct and total effects. Higher second-order embeddedness on average accelerates entry, but decreases game performance both directly and in total.

6.4. Robustness checks

We conducted a series of supplementary analyses to make sure our findings are robust. First, we tried two alternate versions of performance measures in place of a game's aggregate dollar sales. One alternative was to measure the *opening month sales* of the game. This alternate outcome may help rule out some hard-to-observe factors such as word-of-mouth and peer influence among gamers that may affect sales. Another alternative was, instead of using dollar sales, to calculate *units sold*; this performance measure helps account for publishers' different pricing strategies. With both alternate outcome variables, our reported findings held.

Second, we considered some additional variables that might help account for potential publisher level heterogeneity, e.g., the average dollar sales of the focal publisher's prior entrants and the publisher's average performance across all prior games (entrant or not). We ultimately dropped these variables from our analysis due to multicollinearity issues. The publisher's marketing capability may also influence its entrant performance. Unfortunately, fine-grained marketing data were very difficult to obtain in the video game industry. While not perfect, in the main analysis above, we attempted to control for it using a rich set of fixed effects (at publisher, market-, platform-, ESRB rating-, year-, and release month- levels) and allowed for a potential demand shock to be correlated with entry timing. We also tried including an additional set of fixed effects for all 67 game features; the main results remained robust.

7. Discussion and conclusion

In this paper, we respond to calls for research to go back to the original conceptualization of SE and furnish stronger empirical evidence of firms' dynamic struggle to blend opportunity- and advantage-seeking activities. We theorized the nature of that struggle, discussing points of convergence and divergence among resource drivers (experience and networks) around market entry timing and entrant performance. In the context of the US console video game industry, we directly examined the extent to which the three resources—relevant experience, first-order embeddedness and second-order embeddedness—had convergent or divergent impacts on the two outcomes. We also elaborated on the key mechanisms underlying each of our predictions.

Based on statistical analyses of 78 new markets that form around hit games, we find that there is a mixed pattern of convergence and divergence between the type of resources that enable early entry versus those that enhance performance, and this tension persists as the markets evolve. While for some resources (e.g., relevant experience) we observe convergent impacts on entry timing and entrant performance, for other resources (e.g., first-order and second-order embeddedness) their effects on these two outcomes diverge. These findings have important implications for research on strategic entrepreneurship and market entry, as well practical implications for entrepreneurs and managers.

7.1. Implications for strategic entrepreneurship research

Despite being logically plausible and intuitively appealing, the strategic entrepreneurship concept and framework elaborated by Hitt, Ireland, Ketchen and colleagues have not gained much traction. As discussed by Simsek et al. (2017), this is at least in part due to its lack of theoretical specificity that would allow the model to be stepped down into mid-range theory studies, and also to disparate empirical evidence often applicable to only single linkages or components in the model. More importantly, the relationship between opportunity- and advantage-seeking activities, as originally theorized, appears to be one of mutual reinforcement without any tension or tradeoff. Partly because of this, recognized bases for competitive advantage (e.g., experience and networks) have not been explicitly and systematically linked to the two aspects of SE. Our paper addresses these gaps and contributes to SE by contextualizing it in a specific empirical context where opportunities for SE is abundant, identifying the empirical manifestations of the two activities of SE, directly unpacking the convergence/divergent effects of key resources, and revealing the tension that is inherent in the two sides of SE: the entrepreneurial and the strategic. By directly measuring the two aspects of SE and identifying their respective drivers, our paper bolsters SE's conceptual clarity and furnishes its empirical foundation.

The original definition of SE also implies a temporal view of value creation and value capture that results from simultaneously engaging in opportunity- and advantage-seeking activities over time (Hitt et al., 2011). However, it is not clear what simultaneity means and what it entails; the temporal property of SE has remained inadequately defined. Does simultaneity require firms to achieve the two aspects of SE at the same time or do firms need to sequence and vacillate seamlessly between strategic and entrepreneurial actions? How do the nature and drivers of entrepreneurial and strategic activities change over time? Furthermore, from a spatial perspective, it is unclear whether SE and its associated opportunity- and advantage-seeking activities take place within the boundaries of the firm or instead spread across organizational boundaries and different governance modes.

In theorizing the various drivers within and across firm boundaries (e.g., experience and networks) and hypothesizing their changing impacts over the course of a new market's evolution, we are able to bring the temporal and spatial properties of SE to the fore. Furthermore, our findings suggest that there is a more dynamic tension within the SE concept and model than is generally recognized, thus helping inform firms regarding the kind of resources they need in order to gain and sustain competitive advantages. We encourage future research to extend this effort and further build and strengthen the theoretical and empirical foundation of SE research.

7.2. Implications for market entry research

The topic of entry timing has emerged as a prominent field of study in strategy (Mitchell, 1989), organization theory (Lee and Paruchuri, 2008), and innovation and entrepreneurship (Zachary et al., 2015). Accompanying the growing importance and breadth of entry timing research, however, is the conflicting findings across empirical studies regarding the entry timing-performance relationship. Mixed findings prevail because there are both advantages and disadvantages associated with a broad spectrum of market entry strategies. One main approach to reconciling these conflicting findings in the literature is to identify a set of industry- and firm-specific characteristics that moderate the entry timing-performance relationship. For example, past research has suggested that the impact of entry timing on new entrant performance is contingent upon industry conditions such as the level of legitimacy of an industry (Aldrich and Fiol, 1994; Dobrev and Gotsopoulos, 2010), the resolution of technological and market uncertainty (Suarez et al., 2015), the stage of an industry's evolution (Markides and Geroski, 2005), and firm attributes such as firm age (Kotha et al., 2011), resources and capabilities (Lee, 2009; Shamsie et al., 2009), strategic orientation (Durand and Coeurderoy, 2001), and associative rhetoric (Lee and Paruchuri, 2008), just to name a few. A key concern of this approach is that with a growing number of disparate contingencies added to the literature, the study of entry timing-performance relationship becomes increasingly context specific with few regularities. As a result, instead of bringing in clarity and consensus to the literature, the contingency approach may fail to contribute to a generalizable theoretical framework on market entry.

To reorient entry timing research in a more productive direction, there have been repeated calls for studies that move beyond the focus on entry timing as a core predictor of performance and investigate the drivers that underpin the observed differences in entry timing decisions and the associated performance outcomes (Lieberman and Montgomery, 1998; Zachary et al., 2015). The belief is that the success of either early or late movers does not lie in the time of entry per se, but rather in a firm's underlying resources and capabilities that enable its entry into a new product market space and simultaneously enhance its market performance. Following this call, recent studies have started to examine the specific mechanisms underlying the advantages and disadvantages inherent in a certain entry strategy (York and Lenox, 2014), with a particular focus on the antecedents of an entry timing decision and the associated performance impact (e.g., Lee, 2007; Zachary et al., 2015). While these are significant advances in entry timing research, most of these studies fall short of addressing the much debated entry timing-performance relationship since few of them examined drivers of entry and performance simultaneously. Instead, the assumption is that the same factors that enable entry also tend to enhance market performance. In other words, entry timing has been theorized as a second-order function of a firm's resources and capabilities and considered a reflection of optimal managerial decisions (Ethiraj and Zhu, 2008; Mitchell, 1989).

In this paper, we challenge this assumption and show that there might be divergent drivers of entry timing and entrant performance. The dynamic, competitive nature of the video game industry means the entry timing-performance relationship in these emerging markets is very uncertain, and valuable resources that facilitate entry may quickly become anachronistic and thus fail to enhance entrants' performance. Indeed, as environments become more fast paced and competitive, the contradictory demands on firm resources may become increasingly salient and persistent. Our empirical strategy allows us to model entry timing in a survival analysis framework and control for the potential endogeneity issue of entry timing in estimating entrants' performance. Furthermore, it allows us to quantify both the direct and indirect effects of firm resources on performance, thus providing a more comprehensive and precise picture of the relationships between resources, entry timing and entrant performance.

7.3. The practical implications of our findings

For entrepreneurs and firm managers, our findings suggest that it is not productive to debate whether it is more beneficial to enter earlier or later into a new market space. Instead, their priority should be to more precisely understand specific mechanisms underpinning SE in a particular market and the various resources that shape both entry timing and entrant performance. Having done so, entrepreneurs and managers must then evaluate their own resource base and then decide whether a strong emphasis on pioneering is appropriate. Even in specific situations when the resource base enables a market entry opportunity, they may want to exercise caution before deciding whether to pursue it, and if so, how best to enhance its value. Indeed, our results suggest that firms may face challenges of aligning entry and performance across periods in a market's evolution, because some resources like network ties always have competing effects.

In order to resolve this challenge, entrepreneurs and managers need to address key questions: What learning mechanisms can we engage in order to balance between radical and incremental innovations in competitive and dynamic environments? What organizational design and process are optimal for managing exploration and exploitation, efficiency and flexibility simultaneously? Answering these questions will help firms search for an optimal solution to the strategic tension they face in market entry, which in turn will enhance their performance and sustainability. To construct an optimally distinct configuration of resources and adapt that configuration to match the competitive, dynamic environments represents a strong imperative for entrepreneurs and managers (Zhao et al., 2017; Zhao et al., 2018).

7.4. Limitations and future research opportunities

Our paper has several limitations, each of which opens avenue for future research. First of all, like most other studies on market entry, it is impossible to individually verify each entrant's strategic intention of entering a market. While we know from our interviews that publishers care about core features that are hot in the market when developing their games, the common core features shared by the entrant game and the hit game could be either a result of purposeful mimicry or just fortuitous choice. Either way, simply by sharing core features with the hit game the entrant game would be considered part of the choice set for gamers and thus subject to the competitive dynamics of the emerging market. Although it is beyond the scope of our study, future research could more directly investigate the strategic intention behind an entry decision and how that would affect entry timing and entrant performance.

The U.S. video game industry has gained increasing economic and cultural prominence in recent years, and the nature of production and consumption closely mirror other cultural industries like movies and music. Notwithstanding the peculiarities of the console video game market, we believe that our theory and key findings are generalizable at least to these other related industries. If certain boundary conditions are met (e.g., competitive environment with increasing consumer demand for quality and differentiation), we expect the conclusions of this paper to carry over into other industries and products as well. Nevertheless, a systematic empirical test of our theory in other types of products (e.g., cellphone and online games), industries, and countries (e.g., Japan) will be useful.

7.5. Conclusion

The competitive and dynamic nature of an industry frequently opens up new opportunities and market spaces for potential entrants. As highlighted by the SE framework, certain drivers of entry timing decisions and entrant performance may indeed converge, allowing firms to sustain their competitive advantage; but as we have demonstrated, some other drivers may also diverge in their effects on entry timing and performance. Our paper thus suggests that even if some resources have durable value, others do not in the context of strategic entrepreneurship. Firms need to constantly identify and assemble other types of resources that may not appear as entry enablers yet are best positioned to help enhance entrant performance. Ultimately, those who buck the trend and stand out from others are most likely to resolve the strategic tension in market entry and succeed in competitive environments.

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Appendix A

This appendix explains the estimation strategy and the computation of expected time to enter a market.

A.1. A model of entry timing

For each new market m, publisher i decides when to enter (or not enter at all). We model this timing of entry via a discrete-time survival analysis framework. We use a discrete-time version because our data points for entry are aggregated into a six-month period. We employ logistic regression for modeling the hazard, which is commonly used in the literature.

Let d_{mit} denote an entry decision by publisher i at time t for market m:

$$d_{mit} = \begin{cases} 1 & \text{if publisher } i \text{ enters market } m \text{ at time } t\text{,and} \\ 0 & \text{otherwise.} \end{cases}$$

Let T^m be the last period to enter market m during our sample period. If publisher i enters before or in period T^m, we have $d_{mit} = 1$ when it enters. Otherwise, $d_{mit} = 0$ for all $t = 1, \ldots, T^m$.

A logistic regression model assumes that the probability of entry at time t, $\Pr(d_{mit} = 1)$, is given by

$$\Pr(d_{mit} = 1) = \frac{\exp(u_{mit})}{1 + \exp(u_{mit})}, \tag{1}$$

where u_{mit} is the latent variable capturing the effect of covariates, including our key independent variables, on entry. The interpretation of u_{mit} is that an increase in u_{mit} increases the probability of entry. We specify u_{mit} as

$$u_{mit} = X'_{mit}\alpha + Z'_{mit}\beta + \xi_{mit},$$

where X_{mit} is a vector of key independent variables, and α measures the effect of key independent variables on entry; Z_{mit} is a vector of control variables including fixed effects, and β measures their effects on entry; and ξ_{mit} is an *i.i.d.* unobserved shock to entry that is normally distributed. As we will explain below, we allow ξ_{mit} to be correlated with the error in the performance model so as to control for potential endogeneity of entry.

A.2. A model of entrant performance

We model entrant performance in a linear regression framework:

$$y^g_{mit} = W'_{mit}\gamma + (V^g_{mit})'\delta + \nu^g_{mit},$$

where $y_{mit}{}^g$ is the performance measure for entrant game g released by publisher i at time t in market m; W_{mit} is a vector of key independent variables, and γ measures their effects on performance; $V_{mit}{}^g$ is a vector of control variables including fixed effects, and δ measures their effects on performance; and $\nu_{mit}{}^g$ is a normally distributed error term. We note that due to the selection nature, we observed $y_{mit}{}^g$ only for publisher i who entered market m at time t.

A.3. Endogeneity and the likelihood function

An endogeneity issue arises when ξ_{mit} is correlated with $\nu_{mit}{}^g$. For example, this is likely if publisher i decides to enter after observing a demand shock for market m at time t. In order to control for the endogeneity that arises due to the correlation between ξ_{mit} and $\nu_{mit}{}^g$, we assume that $(\xi_{mit}, \nu_{mit}{}^g)$ are independent and identically distributed as

$$\begin{pmatrix} \xi_{mit} \\ \nu^g_{mit} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_\xi & \rho\sigma_\xi\sigma_\nu \\ \rho\sigma_\xi\sigma_\nu & \sigma^2_\nu \end{pmatrix} \right).$$

Then, the likelihood function for market m, publisher i, and time t can be written as

$$\mathscr{L}_{mit} = \begin{cases} \Pr(d_{mit} = 1, y^g_{mit}) & \text{if publisher } i \text{ enters market } m \text{ at time } t\text{,and} \\ \Pr(d_{mit} = 0) & \text{otherwise.} \end{cases}$$

Note that conditional on ξ_{mit}, we can rewrite $\Pr(d_{mit} = 1, y_{mit}{}^g)$ as

$$\Pr(d_{mit} = 1, y^g_{mit} \mid \xi_{mit}) = \Pr(d_{mit} = 1 \mid \xi_{mit}) \bullet \Pr(y^g_{mit} \mid \xi_{mit}),$$

where $\Pr(d_{mit} = 1 | \xi_{mit})$ is given in Eq. (1), and

$$y^g_{mit} | \xi_{mit} \sim N\left(W'_{mit}\gamma + (V^g_{mit})'\delta + \rho\frac{\sigma_\nu}{\sigma_\xi}\xi_{mit}, (1 - \rho^2)\sigma^2_\nu \right).$$

Since we do not observe ξ_{mit}, we need to integrate it out during the estimation.

The joint likelihood across markets, publishers, and time periods is then

$$\mathscr{L} = \prod_m \prod_i \prod_t \int_{\xi_{mit}} \mathscr{L}_{mit}(\xi_{mit}) dF(\xi_{mit}).$$

We estimate the model using the maximum simulated likelihood estimation, i.e., find the vector of parameters that maximizes

$$\ln \mathscr{L} = \sum_m \sum_i \sum_t \ln\left(\frac{1}{R}\sum_{r=1}^{R} \mathscr{L}_{mit}(\xi_{mit}^r)\right),$$

where ${\xi_{mit}}^r \sim N(0, {\sigma_\xi}^2)$ and we use $R = 100$ for our actual estimation.

A.4. Expected time to enter a market

Our hypotheses are concerned with the impact of key independent variables on entry timing. The parameters of the hazard function above measure the impact of covariates on the likelihood of entry in a given period, but a positive impact on the likelihood of entry does not necessarily imply that entry timing becomes earlier. Thus, we compute the impact of covariates on expected time to enter. In particular, since our sample ends in a finite time period, we consider the expected time to enter *conditional on entry within the finite time period.*

Using the same notation above, let T^m be the last period to enter market m during our sample period, and $\Pr(d_{mit} = 1)$ be publisher i's probability of entering market m in period t. Then, the probability of entry at time t conditional on not entering prior to t is given by

$$p_{mit} \equiv \Pr(d_{mit} = 1 \mid d_{mi\tau} = 0 \ \forall \ \tau < t) = \Pr(d_{mit} = 1) \prod_{\tau=1}^{t-1} \Pr(d_{mi\tau} = 0).$$

Also, the probability of entering within the T^m periods is

$$p_{mi} \equiv \Pr(d_{mi\tau} = 1 \text{ for some } \tau \leq T^m) = \sum_{t=1}^{T^m} p_{mit} = 1 - \prod_{t=1}^{T^m} \Pr(d_{mit} = 0).$$

Then, the expected time to enter market m by publisher i conditional on entry within the T^m periods, $E_{mi}[t]$, is expressed as

$$E_{mi}[t] = \frac{1}{p_{mi}} \sum_{t=1}^{T^m} t \bullet p_{mit}.$$

We take the average across all markets and publishers to get the average expected time to enter. We also note that we need to integrate out the unobserved shock to entry, ξ_{mit}, when computing the expected time to enter. Similar to the estimation, we use Monte Carlo integration.

To examine the impact of a covariate on $E_{mi}[t]$, we increase the covariate and examine the change in $E_{mi}[t]$. A change in covariate influences $E_{mi}[t]$ via changes in both p_{mi} and p_{mit}. We then take the average of the change in $E_{mi}[t]$ across all markets and publishers. In Table 3, we assess the impact of a one-unit increase in covariate on the expected time to enter. We also computed the standard errors of the impacts by simulating parameter vectors from the estimated variance covariance matrix, and computing the variance of the change in $E_{mi}[t]$ across each simulated parameter vectors. In Table 4, we use a one standard deviation increase in covariate to quantify the effect size. Finally, in Table 8, we use a one standard deviation increase, and also examine $E_{mi}[\ln t]$ as the time effect in the entrant performance equation is measured in logged time.

Table A.1
Survival analysis models of market entry timing: parameter estimates.

DV: Discrete-time entry decisions	(1)	(2)	(3)	(4)	(5)	(6)
Subset markets	−0.071**	−0.082**	−0.053**	−0.041**	−0.039**	−0.042**
	(0.008)	(0.020)	(0.006)	(0.001)	(0.001)	(0.002)
Superset markets	0.351**	0.314**	0.274**	0.255**	0.307**	0.311**
	(0.048)	(0.066)	(0.073)	(0.044)	(0.042)	(0.030)
Market renewals	−0.096**	−0.102**	−0.093**	−0.090**	−0.078**	−0.081**
	(0.010)	(0.019)	(0.007)	(0.001)	(0.001)	(0.001)
Number of prior entrant games	−0.001**	−0.033**	−0.144**	−0.126 +	−0.193**	−0.189**
	(0.000)	(0.012)	(0.046)	(0.069)	(0.040)	(0.016)
Prior entrant game success	0.005	0.004**	0.010**	0.011**	0.004**	0.004**
	(0.004)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)
Christmas season	0.069**	0.061**	0.112	0.113**	0.052**	0.052**
	(0.022)	(0.018)	(0.085)	(0.029)	(0.000)	(0.000)
Japan branch	0.239**	0.245*	0.427*	0.415**	0.333**	0.328**
	(0.024)	(0.111)	(0.189)	(0.064)	(0.059)	(0.006)
Publisher age	−0.001**	−0.001	−0.001**	−0.001**	−0.001**	−0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Publisher general experience	1.241**	1.258**	1.179**	1.166**	1.432**	1.423**
	(0.059)	(0.058)	(0.060)	(0.077)	(0.143)	(0.135)

Publisher reputation	0.416**	0.446**	0.680**	0.691**	0.469**	0.436**
	(0.073)	(0.042)	(0.073)	(0.031)	(0.037)	(0.017)
Hit publisher	1.095**	1.132**	1.112**	1.049	1.013	1.003**
	(0.259)	(0.213)	(0.213)	(1.166)	(0.677)	(0.133)
Number of past entries	0.216**	0.223**	0.037**	0.073**	0.074**	0.077**
	(0.018)	(0.021)	(0.005)	(0.002)	(0.002)	(0.001)
Time since last entrant game release	−0.008**	−0.009**	−0.004**	−0.005**	−0.005**	−0.005**
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Time since the start of new market		0.132**	0.301**	0.397**	0.861**	0.943**
		(0.028)	(0.066)	(0.061)	(0.033)	(0.031)
Relevant experience			1.727**	1.670**	1.613**	1.595**
			(0.191)	(0.238)	(0.165)	(0.091)
Time since the start of new market × Relevant experience				−0.239**	−0.302**	−0.228**
				(0.047)	(0.054)	(0.014)
First-order embeddedness					−0.184**	−0.186**
					(0.026)	(0.018)
Second-order embeddedness					0.657**	0.659**
					(0.017)	(0.002)
Time since the start of new market × First-order embeddedness						0.257**
						(0.039)
Time since the start of new market × Second-order embeddedness						0.001**
						(0.000)
Constant	−9.537**	−9.930**	−12.277**	−12.408**	−12.896**	−13.060**
	(0.159)	(0.182)	(0.686)	(0.397)	(0.473)	(0.426)
SD(ξ_{mit})	0.724**	0.873**	2.144**	2.130**	2.113**	2.099**
	(0.018)	(0.054)	(0.241)	(0.103)	(0.067)	(0.039)
N	282,825	282,825	282,825	282,825	137,412	137,412
Log likelihood	−24,376.721	−24,372.735	−23,633.661	−23,622.516	−21,406.324	−21,395.308

Two-tailed tests. Standard errors in parentheses (clustered at the publisher level). Significance levels: $+p < 0.10$, $*p < 0.05$, $**p < 0.01$. Market and year fixed effects included in all models.

Sample size (N) corresponds to the total number of (market, publisher, time period) observations. Sample size is smaller for models (5) and (6) because the first- and second-order embeddedness are not defined for publishers with no games released in the past three years.

SD(ξ_{mit}) measures the standard deviation of the unobserved shock to entry.

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