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Follow the crowd or follow the trailblazer? The differential role of firm experience in product entry decisions in the US video game industry.

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Abstract

Firms take cues from their external environment under uncertainty and imitate the actions of others. However, a firm's own experience may either substitute for these external clues because the firm can evaluate uncertain situations more accurately, or it may complement them because the firm can act more successfully on the external cues. We argue that the type of external cues determines which of the two holds in the context of product entry decisions into market niches. If firms observe a large wave of entrants, own experience conveys more information than the imprecise signal of a mass of other firms. Conversely, if firms observe trailblazers, i.e. highly successful and influential products in a niche, own experience can help firms develop a strategy as a fast follower in a growing niche. We expect the supporting role of own experience in following trailblazers to be especially pronounced in niches that have not been discovered by a large mass of other firms. We study and test our hypotheses in the context of the US PC video game industry between 1991 and 2010 and find support for both the substitutive relationship between own experience and niche popularity and the complementary relationship of own experience and niche trailblazers. However, support for the complementary relationship is limited to less populated niches.

Key Words: Product Entry; Information-based Imitation; Pre-entry Experience; Trailblazers.

INTRODUCTION

Which market niches do firms choose for product entry? The answer to this question rests on the expectation of which niche will be most profitable for the firm. Clearly, the profitability of a particular niche for a firm depends on the firm's capabilities and how they match with the requirements for that niche. Firms will typically base their assessment on prior experience in specific niches. However, observing other firms' behavior may also provide cues about a niche's profitability. The intuition is that the entry of other firms who may know about the viability and profitability of a niche conveys valuable information about the niche. Firms can also look to very successful products, or trailblazers, to take cues about which niches are likely to be popular in the future. We combine both internal (experience-based) and external (information-based) drivers for product entry into niches in an uncertain and dynamic market (Lieberman and Asaba, 2006).

Imitation is a key factor in many entry processes, including product entry into market niches. Lieberman and Asaba (2006) identify two types of imitation – information-based and rivalry-based. In the former, firms imitate other firms' actions in the belief that these have better information, whereas in the latter, firms want to maintain competitive parity with close competitors. In uncertain markets, information-based imitation is more prevalent than rivalry-based imitation (Semadeni and Anderson, 2010).

Information-based theories of imitation share a common logic: if firms are uncertain about the profitability of an action, they observe the population of firms and mimic their behavior (Bikhchandani, Hirshleifer, & Welch, 1998; DiMaggio & Powell, 1983; Haunschild & Miner, 1997).[1] Firms considering product entry into a niche will therefore interpret the entry behavior of other firms as a signal for the attractiveness of a niche (Greve, 2000), especially in the early phases of a niche.[2]

This basic intuition has been confirmed in many settings, but its relationship to other key aspects of entry like experiential learning (Lieberman and Asaba, 2006), and imitation of successful innovations (products) under uncertainty (Semadeni and Anderson, 2010) remains understudied. Experiential learning has often been portrayed as a substitute to external information (Belderbos et al., 2011; Henisz and Macher, 2004; Guillen, 2002), yet the previous experience of the firm in a niche can also serve as absorptive capacity when taking cues from the actions of others (Cohen and Levinthal, 1990; Barkema and Schijven, 2008). We develop and test arguments on how firm experience, niche popularity (or "niche density")[3], and the recent arrival of a trailblazer product act together to influence firms' product entry decisions into niches.

We hypothesize that prior experience in a niche can substitute for external information and the consequent mimicry. The intuition is that firms that are active in a niche learn about consumer preferences in it and do not have to rely on cues from the behavior of others. We also argue that the recent entry of a trailblazer in a niche attracts additional entry by firms with prior experience in the niche, as that experience can act as an absorptive capacity to facilitate learning from trailblazers and help them be fast followers (Lee, 2009, Markides and Geroski, 2005; Lieberman and Asaba, 2006). We posit that this effect is further strengthened if the niche is relatively unpopulated, which puts an experienced firm in a position to follow before the bulk of competitors enter. Hence, we hypothesize that internal experience acts as a substitute or as a complement to niche density in determining product entry depending on the type of external information for imitation, either the density of other products in a niche, or the existence of a trailblazer product.

We study the US PC video game industry between 1991 and 2010, an industry in which firms make repeated decisions to launch products in market niches. These launch decisions resemble entry decisions by firms with different degrees of experience and in markets that change rapidly both in terms of the underlying technology and their popularity with consumers. Video games make 80% of their revenues within twelve months after its initial release, meaning that firms have to renew their portfolio constantly simply to maintain their revenues. All this provides a good setting to study information-based imitation because we get an accelerated view of entry processes across different niches by firms that have varying degrees of pre-entry experience in the focal niche (Mitchell, 1989; Helfat and Lieberman, 2002; Lee, 2008; Eggers, 2012). In our empirical analysis, we broadly find our hypotheses confirmed, yet also find that the complementary relationship between experience and trailblazer products is contingent on the current density of the niche.

We contribute to the literature on information-based imitation and in particular the relationship between internal and external processes of learning and imitation (Lieberman and Asaba, 2006; Simon and

Lieberman, 2010) by considering how niche density, experience, and trailblazer products interact with each other in an uncertain environment. Although experiential learning may simply indicate the buildup of capabilities, it also renders external information less relevant. This finding complements studies in other contexts such as international market entry (Guillen, 2002; Belderbos et al., 2011) and technology adoption decisions (Simon and Lieberman, 2010). We also show that experience can also complement external information in following a recent trailblazer product in less competitive niches. Firms rely on their experiential learning if their external information is based on other firms' aggregate entry decisions. However, if firms observe a trailblazer, imitating it requires a deeper assessment of the product and imitation of complex activities. Experience then acts as a complement to the external information from the trailblazer. Our key contribution then is showing when experiential learning substitutes or complements external information depending on how complex imitation is. We also empirically contribute to the fast follower literature by identifying firms that are likely to enter after a trailblazer product has established a market. In line with anecdotal evidence (Markides and Geroski, 2005), we find that firms with sufficient experience are most likely to capture the window of opportunity of following before the bulk of competitors reacts.

THEORY AND HYPOTHESES

Information-based Imitation

Information-based imitation has been studied in parallel by economists, institutional theorists and organizational ecologists. Economists and institutional theorists argue that in uncertain environments with high information asymmetry, a competitor making an entry move (or any other action) based on its private information is likely to be followed by others. In economic approaches, this is because the first competitor is assumed to possess superior market knowledge (Bikhchandani et al., 1992). Product entries are especially informative in this context since they imply a competitor's significant investments on the basis of its private view of market conditions (Semadeni and Anderson, 2010). In institutional theory, firms imitate others to reduce their search costs (Cyert and March, 1963) and to conform to "isomorphic pressures" by becoming more homogeneous with other firms in the market (DiMaggio and Powell, 1983).[4] Further, firms may follow particularly influential actors or products (Abrahamson, 1996; Bikhchandani et al., 1998; Haunschild and Miner, 1997). That said, imitating influential products is not easy since such products reflect the firm's tacit knowledge of interrelated activities that are hard to replicate (Rivkin, 2000; Lieberman and Asaba, 2006).

Organizational ecology addresses information-based imitation through the concept of "legitimation" (Carroll and Hannan, 2000; Lieberman and Asaba, 2006). Here, an organizational form (e.g., a new niche), becomes increasingly "taken-for-granted" as more products (or firms) enter a niche, making more resources available due to the increased cognitive legitimacy of the form. However, the returns from legitimation will decrease with further entries as a form is already established, and further entries will increase competition as products (or firms) compete for limited resources in the niche.

Niche Density

As explained above, in highly uncertain settings, competitors' entry choices are interpreted as the outcome of superior market knowledge, and firms follow others' actions (Bikchandani et al., 1992; Lieberman and Asaba, 2006). Such imitation may also be caused by isomorphic pressures (Haunschild and Miner, 1997) and legitimation concerns (Hannan and Carroll, 1992), so that firms imitate an action because these actions are considered more acceptable and thus rewarded by outside observers, including consumers.

Further, imitating firms may also learn from the experience of other entrants if they can observe the technology or the end product (Abrahamson and Rosenkopf, 1993). For example, imitators can observe how previous entrants designed a product for the focal niche, and benefit from knowledge spillovers that reduce product development costs and improve their ability to target the niche (Simon and Lieberman, 2010).

The informational value of other firms' entries will be offset by the material impact of more firms choosing the same action, which will increase competition in the niche. Even in uncertain environments (when the information value is expected to be highest), competition is likely to limit imitative entries at some point. Information-based imitation theories generally do not impose limits to imitative entry as firms have been observed to imitate despite increasing competitive pressure (Deephouse, 1999), yet organizational ecology argues that entry will reach a natural limit as available resources for firms decline, and entry will create more competition after that point (Carroll and Hannan, 2000). Hence, while we expect a positive relationship between density of products in a niche and the attractiveness of the niche for product entry, we expect this relationship to weaken as density of the niche increases further. To model this empirically, we formulate our baseline hypothesis to state that:

Hypothesis 0 (H0): Niche density is positively correlated with the likelihood of product entry, but with a decreasing marginal effect.

In our section outlining our empirical modelling choices, we explain how we capture this decreasing returns effect by using a log specification of niche density. In a robustness check, we use a more flexible specification by including a linear and a squared term of niche density.

Niche Density and Prior Niche Experience

The link between information-based imitation and experiential learning is of interest (Lieberman and Asaba, 2006) since information-based approaches to imitation describe processes where firms learn and draw inferences from the actions of others, whereas experiential learning asks how firms learn from their own actions. Firms consider external information to be valuable especially in conditions of uncertainty, though firms may draw on both internal and external sources of learning. Findings in a wide range of contexts have shown that firms replace external sources of information with internal knowledge once they accumulate pre-entry experience for a market they consider entering, for example another country (Shaver et al., 1997; Guillen, 2002) or a new technology (Simon and Lieberman, 2010).

This shift from external to internal sources of information has two effects on the entry behavior of firms with prior experience in a niche. First, we expect a direct effect: firms with prior experience in a niche tend to continue re-entering this niche. We do not formulate an explicit hypothesis on this. Second, however, prior experience may also lower the weight that firms assign to niche density. Prior experience implies that a firm can rely more on its own experience regarding the attractiveness of a niche, which reduces the informational value the presence of other firms provides to the focal firm regarding the niche. This implies that the information generated by more firms entering loses value.

However, experiential learning could also complement the external information through absorptive capacity (Lieberman and Asaba, 2006; Barkema and Schijven, 2008), so the firm can tap into and assimilate others' experience. Yet, support for this complementary relationship has been scant. A reason might be that the actions to be imitated may require more or less absorptive capacity due to their inherent complexity, so that the complementary effect of experience only materializes if the imitation process is sufficiently complex. When firms follow previous entries into a market or niche, they are more likely to base their decisions on the simple observation of the aggregate entries of others (Simon and Lieberman, 2010).Therefore, we do not expect this complementary relationship to occur when firms are comparing their internal experience and the external information from entry decisions of other firms, i.e., niche density. Therefore, we hypothesize that the informational value of other active products in a niche is weakened by the prior product entry experience of the focal firm:

Hypothesis 1 (H1): *The extent of a firm's prior niche experience weakens the* positive association between niche density and product entry likelihood.

Empirically, we therefore expect a negative interaction term between prior niche experience and niche density, suggesting that an additional entry by another firm conveys a less impactful signal for the focal firm's entry if the focal firm already has extensive experience in the niche.

Trailblazers and Prior Niche Experience

Information about the attractiveness of a niche can originate from the behavior of many similar actors or of few particularly influential ones. The latter is especially relevant if products come to "represent" and shape the niche they entered (Lieberman and Asaba, 2006). In other words, they act as trailblazers for others that follow. At the product level, trailblazers represent individual products that captured wide attention. For example, Argyres et al. (2015) show how Ford's Model T has changed the dynamics of the car manufacturing industry. In many other industries such as soft drinks or smartphones, a small number of exceptionally successful products shape the competition as well as subsequent design and entry decisions.

However, trailblazers may also pose formidable competition to latecomers – the arrival of Ford's Model T may have attracted imitators, but even more firms exited from the market niche in which the Model T was released. Similarly, de Figueiredo and Silverman (2007) find that the arrival of HP's printer in a market niche triggered both entry by imitators but also increased exit in the focal niche. We therefore expect an ambiguous direct effect of a trailblazer product entry in a niche: it may drive imitation on the one hand, but it may also deter entry by increasing competition on the other one.

However, firms with previous experience in the niche may be more likely to react to trailblazers in a niche by imitating them through product entry. First, firms with prior experience in the niche have specific experience that allows them to understand consumers, technology, and their relationship much better, which helps them to react to product changes quickly as they can rely on an existing body of knowledge in the niche. Second, and more central to information-based imitation, the success of a trailblazer may well be harder to imitate due to its complexity (Lieberman and Asaba, 2006) because many elements and their interactions must be copied to compete successfully with the trailblazer. Moreover, the tacit knowledge of the firm that produced the trailblazer may imply that imitation is difficult without a strong knowledge base.

Hence, firms with prior experience in the niche can use their absorptive capacity to analyze the success of the trailblazer (Lieberman and Asaba, 2006), and to tap into and assimilate information (Cohen and Levinthal, 1990) to enter the niche with their own product. Therefore, we expect that:

Hypothesis 2 (H2): *The extent of a firm's prior niche experience* strengthens the association between prior trailblazers in the niche and product entry likelihood.

Empirically, H2 implies a positive interaction effect between the existence of a recent trailblazer and a firm's experience in a niche on the likelihood of choosing the focal niche for product entry.

Niche Density, Trailblazers, and Prior Niche Experience

Finally, niche density, prior experience and the existence of a trailblazer in a niche may interact with each other. This is already hinted at in our previous hypotheses: Firms with prior experience reduce the weight they assign to external information coming from aggregate entry figures (H1), yet they are more receptive to external information coming from the availability of a trailblazer (H2). Our baseline hypothesis (H0) states that niche density has a positive impact on entry, but there is a competitive effect setting in. Conversely, we have also highlighted that both high density in a niche as well as the trailblazer itself create competition in a niche, which may affect imitative product entries into a niche. Our framework then suggests that firms with prior experience may react differently to a trailblazer depending on niche density.

Niche density has a dual effect: On the one hand, it carries information on the likely overall size of a niche. On the other, it makes the niche more competitive, ultimately splitting overall revenues among more competitors. As firms with more experience are likely to ignore the market information provided by niche density, they will consider the competitive effect of niche density more prominently. This logic leads to our formulation of H1.

The existence of trailblazers is also evaluated differently by experienced and inexperienced firms, as posited in our second hypothesis (H2). Again, there are two effects at play: First, a trailblazer creates demand for a particular niche, thus making it more attractive. Second, however, a trailblazer is also likely to represent strong competition to later entrants. In H2, we argued that the latter effect is less pronounced for firms with prior experience in the niche so that they are more likely to enter niches with prior trailblazers than firms with little experience.

Combining these two effects suggests that firms with prior experience will consider niche density when contemplating entering a niche with a prior trailblazer. While following a trailblazer will seem attractive for experienced firms in principle, the competitive environment will make it less so. This implies that higher niche density will weaken the (positive) connection between trailblazers and own experience in affecting product entry into a niche. Put differently, experienced firms can evaluate the potential benefits and costs of imitating a trailblazer better as they consider the overall competition their product would face in a niche. We do not expect an effect for firms with low niche experience, as they are hypothesized to consider both the positive and negative effects of niche density as well as the countervailing effects of a trailblazer in a niche. Thus, we consider this effect to be ambiguous. Our final hypothesis is then:

Hypothesis 3 (H3): Niche density negatively moderates the effect of the interaction between a *firm's* prior niche experience and prior trailblazers in the niche on the likelihood of product entry.

DATA AND METHODS

Industry and Data

Our empirical setting is the U.S. video game industry. In this industry, game development firms ("developers" in industry terminology and the rest of the article) design,[5] create content, and program video games. Publishers support the development of games by funding, marketing, and distribution. Developers, as creators of video games, develop specific product development routines and capabilities regarding each product they create, whereas publishers provide complementary assets to development activities. Moreover, each product entry decision for a developer is critical regarding their existing routines and capabilities – making a game in a genre they do not know well is highly uncertain. Publishers manage a portfolio of products, and their choice of entry decisions is mainly financial.

Product entry into niches in the video game industry. We study game developers and their choices to enter particular niches with new products. A niche in our empirical context is a game genre, explained in more detail below. Our data and setting let us address our research questions because product entry and niche choice decisions are such a central strategic choice in the industry. In addition to the strategic importance of product entry into niches, the video game industry is a near-perfect petri dish to answer our research questions for multiple reasons. First, video games have a short lifecycle so that a developer needs to release new products consistently to remain competitive. Games typically have a sales cycle of one year with 80% of their total sales happening within the year (Grohsjean et al., 2017). Hence, even "standing still" implies releasing a new game every year. As most entry studies will look at the (often implicit) counterfactual of "no entry" and consequently no revenues, our empirical setting closely resembles this aspect of entry studies. Second, the video game market is subject to rapid changes in consumer tastes and technological changes (Claussen et al., 2015; Grohsjean et al., 2017) so what worked last year is no guarantee for future success. Table 1 shows the top five genres by market share in the PC gaming market for 1996-2008 in three-year intervals. There is constant change in the ranking order of genres as well as the top selling genre. This changing popularity of different game genres counterbalances the specialization tendencies of game developers, and requires the strategic choice of picking the genre of a game before its development. Third, in this market, most firms enter a product in a niche with some degree of experience either in the same or in related niches. This makes the context very similar to many recent (and some classical) studies on product entry. Specifically, recent entry studies explore the role of pre-entry experience in new product entry performance, which is what we can also study in our setting (Nerkar and Roberts, 2004; Eggers, 2012). Finally, our setting gives us sufficient statistical power because we can observe a large number of similar product entry decisions. In quantitative studies on new product entry, to obtain a similar number of entry observations, the observation period has to be significantly longer or the number of market niches studied has to be larger. Our setting presents us with a clearly defined list of genres (i.e. niches) and a sufficiently long period of well-documented product entry decisions into niches.

Dataset construction. We built our dataset from two main sources: the MobyGames and NPD research databases. MobyGames is the largest online video game archive and aims "to meticulously catalog all relevant information about electronic games on a game-by-game basis and then offer up that information through flexible queries and data mining." At the time of data collection, MobyGames had information on over 68,000 titles, all voluntarily entered by site users following a detailed set of data entry instructions. All entries are peer reviewed. For our purposes, the data include title, platform, release date, aggregated and standardized review score, developer, and publisher of each game.

Second, we use the NPD research database on U.S. video game sales. NPD is an international market research company, which tracks hardware and software sales in the video game industry since 1995. The database includes every commercially sold video game in U.S. for the years 1995-2010 and its monthly sales. It also includes data on games released before 1995, but still on shelves by 1995 – which captures games released from 1991 onwards for our study. Critical for our study, NPD research classifies games into genres, each representing distinct market segments for the development and customer base of games. These differences include story writing, art development, graphic technology, development tools, game mechanics, demand segments, marketing, demographics, and so on. Different capabilities are needed to succeed in each genre, similar to the movie industry (Shamsie et al., 2009). The NPD dataset distinguishes between 53 genres (e.g., Soccer, Tactical Shooter, and Real-Time Strategy). We use these genres as niches available to developers for product entry decisions.

We focus on one segment of this dataset – PC games – as opposed to console games. There are several advantages to studying PC games. First, game genre decisions on console games are hard to separate from the different demand characteristics of competing video game consoles. For example, the Nintendo Wii caters more to "casual" audiences likely to play family games whereas the Playstation in its several incarnations caters more to "hardcore" gamers that predominantly play shooter games. The uneven installed bases on each of these platforms further complicate the issue – the decision to release a game in genre X on console Y can be a decision driven by the higher installed base of console Y and the popularity of that genre on that console. Focusing on the PC market allows us to have a single platform – and the one that got the highest number of game releases throughout the observation period. Second, the PC market is more diverse than the console games market, due to lower barriers to entry and no requirements imposed by a platform owner since it is an open system (Mollick, 2012). This gives us a sample of heterogeneous developers and avoids sampling only larger developers usually observed in the console game market. Lastly, PC games are more diverse in the types of games created: developers generally create games with state-of-the-art graphics for consoles, whereas innovative games with lower graphical requirements can also be successful in the PC market. Since graphics constrain game choices to a smaller number of niches, using the PC market lets us observe a higher variety of active niches for product entry decisions compared to video game consoles.

Our matched dataset has 4,038 titles released for the DOS and Windows platforms on PC. We removed compilations of previous games as well as re-releases of existing games. Our final dataset of 3,802 unique titles represents 3,134 developer-years released for PC,[6] each constituting a product entry decision for a developer. The number of titles is higher than the number of developer-years since a developer may enter multiple products in one year. Creating the non-realized entries for each developer-year by considering all niches in a firm's choice set and coding as non-entry choices the niches in which there has been no entry in the focal year has resulted in 166,102 developer year-genre dyads (3,134 developer-years x 53 genres = 166,102).[7] We removed the first year of developers since developers are at risk of entering a niche only after they entered the industry (i.e., after the first observation). Moreover, firms have no observable experience in their first product entry observation. This leaves us with 82,926 developer year-genre dyads.

Dependent Variable

Product Entry in a Niche: Our dependent variable captures whether the developer entered a specific genre in year t by launching a game in it. The unit of analysis is thus (developer-genre) dyad-year (Piezunka, 2013). We measure whether a developer chose to release a game in a specific genre in year t as a binary variable with value one if the developer released at least one title in the specific genre in a year.

Independent Variables

ln(Niche Density): We measured the (product) density of a niche as the number of products competing in a genre in the year before the (potential) release of the focal product (all our variables are lagged by one year, unless otherwise noted, to avoid reverse causality). We logged the density variable to i) deal with overdispersion, and ii) empirically account for the decreasing returns to imitation due to increasing competition. This method captures both the positive information effect at low values of niche density and the negative competition effect gaining importance at higher levels of niche density. In our robustness checks, we run models with the linear and squared terms of niche density as count of products. We find that the squared term's coefficient never dominates, hence decreasing returns capture our relevant parameter range equally well. We add 1 before the log transformation to avoid taking the log of zero values.[8]

ln(Developer Niche Experience): This variable measures the amount of past experience the developer has gained in the focal genre. It is calculated by the log of the number of previous game releases in the genre. To test H1, we interacted this variable with the ln(Niche Density) variable, to test H2, we interacted this variable with the Recent Trailblazer variable, and to test H3 we interacted it with both ln(Niche Density) and Recent Trailblazer variables.

Recent Trailblazer (in the Genre): We created a binary variable that measures whether a trailblazer has been released in the focal genre in the last two years. We determined trailblazers through a combination of market success and creative success. In creative industries such as movies, video games, and music, there are many products that become successful in the market and become "blockbusters", but lack any creative value. Conversely, there are products that become creative successes (i.e., highly scored by professional critics), but fail to make an impact on the market. However, products that are both market and creative successes become trailblazers and have a lasting impact on the market (or submarket) they belong to. The industry and professional press has heated discussions about the "genre-defining" products in many creative industries, with video games being no exception.[9]

We identified trailblazer games as follows: within each genre, we identified those games that sold more than any prior game in the same genre. To exclude best-selling games in very small categories (hence lacking any impact), or which are early released games that meet the criteria (it is easier to become a best-seller early on), we imposed a threshold of $500,000 in minimum total sales. Moreover, although we observe successful games released before 1995 in the dataset (because they were still sold in 1995), the majority of sales (which happens in the first 12 months after the release of a game) was missing for these games. We additionally identified games released before 1995 and known to be best-sellers in their categories (e.g., Street Fighter II in the fighting game genre).[10] To measure the creative success dimension of trailblazers, we used the aggregated and standardized review scores provided by Mobygames, which sets high standards for the reviews indexed in the score.[11] This score ranges from 0 to 100, with 85 and above considered "superstars" in previous research (Binken and Stremersch, 2009). Considering both market and creative success criteria, we identified 67 trailblazer titles. Each of the identified titles represent a well-known title that had a lasting impact on the industry (and especially the genre it belongs to).

Control Variables

We include a series of controls. The first set of control variables includes developer level controls that might influence the product entry decision into a niche. ln(Related Experience) controls if the focal developer has past experience in genres related to the focal genre. To calculate this variable, we have used the 13 "supergenres" that contain the 53 genres that represent our niches available for product entry. For example, the sport games supergenre includes a subset of genres such as football, basketball, baseball, and tennis. We calculated the number of previous games released in the supergenre except the focal genre, and logged this number. We also control if the focal developer has released a previous trailblazer in the focal genre with Developer Previous Trailblazer dummy variable. A previous trailblazer release in the focal genre by the developer may affect the product entry decision due to the success of the previous trailblazer further reinforcing experience effects (Kim et al., 2009).

We further controlled for the possible upstream influences in the niche choice decision as publishers play a critical role in this industry. Publisher Previous Game dummy controls for the publisher's prior experience in the focal genre that can affect the decision to release a game in that genre. This variable takes value 1 if the publisher has released at least one game in the focal genre. Further, we control if the publisher released a trailblazer in the focal genre with the Publisher Previous Trailblazer dummy.

Our final set of controls relates to the genre. First, we control for the number of trailblazers released in genres related to the focal genre with the Related Trailblazers variable. We used the same approach as with the ln(Related Experience) variable and calculate the number of trailblazers released in the past two years in the supergenre except the focal genre. Second, we control for genre size as logged total sales in a genre in the year prior to the release of the focal product. This is an important variable to control for as it lets us separate arguments about niche density from arguments about size (i.e., understanding how density, after controlling for the size of the genre, affects product entry into niche). Failing to control for niche size would make our results on niche density hard to interpret as we do not know the size of niche demand.

The estimation method we use (conditional logit) factors out any developer-level variable invariant within the choice set (i.e., different genres within the same developer-year), which explains the absence of additional control variables. However, we control for overall genre attractiveness using genre fixed effects.

Estimation Technique

To test our hypotheses, we estimate how the probability of making a product entry to a genre changes as a function of ln(Niche Density) and its interactions with ln(Developer Niche Experience) and Recent Trailblazer. We model how our variables of interest and their interactions affect the probability of entry using a fixed effects conditional logit model (McFadden, 1974). Previous studies that modeled choices by firms used the same method, with the choices being technological class entry (Carnabuci et al., 2015), intermediary product release (Piezunka, 2013), and niche entry (Greve, 2000). The difference between conditional logistic regression and ordinary logistic regression is that the data occur in groups. Therefore, the method fits a logistic model that explains why a given choice occurs conditional on other alternatives within the same group (choice set). Our dependent variable is set to one if developer chooses to release a product within a genre in a particular year, and zero otherwise. Therefore, we grouped our observations for each year. In total, there are 80,910 potential dyads in our data, of which 2,016 were actually realized. In our robustness checks, we also run a non-conditional (ordinary) logit model. Each (developer-genre) dyad-year consists of this dependent variable as well as covariates for developer and genre. We computed all dyadic variables for all observations in our data – such as the prior game and prior trailblazer dummies - both for realized and non-realized dyads. Our full model is as follows (ρ denotes the likelihood of the developer choosing the genre for game release):

$$\rho = \beta_0 + \beta_1 Ln\,(Niche\ Density) + \beta_2\, Ln(Developer\ Niche\ Experience) + \beta_3\, Recent\ Trailblazer + \beta_4\, Ln\,(Niche\ Density) \cdot Ln(Developer\ Niche\ Experience) + \beta_5\, Ln(Developer\ Niche\ Experience) \cdot Recent\ Trailblazer + \beta_6\, Ln\,(Niche\ Density) \cdot Recent\ Trailblazer + \beta_7\, Ln\,(Niche\ Density) \cdot Ln(Developer\ Niche\ Experience) \cdot Recent\ Trailblazer + controls + Genre\ Fixed\ Effects$$

Note that all observations in which a developer did not release any game in a particular year are dropped as there is no variance in the dependent variable across genres within a developer-year.

RESULTS

Descriptive Results

Table 2 (full sample) and in Table 3 (realized entries) report the descriptive statistics. We can see a strong correlation between product entry in a genre and ln(Developer Niche Experience) (0.48 in Table 2). ln(Niche Density) is also correlated with product entry in a genre (0.17). The highest correlation is between ln(Niche Density) and ln(Niche Size) as expected (0.69). Overall, our variables show a good amount of variance and low to medium levels of correlation.

Insert Table 2 and Table 3 about here

Analysis

Table 4 reports results for the estimation of the likelihood of niche entry using a conditional logit regression. Model 1 estimates the likelihood of entry using the direct effects of our independent variables and control variables only. Regarding the developer-level controls, ln(Related Experience) is significant across all models and showing that developers leverage their experience in related genres in entering a niche, whereas Developer Previous Trailblazer is only significant for Model 1. This may be because when accounting for our additional interactions with experience, the experience of the developer is stronger than the impact of having a trailblazer in a genre.[12] Both publisher-level controls are positive and significant, indicating the influence of publishers on the choice of genre in product entry. Regarding the control variables at the niche level, trailblazers released in the last two years in related genres significantly drive entry in the focal genre, showing that firms may seek to profit from the associated surge in popularity for related niches if a trailblazer raises the attention for a broader class of niches. Niche size shows the expected positive and significant ($p<0.05$) coefficient across all models. Regarding the direct effects of our independent variables, we see that the coefficient of ln(Niche Density) is positive and significant ($p<0.001$), so niches with more products attract further entries by developers – though with decreasing returns due to the logged nature of the variable (we will explain this in detail later in the robustness checks). This supports our baseline Hypothesis H0. We also see that ln(Developer Niche Experience) is significant ($p<0.001$). Hence, a developer's experience in the focal genre increases the likelihood of product entry in the focal genre. Finally, Recent Trailblazer is not significant, reflecting our intuition that trailblazers in a focal genre have ambiguous effects: while it is a strong signal that could be imitated by others to tap into demand within the niche, a recent trailblazer is also a strong competitor, thus possibly canceling out the positive effect of trailblazers.

Turning to our hypothesized relationships, H1 focuses on the interaction between experience and focal-niche density. Model 2 interacts ln(Niche Density) and ln(Developer Niche Experience) and finds a negative and significant coefficient ($p<0.001$). This supports H1 that a firm's previous experiences in the focal niche will weaken the relationship between niche density and product entry likelihood. Model 3 tests the interaction between ln(Developer Niche Experience) and Recent Trailblazer. The interaction is not significant (though positive), showing that on average, developer experience does not interact with the availability of a recent trailblazer in the genre. H2 is therefore not supported unconditionally, although the coefficient becomes significant (at $p<0.05$) once we include all interaction terms in Model 4.

H3 focuses on the 3-way interaction between our independent variables. Model 4 includes the 3-way interaction between ln(Niche Density), ln(Developer Niche Experience) and Recent Trailblazer. The 3-way interaction is negative and significant ($p<0.05$), as are the two way interactions between ln(Developer Niche

Experience) · ln(Niche Density) and ln(Developer Niche Experience) · Recent Trailblazer. This lends support to H3, which states that the interaction between ln(Developer Niche Experience) and Recent Trailblazer decreases in magnitude (and significance) with increasing density. Moreover, the coefficient of the three-way interaction means that the substitutive relationship between internal experience (ln(Developer Niche Experience)) and external information (ln(Niche Density)) is stronger in the presence of a recent trailblazer in the genre as both the two-way and the three-way coefficients add up in this case. This is supported by our subsample analyses in Table 5. Comparing Models 1 and 2 of Table 5, the interaction between ln(Developer Niche Experience) and ln(Niche Density) has a larger magnitude in the sample with recent trailblazers, suggesting a stronger substitution pattern, although the difference between coefficients across subsamples is not significant. Interestingly, ln(Niche Density) is insignificant in the trailblazer subsample, which implies that niche density as such carries no information for firms if the niche has seen a recent trailblazer. Models 3 and 4 are subsamples based on the median ln(Niche Density) value. Taking an alternative look at our three-way interaction, we see that the interaction between ln(Developer Niche Experience) and Recent Trailblazer is significant only for the subsample with low density. This indicates that experienced firms will follow a trailblazer in a niche only if there are not too many other active firms.[13]

Insert Table 4 and Table 5 about here

We computed the odds ratios of our coefficients to interpret the results. We examined the odds ratios predicted by Model 5, but centered our two continuous variables to values that facilitate interpretation: we used a value of 1 (before log transformation) for previous game release experience in the focal genre, and the mean of niche density (both variables are transformed to logs). We find that for a developer with niche experience of 1 in a genre with no recent trailblazer, one unit of ln(Niche Density) added to the mean value of the variable increases the odds of product entry by 21.7%. However, if the same firm has an additional unit of the logged value of experience, ln(Developer Niche Experience), one unit of ln(Niche Density) decreases the odds of product entry by 10.6%. Hence, the effect does not simply get weaker, but switches signs within the variable range. Repeating the same exercise for Recent Trailblazer, we find that the availability of a trailblazer in a genre increases the odds of product entry by 51.6% at the centered values for our two main continuous variables.[14] If the firm has one more unit of ln(Developer Niche Experience), the odds of entering increase by 176.3%. However, given our three-way interaction introduced in H3, increasing ln(Niche Density) by one unit reduces this effect by almost 30%, resulting in an increase in the odds of entering by 95.6% (instead of 176.3%). Hence, the changes in the products entry likelihoods differ widely across developers with different levels of prior experience and for niches with or without recent trailblazers and with differing levels of niche density.

Robustness Checks

The results of a number of robustness checks are given in Table 6. Model 0 repeats the preferred model (Model 4) from Table 4. Model 1 replicates our analysis with publisher-year observations instead of developer-year observations to analyze the product entry choices of publishers. We calculated each of the main variables for the publishers, and used developer variables as controls. This lets us see if results change when we focus on publishers as their product entry decisions might follow a different logic, e.g. based on portfolio considerations. Model 2 uses an ordinary logit model instead of a conditional fixed-effects logit model. In Model 3, we use the linear and squared terms of the (non-logged) density variable. Finally, in Model 4, we restrict our sample of games to genres that have observed a trailblazer in their history. This lets us check if our results are driven by "non-popular" genres with likely lower densities.

Model 1 shows very similar results compared with Model 0 regarding our hypotheses. This gives us additional confidence that the logic for our main findings is correct since developers' and publishers' decisions follow the same drivers. Model 2 uses an ordinary logit regression and gives more significant results for our interactions. As the conditional logit allows for the inclusion of fixed-effects, however, we persist with Model 4 from Table 4 as our preferred model, which is more conservative regarding the effects of our variables of interest. In Model 3, we use linear and squared terms of the (non-logged) density variable. We see that the linear term is positive and the squared term is negative, reflecting the positive impact of density due to information-based imitation and subsequent decreasing returns due to competition. However, the squared term is weaker, and at the maximum value of the density distribution (72 active games in the genre), the impact of the density on the outcome probability does not turn significantly negative. Our hypothesized interactions all remain significant.[15] Finally, our results are qualitatively unchanged if we restrict our sample to genres with a trailblazer, i.e. more popular genres. Hence, our results are robust to several alternative specifications.

Insert Table 6 about here

DISCUSSION AND CONCLUSION

We ask how niche density, experiential learning by the firm, and the recent arrival of a trailblazer product impacts niche entry choices of firms by drawing on theories of information-based imitation and experiential learning. Our findings offer implications for the imitation literature, especially studies looking at information-based imitation drivers of entry or adoption (Belderbos et al., 2011; Semadeni and Anderson, 2010; Simon, and Lieberman, 2010). First, we find that there is a substitutive relationship between a *firm's* own experience and niche density in driving product entry decisions. Both factors individually positively influence the decision to enter a product in a particular niche, yet the informative content of other products in a niche is diminished by the firm's own experience about the niche. Second, we identify a complementary relationship between a *firm's own experience* and the presence of a recent trailblazer in the niche. However, this relationship is contingent on the density of the niche. Specifically, a firm's prior experience in a niche with a trailblazer will lead to a higher likelihood of entering that niche if the niche has relatively few active (competing) products. This has direct implications for studies on imitation in entry and adoption (Haunschild & Miner, 1997; Delios, Gaur, and Makino, 2008; Semadeni and Anderson, 2010), but connects to prior work on inter- and intra-organizational learning (Miner & Haunschild, 1995, Beckman & Haunschild, 2002), managerial decision making (Greve, 2000; Greve, 2013), and industry evolution (Hannan and Carroll, 1992; Argyres et al., 2015).

Our first key finding that experiential learning replaces the external information from the number of products in a niche contributes to the recently explored link between information-based imitation's emphasis on vicarious (or mimetic) learning (Lieberman and Asaba, 2006) and experiential learning by showing that firms emphasize their internal learning over the external information obtained from the number of active products. This substitution may occur because of a multitude of factors: i) firms may use their better internal knowledge instead of imperfect external information; ii) they may benefit less from knowledge spillovers; and/or iii) they may also feel less pressure to conform to sociopolitical demands. These results line up with Simon and Lieberman (2010) who show that even a solitary experience is enough to almost render the effect of external information the number of other adopters of a new technology unimportant. This has implications for experience giving way to a momentum strategy, where firms repeat their past behaviors without examining its consequences (Amburgey & Miner, 1992; Greve, 2000; Greve, 2013). Although we cannot measure if momentum is one of the factors causing the substitutive effect (its main effect may lie in the strong positive direct effect of previous niche experience), it is plausible that momentum causes substitution between internal experience and external information – external information becomes unimportant once the firm has built up momentum. However, if internal experience indeed creates momentum we would expect this to substitute for any type of external information.

This brings us to our second and possibly more counterintuitive key finding of a complementary relationship between a firm's prior experience and the presence of a recent trailblazer in the niche, contingent on niche density. That is, experienced firms follow recent trailblazers by entering products in the niche if the niche is not already too populated. This finding reaffirms and extends the importance of pre-entry experience (Helfat and Lieberman, 2002) in the form of absorptive capacity (Cohen and Levinthal, 1990) and clarifies why previous empirical tests of prior experience as an absorptive capacity to learn from external information in the context of imitation have produced mixed results (Simon and Lieberman, 2010). Prior experience helps firms process information from a singular event that is likely to reshape the niche itself – a trailblazer. This creates a complementary relationship between internal experience and complex external information. In the context of information-based imitation, this suggests that firms without prior experience in the niche are less likely to able to replicate many "elements and their interactions…to achieve success" (Lieberman and Asaba, 2006; p. 378) when imitating a trailblazer. Such complexities may stem from the product itself or from the supply side – the firm developing the product may also need to replicate many capabilities and their interactions to come up with a successful imitation. Finally, given this finding is contingent on having a market with relatively few products, we can speculate that experienced firms can successfully evaluate markets while leveraging their internal experience to follow trailblazers. This suggests that internal experience creates evaluation capability rather than myopic momentum – the firm will avoid entry if the market is very crowded, yet it follows the trailblazer otherwise. As Greve (2013) points out, a momentum strategy mostly occurs when there are ambiguous evaluation criteria, yet firms with prior experience in a niche can assess the intensity of competition in the market.

We also add to and amend the established literature in organizational ecology on niche entry. While most work assumed that niche density affects all potential entrants in the same way, we find that firms respond differently to the same degree of niche entry by other firms. Specifically, a firm's prior experience in the focal niche acts as a substitute for the legitimacy offered by niche density. Another implicit homogenizing assumption of organizational ecology literature is that potential entrants are mainly driven by the number of products active in the niche, not their type and/or character. We find that trailblazer products, i.e. products that were significantly more successful than previous games in their respective market niche, play a specific role in product entry into niches by firms.

From a managerial perspective, we find that firms do not respond equally to the actions of the crowd and the release of a trailblazing product. Interestingly, while managers tend to pay less attention to a big mass of competitors as they gain experience for themselves, they are more responsive to the behavior of a trailblazer. Specifically, managers assess a market niche both in terms of its growth prospects (as indicated by the presence of a trailblazer) and its own chances of achieving a strong competitive position in this market (as indicated by the number of products already active). A fast second strategy following a major shakeup in an industry may therefore only be available to firms that have gathered prior experience in this, or closely related industries. Our results also suggest that prior experience in a niche carries a dual meaning for firms: First, it helps a firm assess the attractiveness of markets without needing to rely on cues from the aggregate behavior of others. Second, it enables firms to devise strategies to respond to a product that is likely to change the logic of a niche earlier than other, less experienced firms.

Our results will have most traction in markets in which both entrants and existing products in a niche are highly heterogeneous. Our empirical setting of PC video games clearly is one such industry, but it is generalizable to industries that have had time to mature and for firms to develop heterogeneous levels of experience. Further, we note that in our theoretical and empirical setting, entry is largely "non-strategic", i.e. entry deterrence and oligopolistic competition do not feature prominently in our theoretical considerations, and our empirical results do not suggest this is a major omission. In more concentrated markets, we would expect the number of firms to enter negatively in the entrant's profit function, implying a lower entry likelihood as there are more firms in the niche (Schmalensee, 1978). The aspects mentioned above are clear boundary conditions – we would not expect to see our results replicated in a completely new market populated by de-novo entrepreneurs, or in highly concentrated markets in which additional firms simply decrease the rents available to entrants and thus decrease the attractiveness of entering.

One specific aspect of our study setting in the US PC video game industry presents a significant strength in our empirical implementation. The fact that we can observe many product entry decisions by firms in different niches affords us the necessary variation in the data to identify empirically the factors we put forward in our theory. This would of course be problematic if entry decisions in our setting would follow a significantly different logic than in other industries with a slower entry cycle. However, a number of factors make us optimistic that this is not the case. First, cannibalization of existing games through new games is not a relevant concern as most games only generate significant revenues for the first year after their release and therefore firms' consideration is rather how to maintain a steady stream of revenues rather than one cannibalizing the other. Second, our results are robust to omitting the games that arguably have the strongest link between existing and new games, namely sequels and spin-off games.[16] Third, especially in the market for PC games there is ongoing technological progress, which makes it unattractive to simply develop a marginally changed version of a previously successful game, which would probably dominate any population-related considerations of niche entry. Instead, our specific empirical setting lets us observe high–frequency entry decisions in fairly large numbers. In slow-cycle markets, observing the same number of entry instances would create its own problems as only a longer time horizon would deliver that, which in turn may lead to a fundamental shift in technologies, preferences, the emergence of superior substitutes etc.

We have shown how the process of product entry into market niches in the US PC video games industry is affected by firm- and niche-specific factors, which creates heterogeneity in the responses to niche density. Specifically, prior experience in a niche can substitute for the informational cues taken from the number of previous entrants into a niche. Moreover, the existence of a highly popular product in a niche will encourage firms with prior experience in that niche to enter as "fast second", i.e. if the niche is not yet populated by a large number of entrants. Our results suggest that the various conceptual approaches of explaining entry interact in nuanced ways, which calls for a more integrative view on entry phenomena. We believe our study represents a step in this direction.

NOTES

1. In a broader context, neoinstitutional theory focuses on sociopolitical legitimacy, which indicates regulatory and legal-bureaucratic acceptance, whereas in organizational ecology, legitimation is about cognitive (constitutive) legitimacy, the widespread social acceptance of an organizational form or niche (Hannan & Carroll, 1992; Dobrev and Gotsopoulos, 2010). See Suchman (1995) for a review on legitimacy.
2. The term "niche" is used by organizational ecologists to describe "the social, economic, and political conditions that can sustain the functioning of organizations that embody the form" (Hannan and Carroll, 1992). We use niche as a (sub-)market that encompasses products sufficiently similar to each other and sufficiently different from products in other niches. Hence, we study instances of (potential or realized) product entry decisions into niches. In our empirical implementation, a niche is defined as a game genre, in which all games follow a similar basic logic.
3. We refer to actively competing products in a niche as niche density (Carroll and Hannan, 2000; Greve 2000; Dobrev, 2007), also in line with other work on niche entry (de Figueiredo and Silverman, 2007).
4. In sociological approaches, firms follow both economic and sociopolitical rationality (Lieberman and Asaba, 2006).
5. As Mollick notes (2012): "Game developers are almost always organizations as well as firms; less than one percent of all games with identifiable revenues were the work of lone individuals, and less than 2.5 percent of all games credited fewer than five people."
6. This process leaves out 6,586 (non-unique) titles developed for a console platform.
7. For a similar procedure that studies the selection of one choice (in their case, takeover target) from a large number of potential (but unrealized) choices, see Claussen et al. (2018).
8. We followed the same procedure for all logged variables.
9. For an example article: http://www.escapistmagazine.com/articles/view/video-games/editorials/misc/8407-12-Games-That-Defined-Their-Genres

10. We also verified this with data whenever possible – e.g. for Street Fighter II the following page shows sales numbers: https://web.archive.org/web/20150208030840/http://www.capcom.co.jp/ir/english/business/million.html.
11. See http://www.mobygames.com/info/mobyrank for more information (accessed December 13, 2016).
12. This allows for another interpretation: developers may well be developing trailblazers through their continuous releases of titles in the same genre – which would be reminiscent of doing incremental innovations to reach a breakthrough innovation. This is an open issue for future research.
13. A concern could be that because of the non-linear nature of the conditional logit model, the effect and significance levels of the independent variables and their interaction terms do not apply to the entire sample range (Zelner, 2009). Conditional logit models are ill-suited to undertake partial effects analysis as most programs calculate such effects under the assumption that fixed effects are zero, which is unrealistic and may cause problems with the partial effect estimates (Kemp and Silva, 2016). We therefore used our simple logit model and converted the continuous variable ln(Niche Density) to a categorical one based on mean, Crowded Genre, to be able to interpret the interactions for our entire sample easily. Interactions are significant well in our sample range. We thank a reviewer for pointing this out.
14. The odds ratio of Recent Trailblazer is higher than our main regressions in Model 5 due to centering of the two independent variables.
15. We interacted only the linear term of the density in this model since the squared terms were not significant in their interactions, and it over-saturated our model.
16. Results are available from the authors.

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Table 1: Top 5 Genres by Market Shares for PC Games in the US between 1996 and 2008 (Source: NPD Market Research)

	1996		1999		2002		2005		2008	
#1	1st Person Shooter	10%	Children's Games	11%	Life Simulations	18%	Life Simulations	19%	MMORPG	22%
#2	General Adventure	8%	Real-Time Strategy	9%	Real-Time Strategy	13%	Real-Time Strategy	12%	Life Simulations	21%
#3	Real-Time Strategy	8%	1st Person Shooter	7%	1st Person Shooter	11%	1st Person Shooter	12%	Real-Time Strategy	13%
#4	RPG	7%	Life Simulations	7%	Children's Games	10%	MMORPG	11%	1st Person Shooter	10%
#5	Air Combat Simulations	6%	RPG	7%	RPG	8%	RPG	6%	RPG	7%

Table 2: Correlation Table – All Dyads

	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10
1. Product Release in Genre	0.02	0.15	0	1	1									
2. ln(Niche Density)	1.39	1.03	0	4.32	0.17	1								
3. ln(Developer Niche Experience)	0.04	0.22	0	3.56	0.48	0.19	1							
4. Recent Trailblazer	0.12	0.32	0	1	0.06	0.29	0.05	1						
5. ln(Related Experience)	0.12	0.39	0	3.56	0.07	0.03	0.12	0.03	1					
6. Previous Trailblazer (Developer)	0	0.05	0	1	0.18	0.04	0.33	0.04	0.04	1				
7. Publisher Previous Game	0.24	0.43	0	1	0.15	0.34	0.21	0.09	0.07	0.07	1			
8. Publisher Previous Trailblazer	0.02	0.13	0	1	0.08	0.08	0.12	0.1	0.05	0.24	0.24	1		
9. Related Trailblazers	0.47	0.94	0	4	0.03	0.1	0.01	0.22	0.04	0.01	0.01	0.02	1	
10. ln(Niche Size)	14.09	4.02	0	19.34	0.1	0.69	0.12	0.25	0.02	0.03	0.26	0.07	-0.03	1

Table 3: Correlation Table – Realized Dyads

	Mean	S.D.	Min	Max	2	3	4	5	6	7	8	9	10
1. Product Release in Genre	1	0	1	1									
2. ln(Niche Density)	2.47	0.92	0	4.32	1								
3. ln(Developer Niche Experience)	0.7	0.7	0	3.56	0.18	1							
4. Recent Trailblazer	0.25	0.43	0	1	0.15	-0.03	1						
5. ln(Related Experience)	0.29	0.57	0	3.43	-0.13	0.04	-0.02	1					
6. Previous Trailblazer (Developer)	0.06	0.23	0	1	-0.04	0.33	0.15	0.06	1				
7. Publisher Previous Game	0.65	0.48	0	1	0.2	0.34	0.05	-0.03	0.15	1			
8. Publisher Previous Trailblazer	0.08	0.28	0	1	0	0.23	0.21	0.08	0.59	0.22	1		
9. Related Trailblazers	0.63	0.9	0	4	-0.03	-0.09	0.23	0.03	0.05	-0.02	0.05	1	
10. ln(Niche Size)	16.69	2.04	0	19.34	0.74	0.19	0.24	-0.08	0.01	0.21	0.06	-0.04	1

Table 4. Conditional Logit Fixed Effects Logit Estimates of Product-market Niche Choice

VARIABLES	Model 1 DV=Product Released in Genre-Year	Model 2 DV=Product Released in Genre-Year	Model 3 DV=Product Released in Genre-Year	Model 4 DV=Product Released in Genre-Year
ln(Niche Density)	0.264***	0.396***	0.397***	0.410***
	(0.065)	(0.070)	(0.070)	(0.074)
ln(Developer Niche Experience)	2.844***	3.719***	3.720***	3.612***
	(0.060)	(0.165)	(0.165)	(0.173)
Recent Trailblazer	0.024	0.021	-0.007	0.008
	(0.081)	(0.080)	(0.091)	(0.273)
ln(Developer Niche Experience) · ln(Niche Density)		-0.345***	-0.352***	-0.309***
		(0.060)	(0.061)	(0.065)
ln(Developer Niche Experience) · Recent Trailblazer			0.083	1.076*
			(0.127)	(0.479)
ln(Niche Density) · Recent Trailblazer				-0.008
				(0.099)
ln(Niche Density) · ln(Developer Niche Experience) · Recent Trailblazer				-0.345*
				(0.164)
ln(Related Experience)	0.917***	0.871***	0.871***	0.875***
	(0.067)	(0.068)	(0.068)	(0.068)
Developer Previous Trailblazer	0.523*	0.310	0.292	0.203
	(0.254)	(0.253)	(0.255)	(0.254)
Publisher Previous Game	1.032***	0.996***	0.994***	0.990***
	(0.074)	(0.073)	(0.074)	(0.074)
Publisher Previous Trailblazer	0.263^	0.303*	0.302*	0.292^
	(0.151)	(0.149)	(0.150)	(0.150)
Related Trailblazers	0.119**	0.121**	0.121**	0.122**
	(0.041)	(0.041)	(0.041)	(0.041)
ln(Niche Size)	0.071**	0.058*	0.059*	0.054*
	(0.025)	(0.026)	(0.026)	(0.026)
Observations	82,926	82,926	82,926	82,926
Unit of Analysis	Developer-Year-Genre	Developer-Year-Genre	Developer-Year-Genre	Developer-Year-Genre
Developer-Year FE	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, ^ p<0.10

Table 5. Subsample Analyses

VARIABLES	(1) No Trailblazer Subsample	(2) Trailblazer Subsample	(3) Density<Median	(4) Density>=Median
ln(Niche Density)	0.476***	-0.098	0.315	0.290**
	(0.081)	(0.250)	(0.286)	(0.110)
ln(Developer Niche Experience)	3.622***	4.015***	3.158***	3.445***
	(0.181)	(0.684)	(0.509)	(0.249)
Recent Trailblazer			1.484^	0.103
			(0.764)	(0.335)
ln(Developer Niche Experience) · ln(Niche Density)	-0.296***	-0.423^	0.683	-0.253**
	(0.068)	(0.228)	(0.590)	(0.088)
ln(Developer Niche Experience) · Recent Trailblazer			5.683*	0.097
			(2.409)	(0.134)
ln(Niche Density) · Recent Trailblazer			-1.458^	-0.042
			(0.845)	(0.116)
ln(Related Experience)	0.844***	1.068***	0.526*	0.913***
	(0.079)	(0.170)	(0.205)	(0.075)
Developer Previous Trailblazer	-0.451	1.890**	-0.893	0.337
	(0.365)	(0.650)	(1.546)	(0.292)
Publisher Previous Game	1.050***	0.572**	0.912***	1.009***
	(0.086)	(0.180)	(0.243)	(0.080)
Publisher Previous Trailblazer	0.094	0.731**	-0.684	0.264
	(0.224)	(0.261)	(0.659)	(0.162)
Related Trailblazers	0.139**	-0.008	0.352*	0.081^
	(0.048)	(0.145)	(0.139)	(0.047)
ln(Niche Size)	0.044^	0.186	-0.004	0.193**
	(0.026)	(0.198)	(0.036)	(0.066)
Observations	59,007	3,903	5,604	38,896
Unit of Analysis	Developer-Year-Genre	Developer-Year-Genre	Developer-Year-Genre	Developer-Year-Genre
Developer-Year FE	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, ^ p<0.10

Table 6. Robustness Checks

VARIABLES	Model 0 Base	Model 1 Publisher-Year-Genre Analysis	Model 2 Simple Logit	Model 3 Linear and Squared Density	Model 4 Only Genres with a Trailblazer
ln(Niche Density)	0.410***	0.548***	0.586***	0.042***	0.257*
(Niche Density is used throughout Model 3)	(0.074)	(0.070)	(0.071)	(0.011)	(0.100)
Niche Density Squared/10				-0.004*	
(divided by 10 for re-scaling)				(0.002)	
ln(Developer Niche Experience)	3.612***	1.669***	3.523***	3.181***	3.404***
	(0.173)	(0.119)	(0.158)	(0.099)	(0.248)
Recent Trailblazer	0.008	0.012	0.449^	-0.039	-0.064
	(0.273)	(0.260)	(0.264)	(0.152)	(0.292)
ln(Developer Niche Experience) · ln(Niche Density)	-0.309***	-0.182***	-0.327***	-0.021***	-0.246**
	(0.065)	(0.043)	(0.060)	(0.005)	(0.090)
ln(Developer Niche Experience) · Recent Trailblazer	1.076*	0.724*	1.415**	0.497*	1.223*
	(0.479)	(0.351)	(0.459)	(0.253)	(0.519)
ln(Niche Density) · Recent Trailblazer	-0.008	0.026	-0.111	0.001	0.025
	(0.099)	(0.099)	(0.096)	(0.007)	(0.105)
ln(Niche Density) · ln(Developer Niche Experience) · Recent Trailblazer	-0.345*	-0.252*	-0.456**	-0.022*	-0.362*
	(0.164)	(0.121)	(0.158)	(0.011)	(0.179)
ln(Related Experience)	0.875***	0.197***	0.162**	0.881***	0.954***
	(0.068)	(0.044)	(0.054)	(0.067)	(0.077)
Focal Firm Previous Trailblazer	0.203	0.599***	-0.004	0.271	0.354
	(0.254)	(0.181)	(0.224)	(0.255)	(0.267)
Control Firm Previous Game	0.990***	1.887***	0.587***	1.000***	0.840***
	(0.074)	(0.098)	(0.058)	(0.074)	(0.087)
Control Firm Previous Trailblazer	0.292^	-0.061	-0.044	0.286^	0.215
	(0.150)	(0.405)	(0.139)	(0.150)	(0.156)
Related Trailblazers	0.122**	0.061	0.182***	0.125**	0.129**
	(0.041)	(0.038)	(0.034)	(0.041)	(0.049)
ln(Niche Size)	0.054*	0.058**	-0.013	0.087***	0.078*
	(0.026)	(0.022)	(0.022)	(0.024)	(0.035)
Constant			-5.158***		
			(0.353)		
Observations	82,926	37,842	78,048	82,926	35,360
Unit of Analysis	Developer-Year-Genre	Publisher-Year-Genre	Developer-Year-Genre	Developer-Year-Genre	Developer-Year-Genre
Developer-Year FE	YES	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, ^ p<0.10