

BIG FISH VS. BIG POND? ENTREPRENEURS, ESTABLISHED FIRMS, AND
ANTECEDENTS OF TIE FORMATION

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Abstract

Entrepreneurial and established firms form collaborative relationships to commercialize products. Through such ties, entrepreneurs seek (1) development help to hone ideas into marketable products and (2) access to markets. In most cases, entrepreneurs face a trade-off: they can be a *big fish in a small pond*, getting more attention and development help from a smaller firm with less market access; or a *small fish in a big pond*, getting less attention and help from a larger firm with more market access. Our study investigates what goes into choosing between these options. Drawing from resource dependence theory and an empirical study of tie formation between developers and publishers of PlayStation2 video games, we develop and test a framework that identifies the key decision variables and focuses on two moderators—resource need evolution and resource uncertainty related to competition—that explain whether big fish (more development help) or big pond (more market access) drives tie formation. Our findings point to prospective peers as one of the significant decision criteria at tie formation and highlight the dynamic nature of resource dependence. Altogether, the results give resource dependence theory a dynamic element it has lacked in the past.

“[Think about a choice of] going with a big publisher versus going with a ‘niche’ publisher if you’re a book writer. When you go with a niche player, you’re the only game in town. You are it. They are smaller but you know they’re going to do what it takes to make your title successful ... But if your goal is to get as many people as possible to touch your title, get in with one of the bigger publishers. Of course, the risk is that they may put your title in the back of the 50 [similar] books they’re promoting this quarter, and you’re the one they barely talk about... So, the answer might be different depending on what your goal is.”—Entrepreneur describes the big fish, big pond choice in tie formation, in-person interview.

Resource-constrained entrepreneurial firms look for established firm partners to get hold of the resources they need. Authors partner with publishers, digital content creators with platforms, and biotechnology entrepreneurs with pharmaceutical firms to hone their products and to reach the market. In turn, the established firm gets fresh ideas from the entrepreneurial firm. Whom entrepreneurs form a tie with depends on what resources they already have and what resources they need to accomplish their goals (Gulati & Sytch, 2007; Katila, Rosenberger & Eisenhardt, 2008; Katila, Thatchenkery, Christensen, & Zenios, 2017). Established firms present attractive partners because they often (a) own resources that they do not fully use internally, and (b) can regulate access to other resources without fully owning them (Penrose, 1959: 77; Pfeffer & Salancik, 1978: 47-48). A particularly relevant example is biotechnology, where established pharmaceutical firms offer excess clinical testing capabilities and access to markets, resources that biotechnology entrepreneurs often do not have, but need (Katila & Mang, 2003; Leaf, 2020).

A relationship with both significant access to markets and significant development help is naturally the most attractive. However, as we show through empirical evidence, it is difficult to achieve both, inducing what is colloquially known as the “big fish vs. big pond” trade-off at tie formation (Ozmel & Guler, 2015; Piezunka, Katila & Eisenhardt, 2016). As our opening vignette suggests, entrepreneurs often need to decide whether to form a tie with a bigger established firm that may include more—and more accomplished—entrepreneurs in its portfolio (big pond), or to sign with a smaller firm where they may be more of a priority (big fish). Despite the common occurrence of this dilemma, especially in “markets for know-how”

where entrepreneurs and established firms co-create products (Katila, Chen, & Piezunka, 2012), the conditions under which each option is preferred are not well-understood.

The purpose of this paper is to ask what conditions are likely to result in an entrepreneur becoming a big fish in a small pond vs. a small fish in a big pond. This choice is not only the entrepreneur's, of course. Although it is the entrepreneur who faces the core “big fish, big pond” decision, ties require joint decision-making and we also confirm established-firm preferences to be consistent. Drawing from resource dependence theory, we develop and test a framework that identifies the key decision variables and focuses on two moderators—resource need evolution and competition-induced resource uncertainty—that explain whether big fish (more development help) or big pond (more market access) drives tie formation. To that end, we use a longitudinal analysis of 367 developers (entrepreneurial firms) and 170 publishers (established firms) of video games, supplemented with two waves of in-depth interviews. To focus on tie formation between developers and publishers, we hold the platform constant, focusing on PlayStation2 games only. Strength of the data is a complete global population of PlayStation2 games, including an analysis of cancelled games.

This study advances resource dependence theory on several fronts. First, it highlights the fundamentally *dynamic* nature of resource dependence, which remains under-examined (Hillman, Withers, & Collins, 2009; Wry, Cobb, & Aldrich, 2013; Hallen, Katila, & Rosenberger, 2014; Rogan & Greve, 2015). In particular, we emphasize how both resource needs and resource uncertainty evolve over time, making the firm's efforts to reduce dependence dynamic. Thus, we contribute to the gap identified by Pfeffer and Salancik (2003: xv) in the foreword to their seminal text about the static nature of existing resource dependence scholarship by examining “dynamic aspects about arguments about changes in organizations and environments.”

Second, although research has spotlighted uncertain access to partner resources *after* the relationship has formed (Aggarwal, 2020), it has mostly remained silent on *ex ante* decisions about partners, where actual resource commitments are yet to be known (Katila & Mang, 2003). In fact, we are not aware of any prior study that has examined how prospective competition with peers over resources influences partner choice. As our data show, in these *ex ante* decisions resource commitments are anticipated as part of the actors' decision calculus. Both of these contributions reinvigorate resource dependence as a relevant theoretical lens.

Third, we contribute by enhancing understanding of the big fish, big pond dilemma that is common in many settings (c.f., Huston & Sakkab, 2006; Pisano, 2006; Piezunka, Katila & Eisenhardt, 2016) and particularly in strategic partnerships in technology industries. For tie formation, our results fall short of confirming the simple "sorting" view that underlies the conventional wisdom of how ties form. Instead, we find that prospective partners take into account potential resource complementarities, i.e. how different puzzle pieces fit together to yield high-value products, and, the perceived likelihood that the desired resources will actually be available once the relationship is formed. Both represent situations in which the partner with the "best" resources may not always be the most sought-after (c.f., Katila et al., 2008; Alexy, George, & Salter, 2013), making big fish, big pond considerations relevant.

RESEARCH BACKGROUND

Tie Formation: The Resource Dependence Theory View

Resource dependence theory is a key approach to explain interorganizational relationships (Pfeffer & Salancik, 1978; Katila et al., 2008). Resource dependence scholars argue that mutual resource needs push partners to form ties. When goals of the relationship (such as a market-ready product) require parties to work together, a firm's decision calculus for picking

a partner is motivated by joint value creation – that is, by expected resource complementarities with a particular partner (Gulati, 1995; Sun, Hu, & Hillman, 2016).¹

Prior work confirms that entrepreneurs and established firms form ties to satisfy mutual resource needs (Hallen et al., 2014; Pahnke, Katila, & Eisenhardt, 2015). Entrepreneurs have early-stage product ideas but lack resources for refinement and marketing of the product. Established firms, in turn, have these resources but lack entrepreneurial ideas (Eisenhardt & Schoonhoven, 1996). This general relationship pattern is common in many “markets of know-how” in technology industries where entrepreneurs develop high-uncertainty products and seek established firm partners with manufacturing and marketing capabilities to commercialize them. In particular, established firms often (a) own excess development resources that they do not fully use internally, and (b) can regulate access to other resources such as markets without owning them (Pfeffer & Salancik, 1978: 47-48).

A good example is biotechnology. Biotech entrepreneurs focus on highly uncertain knowledge production but collaborate with established drug companies to develop products and to bring them to market (Pisano, 2006). In these relationships biotech entrepreneurs focus on technology, where drug companies are at a disadvantage. Drug companies in turn focus their offerings on excess clinical testing capabilities and access to markets that biotechnology entrepreneurs often lack. Altogether, relationships are motivated by mutual dependence: ties give established firms access to fresh ideas that they lack but need in order to survive, and they give entrepreneurs the needed co-development help to create a valuable product and needed access to markets (Katila & Mang, 2003; Vandaie & Zaheer, 2014).

While research on resource dependence illustrates the potential of ties to serve as conduits through which firms can satisfy resource needs, some work highlights situations in which firms enter a collaboration but do not actually receive the needed resources (Gulati,

¹ Power imbalance is also important (Casciaro & Piskorski, 2005), and we controlled for it in empirical analyses.

Wohlgezogen, & Zhelyazkov, 2012). A salient case is when the established firm is also a potential competitor and therefore may not provide the resources that were promised at the time of tie formation (Diestre & Rajagopalan, 2012; Hallen, Katila, & Rosenberger, 2014).

Research points out that peers can also become problematic. Established firms in technology industries often enter collaborations with more entrepreneurs than they can eventually support, allowing them to manage the uncertainty that comes with the uncertain success of any given entrepreneur. For instance, established firms that seek new technologies (Wadhwa & Kotha, 2006) or invest in screenwriters and book authors in creative industries (Vandaie & Zaheer, 2014) or in early-stage ventures (Ozmel & Guler, 2015; Pahnke, Katila, & Eisenhardt, 2015) all form a portfolio of relationships with various entrepreneurs. Pharma companies, for example, “enter into 40 such arrangements” with biotechnology entrepreneurs at a given time (Bernstein, 2007), and publishers have “50 horses in the race” (in-person interview). As a result, the focal entrepreneur may not get the personalized resources it desired (Pahnke et al., 2015). A developer illustrated this tension to us: “Do they just have too many things on their plate, and is my title going to get the attention it needs?”

Empirical research (Katila & Chen, 2008; Ozmel & Guler, 2015; Piezunka, Lee, Hynes, & Bothner, 2018) confirms that once ties are formed, peers matter and can become problematic for the focal firm. What is far less understood, however, is how *partner choices* are made when competition is anticipated from peers. This is particularly true for cases when there are trade-offs between different types of resources that are anticipated from the relationship as in our focus on the tradeoff between (1) personalized development help (which is often rationed in rank order to peers) and (2) market access (a resource that is more scalable) (Pfeffer & Salancik, 1978: 47-48). How these two factors are weighted at tie formation is the core question of the big fish, big pond dilemma that we examine.

Resource needs and resource uncertainty. What motivates tie formation in the first

place is entrepreneurs' resource dependence. Prior work typically treats this factor as rather stable. In contrast, we recognize resource dependence as a fundamentally dynamic phenomenon that concerns "arguments about changes in organizations and environments" (Pfeffer & Salancik, 2003: xv). One significant aspect of the dynamism of organizations pertains to resource stocks. As entrepreneurs gain experience, it seems plausible that they confront different problems and challenges, and thus face different resource requirements (Kazanjian, 1988; Eisenhardt & Schoonhoven, 1990; Huang & Knight, 2017; Leatherbee & Katila, 2020). In markets for know-how, as entrepreneurs gain experience, their needs for resources likely shift—specifically, from internal resources (i.e., upstream resources such as development help) to external ones (i.e., downstream resources such as market access).² Changes in the resource needs as the firm evolves suggest the dynamic perspective as relevant.

Regarding environments, a significant dynamism is spurred by competition. It seems likely that as competition intensifies in the entrepreneur's markets, its resource needs shift from general resources to more personalized, tailored resources that help differentiate the firm (c.f. Thatchenkery & Katila, 2021). Thus, because both the organization and the environment evolve over time, the factors driving tie formation can shift with them.

HYPOTHESES

Building on resource dependence, we propose four hypotheses about entrepreneur-established firm tie formation. We develop a framework about how development help (H1) and market access (H2) drive entrepreneurs' tie formation with established firms, and how the weighting of each of these predictors is influenced by two dynamically changing moderators:

² Consistent with theorizing on entrepreneurial firms, different kinds of resources are most beneficial at different stages of entrepreneurial development (see e.g. Huang & Knight, 2017; Gruber et al., 2012). Internal resources relate to the execution of any technical function or R&D activity within the firm, including the ability to develop new products. External resources in contrast relate to commercializing the firm's product and its relationships with customers (Katila, Rosenberger, & Eisenhardt, 2008).

entrepreneur's resource needs (H3) and competition-induced resource uncertainty (H4). See Figure 1.

Insert Figure 1 about here

Anticipated Resources

Development help. Because of their history of developing products, established firms often possess excess development resources that they do not fully use internally. These resources could help transform fledgling ideas into marketable products (Penrose, 1959; Katila et al., 2008), making established firms attractive partner-candidates for entrepreneurs. In the words of one of our entrepreneur-interviewees, “when you're innovating something new, there's always some snag and always some complication that you did not foresee. It is crucial that [an established firm] is going to support you and work with you through these tough times.” But, this development help is not readily available if too many prospective *peers* are also looking for established firm's attention – a point that is often overlooked by prior research on tie formation (Katila & Chen, 2008; Piezunka & Dahlander, 2015).

Drawing from resource dependence, we propose that an entrepreneur who is looking to transform a product idea into a marketable product is motivated to form a tie by the promise of getting a share of an established firm's excess development resources. In particular, to refine a product, entrepreneurs are looking for personalized help for late-stage product development. Such development help is, however, limited by the attention available from the established firm (because it is personalized to each entrepreneur), thus making those established firms that can devote more attention to the entrepreneur more attractive partners (Hallen et al., 2014). Although prior research on tie formation often focuses on resource stocks of potential partners (i.e. established-firm partner itself), we spotlight prospective peers as the often-ignored, but consequential source of competition, because it directly relates to attention that the established firm has available. In H1 we propose that the more significant

the expected development help (i.e. the larger the share that the focal entrepreneur expects to receive of the excess resources from a particular established-firm partner), the more likely a tie is to form:

Hypothesis 1 (H1). The more development help the entrepreneur anticipates from the established firm, the more likely the tie between the entrepreneur and the established firm.

Market access. Established firms often also regulate access to resources without owning them (Pfeffer & Salancik, 1978). Access to markets is a particularly significant such resource that entrepreneurs need (Katila et al., 2008). In H2 we propose that potential partner's ability to act as a gatekeeper who regulates access to *others'* resources is surprisingly little-understood but significant antecedent of tie formation. Drawing from resource dependence theory, we propose that an entrepreneur who is looking to bring a product to market is motivated to form a tie with an established-firm partner by the promise of getting access to buyers. Established firms typically have such access through their existing marketing or branding efforts (Pahnke et al., 2015). For instance, they can leverage their brand name to influence the allocation of customer attention.

While established firms act as “gatekeepers” by granting market access, this resource is not tailored. That is, unlike development help, it is not personalized to individual needs. As a result, it is scalable across many entrepreneurs (Pfeffer & Salancik, 1978). In H2 we propose that the higher the entrepreneur's expectation to receive market access, the more likely a tie is to form with an established firm.

Hypothesis 2 (H2). The higher the market access that the entrepreneur anticipates from the established firm, the more likely the tie between the entrepreneur and the established firm.

Moderators

While a relationship with both significant development help (H1) and significant market access (H2) is naturally the most attractive, the colloquially named big fish, big pond

tradeoff suggests that it is rarely possible. The intuitive reason is that the partners with significant market access (“big pond”) are also likely to attract more and better peer entrepreneurs. This, in turn, makes it harder to achieve personalized help (“big fish”) in the queue of entrepreneurs seeking the partner’s attention. Given the tradeoff, then, what goes into choosing between the two options? In H3 and H4 we suggest that entrepreneur’s evolving resource needs (H3) and competition-induced resource uncertainty (H4) influence when market access vs. development help weighs more as a driver (i.e. antecedent) of tie formation.

Resource need evolution. In H3 we propose that entrepreneurs weigh one option over the other at tie formation (big fish vs. big pond) depending on their dynamically evolving resource needs. Although many studies treat resource needs as relatively stable, we build on the suggestion that entrepreneurs face categorically different problems at different stages of development (Huang & Knight, 2017; Knight, Greer, & De Jong, 2020; Leatherbee & Katila, 2020), and suggest that entrepreneur’s evolving resource needs thus become an important moderator (Pfeffer & Salancik, 2003: xv). Consistent with the theoretical argument that resource dependence drives relationship formation (Gulati, 1995; Gulati & Gargiulo, 1999), we expect that inexperienced entrepreneurs who are still in the process of establishing their internal production processes would seek to partner with established firms that can grant them personalized help to make their product succeed. For these entrepreneurs, development help is likely an important “internal” resource they require (Katila et al., 2008). These entrepreneurs, we propose, choose to put less weight on external market access because it is likely too early to expand their buyer base, and market access cannot be easily tailored to early needs (Gulati, 1995). “The worst thing that could happen to us right now would be a lot of press. We’re not ready for it,” one entrepreneur told us. “It’s like a new restaurant that has a successful first day but cannot deal with the masses.” Because early exposure to numerous

buyers may jeopardize the end-product's success and dilute the entrepreneur's focus on products, we propose that entrepreneurs who still need internal resources to hone their products are likely to prioritize development help over market access in tie formation decisions to help the product succeed, thus making evolution of entrepreneur's resource needs an important moderator.

Consistent with dynamic resource dependence arguments (Pfeffer & Salancik, 2003), we also argue that over time, entrepreneurs shift from internal to external aims (Eisenhardt & Schoonhoven, 1996; Maurer & Ebers, 2006; Leatherbee & Katila, 2020), and particularly to attracting more buyers. Market access is now more needed and development help is less needed to create the most product value. We propose:

Hypothesis 3 (H3). The more evolved the entrepreneur's resource needs, the more heavily market access (big pond) weighs over development help (big fish) in tie formation decisions between entrepreneurs and established firms.

Resource uncertainty: Competition. In H4 we propose that not only dynamism of organizations but also that of environments (Pfeffer & Salancik, 2003: xv) matters, and so that development help weighs more as a driver of tie formation the more intense the competition that the entrepreneur anticipates in the environment (Katila et al., 2012). When competitive intensity is high, it is particularly important to have a differentiated product. In other words, ability to receive personalized resources from a partner becomes important. In game development or book publishing, for example, intense competition may mean that it becomes attractive to go back to the drawing board to further develop a title with personalized attention of a publisher in order to differentiate from competition. If competition is sparse, needs for tailoring a more differentiated product are lower and getting market access to push the product to market becomes a more attractive partner resource.

We propose that entrepreneurs are likely to be particularly concerned about procuring needed resources for differentiation (Gulati et al., 2012; Alexy et al., 2013) and,

consequently, about their product succeeding, as the competitive intensity in the entrepreneur's markets switches from low to high. Standing out from the pack through personalized development help mitigates uncertainty in competitive environments because it helps the entrepreneur differentiate (Katila et al., 2012). Resources that established firms regulate but do not own (including market access) do not provide opportunities for personalization the same way as development help does.

Hypothesis 4 (H4). The higher the resource uncertainty due to competition, the more heavily development help (big fish) weighs over market access (big pond) in tie formation decisions between entrepreneurs and established firms.

METHOD

Sample. We constructed a comprehensive panel dataset of the population of global firms—367 developers and 170 publishers—that collaborated on games for the PlayStation2 (PS2) console over a 10-year period from 2000 to 2009.³ This was a time period when console rather than PC or mobile device games were dominant. Because self-publishing was not yet an option for PS games, developer-publisher ties were necessary for a developer to commercialize a game. For these collaborations, entrepreneurial game developers brought with them game concepts and initial development while established-firm publishers brought late-stage development and access to markets.

Our complete global population of firms (developers and publishers) that commercialized PS2 games provides robust and representative data. The firms were based predominantly in the three countries that dominate the industry: Japan (31%), the U.S. (29%), and the U.K. (16%). Altogether, our data include 1,416 observed ties between 2000 and 2009. We used dyad-years for analysis (i.e., a developer-publisher matrix of all active firm-years) to include both actual ties and those that could have taken place but did not.

³ When a publisher was also active as a developer (50 firms), we included it only in the sample of publishers because that developer did not make a publisher choice (i.e., always “picked” the in-house publisher).

PS2 is a particularly appropriate setting to test our hypotheses, as the system's cutting-edge technological capabilities made game development for PS2 more challenging than for PC and other previous (and later) consoles. Therefore, the attention that publishers devoted to developers was relevant. As a developer described, "PS2 was very, very difficult [to develop for]... but everyone did it because...you knew that when you put in the time it was going to be awesome." Moreover, ties between developers and publishers were required to commercialize PS2 games. Self-publishing options were available only for the PS3 and later consoles. Finally, PS2's market dominance ensured that it attracted a high number, and a broad cross-section, of developers and publishers. Released in 2000, the PS2 became the best-selling video game console ever.⁴

We used several sources to gather data on developers, publishers, and their tie formation. MobyGames was our primary data source (see Appendix). We triangulated the information obtained from MobyGames with data from Factiva, GiantBomb, IGN, AllGame, Wikipedia, and individual firm websites.⁵ We also used other gaming websites (e.g. "unseen 64") that compiled information on "*cancelled*" games, enabling us to include data on ties that were initially formed but eventually discontinued.⁶ Finally, we examined each firm's website for any information that was still missing. For firms that were no longer active, we used the Internet archive (archive.org). This data collection strategy enabled us to build a comprehensive dataset on the activities of the mostly private developers and publishers in the industry. Such data are notoriously difficult to obtain and are a strength of our study.

Measures

DV: Tie formation. For the outcome variable, we examined whether a developer

⁴ A developer illustrated the difference to us, "Xbox [a rival console] tends to produce first-person shooter games versus PlayStation has...a more varied set...more adventure games, great racing games, and so on."

⁵ GiantBomb, AllGame, and IGN are only partially crowdsourced – i.e. they also employ editors.

⁶ We added data from the "unseen64" database on a subset of PS2 games that were reportedly cancelled after the initial tie was formed. We triangulated these data with our own in-depth research on each "cancelled" case. After extensive data cleaning, 26 ties were added to our data in an alternate test.

(entrepreneur) and a publisher (established firm) formed a tie to collaborate on PS2 game(s) in focal year t . We included all ties to jointly develop a game, including sequels.⁷ We used several methods to determine when the collaboration started. Since our interviews indicated that a collaboration between a developer and a publisher was typically formed within a year of a game's release, we used the game release year as the year of collaboration. For collaborations that were initiated but fundamentally repurposed or subsequently discontinued (as described above), we used the year when this change occurred as provided by the gaming websites. Finally, because developers and publishers collaborate at the game level,⁸ using individual games to measure the relationship was appropriate. We coded the dyad-year tie as a dummy variable that equals 1 if a developer and a publisher formed a tie to develop one or more PS2 games in year t and 0 otherwise (count of ties produced similar results).

Independent variables. We measured the **development help** (H1) that the developer anticipates from the prospective publisher partner by developer's ranking compared to publisher's other developers. To measure ranking, we chose a well-accepted measure: review scores assigned to a developer's games as aggregated by MobyGames. This is a particularly appropriate measure of anticipated attention, as we learned in our interviews that publishers ration their attention based on developers' past game performance. We also learned that it was common practice to use review scores as an indicator of a developer's ability. A game analyst told us, "One of the things we look at a lot is the review score...Bad reviews, it can really burn the reputation of the developer."⁹

⁷ We did not include special editions or extension packages because developers and publishers do not form a new tie for these types of releases. Extension packages are add-ons to an already-released game that add objects, characters, or an extended storyline. Special editions are collector's items such as a re-release of a previous game with bonus materials.

⁸ Typically, each video game has a single developer and a single publisher. In rare cases (fewer than 3%), more than one firm fulfilled the role of either the publisher or the developer. In these cases, we randomly picked one publisher or one developer (Ahuja, 2000) with consistent results.

⁹ It was commonly viewed as the developer's responsibility to create a high-quality game, which is reflected in the review score. We also considered alternate measures such as past game sales. However, both developers and publishers saw sales as an imperfect indicator of a *developer's* potential because of publisher influence on sales.

To compute anticipated development help, we first examined the review scores of our sample developers' games (including their non-PS2 games). To account for different rating systems, we normalized the scores on a scale of 1 to 100 and took an average of all scores received by a developer in the three years prior to year t ($t-1$ provided consistent results).¹⁰ Average updating procedure (Bush & Mosteller, 1955) was used to give more weight to developers who more consistently developed high-quality games, scoring developer's quality $\frac{\text{Average quality score of all games} + \sum_1^n \text{Quality score of games released by focal developer}}{1 + n}$.¹¹ To compute the variable, we then compared the focal developer's scores with those of the other developers in the publisher's portfolio by counting the number of "inferior" developers and dividing it by the total number of developers affiliated with the publisher. If, for example, the publisher was affiliated with five developers and three of those scored lower than the focal developer, the developer's score was 0.6. Thus, the variable is always positive, and a higher score is better. In cases in which there were no other developers, we set the variable to one because the focal developer would be the only developer to join the portfolio and receive the publisher's full attention. We also computed an alternative measure that captured developers' past sales using data from the NPD Group (Zhu & Zhang, 2010), with consistent results.

We measured the **market access** (H2) that a developer anticipates from a publisher by the number of reviews the games released by the publisher received. An expert told us, "When developers assess publishers, they look at the number of reviews a publisher's games have received." This is an appropriate measure for multiple reasons. First, our interviewees noted that it is an industry norm to evaluate a publisher's potential to sell a game in this way, because buyers tend to buy the games that get the most publicity, not necessarily those with

¹⁰ For newly founded developers without any reviews, we followed a common heuristic in the industry and assigned a score corresponding to the average quality achieved by new developers (with no experience) in the prior year. We also estimated the models without assigning scores to new developers, with no qualitative changes to the results.

¹¹ An alternative, i.e., the average quality score of games released by the developer produced consistent results.

the highest quality (Matthews, 2012). Second, third-party magazines are likely to review publishers whose games they have already reviewed in the past (Piezunka, 2015). Third, review data are publicly available. In contrast, other information such as a publisher's past sales is often unavailable, particularly for resource-constrained developers. Further, attracting reviews is often mentioned as one of the main responsibilities of the publisher. One interviewee noted, "It is the publisher's job to get games reviewed. They have the rolodex of journalists." To operationalize **market access**, we counted the average number of reviews (in hundreds) received by a publisher's games in the three years prior to the focal year t (number of reviews divided by number of games published) and took a logarithm to reduce skew (see Appendix). In total, our sample included 148,638 reviews in 1,088 magazines for the games that the publishers had released.

Moderators. We measured resource need evolution (**resource needs** for short) (H3) by developer's product experience. This is an appropriate measure because developers who have launched many games typically have built their own internal resources for late-stage product development (e.g., engineering teams) and have so shifted their resource needs to external ones. Resource needs are measured by the number of games launched by the developer (prior years, including non-PS2 games), with high values indicating high external resource needs. Alternative measures, such as the number of games in the prior three years and developer age (Hoisl, Gruber, & Conti, 2017), produced consistent results.

We measured **competition-induced resource uncertainty** (H4) by the anticipated count of PS2 games that are likely to overlap with games of the focal developer in a year. To compute overlap, we compared the population developers' games with each of the focal developer's games using genre categories. This is an appropriate measure because overlap with a greater number of games creates competition (Katila & Chen, 2008), making differentiation important. To construct the measure, we counted all published games in the

focal developer's genres over the last three years and took an average. We also created two alternative measures by adding "cancelled" games, and weighting them with a factor of 1 and 0.5 (giving a subsequently cancelled game either equal or partial weight, respectively, relative to published games) because they represent competition, but perhaps of an inferior kind, with consistent results.¹² As an additional alternative measure, we constructed a genre relatedness index, and counted as overlapping competition all games in the focal developer's genres plus the related games from other genres using the relatedness index over the last three years and took an average, with consistent results (for details see Appendix).

Control variables

Prior collaboration. Because firms may prefer past collaborators as partners (Gulati & Gargiulo, 1999), we controlled for it. Our measure was a binary variable that equals 1 if a developer and publisher had a prior tie (including non-PS2 ties) and 0 otherwise.

In-house development. A publisher's vertical integration (i.e., its development of its own games) might affect tie formation. In-house experience may inspire ties, as it may indicate publisher capabilities with similar development projects. Or, it may pull away from ties due to the negative influences that may be tied to the "not-invented-here" syndrome (Katz & Allen, 1982).¹³ A publisher's dual roles may also increase the competitive tension perceived by developers (Diestre & Rajagopalan, 2012). An informant noted, "Developers are always cognizant of 'are you [publisher] going to give my game the same love as your internal games? And if somebody likes a cool feature [in our game], will you make that in your game, too?'" We computed a measure of overlap between the developer's games and the publisher's in-house games using the same approach as above to compare genre overlap (0 no

¹² Cancelled games were compiled using the "unseen64" database. We thank the editor for suggesting this test.

¹³ We appreciate a reviewer raising these possible alternative mechanisms.

overlap; 1 complete overlap). We also estimated a version with a value of 1 if the publisher was also a developer and 0 otherwise, with consistent results.

Quality difference. Because ties may be more likely between partners of similar quality, we controlled for quality difference. We computed the quality of developers and publishers using the average review scores of their games over the prior three years and squared the difference. A similar control for **genre difference** produced consistent results.

Geographic distance. We control for geographic distance between a publisher's and a developer's headquarters in thousands of miles using data from the Google Maps API.

Country location. Because collaboration patterns may differ across countries (Owen-Smith & Powell, 2004), we controlled for it. We used a **same-country** variable that records whether the developer and the publisher were based in the same country (coded as 1, and 0 otherwise), as domestic collaborations may be more likely than cross-border ones (De Vaan, Vedres, & Stark, 2015). We also controlled for a developer's geographic location using three unreported dummy variables for U.S., Japan, and U.K. ("other" was the omitted variable).

Established firm size. To distinguish the focal variable personalized development help (H1) from the pure scale of the established firm's operations, we controlled for firm size.¹⁴ Because large publishers have experts in game commercialization that developers often need, we used the average number of employees involved in publisher's commercialization of games in the three years prior to year *t* to control for publisher size.¹⁵

Established firm experience. Publisher's general experience in game development can also be a valuable resource that motivates ties, so we also separated its influence from that of personalized development help (H1). A developer described an experienced publisher as being "Like a machine. You're going to be put through a process that is going to take you

¹⁴ See also matching, reported below, to address other "sorting" types of explanations.

¹⁵ We coded employment relationships from role descriptions in game credits (e.g., Blizzard Marketing Manager in a game where publisher is Blizzard).

and shape you and mold you and push you out at the other end...with a professional-looking product.” Our interviewees also noted that experienced publishers excelled at knowing the “right” amount to invest. One said, “They provide the right amount of time and right amount of resources” and may have learned to anticipate developers’ needs and work styles, thus facilitating tie formation. We measured publisher experience by the number of games a publisher released for any platform in the three years prior to year t. We also used age of the publisher with consistent results. Because established firm size and established firm experience are relatively highly correlated, we ran models including the variables both separately and together, with consistent results.

Established firm portfolio size. To distinguish personalized attention and market access from the sheer size of publisher’s portfolio, we controlled for the yearly count of portfolio developers. Dyadic version of the variable using same-genre developers only produced consistent results.

Entrepreneur size was measured by the number of developer’s employees.

Year fixed effects were added to control for any yearly changes in macroeconomic conditions that may influence tie formation.

Estimation Techniques

We conducted a dyad-level analysis using a yearly developer-by-publisher matrix. The matrix included all developers and all publishers who were at risk of forming a tie. A cell took the value of 1 if a PS2 game tie formed between a developer and a publisher, and 0 otherwise.

We conducted *conditional logit* analyses on split and full samples. Conditional logit is well suited for testing how characteristics of publishers influence developer’s partner choice (Hallen et al., 2014). It provides estimates that are robust to unobserved developer and industry characteristics that are constant across partner choices, thus addressing unobserved

heterogeneity that may influence tie formation (see Appendix). The tradeoff is that we are unable to report variables that are invariant at the developer (e.g., resource needs) or industry (e.g., resource uncertainty) level in a year. We also report *random effects logit* analyses that show all covariates.

In reporting the analyses, we follow the standard by Kapoor and Furr (2015) by first reporting a split sample analysis in which we divide the sample into subgroups based on moderator variables (Lee, Hoetker, & Qualls, 2015). We created subgroups based on the mean value of the focal variables (i.e., resource need, resource uncertainty; robust to median values). It is important to note that statistical inferences for testing H3 and H4 can only be drawn by looking at the relative importance of development help vs. market access across models. Thus, we first compute the ratio of these coefficients in each subsample. We then compare the ratio across the subsamples (e.g., internal vs. external need) and determine whether a coefficient of either variable is significant in one subsample but not in the other (Train, 1998). In this way, we avoid making the (incorrect) assumption that unobserved variation is the same across subgroups. Following the split-sample analyses, we repeat with the full sample.

We confirmed the results with rare events, and Sørensen's (2007) matching analyses. These and other robustness analyses, described below, confirm our original findings.

RESULTS

Qualitative Results: Tie Formation in Video Games

To ground our quantitative analyses, we first conducted interviews in the global video games industry. We interviewed employees on both sides of the relationship—entrepreneurs (developers) and established firms (publishers)—to better understand motives for tie

formation.¹⁶ Our goals were to illustrate why and how ties form between developers and publishers, what agreements are signed, how partners are picked, and what the significant questions are at tie formation. In total, we conducted 30 interviews, all of which featured the following open-ended questions: “What kinds of resources do you expect from your partner? What resources do you offer to your partner? What worries you about working with a [particular] partner? Tell me about a time you had to pick between multiple partners.” Two of the authors also attended game conventions where developers presented ideas for games and met publishers. In the following, we outline the key insights from these interviews. We also discuss additional evidence specific to PS2 in the online appendix.

Resource Needs: Interviews. As in biotech-pharma collaborations, or feature film production or book publishing (Katila & Mang, 2003; Balland, De Vaan, & Boschma, 2013), tie formation in the video game industry is driven by mutual dependence (Piezunka, 2015). We learned in our interviews that developers and publishers form ties when they depend on each other for resources (Pfeffer & Salancik, 1978). In particular, publishers depend on game developers to conceptualize, design, and code video games. Developers are focused on “the vision and the creation of the game.” In turn, developers depend on publishers to co-develop games, suggest improvements, provide financing, and market games to buyers. Thus, the publisher’s role is to “fill in the gaps...technical, artistic, creative support...critique and quality control...brand awareness and marketing.”

The joint value creation of developers and publishers was also emphasized by informants who told us that established-firm publishers “struggle with internal innovation”

¹⁶ Our list of interviewees appears in Table 6. We spoke with a panel of informants directly involved in decisions about relationships, including former and current chief executive officers, other key executives (CFO, COO, VP Business Development), and venture capitalists that funded them. We also included interviews with game designers, artistic directors, producers, and product managers to gain understanding of game development, and to understand the relationships that their companies were involved in. These interviews often took place on-site so that we also interacted with staff beyond the focal interview. We supplemented these interviews by talking with industry consultants, employees of middleware companies, and journalists covering the video game industry.

and often generate “rinse and repeat” projects that offer incremental changes to existing games rather than “try to create something entirely new.” Thus, publishers seek developers with promising, novel content that attracts buyers. At the same time, publishers also seek to employ their excess development resources and market access. In turn, developers seek publishers who can provide the resources needed to fully co-develop products and reach buyers. Finally, typical of entrepreneurial firms, developers in this industry tend to be young and small in size, while publishers are typically established firms, older, and much larger in size. In fact, many publishers started as developers and pivoted to publishing once they gained experience.

We also learned that both developers and publishers focused on choosing a partner that could help them achieve a blockbuster game (Balland et al., 2013). Many in the industry used the analogy of “growing the pie” rather than getting a “bigger slice” to emphasize this point (Gulati & Sytch, 2007). This reasoning also makes particular sense in a hit-driven industry such as video games. An industry expert noted that “the only way to strike it rich is to land a blockbuster.” Another summarized, “Financial conditions hardly move the needle when choosing between [partners],” indicating that financial success is about creating a hit, not getting a bigger share of very little. This is similar to many technology settings, such as biotech or fast-moving consumer products where firms partner along the value chain to co-develop products by capitalizing on each other’s capabilities (Huston & Sakkab, 2006). However, it is very different from, for example, car engines or software, in which value chains are more disintegrated and the tie decisions focus on outsourcing work to lower-cost providers. In these latter settings arbitrating among partners and getting a “bigger slice” from low-power partners are at the forefront.

During our interviews, we also had a chance to examine *contracts* that specify the legal and financial terms of the collaboration. If the exact terms of collaborations could be

specified in detail, contract language would explain the ties that are formed. Our examination of contracts provided by our informants does not support this reasoning. As in any R&D contract, it is impossible to specify the exact nature, amount, and quality of development resources needed in a game project. Access to publisher resources is a good example. It is often described in general terms, permitting room for preferential treatment. For instance, game contracts often fail to specify which individual publishers' employees will work on the game. In the sample contracts we read, the publisher was required to "supply dedicated production staff" including "a senior level producer to oversee development." No other specifics were given. Overall, although contracts described access to resources, the exact nature was not well-specified. This leaves freedom for publishers to prioritize based on rank.

Our interviews also helped us confirm why the *split in value capture* (revenue sharing specified by contracts that is common in other industries) was not the driver of tie formation. For example, an established firm with limited market access could plausibly try to attract a superstar entrepreneur by promising to share more value. However, as noted above, the created value is difficult to project (a one-time superstar entrepreneur may never create a second blockbuster), and standardized contracts are more typical. Consistent with this observation, we learned in our interviews that financial agreements vary little across developer-publisher relationships. Instead, a standard revenue sharing ratio (70/30) is employed. Thus, the developer-publisher contract may vary across consoles (e.g., PS2 vs. Xbox) but does not vary much on a single console, PS2.

Rather than contracts, publisher's available attention mattered to developers. Because the potential value of each developer's game idea was highly uncertain, game publishers formed ties with many developers; but due to cognitive constraints, publishers could not devote equal attention to them all (Piezunka et al., 2018; Thatchenkery & Katila, 2021). Multiple interviewees mentioned that publishers paid more attention to promising developers

in their portfolios while the rest were overlooked – if there were too many to support all. This meant that the relatively strong, not the weak, in the pack were likely to receive more support. One developer told us: “You have to worry about the competitive set that the publisher supports. The publisher may have great capability in your title because they also publish your major competitor. Then you have to ask yourself, is it going to lead them to prioritize your project lower?” Personalized resources of publishers, such as development help, made high ranks in the publisher’s partner portfolio particularly desirable to achieve: “The president of [our publisher] comes to our studio... multiple times. It’s not just a teleconference and it’s not just a phone call. They actually have a physical presence...A lot of eyes and a lot of feedback around everything we make,” said a young game developer. Another interviewee described, “If you’re a marginal project in EA, life is very lonely. You get nothing because you’re pretty much the tenth line item on some overworked central publishing team’s [to-do list].” Another interviewee was more detailed about the preferential treatment: “The type of talent that a publisher will deploy against a project is correlated with the publisher’s assessment of your strategic potential.”

Finally, our informants suggested that games by lower ranked developers often risked being *cancelled* mid-development. Our subsequent quantitative analysis indeed confirmed that if a developer ranked lower than average, it was 26% more likely to have its projects cancelled than its higher-ranked peers, further confirming the association between higher ranks and attention from the publisher as a significant concern at tie formation.

Insert Tables 1–5 about here

Quantitative Results

Table 1 reports descriptive statistics. Overall, the variables show considerable variance, and the correlation matrix indicates low correlations. An exception is the moderately high correlation of established firm experience with portfolio size and with

established firm size, respectively, as well as the correlation between geographic distance and same-country variables. We ran the analyses with and without these variables with consistent results.¹⁷ Per Echambadi, Campbell, and Agarwal (2006), we also randomly estimated subsets of the data by dropping a year at a time from the data. These results (available from the authors) indicate stability of coefficients. Across all analyses, we find that a tie is more likely when developer and publisher are geographically proximate, of similar quality, and prior partners, confirming predictions of prior work (Gulati, 1995).

We first proceeded to empirically verify the *big fish, big pond trade-off* between development help and market access. We used four methods. First, like Amit and Livnat (1988) and Fiegenbaum and Thomas (1986), we observed a simple negative correlation between development help and market access in the data ($r = -0.22$; $p < 0.01$). We then used Aral and Van Alstyne's (2011) test of trade-offs by regressing the two variables on each other. Market access had a negative and significant coefficient predicting development help, and development help had a negative coefficient predicting market access. Third, we used Hwang's (1991) method of clustering residuals of regressions. The cluster centers traced a 45° line with negative slope confirming the presence of a trade-off. Lastly, we generated combined high-high and low-low cases of the two variables using splines per Stern, Dukerich, and Zajac (2014) and found positive and negative coefficients predicting tie formation, respectively, as expected. Altogether, all four tests provide strong confirmation of the big fish, big pond tradeoff. Detailed results are available from the authors.

Tables 2 and 3 report the *conditional logit* and tables 4 and 5 the *random effects logit* split and full-sample analyses, respectively. In H1 and H2 we hypothesized that tie formation

¹⁷ We also computed variance inflation factors (VIF) to detect multicollinearity. All were below the conservative threshold of 5.0. As Belsley (1991) notes, high VIFs are a sufficient but not a necessary indicator for multicollinearity. We thus used other diagnostic tools (condition index, subsample analyses) to detect other signals of collinearity problems but did not find them. Condition indices were below the suggested cut-off of 10.0.

is more likely when a developer anticipates more development help and market access, respectively, from a publisher. Across the models in tables 2-5, we find that development help (e.g. $\beta = 0.96$, $p < 0.01$ in model 4 in table 3) and market access (e.g. $\beta = 2.06$, $p < 0.01$ in model 4 in table 3) are significantly and positively associated with tie formation, thus providing support for hypotheses 1 and 2.

In H3 we hypothesized that when developers gain more experience, market access is weighted more and development help weighted less as a predictor of tie formation. To test the hypothesis on the tradeoff, as described above, we assessed the ratio of coefficients of market access over development help in models 1 vs. 2 in tables 2 and 4 (Kapoor & Furr, 2015). A comparison of the ratios of coefficients across the two entrepreneur groups provides an understanding of the relative importance of these partner characteristics for inexperienced vs. experienced entrepreneurs, respectively. As expected, the ratio of market access to development help increases as resource needs shift: 1.33 for inexperienced vs. 5.08 for experienced entrepreneurs in table 2, indicating that an experienced entrepreneur is willing to give up almost four times as much development help for the availability of market access than an inexperienced entrepreneur would. The preference shift from development help to market access as the developer's needs shift from internal to external thus supports H3. Random effects split sample results in models 1 and 2 in table 4, and full-sample interaction results in models 5 and 7 in tables 3 and 5 are consistent (please refer to the Online Appendix for visualizations of the interaction results).

In H4 we hypothesized that when competition intensifies, development help is preferred at tie formation to differentiate the focal firm. Models 3–4 in table 2 provide tests for H4. The comparison of the ratio of coefficients of market access over development help in models 3 vs. 4 shows a decrease in ratios as expected from 2.46 to 1.77, indicating a shift in preference from market access towards development help as competition intensifies, in other

words, supporting H4. Random effects split sample results in models 3 and 4 in table 4, and full-sample interaction results in models 6 and 7 in tables 3 and 5 are again consistent.

Additional Analyses

Because realized ties were relatively rare, we ran several rare events models. Because potential interdependence among dyads may result in autocorrelation (each developer and each publisher were included multiple times), making standard errors difficult to interpret, we re-ran the analyses with all realized dyad-years and a sample of 5, 7, and 10 unrealized randomly selected dyads, respectively, per each realized dyad (Shipilov, Li, & Greve, 2011). We then re-ran the analyses by selecting unrealized dyads to match each realized dyad as closely as possible in observable characteristics, using propensity score matching, to achieve a higher-quality match as suggested by Rathje and Katila (2021). We also ran the results with the relogit rare events logistic regression function in Stata (Tomz, King, & Zeng, 1999). All results were consistent.

We also used a two-sided *matching model* with Bayesian (MCMC) estimation (Sørensen, 2007) implemented in R (Klein, 2018). Because we hypothesized about the first-stage matching of developers and publishers but needed to make assumptions about the outcomes that matter for both parties in second stage (we use game reviews), this analysis was used as a robustness check only. The first stage confirmed our results. These analyses (and those noted in Methods) yield results that strongly parallel our original findings.

Established-firm viewpoint. It is the entrepreneur who faces the core “big fish, big pond” decision we have discussed. Entering a collaboration requires mutual agreement, however. What drives the established firm’s decision to enter a tie? We first used qualitative data to examine established-firm motivations. For example, when would publishers form ties with inexperienced developers? We found that these relations can help small-pond publishers innovate and expand their reach. For example, the then-obscure publisher of the first Harry

Potter book invested much time in developing the manuscript (e.g., the publisher's CEO read the book draft to his daughter), later reaping benefits from the book's success. An important part of the established firm's value proposition to an inexperienced entrepreneur is thus the amount of personalized resources (e.g., time and attention) that the established firm can offer the entrepreneur.

In contrast, established firms with high market access likely prefer adding experienced entrepreneurs. This allows them to leverage their market access and supply their large customer base with proven products, consistent with the mutual dependence logic (Katila et al., 2008). Market access is a relatively scalable resource – unlike resources that are directly rationed by the established firm – and is difficult to deny after a partnership has formed (Ter Wal, Alexy, Block, & Sandner, 2016). Thus, established firms with significant market access are unlikely to want to collaborate with inexperienced entrepreneurs, because such collaborations might result in obligations to market high-uncertainty products that may violate quality standards of the established firms' customer base. Similarly, established firms in crowded segments are more likely to form another tie if they have the bandwidth to devote attention to the entrepreneur and thus jointly create more value (Gulati, 1995). For the established firm, from the resource procurement perspective, adding an entrepreneur who is weaker than the other partners is inefficient. The reason is that the potential new tie fails to address any new resource dependencies (Pfeffer & Salancik, 2003), instead presenting redundancies in handling the uncertainties in the established firm's environment.¹⁸ Thus, when an established firm considers adding an entrepreneur, it is likely to prefer adding only those with the most value-creating potential (Penrose, 1959:77; Gulati et al., 2012).

After the qualitative analysis, we examined established-firm motivations

¹⁸ An opposite reasoning would be that it is more (rather than less) efficient for publishers to collaborate with similar developers. Alexy et al. (2013) address this exact question by noting, "Regarding collaboration by competitors of similar resource endowment in consortia, ... efficiency gains from such endeavors may well be eaten up in subsequent market competition," an argument that underlies our H4.

quantitatively. These analyses again provide confirmation for aligned preferences and contradict tie formation as a one-sided decision driven only by the (powerful) publishers.

First, we relaxed the “*preferential treatment*” assumption that underlies rationing development help in rank order. That is, we restricted our analysis to the risk set of publishers that had high levels of resources (the second-highest game-expert personnel quartile). In this quartile, publishers can provide personalized resources to all developers they partner with, but this resource availability is not obvious to prospective developer-partners. If development help were simply a publisher-driven decision variable (with no developer influence), we should see it become insignificant in this quartile. It does not.

To further examine power considerations, we controlled for developer-publisher *power imbalance* and *mutual dependence* using measures from Casciaro and Piskorski (2005).¹⁹ Our original findings were consistently supported (results available from the authors). We also switched directionality and ran a conditional logit analysis by holding publisher characteristics constant (i.e., treating publisher as the one choosing among developers).²⁰ Although we cannot test the main effects of market access in this way, our findings on development help are strongly supported, providing added confidence in our results. Altogether, our empirical data confirm that established firm preferences are consistent with those of the entrepreneur.

DISCUSSION

Entrepreneurs often need to form partnerships to get the resources they need. Highlighting the multifaceted and dynamic nature of resource dependence, we examine tie formation between entrepreneurs and established firms—in this case, developers and publishers of PS2 games. In particular, we explore nuances of the “big fish, big pond” tradeoff at tie formation that occurs

¹⁹ Detailed measures and PS2-specific calculations are provided in the Appendix.

²⁰ Although the big fish, big pond dilemma is typically formulated from the entrepreneur’s perspective, we thank a reviewer for suggesting this test to examine publisher vs developer side decisions.

across a wide range of technology-based industries, and draw attention to the neglected role of dynamically changing (1) resource needs of organizations and (2) resource uncertainties of environments in this choice. How do these two factors affect entrepreneurs' relative weighting of anticipated development help (big fish) and anticipated market access (big pond) in tie formation?

Key Contributions

Resource Dependence. Our focus on unraveling the big fish, big pond dilemma critically extends the resource dependence theory by showing how prospective peers are at the core of big fish tie formation: if prospective peers and preference ordering did not matter, partnering choice would simply become one of finding the biggest pond. It does not. We contribute by providing empirical evidence that both big pond (market access) *and* big fish (development help) resources are part of the decision calculus at tie formation—the critical time period when entrepreneurs seek to determine what partner they want, rather than later when they may be stuck with the one they have chosen. Although prior research spotlights how peers can influence the resources a partner gains *after* a tie has formed (Ozmel & Guler, 2015; Pahnke et al., 2015; Aggarwal, 2020), this research has neglected how peers affect ex-ante selection of partners. Unpacking and empirically confirming the colloquially known big fish vs. big pond trade-off spotlights the neglected but significant role of prospective peers at tie formation.

Another key contribution is to draw attention to the excessively static conception of resource dependence identified by Pfeffer and Salancik (2003) and many recent authors (Hillman et al., 2009; Wry et al., 2013; Hallen et al., 2014) in existing scholarship. Resource dependence in an organization changes over time, and for particular reasons. We suggested that to fully understand how organizations navigate resource dependence, we needed to uncover the dynamic aspects about organizations (resource needs) and about environments

(resource uncertainty) to shed light on the big fish vs. big pond partner choice. Our pattern of findings is consistent with this dynamic view.

Our results on entrepreneur's choice of established firm partners provide strong support of resource dependence as fundamentally dynamic. Notably, we find that as entrepreneurs gain experience, their preferences shift from a big fish to a big pond partner to satisfy changing resource needs. Illustrating this shift in focus from personalized development help to market access, a video game investor we interviewed explained: “[If you're an experienced developer], you are already amazing at game design. You are looking for someone to help you be successful at the highest level. First and foremost, then, you stack potential publisher candidates by simple marketing muscle.” In parallel, as competition in the entrepreneur's environment intensifies, we find that partner preferences shift from a big pond to a big fish partner to support differentiation of the entrepreneur.

Some recent work questions the relevance of the resource dependence perspective altogether (Villanueva, Van de Ven, & Sapienza, 2012). Our key finding is that, although resource misappropriation may not be a consideration, other types of dependencies, and particularly peer competition, do matter. Therefore, this study should help serve to reinvigorate resource dependence as a relevant theoretical perspective.

Tie formation. Generally, research assumes that actors choose the partner with the “best” resources. We show that actors also take into account (1) mutual resource dependencies that yield high-value products, and (2) the perceived likelihood that the desired resources will actually be available once the relationship is formed. Both represent situations in which the partner with the “best” resources may not always be the most sought-after. Thus, we contribute to an emerging literature illustrating why actors may forgo forming ties with the partner with the best resources (c.f., Ahuja, 2000; Katila & Mang, 2003; Katila et al., 2008; Alexy et al., 2013).

We also contribute to tie formation literature by unpacking and confirming the existence of the choice between big fish and big pond partners at tie formation. Prior research typically examines the two sides of the big fish, big pond dilemma separately and focuses on the consequences of choices, not on antecedents. We contribute by examining how actors steer tie formation before it occurs by weighing anticipated development help (big fish) and anticipated market access (big pond).

Our study also illustrates how firms can successfully attract partners even when they lack resources (Katila et al., 2017). We show that established firms may compensate for a lack of market access by providing development resources such as personalized attention. Similarly, we show how entrepreneurs may overcome a lack of experience via their relative potential vis-à-vis peers. This, in turn, may catalyze tie formation for younger, resource-constrained entrepreneurs that may otherwise be disadvantaged and eventually, as Pollock and Gulati (2007) noted, “Help young companies stand out from the crowd and [...] turn early predictions of success into self-fulfilling prophecies.”

One specific contribution is to illuminate the boundary conditions to entrepreneurs seeking personalized development help. These boundary conditions suggest which resource dependencies are the most central for the focal partner, and as a consequence alter with whom ties are likely to form. We find that when the entrepreneur is early stage and needs personalized help, or competition intensity and the underlying need for differentiation is high, ties are more likely to form with partners in whose portfolio the focal entrepreneur would be expected to be a big fish relative to peers (thus getting the entrepreneur more development help with the product). In contrast, when internal resources are no longer the main ones needed or competitive intensity is low, tie formation leans toward market access – being part of a big pond – over development help. Altogether, strategically constrained entrepreneurs, we find, prioritize “big fish” over “big pond” ties.

Our findings also have intriguing implications when an established firm is a *digital platform*. Instead of just providing a passive “infrastructure” to connect sellers with buyers, some platforms may choose to become more active in helping sellers succeed. For example, platforms may choose to provide personalized development help, thus becoming more attractive to early-stage sellers and to those who face intense competition in their niche. This strategy may be particularly attractive for small, up-and-coming platforms that can thus differentiate themselves from the more rigid approach of bigger platforms (c.f., Rathje & Katila, 2021; Thatchenkery and Katila, 2020).

As in all research, there exist potential alternative explanations. One is that dependence *asymmetry* (i.e., power imbalance), not mutual dependence, drives tie formation. Indeed, this is the case in settings such as car engines or software, where tie decisions focus on outsourcing work to lower-cost providers. Settings like biotech and gaming (i.e. markets of know-how) are qualitatively different, however, and our study provides quantitative evidence from a technology-driven setting to illustrate the difference. If power asymmetry were the underlying mechanism at work, we would expect the hypotheses (esp. H1) not to be supported; publishers would seek to form relationships with developers who have low (rather than high) rank relative to peers in the expectation that they can extract more effort from them. Or, perhaps rank would not matter at all for tie formation. This is not the case in our setting. The additional power imbalance calculations, two-sided matching analyses, and conditional logit analyses (developer vs. publisher) that we have discussed above do not support these alternative explanations either. Rather, they provide confirmation for mutual dependence, as we have argued.

Another question is whether some particularly superior prospective peers (i.e. stars) truly have a deterring effect, given positive “*halo*” effects of peers seen in prior work (e.g., Sine, Shane, & Di Gregorio, 2003). If peer competition matters for tie formation, as we have

argued, star entrepreneurs that have signed with the same established firm should be seen as a threat that dilutes resources and attention, leaving less for the other entrepreneurs, thus deterring future ties. However, if the contrasting assumption holds, star entrepreneurs should have a halo effect that enhances the competence of their peers and acts as an inducement for tie formation, thereby contradicting our explanation. Additional analyses of our data showed that star peers²¹ *deterred* prospective developers at tie formation, thus confirming our expectation that publisher attention and the threat for a resource loss go hand in hand.

Finally, we also examined the established firms' motivations as an alternative explanation, as noted above. We argued theoretically, and showed empirically that established firms with little market access ("small ponds") create value in their relationships by focusing on those entrepreneurs to whom the established firms' resources can make the biggest difference. These relations can then help the established firm innovate and expand its reach. An important part of the established firm's value proposition to an inexperienced entrepreneur is then the amount of personalized resources (e.g., time and attention) that the established firm can offer the entrepreneur. Altogether, both the empirical results and the theoretical arguments suggest that established firm decisions are consistent with our hypothesized arguments. To answer Huang and Knight's (2017) question who is the "protagonist" in the story, our results suggest that the two of them co-star to jointly create value; not only the entrepreneur, or the established firm alone.

Future Directions

Our work is subject to boundary conditions providing opportunities for future work. One is the scalability of the established firm's resources. The "big fish, big pond" dilemma is induced when some of the resources that entrepreneurs need do not scale well with the

²¹ We measured superstars in a publisher's portfolio by game awards (awards received by any prospective peer in the publisher's portfolio; awards received by superior peers, with consistent results).

number of peers. With limited scalability, it is difficult for established firms to expand and accommodate many entrepreneurs. This is frequently true in “markets of know-how” where established firms provide resources in the form of personalized interactions with specialized experts. In contrast, when all needed resources are scalable (e.g. a typical platform context; Zhu & Liu, 2018), the big fish, big pond dilemma is less acute. In effect, all entrepreneurs can be big fish, and the choice becomes simply a matter of picking the biggest pond.

A second boundary condition is heterogeneity of established firms. We assume in our hypotheses that there is variation in market access across established firms, with at least some established firms having limited market access (that aim for diversification or growth) to partner with less-experienced entrepreneurs. In contrast, in settings where established firms are homogeneous (or few) (c.f., Zhu & Liu, 2018), inexperienced entrepreneurs will be unlikely to form ties and therefore may become under-represented.

Another boundary condition is the unpredictability of breakthrough ideas that is typical of “markets of know-how.” In contexts where forecasting which product becomes a breakthrough success is largely impossible, even inexperienced entrepreneurs have a chance to succeed. In such contexts, traditional ways to reduce uncertainty (e.g., repeat ties) become less important and new ways (e.g., personalized mentoring of new entrepreneurs) more important. Empirical data from many technology settings provide confirmation of these patterns. As a consequence, the “big fish, big pond” dilemma becomes a central issue when novice entrepreneurs are a significant source of ideas.

We observe several opportunities for future research. One is ecosystem scholarship (Baldwin, 2012; Dattée, Alexy, & Autio, 2017) that may benefit from our framework of “big fish, big pond”. For example, this framework may be used to inform ongoing debates about the types of platforms that attract complementors (Tavalaei & Cennamo, 2020), the types of funding partners that are desirable for startups (Katila et al., 2008), and the types of support

that buyers may offer to attract the most attractive acquisition targets (Graebner & Eisenhardt, 2004). A related open question is whether established firms develop “reputations” regarding their desirability as partners. We are hopeful that scholars active in these debates will further test our framework to clarify the boundaries of our theoretical arguments.

Another is to study the effectiveness of relationships that are formed. Our preliminary analyses using two-sided matching (Sørensen, 2007) show that while our predictions of tie formation are confirmed, the outcomes of ties (reviews received by games) are driven mainly by developer and publisher experience. Although inexperienced developers have a chance to enter ties as we have discussed, the actual success of the partnership still heavily depends on experience, perhaps because experienced entrepreneurs are better able to navigate the relationship once it has formed. The role of experience in the outcomes of these partnerships is therefore a useful avenue for future research. Another opportunity is to explore the implications of our work for the evolution of alliance portfolios and industry networks (c.f., Kumar & Zaheer, 2019; Thatchenkery & Katila, 2020). We study the mutual decisions of many individual actors to form ties. These decisions ultimately accumulate to shape the evolution of alliance portfolios and industry networks. Studying how ties between established firms and entrepreneurs drive a continual reshaping of portfolios and industry networks offers exciting future directions.

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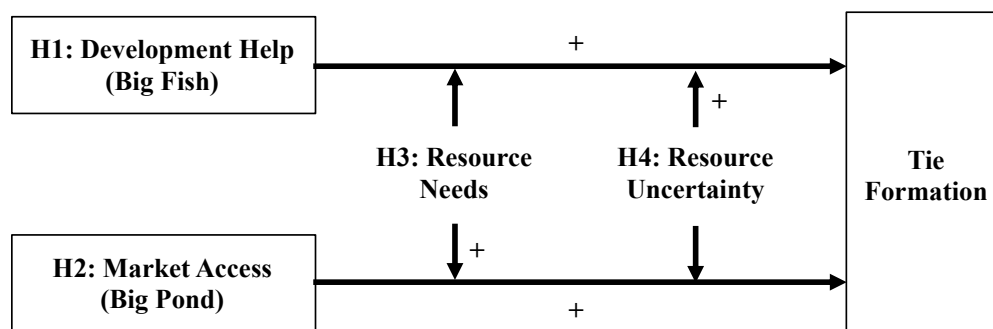
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FIGURES

Figure 1. Hypothesis overview.



TABLES

Table 1. Descriptive Statistics and Correlations

Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Tie formation	0.01	0.10													
2 Development help	0.79	0.37	-0.01												
3 Market access	0.09	0.08	0.05	-0.22											
4 Resource needs	12.51	26.77	0.004	0.03	0.005										
5 Resource uncertainty	52.15	34.29	0.002	-0.10	0.14	0.005									
6 Prior collaboration	0.02	0.14	0.24	-0.05	0.10	0.05	0.02								
7 In-house development	0.10	0.25	0.06	-0.18	0.12	-0.001	0.19	0.08							
8 Quality difference	0.004	0.01	-0.003	-0.07	0.06	0.08	0.07	0.01	-0.001						
9 Geographic distance	6.51	4.08	-0.06	-0.004	0.01	-0.01	-0.01	-0.05	-0.03	0.01					
10 Same country	0.23	0.42	0.06	-0.002	0.01	0.01	0.0001	0.06	0.04	0.002	-0.74				
11 Entrepreneur size	3.39	0.71	0.01	0.03	0.06	0.47	0.09	0.04	0.002	0.08	0.01	0.02			
12 Established firm portfolio size	1.48	2.93	0.11	-0.29	0.33	-0.003	0.10	0.15	0.34	0.09	-0.001	0.04	0.02		
13 Established firm experience	13.76	22.07	0.11	-0.22	0.31	-0.003	-0.001	0.18	0.35	0.03	-0.001	0.03	0.003	0.75	
14 Established firm size	3.55	1.11	0.06	-0.17	0.28	0.001	0.04	0.11	0.21	-0.004	0.01	0.03	0.02	0.40	0.53

N = 74,628 dyads; correlations larger than 0.007 or smaller than -0.005 are significant at a level of $p < 0.05$.

Table 2. Conditional Logit Analysis of Entrepreneur-Established Firm Tie formation (Split Sample)

	Model 1	Model 2	Model 3	Model 4
DV: Tie formation	Internal resource needs	External resource needs	Low resource uncertainty	High resource uncertainty
Independent variables				
Development help	1.01*** (0.14)	0.84*** (0.23)	0.79*** (0.16)	1.22*** (0.17)
Market access	1.34** (0.56)	4.27*** (0.89)	1.94*** (0.71)	2.16*** (0.62)
Controls				
Prior collaboration	2.91*** (0.14)	2.59*** (0.22)	3.05*** (0.15)	2.50*** (0.19)
In-house development	0.63*** (0.16)	0.79*** (0.29)	0.88*** (0.21)	0.67*** (0.18)
Quality difference	-6.72 (6.16)	-12.02 (7.58)	-13.83** (6.22)	-3.28 (5.94)
Geographic distance	-0.06*** (0.02)	-0.03 (0.03)	-0.03* (0.02)	-0.08*** (0.02)
Same country	0.84*** (0.18)	0.78** (0.32)	0.77*** (0.21)	0.80*** (0.23)
Established firm portfolio size	0.08*** (0.01)	0.04 (0.03)	0.05*** (0.02)	0.11*** (0.02)
Established firm experience	0.01*** (0.002)	0.02*** (0.01)	0.02*** (0.003)	0.002 (0.004)
Established firm size	-0.03 (0.05)	-0.18** (0.09)	-0.14** (0.05)	0.01 (0.07)
Observations	57092	16627	44873	28846
pseudo R2	0.22	0.27	0.25	0.22
Log likelihood	-2141.93	-637.02	-1628.55	-1138.73

Standard errors are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; two-tailed tests for all variables. Comparisons across split models are conducted using ratios of coefficients per Train (1998).

Table 3. Conditional Logit Analysis of Entrepreneur-Established Firm Tie formation (Full Sample)

DV: Tie formation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Independent variables							
Development help		0.88*** (0.12)		0.96*** (0.12)	0.90*** (0.13)	0.42** (0.20)	0.36* (0.21)
Market access			1.53*** (0.48)	2.06*** (0.47)	1.49*** (0.52)	1.83** (0.88)	1.28 (0.89)
Development help x Resource needs					0.01 (0.01)		0.01 (0.004)
Market Access x Resource needs					0.04*** (0.02)		0.04*** (0.02)
Development help x Resource uncertainty						0.01*** (0.003)	0.01*** (0.003)
Market access x Resource uncertainty						0.004 (0.01)	0.003 (0.01)
Controls							
Prior collaboration	2.84*** (0.12)	2.85*** (0.12)	2.82*** (0.12)	2.82*** (0.12)	2.81*** (0.12)	2.82*** (0.12)	2.81*** (0.12)
In-house development	0.53*** (0.14)	0.67*** (0.14)	0.51*** (0.14)	0.66*** (0.14)	0.66*** (0.14)	0.71*** (0.14)	0.71*** (0.14)
Quality difference	-9.17* (4.95)	-7.60* (4.57)	-9.99* (5.40)	-8.18 (5.05)	-7.90 (5.05)	-8.11 (4.99)	-7.83 (4.99)
Geographic distance	-0.05*** (0.02)	-0.05*** (0.02)	-0.05*** (0.02)	-0.05*** (0.02)	-0.05*** (0.02)	-0.05*** (0.02)	-0.05*** (0.02)
Same country	0.79*** (0.16)	0.83*** (0.16)	0.77*** (0.16)	0.80*** (0.16)	0.81*** (0.16)	0.81*** (0.16)	0.81*** (0.16)
Established firm portfolio size	0.06*** (0.01)	0.07*** (0.01)	0.06*** (0.01)	0.07*** (0.01)	0.07*** (0.01)	0.08*** (0.01)	0.08*** (0.01)
Established firm experience	0.01*** (0.002)	0.01*** (0.002)	0.01*** (0.002)	0.01*** (0.002)	0.01*** (0.002)	0.01*** (0.002)	0.01*** (0.002)
Established firm size	-0.03 (0.04)	-0.03 (0.04)	-0.05 (0.04)	-0.06 (0.04)	-0.06 (0.04)	-0.06 (0.04)	-0.07 (0.04)
pseudo R^2	0.22	0.23	0.22	0.23	0.23	0.23	0.23
Log likelihood	-2815.71	-2795.58	-2810.85	-2787.06	-2783.34	-2783.45	-2779.77

Standard errors are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; two-tailed tests for all variables. Models are based on a sample of 73,719 dyads, with tie formation occurring in 795 dyads.

Table 4. Random-Effects Logit Analysis of Entrepreneur-Established Firm Tie formation (Split Sample)

	Model 1	Model 2	Model 3	Model 4
DV: Tie formation	Internal resource needs	External resource needs	Low resource uncertainty	High resource uncertainty
Independent variables				
Development help	0.91 ^{***} (0.15)	0.76 ^{***} (0.23)	0.74 ^{***} (0.17)	1.09 ^{***} (0.18)
Market access	1.77 ^{**} (0.70)	4.35 ^{***} (1.00)	2.13 ^{**} (0.89)	2.19 ^{***} (0.71)
Resource needs			-0.003 (0.004)	-0.003 (0.003)
Resource uncertainty	-0.003 [*] (0.002)	-0.004 (0.003)		
Controls				
Prior collaboration	2.33 ^{***} (0.23)	2.10 ^{***} (0.32)	2.90 ^{***} (0.23)	2.35 ^{***} (0.22)
In-house development	0.64 ^{***} (0.18)	0.89 ^{***} (0.33)	0.97 ^{***} (0.22)	0.49 ^{**} (0.19)
Quality difference	-4.12 (4.68)	-8.85 (7.44)	-9.04 (5.98)	-1.98 (5.02)
Geographic distance	-0.08 ^{***} (0.02)	-0.05 (0.04)	-0.05 ^{**} (0.02)	-0.08 ^{***} (0.03)
Same country	1.10 ^{***} (0.22)	0.81 ^{**} (0.38)	1.08 ^{***} (0.25)	0.89 ^{***} (0.26)
Entrepreneur size	-0.01 (0.11)	-0.06 (0.09)	-0.04 (0.10)	-0.02 (0.10)
Established firm portfolio size	0.07 ^{***} (0.02)	0.04 (0.03)	0.01 (0.02)	0.12 ^{***} (0.02)
Established firm experience	0.02 ^{***} (0.003)	0.02 ^{***} (0.01)	0.03 ^{***} (0.004)	0.01 (0.004)
Established firm size	-0.01 (0.06)	-0.10 (0.10)	-0.07 (0.07)	0.02 (0.07)
Observations	57742	16886	45338	29290
Log likelihood	-2651.43	-783.85	-2014.16	-1435.45

Standard errors are in parentheses * p < 0.10, ** p < 0.05, *** p < 0.01; two-tailed tests for all variables. Robust standard errors and random effects are used. All models include unreported entrepreneur geographic location effects. Comparisons across split models are conducted using ratios of coefficients per Train (1998).

Table 5. Random Effects Logit Analysis of Entrepreneur-Established Firm Tie formation (Full Sample)

DV: Tie formation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Independent variables							
Development help		0.80*** (0.12)		0.88*** (0.13)	0.79*** (0.14)	0.43** (0.18)	0.36* (0.19)
Market access			1.97** (0.82)	2.48*** (0.88)	1.87* (0.97)	2.33** (1.12)	1.78 (1.15)
Resource needs	-0.002 (0.002)	-0.003 (0.002)	-0.003 (0.003)	-0.003 (0.003)	-0.02** (0.01)	-0.003 (0.002)	-0.02** (0.01)
Resource uncertainty	-0.002 (0.002)	-0.003* (0.001)	-0.002 (0.002)	-0.003* (0.001)	-0.003* (0.001)	-0.01** (0.004)	-0.01** (0.004)
Moderators							
Development help x Resource needs					0.01 (0.01)		0.01 (0.01)
Market Access x Resource needs					0.05*** (0.02)		0.05*** (0.02)
Development help x Resource uncertainty						0.01*** (0.003)	0.01*** (0.003)
Market access x Resource uncertainty						0.002 (0.02)	0.001 (0.01)
Controls							
Prior collaboration	2.20*** (0.19)	2.24*** (0.18)	2.16*** (0.19)	2.19*** (0.18)	2.20*** (0.19)	2.20*** (0.18)	2.21*** (0.19)
In-house development	0.59*** (0.17)	0.70*** (0.17)	0.57*** (0.17)	0.69*** (0.18)	0.69*** (0.17)	0.72*** (0.18)	0.72*** (0.18)
Quality difference	-7.31 (5.14)	-5.05 (4.38)	-7.49 (5.59)	-4.77 (4.78)	-4.41 (4.76)	-4.78 (4.68)	-4.44 (4.65)
Geographic distance	-0.07*** (0.03)	-0.07*** (0.03)	-0.08*** (0.03)	-0.07*** (0.03)	-0.07*** (0.03)	-0.07*** (0.03)	-0.07*** (0.03)
Same country	0.99*** (0.28)	1.03*** (0.29)	0.98*** (0.29)	1.02*** (0.29)	1.02*** (0.29)	1.02*** (0.29)	1.02*** (0.29)
Entrepreneur size	0.004 (0.05)	-0.02 (0.05)	0.004 (0.05)	-0.02 (0.05)	0.003 (0.05)	-0.02 (0.05)	-0.002 (0.05)
Established firm portfolio size	0.06** (0.03)	0.07*** (0.03)	0.05** (0.03)	0.07** (0.03)	0.07** (0.03)	0.07*** (0.02)	0.07*** (0.02)
Established firm experience	0.02*** (0.01)	0.02*** (0.01)	0.02*** (0.004)	0.02*** (0.004)	0.02*** (0.004)	0.02*** (0.004)	0.02*** (0.004)
Established firm size	0.01 (0.07)	0.01 (0.07)	-0.01 (0.07)	-0.02 (0.07)	-0.02 (0.07)	-0.02 (0.08)	-0.02 (0.08)
Log likelihood	-3457.47	-3441.50	-3452.35	-3433.65	-3429.50	-3431.40	-3427.35

Standard errors are in parentheses and two-way clustered on the level of the entrepreneur and the established firm. * p < 0.10, ** p < 0.05, *** p < 0.01; two-tailed tests for all variables. Models are based on a sample of 74,628 dyads, with tie formation occurring in 795 dyads. All models include unreported entrepreneur geographic location and year effects.

Table 6. Interview Overview¹

Industry Participant Type	Role of Interviewee	Industry Experience (in years)	Geographical Location	No of Interviews	Length of Interview	Interview Recorded & Transcribed
Game Publisher	Executive Producer	15	Oceania	1	1h 06 min	Yes
	Chief Financial Officer	2	Europe	1	39 min	Yes
	Chief Project and Risk Officer	2	Oceania	1	37 min	Yes
Game Publisher-Developer	Sourcing	6	North America	1	20 min	
	Marketing Manager	1	North America	2	54 min; 29 min	Yes
	Co-founder / President / Senior Programmer	25	North America	1	1h 1 min	Yes
	Intern	1	North America	1	56 min	Yes
	Associate Producer	13	North America	1	46 min	Yes
	Executive Development	1	North America	1	44 min	Yes
	Executive Vice President Digital	N/A	North America	1	30 min	Yes
	VP Chief Creative Director	31	North America	1	28 min	Yes
	Senior Director of Corporate Development	9	North America	1	30 min	Yes
	Chief Operating Officer	3	Europe	1	30 min	Yes
Game Developer	Chief Operating Officer	8	Europe	4	2h; 1h 20 min; 1h 15 min; 1h	Yes
	Senior Software Engineer in R&D Group	N/A	North America	1	2h 39 min	Yes
	General Manager	1	North America	1	1h	
	Founder-CEO	3	Europe	1	1h	
	Founder-CEO	6	North America	1	1h	
	Program Manager	4	Europe	1	1 hour	Yes
	Founder-CEO	13	North America	1	49 min	Yes
	General Manager	16	North America	1	44 min	Yes
	Business Development Manager	2	North America	1	42 min	Yes
	Lead Game Designer	26	Europe	1	42 min	Yes
	Program Manager	10	North America	1	40 min	Yes
	Founder-CEO	3	North America	1	30 min	
	Chief Financial Officer	3	Asia	1	28 min	Yes
	Artistic Director	16	North America	1	24 min	Yes
	Founder-CEO	18	North America	1	23 min	Yes
	Senior Content Editor	4	North America	1	12 min	Yes
	Game Engine Developer	Product Director	N/A	North America	1	24 min
VP Business Development		21	North America	3	1h; 1h; 1h 25 min	Yes
Industry Expert	Blogger	10	North America	1	30 min	
	Researcher	10	Europe	2	25 min; 45 min	
	Managing Director, Venture Capital	N/A	North America	1	58 min	Yes
	Journalist / Game Reviewer	5	Europe	1	45 min	
	Partner Manager, Game Conference Organizer	8	North America	1	30 min	
	Journalist / Game Reviewer	5	North America	1	30 min	
	Director Insights, Industry Research Firm	7	North America	1	29 min	Yes

¹ Only interviews that were conducted in the video games industry are listed in this table.

APPENDIX.

Power imbalance. We define *dependence* by multiplying *resource criticality* with *lack of alternative providers* for the resource. *Resource criticality* is high if industry *i* (e.g., developer) procures a significant proportion of goods from industry *j* (e.g., publisher) to commercialize products; we use the proportion of firms in industry *i* that work with partners from industry *j* to commercialize games. *Lack of alternative providers* for industry *i* is calculated by four-firm concentration ratio in industry *j* based on game reviews (Casciaro & Piskorski, 2005: 184–185). *Power imbalance* is the difference between publisher and developer dependence.

PlayStation2 developers and publishers. Consistent with our theory, PS2 as a setting substantiates the focus on mutual dependence. Our analyses that examined market concentration ratios in the setting revealed relatively small power imbalances between developers and publishers. Drawing on McEvily, Zaheer, and Kamal (2017), we found that power imbalance of PS2 publishers and developers was relatively low in the beginning (0.17 with slight publisher tilt in 2002) and decreased significantly and linearly to balanced (0.03 in 2008). One interviewee confirmed, “I wouldn't say that developers have all the

power... While there is not a huge number of good, quality, dependable, solid content developers, there's still many of them ... But at the same time, there's a lot of different publishers and there's a lot of people trying to get into the space and own audiences. Publishers... don't have all the power either. It's more of a balancing act." Altogether, the evidence strongly suggested that resource needs of both parties were germane at tie formation.

As a context, PS2 also motivated our theoretical focus on prospective peers as a concern at tie formation. While peer-to-peer learning effects are often the focus of theorists, in PS2, there was often minimal contact among peers which allowed us to isolate prospective peers' attention grab, if any, from learning. PS2 developers who worked with the same publisher were also physically separated, and there were no efforts to build community as "everybody is worried about meeting their own deadlines." Further, the relationships were relatively short-term (game, not firm) which made peer learning difficult. Overall, this field evidence pointed to an important theoretical mechanism at tie formation due to prospective peers that is not commonly studied.

MobyGames. The crowd-sourced MobyGames database has been found to provide the most exhaustive repository of the global game industry data (De Vaan et al., 2015; Mollick, 2012). To ensure accuracy, MobyGames entries are moderator-verified before they are accepted into the database and peer-reviewed. MobyGames also aggregates reviews, covering a comprehensive set of sources from offline magazines to online game review sites. The source data for calculating anticipated development help for our sample firms included 1,088 different sources. During the time period that we study, the video games industry was not yet influenced by social media. For the PS2, in particular, market access is thus not influenced by the online community to the extent that it is today, providing further confirmation for MobyGames and the game reviews as a robust source.

Market access. We tested alternative measures for market access – i.e., *publisher rank* (publisher's rank relative to other publishers using published games), a four-item score of *publisher quality* using Metacritic's criteria (Metacritic started issuing rankings of top publishers only after our study period had ended so we constructed the data from scratch), *publisher's game sales* (domestic, international), and the number of magazines reviewing a publisher's games, with different time lags and different (or no) logarithms. Results were consistent (available from the authors). While these data provide alternative measures of market access, our informants advised us to use the number of reviews as a measure because the data used for the other measures were not easily available to the private developer firms whose choices we study.

Genre relatedness. To construct a measure of overlap that accounts for relatedness across genres, as a robustness test, we built on our experts' observation that some game genres are more related than others. To capture this relatedness we created a normalized co-occurrence matrix using all games in the sample and coded co-occurrences where a game categorized in one genre was also categorized in another genre (Stuart, 1998).²² If the games

²² For example, 31% of the games associated either with the action or adventure genre were associated with both genres. Their co-occurrence is thus 0.31. If two games are associated with the same genre(s), co-occurrence is one.

belonged to different genres, we used the co-occurrence value from the matrix as a weight (values ranged from 0–1 with higher values indicating higher overlap). In the case where one or both games being compared were associated with multiple genres, we summed the co-occurrence value of each genre combination across the two games and averaged them.

ONLINE APPENDIX.

Conditional logit. Conditional logit model estimates the probability that entrepreneur i chooses to form a tie with an established firm j among n available choices. The argument is that the entrepreneur chooses the partner that offers the highest level of utility (U), that is, maximizes $U_{ij} = \beta'X_{ij} + \epsilon_{ij}$ where β is the vector of coefficients to be estimated that influence the choice and ϵ_{ij} is an error term that reflects unobserved heterogeneity in entrepreneur's decision making. The conditional logit model estimates the probability that entrepreneur i chooses established firm j : $\text{Prob}(Y_i = j) = \frac{\exp(\beta'X_{ij})}{\sum_{j=1}^n \exp(\beta'X_{ij})}$. Variables that do not vary across established firm alternatives (e.g., entrepreneur and industry-level covariates) cancel out. Thus, they do not appear in conditional logit tables as covariates.

Conditional logit has been widely used to test predictions about decision-making across multiple alternatives such as a firm's choice of a supplier (Hoetker, 2005), technology alternative (Kapoor & Furr, 2015), and investor (Hallen, Katila, & Rosenberger, 2014).

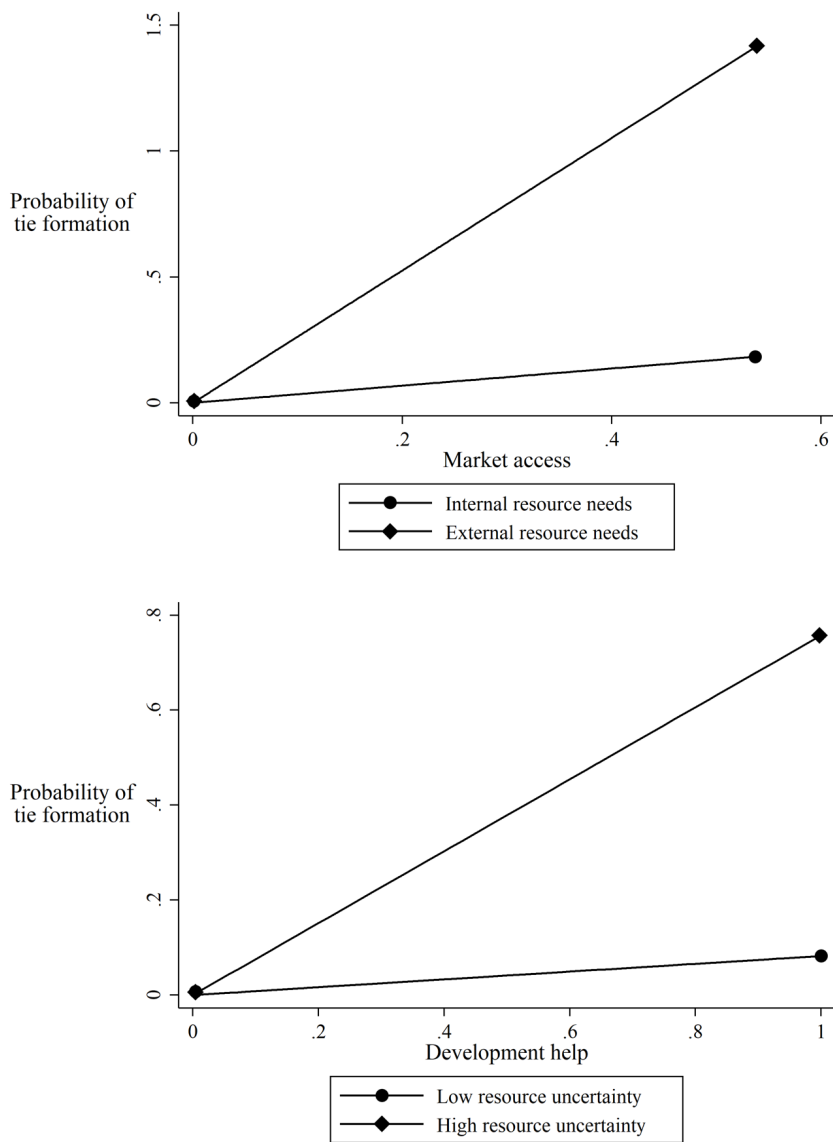
Big fish, big pond studies. An emerging body of research – mostly outside of or at the periphery of managerial research – has begun to examine “big fish, big pond” questions. It typically takes a normative view, i.e., it examines outcomes, not antecedents, and studies the two components separately – big fish or big pond, but not the trade-off. Particularly relevant for our study is that this work establishes both big fish and big pond positioning as desirable during relationships.

Research spotlighting the benefits of “big fish” ties – often measured by a higher standing relative to peers – shows improved access to resources and performance outcomes (Gong, Sun, & Wei, 2018). Elsner and Isphording (2017), for example, show that equally able students have higher future achievement when they rank high relative to classmates. In studies on venture capital, Ozmel and Guler (2015) show that higher-ranked rivals in a portfolio matter and can become problematic for the focal firm.

Other prior research, in turn, outlines the advantages of “big ponds.” Big ponds offer the opportunity to reach larger audiences. Lazega, Jourda, Mounier, and Stofer (2008), for example, show that French research scientists produce more impactful research in central research labs (big ponds). Altogether, prior work points to distinct advantages of either big fish or big pond positioning, but it does not examine the trade-off, or what shapes the choice between the two.

Overall, it remains unexamined how the big fish vs big pond tie formation choices are made in the first place. Assignment to one pond as opposed to another is unlikely to be random. Lazega et al. (2008: 29) point out that they do not have full understanding of how “[research scientists] made it, in the first place, into the central organizations dominating these systems...upstream of the [outcome] processes observed here.” The choice that actors make when faced with the “big fish vs big pond” trade-off in tie formation is thus poorly understood. This is the gap that we address.

Figure A1. Visualization of Significant Interactions in Table 3



Lines visualize values 1 standard deviation below and above the mean value of the interaction variable respectively.

Biographical sketches

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