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Collaborations that hurt firm performance but help employees' careers

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Abstract

Research Summary: When a firm and a competitor collaborate with the same partner, they compete for the shared partner's resources and attention. Such "peer competition" has been shown to negatively affect a firm's access to resources and its performance. One might expect that also the employees' careers to suffer as a result. However, we argue that the firm's employees *benefit* from such collaborations. They leverage these collaborations to build social capital—helping their mobility and careers. We find empirical support for our theory using a large sample dataset of video game companies. Our study points to an important yet hitherto neglected agency conflict: employees seek interfirm collaborations that benefit them personally but hurt their firm.

Managerial Summary: We show that some alliances can be detrimental to a firm's performance yet can benefit its employees. Specifically, we find that collaborating with the same partner as a competing firm hurts firm performance but can be leveraged by employees to advance their careers—by using the opportunity to connect with competing firms and find better job opportunities. We also find that firms often take on more collaboration than is good for them but entering

Henning Piezunka and Thorsten Grohsjean contributed equally to this study.

many collaborations can benefit employees. Our study shows that the interests of firms and their employees are not always aligned when it comes to interfirm collaborations.

KEYWORDS

agency conflict, career, collaboration, competition, employee mobility, social capital

1 | INTRODUCTION

When developing and commercializing new products, firms often collaborate with partners to access complementary resources (Ahuja, 2000; Baum & Silverman, 2004; Gulati, 1998; Stuart, 2000). Such collaborations are common in various empirical contexts, for example, between technology ventures and corporations (Diestre & Rajagopalan, 2012; Dushnitsky & Lavie, 2010; Hallen, Katila, & Rosenberger, 2014), movie studios and movie publishers (Vandaie & Zaheer, 2015), biotech and pharma (Powell, White, Koput, & Owen-Smith, 2005; Rothaermel & Hill, 2005), or start-ups and investors (Bernstein, Giroud, & Townsend, 2016; Hallen, 2008; Pahnke, Katila, & Eisenhardt, 2015a; Zhelyazkov & Tatarynowicz, 2021).

Partners with complementary resources often collaborate not only with the focal firm but also with its competitors. These simultaneous collaborations expose all the firms in the partner's portfolio to *peer competition*, whereby they have to compete for the resources of the shared partner. Research shows that such peer competition negatively affects firms' access to resources and performance (Aggarwal, 2020; Ozmel & Guler, 2015; Pahnke, McDonald, Wang, & Hallen, 2015b). However, despite these negative implications, collaborations that expose firms to peer competition are quite common. One would expect that firms' employees take action to avoid such collaborations as these collaborations can be expected, ceteris paribus, to also hurt their careers (Faulkner & Anderson, 1987; Phillips, 2001; Sutton & Callahan, 1987). We hypothesize, however, that the ceteris paribus assumption does *not* hold. We suggest that such collaborations *benefit* employees by allowing them to build social capital, which they use in turn to advance their careers. If true, this would indicate an agency conflict: employees may pursue interfirm collaborations that benefit their careers at the expense of firm performance.

We test our theory on the divergent outcomes of such collaborations—bad for the business, beneficial for the employee—by studying collaborations between video game developers (firms) and publishers (partners). The video game industry, which has been examined in other studies (e.g., Lee, 2022; Mollick, 2012; Rietveld & Eggers, 2018), is an apt testing ground for two reasons. First, publishers collaborate with different sets of developers, which results in variation in the degree of peer competition (i.e., the explanatory variable). Second, fine-grained data on individuals, products, and firms allow us to track collaboration success and the evolution of employees' careers. Beyond compiling and analyzing a comprehensive data set, we also conducted 38 interviews with industry experts to deepen our understanding of the industry and strengthen our research design.

We start by replicating research on the negative effect of peer competition on firm performance. We then test and find supporting evidence for our theory on the positive effect of peer competition on employees' careers. Finally, we explore the underlying mechanisms and find

that peer competition allows employees to develop their *social capital*, and helps them to find better job opportunities, thus benefitting them personally.

Our study contributes to the literature on inter-organizational collaborations and alliance portfolios (Baum & Silverman, 2004; Gulati, 1998; Hallen et al., 2014; Lavie, 2007; Ozcan & Eisenhardt, 2009). We start out by replicating research on the adverse effect of peer competition among firms collaborating with the same partner (Aggarwal, 2020; Ozmel & Guler, 2015; Pahnke et al., 2015b) and by extending it to a different context by consolidating previous results. The finding that interorganizational collaborations shape employees' mobility and careers also complements work on interorganizational collaborations that examined how employees' social networks shape interorganizational collaborations (Broschak, 2004; Devarakonda, Pavićević, & Reuer, 2022; Dokko & Rosenkopf, 2010; Rogan, 2014; Somaya, Williamson, & Lorinkova, 2008; Young-Hyman & Kleinbaum, 2020). We examine the reverse: how interorganizational collaborations can help employees develop their social capital. Our study further provides an alternative portrait of partners' alliance portfolios. They are not just an arena for interfirm peer competition but also a seedbed for employees' social capital.

We also contribute to research on employee mobility and careers. A rich body of work has examined how different features of organizations affect peoples' mobility and careers (Bidwell, Won, Barbulescu, & Mollick, 2015; Burton, Sørensen, & Beckman, 2002; Chattopadhyay & Choudhury, 2017; Kacperczyk & Younkin, 2021; Mawdsley & Somaya, 2016; Small, 2009; Sorenson, Dahl, Canales, & Burton, 2021). We complement this work by highlighting an essential but neglected organizational feature: *interorganizational collaborations*. We illustrate how interfirm alliances provide employees with the *chance* and *coverage* to develop their social capital—eventually benefitting their careers.

Our broadest—and probably most important—contribution lies in uncovering a potential agency conflict in interfirm collaboration: employees may favor alliances that benefit themselves personally but hurt their employer. Despite an abundance of research on agency conflicts between employees and employers as well as interfirm alliances, these two literatures have yet to speak to one another. We are not the first to point out that firms often pick the wrong partner (Rogan & Sorenson, 2014; Sorenson & Waguespack, 2006), but we add an important twist: what may be the "wrong" partner for the firm may be the "right" partner for its employees.

2 | THEORETICAL BACKGROUND AND HYPOTHESES

2.1 | Collaborations between firms and their partners

Firms working on new ideas often benefit from collaborating with partners. Partners support them by providing complementary resources (Baum & Silverman, 2004; Hallen, Cohen, & Bingham, 2020; Yu, 2020) or helping them to connect with others, for example, with start-ups (Hallen et al., 2014; Pollock & Gulati, 2007), investors (Zhang, Gupta, & Hallen, 2017; Zhelyazkov & Gulati, 2016) and the media (Petkova, Rindova, & Gupta, 2013; Santos & Eisenhardt, 2009).

Although such benefits are possible, they are far from guaranteed. While the firm and its partner may have an agreement about the support the partner is supposed to provide, such agreements often fall apart (Contractor & Reuer, 2014; Faulkner & Anderson, 1987). Also, certain kinds of support such as providing advice and making introductions, are difficult to contract for. Consequently, support is mainly at the partner's discretion so that firms constantly

face the risk of their partner reducing or stopping its support (Guler, 2007; Katila, Piezunka, Reineke, & Eisenhardt, 2022; Ozmel & Guler, 2015; Zhelyazkov & Gulati, 2016).

2.2 | Peer competition among firms collaborating with the same partner

Whether and to what degree a partner supports a firm depends partly on whether it also collaborates with that firm's competitors. While it may seem plausible that the firm could benefit from such an indirect linkage to competitors (Bothner, 2003; Clough & Piezunka, 2020; Waldinger, 2012), research shows that such linkages result in peer competition, which reduces the support that firms receive from their partner and the focal firm's success (Aggarwal, 2020; Ozmel & Guler, 2015; Pahnke et al., 2015b; Zhelyazkov, 2018). Prior studies suggest that the extent to which peer competition reduces the partner's support will depend on the number and the quality (or superiority) of peers through the following three main mechanisms.

First, other firms collaborating with the same partner—particularly superior ones—reduce the focal firm's access to a partner's resources. Because a partner's resources—especially its attention—are limited (March & Simon, 1958; Ocasio, 1997; Piezunka & Dahlander, 2015), the number of peers is inversely proportional to the attention they can receive. Such peer competition may be difficult for the partner to attenuate, as certain resources cannot be scaled (Levinthal & Wu, 2010). For example, a book publisher can market only one author's book as "book of the year". The negative effect of peer competition is unequally distributed as partners will distribute the nonscalable resources unequally—focusing resources on the most promising firms in their portfolio (Ozmel & Guler, 2015).[1] This resource allocation is thus most harmful to firms that face competition from superior peers. In brief, peer competition, particularly with superior peers, hinders firms' access to the partner's resources and limits performance.

Second, peer competition can result in harmful leakage of information. While firms must grant their partner access to proprietary information to get feedback on their progress, there is evidence that partners pass on information to peer firms (Garg & Eisenhardt, 2017). Clearly, such leakage can be harmful to firms (Pahnke et al., 2015b). While firms may control how much information they share with their partner, they cannot control leakage to peer firms with which they are indirectly connected. Such leakage is most harmful to firms with a low relative standing, as partners are likely to focus their advice on superior peers in which they see the most potential. Such firms are therefore more likely to be harmed by the partner's knowledge brokering. Of course, firms may choose not to share information with a partner in the presence of peer competition (Hernandez, Sanders, & Tuschke, 2015), but the consequences of this may be even worse, as they will miss out on helpful feedback during product development (Brown & Eisenhardt, 1997; MacCormack, Verganti, & Iansiti, 2001).

Third, peer competition can result in detrimental conflict. Peer firms are structurally equivalent as they compete for the partner's resources and potential for the same consumers. Research shows that structural equivalence can turn competition into a conflict where peers attack one another (Gould, 2003; Li & Piezunka, 2020; Piezunka, Lee, Haynes, & Bothner, 2018a). When collaborating with the same partner, such conflict is particularly likely given its importance (Piezunka, Lee,

[1]Partners tend to discriminate among the firms they collaborate with to maximize return. As the success of collaborations is often skewed, partners would rather focus their resources than spread them equally. They also need to make sure to differentiate their portfolio and may thus cull it (Katila et al., 2022; Pahnke et al., 2015b).

Haynes, & Bothner, 2018b): winning the upstream competition for the partner's resources substantially increases their chances of winning the downstream competition for consumers (Ozmel & Guler, 2015). Firms of low relative standing are particularly likely to become involved in the conflict; they are concerned about the expected down-spiraling dynamic and take unreasonable actions (Bothner, Kang, & Stuart, 2007). One can imagine that peer firms may sabotage or bad-mouth each other to win an edge—ultimately to the detriment of everyone.

Our baseline hypothesis, in line with prior research (Aggarwal, 2020; Ozmel & Guler, 2015; Pahnke et al., 2015b) is:

> **Hypothesis 1.** *Exposure to more (H1a)/superior (H1b) peer firms in a partner's portfolio decreases the performance of firms.*

2.3 | The effect of peer competition on firms' employees

The adverse effect of peer competition on a firm's success raises the question of why firms enter partnerships that expose them to it. As firms are generally savvy about which partner they collaborate with (Hallen & Pahnke, 2016; Hoetker, 2005; Mindruta, Moeen, & Agarwal, 2016; Mulotte, Ren, Dussauge, & Anand, 2022) and have agency in the process (Hallen, Davis, & Murray, 2020; Katila et al., 2022), one might expect them to avoid such collaborations—whereas, in fact, they are quite common.

Puzzled by this, we conducted interviews with employees of firms in our sample. We were surprised to learn that they were aware of the competition among peers for their partner's resources but did not seem bothered by it. In fact, they often spoke enthusiastically about the peer firm. Some outlined how they could connect to people they would not have met otherwise. Some provided examples of such connections leading to *personal* benefits, such as finding a job at a peer firm. If such reports are representative, it would indicate that employees benefit personally from peer competition despite its negative effect on their firm's success.

We hypothesize that employees do indeed benefit from peer competition. We do so on three grounds. First, following an abductive approach, this would help explain the surprising commonality of collaborations that hurt firm performance. Second, our interviews suggest that employees benefit personally from peer competition despite its negative effect on their firm's success. Third, it can be derived from the theoretical mechanisms outlined below.

The hypothesis that peer competition benefits employees may at first seem counterintuitive. Typically, the opportunities available to employees depend partly on the success of their employer (Bidwell et al., 2015; Burton et al., 2002; Sutton & Callahan, 1987), such that any factor that reduces the firm's success (like peer competition) can be expected, ceteris paribus, to negatively affect the personal success of the employee. We propose, however, that the ceteris paribus assumption does not hold because of a side-effect of peer competition. Peer competition allows employees to develop *social capital* as they connect with employees of peer firms that collaborate with the same partner.

2.3.1 | The challenge of developing social capital

A rich body of research illustrates the role played by social capital within and beyond firm boundaries in career advancement (Fernandez, Castilla, & Moore, 2000; Granovetter, 1973;

Ibarra, 1993). While connections with employees of peer firms can be crucial for people's careers, they are difficult to develop (Engel, Kaandorp, & Elfring, 2017); employees may lack the time, energy, or bandwidth to do so. In addition, geographical distance makes it harder to connect to employees of other firms. Moreover, employees may face social obstacles as they may be expected to show allegiance to their current firm (Grohsjean, Kober, & Zucchini, 2016). Meeting with employees from other firms may therefore be frowned upon. While research illustrates that employees are interested in relationships with employees at competing firms (Ingram & Roberts, 2000), all these factors may prevent it. It is thus not surprising that employees typically develop relationships with co-located co-workers (Dahlander & McFarland, 2013; Gargiulo & Benassi, 2000; Small, 2009).

2.3.2 | Indirect linkage to peers as a solution

We suggest that collaborations that link firms to structurally equivalent peers (and thus expose them to peer competition) help employees connect to employees of peer firms and develop valuable *social capital*. Such connections occur either through chance encounters at the partner's site or because the partner actively fosters them. We learned from our interviewees that partners also take an active brokering role. For example, they referred employees from one firm to employees at a peer firm to discuss operational challenges (Burt, 2005; Obstfeld, 2005) and organized informal get-togethers at which employees of peer firms could mingle (Ingram & Morris, 2007). Thus, collaboration with a partner gave employees the *chance* to connect to employees of peer firms.

Interestingly, such interactions also provide employees with *coverage* for forming otherwise frowned-upon relationships. Piskorski (2013, 2014) develops the idea of networks as coverage, citing the example of LinkedIn. Employees may claim—perhaps truly—to be on LinkedIn for their work, but they also make themselves known to headhunters and alternative employers. Coverage to connect with employees at competing firms can also be provided when a partner invites the employees of its portfolio firms to consult with each other or to attend social events. Hence, collaboration with a shared partner gives employees the *chance* and *coverage* to overcome time and distance constraints and connect with employees of peer firms.

2.3.3 | The benefits of peer-competition-induced social capital

The connections that employees develop with employees of (competing) peer firms can benefit them personally in two ways. First, they may benefit from *job opportunities* in those firms. When an employer and potential employee already know each other, there is a greater likelihood of a match, and the match is likely to be of higher quality (Campbell, Di Lorenzo, & Tartari, 2021; Fernandez et al., 2000; Weller, Hymer, Nyberg, & Ebert, 2019). Peer firms are likely to be particularly attractive given the potential similarities (e.g., type of work, geographical location). Our interviewees described instances in which employees at peer firms informed them of a job opportunity they were a good fit for. Such connections may be beneficial in moving to superior firms. Joining a superior firm may generally be hindered by status barriers, but such barriers have less of an effect if the hiring firm and the employee already know one another.

Second, the social connections formed with employees at other firms can help focal employees *develop their skills*. The linkage between people's connections and skills is well documented (Burt, 2005), showing how employees at peer firms play an essential role as they often face similar challenges, how employees interact with employees at peer firms, and how it helps them develop their knowledge (von Hippel, 1987). Losing access to peer employees hinders skills development, as shown by research using evidence from the dismissal of scientists in Nazi Germany (Waldinger, 2012). While plausible, there is no evidence that connections to peer firms to which employees are indirectly linked helps them develop their skills.

Both mechanisms—job opportunities and skill development—can contribute to future success. Employees strive to work on more and more successful projects as this allows them to increase their income and long-term employment opportunities etc. (Bidwell & Mollick, 2015). Both mechanisms can help. More job opportunities may bring more and better projects to work on. Beyond simply "finding a job", employees may find a job that constitutes a better match and/or at a superior peer (Campbell et al., 2021), whereas skill development may increase the success of whatever projects they work on.

> **Hypothesis 2.** *Exposure to more (H2a)/superior (H2b) peer firms in a partner's portfolio increases a firm's employee's personal success.*

3 | METHODS

3.1 | Setting: The global video game industry

Our empirical context is the global video games industry. While video game developers (firms) conceive and develop games (projects), video game publishers (partners) finance and market them. In addition, the publisher supports and oversees the development process, and employees from the developer and the publisher meet regularly to discuss milestones and problems. While syndicates are common in venture capital (Zhang et al., 2017; Zhelyazkov & Gulati, 2016), video game publishers usually do *not* co-invest.

3.2 | Data sources and sample

We build a comprehensive dataset that entails detailed information on video games, the employees involved in their development, the developers they work for, and the publishers. MobyGames, our primary data source,[2] allowed us to track employees' entire careers in both public and private firms around the globe. Information entry follows strict coding standards and instructions specified on the MobyGames website. All entries are peer-reviewed before they

[2]One of the world's largest video game documentation projects, it contains comprehensive information on games past and present from public and private firms from all around the world. The data include, among other things, a game's release date, the employees and firms involved in making it, whether it draws on licensed or franchised material, and reviews from print and online game magazines. A key reason for the quality of the data is that those involved in game development have an incentive to document their participation in detail. Employees point to MobyGames to validate their track records when interacting with industry stakeholders.

are published. For these reasons, research has widely used MobyGames (e.g., Claussen, Grohsjean, Luger, & Probst, 2014; Katila et al., 2022; Mollick, 2012).

We match the data from MobyGames with revenue data collected by NPD Group,[3] that has tracked sales of video games in the United States since 1995, covering all distribution channels. We have monthly sales data from January 1995 through December 2018. NPD data is the primary source for video game sales information in many studies (e.g., Kretschmer & Claussen, 2016; Zhu & Iansiti, 2012). We complement our dataset by manually gathering information on the ownership of the developing and publishing firms from various websites, including MobyGames, RAWG, GiantBomb, VGChartz, and Wikipedia.

We test our baseline hypothesis H1 by examining the effect of peer competition on two levels: the project (game) level and the year level. At the project level, we study the revenue-based performance of 28,560 video games. At the year level, we study the revenue-based performance of 3,420 developers, relying on 20,020 firm-year observations. As some developers are involved in multiple projects in a year, we use the average of the variables across the games with which the developer was involved in the focal year.

To test our hypothesis on the effect of peer competition on employees' personal success (H2), we created an unbalanced panel of all employees active in the video games industry. Though we analyze only 1995–2017, we collect data from the dawn of the industry in the 1970s to allow for accurate historical measures at the beginning of our panel regression (e.g., experience-related measures). The unit of analysis to test H2 is the employee-year. This dataset has 582,272 employee-year observations from 135,580 employees. As some employees are involved in multiple projects in a year, we build the average of our measures across all games with which the employee was involved in the focal year to test H2.

3.3 | Dependent variables

3.3.1 | H1: Firm performance

We measure firm performance at the individual project level and across all projects at the level of the year. At the project level, we operationalize *firm performance (project level)* as a game's revenues measured in millions of USD.[4] As the distribution of revenues in the video game industry is skewed, we use the natural logarithm of the revenues as a robustness check. At the year level, we operationalize *firm performance (year level)* as the sum of the revenues of all games a developer released in the focal year.

[3]We used a five-step process to merge the MobyGames and NPD data. (a) We identified all versions of a single game listed in NPD and aggregated their revenues. (b) We matched the two data sources—based on the game's name, platform, and release date. (c) We manually reviewed all matching results to ensure accuracy. (d) To improve the merge, we gave the unmatched observations to three research assistants who independently tried to identify the corresponding titles in NPD and MobyGames. If they did not identify the same pair of names in NPD and MobyGames as belonging to the same game, we tried to match them ourselves. (e) We managed to merge 83% of all the revenues listed in the NPD data to games in MobyGames.

[4]To compare games released at different times, we focus on the revenues in the first 12 months after release. This is reasonable as the games in our sample made 83% of the recorded revenues in their first year.

3.3.2 | H2: Employee's personal success

For the dependent variable at the employee level, we add the revenues of all games in which an employee participated in year $t + 1$.[5]

3.4 | Explanatory variables

3.4.1 | Number of peers

We measure the number of peer firms by counting the other developers releasing games with the publisher in the same year as the focal developer.

3.4.2 | Superiority of peers

We operationalize the *superiority of peers* by dividing the average review score that all games of developers working with the publisher received in the focal year by the review score of the focal developer's game (Katila et al., 2022). Thus, *superiority of peers* is always positive. The higher the score, the more superior the other developers in the publisher's portfolio. We set the variable to zero if a developer is the only one working with a publisher. To identify whether peers are superior we build on game review scores by third-party sites as aggregated by MobyGames.

3.5 | Project-level control variables

We use control variables at the project, firm, partner, and dyad levels to predict firm performance at the project and the year level (H1) and to predict an eemployee's personal success (H2).

3.5.1 | Project is based on a license

Video games often build on intellectual property licensed from other domains, such as movies, books, and sports. Accounting for licensed content is important because a well-known name, story, or brand in another field may drive a game's success. *Project is based on a license* is a dummy equal to 1 if a game draws on licensed content and 0 otherwise.

3.5.2 | Project is part of a series

Many popular games are developed as a franchise title, that is, a series of games developed around some intellectual property involving the characters, setting, and trademarks. Games

[5]How much revenues a game generates is important to employees because their personal income depends on it. Also, being affiliated with high-grossing games increases their chances to work on interesting games in the future. Finally, it is meaningful and satisfying, as it earns recognition (Boudreau & Jeppesen, 2015). Interviewees often reported with great pride that they had worked on games that had generated hundreds of millions in revenues.

based on franchises are responsible for a large share of revenues. We use a dummy equal to 1 if a game is a franchise title and 0 otherwise.[6]

3.5.3 | Team size

As labor costs are the largest segment of game development costs, the size of the development team is a good proxy for the cost of game development. Therefore, we control for team size, defined as the number of all people involved in creating the game.[7]

3.6 | Firm-level control variables

3.6.1 | Number of partners the firm collaborates with

The performance of a project may depend not only on the partner's attention to the focal firm but also on the focal firm's attention to the partner. Hence, we control for the *number of partners the firm collaborates with* by counting the number of publishers the developer works with.

3.6.2 | Firm's number of projects

A project might suffer when the firm works on many projects. We thus control for the number of games released in the same years as the focal game.

3.6.3 | Firm's average past performance

To account for time-variant differences in a video game developer's performance, we include the variable *firm's average past performance*, which is the average of the revenues of all games created by the developer in $t - 1$.[8]

3.6.4 | Firm age

The difference between the year in which a developer produced its first game and the release year of the focal game.

[6]Although it may not always be clear that a developer will turn a game into a series when releasing the first title, MobyGames codifies the first title of a series as being part of a series. We follow their procedure for our analysis. However, we also run the analysis coding *project is part of a series* for the first title of a series 0. Results are similar.

[7]In some cases, MobyGames provides no information on the number of employees on a game. We coped with this in two ways. First, we dropped those games. Second, we assumed those games to have an average team size. Our results hold up for specifications at both the game and firm levels.

[8]We also run a robustness check using the natural logarithm of this average and get very similar results.

3.7 | Partner-level control variable

3.7.1 | Partner's past performance

We conceptualize *partner's past performance* as the total of revenues of all games released by the publisher in the year before the release of the focal game.

3.8 | Dyad-level control variables

3.8.1 | Number of prior iterations of collaboration

Developers and publishers with greater experience working together might be better able to produce more successful games. We thus count the number of games on which a focal developer and publisher have collaborated.

3.8.2 | Firm and partner based in the same country

As domestic collaborations may be easier than cross-border ones, we include a dummy variable that equals 1 if the developer and the publisher were based in the same country, and 0 otherwise.

3.9 | Employee-level control variables

When predicting an employee's personal success, we need to account for their salient characteristics. Besides controlling for time-invariant differences across employees by including employee fixed effects, we also control for the following time-variant employee characteristics.

3.9.1 | Employee's industry experience

Employees who work longer in the industry may not only have more knowledge and skills but also have access to better job opportunities. We thus control for the difference between the release year of the focal game and the release year of the first game on which an employee worked.

3.9.2 | Employee's number of projects

An employee's personal success is determined not only by overall experience but also—and especially—by their most recent experience. Those working on more games now may work on even more or better games in the future. We, therefore, control for the number of games on which an employee worked in the current year.

3.10 | Estimation procedure

We use ordinary least squares (OLS) regressions with firm and partner fixed effects and standard errors clustered at the firm-level to predict its performance at the project level. To predict the firm performance at the year level, we apply OLS regressions with firm fixed effects and standard errors clustered at the firm-level. As a developer may work with multiple publishers in a year, we cannot include partner fixed effects in this regression model. Finally, we estimate a series of OLS panel regressions with employee fixed effects and standard errors clustered at the employee-level to predict an employee's personal success. Employee-level fixed effects allow us to control for unobserved time-invariant employee characteristics.

4 | RESULTS

Table 1 reports descriptive statistics and pairwise correlations at the employee-year level. Overall, the variables display considerable variance.

We report the main results for H1 and H2 in Table 2. Model 1 and Model 2 show the results of an OLS regression predicting firm performance at the project level and at the year level, respectively. Models 3–6 show the results of the OLS regressions with employee fixed effects predicting the personal success of an employee. Our control variables generally have the expected impact on the dependent variables, but one finding is notable: divergent effects for the number of partners with which a firm collaborates. While *number of partners the firm collaborates with* has a negative effect (p-value = .001) on firm performance (project level), it has a positive effect (p-value = .000) on an employee's personal success. This is consistent with our main theory that features of a firm's collaboration strategy can be harmful to the firm but beneficial to employees.

We first replicate the findings in the literature that peer competition harms the focal firm's performance (Baseline H1). In line with prior research, we find a negative effect at the project level (p-value = .017 in Model 1) and at the year level (p-value = .010 in Model 2). A one-standard-deviation increase in *number of peers* is associated with approximately 583k USD less revenue—an economically significant amount given that the average game revenue in our sample is 2.07 million USD. At the year level, a one-*SD* increase in *number of peers* is associated with approximately 1,192k USD less revenue. Moreover, the coefficient of *superiority of peers* is negative at the project level (p-value = .000 in Model 1) and at the year level (p-value = .003 in Model 2). While a one-*SD* increase in *superiority of peers* results in roughly 267k USD less revenue at the project level, it reduces firm performance at the year level by approximately 581k USD. Overall, this analysis corroborates the finding that peer competition negatively affects firm performance.

In H2, we suggested that peer competition increases an employee's personal success. We conduct the corresponding tests in Models 4–6 in Table 2. We find indeed a positive effect on employee personal success (p-value = .000 in Models 4 and 6). The effect size indicates that a one-*SD* increase in the variable increases the revenue of the games with which the employee is affiliated by roughly 824k USD. We also find a positive effect of *superiority of peers* on an employee's personal success (p-value = .000 in Models 5 and 6). A one-*SD* increase in *superiority of peers* is associated with an increase in the revenues of the games with which the employee is affiliated in the next year of roughly 696k USD.

TABLE 1 Summary statistics at employee level ($N = 582{,}272$)

No.	Variable	Mean	*SD*	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Employee's personal success	10.00	38.18	0.00	870.65	1.00													
Explanatory variables																			
2	Number of peers	10.35	10.44	0.00	65.00	0.09	1.00												
3	Superiority of peers	0.85	0.35	0.00	2.98	0.04	0.35	1.00											
Employee-level control variables																			
4	Employee's industry experience	5.47	5.84	0.00	34.00	−0.04	0.01	0.05	1.00										
5	Employee's current involvement	2.34	2.15	1.00	60.00	0.24	0.08	0.07	0.03	1.00									
Project-level control variables																			
6	Project is based on a license	0.20	0.38	0.00	1.00	0.08	0.12	0.09	−0.04	0.15	1.00								
7	Project is part of a series	0.69	0.44	0.00	1.00	0.06	0.00	−0.01	0.09	0.04	−0.13	1.00							
8	Team size	458.57	702.38	1.00	4,970.00	0.17	0.01	−0.05	0.00	0.20	0.04	0.24	1.00						
Firm-level control variables																			
9	Number of partners the firm collaborates with	1.78	1.06	1.00	9.00	−0.02	−0.02	0.10	0.05	0.08	0.05	−0.01	−0.12	1.00					
10	Firm's number of projects	5.37	6.96	1.00	107.00	0.05	0.06	0.09	0.12	0.21	0.08	0.09	0.02	0.47	1.00				
11	Firm's average past performance	4.61	13.02	0.00	294.81	0.13	0.07	−0.01	−0.03	0.04	0.10	0.10	0.18	−0.02	0.05	1.00			
12	Firm's age	11.00	7.31	1.00	34.00	0.07	0.01	0.05	0.37	0.08	0.02	0.24	0.31	0.20	0.33	0.13	1.00		
Partner-level control variable																			
13	Partner's past performance	171.81	327.88	0.00	1737.66	0.14	0.56	0.17	−0.04	0.16	0.14	0.06	0.11	−0.10	0.10	0.22	0.04	1.00	
Dyad-level control variables																			
14	Number of prior iterations of collaboration	13.71	32.94	0.00	346.00	0.13	0.08	0.05	0.00	0.11	0.14	0.12	0.15	0.07	0.37	0.14	0.24	0.25	1.00
15	Firm and partner based in same country	0.39	0.46	0.00	1.00	−0.01	−0.04	−0.07	−0.02	−0.07	0.05	0.02	−0.09	0.01	0.03	0.01	0.03	−0.01	0.08

TABLE 2 Results of OLS regressions on *firm performance* and *employee's personal success*

Dependent variable	Model 1 H1a and H1b: Firm performance (project level)	Model 2 H1a and H1b: Firm performance (year level)	H2a and H2b: Employee's personal success			
			Model 3	Model 4	Model 5	Model 6
H1a and H1b: Number of peers	−0.051 [.015]	−0.124 [.014]		0.085 [.000]		0.069 [.000]
H1b and H2b: Superiority of peers	−0.646 [.000]	−1.068 [.005]			2.021 [.000]	1.581 [.000]
Employee-level control variables						
Employee's industry experience			−0.308 [.000]	−0.312 [.000]	−0.305 [.000]	−0.309 [.000]
Employee's number of projects			0.804 [.000]	0.813 [.000]	0.795 [.000]	0.805 [.000]
Project-level control variables						
Project is based on a license	0.734 [.004]	2.635 [.006]	2.148 [.000]	2.067 [.000]	2.071 [.000]	2.021 [.000]
Project is part of a series	1.342 [.000]	2.511 [.000]	0.921 [.000]	0.957 [.000]	0.997 [.000]	1.010 [.000]
Team size	0.010 [.000]	0.020 [.000]	−0.004 [.000]	−0.003 [.000]	−0.004 [.000]	−0.004 [.000]
Firm-level control variables						
Number of partners the firm collaborates with	−0.304 [.000]	0.599 [.371]	0.275 [.000]	0.263 [.000]	0.259 [.000]	0.252 [.000]
Firm's number of projects	0.004 [.702]	1.250 [.001]	−0.039 [.000]	−0.043 [.000]	−0.041 [.000]	−0.044 [.000]
Firm's average past success	0.047 [.346]	0.330 [.002]	−0.059 [.000]	−0.056 [.000]	−0.055 [.000]	−0.054 [.000]
Firm's age	−0.376 [.000]	−0.432 [.000]	−0.029 [.016]	−0.031 [.012]	−0.033 [.008]	−0.033 [.007]
Partner-level control variable						
Partner's past success	0.001 [.280]	0.025 [.000]	0.002 [.000]	0.001 [.071]	0.002 [.000]	0.001 [.051]
Dyad-level control variables						
Number of prior iterations of collaboration	0.001 [.947]	−0.069 [.527]	0.083 [.000]	0.084 [.000]	0.083 [.000]	0.084 [.000]
Firm and partner based in same country	−0.279 [.231]	0.552 [.265]	0.640 [.000]	0.717 [.000]	0.745 [.000]	0.785 [.000]

TABLE 2 (Continued)

Dependent variable	Model 1 H1a and H1b: Firm performance (project level)	Model 2 H1a and H1b: Firm performance (year level)	H2a and H2b: Employee's personal success			
			Model 3	Model 4	Model 5	Model 6
Constant	4.831 [.000]	1.401 [.172]	8.952 [.000]	8.297 [.000]	7.271 [.000]	7.101 [.000]
Fixed effects						
Firm fixed effects	Yes	Yes				
Partner fixed effects	Yes					
Employee fixed effects			Yes	Yes	Yes	Yes
Observations	28,560	20,020	582,272	582,272	582,272	582,272
Adjusted R^2	0.146	0.428	0.126	0.126	0.126	0.126

Note: All models show OLS regressions with clustered standard errors. Exact *p* values are reported in brackets.

Overall, our results support the hypothesized divergent effects: a negative effect of peer competition on firm performance, but a positive effect on an employee's personal success.

4.1 | Robustness checks

We run additional tests to ensure the robustness of our results. First, we show that the results for our predictions on an employee's personal success hold for alternative specifications of our dependent variable (Table 3). Although firms in the video game industry always strive to create a blockbuster game, we check whether our results are robust by using the natural logarithm to account for the extreme dispersion of our dependent variable. Results are in line with our main results (Model 1). We also adjust the dependent variable for the size of the game's development team by dividing the sum of the revenues by the number of employees involved in developing the game (Model 2). In Model 3, we adjust the dependent variable by dividing the sum of the game's revenues by the natural logarithm of the number of employees involved in its development. We find in both cases a positive sign for *number of peers* (p-value < .006) and for *superiority of peers* (p-value < .007). In Model 4, we extend our dependent variable by taking the sum of all revenues of all games an employee was involved with in the following 2 years instead of 1 year. Again, we find a positive sign for the *number of peers* (p-value = .000) and for the *superiority of peers* (p-value = .000). Overall, our robustness checks against alternative specifications of the dependent variable further support H2.

Second, although we provided theoretical reasons for selecting our control variables, these decisions could always reflect the subjective and defensible views of the researchers (King, Goldfarb, & Simcoe, 2021). We therefore checked the robustness of our results across all possible combinations of control variables using the specification curve analysis suggested by Simonsohn, Simmons, and Nelson (2020). To validate the results for H1a (H1b), we ran 1,024 regressions of project-level firm performance on *number of peers* (*superiority of peers*) and developer and publisher fixed effects, systematically alternating the set of control variables. To validate the results for H2a (H2b), we ran 8,192 regressions of *employee's personal success* on *number of peers* (*superiority of peers*) and employee fixed effects, alternating systematically the set of control variables. We use Stata's speccheck module (Cook, 2019) to visualize the results of these regression analyses (Figure 1). Each panel on the left shows the distribution of the coefficient of the focal explanatory variable derived from each regression analysis; for example, the first panel on the left shows 1,024 coefficients for *number of peers*. On the right of each panel, we display the distribution of the t-statistic for the coefficient of the variable of interest. The vertical line in the right panels corresponds to a t-statistic of 1.96.

Our specification curve analysis reveals that *number of peers* and *superiority of peers* harm the performance of the firm at the project level irrespective of the set of control variables; the corresponding t values are all above 1.96. Second, we find that irrespective of how many and which control variables we include, *number of peers* and *superiority of peers* improve an employee's personal success; again, the corresponding t values are all above 1.96. Overall, the specification curve analyses show that our results are robust to the inclusion or exclusion of control variables, providing additional support for our findings.

TABLE 3 Robustness checks: OLS regressions on employee level using alternative dependent variables

	Employee-level analysis: Alternative dependent variables			
Dependent variable	**Model 1** **Employee's personal success (ln)**	**Model 2** **Employee's personal success adjusted for team size**	**Model 3** **Employee's personal success adjusted for ln of team size**	**Model 4** **Employee's personal success next 2 years**
H2a: Number of peers	0.009 [.000]	0.000 [.003]	0.014 [.000]	0.176 [.000]
H2b: Superiority of peers	0.184 [.000]	0.006 [.001]	0.238 [.000]	1.307 [.000]
Employee-level control variables				
Employee's industry experience	−0.309 [.000]	−0.010 [.000]	−0.094 [.000]	−0.606 [.000]
Employee's number of projects	0.308 [.000]	0.004 [.000]	0.136 [.000]	1.237 [.000]
Project-level control variables				
Project is based on a license	0.771 [.000]	0.021 [.000]	0.424 [.000]	3.349 [.000]
Project is part of a series	0.371 [.000]	0.005 [.007]	0.179 [.000]	2.000 [.000]
Team size	−0.000 [.000]	−0.000 [.000]	−0.001 [.000]	−0.008 [.000]
Firm-level control variables				
Number of partners the firm collaborates with	0.014 [.260]	0.002 [.006]	0.052 [.000]	0.416 [.000]
Firm's number of projects	0.006 [.001]	0.000 [.231]	−0.005 [.004]	0.032 [.054]
Firm's average past success	−0.005 [.000]	0.001 [.000]	−0.003 [.129]	−0.088 [.000]
Firm's age	−0.009 [.000]	−0.001 [.000]	−0.009 [.000]	−0.168 [.000]
Partner-level control variable				
Partner's past success	−0.000 [.392]	0.000 [.593]	0.000 [.002]	0.002 [.001]
Dyad-level control variables				
Number of prior iterations of collaboration	0.008 [.000]	0.000 [.000]	0.013 [.000]	0.117 [.000]
Firm and partner based in same country	0.299 [.000]	0.004 [.065]	0.139 [.000]	−0.617 [.003]
Constant	5.270 [.000]	0.110 [.000]	1.631 [.000]	18.230 [.000]
Employee fixed effects	Yes	Yes	Yes	Yes

TABLE 3 (Continued)

	Employee-level analysis: Alternative dependent variables			
Dependent variable	**Model 1** Employee's personal success (ln)	**Model 2** Employee's personal success adjusted for team size	**Model 3** Employee's personal success adjusted for ln of team size	**Model 4** Employee's personal success next 2 years
Observations	582,272	582,272	582,272	542,100
Number of employees	135,580	135,580	135,580	127,708
Adjusted R^2	0.152	0.006	0.110	0.307

Note: All models show OLS regressions with clustered standard errors. Exact *p* values are reported in brackets.

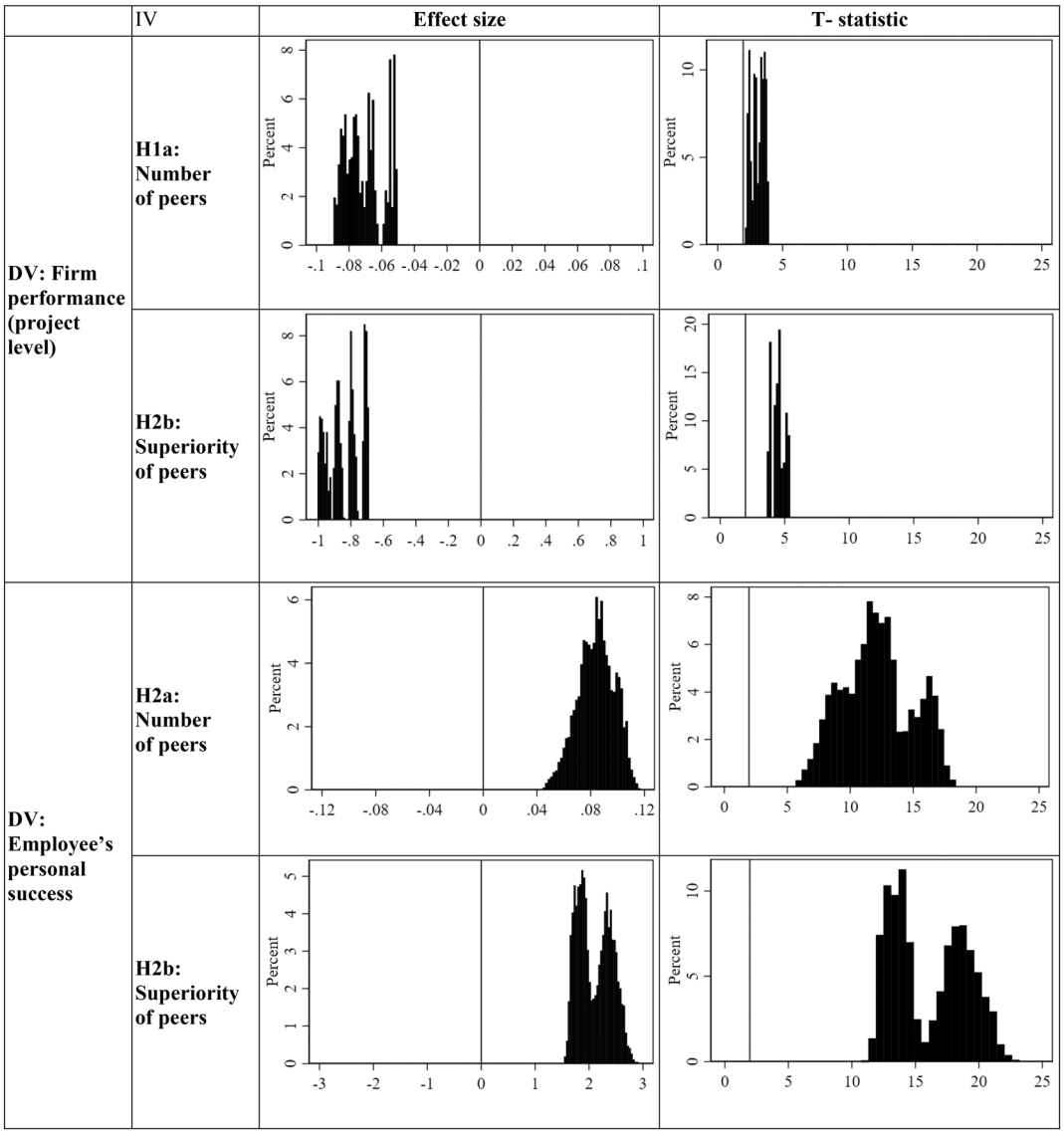

FIGURE 1 Specification curves. Results from our specification curves. On the left, we show the distribution of the coefficient estimates obtained by estimating the effect of the independent variable on the dependent variable for different sets of control variables. On the right, we show the distribution of the *t*-statistic for the coefficient of the variable of interest. The vertical line in the right panels corresponds to a *t*-value of 1.96. These figures show that we find, irrespective of the set of control variables in our analysis, a negative and significant effect for H1a and H1b on the project level, but a positive and significant effect for H2a and H2b

4.2 | Exploring the mechanism and ruling out alternative explanations

Having tested the robustness of our results, we want to shed light on the mechanisms proposed in the theory. We suggested that employees whose firms were exposed to greater peer competition would accumulate more social capital which, in turn, might help them get *job opportunities* at peer companies and/or *develop their skills*.

TABLE 4 Mechanisms

	Examination of job opportunities as mechanism				Examination of skill development as mechanism	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent variable	**Employee works for peer firm**	**Employee works for superior peer firm**	**Employee works for nonpeer firm**	**Employee works for firm owned by the partner**	**Firm performance**	**Promotion of employee staying**
H1a and H1b: Number of peers	0.025 [.000]	0.023 [.000]	−0.007 [.000]	−0.016 [.000]	−0.151 [.000]	−0.001 [.696]
H1b and H2b: Superiority of peers	1.312 [.000]	2.843 [.000]	0.007 [.692]	−0.404 [.000]	−0.939 [.010]	−0.034 [.612]
Number of peers lagged					0.131 [.052]	
Superiority of peers lagged					−0.746 [.276]	
Number of employees lost lagged					−0.033 [.006]	
Employee-level control variables						
Previously known employees at peers	0.001 [.000]	0.000 [.000]	−0.002 [.000]	−0.001 [.000]		
Employee's industry experience	−0.034 [.000]	−0.014 [.000]	−0.066 [.000]	−0.059 [.000]		−0.056 [.000]
Employee's number of projects	0.316 [.000]	0.195 [.000]	−0.074 [.000]	0.184 [.000]		−0.024 [.001]
Project-level control variables						
Project is based on a license	0.105 [.000]	0.035 [.208]	0.014 [.338]	0.113 [.000]	2.622 [.004]	0.073 [.195]
Project is part of a series	0.332 [.000]	−0.292 [.000]	−0.074 [.000]	0.262 [.000]	2.538 [.000]	−0.023 [.594]
Team size	−0.000 [.000]	−0.000 [.000]	0.000 [.000]	−0.000 [.848]	0.021 [.000]	−0.000 [.011]
Firm-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
Partner-level control variable	Yes	Yes	Yes	Yes	Yes	Yes
Dyad-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
Employee fixed effects	Yes	Yes	Yes	Yes		Yes
Firm fixed effects					Yes	
Observations	183,972	126,495	254,220	303,154	20,018	26,767

TABLE 4 (Continued)

	Examination of job opportunities as mechanism				Examination of skill development as mechanism	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent variable	**Employee works for peer firm**	**Employee works for superior peer firm**	**Employee works for nonpeer firm**	**Employee works for firm owned by the partner**	**Firm performance**	**Promotion of employee staying**
Number of employees	27,140	17,507	40,191	53,291		5,783
Number of firms					4,551	
Log-likelihood	−57,641	−35,189	−85,202	−112,489		−7,980
Adjusted R^2					0.431	

Note: Exact *p* values are reported in brackets. Models 1–4 and Model 6 show logit regressions with clustered standard errors. We also run these models as OLS regressions with clustered standard errors; the results are similar to those reported here. Model 5 shows coefficient estimates of OLS regression with clustered standard errors.

Our first set of analyses, shown in Models 1–4 in Table 4, focuses on the *job opportunities* mechanism. We run logit models predicting the likelihood that an employee will join different types of firms.[9] In Model 1, we predict how *number of peers* and *superiority of peers* influence the likelihood of joining a peer developer finding a positive effect. However, it is possible that it was employees' connection to a peer firm that led them to choose the same partner. To mitigate this problem of reverse causality when predicting the likelihood that an employee will join a peer firm, we control for the number of employees at peer firms with whom the focal employee worked before collaborating with the partner. We find a positive effect of *number of peers* (p-value = .000) and *superiority of peers* (p-value = .000) on joining a peer firm, as shown in Model 1 in Table 4, suggesting those job opportunities is indeed a mechanism.

We examine in Model 2 in Table 4 how peer competition affects the likelihood of working for a superior peer firm. *Number of peers* (p-value = .000) and especially *superiority of peers* (p-value = .000) have a positive effect, suggesting that employees exposed to peer competition are more likely to join a superior peer.

In Model 3, we investigate whether the job opportunities available to employees exposed to peer competition are indeed due to the social capital they have formed with employees at peer firms. It would also be plausible that peer competition increases employees' visibility in the industry in general or fosters their skills, improving their odds of finding job opportunities elsewhere. However, we find that *number of peers* negatively (p-value = .000) influences the likelihood of working for a nonpeer firm in the next year. Our finding that employees exposed to peer competition are more likely to find a job at a peer firm but less likely to find a job at another firm provides suggestive evidence that job opportunities are the key mechanism by which firm-level peer competition increases an employee's personal success.

Finally, we propose that it is a firm's *indirect* ties to peer developers, not its direct ties to publishers, that benefits employees. Although publishers also have some employees working in the typical occupations found at developers, that is, artists, designers, programmers, and producers, most employees looking for a new job would find it at a developer owned by the publisher. We therefore ran a logit regression predicting the likelihood of joining the publisher or a developer owned by the publisher directly. We found that *number of peers* and the *superiority of peers* had a negative effect on the likelihood of joining a publisher or a developer owned by the publisher, indicating that it was the *indirect* ties that were providing job opportunities.

In Models 5 and 6 in Table 4, we want to explore whether peer competition helps employees in *developing their skills* and thus contributes to their subsequent success. We do so by running additional models at both the firm (Model 5) and the employee level (Model 6). In Model 5, we investigate the idea that although peer competition is detrimental to firm performance in the short run (as illustrated by prior research and replicated by us in Models 1 and 2 in Table 2), it may be beneficial in the long run, as the employees may develop their skills by interacting with employees from peer firms. Also, even if employees depart the focal firm may still derive benefits from these connections (Corredoira & Rosenkopf, 2010). To test this idea, we include the number of peers and the superiority of peers in not only the focal but also the previous year (*number of peers lagged*/*superiority of peers lagged*). We also control for the number of employees that the firm lost in the previous year. Our analysis, however, provides inconsistent evidence, casting doubt on the skill-based explanation. We find in Model 5 in Table 4 that *superiority of peers lagged* has a negative impact (p-value = .098) on firm performance while *number of peers lagged* has a positive impact (p-value = .097). Given such inconsistent evidence, we looked for more direct evidence of an improvement of skills at the employee level.

[9]As a robustness check, we also ran Models 1–4 with an OLS model; the results are consistent.

TABLE 5 Potential mediation on employee's personal success

	Mediation by *employees works for peer*			Mediation by *employees works for superior peer*		
	Direct effect of peers on *employee works for peer*	**Indirect effect of peers on employee's personal success mediated by *employee works for peer***	**Total effect of peers on employee's personal success**	**Direct effect of peers on *employee works for superior peer***	**Indirect effect of peers on employee's personal success mediated by *employee works for superior peer***	**Total effect of peers on employee's personal success**
Number of peers	0.001 (CI: 0.001–0.001)	0.042 (CI: 0.039–0.044)	0.117 (CI: 0.103–0.130)	0.0007 (CI: 0.0007–0.0008)	0.024 (CI: 0.022–0.027)	0.108 (CI: 0.095–0.121)
Superiority of peers	0.047 (CI: 0.046–0.049)	1.295 (CI: 1.247–1.342)	1.845 (CI: 1.650–2.039)	0.034 (CI: 0.033–0.036)	1.074 (CI: 1.023–1.124)	1.861 (CI: 1.669–2.053)

Note: We estimated the 95% CI using bootstrapping and 1,000 replications with replacement.

TABLE 6 T-test comparing tenure for employees joining from peer firm versus employees not joining from peer firm

Joined from peer firm	*N*	Mean	SE	*SD*	95% CI
No	463.611	1.74	0.01	4.07	1.73–1.75
Yes	51,542	4.02	0.02	5.48	3.98–4.07

To do so, we restricted our analysis in Model 6 to those in our sample who stayed with the focal firm. If peer competition helps them improve their skills, they may do better in the focal firm and be promoted. We found, however, no significant effect of peer competition on promotion. Overall, the results shown in Models 5 and 6 do not provide compelling evidence that employees benefit from peer competition by developing their skills.

Building on our result that peer competition improves employee's personal success through the job opportunities mechanism, we directly tested these relationships in a *mediation* analysis. Following recent literature (Choudhury & Haas, 2018; Hallen, Cohen, & Bingham, 2020), we tested for potential mediation by running a structural equation model with bootstrapping. Structural equation modeling fits a single model to test the significance of the indirect paths from the independent variables (*number of peers*/*superiority of peers*) to the dependent variable (*employee's personal success*) through the potential mediator (*employee works for peer firm*/*employee works for superior peer firm*). There are two advantages to this approach. First, it allows the error terms in the model specification to correlate (Shaver, 2005). Second, bootstrapping is a nonparametric approach that imposes no assumptions about the distributions of the variables or the sampling distribution of the statistic. We used the same independent and control variables and employee fixed effects used in our analysis so far. Table 5 presents the results.

We find that the positive effect of *number of peers* and *superiority of peers* on an employee's personal success is partially mediated through *employee works for a peer firm*. While the variable mediates about 36% (0.042/0.117) of the effect of *number of peers* on the employee's personal success, it accounts for roughly 70% (1.295/1.845) of the effect of *superiority of peers* on an employee's personal success. Using *employee works for superior peer firm* as a mediator reduces the mediation effect. While the variable mediates roughly 23% (0.024/0.108) of the effect of *number of peers* on an employee's personal success, it mediates 58% (1.074/1.861) of the effect of *superiority of peers* on an employee's personal success. The mediation analysis thus provides further evidence that the positive effect of peer competition on an employee's personal success is mainly driven by a job opportunities mechanism.

As a final step in our analysis, we build on the idea of Campbell et al. (2021) to investigate whether interorganizational ties provide better matches between employees and employers. If so, then employees who join a firm via peer competition should stay longer than those who join by ordinary routes. Indeed, as shown in Table 6, we find that employees joining peer firms stay on average more than 4 years (95% CI = 3.98–4.07), while those who join by ordinary routes stay only 1.74 years (95% CI = 1.73–1.75).

5 | DISCUSSION

We found divergent effects. Sharing a partner with peer firms exposes a firm to peer competition—hindering the firm's success but benefitting its employees. Peer competition

enables employees to develop their social capital, opening up access to better job opportunities at peer firms. The theoretical implications of these findings are discussed below.

5.1 | Alliance portfolios: Arenas of peer competition and seedbeds of social capital

While replicating work on peer competition is not our primary contribution, we consider it important. Scholars have pointed to a need for replication in strategic management (Ethiraj, Gambardella, & Helfat, 2016), and recent work underscores its potential (Goldfarb & Yan, 2021; Goldfarb, Zavyalova, & Pillai, 2018). Our results on H1 replicate the finding on the detrimental effect of peer competition on firm success in a different context and across different levels of analysis—firm and project—thus fortifying earlier findings. They also reveal an additional downside of collaborations in which firms are exposed to peer competition: a potential exodus of employees. Our study thus underscores the conceptualization of alliance portfolios as *arenas of peer competition*.

We offer an alternative complementary conceptualization of partners' portfolios as *seedbeds of social capital*. We present evidence in support of our theory that partners' alliance portfolios give employees the chance and coverage to form interpersonal relationships that will benefit their participation in the labor market. While research on alliance portfolios has taken the perspective of alliance portfolio owners or member firms (Cennamo & Santalo, 2013; Lavie, 2007; Ozcan & Eisenhardt, 2009), we complement such work by illustrating their implications for the employees of member firms.

Our study also contributes to research that examines the role of individual employees in the context of interfirm relationships (Broschak, 2004; Devarakonda et al., 2022; Dokko & Rosenkopf, 2010; Rogan, 2014; Rosenkopf, Metiu, & George, 2001; Somaya et al., 2008; Wang, Pahnke, & McDonald, 2022; Young-Hyman & Kleinbaum, 2020). Prior work has shown how employees' inter*personal* ties shape inter*organizational* ties (Broschak, 2004; Devarakonda et al., 2022; Dokko & Rosenkopf, 2010; Rogan, 2014; Rosenkopf et al., 2001; Somaya et al., 2008; Young-Hyman & Kleinbaum, 2020). We illustrate the reverse: how inter*organizational* ties shape employees' inter*personal* ties.

5.2 | Inter*organizational* ties: A catalyst for *employees'* ties, mobility, and careers

Our study contributes to research on mobility and careers, pointing to the importance of *a specific type of social capital*: *employees' relationships with their employer's competitors*. The linkage between social capital and successful intra- and inter-firm mobility is well established (Carnabuci & Wezel, 2011; Hasan, 2019; Kleinbaum, 2012; Lee & Gargiulo, 2021; Seibert, Kraimer, & Liden, 2001; Somaya et al., 2008).[10] We illustrate that it is essential to be connected

[10]Social capital is important for employees to find a new job and change employers (Fernandez et al., 2000) and improve their matching with employers (Campbell et al., 2021; Weller et al., 2019). Increased employer–employee matching, in turn, has been shown to positively influence productivity (Lazear & Oyer, 2004) as well as to reduce turnover (Hom, Lee, Shaw, & Hausknecht, 2017). Further, not knowing the colleagues at the new employer well is often seen as one of the reasons why employees' performance falls, temporarily at least, when they move between organizations (Bidwell, 2011; Groysberg, Lee, & Nanda, 2008; Huckman & Pisano, 2006; Mawdsley & Somaya, 2016).

to one's employer's competitors, as the same features that render a peer firm a competitor also make it an alternative employer.

Our study also illustrates *how* employees develop relationships with their employer's competitors. Sharing a partner (so that the firm is indirectly linked to its competitors) provides employees with the *chance* and the *coverage* to develop this kind of relationship. The shared partner provides coverage as it allows employees to devote time to developing that relationship (and connect with peers) yet claim that their networking benefits the organization. One can think of other examples: employees may attend conferences claiming that it helps them recruit—which it may well do—but with the added effect of getting to know potential recruiters. Our paper thus contributes to an emerging stream of research on how actors form ties that may have benefits but are difficult to form as they lack legitimacy (Piskorski, 2013, 2014; Schilke & Rossman, 2018; Zhang, Aven, & Kleinbaum, 2022).

An interesting feature of our study is that it shows how organizations may foster interfirm mobility. Research, notably on noncompetes (Marx, Strumsky, & Fleming, 2009; Starr, Ganco, & Campbell, 2018) illustrates that firms often take action to reduce interfirm mobility. We show that they can also be a catalyst for their own employees' departure—albeit unwittingly, they may do so via interfirm collaborations.

Our study also re-conceptualizes the types of networks that organizations can help their employees form. Research suggests that organizations help employees form *closed* networks as they connect with co-located colleagues with whom they share a departmental affiliation and geographical space (Dahlander & McFarland, 2013; Kleinbaum, Stuart, & Tushman, 2013). We show that organizations—via their interorganizational ties—also help people form *open* networks that cross organizational boundaries (Burt, 2004; Tandon, Ertug, & Carnabuci, 2020). While beneficial, such relationships are difficult to develop.

Our study also illustrates the role that organizations play in the career of their employees (Bidwell et al., 2015; Burton et al., 2002; Carnahan, Rabier, & Uribe, 2022; Chattopadhyay & Choudhury, 2017; Choudhury, Khanna, & Sevcenko, 2022; Clement & Puranam, 2018; Kacperczyk & Younkin, 2021; Mawdsley & Somaya, 2016; Small, 2009; Sorenson et al., 2021). While prior work has examined how various characteristics of an organization shape the career of individuals, for example, firm age (Burton, Dahl, & Sorenson, 2018; Sorenson et al., 2021), survival (Sutton & Callahan, 1987), or status (Bidwell et al., 2015; Burton et al., 2002), our paper focusses on a neglected organizational feature: interfirm collaboration.

5.3 | Agency conflict and interorganizational collaboration

Our study illustrates a potential agency conflict. We show that collaborations that undermine the success of firms often benefit their employees, specifically those that expose the firm to more and/or superior peer competition (hypothesized) and those with multiple partners (serendipitously found). The divergent effects in each case create the potential for agency conflict if employees pursue their own rather than their firm's interests (Gottschalg & Zollo, 2007).

Employees may (ab)use interorganizational collaborations for their own benefit. Those who can influence which ones their firm enters may seek out—and/or manage—collaborations that benefit themselves but not their employer. For example, instead of focusing on outcompeting their peers and guarding their employer's intellectual property, employees may focus on developing relationships with their peers. In some cases, developing personal relationships may further hurt their employer, for example, if they share proprietary knowledge to present

themselves as knowledgeable potential hires (Schrader, 1995; von Hippel, 1987). In brief, they focus on their own benefit to the detriment of the employer.

For our theory to hold, employees do *not* need to act with "guile"—none of our interviews suggested that people deliberately traded off the success of their employer for personal gain. The effect may be more subtle: employees seemed to associate peer competition mostly with opportunities to connect to other firms and their employees, which in turn helped them personally. And while they may not have actively pursued such ties, they did not object to their formation. In so doing, they simply did not pay sufficient attention to the detrimental effects of peer competition.

Our study emphasizes the need to examine the role of agency conflict in shaping interorganizational networks. We are not the first to postulate a tension between organizationally and personally optimal network structures (Clement, Shipilov, & Galunic, 2018; Jackson & Wolinsky, 1996). Our paper provides empirical evidence of the potential for agency conflict by pointing to divergent effects. Future research could examine how personal motives affect the formation and management of social networks.

Our argument that agency conflicts shape the selection of partners also has methodological implications. Matching models simultaneously estimate the antecedents and consequences of collaborations but use as a critical ingredient the variable managers strive to optimize (Chen, Huang, Meyer-Doyle, & Mindruta, 2021; Mindruta et al., 2016). For example, research on the effect of collaborating with certain types of venture capitalists assumes that ventures strive to maximize their chances of a successful exit (Sørensen, 2007). Our study shows that when selecting partners, managers may not (only) strive to maximize firm performance. The assumption that they do may result in biased estimates regarding the antecedents and consequences of ties.

5.4 | Boundary conditions

Underlying the positive effect of peer competition on employee success are countervailing forces. Peer competition hinders employees' current firms, which, ceteris paribus, hinders their own success yet can also help them develop social capital, which can help their success. We found the latter to outweigh the former, but this may be specific to the context. Thus, while we suggest that peer competition generally enables the development of social capital, there are boundaries to the notion of an overall positive effect of peer competition on career success. Interestingly, the agency conflict may persist. If peer competition is highly detrimental to firms, but only slightly so to employees, employees may insufficiently take it into account.

The effect of social capital on people's careers is likely to vary across industries and regions (Powell, Koput, & Smith-Doerr, 1996). In project-driven industries, in which it is common to change employers (Lee & Gargiulo, 2021; Petriglieri, Ashford, & Wrzesniewski, 2019), an increase in social capital is likely to be particularly consequential. Also, we have pointed out that interfirm alliances provide employees with the otherwise scarce opportunity to build social capital; in certain industries, such opportunities may not be scarce.

Our study on peer competition from shared partnerships only applies to firms that compete for the partner's resources, and who may provide job opportunities to their respective employees. Such peer competition is particularly likely to occur when a partner collaborates with firms that are active in the same domain (e.g., the same segment of the value chain in the same industry). Moreover, the formation of social capital may be contingent on face-to-face

encounters (Chai & Freeman, 2019; Choudhury, 2017). Thus, when face-to-face meetings are uncommon, for example, because of remote work, the effects we observe are less likely to materialize.

5.5 | Limitations

Our limitation is our operationalization of employee success. While we base our measure on the feedback of our interviewees, we would ideally have alternative measures, such as their salaries. Another limitation is that our assignment is nonrandom. Our discussion of agency conflict suggests that employees may intentionally form ties that expose them to peer competition to foster their careers. One could thus argue that it is not peer competition per se but employees who prioritize their careers that hurt the firm's success. Although this alternative explanation casts doubt on the effect of peer competition on firm success, our main argument that ties in which firms face peer competition foster employee success—and may have been entered into for precisely that reason—remains robust. In brief, the treatment of exposure to peer competition is not exogenous.

While our research design aims to establish a linkage between peer competition and firm/individual performance, it does not feature an experimental treatment. Although such designs have been hard to establish in the setting of interfirm networks, recent work on individual networks illustrates the potential and need for causal evidence on social networks (Hasan & Koning, 2019, 2020; Maoret, Dufour, & Fonti, 2022).

5.6 | Managerial implications

Our study has important managerial implications. For principals, it points out the danger that employees may engage in collaborations that are in their own—but not their firms'—best interests. For employees, it points out the potential to leverage interorganizational collaborations for personal success. For partners, it suggests that they may attract firms by pointing out that even if the firm fails, the partner's portfolio may still aid individual careers.

6 | CONCLUSIONS

This work was inspired by Sutton and Hargadon (1996), who illustrates that is critical to ask, "effectiveness at what" and "effectiveness for whom" (also see Berger (2011) on the need for a dual perspective). At the time of their study, brainstorming was seen critically as alternative techniques were considered superior in generating ideas. Sutton and Hargadon (1996) showed that brainstorming had numerous additional purposes beyond generating ideas—and was highly effective. Inspired by their work, we studied collaborations, specifically collaborations that led to peer competition, which were often labeled ineffective (Aggarwal, 2020; Ozmel & Guler, 2015; Pahnke et al., 2015b). We found them to be highly effective for employees as they helped them build social capital and find new jobs. Taking a broader perspective and examining the consequences for firms *and* employees led us (1) to reassess these collaborations and (2) to uncover the tensions to which they give rise between employees and organizations. We thus hope that our study serves as further encouragement to ask "effectiveness at what" and "effectiveness for whom."

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from MobyGames and NPD. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of MobyGames and NPD.

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REFERENCES

Aggarwal, V. A. (2020). Resource congestion in alliance networks: How a firm's partners' partners influence the benefits of collaboration. *Strategic Management Journal*, *41*(4), 627–655.

Ahuja, G. (2000). The duality of collaboration: Inducements and opportunities in the formation of interfirm linkages. *Strategic Management Journal*, *21*(3), 317–343.

Baum, J., & Silverman, B. (2004). Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. *Journal of Business Venturing*, *19*(3), 411–436.

Berger, P. L. (2011). *Invitation to sociology: A humanistic perspective*. New York, NY: Open Road Media.

Bernstein, S., Giroud, X., & Townsend, R. R. (2016). The impact of venture capital monitoring. *The Journal of Finance*, *71*(4), 1591–1622.

Bidwell, M. (2011). Paying more to get less: The effects of external hiring versus internal mobility. *Administrative Science Quarterly*, *56*(3), 369–407.

Bidwell, M., & Mollick, E. (2015). Shifts and ladders: Comparing the role of internal and external mobility in managerial careers. *Organization Science*, *26*(6), 1629–1645.

Bidwell, M., Won, S., Barbulescu, R., & Mollick, E. (2015). I used to work at Goldman Sachs! How firms benefit from organizational status in the market for human capital. *Strategic Management Journal*, *36*(8), 1164–1173.

Bothner, M. S. (2003). Competition and social influence: The diffusion of the sixth-generation processor in the global computer industry. *American Journal of Sociology*, *108*(6), 1175–1210.

Bothner, M. S., Kang, J.-h., & Stuart, T. E. (2007). Competitive crowding and risk taking in a tournament: Evidence from NASCAR racing. *Administrative Science Quarterly*, *52*(2), 208–247.

Boudreau, K. J., & Jeppesen, L. B. (2015). Unpaid crowd complementors: The platform network effect mirage. *Strategic Management Journal*, *36*(12), 1761–1777.

Broschak, J. P. (2004). Managers' mobility and market interface: The effect of managers' career mobility on the dissolution of market ties. *Administrative Science Quarterly*, *49*(4), 608–640.

Brown, S. L., & Eisenhardt, K. M. (1997). The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations. *Administrative Science Quarterly*, *42*(1), 1–34.

Burt, R. S. (2004). Structural holes and good ideas. *American Journal of Sociology*, *110*(2), 349–399.

Burt, R. S. (2005). *Brokerage and closure: An introduction to social capital*. New York, NY: Oxford University Press.

Burton, M. D., Dahl, M. S., & Sorenson, O. (2018). Do start-ups pay less? *ILR Review*, *71*(5), 1179–1200.

Burton, M. D., Sørensen, J. B., & Beckman, C. M. (2002). Coming from good stock: Career histories and new venture formation. In *Research in the sociology of organizations: Social structure and organizations revisited*. Greenwich, CT: JAI Press.

Campbell, B. A., Di Lorenzo, F., & Tartari, V. (2021). Employer-employee matching and complementary assets: The role of cross-organization collaborations. *Academy of Management Journal*, *64*(3), 799–823.

Carnabuci, G., & Wezel, F. C. (2011). Back to the future: Career transitions at the dawn of capitalism: The immigration of merchants from the southern Netherlands to Amsterdam, 1578–1602. *Organization Studies*, *32*(12), 1621–1637.

Carnahan, S., Rabier, M., & Uribe, J. (2022). Do Managers' affiliation ties have a negative relationship with Subordinates' interfirm mobility? Evidence from large US law firms. *Organization Science*, *33*(1), 353–372.

Cennamo, C., & Santalo, J. (2013). Platform competition: Strategic trade-offs in platform markets. *Strategic Management Journal*, *34*(11), 1331–1350.

Chai, S., & Freeman, R. B. (2019). Temporary colocation and collaborative discovery: Who confers at conferences. *Strategic Management Journal*, *40*(13), 2138–2164.

Chattopadhyay, S., & Choudhury, P. (2017). Sink or swim: The role of workplace context in shaping career advancement and human-capital development. *Organization Science*, *28*(2), 211–227.

Chen, G., Huang, S., Meyer-Doyle, P., & Mindruta, D. (2021). Generalist versus specialist CEOs and acquisitions: Two-sided matching and the impact of CEO characteristics on firm outcomes. *Strategic Management Journal*, *42*(6), 1184–1214.

Choudhury, P. (2017). Innovation outcomes in a distributed organization: Intrafirm mobility and access to resources. *Organization Science*, *28*(2), 339–354.

Choudhury, P., & Haas, M. R. (2018). Scope versus speed: Team diversity, leader experience, and patenting outcomes for firms. *Strategic Management Journal*, *39*(4), 977–1002.

Choudhury, P., Khanna, T., & Sevcenko, V. (2022). Firm-induced migration paths and strategic human-capital outcomes. *Management Science*.

Claussen, J., Grohsjean, T., Luger, J., & Probst, G. (2014). Talent management and career development: What it takes to get promoted. *Journal of World Business*, *49*(2), 236–244.

Clement, J., & Puranam, P. (2018). Searching for structure: Formal organization design as a guide to network evolution. *Management Science*, *64*(8), 3879–3895.

Clement, J., Shipilov, A., & Galunic, C. (2018). Brokerage as a public good: The externalities of network hubs for different formal roles in creative organizations. *Administrative Science Quarterly*, *63*(2), 251–286.

Clough, D. R., & Piezunka, H. (2020). Tie dissolution in market networks: A theory of vicarious performance feedback. *Administrative Science Quarterly*, *65*(4), 972–1017.

Contractor, F. J., & Reuer, J. J. (2014). Structuring and governing alliances: New directions for research. *Global Strategy Journal*, *4*(4), 241–256.

Cook, N. (2019). *SPECCHECK: Stata module to check model specification*. Boston, MA: Boston College Department of Economics.

Corredoira, R., & Rosenkopf, L. (2010). Should auld acquaintance be forgot? The reverse transfer of knowledge through mobility ties. *Strategic Management Journal*, *31*(2), 159.

Dahlander, L., & McFarland, D. A. (2013). Ties that last: Tie formation and persistence in research collaborations over time. *Administrative Science Quarterly*, *58*(1), 69–110.

Devarakonda, R., Pavićević, S., & Reuer, J. J. (2022). Microfoundations of R&D Alliance formation: The interplay of scientist mobility and the cooperative context of collaboration. *Strategy Science*, *7*(1), 56–70.

Diestre, L., & Rajagopalan, N. (2012). Are all 'sharks' dangerous? New biotechnology ventures and partner selection in R&D alliances. *Strategic Management Journal*, *33*(10), 1115–1134.

Dokko, G., & Rosenkopf, L. (2010). Social capital for hire? Mobility of technical professionals and firm influence in wireless standards committees. *Organization Science*, *21*(3), 677–695.

Dushnitsky, G., & Lavie, D. (2010). How alliance formation shapes corporate venture capital investment in the software industry: A resource-based perspective. *Strategic Entrepreneurship Journal*, *4*(1), 22–48.

Engel, Y., Kaandorp, M., & Elfring, T. (2017). Toward a dynamic process model of entrepreneurial networking under uncertainty. *Journal of Business Venturing*, *32*(1), 35–51.

Ethiraj, S. K., Gambardella, A., & Helfat, C. E. (2016). Replication in strategic management. *Strategic Management Journal*, *37*(11), 2191–2192.

Faulkner, R. R., & Anderson, A. B. (1987). Short-term projects and emergent careers: Evidence from Hollywood. *American Journal of Sociology*, *92*(4), 879–909.

Fernandez, R. M., Castilla, E. J., & Moore, P. (2000). Social capital at work: Networks and employment at a phone center. *American Journal of Sociology*, *105*(5), 1288–1356.

Garg, S., & Eisenhardt, K. M. (2017). Unpacking the CEO–board relationship: How strategy making happens in entrepreneurial firms. *Academy of Management Journal*, *60*(5), 1828–1858.

Gargiulo, M., & Benassi, M. (2000). Trapped in your own net? Network cohesion, structural holes, and the adaptation of social capital. *Organization Science*, *11*(2), 183–196.

Goldfarb, B., & Yan, L. (2021). Revisiting Zuckerman's (1999) categorical imperative: An application of epistemic maps for replication. *Strategic Management Journal*, *42*(11), 1963–1992.

Goldfarb, B., Zavyalova, A., & Pillai, S. (2018). Did victories in certification contests affect the survival of organizations in the American automobile industry during 1895–1912? A replication study. *Strategic Management Journal*, *39*(8), 2335–2361.

Gottschalg, O., & Zollo, M. (2007). Interest alignment rents and competitive advantage. *The Academy of Mangement Review*, *32*(2), 418–437.

Gould, R. V. (2003). *Collision of wills*. Chicago, IL: University of Chicago Press.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380.

Grohsjean, T., Kober, P., & Zucchini, L. (2016). Coming back to Edmonton: Competing with former employers and colleagues. *Academy of Management Journal*, *59*(2), 394–413.

Groysberg, B., Lee, L., & Nanda, A. (2008). Can they take it with them? The portability of star knowledge Workers' performance. *Management Science*, *54*(7), 1213–1230.

Gulati, R. (1998). Alliances and networks. *Strategic Management Journal*, *19*(4), 293–317.

Guler, I. (2007). Throwing good money after bad? A multi-level study of sequential decision making in the venture capital industry. *Administrative Science Quarterly*, *52*(2), 248–285.

Hallen, B. L. (2008). The causes and consequences of the initial network positions of new organizations: From whom do entrepreneurs receive investments? *Administrative Science Quarterly*, *53*(4), 685–718.

Hallen, B. L., Cohen, S. L., & Bingham, C. B. (2020). Do accelerators work? If so, how? *Organization Science*, *31*(2), 378–414.

Hallen, B. L., Davis, J. P., & Murray, A. (2020). Entrepreneurial network evolution: Explicating the structural localism and agentic network change distinction. *Academy of Management Annals*, *14*(2), 1067–1102.

Hallen, B. L., Katila, R., & Rosenberger, J. D. (2014). How do social defenses work? A resource-dependence lens on technology ventures, venture capital investors, and corporate relationships. *Academy of Management Journal*, *57*(4), 1078–1101.

Hallen, B. L., & Pahnke, E. (2016). When do entrepreneurs accurately evaluate venture capital firms' track records? A bounded rationality perspective. *Academy of Management Journal*, *59*(5), 1535–1560.

Hasan, S. (2019). Social networks and careers. In D. J. Brass & S. P. Borgatti (Eds.), *Social networks at work*. London: RoutledgePublishing.

Hasan, S., & Koning, R. (2019). Prior ties and the limits of peer effects on startup team performance. *Strategic Management Journal*, *40*(9), 1394–1416.

Hasan, S., & Koning, R. (2020). Designing social networks: Joint tasks and the formation and endurance of network ties. *Journal of Organization Design*, *9*(1), 1–19.

Hernandez, E., Sanders, W. G., & Tuschke, A. (2015). Network defense: Pruning, grafting, and closing to prevent leakage of strategic knowledge to rivals. *Academy of Management Journal*, *58*(4), 1233–1260.

Hoetker, G. (2005). How much you know versus how well I know you: Selecting a supplier for a technically innovative component. *Strategic Management Journal*, *26*(1), 75–96.

Hom, P. W., Lee, T. W., Shaw, J. D., & Hausknecht, J. P. (2017). One hundred years of employee turnover theory and research. *Journal of Applied Psychology*, *102*(3), 530–545.

Huckman, R. S., & Pisano, G. P. (2006). The firm specificity of individual performance: Evidence from cardiac surgery. *Management Science*, *52*(4), 473–488.

Ibarra, H. (1993). Network centrality, power, and innovation involvement: Determinants of technical and administrative roles. *Academy of Management Journal*, *36*(3), 471–501.

Ingram, P., & Morris, M. W. (2007). Do people mix at mixers? Structure, homophily, and the "life of the party". *Administrative Science Quarterly*, *52*(4), 558–585.

Ingram, P., & Roberts, P. W. (2000). Friendships among competitors in the Sydney hotel industry. *American Journal of Sociology*, *106*(2), 387–423.

Jackson, M. O., & Wolinsky, A. (1996). A strategic model of social and economic networks. *Journal of Economic Theory*, *71*(1), 44–74.

Kacperczyk, O., & Younkin, P. (2021). A founding penalty: Evidence from an audit study on gender, entrepreneurship, and future employment. *Organization Science*, *33*, 716–745.

Katila, R., Piezunka, H., Reineke, P., & Eisenhardt, K. (2022). Big fish vs. big pond? Entrepreneurs, established firms, and antecedents of tie formation. *Academy of Management Journal*, *65*(2), 427–452.

King, A., Goldfarb, B., & Simcoe, T. (2021). Learning from testimony on quantitative research in management. *Academy of Management Review*, *46*(3), 465–488.

Kleinbaum, A. M. (2012). Organizational misfits and the origins of brokerage in intrafirm networks. *Administrative Science Quarterly*, *57*(3), 407–452.

Kleinbaum, A. M., Stuart, T. E., & Tushman, M. L. (2013). Discretion within constraint: Homophily and structure in a formal organization. *Organization Science*, *24*(5), 1316–1336.

Kretschmer, T., & Claussen, J. (2016). Generational transitions in platform markets—The role of backward compatibility. *Strategy Science*, *1*(2), 90–104.

Lavie, D. (2007). Alliance portfolios and firm performance: A study of value creation and appropriation in the U.S. software industry. *Strategic Management Journal*, *28*(12), 1187–1212.

Lazear, E. P., & Oyer, P. (2004). Internal and external labor markets: A personnel economics approach. *Labour Economics*, *11*(5), 527–554.

Lee, S. (2022). The myth of the flat start-up: Reconsidering the organizational structure of start-ups. *Strategic Management Journal*, *43*(1), 58–92.

Lee, Y., & Gargiulo, M. (2021). Escaping the survival trap: Network transition among early-career freelance songwriters. *Administrative Science Quarterly*, *67*, 339–377.

Levinthal, D. A., & Wu, B. (2010). Opportunity costs and non-scale free capabilities: Profit maximization, corporate scope, and profit margins. *Strategic Management Journal*, *31*(7), 780–801.

Li, J. B., & Piezunka, H. (2020). The uniplex third: Enabling single-domain role transitions in multiplex relationships. *Administrative Science Quarterly*, *65*(2), 314–358.

MacCormack, A., Verganti, R., & Iansiti, M. (2001). Developing products on "internet time": The anatomy of a flexible development process. *Management Science*, *47*(1), 133–150.

Maoret, M., Dufour, L., & Fonti, F. (2022). Structural holes and individual performance: Causal evidence from a field experiment.

March, J. G., & Simon, H. S. (1958). *Organizations*. New York: John Wiley.

Marx, M., Strumsky, D., & Fleming, L. (2009). Mobility, skills, and the Michigan non-compete experiment. *Management Science*, *55*(6), 875–889.

Mawdsley, J. K., & Somaya, D. (2016). Employee mobility and organizational outcomes: An integrative conceptual framework and research agenda. *Journal of Management*, *42*(1), 85–113.

Mindruta, D., Moeen, M., & Agarwal, R. (2016). A two-sided matching approach for partner selection and assessing complementarities in partners' attributes in inter-firm alliances. *Strategic Management Journal*, *37*(1), 206–231.

Mollick, E. (2012). People and process, suits and innovators: The role of individuals in firm performance. *Strategic Management Journal*, *33*(9), 1001–1015.

Mulotte, L., Ren, C., Dussauge, P., & Anand, J. (2022). Alliance performance and subsequent make-or-ally choices: Evidence from the aircraft manufacturing industry. *Strategic Management Journal*.

Obstfeld, D. (2005). Social networks, the tertius iungens orientation, and involvement in innovation. *Administrative Science Quarterly*, *50*(1), 100–130.

Ocasio, W. (1997). Towards an attention-based view of the firm. *Strategic Management Journal*, *18*(S1), 187–206.

Ozcan, P., & Eisenhardt, K. M. (2009). Origin of alliance portfolios: Entrepreneurs, network strategies, and firm performance. *Academy of Management Journal*, *52*(2), 246–279.

Ozmel, U., & Guler, I. (2015). Small fish, big fish: The performance effects of the relative standing in partners' affiliate portfolios. *Strategic Management Journal*, *36*(13), 2039–2057.

Pahnke, E., Katila, R., & Eisenhardt, K. M. (2015). Who takes you to the dance? How partners' institutional logics influence innovation in young firms. *Administrative Science Quarterly*, *60*(4), 596–633.

Pahnke, E., McDonald, R., Wang, D., & Hallen, B. (2015). Exposed: Venture capital, competitor ties, and entrepreneurial innovation. *Academy of Management Journal*, *58*(5), 1334–1360.

Petkova, A. P., Rindova, V. P., & Gupta, A. K. (2013). No news is bad news: Sensegiving activities, media attention, and venture capital funding of new technology organizations. *Organization Science*, *24*(3), 865–888.

Petriglieri, G., Ashford, S. J., & Wrzesniewski, A. (2019). Agony and ecstasy in the gig economy: Cultivating holding environments for precarious and personalized work identities. *Administrative Science Quarterly*, *64*(1), 124–170.

Phillips, D. J. (2001). The promotion paradox: Organizational mortality and employee promotion chances in Silicon Valley law firms, 1946–1996. *American Journal of Sociology*, *106*(4), 1058–1098.

Piezunka, H., & Dahlander, L. (2015). Distant search, narrow attention: How crowding alters organizations' filtering of suggestions in crowdsourcing. *Academy of Management Journal*, *58*(3), 856–880.

Piezunka, H., Lee, W., Haynes, R., & Bothner, M. S. (2018). Escalation of competition into conflict in competitive networks of formula one drivers. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(15), E3361–E3367.

Piezunka, H., Lee, W., Haynes, R., & Bothner, M. S. (2018b). The Matthew effect as an unjust competitive advantage: Implications for competition near status boundaries. *Journal of Management Inquiry*, *27*(4), 378–381.

Piskorski, M. J. (2013). Networks as covers: Evidence from an on-line social network. In *Harvard Business School working papers*. Boston, MA: Harvard Business School.

Piskorski, M. J. (2014). *A social strategy: How we profit from social media*. Princeton, NJ: Princeton University Press.

Pollock, T. G., & Gulati, R. (2007). Standing out from the crowd: The visibility-enhancing effects of IPO-related signals on alliance formation by entrepreneurial firms. *Strategic Organization*, *5*(4), 339–372.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative Science Quarterly*, *41*(1), 116–145.

Powell, W. W., White, D. R., Koput, K. W., & Owen-Smith, J. (2005). Network dynamics and field evolution: The growth of interorganizational collaboration in the life sciences. *American Journal of Sociology*, *110*(4), 1132–1205.

Rietveld, J., & Eggers, J. (2018). Demand heterogeneity in platform markets: Implications for complementors. *Organization Science*, *29*(2), 304–322.

Rogan, M. (2014). Executive departures without client losses: The role of multiplex ties in exchange partner retention. *Academy of Management Journal*, *57*(2), 563–584.

Rogan, M., & Sorenson, O. (2014). Picking a (poor) partner: A relational perspective on acquisitions. *Administrative Science Quarterly*, *59*(2), 301–329.

Rosenkopf, L., Metiu, A., & George, V. P. (2001). From the bottom up? Technical committee activity and alliance formation. *Administrative Science Quarterly*, *46*(4), 748–772.

Rothaermel, F. T., & Hill, C. W. L. (2005). Technological discontinuities and complementary assets: A longitudinal study of industry and firm performance. *Organization Science*, *16*(1), 52–70.

Santos, F. M., & Eisenhardt, K. M. (2009). Constructing markets and shaping boundaries: Entrepreneurial power in nascent fields. *Academy of Management Journal*, *52*(4), 643–671.

Schilke, O., & Rossman, G. (2018). It's only wrong if it's transactional: Moral perceptions of obfuscated exchange. *American Sociological Review*, *83*(6), 1079–1107.

Schrader, S. (1995). Gaining advantage by 'leaking' information: Informal information trading. *European Management Journal*, *13*(2), 156–163.

Seibert, S. E., Kraimer, M. L., & Liden, R. C. (2001). A social capital theory of career success. *Academy of Management Journal*, *44*(2), 219.

Shaver, J. M. (2005). Testing for mediating variables in management research: Concerns, implications, and alternative strategies. *Journal of Management*, *31*(3), 330–353.

Simonsohn, U., Simmons, J. P., & Nelson, L. D. (2020). Specification curve analysis. *Nature Human Behaviour*, *4*, 1208–1214.

Small, M. L. (2009). *Unanticipated gains: Origins of network inequality in everyday life*. Oxford: Oxford University Press.
Somaya, D., Williamson, I., & Lorinkova, N. (2008). Gone but not lost: The different performance impacts of employee mobility between cooperators versus competitors. *Academy of Management Journal*, *51*(5), 936–953.
Sørensen, M. (2007). How smart is smart money? A two-sided matching model of venture capital. *The Journal of Finance*, *62*(6), 2725–2762.
Sorenson, O., Dahl, M. S., Canales, R., & Burton, M. D. (2021). Do startup employees earn more in the long run? *Organization Science*, *32*(3), 587–604.
Sorenson, O., & Waguespack, D. M. (2006). Social structure and exchange: Self-confirming dynamics in Hollywood. *Administrative Science Quarterly*, *51*(4), 560–589.
Starr, E. P., Ganco, M., & Campbell, B. A. (2018). Strategic human capital management in the context of cross-industry and within-industry mobility frictions. *Strategic Management Journal*, *39*(8), 2226–2254.
Stuart, T. E. (2000). Interorganizational alliances and the performance of firms: A study of growth and innovation rates in a high-technology industry. *Strategic Management Journal*, *21*(8), 791–811.
Sutton, R. I., & Callahan, A. L. (1987). The stigma of bankruptcy: Spoiled organizational image and its management. *Academy of Management Journal*, *30*(3), 405–436.
Sutton, R. I., & Hargadon, A. (1996). Brainstorming groups in context: Effectiveness in a product design firm. *Administrative Science Quarterly*, *41*, 685–718.
Tandon, V., Ertug, G., & Carnabuci, G. (2020). How do prior ties affect learning by hiring? *Journal of Management*, *46*(2), 287–320.
Vandaie, R., & Zaheer, A. (2015). Alliance partners and firm capability: Evidence from the motion picture industry. *Organization Science*, *26*(1), 22–36.
von Hippel, E. (1987). Cooperation between rivals: Informal know-how trading. *Research Policy*, *16*(6), 291–302.
Waldinger, F. (2012). Peer effects in science: Evidence from the dismissal of scientists in Nazi Germany. *The Review of Economic Studies*, *79*(2), 838–861.
Wang, D., Pahnke, E. C., & McDonald, R. M. (2022). The past is prologue? Venture-capital syndicates' collaborative experience and start-up exits. *Academy of Management Journal*, *65*(2), 371–402.
Weller, I., Hymer, C. B., Nyberg, A. J., & Ebert, J. (2019). How matching creates value: Cogs and wheels for human capital resources research. *Academy of Management Annals*, *13*(1), 188–214.
Young-Hyman, T., & Kleinbaum, A. M. (2020). Meso-foundations of Interorganizational relationships: How team power structures shape partner novelty. *Organization Science*, *31*(6), 1385–1407.
Yu, S. (2020). How do accelerators impact the performance of high-technology ventures? *Management Science*, *66*(2), 530–552.
Zhang, E., Aven, B., & Kleinbaum, A. M. (2022). Left but not forgotten: Gender differences in networks and performance following mobility. SSRN Working Paper. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3692599.
Zhang, L., Gupta, A. K., & Hallen, B. L. (2017). The conditional importance of prior ties: A group-level analysis of venture capital syndication. *Academy of Management Journal*, *60*(4), 1360–1386.
Zhelyazkov, P. I. (2018). Interactions and interests: Collaboration outcomes, competitive concerns, and the limits to triadic closure. *Administrative Science Quarterly*, *63*(1), 210–247.
Zhelyazkov, P. I., & Gulati, R. (2016). After the break-up: The relational and reputational consequences of withdrawals from venture capital syndicates. *Academy of Management Journal*, *59*(1), 277–301.
Zhelyazkov, P. I., & Tatarynowicz, A. (2021). Marriage of unequals? Investment quality heterogeneity, market heat, and the formation of status-asymmetric ties in the venture capital industry. *Academy of Management Journal*, *64*(2), 509–536.
Zhu, F., & Iansiti, M. (2012). Entry into platform-based markets. *Strategic Management Journal*, *33*(1), 88–106.

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