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함께 엮다: 인수합병 후 공동 발명에서 적소 밀집과 협력·경쟁의 이중적 역학
Woven Together: Niche Crowding and the Dual Forces of Cooperation and Competition After M&A

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The success of mergers and acquisitions (M&As), particularly in knowledge-intensive industries, depends heavily on human capital dynamics. This study examines how acquirer inventors collaborate with the incoming target workforce, focusing on joint invention—a critical but often overlooked aspect of post-acquisition integration. Drawing on niche theory, we investigate how acquirer inventors respond to niche crowding caused by the addition of the target workforce. We explore how they manage the tension between cooperation and competition in joint invention efforts. Using data from inventors in the U.S. high-tech sector involved in acquisitions between 2002 and 2015, we find that acquirer inventors are more likely to collaborate when their competitiveness is relatively low—marked by declining performance and peripheral positions in the inventor network. In contrast, when both groups operate in similar technological domains or within related acquisitions, competitive pressure intensifies. This often shifts the dynamic toward rivalry, reducing joint invention engagement. These findings contribute to the literature on post-acquisition integration and extend niche theory by showing how niche crowding shapes the balance between cooperation and competition among merged workforces.

Keyword: acquirer inventors, collaborative behavior, competitive dynamics, joint invention, niche crowding, post-acquisition integration

Ⅰ. Introduction

Mergers and acquisitions (M&As) represent critical strategic decisions for organizations seeking to enhance their competitive advantage (Ahuja and Katila, 2001; Ranft and Lord, 2002; Sears and Hoetker, 2014), expand their market reach (Reuer et al., 2004), and achieve synergies (Eccles et al., 1999; Larsson

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and Finkelstein, 1999). However, the success of M&As is not solely determined by strategic complementarities or financial metrics; it is profoundly influenced by the human capital involved and the complex dynamics of cooperation and competition that arise during the integration process (Boyacıoğlu et al., 2024). This is especially evident in technological acquisitions, where firms aim to enhance capabilities and drive innovation renewal (Ahuja and Katila, 2001; Makri et al., 2010; Sears and Hoetker, 2014). In this paper, we adopt the perspective of acquirer inventors, central actors in these processes who have been largely overlooked in acquisition research. Specifically, we examine how acquirer inventors initiate collaborative development efforts with inventors from the acquired firm to foster innovation—a process we call *joint invention*.

To understand this dynamic, we draw on niche theory, originally rooted in ecology and later adapted for organizational studies. Niche theory posits that entities, ranging from species in ecosystems to companies in markets, rely on their ability to establish and maintain unique niches for survival and growth (Freeman and Hannan, 1983; Hannan et al., 2003; Hannan and Freeman, 1977; Popielarz and Neal, 2007). These niches are characterized by specific resource utilizations and competitive strategies that differentiate entities from one another (Freeman and Hannan, 1983; Hannan and Freeman, 1977; Khessina and Reis, 2024; Podolny et al., 1996).

By examining post-acquisition joint inventions, we extend niche theory in two significant ways. First, M&As often trigger significant shifts in an organization's resource environment, which in turn influences employees' assessment of their positions and behaviors (e.g., Buono et al., 1985; Fried et al., 1996; Gutknecht and Keys, 1993; Paruchuri et al., 2006; Puranam and Srikanth, 2007; Schweiger and Walsh, 1990). By exploring how employees adapt to evolving workplace conditions post-M&A, this study broadens niche theory from its conventional emphasis on entities to encompass individual-level adjustments. This perspective provides a more nuanced understanding of how employees navigate and adapt within changing organizational environments (Liu et al., 2016).

Second, niche theory suggests that overlapping niches—such as those found in merged organizations—can precipitate both cooperative and competitive dynamics (Ingram and Yue, 2008; Khessina and Reis, 2024). These dynamics are especially pertinent during the integration phase of M&As, when employees from distinct organizational cultures and structures are brought together. By extending these insights to individual behaviors, we can uncover the underlying mechanisms of employee interactions, particularly the factors that shape their decisions to engage in either cooperation or competition.

Building on these insights, we propose that the niche crowding within the target workforce can be seen either as an opportunity for collaboration or as a precursor to competition. These dual forces are shaped by the competitive standing of individuals and the nature of the acquisition. We specifically focus on acquirer inventors occupying crowded positions in the knowledge space of the target workforce. These situations occur when multiple inventors possess overlapping expertise, compete for similar resources, or operate within closely related technological domains. Such overlap heightens competition, as inventors vie for leadership in innovation and access to critical organizational resources. As a result, the balance between collaboration and rivalry becomes a decisive factor in shaping outcomes (Stuart, 1998).

Acquirer inventors in crowded niches are particularly susceptible to the disruptive effects of a merger due to their direct exposure to substantial shifts in resource allocation and organizational dynamics. However, collaboration with target inventors in these niches can help mitigate such challenges. For acquirer inventors, collaboration enables resource sharing and alleviates direct competition. Likewise, target inventors benefit by aligning interests and diffusing rivalry, thereby improving their standing within the newly merged organization.

Inventors in crowded niches are more likely to engage in joint inventions when they occupy a competitively disadvantaged position within their organization. For some, declining performance may indicate reduced competitiveness, driving them to pursue joint projects as a strategy to enhance visibility and demonstrate value in the post-merger organization. For others, positions on the organizational periphery—characterized by limited access to influential networks or decision-making roles—present collaboration as an opportunity to build mutually beneficial relationships and leverage collective efforts to improve their standing within the evolving organizational hierarchy.

On the other hand, the likelihood of collaborative efforts may decrease when the target workforce exhibits significant similarities. Although overlap in technical expertise may create opportunities for knowledge sharing, it can also heighten competition for leadership in innovation and access to critical organizational resources. Additionally, acquisitions involving organizations operating in overlapping industries are likely to intensify concerns about career stability, including role ambiguity and interpersonal conflict. These challenges diminish the attractiveness of collaboration and threaten its sustainability in the post-merger environment.

We find empirical support for our ideas by analyzing data from inventors in the U.S. high-tech sector who were part of acquisitions from 2002 to 2015. Our findings make a significant contribution to the M&A literature by illuminating the underexplored dynamics of how employees from merging organizations navigate the balance between cooperation and competition. This balance is crucial for the success of integration efforts and the realization of synergistic gains. Notably, our findings suggest that an inventor's decision-making process regarding collaboration extends beyond traditional organizational rewards and penalties, such as salary. Instead, these decisions are shaped by how individuals navigate the competing demands of collaboration and rivalry within the newly integrated organization.

This research responds to calls for a deeper investigation into the micro-foundations of innovation at the individual level (Tandon and Toh, 2022), providing fresh insights into the personal motivations that drive collaborative behavior during M&As. By examining how inventors' concerns about competition influence their innovative activities, our study broadens the understanding of workplace interactions, moving beyond conventional organizational factors such as cultural distance and structural integration.

Furthermore, we build on niche theory to explore the interplay between individual competition and cooperation during post-merger integration. Our study identifies the specific conditions that bring cooperative or competitive forces to the forefront, shedding light on how employees from merging organizations engage with one another as collaborators or competitors. By examining mechanisms such as performance trajectories, structural positioning, and technological overlap, we offer a more detailed perspective on how niche crowding shapes joint invention efforts. In doing so, the research contributes to niche theory in organizational behavior (Liu et al., 2016) and demonstrates its value in understanding the nuanced dynamics of post-merger integration (Birkinshaw et al., 2000; Ranft and Lord, 2000).

The implications of our findings extend beyond theoretical contributions. Practically, they offer actionable insights for managers and policymakers involved in M&As, emphasizing the need to consider individual-level factors, such as inventors' behaviors (i.e., cooperative and competitive actions), when designing integration strategies. Understanding these micro-level dynamics can lead to more effective interventions that enhance human integration, mitigate destructive competition, and ultimately improve the likelihood of achieving the desired synergies in M&As.

Ⅱ. Theory and Hypotheses

2.1 Niche Theory: A Lens for Organizational Dynamics

Niche theory, which originates from the

biological sciences, explains how species thrive by exploiting unique ecological positions, or niches, that minimize direct competition and optimize resource utilization (Hannan and Freeman, 1977; Hutchinson, 1957). When transposed into the organizational context, niche theory offers a powerful lens for understanding how individuals navigate internal structures, define their roles, and compete or collaborate to secure resources (Liu et al., 2016).

At its core, niche theory underscores the value of specialization. In organizations, individuals' knowledge, expertise, and professional domains form the basis of their niche, shaping their roles and their perceived value as contributors (Simmel, 1902; Tsai, 2002). An organization may thus be understood as a collective of differentiated niches working toward shared goals that cannot be achieved through market mechanisms alone (Simon, 1991). The more distinctive and valuable the niche an individual occupies, the more likely they are to contribute meaningfully to organizational outcomes. These contributions, in turn, often serve as the basis for recognition, rewards, and advancement (Liu et al., 2016).

Yet niches are neither static nor isolated. They are inherently relational, shaped by proximity to others and embedded within broader social and organizational networks (Baum and Mezias, 1992; Chung and Shin, 2017; Podolny, 1996). Individuals occupying similar or overlapping niches tend to collaborate closely, particularly as organizations grow and interdependence across departments increases (Hannan and Freeman, 1977; Simmel, 1902; Simon, 1991). At the same time, such proximity can foster competition, as individuals vie for influence, visibility, and limited organizational resources such as promotions or managerial support (Baum and Mezias, 1992; Carroll, 1985). This tension becomes most apparent in conditions of niche crowding, where multiple individuals occupy closely related niches, heightening both their interdependence and the likelihood of competition (Liu et al., 2016).

Although niche crowding is frequently associated with rivalry, it can also provide a foundation for collaboration. As Stuart (1998) suggests in his study of interfirm partnerships, technological crowding—where firms share overlapping knowledge or capability domains—creates conditions that can generate both competitive tension and opportunities for joint action. Supporting this view, an ecological principle posits that when competition stems from a lack of differentiation, actors often form collusive arrangements to limit, structure, or otherwise manage the competitive relationship (Hawley, 1986: Laumann and Knoke, 1987). Because unrestrained competition can be detrimental to the interests of competing firms, alliances become particularly valuable when they create formalized pathways for collaboration among direct rivals. In this context, collaboration is not limited to knowledge exchange; it may also involve cost-sharing, mutual support, and mechanisms that reduce direct competition. Rather than duplicating efforts or working at cross-purposes, individuals may benefit from cooperating by pooling resources, coordinating responsibilities, and jointly navigating the constraints of their shared environment (Stuart, 1998; Ingram and Yue, 2008).

This interplay between cooperation and competition is central to understanding how niche theory applies within organizations. Knowledge overlap, a defining characteristic of crowded niches, presents both challenges and opportunities. It can result in status competition and conflict over limited resources, but it also facilitates collaboration by lowering barriers to communication, coordination, and collective action (Ingram and Yue, 2008; Liu et al., 2016). As individuals seek to establish and maintain their niche positions, they must continually navigate the tension between standing out and aligning with others.

To fully capture the dynamic interplay of cooperation and competition in organizations, niche theory requires a refined framework—a contingency approach that considers various influencing factors (Echols and Tsai, 2005). This approach acknowledges that the effects of knowledge overlap are not uniform but vary depending on a range of internal and external factors. These factors include the relative status of the involved parties (Liu et al., 2016), the structural equivalence and differentiation of their original niches (Echols and Tsai, 2005; Podolny et al., 1996), and the degree of resource scarcity or abundance (Baum and Singh, 1994; Dobrev et al., 2001). By analyzing these components separately, researchers can better understand the conditions under which either competition or cooperation is more likely to dominate within organizational settings (Ingram and Yue, 2008; Liu et al., 2016). In essence, while both dynamics are always present, their relative significance can shift considerably based on specific contextual factors.

2.2 The Role of Niche Dynamics in Post-Acquisition Inventions

In the context of M&As, niche theory becomes particularly relevant. M&As thrust disparate organizational cultures, knowledge systems, and social networks into forced integration, creating fertile ground for both collaborative synergies and competitive tensions (Birkinshaw et al., 2000; Datta, 1991; Graebner et al., 2017; Haspeslagh and Jemison, 1991; Pablo, 1994; Singh and Zollo, 1999). The post-merger phase is particularly critical, involving the reconfiguration of niches within the newly formed entity. This period demands careful navigation for employees to leverage potential collaboration while mitigating the risks of fragmentation and conflict (Graebner et al., 2017; Seo and Hill, 2005).

The confluence of overlapping niches post-merger creates a dynamic environment where cooperation and competition are not only present but essential for survival and growth (e.g., Makri et al., 2010; Sears and Hoetker, 2014). This dynamic setting offers a rich opportunity to enrich niche theory by exploring how individuals' positions within these overlapping niches influence their strategic behaviors and outcomes. For example, Stuart (1998) highlights how a firm's niche within a technological network impacts its propensity to form alliances. Similarly, Liu et al. (2016) show how individual roles within organizational niches contribute to personal achievements. These insights suggest that analyzing niche overlap can enhance our understanding of how positioning within organizational networks drives strategic actions and performance.

To further refine niche theory and capture the factors influencing the balance between cooperation and competition, we begin with the baseline hypothesis: acquirer inventors are more likely to collaborate when they occupy increasingly crowded niches within the target workforce's knowledge base. Niche theory suggests that distinct niches are essential for thriving, as they allow for optimal resource utilization and reduced direct competition (Hannan et al., 2003; Hannan and Freeman, 1977). However, in crowded niches, intense competition for resources and recognition can impede individual performance and stifle innovation (Baum and Mezias, 1992; Baum and Singh, 1994; Podolny et al., 1996).

Despite these challenges, overlapping niches also provide opportunities for collaboration. Shared cognitive ground and complementary expertise can foster knowledge exchange and enhance problem-solving (Stuart, 1998). In the post-merger context, where individuals must reestablish their value within a restructured organization, joint invention can serve as a strategic response to competitive pressures. Collaboration in crowded niches not only facilitates mutual learning but also enables cost sharing and helps reduce direct competition by channeling overlapping efforts into coordinated outcomes. By pooling resources, distributing responsibilities, sharing recognition, and leveraging similar capabilities, inventors can mitigate the risks associated with niche crowding and strengthen their collective innovation potential (Stuart, 1998). In this way, niche crowding creates conditions that support joint invention by enabling mutual understanding and easing competitive tensions.

Therefore, we hypothesize that, holding individual performance constant, acquirer inventors situated in more crowded niches within the target workforce are more likely to engage in joint inventions.

Building on this foundation, and as illustrated in Figure 1, we propose that the effects of crowding in the target's knowledge space depend on an inventor's competitive standing and the nature of the acquisition. Collaboration is more likely among inventors who have experienced a recent decline in performance or who occupy peripheral positions within their existing networks. These inventors may view niche crowding as an opportunity to strengthen capabilities, improve visibility, and rejuvenate their careers. Thus, niche crowding creates a strategic inflection point, and whether it results in cooperation or conflict depends on how inventors assess their position within the evolving post-acquisition landscape.

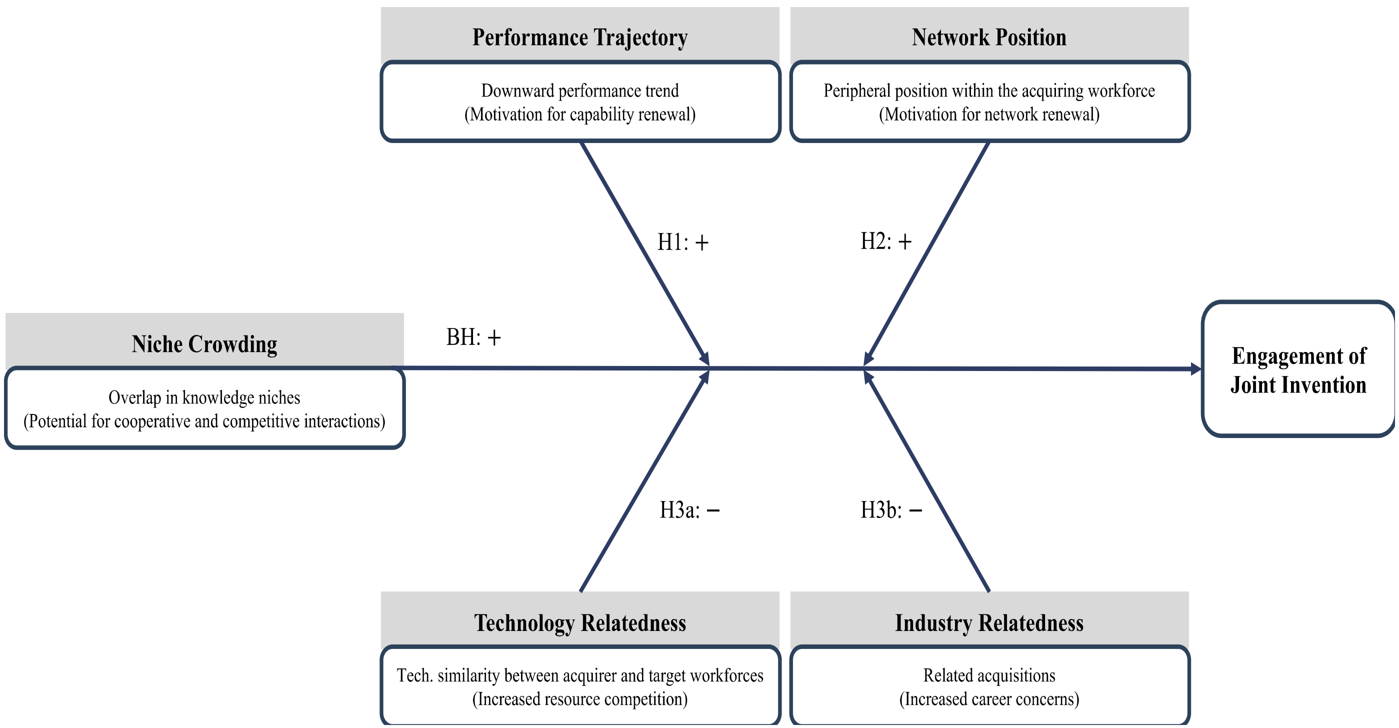
At the same time, structural similarity between the acquirer and target at the organizational level may reduce the likelihood of collaboration. Although technological similarity between the two firms can create opportunities for knowledge exchange, it also tends to heighten internal competition and elevate status concerns within the workplace (Sears and Hoetker, 2014). Likewise, when firms operate in the same or closely related industries, role redundancies and ambiguity are more likely to emerge, generating friction between merging entities (Barkema and Schijven, 2008; Coff, 2002; Lee et al., 2018). In these contexts, individual inventors may become attuned to the competitive risks associated with crowded positions, making them more likely to prioritize self-preservation over cooperation.

In the sections that follow, we develop our theoretical arguments regarding how niche crowding interacts with individual and organizational factors to shape the decision calculus through which inventors determine whether to engage in cooperative or competitive interactions.

2.3 Performance Trajectory

The performance trajectory plays a critical role in strategic decision-making, particularly when firms or individuals face a decline. In such situations, they often pursue external partnerships or collaborations to mitigate the adverse effects of their downward trend (Zhelyazkov and Tatarynowicz, 2021). This urgency is driven by the need to access additional resources, knowledge, or capabilities that can reverse their fortunes and improve their competitive position.

In the context of M&As, acquirer inventors facing declining performance are likely to seek collaboration with target inventors to leverage new technological capabilities and knowledge. This strategic move allows them to combine expertise and potentially achieve innovations that neither party could independently create (Aldrich and Herker, 1977; Fleming and Waguespack, 2007). The pressure to enhance innovative outputs and maintain relevance within the organization drives acquirer inventors to engage in joint inventions, utilizing the resources brought by the acquisition.



Note. BH indicates the baseline hypothesis

〈Figure 1〉 Hypothesized Relationships

Technological acquisitions aim to introduce new capabilities and knowledge, facilitating capability renewal and fostering innovation and growth (Ahuja and Katila, 2001; Ranft and Lord, 2002). As a result, collaboration through joint inventions becomes a key strategy to tap into new resources and achieve otherwise unattainable innovations.

When acquirer inventors in crowded niches experience a decline in performance, the pressure to improve their standing intensifies due to heightened visibility and scrutiny from their peers and organizational leadership. As they struggle to maintain their relevance and influence within the merged entity, the stakes for demonstrating value and productivity increase (Schweiger et al., 1987). Engaging with target inventors in joint inventions emerges as an effective strategy to counter this decline. These collaborations provide access to new information and capabilities that are not available within the acquirer's existing setup or networks (Ranft and Lord, 2000).

Collaborating with target inventors can also enable acquirer inventors to reverse their declining performance trajectory by leveraging complementary strengths. The infusion of new ideas and technologies from target inventors can rejuvenate the innovation process and lead to improved outcomes (Kneeland et al., 2020; Ranft and Lord, 2000). Collaborative efforts can also enhance the overall quality of inventions, making them more competitive in the evolving landscape and increasing the likelihood of success (Kneeland et al., 2020; Tandon and Toh, 2022). Thus, joint efforts in crowded niches not only help mitigate competitive pressures but also present opportunities for capability renewal and performance improvement.

For target inventors, collaborating with acquirer inventors facing declining performance presents the possibility of unique opportunities. In mergers, the ownership structure typically creates a status imbalance between the merging workforces, with acquirer inventors often holding greater influence and access to resources (Ranft and Lord, 2000). This dynamic can make target inventors feel subordinate or pressured to conform. However, when acquirer inventors are in a disadvantaged position within the organization due to declining performance—something target inventors can readily observe—the balance of power may shift. Target inventors might no longer feel the same implicit obligation to defer to their acquirer counterparts. Instead, they could approach collaboration on more equal terms, with the potential to negotiate more favorable roles in joint projects, greater recognition for their intellectual contributions, or improved access to critical organizational resources.

This shifting power dynamic opens the door for target inventors to engage with acquirer inventors without traditional hierarchies necessarily constraining their input or influence. Furthermore, the acquirer inventors' pressing need to reverse their performance trajectory might create an environment where collaboration becomes a focused and committed effort. For target inventors, this situation could enhance the visibility and value of their contributions, offering the potential to elevate their status and standing within the merged organization.[1)]

Following this reasoning, we argue that acquirer inventors in crowded niches are more likely to engage in joint inventions when they have experienced a decline in performance prior to the acquisition. The downward trend in performance creates a strong motivation for inventors to seek collaborations that can provide the necessary resources and capabilities for improvement. At the same time, the competitive nature of their niche makes collaboration a strategically appealing option to mitigate rivalry and enhance innovative outcomes. Therefore, we hypothesize the following.

Hypothesis 1 (H1): Acquirer inventors in crowded niches are more likely to engage in joint inventions when their performance exhibits a downward trend, rather than an upward trend, before the acquisition.

2.4 Core/Periphery Network Position

As performance decline motivates acquirer inventors in crowded niches to engage in joint inventions, we also propose that this tendency depends on the inventors' network position within their group.

Central inventors are recognized for their significant prestige, often enjoy increased visibility, and are therefore more frequently sought for collaborative tasks (Allen, 1966; Allen and Cohen, 1969; Paruchuri, 2010; Paruchuri and Eisenman, 2012). However, these inventors already have strong positions in their networks and are ready to access organizational resources (Coleman, 1988; Paruchuri and Awate, 2017; Reinholt et al., 2011; Singh et al., 2016; Singh et al., 2010). They might prefer maintaining current collaborative relationships rather than initiating new relationships with the target, which would require additional coordination and effort (Nerkar and Paruchuri, 2005) and cause cognitive limitations in effectively utilizing knowledge of the target side (Oldroyd and Morris, 2012; Paruchuri, 2010).

1) Collaboration is, by nature, a two-way process. While our theory focuses on acquirer inventors who seek to initiate joint inventions, the success of these partnerships inevitably hinges on the interests and motivations of target inventors as well. We acknowledge that understanding how these two sides align is an important and meaningful question, but it lies beyond the scope of this study. Instead, we take a focused and pragmatic approach by examining the perspective of acquirer inventors. This lens allows us to explore their decision-making processes in depth while holding the characteristics of target inventors constant.

In contrast, peripheral inventors, who may lack visibility and access to critical resources within their networks, often seek collaboration as a strategy to gain legitimacy and support from core members (Paruchuri, 2010). Engaging in joint inventions helps these peripheral inventors navigate competitive pressures by polling resources and leveraging the diverse perspectives and expertise found in overlapping niches. Consequently, peripheral inventors view crowded niches as opportunities for network renewal (Lavie and Rosenkopf, 2006), allowing them to improve their standing in the merged organization. This makes them more inclined to engage in joint inventions.

From the perspective of target inventors, partnering with acquirer inventors—regardless of their status within the organization—can present meaningful opportunities for integration and advancement in the post-merger organization. These collaborations may open doors to new knowledge domains, increase visibility in unfamiliar organizational structures, and create entry points into cross-unit projects. Because the acquiring firm now owns the target organization, target inventors operate within a hierarchical relationship that may influence their willingness to engage. Even when prospective acquirer collaborators are not highly central or high-performing, target inventors may view these interactions as part of a constrained but potentially valuable opportunity set within the new firm. Through co-development work, target inventors can reestablish their internal standing, develop social capital, and access critical resources. These efforts are essential for navigating the uncertainties of the post-merger environment and addressing the inherent disadvantages of being part of the acquired firm.

As argued in the first hypothesis regarding declining performance, collaborating with acquirer inventors in peripheral positions may be particularly appealing because these situations shift the typical power dynamic. Target inventors may feel less pressure to defer to their acquirer counterparts and instead engage on more equal terms, with opportunities to negotiate favorable roles in joint projects and gain recognition for their contributions. These advantages make it likely that target inventors will pursue joint inventions to integrate with new colleagues and strengthen their positions. While some target inventors may prefer to collaborate with high-status inventors in the acquiring firm, the asymmetry in ownership and authority may make those central actors less inclined to accept such collaborations. Consequently, collaborations may be more likely to occur with peripheral inventors, where power dynamics are less rigid and the barriers to engagement are lower.

Hypothesis 2 (H2): Acquirer inventors in crowded niches are more likely to engage in joint inventions when they are positioned on *the periphery, rather than at the core, of their existing network.*

2.5 Target Similarity

Target similarity, which encompasses both technological and industry relatedness, plays a significant role in shaping post-acquisition collaboration. While some conditions may encourage cooperation, high similarity in either dimension often intensifies competition between the merging entities, particularly when it involves shared areas of expertise and strategic focus (Lee et al., 2018; Pablo, 1994; Sears and Hoetker, 2014; Song and Yoon, 2005).

When the technological fields of both firms significantly overlap, inventors may view one another as direct competitors vying for innovation leadership, even after the acquisition (Cartwright and Cooper, 1993). This internal rivalry is often intensified by uncertainty over which group—the acquirer or the target—will lead innovation efforts. The integration phase, intended to enhance operational efficiency and effectiveness, can thus become a battleground for dominance rather than a collaborative effort (Haspeslagh and Jemison, 1991; Lee et al., 2018; Pablo, 1994).

Strong group identities can further fuel this dynamic, as inventors aim to assert their status and secure key roles in future innovation initiatives (Haunschild, Moreland, and Murrell, 1994; Schweiger et al., 1987). In such contexts, knowledge sharing may be limited, as inventors choose to safeguard their expertise while selectively drawing from the knowledge of the other group to strengthen their own positions (Edwards et al., 2017; Seo and Hill, 2005). This behavior can lead to a stalemate in which neither side is willing to engage in collaboration (Nash, 1950, 1951). The pursuit of innovation leadership may obstruct effective cooperation, thereby impeding the realization of meaningful innovation outcomes (Jehn and Mannix, 2001). These tensions become particularly acute when the acquirer and target possess highly similar technological foundations, as overlapping expertise amplifies internal rivalry and reduces the likelihood of productive integration (Lee et al., 2018; Seo and Hill, 2005).

Although target similarity can offer strategic advantages, such as enabling alignment in R&D or market focus, acquirer inventors operating in crowded niches may be especially inclined to interpret similarity through a competitive lens. In these environments, overlapping knowledge domains are already associated with heightened rivalry, and further similarity introduced through acquisition can amplify competitive tensions rather than support cooperation. Target inventors in such contexts may also respond in kind, focusing on defending their domain rather than seeking integration.

In contrast, when the technological bases of the acquirer and target differ significantly, the struggle for innovation leadership tends to subside. Although decisions about innovation leadership remain important, clear distinctions between the firms' technological domains help reduce direct rivalry at the organizational level. Individuals are less likely to view their positions within the merged entity as threatened, particularly with regard to potential competition for resources in already crowded niches. This technological differentiation shifts the decision-making calculus toward cooperation, as the structural basis for rivalry weakens and the advantages of joint innovation become more salient. From this understanding, we propose the following hypothesis.

Hypothesis 3a (H3a): In acquisitions where the acquirer and target workforces operate in highly similar technological domains, acquirer inventors in crowded niches are less likely to engage in joint inventions.

Industry relatedness, defined as the extent to which the acquirer and target operate in similar sectors (Cefis et al., 2020), also shapes post-acquisition collaboration. While this relatedness is expected to generate synergies through alignment in market envilprocesses, it can simultaneously create redundancies in capabilities and resources (Graebner et al., 2017; Haspeslagh and Jemison, 1991).

For inventors, these redundancies can spark concerns about job security and the relevance of their expertise, leading to behaviors aimed at self-preservation. Political maneuvering and competition for recognition and resources can override collaborative intentions, particularly when organizational boundaries become ambiguous and status hierarchies remain unsettled (Schweiger et al., 1987). As tensions escalate, individual priorities may shift from joint innovation to organizational survival, weakening trust and constraining collective efforts (Jehn and Mannix, 2001).

Thus, although industry relatedness holds the potential to facilitate collaboration through shared contextual understanding, increasing similarity with the target organization can intensify competitive dynamics. Inventors occupying overlapping roles in crowded niches are particularly exposed to these tensions, as the convergence between organizations reshapes internal boundaries and sharpens competition over influence and resources. Under these conditions, the decision-making process tends to favor rivalry over cooperation, undermining the very synergies the acquisition was intended to create (Lee et al., 2018).

Hypothesis 3b (H3b): In acquisitions where the acquirer and target workforces operate in highly similar industries, acquirer inventors in crowded niches are less likely to engage in joint inventions.

Ⅲ. Data and Methods

3.1 Research Context and Sample

Our sample consists of technological acquisitions obtained from the Securities Data Corporation's (SDC) *Platinum* database from 2002 to 2015. While data collection began in 1997, we confined our study to the 2002-2015 timeframe to ensure a consistent analysis with a five-year moving window for patent-related variables from the outset. The end year of 2015 was chosen to facilitate a comparable five-year patent analysis following each acquisition. Consistent with previous research (Ahuja and Katila, 2001; Puranam et al., 2009; Sears and Hoetker, 2014), we defined technological acquisitions as transactions in which both the acquiring and acquired companies were classified as "high-tech" in the SDC database. The sectors considered under this category include semiconductors, materials, electronics, telecommunications, aerospace, and biopharmaceuticals.

In our study investigating the link between niche crowding and inventor collaboration, we carefully curated a sample of technological acquisitions. From the SDC Platinum database, we obtained equity transactions between high-tech companies in the U.S. between 2002 and 2015 with a few criteria: excluding stock buyback, division acquisitions (i.e., business unit divestiture), transactions involving companies under the same corporate umbrella, or transactions where the acquirer obtained a minority stake of target's equity (less than 50.1%) (Bettinazzi et al., 2020; Capron and Shen, 2007; Chen et al., 2018). We included 18,163 transactions with acquirers' managerial control over their targets.

In addition, we focused on transactions involving publicly traded U.S. companies. These companies are known for their robust organizational frameworks and substantial investor bases, fostering a competitive environment (Haspeslagh and Jemison, 1991; Puranam and Srikanth, 2007). This approach helped us address the unique challenges that inventors encounter when integrating into new corporate systems. At this stage, 818 deals remained in our sample.

In the final phase of our selection process, we ensured that both entities in each deal were scientifically active. To verify this, we compiled patent application data from the U.S. Patent Trademark Examiner's Office (USPTO) and the PatentView database and the Coleman Fung Institute at the University of California, Berkeley. We matched company names from the SDC Platinum database with the assignees listed in the patent records to identify firms with patent activities in the five years leading up to the acquisition closure date. This led us to a group of 487 acquisition deals.

Furthermore, we ensured that each deal was driven primarily by technological motivations, as some high-technology industry deals are not centered on technological integration. A notable example is Akorn, Inc's acquisition of Hi-Tech Pharmacal Co., Inc. in 2014, which was motivated by market expansion goals such as expanding the product portfolio on its retain platform and leveraging Hi-Tech Pharmaceutical's manufacturing capabilities to enter new markets (Dick, 2013, April 17). Given its limited impact on inventors' innovation activities, this transaction was excluded from our study.

To scrutinize the primary motives behind each acquisition, we utilized a comprehensive set of resources. This included searches across FACTIVA, LexisNexis, and Google for relevant news articles and press releases. We also conducted detailed examinations of public filings, specifically Form 10-K, DEFM14A, and PREM14A, accessible through the EDGAR system of the U.S. Securities and Exchange Commission (SEC). These varied resources enabled us to gain a comprehensive understanding of the motivations behind each deal. The authors individually reviewed the documents to identify the phrases that signaled a focus on technological progress or integration. Key phrases, such as "*the combination with msystems will be a catalyst in the development of next generation flash…*" and "*by combining our [acquirer and target] powerful technologies…*" were markers of a deal's focus on technological progress or integration. This comprehensive analysis allowed us to discern 276 deals that aligned with our stringent definition of technological acquisitions.[2] After further refining our dataset to remove transactions with insufficient data, this led us to a refined group of 261 acquisition deals, involving 170 acquirers and 261 targets, with 51 of the acquirers participating in multiple deals.

Next, we tuned our attention to pinpointing the inventors, or the authors of a patent, linked to these companies. Using patent coauthorship data – a widely used metric in innovation studies to assess inventor productivity and collaboration (e.g., Almeida et al., 2002; Ernst and Vitt, 2000; Nerkar, 2003; Song et al., 2003) – we tranced patents filed by the 170 acquiring firms. Our aim was to capture the full set of inventors who were involved in patenting activities prior to and following the acquisition. This method allowed us to complete a comprehensive sample

2) Our focus on technologically motivated acquisitions provides an ideal context for exploring the dynamics central to our theoretical framework. These transactions highlight the unique challenges and opportunities tied to integrating overlapping expertise and navigating competition within shared knowledge spaces. While the scope conditions of our theory do not limit the types of acquisitions that can be studied, prioritizing deals with technological motivations ensures that our analysis aligns closely with the core mechanisms of niche crowding, competition, and collaboration. This approach enables us to examine the most relevant factors with precision and depth.

of 134,685 acquirer inventors, forming the basis for our analysis.

3.2 Dependent Variable and Analytical Approach

Following prior studies, we considered the listing of inventors on patent applications as an indicator of their collaboration (e.g., Carnabuci and Operti, 2013; Fleming et al., 2007). We used patent application records over granted patents since they more accurately reflect inventors' collaborative efforts, irrespective of whether the patents are eventually granted (Balachandran and Hernandez, 2018; Paruchuri, 2010). To measure our dependent variable, *joint invention*, we counted the number of patent applications that each acquirer inventor filed in collaboration with one or more target inventors during the five years following the effective date of the observed acquisition (Carnabuci and Operti, 2013; Fleming et al., 2007; Katila and Ahuja, 2002).

However, this approach might not capture the full extent of collaboration. For example, an inventor from the acquiring company could be connected to five target inventors either through one invention or across five distinct inventions. To provide a more nuanced view, we also counted the number of unique target inventors with whom each acquirer inventor collaborated on these patents during the five years following the acquisition. This count was then used as an alternative measurement in our robustness analysis.

Given that our dependent variable is comprised of count data with non-negative integers, we employed a negative binomial regression model (Hausman et al., 1984). In all the models, we included indicator variables for each industry to control for differences in the collaboration probability across industries. For this purpose, we utilized the four-digit SIC code of the acquirer's industry, which is based on the understanding that four-digit SIC codes could effectively capture industry effects in acquisition research (Ahuja and Katila, 2004; Rabier, 2017). Furthermore, to control for any annual variations that could impact collaboration among inventors, we included indicator variables for each year, based on the closure year of each acquisition. We clustered the error terms at the inventor level to account for autocorrelation in the data across individuals.

Our study encountered a sample selection bias issue, as we could only assess collaborative relationships among "ongoing inventors" - those who continued to file patent(s) at the combined firms. This selective group posed a potential for bias due to its non-random nature. To address this concern, we applied Heckman's two-stage correction method (Heckman, 1979). We coded those "ongoing inventors" as one and non-ongoing inventors as zero. Initially, we used a probit model to predict the likelihood of each inventor continuing to patent post-acquisition, considering their post-acquisition patent filings as an indicator of ongoing involvement (i.e., selection model) (Paruchuri et al., 2006). This prediction was based on instrumental and other variables. We then calculated the predicted probability of continued patenting for each acquirer inventor and used this to compute an inverse Mills ratio. This ratio was entered as a covariate in our second-stage regression model to correct for potential selection bias (Certo et al., 2016; Greene, 2007).

The Heckman model is based on the principle that the selection process should include at least one variable - an instrument - that is related to "ongoing" patenting in the post-acquisition period but unrelated to the likelihood of collaboration post-acquisition. This model employed the inventor's gender as an instrument variable. Gender is represented by a binary variable where male is coded as 1 and female as 0. The rationale behind choosing gender as an instrument is based on empirical evidence indicating turnover differences between male and female employees (Weisberg and Kirschenbaum, 1993) and ambiguous patenting differences by gender (Whittington and Smith-Doerr, 2008). In Results section, we will discuss the empirical evidence for the second-stage analysis and the use of gender as an instrumental variable in our analysis.

3.3 Independent Variables

3.3.1 Niche crowding (in the knowledge space of the target workforce)

To grasp the competitive environment surrounding individual inventors, we applied principles commonly used in firm-level crowding analyses to assess technological positioning from an individual perspective. Inventors, akin to organizations, construct their innovations based on previous patents, including their own work and the patents they have cited. This is particularly evident in technological networks, where inventors are defined by their distinct segments of expertise (Podolny et al., 1996; Stuart, 1998). Crowding occurs when numerous inventors gather in the same technological segment, resulting in overlapping knowledge and reduced distinctiveness (Baum and Singh, 1994; Podolny et al., 1996; Stuart, 1998).

A critical aspect of our analysis is the notion of niche overlap, derived from niche theory. This concept suggests that an inventor's competitive landscape intensifies as their technological or scientific domains and areas of expertise increasingly overlap with those of others (Podolny et al., 1996; Stuart and Ding, 2006). Such overlaps can signal either commonality or redundancy in skills, thereby affecting inventors' opportunities and growth within an organization (Liu et al., 2016). In essence, the career prospects of an inventor are negatively correlated with the extent to which their knowledge domain overlaps with that of their peers.

To quantify the concept of crowding in an inventor's niche, we aggregated individual overlaps in the technological or scientific space. Leveraging the principles of technological positioning (Podolny et al., 1996), we assessed the niche crowding experienced by an inventor from the acquiring company in the target workforce using patent backward citations: that is, an inventor's patent references serve as a window into their position in the technological network. By focusing on patent citations from the most recent five years, we can effectively gauge the current innovative activities of these inventors (Carnabuci and Operti, 2013; Corredoira and Rosenkopf, 2010; Fleming et al., 2007; Katila and Ahuja, 2002).

Using the guidance of prior studies (Baum and Mezias, 1992; Baum and Singh, 1994; McPherson, 1983; Podolny et al., 1996; Stuart, 1998), we developed a metric to measure the degree to which the technological space of a target inventor *j* overlaps with that of a focal acquirer inventor *i* during a period *t*. This metric, denoted as c_{ijt}, is computed as follows:

$$c_{ijt} = \frac{\sum_p R_{ipt} R_{jpt}}{\sum_p R_{ipt}}$$

where *p* represents all patents issued since the first patent on February 4, 1947. The variable R_{ipt} is assigned a value of one if acquirer inventor *i*'s patents cite a particular patent, p, during a period t, and zero otherwise. The same applies to R_{jpt} for target inventor *j*. Thus, each instance where a patent cited by acquirer inventor *i* is also cited by target inventor *j* contributes one unit to the numerator of this equation. The denominator of this equation represents the total number of patent citations made by acquirer inventor *i*'s patent portfolio. Accordingly, the value of c_{ijt} indicates the proportion of citations by acquirer inventor *i* that are also cited by target inventor *j*.

$$C_{it} = \sum_{j \in Target\,Inventors} c_{ijt}$$

We then calculated the overall crowding of acquirer inventor *i*'s position during a period t, denoted as C_{it}, by summing the dyadic overlap scores across all target inventors in a given acquisition. We logged the value (after adding one) to reduce its skewness.

3.3.2 Downward performance trend

We measured the trend of an inventor's performance using a binary variable, where a value of one represents a downward trend and zero represents an upward trend. To calculate this, we first counted the number of patent applications filed by the focal inventor each year over the five years prior to the acquisition. This five-year window is consistent with prior research, which highlights its relevance for evaluating productivity, job changes, and employee mobility between firms (Carnabuci and Operti, 2013; Corredoira and Rosenkopf, 2010; Groysberg et al., 2008).

Next, we conducted a regression analysis of the annual number of patent applications over time, using the periods from t-5 to t-1. The coefficient generated from this regression reflects the slope of the inventor's performance trajectory. A negative coefficient, indicating a decline in patent applications, was coded as a downward trend (1), while a non-negative coefficient was coded as an upward trend (0).

3.3.3 Network centrality

In line with prior studies, we measured each inventor's network position using normalized eigen centrality (Bonacich, 1987, 2007; Wasserman and Faust, 1994). This measure is particularly relevant at the individual level, as it encapsulates the concepts of influence (Ibarra, 1993; Nerkar and Paruchuri, 2005), resource access (Coleman, 1988; Paruchuri and Awate, 2017; Singh et al., 2016; Singh et al., 2010), and information overload (Oldroyd and Morris, 2012; Paruchuri, 2010).

For each acquiring company, we constructed networks of inventor collaboration based on patent applications filed in the USPTO during the five years prior to the focal acquisition (Nerkar and Paruchuri, 2005; Paruchuri, 2010). A five-year timeframe was chosen to account for the diminishing nature of relationships among inventors over time (Carnabuci and Operti, 2013; Corredoira and Rosenkopf, 2010; Katila and Ahuja, 2002). We then assessed each inventor's network position within their respective company's collaboration network at the time of acquisition. The eigenvector centrality for the inventors of each acquirer was measured via the following formula:

$$s(\alpha, \beta) = \alpha \sum_{k=0}^{\infty} \beta^k R_{i,j}{}^{k+1} \mathbf{1}$$

where α is a scaling constant chosen such that the highest status in a given network is normalized to one ($\alpha=1$). The term i, j represents the adjacency matrix $R_{i,j}$, indicating collaboration ties between inventors i and j across the specified sliding window; $\mathbf{1}$ is a column vector consisting of 1s. β is another scaling constant that dictates the extent to which an actor's status is influenced by the status of its connections. The β constant spans from zero (where the measure corresponds with degree centrality) to the inverse of the largest eigenvalue (where the measure corresponds with eigenvector centrality). To account for the network positions of each inventor's connections, we set the value of β as three quarters (Bonacich, 1987; Nerkar and Paruchuri, 2005; Paruchuri, 2010; Wasserman and Faust, 1994). For ease of interpretation, we multiplied the measure by -1, so that a higher value indicates greater peripheral positioning.

3.3.4 Target technological relatedness

To evaluate technological relatedness between an acquirer and its target, we developed vector spaces representing the three-digit main patent classes in which both the acquirer and target were active, using their patent filings from the five years preceding the acquisition. We then calculated the cosine similarity between these vector spaces to gauge the technological relatedness of the two firms. The measure was then created by the cosine similarity value as follows:

$$Target\ tech\ relatedness = cos\,\theta = \frac{\vec{A} \cdot \vec{T}}{|\vec{A}| \cdot |\vec{T}|}$$

where $\vec{A}$ represents the vector consisting of the acquirer's main class and $\vec{T}$ denotes that of the target's main class. The range of *target tech. relatedness* is between zero and one: the closer to one, the more technologically similar the two firms (i.e., acquirer and target) are.

3.3.5 Target industry relatedness

We measured target industry relatedness as the extent to which the target's industry is close to the acquirer's industry. We utilized four-digit Standard Industrial Classification (SIC) codes, which represent the industries in which both the acquirer and target operated (Ahuja and Katila, 2004; Rabier, 2017). For each digit that differed between the SIC codes of the target and acquirer, we subtracted one from 4. Therefore, if the acquirer and target shared the same four-digit SIC code, the industry relatedness value was set to four, whereas it was set to zero if all four digits differed.

3.4 Control Variables

We included a number of controls to account for potential alternative explanations.

3.4.1 Geographical distance

The geographical distance between an acquirer and its target can impact the frequency and effectiveness of communication and collaboration among inventors located in different areas (Chakrabarti and Mitchell, 2013). To calculate the geographical distance, we utilized the zip codes of the headquarters of both the acquirer and target firms, retrieved via the Google Map API service. From these zip codes, we extracted the latitude and longitude coordinates of each firm. We then computed the distance in kilometers between the acquirer and its target using these coordinates, applying the WGS84 ellipsoid standard (which has a radius of 6,378,137 meters and a flattening of 1/298.257223563). We logged the value (after plus one) to reduce skewness and ensure the symmetry of the measure.

3.4.2 Preacquisition alliance

The presence of a pre-acquisition alliance can enhance coordination, thereby aiding in effective integration post-acquisition and in realizing synergistic benefits (Martin and Shalev, 2017; Porrini, 2004; Zaheer et al., 2010). To capture this, we created a binary variable for the pre-acquisition alliance. Considering that alliances typically have a lifespan of no more than five years (Yang et al., 2011), we selected a corresponding five-year period for analysis. The variable was coded as one if the acquirer had established a strategic alliance with the target during the preceding five years and zero otherwise.

3.4.3 Hostile acquisition

A firm's attitude toward an acquisition can influence employee anxiety levels (Larsson and Finkelstein, 1999; Ranft and Lord, 2000). To account for this, we included a variable for hostile acquisitions. This variable was coded as one if the focal deal was identified as a hostile takeover according to the SDC Platinum database and zero otherwise.

3.4.4 Structural integration

When acquirers consolidate their targets into their organizational boundary, rather than providing autonomy to their targets, this integration event may affect perceptions and behaviors of both side employees (Graebner et al., 2017; Pablo, 1994; Pak et al., 2015; Puranam and Srikanth, 2007). We measured structural integration by identifying whether the target's name disappeared from the subsidiary list in the acquirer's 10-K filing for the year following the acquisition date. If the target's name was no longer listed in the acquirer's next annual report, the structural integration variable was coded as one, and zero otherwise.

3.4.5 Inventor's productivity

The innovation capability of an acquirer inventor could be linked to their collaboration with target inventors (Lee, 2010; Liu et al., 2018). To capture inventors' capacity for innovation, we measured the number of patents filed by each inventor during the preceding five years (Carnabuci and Operti, 2013; Corredoira and Rosenkopf, 2010; Groysberg et al., 2008). We logged the value (after plus one) to reduce skewness and ensure the symmetry of the measure.

3.4.6 Inventor's tenure

To assess the duration of an inventor's association with his or her pre-acquisition company (i.e., acquirer), we first identified the year when each inventor filed his or her initial patent with the acquiring firm. We then calculated the total number of years from that first patent year to the year of acquisition. In cases where an inventor had filed successive patents with different companies prior to the acquisition, we determined their tenure at the acquiring firm by calculating the midpoint between the last patent date at the previous firm and the first patent date at the acquiring firm (Almeida et al., 2003; Dokko and Rosenkopf, 2010; Singh and Agrawal, 2011). We logged the value (after plus one) to reduce skewness and ensure the symmetry of the measure.

3.4.7 Inventor's diverse expertise

The range of an inventor's patent portfolio reflects the diversity of their expertise, which plays a role in their ability to engage in collaborative integration (Carnabuci and Operti, 2013). To capture an inventor's diverse expertise, we measured the total number of distinct (three-digit) main classes of patents each inventor filed during the preceding five years.

3.4.8 Inventor's collaborators

To control for an inventor's relational capability, we created a measure of an inventor's collaborators by counting the total number of distinct coauthors of a focal inventor (co-inventors with whom a focal inventor filed patents) during the preceding five years.

3.4.9 Inventor's familiarity with target's technological resources.

The degree of an inventor's knowledge about the target firm's technological resources can impact their post-acquisition innovative activities (Cloodt et al., 2006; Kapoor and Lim, 2007). To consider this potential impact, we created a measure for an inventor's pre-acquisition technology familiarity. It was calculated based on the number of citations of the target firm's patents in the focal inventor's patent filed during the preceding five years, divided by the total number of citations in those patents.

3.4.10 Inventor's reliance on acquirer's technological resources

Inventors often vary in their reliance on their own firm's technological resources as opposed to exploring and using external technologies (Grant, 1996). To capture this variation, we measured an inventor's reliance on the acquirer's technology based on the number of citations of the acquiring firm's patents in the focal inventor's patents filed during the preceding five years, divided by the total number of citations in those patents.

Ⅳ. Results

4.1 Primary Analysis Results

Table 1 presents the descriptive statistics and correlations for all the variables in our sample. The observed correlations are relatively low, indicating that multicollinearity is unlikely to bias our regression models. In support of this, all the variance inflation factors (VIFs) in our regression models are well below the standard threshold of 10, and even fall under the more stringent threshold of 2.5 (Vittinghoff et al., 2012); the mean VIF stands at 1.31, with the highest at 2.17. These findings reinforce the idea that multicollinearity is unlikely to be an issue in our analysis models.

The results of the negative binomial regression analysis are presented in Table 2. Model 1 includes all the control variables, the inverse Mills ratio from the first-stage regression, and year and industry fixed effects. The positive and significant coefficient of the inverse Mills ratio implies that the sample was not randomly selected and could influence the analysis results: unobserved factors are positively associated with sample selection (Heckman, 1979). The coefficients of the inverse Mills ratio are positive and significant across all the models in Table 2. These results provide empirical evidence of sample selection and justify the use of a two-stage model in our analysis (Certo et al., 2016; Heckman, 1979).

Noteworthy variables pertain to those concerning distance and familiarity. The observed negative coefficient for geographical distance in Model 1 suggests that inventors from the acquiring firm are less likely to collaborate with those from the target firm if there is a significant distance between them. On the other hand, variables related to familiarity, such as preacquisition alliance, target technological relatedness, and target industry relatedness, show positive coefficients across all the models, significantly enhancing joint invention engagement in the merging entities. These patterns in familiarity-related variables remain consistent across all five models presented in Table 2. In line with prior studies, our results affirm that geographical closeness (e.g., Chakrabarti and Mitchell, 2016), technological alignment (e.g., Cloodt et al., 2006; Rao et al., 2016), cultural similarity (e.g., Rao et al., 2016), and previous alliance experiences (e.g., Porrini, 2004; Zaheer et al., 2010) play crucial roles in facilitating interactions between entities undergoing a merger.

〈Table 1〉 Descriptive Statistics and Pairwise Correlations

Variables	*Mean*	*S.D.*	*1.*	*2.*	*3.*	*4.*	*5.*	*6.*	*7.*	*8.*	*9.*	*10.*	*11.*	*12.*	*13.*	*14.*	*15.*	*16.*
1. Joint inventions	0.01	0.13	1.00															
2. Niche crowding	0.08	0.34	0.16*	1.00														
3. Downward performance trend	0.32	0.47	0.00	0.01*	1.00													
4. Network centrality	-0.03	0.11	-0.00	-0.04*	-0.01*	1.00												
5. Target tech. relatedness	0.48	0.24	0.04*	0.23*	0.00	-0.01*	1.00											
6. Target industry relatedness	1.25	1.70	0.03*	0.18*	-0.00	-0.10*	0.44*	1.00										
7. Geographical distance	6.52	2.09	-0.02*	-0.08*	0.01*	0.02*	-0.23*	-0.22*	1.00									
8. Preacquisition alliance	0.07	0.26	0.00	-0.01*	0.02*	0.01*	-0.19*	-0.13*	0.09*	1.00								
9. Hostile acquisition	0.02	0.13	0.03*	-0.01*	0.01*	-0.01*	-0.11*	0.00	-0.00	-0.04*	1.00							
10. Structural integration	0.31	0.46	-0.02*	-0.10*	0.00	0.04*	-0.19*	-0.26*	0.16*	0.26*	0.08*	1.00						
11. Inventor's productivity	1.05	0.98	0.01*	0.02*	0.11*	-0.20*	0.00	-0.04*	-0.01*	0.00	-0.02*	0.01*	1.00					
12. Inventor's tenure	1.61	0.80	-0.02*	-0.04*	0.34*	-0.08*	-0.01*	-0.04*	0.04*	0.03*	-0.01*	0.04*	0.43*	1.00				
13. Inventor's diverse expertise	3.82	4.39	0.01*	-0.01*	0.11*	-0.09*	-0.07*	-0.07*	0.03*	0.06*	0.03*	0.06*	0.41*	0.19*	1.00			
14. Inventor's collaborators	8.66	10.01	0.00	0.01*	0.07*	-0.45*	0.04*	0.00	-0.02*	0.00	0.01*	-0.00	0.65*	0.32*	0.31*	1.00		
15. Inventor's familiarity with target's tech. resources	0.00	0.01	0.13*	0.24*	-0.00	-0.01*	0.06*	0.05*	-0.04*	0.00	0.02*	-0.02*	-0.00	-0.03*	-0.01*	-0.01*	1.00	
16. Inventor's reliance on acquirer's tech. resources	0.06	0.12	-0.00	-0.02*	0.01*	-0.07*	0.02*	0.02*	-0.02*	0.04*	0.02*	-0.00	0.12*	0.09*	-0.01*	0.13*	-0.00	1.00

Note. N = 134,685; * p 〈 0.05

〈Table 2〉 Results of Negative Binomial Regression Analysis

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	-14.80***	-16.03***	-15.84***	-15.55***	-16.23***	-16.17***	-15.48***
	(2.41)	(2.41)	(2.42)	(2.33)	(2.36)	(2.39)	(2.29)
Inverse Mills ratio	5.64**	5.57**	5.49**	5.19**	5.12**	5.47**	4.60**
	(1.82)	(1.84)	(1.85)	(1.78)	(1.82)	(1.83)	(1.77)
Geographical distance	-0.11*	-0.04	-0.04	-0.04	-0.06	-0.04	-0.05
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Preacquisition alliance	1.50***	1.53***	1.53***	1.53***	1.52***	1.54***	1.52***
	(0.27)	(0.27)	(0.27)	(0.27)	(0.29)	(0.27)	(0.28)
Hostile acquisition	2.44***	2.50***	2.52***	2.50***	2.73***	2.39***	2.73***
	(0.47)	(0.45)	(0.45)	(0.45)	(0.49)	(0.45)	(0.49)
Structural integration	-1.34***	-1.80***	-1.82***	-1.80***	-1.81***	-1.81***	-1.86***
	(0.29)	(0.31)	(0.31)	(0.32)	(0.32)	(0.32)	(0.32)
Inventor's productivity	0.98***	0.78***	0.77***	0.75***	0.75***	0.76***	0.70***
	(0.16)	(0.17)	(0.17)	(0.16)	(0.16)	(0.17)	(0.16)
Inventor's tenure	-1.43***	-1.20**	-1.18**	-1.13**	-1.11**	-1.18**	-1.00**
	(0.37)	(0.37)	(0.38)	(0.36)	(0.37)	(0.37)	(0.36)
Inventor's diverse expertise	-0.06*	-0.04	-0.04	-0.04	-0.04	-0.04	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Inventor's collaborators	0.05**	0.06**	0.06**	0.05**	0.06**	0.06**	0.05**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Inventor's familiarity with target's tech resources	25.58***	11.63***	11.54***	11.44***	10.90***	11.54***	10.79***
	(3.11)	(1.90)	(1.87)	(1.92)	(1.93)	(1.88)	(1.88)
Inventor's reliance on acquirer's tech. resources	2.30*	2.63**	2.54**	2.45**	2.38**	2.59**	2.15*
	(1.01)	(0.95)	(0.95)	(0.93)	(0.91)	(0.94)	(0.89)
Downward performance trend	0.13	-0.00	-0.20	-0.01	0.04	0.01	-0.24
	(0.14)	(0.14)	(0.16)	(0.14)	(0.14)	(0.14)	(0.16)
Network centrality	1.14*	0.85^{+}	0.87^{+}	0.23	0.91^{+}	0.88^{+}	0.30
	(0.45)	(0.48)	(0.49)	(0.46)	(0.47)	(0.49)	(0.45)
Target tech relatedness	3.13***	2.89***	2.85***	2.92***	4.02***	2.84***	4.03***
	(0.45)	(0.43)	(0.43)	(0.43)	(0.54)	(0.43)	(0.54)
Target industry relatedness	0.13*	0.14*	0.14*	0.14*	0.12*	0.22***	0.12^{+}
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
Niche crowding		1.51***	1.39***	1.56***	3.37***	1.91***	3.33***
		(0.08)	(0.09)	(0.09)	(0.41)	(0.17)	(0.40)
H1: Niche crowding × Downward performance trend			0.40**				0.54***
			(0.13)				(0.13)
H2: Niche crowding × Network centrality				1.60***			1.68***
				(0.30)			(0.32)
H3a: Niche crowding × Target tech. relatedness					-2.66***		-2.68***
					(0.49)		(0.52)
H3b: Niche crowding × Target industry relatedness						-0.17**	-0.03
						(0.05)	(0.06)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LnAlpha	3.39***	2.96***	2.94***	2.94***	2.93***	2.94***	2.89***
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Log Likelihood	-3391.153	-3169.207	-3165.401	-3164.403	-3143.304	-3163.851	-3131.013
Pseudo R-Squared	0.19	0.24	0.24	0.25	0.25	0.25	0.25

Note. N=134,685; $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; Robust standard errors, shown in parentheses, are clustered by inventor.

In Model 2, we tested the baseline hypothesis, which posits that acquirer inventors are more likely to engage in collaborations with target inventors as crowding in their niche increases. The results show a significant positive coefficient for niche crowding (β = 1.51, p = .000). This pattern persists across all models, providing strong empirical support for our baseline hypothesis.

In H1, we argued that a decline in inventor performance would strengthen the positive relationship between niche crowding and joint invention engagement. In Model 3, the interaction coefficient between niche crowding and downward performance trend is positive and significant (β = 0.40, p = .002). The full Model 7 also confirms this with a positive and significant coefficient (β = 0.54, p = .000), further supporting H1.

H2 suggests that an inventor's peripheral position strengthens the positive relationship between niche crowding and joint invention engagement. In support of this argument, we find that the interaction of niche crowding and peripheral position is positive and significant in both the partial Model 4 (β = 1.60, p = .000) and the full Model 7 (β = 1.68, p = .000). These results support H2.

In H3a, we argued that proposed that target technological relatedness weakens the effect of niche crowding among acquirer inventors. The interaction between niche crowding and target tech relatedness is negative and significant in both the partial Model 5 (β = -2.66, p = .000) and the full Model 7 (β = -2.68, p = .000), supporting H3a.

Finally, we hypothesized that target industry relatedness negatively influences the positive effect of niche crowding on joint invention engagement (H3b). In Model 6, the interaction between niche crowding and target industry relatedness is negative and significant (β = -0.17, p = .002). However, in the full Model 7, the interaction remains negative but is not significant. These results thus provide marginal support for H3b.

While we hypothesized that target industry relatedness would increase anxiety about role security, it is possible that this construct overlaps with target technological relatedness. Both constructs reflect dimensions of similarity between acquirer and target workforces, which could influence how inventors navigate their roles and assess future opportunities. This overlap may dilute the distinct effect of industry relatedness on career concerns, as inventors might interpret both forms of relatedness in similar ways. This overlap could partially explain the marginal support for H3b, compared to the more robust findings for H3a.

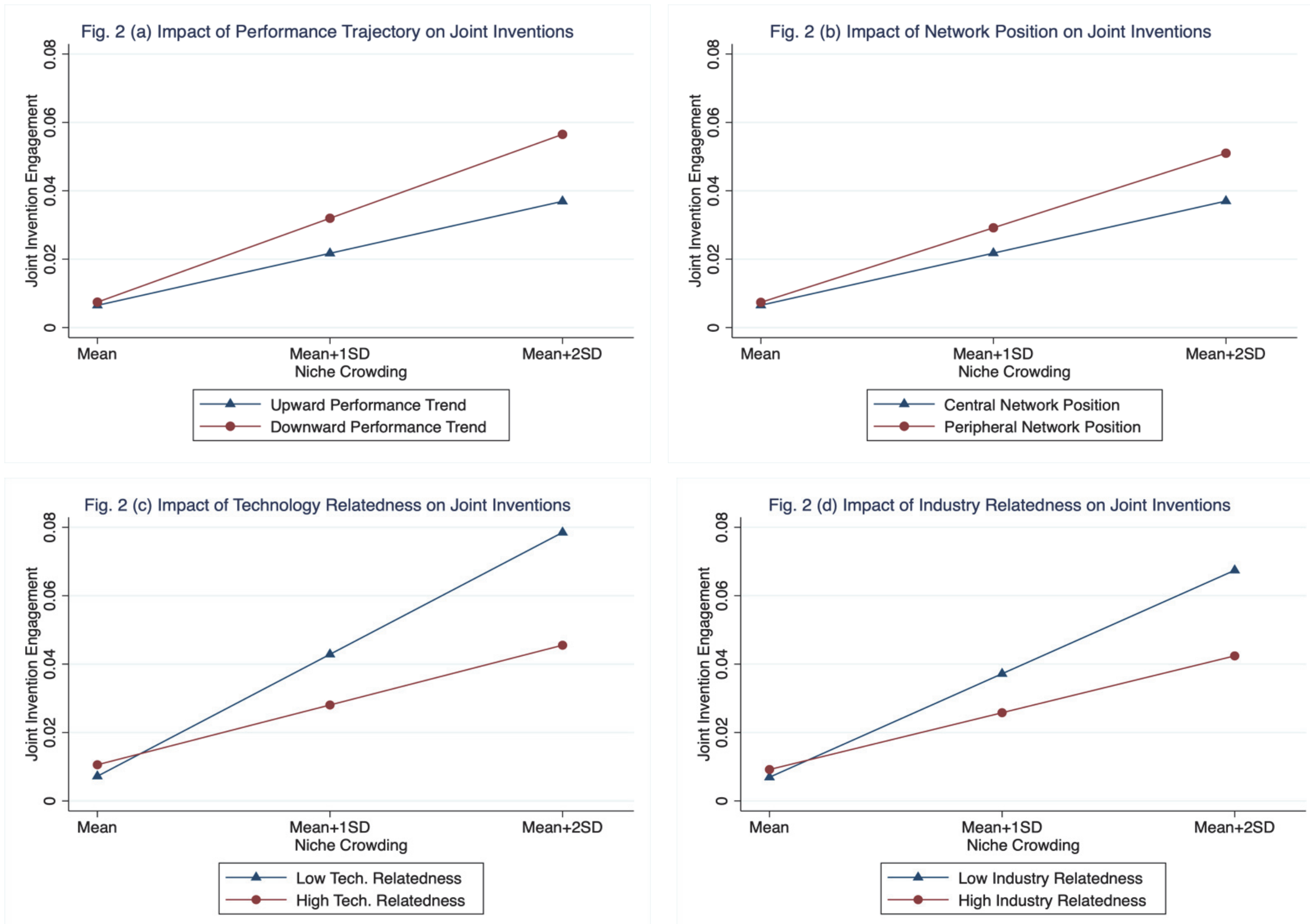
To interpret the economic value of our findings, we employed ordinary least squares (OLS) models. Although OLS may be suboptimal for countable dependent variables due to the constraints of non-negative values and non-constant variance inherent in these types of variables (Cameron and Trivedi, 2013; Greene, 2012), it offers intuitive and straightforward interpretations due to the linear relationship between predictors and dependent variables (Greene, 2012).

As illustrated in Figure 2(a), a one standard deviation increase in niche crowding from its mean results in a 61.8 % greater engagement in joint invention ($=100\times(\frac{0.0320-0.0074}{0.0217-0.0065}-1)$), when performance trend is downward compared to when it is upward. Figure 2(b) demonstrates the impact of network position on joint inventions. A one standard deviation increase in niche crowding from its mean results in a 42.5 % greater engagement in joint invention ($=100\times(\frac{0.0292-0.0074}{0.0218-0.0065}-1)$), when the position is peripheral (i.e., one standard deviation above the mean) compared to when it is central (i.e., one standard deviation below the mean)[1]. These trends persist when niche crowding increases from the mean plus one standard deviation to the mean plus two standard deviations.

Figure 2(c) shows that a one standard deviation increase in niche crowding from its mean results in a 51.0% lower engagement in joint invention ($=100\times(\frac{0.0291-0.0106}{0.0429-0.0072}-1)$), when target technological relatedness is high (i.e., one standard deviation above the mean) compared to when it is low (i.e., one standard deviation below the mean). Similarly, Figure 2(d) shows that a one standard deviation increase in niche crowding from its mean leads to a 45.2 % lower engagement in joint invention ($=100\times(\frac{0.0258-0.0092}{0.0372-0.0069}-1)$), when target industry relatedness is high (i.e., one standard deviation above the mean) compared to when it is low (i.e., one standard deviation below the mean). These trends also persist when niche crowding increases from the mean plus one standard deviation to the mean plus two standard deviations.

4.2 Robustness Checks

We conducted several robustness checks to ensure the robustness of the study's results (see Table 3). First, we employed an OLS regression model to analyze our data. The test results, presented in Model 1 of Table 3, show that the coefficients for our baseline and four hypotheses are consistent with our primary analysis, and all are statistically significant. Notably, although the interaction between niche crowding and target industry relatedness (H3b) was not significant in the full Model 7 of Table 2 (our primary analysis), it reached significance in Model 1 of Table 3 (β = -0.01, p = .049). In unreported analyses, we tested our hypotheses using the OLS model with the log-transformed dependent variable (logarithm applied after adding one) and found the pattern of results were generally consistent with our main findings.



Note. *We plot the impacts of motivational and competitive factors on joint inventions within the range of niche crowding from its mean to the mean plus two standard deviations, rather than from the mean ± one standard deviation. This approach allows us to assess the moderating effects within the actual range of niche crowding. By definition, niche crowding values are greater than or equal to zero, with a mean of 0.08 and a standard deviation of 0.34 (see Table 1). Setting low niche crowding at the mean minus one standard deviation would result in values below zero, which could introduce potential bias in plot interpretation.*

〈Figure 2〉 Contingent Influences on Joint Inventions under Niche Crowding Conditions

These results lend further credence to the conclusions drawn from our primary analysis.

Second, we explored alternative clustering options. In our primary analysis, we clustered standard errors at the inventor level to account for autocorrelation across individuals. However, since some acquirers appear multiple times in our sample (among 170 acquirers, 51 participate in more than one deal), unobserved factors at the acquirer level might influence the results. To address this, we reanalyzed the data with standard errors clustered by acquirers. The test results in Model 2 are consistent with those from our primary analysis.

Third, we tested an alternative specification of the dependent variable. While our theoretical and empirical approach focused on the count of co-inventions, we introduced this alternative metric as a robustness check. This approach helps mitigate concerns regarding potential underestimations of our original measure and provides a broader perspective on the expansion of acquirer inventors' social capital and their integration into the target's collaborative networks. The test results in Model 3 are generally consistent with our main findings, except for the interaction between niche crowding and target industry relatedness in H3b.

Additionally, we explored the robustness of our independent variables by testing alternative measures. In Model 4, we analyzed our data using a continuous measure of the inventor's performance trajectory instead of a binary variable. To facilitate interpretation, we multiplied the performance trajectory slope by -1, so that a higher value indicates a steeper decline in performance. In Model 5, we employed closeness centrality as an alternative measure of eigenvector centrality. Closeness centrality reflects an inventor's efficient access to others in the network, including those beyond direct relationships (Freeman, 1979; Wasserman and Faust, 1994). To facilitate interpretation, we multiplied the closeness centrality measure by -1, so that a higher value indicates more peripheral positioning. In Model 6, we used a binary variable for target relatedness, measured by the two-digit SIC codes instead of the original four-digit SIC codes of the acquirer and target industries: one for related (same two-digit SIC code) and zero for unrelated. Recent acquisition studies suggest that four-digit SIC codes may be too granular to capture industry effects effectively in acquisition research (Meyer-Doyle, Lee, and Helfat, 2019). Across all three models with alternative measures, the results remained materially consistent.

In summary, these robustness tests reinforce the credibility to the conclusions drawn from our primary analysis.

〈Table 3〉 Robustness Checks

Variables	Alt. Models		Alt. DV	Alt. IVs		
	OLS	NB Clustering (Acquirer)	Joint Invention (# of ties)	Downward Perf. Trend (Slope)	Network Centrality (Closeness)	Target Relatedness (SIC2 binary)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.07***	-15.48***	-17.45***	-13.73***	-15.07***	-13.32***
	(0.02)	(3.17)	(1.99)	(2.42)	(2.47)	(2.23)
Inverse Mills ratio	0.05***	4.60+	7.28***	3.61+	4.72*	3.67*
	(0.01)	(2.49)	(1.47)	(1.87)	(1.88)	(1.61)
Geographical distance	-0.00	-0.05	-0.14**	-0.04	-0.06	-0.12***
	(0.00)	(0.09)	(0.04)	(0.05)	(0.05)	(0.04)
Preacquisition alliance	0.01	1.52**	1.35***	1.58***	1.56***	1.65***
	(0.00)	(0.54)	(0.24)	(0.28)	(0.28)	(0.28)
Hostile acquisition	0.00	2.73**	2.84***	2.67***	2.76***	2.87***
	(0.00)	(0.89)	(0.40)	(0.49)	(0.49)	(0.35)
Structural integration	-0.00+	-1.86***	-1.31***	-1.86***	-1.83***	-1.05***
	(0.00)	(0.55)	(0.27)	(0.32)	(0.31)	(0.30)
Inventor's productivity	0.01***	0.70***	0.89***	0.64***	0.71***	0.63***
	(0.00)	(0.20)	(0.14)	(0.17)	(0.17)	(0.13)
Inventor's tenure	-0.01***	-1.00*	-1.61***	-0.83*	-1.02**	-0.76*
	(0.00)	(0.50)	(0.30)	(0.38)	(0.38)	(0.30)
Inventor's diverse expertise	-0.00*	-0.03	-0.06**	-0.02	-0.03	-0.02
	(0.00)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)
Inventor's collaborators	0.00*	0.05*	0.08***	0.04+	0.05*	0.04*
	(0.00)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Inventor's familiarity with	0.87***	10.79**	11.32***	10.63***	10.89***	15.79***
target's tech resources	(0.20)	(3.31)	(2.17)	(1.94)	(1.87)	(2.36)
Inventor's reliance on	0.02**	2.15*	2.10**	1.73+	2.21*	1.47+
acquirer's tech. resources	(0.01)	(1.09)	(0.80)	(0.91)	(0.93)	(0.83)
Downward performance trend	-0.00*	-0.24	0.09	-0.10+	-0.25	-0.28+
	(0.00)	(0.21)	(0.14)	(0.05)	(0.16)	(0.16)
Network centrality	-0.00	0.30	-0.08	0.27	-6.90**	-0.45
	(0.00)	(0.75)	(0.48)	(0.45)	(2.31)	(0.50)
Target tech. relatedness	0.01***	4.03***	3.93***	4.04***	4.03***	3.47***
	(0.00)	(1.13)	(0.50)	(0.55)	(0.54)	(0.38)
Target industry relatedness	0.00+	0.12	0.11	-0.13+	-0.13+	0.36
	(0.00)	(0.13)	(0.07)	(0.07)	(0.07)	(0.24)
Niche crowding	0.14***	3.33***	3.19***	3.49***	3.30***	3.86***
	(0.03)	(0.78)	(0.34)	(0.41)	(0.40)	(0.35)
H1: Niche crowding ×	0.03**	0.54***	0.25*	0.29***	0.55***	0.45***
Downward performance trend	(0.01)	(0.16)	(0.11)	(0.09)	(0.13)	(0.14)
H2: Niche crowding ×	0.08***	1.68**	1.28***	1.68***	4.63***	1.20**
Network centrality	(0.01)	(0.57)	(0.32)	(0.31)	(1.34)	(0.43)
H3a: Niche crowding ×	-0.10**	-2.68**	-2.52***	-2.64***	-2.69***	-3.19***
Target tech. relatedness	(0.03)	(0.93)	(0.48)	(0.53)	(0.52)	(0.49)
H3b: Niche crowding ×	-0.01*	-0.03	0.05	-0.02	-0.03	-0.22
Target industry relatedness	(0.00)	(0.10)	(0.05)	(0.06)	(0.06)	(0.20)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
LnAlpha		2.89***	2.52***	2.90***	2.91***	3.14***
		(0.29)	(0.12)	(0.13)	(0.14)	(0.13)
Log Likelihood		-3131.01	-3733.89	-3134.72	-3135.93	-3250.01
Pseudo R-Squared		0.25	0.28	0.25	0.25	0.22
F	5.07					
R-Squared	0.05					

Note. *N=134,685; + p〈0.10; * p〈0.05; ** p〈0.01; *** p〈0.001; Robust standard errors, shown in parentheses, are clustered by acquiring firm for Model 2 and by inventor for the other models.*

Ⅴ. Discussion and Conclusion

The findings of this study provide important insights into the intricate dynamics that acquirer inventors experience during the post-merger integration phase. The results support the proposition that niche crowding within the target workforce influences the propensity of acquirer inventors to engage in joint inventions. This relationship is shaped by the inventors' assessment of collaboration and competition, which are, in turn, informed by their prior performance trajectories and positions within their original organizations.

First, our analysis affirms that acquirer inventors who occupy crowded niches in the target organization are more likely to pursue joint inventions. Specifically, inventors who have experienced a downward trend in performance or who occupy less central (more peripheral) positions in their original organizations appear more motivated to collaborate. This pattern of findings is consistent with the niche theory framework, which suggests that entities seek to maintain or enhance their competitive position by adjusting their resource utilization strategies. In the context of M&As, where resource distribution undergoes significant changes, collaboration through joint inventions provides a means for inventors to navigate new organizational dynamics and re-establish their niche within the altered competitive landscape.

Conversely, we found that a high level of technological similarity between the acquiring and acquired workforces tends to diminish the propensity for joint inventions. While shared expertise can facilitate knowledge sharing and synergy, it also increases the risk of internal competition. This competitive tension can discourage collaboration, as employees may view their counterparts as rivals rather than partners. This reduced propensity is also observed, albeit marginally, in related acquisitions where the target operates in similar industries. In such cases, concerns over job security or professional standing may further exacerbate reluctance to collaborate, as employees may fear redundancy or demotion. These findings highlight a nuanced aspect of niche theory in M&As: although niche overlap can encourage collaboration under certain conditions, it can also heighten competitive concerns, particularly in environments where significant expertise overlap or fears regarding job security are prevalent.

Overall, this study enriches the M&A literature, particularly concerning human integration, by highlighting the importance of individual-level factors—specifically, the motivations of inventors—in shaping post-merger integration outcomes. Traditional models of M&A success have focused predominantly on organizational-level determinants, such as strategic alignment and financial performance

(Datta, 1991; Graebner et al., 2017; Larsson and Finkelstein, 1999; Rao et al., 2016). However, our study underscores the need to consider the micro-foundations of innovation, particularly how individual actors manage the delicate balance between cooperation and competition following a merger. Moreover, by analyzing patent data from corporate inventors during technological acquisitions, we provide empirical insights into the factors that facilitate effective human integration within new organizational frameworks.

In addition, this research extends niche theory by demonstrating that niche crowding not only affects competitive dynamics but also shapes the decision-making processes of individuals within merging organizations. It adds depth to recent discussions suggesting that intraorganizational niches emerge from the activities in which employees engage and, in turn, influence the outcomes of internal competition triggered by these activities (Liu et al., 2016). By identifying the conditions that amplify either cooperative or competitive forces, this study offers a more nuanced understanding of how intraorganizational relationships develop during the integration process. In doing so, we move beyond merely applying niche theory to organizational behavior; we expand the theory itself to better account for the complexities of human dynamics in post-merger integration.

The practical implications of this study are evident. By understanding how niche crowding affects the behavior and collaboration of employees who stay after a merger, management can better tailor their integration strategies to create a more cohesive work environment. For example, given that technological similarity can lead to increased internal competition, leaders can implement structures that promote collaboration rather than rivalry, such as cross-functional teams or joint innovation projects. Additionally, by focusing on the individual experiences of employees, organizations can provide the support needed to ease their transition during the merger. This aids in retaining talent and maintaining high morale. In the end, these insights can ultimately help companies develop more effective integration plans that not only unite different organizational cultures but also unlock the full collaborative potential of their workforce, leading to more successful outcomes over time.

5.1 Limitations and Directions for Future Research

This paper presents several limitations that open up avenues for future research. First, our analysis, from the acquirer perspective, explores the motivations and behaviors of inventors within acquiring organizations. However, it is essential to recognize that inventors from both acquiring and target firms might have different perspectives and incentives for innovation post-acquisition. Future research could investigate collaborative dynamics from the perspective of target inventors, focusing on the factors that influence their decision-making processes.

Second, our study assumes that joint inventions are uniform, which overlooks the variability in risk and purpose these collaborations might entail. This is especially relevant for exploratory projects, which typically carry greater risks (March, 1991). Future research should explore the diverse natures of joint inventions and examine how inventors respond to various types of collaboration. Additionally, examining the long-term outcomes of joint inventions arising from M&As could provide deeper insights into the factors that determine the success or failure of post-merger integration.

Third, while this study focuses on the behavioral choice between cooperation and competition among acquirer inventors in response to niche crowding, inventors may also pursue an alternative strategy. When acquirer inventors find themselves in increasingly crowded knowledge spaces due to overlapping expertise with target inventors, they may choose to pivot toward less congested niches. For instance, inventors may redirect their efforts toward emerging subfields, interdisciplinary applications, or peripheral domains that are undervalued within the merged organization. These shifts can enhance inventors' visibility and long-term value by allowing them to avoid direct competition and reestablish distinctiveness. Future research could examine this alternative pathway, exploring the conditions under which inventors are more likely to shift their niche focus and the factors that facilitate or constrain such strategic redirection.

Our research primarily utilizes patent data, which represents a specific segment of knowledge workers: corporate inventors. While these inventors are central to organizational innovation, they do not represent the full spectrum of employees in a firm. Future research should expand its scope to include a wider range of employees, thereby providing a more comprehensive understanding of post-acquisition dynamics.

Moreover, our empirical analysis is limited to technological acquisitions among public companies. This leaves a gap in our understanding of inventor behaviors in acquisitions that involve both public and private companies, as well as those exclusively between private companies. Different mechanisms of joint inventions may exist in various types of acquisitions: between private companies, between public and private companies, and between subsidiaries of the same parent company. We also limited our scope to acquisitions for technological integration purposes to minimize managerial effects. Future research should explore different acquisition contexts to provide a more comprehensive picture.

Our study also focuses on the immediate

aftermath of acquisitions. A more extensive exploration of how inventors' collaborative and innovative behaviors evolve over time would yield valuable insights. Understanding how cooperative and competitive dynamics change in the longer term could enhance our understanding of niche crowding as a dynamic process. Longitudinal research that tracks inventors' engagement in joint invention over extended periods could shed light on the evolving structure of post-acquisition collaboration networks and the diverse trajectories they may follow. Ultimately, such research could help explain how these changes affect innovation outcomes, including quality, quantity, novelty, and economic value (Balsmeieri et al., 2018).

Lastly, we acknowledge that while our analysis identifies patterns in inventor behavior, it offers no direct access to the cognitive processes that shape those actions. This well-recognized limitation of quantitative research presents an opportunity for future studies to deepen our understanding through qualitative methods such as interviews or surveys, which could clarify the mechanisms driving inventors' post-acquisition decisions—particularly those related to motivation, interpretation, and the balance between collaboration and competition. For example, future research could explore how target inventors perceive collaborative opportunities in the context of high technological similarity, or how concerns about internal competition might dampen their willingness to engage. It would also be valuable to examine how inventors' intentions vary depending on the relative technological standing of the acquiring and target firms, providing important contextual nuance.

In conclusion, this study emphasizes the importance of further exploring the individual-level dynamics that impact post-merger integration. We hope that our study encourages other researchers to pay closer attention to the experiences of individuals who remain with the company after a merger, as their roles are vital in shaping the integration process. In essence, our research makes a significant contribution to understanding how niche crowding impacts post-merger human integration, with valuable implications for both theory and practice.

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