Too Crowded to Innovate: Competitive Crowding and Inventor Productivity Slowdown in Acquiring Firms

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Firms in high-tech industries frequently pursue technological acquisitions to enhance innovation and sustain a competitive advantage. While prior research has offered valuable insights into organizational-level outcomes, relatively little attention has been paid to individual-level consequences, particularly for employees in the acquiring firm who constitute the technical core of innovation. This study examines how social dynamics that unfold in the post-acquisition context shape the innovation productivity of these acquirer inventors. Drawing on network theory, we argue that competitive crowding—defined as intensified rivalry with inventors from the acquired firm within overlapping technological domains—inhibits collaboration and intensifies competition for organizational resources and recognition. These dynamics contribute to a productivity slowdown during the initial post-acquisition period. We further suggest that the impact of competitive crowding is contingent upon the network context, specifically the degree of status similarity and the extent of network segregation. Analyzing data on 130,600 acquiring inventors involved in U.S. high-tech acquisitions between 2002 and 2015, we find empirical support for these claims. By uncovering how social structures influence individual productivity during periods of organizational change, this research contributes significantly to the acquisition literature and broadens the theoretical scope of network theory.

Keyword: Technological acquisitions, Acquirer inventors, Innovation productivity, Competitive crowding, Status similarity, Network segregation

Ⅰ. Introduction

Firms are increasingly pursuing technological acquisitions—that is, acquisitions aimed at enhancing technological capabilities and rejuvenating innovation performance—as strategic vehicles for sustaining competitive advantage. This trend has spurred considerable scholarly interest in understanding how acquisitions shape firms' innovative outcomes (Ahuja and Katila, 2001; Puranam et al., 2009). To date, however, most research has concentrated on outcomes at the organizational level, with

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particular emphasis on integration processes, resource reconfiguration, and knowledge transfer (Graebner et al., 2010; Kapoor and Lim, 2007). While these studies have yielded important insights, they have paid limited attention to individual-level performance outcomes.

This oversight is especially salient given the disruptive nature of acquisitions. The integration of formerly distinct organizational units often reshapes collaborative networks, heightens internal competition, and introduces uncertainty around status and access to resources, all of which can profoundly alter inventors' day-to-day environments (Kapoor and Lim, 2007; Paruchuri and Eisenman, 2012). Several studies have begun to examine how inventors in *target* firms respond to such disruptions (Kapoor and Lim, 2007; Paruchuri et al., 2006). However, theoretical explanations remain largely focused on the target side, offering limited insight into the mechanisms through which inventors in *acquiring* firms are affected by acquisitions. Because inventors are embedded within evolving networks of collaboration and status hierarchies, post-acquisition organizational changes may destabilize the social and structural foundations that support innovation within acquiring firm workforces (Buono and Bowditch, 2003; Graebner et al., 2017; Pak et al., 2015). These micro-level shifts, in turn, can carry far-reaching implications for firm-level innovation outcomes.

We address this research gap by drawing on insights from the social networks literature. Specifically, we investigate how inventors' innovation performance is shaped by competitive crowding, defined as intensified rivalry among inventors operating in overlapping technological domains. Crowding, in general, refers to niche overlap—the extent to which actors depend on an identical or similar set of resources. Prior research shows that such overlap can generate both cooperative opportunities and competitive pressures (Baum and Mezias, 1992; Baum and Singh, 1994; Podolny et al., 1996). Competitive crowding represents a more specific conceptualization that highlights situations in which overlap primarily manifests as rivalry. In these cases, actors contest scarce resources, visibility, and recognition, and competition rather than collaboration becomes the dominant consequence of crowding (Bothner et al., 2007; Podolny et al., 1996).

In the acquisition context, these competitive dynamics become especially pronounced. As the inflow of target inventors reshapes the balance within technological domains, acquirer inventors face greater substitute pressure and heightened competition for organizational resources (Liu et al., 2016; Seo and Hill, 2005). Inventors situated in more densely populated niches are therefore more likely to experience a slowdown in innovation productivity. This slowdown reflects heightened rivalry for resources and recognition, together with the increased costs of pursuing collaboration in contested environments, such as the additional effort required to coordinate with potential rivals, negotiate roles, and establish trust.

Building on the idea that competitive pressures are shaped by the structural context in which crowding occurs (Liu et al., 2016), we introduce two boundary conditions in our theoretical model. First, we propose that the negative effects of crowding are amplified when inventors share similar status positions. Status similarity heightens rivalry for organizational rewards and weakens the deferential norms that often promote cooperation and knowledge sharing (Kilduff et al., 2024; Menon et al., 2006). Second, we argue that network segregation, defined as the extent to which the target firm's inventor network is fragmented into relatively disconnected subgroups, can attenuate the adverse effects of crowding. By limiting exposure to direct competitors and curbing visibility-based comparisons, structural segregation serves as a buffering mechanism that helps preserve innovation output among acquiring firm inventors.

We find empirical support for our hypotheses by analyzing data on inventors in the U.S. high-tech sector who were involved in acquisitions between 2002 and 2015. Our findings contribute to the acquisition literature in several ways. First, we shift the theoretical focus from firm-level integration processes to the micro-level experiences of individual inventors. In doing so, we respond to growing calls within the strategy field to unpack the microfoundations of post-acquisition innovation performance (Eisenman and Paruchuri, 2019; Meyer-Doyle et al., 2019). By examining how social and status dynamics shape inventor productivity, we provide a more granular understanding of how acquisitions influence innovation from the bottom up. Second, we develop and empirically examine the construct of competitive crowding, which arises from the integration of acquirer and target firm workforces. This construct captures a socially embedded mechanism through which post-acquisition network structures give rise to localized rivalry among inventors, affecting their individual innovation outcomes. In introducing this concept, we bring a social networks perspective into acquisition research, complementing existing explanations grounded in resource reconfiguration and formal integration. Third, we identify boundary conditions that moderate the relationship between competitive crowding and innovation performance. These contingencies advance theory by demonstrating how network position and social hierarchy interact to shape the consequences of organizational restructuring. Rather than treating crowding as uniformly detrimental, our framework highlights when and for whom its effects are amplified or mitigated (Liu et al., 2016).

Beyond theoretical contributions, our findings offer practical implications for managers seeking to sustain innovation in the wake of acquisitions.

Specifically, we highlight the importance of monitoring not only technological overlap between acquirer and target firms but also the configuration of inventor networks and the distribution of status within them. Attending to these social dimensions can help firms mitigate unintended disruptions and preserve the innovative capacity of their technical workforce.

Ⅱ. Theory and Hypotheses

2.1 Innovation Implications of Acquisitions

Firms frequently pursue acquisitions as a means of rapidly achieving technological advancement, entering new markets, and strengthening their innovation capabilities (Ahuja and Katila, 2001; Kapoor and Lim, 2007). Compared to internal R&D, which typically involves lengthy development timelines and high uncertainty, acquisitions allow firms to externally source advanced technologies, skilled human capital, and complementary knowledge bases (Coff, 2002; Makri, Hitt, and Lane, 2010; Lee and Huh, 2021; Ranft and Lord, 2002). This strategic logic is particularly salient in fast-moving industries where time-to-market and technological convergence are critical to maintaining competitive advantage (Makri et al., 2010; Ranft and Lord, 2000; Ranft and Lord, 2002).

A substantial body of research points to the potential of acquisitions to support innovation, especially when they enable the integration of complementary technological and organizational resources (Cassiman, Colombo, Garrone, and Veugelers, 2005; Graebner et al., 2010; Makri et al., 2010). By blending newly acquired assets with existing capabilities, firms can create synergies that foster more effective problem-solving and expand their technological reach (Ahuja and Katila, 2001; Graebner et al., 2010; Lee and Huh, 2021). Effective integration further enables the restructuring of R&D processes, reducing redundancies and promoting the transfer of knowledge across previously disconnected organizational domains (Graebner et al., 2017; Pablo, 1994; Safavi, 2021).

These benefits are often multiplicative rather than merely additive, particularly when integration is strategically managed and aligned with broader innovation objectives. Empirical studies corroborate this perspective, linking successful acquisitions to increased patent output, wider technological reach, and stronger positioning in competitive markets (Ahuja and Katila, 2001; Kapoor and Lim, 2007; Puranam et al., 2009). Over time, these advantages can also enhance firms' absorptive capacity, improving their ability to identify and assimilate external knowledge in future innovation efforts (Ranft and Lord, 2002; Trichterborn et al., 2016; Zollo and Singh, 2004).

However, acquisitions also introduce substantial complexity that can undermine innovation performance. Integration challenges, including cultural misalignment, communication barriers, incompatible technological infrastructures, and conflicting organizational routines, frequently impede knowledge transfer and resource reconfiguration (Kapoor and Lim, 2007; Paruchuri et al., 2006; Puranam et al., 2009; Schweizer, 2005). Organizational disruptions of this nature often interfere with ongoing innovation processes, delaying projects and reducing the effectiveness of R&D activities (Puranam et al., 2006). Uncertainties introduced during integration can further erode employee motivation, morale, and commitment to innovation initiatives (Graebner, 2004; Graebner et al., 2017; Paruchuri and Eisenman, 2012; Puranam et al., 2009).

Although the performance implications of acquisitions are typically examined at the organizational level, the real impact materializes in the daily work of individuals—particularly corporate inventors—who are central to innovation (Kapoor and Lim, 2007; Paruchuri et al., 2006). Inventors are not passive recipients of structural change but active agents navigating a reconfigured social and technical environment (Vuori et al., 2018). Understanding the conditions that shape their ability to sustain or adapt innovation efforts following an acquisition is essential to explaining how integration produces innovative outcomes. A more comprehensive view of post-acquisition innovation processes, therefore, requires close attention to the inventors embedded in these transitions, as their responses ultimately shape the realization of acquisition goals.

Research suggests that acquisitions alter the environment in which inventors operate, reshaping the social and technical structures that support their work (Haspeslagh and Jemison, 1991; Pablo, 1994; Paruchuri et al., 2006; Puranam et al., 2009). As central contributors to a firm's innovative capacity, inventors depend on access to resources, managerial support, peer recognition, and well-defined opportunities for advancement (Katila and Chen, 2008; Singh and Fleming, 2010). In acquiring firms, these conditions often shift following acquisition, particularly with the influx of inventors from the target organization (Lee et al., 2018; Sears and Hoetker, 2014). The resulting reconfiguration can intensify internal competition, constrain resources, and divert managerial attention from innovation efforts (Graebner, 2004; Meyer and Lieb-Doczy, 2003; Puranam and Srikanth, 2007). Internal pressures of this kind can disrupt established routines and diminish individual engagement with innovation activities (Paruchuri et al., 2006).

Although considerable attention has been devoted to the integration experiences of target firm inventors (Paruchuri et al., 2006), the dynamics affecting acquiring inventors remain far less understood. Inventors in acquiring firms may face the dual challenge of preserving established innovation momentum while adapting to heightened competitive pressures and organizational disruptions triggered by the acquisition. Understanding how acquiring inventors navigate these changes is theoretically important, as it offers insight into the micro-level mechanisms through which acquisitions influence organizational innovation.

Organizational disruption associated with acquisitions frequently generates complex competitive dynamics, particularly when technological overlap exists between acquiring and target firms (Sears and Hoetker, 2014). Overlapping domains bring inventors into direct competition for resources, recognition, and strategic influence, giving rise to a phenomenon we refer to as competitive crowding. Competitive crowding reflects localized rivalry that emerges within specific technological areas as inventors contend for visibility and organizational support in an increasingly dense innovation environment (Liu et al., 2016; Podolny et al., 1996). In these settings, inventors may find themselves directly competing for scarce resources (Kapoor and Lim, 2007; Katila and Chen, 2008). Consistent with this view, empirical studies show that intensified competition in overlapping domains undermines the effective application of specialized knowledge and skills (Menon et al., 2006; Puranam and Srikanth, 2007). Psychological consequences are also common, including heightened status concerns, interpersonal strain, and a breakdown of cooperative norms essential for sustained innovation (Singh and Fleming, 2010).

Despite its relevance, competitive crowding remains an under-theorized aspect of post-acquisition change. To address this gap, we develop a theoretical framework that explains how competitive crowding unfolds in the context of acquisitions and how it affects inventors' innovation performance.

2.2 Competitive Crowding

The notion of crowding has long been central in organizational ecology and network research, where it describes the extent of niche overlap—the degree to which actors depend on similar or identical sets of resources (Baum and Mezias, 1992; Baum and Singh, 1994; Hannan and Freeman, 1977; Podolny, 2001). Crowding increases the density of actors within a domain and can create both collaborative opportunities, by facilitating knowledge sharing, and competitive pressures, by constraining differentiation and intensifying contests for scarce rewards (Baum and Mezias, 1992; Podolny, 1993).

Building on this foundation, the concept of competitive crowding has been developed to capture situations where the competitive dimension of overlap dominates. In such contexts, actors do not simply coexist within the same niche; they actively vie for recognition, visibility, and advancement, often under conditions of resource scarcity (Bothner et al., 2007; Podolny et al., 1996). Dense environments heighten these pressures by reducing opportunities for distinction and amplifying direct comparisons among peers (Bothner et al., 2011). Within organizations, overlapping domains of expertise can thus generate heightened rivalry, status contests, and constraints on access to both material and social resources (Burt, 1992).

Research further indicates that whether crowding becomes competitive depends on general organizational conditions that tilt interaction toward contest rather than collaboration. In dense fields, similarity and proximity constrain differentiation and intensify rivalry for indivisible or status-laden rewards, such as influence, attention, or leadership roles (Bothner et al., 2011; Podolny, 1993; Burt, 1992). Competitive crowding is thus more likely when rivalrous scarcity is salient (limited budgets, slots, or sponsorship), role substitutability/redundancy heightens direct contests among near-peers, and comparability and status ordering make within-domain performance differences highly visible —amplifying social comparison and defensive behaviors that suppress knowledge sharing (Festinger, 1954; Barnett and Miner, 1992; Menon et al., 2006). These mechanisms are domain-general; in our empirical setting of post-acquisition integration, they are typically present, which makes overlapping niches prone to be experienced as competitive. This distinction also motivates boundary conditions for the effect of competitive crowding.

Competitive crowding reflects more than a structural condition of overlapping niches; it is a socially embedded dynamic that reshapes how individuals engage with their work (Liu et al., 2016). Proximity to similarly skilled peers fosters status struggles and defensive behaviors, such as reduced trust and guardedness toward colleagues (Barnett et al., 2000; Barnett and Miner, 1992; Stewman and Konda, 1983). In such settings, employees often protect their ideas, limit openness to peers, and prioritize personal visibility over collective goals. These shifts gradually erode collaborative norms and weaken the trust and reciprocity needed to sustain innovation (Menon et al., 2006).

Following acquisitions, crowding becomes particularly salient for inventors in acquiring firms. The integration of target firm inventors into overlapping technological areas increases the local density of expertise, heightening competition for critical innovation resources, including managerial attention, project funding, and strategic sponsorship (Sears and Hoetker, 2014). For inventors who previously operated within stable collaborative networks and had reliable access to resources, the post-acquisition environment introduces new competitive threats that challenge established workflows and performance expectations (Menon et al., 2006; Sears and Hoetker, 2014). Localized competition can constrain resource access, intensify concerns over status and recognition, and weaken established innovation routines, reducing incentives for knowledge sharing and ultimately undermining individual productivity (Kilduff et al., 2024; Menon et al., 2006; Paruchuri et al., 2006).

Competitive crowding also introduces several social and psychological constraints that can impair innovation performance. One key effect is increased status ambiguity, as previously well-positioned inventors face uncertainty regarding their relative standing and organizational role (Paruchuri et al., 2006). Ambiguity of this kind can obscure an inventor's visibility and influence, complicating advancement opportunities (Liu et al., 2016). Another consequence involves collaboration strain: when proximate peers are perceived as rivals, inventors may become more guarded about sharing ideas and be less willing to collaborate (Kilduff et al., 2024; Menon et al., 2006). In highly contested environments, intensified rivalry may also reduce inventors' intrinsic motivation to innovate, particularly if the perceived payoff from inventive effort is low or uncertain. Over time, such conditions can lead to withdrawal from collaborative activities or a preference for incremental, lower-risk contributions that offer clearer personal returns.

Together, these dynamics suggest that competitive crowding does not merely require inventors to exert more effort; rather, it fundamentally alters the social and structural context in which innovation takes place. As crowding increases, the conditions for effective innovation deteriorate, ultimately undermining individual performance. Accordingly, we expect that inventors situated in more competitively crowded technological domains following an acquisition will experience a greater decline in innovation output relative to their own pre-acquisition levels.

Hypothesis 1: The more competitively crowded the technological domains of the target workforce in which inventors from the acquiring firm are situated, the greater the slowdown in their productivity growth following the acquisition.

2.3 Status Similarity

The effects of competitive crowding on innovation performance are not uniform; instead, they depend on the social composition of the individuals involved. One important factor that shapes the intensity of competitive pressure in crowded environments is status similarity, especially when status is defined by performance-related attributes such as prior accomplishments, organizational rank, or perceived influence (Paruchuri et al., 2006). Intraorganizational research suggests that individuals are especially sensitive to competition from others who occupy comparable positions in the performance hierarchy, as these actors are viewed as direct comparators and credible rivals for similar organizational rewards (Liu et al., 2016).

When acquiring firm inventors experience crowding from target firm inventors of similar performance status, they are more likely to view these incoming peers as legitimate competitors for organizational attention, resources, and recognition. This perception intensifies social comparison processes and increases the psychological salience of rivalry (Festinger, 1954). Status similarity heightens perceived threat because similarly positioned individuals are seen as particularly capable of displacing one another in the competition for scarce innovation-related opportunities, such as influential project assignments or executive sponsorship (Baum and Mezias, 1992; Kilduff et al., 2024; Menon et al., 2006; Podolny, 1993).

Moreover, competition among status equals tends to be more zero-sum in nature. Unlike hierarchical relationships, where deference or mentorship may facilitate collaboration, interactions among similarly ranked individuals are more often characterized by defensiveness and efforts to protect intellectual territory (Kilduff et al., 2024). In such settings, inventors may become less collaborative and more reluctant to share knowledge or resources. These behavioral shifts erode the social capital necessary for innovation and compound the effects of crowding by introducing interpersonal friction alongside resource constraints.

In contrast, when crowding involves individuals of dissimilar performance status, the perceived threat of rivalry tends to be lower. Lower-status individuals may not be viewed as credible competitors, while higher-status peers may elicit deference rather than rivalry (Blader and Chen, 2012; Kilduff et al., 2010). In these cases, the social comparison processes and threat responses that typically amplify the effects of crowding are less likely to be triggered.

Taken together, this logic suggests that the negative consequences of competitive crowding are more pronounced when inventors are crowded by peers of similar performance status. The combination of high domain overlap and status similarity creates an especially intense and psychologically salient form of internal competition. This dynamic undermines collaboration, increases political tension, and ultimately reduces innovation performance.

Hypothesis 2: For acquiring inventors, the productivity slowdown associated with com-

petitive crowding by the target workforce is more pronounced when the crowding involves target inventors of similar status.

2.4 Network Segregation

Network effects are shaped not only by *who* is involved, but also by *how* actors are embedded within the broader social structure of the organization (e.g., Brass et al., 2004; Burt, 1992; Ibarra et al., 2005). One key feature of intraorganizational networks that influences how inventors encounter one another and access shared organizational support is the degree of integration or segregation (Allen et al., 2007; Allen and Cohen, 1969; Carnabuci and Operti, 2013; Chandler, 1962; Mell et al., 2022). Network segregation refers to the extent to which an intraorganizational network is fragmented into multiple disconnected inventor groups, as opposed to forming a single, highly interconnected component (Carnabuci and Operti, 2013; Fleming et al., 2007; Lazer and Friedman, 2007). By altering patterns of interaction and access, network segregation can moderate the salience and perceived threat of competition, shaping how the scope of competitive crowding is defined within the acquired firm.

In socially segregated network structures, inventors from the target firm are embedded in clusters that have limited connectivity to other subgroups, including those in the acquiring firm. Such subgroups are not only disconnected from one another but also possess distinct technological backgrounds and inventors tend to have different technological capabilities despite sharing the same technological domains (Carnabuci and Operti, 2013; Fleming et al., 2007). As a result, technological overlap between acquirer and target inventors translates into competition that is confined to localized clusters rather than spanning the acquired firm as a whole. Resource contestation primarily emerges within small subgroups, reducing the salience of competitive threat because acquirer inventors are less likely to directly perceive or engage with counterparts in other clusters of the target firm. Network distance lowers the likelihood of rivalry activation by limiting encounters, idea exchanges, and visibility within the same organizational arena (Singh et al., 2016).

By contrast, integrated networks facilitate interaction and mutual visibility among inventors (Carnabuci and Operti, 2013; Mell et al., 2022). In such networks, technological diversity tends to be more constrained and inventors exhibit relatively homogenous capabilities (Carnabuci and Operti, 2013; Fleming et al., 2007). Greater exposure to one another and to decision-makers means that even moderate levels of technological overlap can trigger rivalry and perceptions of encroachment. Under these conditions, acquirer inventors face competition not only from their immediate peers but also from the broader set of inventors across the acquired firm. Thus, integration broadens the scope of competition and intensifies the effects of crowding.

Consistent with this view, prior network research suggests that structural separation weakens the intensity of social comparison and interpersonal friction by minimizing the frequency and immediacy of contact between actors who might otherwise be perceived as rivals (Burt, 1992; Podolny, 2001). In less connected network structures, individuals are shielded from direct exposure to those who may threaten their status or compete for similar resources. The low cohesion of the inventor network in such settings functions as a buffering mechanism, dampening the activation of competitive dynamics that would otherwise reduce innovation performance.

Segregated structures may also help preserve local autonomy for acquiring inventors. When target inventors remain confined within tight-knit subgroups and maintain few bridging ties, they often lack access to the broader organizational channels through which influence and innovation resources are allocated (Carnabuci and Operti, 2013; Mell et al., 2022; Singh et al., 2016). This fragmentation insulates acquiring inventors from direct competition over critical organizational assets such as project sponsorship, leadership visibility, and cross-functional collaboration. In this way, segregation helps contain the effects of crowding by limiting their spread across organizational subgroups.

Taken together, this logic suggests that the negative relationship between crowding and inventor productivity is attenuated when crowding occurs within a socially segregated target workforce. Limited interaction and structural distance between inventors in these networks can reduce interpersonal frictions and resource-based competition that make crowding so harmful in more integrated settings.

Hypothesis 3: For acquiring inventors, the productivity slowdown associated with competitive crowding by the target workforce is attenuated (amplified) when the crowding occurs within a more segregated (integrated) network structure.

Ⅲ. Data and Methods

3.1 Research Context and Sample

The research context of this study is mergers and acquisitions (M&As) in high-tech industries in the United States from 2002 to 2015. As our research context, we set the sectors classified as high-tech industries in the Securities Data Company (SDC) Platinum database, which include biopharmaceutical, electronics, telecommunications, computer, materials, information technology, and aerospace sectors. In these industries, M&As are commonly undertaken to enhance firms' innovation capabilities, often in the form of technological acquisitions (Ahuja and Katila, 2001; Sears and Hoetker, 2014). While our data collection begins in 1997 to construct key pre-acquisition variables, our analysis focuses on deals from 2002 onward to accommodate five-year windows used in the measurement of several variables.

From the SDC Platinum database, we obtained 120,212 equity exchange data points between 2002 and 2015. Among these equity exchange deals, we screened out the deals in the non-high-tech industry, stock buyback, division acquisitions, and transactions between firms of the same parent firm. Specifically, if either an acquirer or its target did not belong to the high-tech industry, we screened out these deals guided by the definition of technological acquisition (Ahuja and Katila, 2001). We also excluded equity transactions where the buyer (i.e., acquire) did not have more than 50.1% of the seller's share (i.e., target) from our sample (Bettinazzi et al., 2020; Chen et al., 2018). At this stage, we had 18,163 transactions, which can be called 'acquisition deals'. Among the remaining equity deals, 818 transactions between public firms were included in the sample because those deals between public firms could provide the competitive context (Puranam and Srikanth, 2007) unlike nurturing purposes often in startup acquisition. Additionally, we included equity transactions where both an acquirer and its target had at least one patent application filed to the United States Patent and Trademark Office (USPTO) within the five-year window before and after the equity transaction date. At this stage, 487 acquisition deals remained in our sample. After reviewing the company reports (i.e., 10-K, DEFM14A, and PREM14A) from the EDGAR system of the United State and Exchange Commission (SEC), we included acquisition deals for technological purposes such as combining the technologies of the two firms because this purpose is related to the integrated innovation activities, which we assumed the competitive environment in the workplaces. At this stage, we had 276 acquisition deals.

In each of these acquisition deals, we identified inventors (i.e., acquirer and target inventors) from the patent application data filed in the PatentView database provided by the USPTO. This PatendView database provides disambiguated information about the assignees (i.e., firm names), inventors, patent application dates, and patent classes (i.e., technological categories and classification codes). With this information, we constructed various variables at different levels (e.g., inventor, firm, and deal levels). With the five-year window criterion, we extracted all inventors of an acquirer and its target from the patent application data for each acquisition deal (Carnabuci and Operti, 2013; Paruchuri, 2010; Paruchuri et al., 2006), and combined the acquisition data with patent application records. After our data manipulation process and exclusion of observations with insufficient data, in our final sample, we had 130,600 acquirer inventors from 249 acquisition deals between 162 acquirers and 249 targets (49 acquirers involved in multiple acquisition deals).

3.2 Dependent Variable and Analytical Approach

3.2.1. Dependent Variable

(1) Productivity growth

We measured innovation productivity growth as the change in an acquirer inventor's patenting activity following an acquisition. Specifically, we calculated the ratio of the number of patent applications filed by the inventor in the five years after the acquisition to the number filed in the five years before the acquisition, using USPTO data (e.g., Carnabuci and Operti, 2013; Paruchuri et al., 2006). Although patents are typically the outcome of collaborative efforts, the number of applications has been widely used as a proxy for individual inventors' innovation productivity in the literature (Ahuja, 2000; Kapoor and Lim, 2007; Khanna and Guler, 2022; Paruchuri et al., 2006).

To identify acquirer inventors, we examined both single-assignee patents (listing only the acquirer) and multiple-assignee patents (listing the acquirer and other entities). By matching inventor names across these applications, we determined inventor affiliations and then counted the total number of applications in which the focal inventor appeared. Patents with multiple assignees were included in this count, as they capture inventors' contributions regardless of firm boundaries.

To address skewness in the distribution, we took the natural logarithm of this ratio. This logged measure allows for a straightforward interpretation of changes in innovation productivity, such that negative (positive) coefficients in the regression models indicate declines (increases) in productivity relative to the pre-acquisition period.

3.2.2 Analytical Approach

We employed ordinary least squares (OLS) regression to estimate the effects of our independent variables on innovation productivity growth. The dependent variable is a continuous real-valued measure that can take on both positive and negative values, including zero. Since the variable is unbounded, OLS is appropriate for estimating its conditional mean (Cameron and Trivedi, 2005; Greene, 2012).

A key concern in this analysis is sample selection bias, as we focus on inventors who remained active following the acquisition. We define active inventors as those who filed at least one patent in the post-acquisition period. These individuals may differ systematically from those who exited or became inactive, which introduces the possibility of non-random selection into the sample. The analysis may also be subject to concerns about sampling on the dependent variable, given that it is based on post-acquisition patenting activity (see also Paruchuri et al., 2006).

To address this concern, we employed Heckman's two-stage correction model. In the first stage, we estimated the probability that an acquiring-firm inventor remained active using a probit model. Following prior research (Whittington and Smith-Doerr, 2008), we used inventor gender as an instrumental variable: it has been shown to influence patterns of retention but is unlikely to directly affect patent output. We then derived the inverse Mills ratio from the first-stage model and included it as a correction term in the second-stage OLS regression estimating productivity growth (Certo et al., 2016; Heckman, 1979; Kang et al., 2017). We discuss the validity of our two-stage model with inventor's gender as an instrumental variable at the Results section.

Although this approach does not fully distinguish between inventors who left the firm and those who remained but disengaged from innovation activity, it offers a conservative correction that improves the accuracy of our estimates by adjusting for potential selection bias (Paruchuri et al., 2006). To account for unobserved heterogeneity, we also included industry and year fixed effects, which control for differences across sectors and time-specific shocks. Industry dummies were based on the acquirer's 4-digit SIC codes, and year dummies were defined by the acquisition's effective year.

3.3 Independent Variables

3.3.1 Crowding

Competitive crowding refers to intensified rivalry among actors within a certain domain (Hannan and Freeman, 1977; Podolny et al., 1996). While this construct has traditionally been used to explain organizational behaviors, it also applies to individuals within organizations (Liu et al., 2016). As with organizational-level studies, two components are essential for capturing individual-level crowding: the inventor's niche and their competitive relationships with others. An inventor's niche can be understood as their specialized knowledge domain, which provides the basis for their success (e.g., career advancement, rewards) and survival (e.g., job security) within the organization (Liu et al., 2016; Podolny et al., 1996). Competitive pressure arises when this niche overlaps with that of other inventors—greater overlap implies greater niche crowding and, consequently, heightened competition within the same knowledge domain (Hannan and Freeman, 1977; Podolny et al., 1996).

Building on this perspective, we define an acquirer inventor's knowledge domain as their niche and measured niche crowding as the degree of overlap between their domain and those of target inventors (Podolny et al., 1996; Stuart and Ding, 2006). Niche overlap implies that target inventors possess knowledge expertise that is similar to that of the focal acquirer inventor, thereby intensifying competition for innovation-related attainments such as recognition, rewards, and promotions (Liu et al., 2016). To operationalize niche and niche overlap, we relied on the focal inventor's patent backward citations, which reflect their technological knowledge base during the five-year window preceding the acquisition (Carnabuci and Operti, 2013; Singh and Agrawal, 2011; Song et al., 2003). This five-year window is widely adopted in innovation and inventor network research, as it captures the effective lifespan of technological knowledge and professional relationships (e.g., Carnabuci and Operti, 2013; Corredoira and Rosenkopf, 2010; Paruchuri, 2010). Using the guidance of prior studies (Baum and Mezias, 1992; Podolny et al., 1996; Stuart, 1998), we computed the crowding variable as the natural logarithm of one plus the sum of the ratios of common patent references between the focal acquirer inventor and each target inventor, divided by the total number of unique patent references cited by the acquirer inventor:

$$\mathit{Crowding}_i = \ln\left(1 + \sum_j^n \frac{\text{The number of common references between acquire inventor}_i\text{ and target inventor}_j}{\text{The number of unique references of acquirer inventor}_i}\right)$$

where n denotes the number of target inventors. A higher value of this measure indicates greater overlap with target inventors and, accordingly, more intense competitive crowding within the focal inventor's knowledge domain.

3.3.2 Higher-, Similar-, and Lower-status crowding

We measured higher-, similar-, and lower-status crowding based on the focal acquirer inventor's relative position within the productivity distribution of target inventors. To construct this distribution, we counted the number of patent applications each target inventor filed with the USPTO in the five years preceding the acquisition (Singh and Agrawal, 2011; Song et al., 2003). We then divided this productivity distribution of the target into ten equal parts by percentile, each representing 10% (e.g., 10%, 20%, … up to 100%), and obtained the cutoff values that define the boundaries of each quantile. We then divided the distribution into ten equal percentile segments (e.g., 0-10%, 10-20%, ..., 90-100%) and recorded the cutoff values for each decile.

We then identified the percentile segment in which the focal acquirer inventor's productivity fell and used this segment as the reference point for categorizing crowding. Similar-status crowding includes target inventors in the same percentile segment as the focal inventor. Higher-status crowding includes those in higher percentile segments, and lower-status crowding includes those in lower segments. For example, if the focal acquirer inventor falls at the 75th percentile of the target distribution, target inventors between the 70th and 80th percentiles are considered similar-status peers. Those above the 80th percentile contribute to higher-status crowding, while those below the 70th percentile contribute to lower-status crowding.

3.3.3 Network segregation

We measured the network segregation of the corresponding target as the inverse of the relative size of the largest component in its collaboration network. The largest component represents the largest subset of inventors who are directly or indirectly connected through co-inventorship ties. A relative size of one indicates that all inventors are part of a single cohesive group, meaning that any two inventors are connected either directly or through intermediaries—thus reflecting full network integration and no segregation (Carnabuci and Operti, 2013; Wasserman and Faust, 1994).

To construct this variable, we first identified the target's patent applications filed with the USPTO during the five years preceding the acquisition. From these patents, we extracted the list of inventors and constructed the target's inventor collaboration network, where nodes represent inventors and edges represent co-inventorship relationships. Within the inventors' collaboration network, we identified the largest component. The component refers to the group of actors (i.e., inventors) connected with one another via others (Wasserman and Faust, 1994). Within this network, we identified the largest component—the group of inventors connected directly or indirectly through co-inventorship. To compute the relative size of the largest component, we divided the number of inventors in the largest component by the total number of inventors in the full collaboration network. Following prior research (Carnabuci and Operti, 2013), we defined network segregation as the inverse of this proportion:

$$Network\ segreation = 1/\left(\frac{The\ number\ of\ inventors\ belonging\ to\ the\ largest\ component}{The\ total\ number\ of\ inventors\ belong\ to\ the\ whole\ network}\right)$$

Higher values of this measure indicate a more fragmented network, with fewer inventors connected in the dominant component and greater overall segregation within the target's innovation structure.

3.4 Control Variables

We included a number of covariates at the firm, deal, and individual levels to account for potential alternative mechanisms.

3.4.1 Geographical distance.

The geographical distance between an acquirer and its target influences access to the other firm's resources and interaction between employees of the two firms (Chakrabarti and Mitchell, 2013). Based on the addresses of an acquirer and its target, we obtained the latitude and longitude of each side firm via Google Map APT services. The distance between the two firms was computed in kilometers by employing the WGS84 ellipsoid standard. Due to the skewness, we took the logarithm of this distance value.

3.4.2 Industrial distance.

When an acquirer and its target operate in the same industry, it is highly likely that employees of the two firms are redundant and may perceive each other as a competitor (Cartwright and Cooper, 1993). Based on the four-digit Standard Industrial Classification (SIC) codes of the two firms, we assigned a value by adding one point for each digit that differed from the last digit. For example, if all four digits were different, the value was 4. Conversely, if the two firms shared the same SIC codes, zero was assigned.

3.4.3 Technological similarity

Acquirer inventors may perceive the target inventors as competitors when the two firms share similar technological foundations due to the duplicate knowledge basis (Ahuja and Katila, 2001; Sears and Hoetker, 2014). We measured technological similarity by using the cosine value obtained from the inner product of the patent class vectors of the two firms with the five-year criterion (i.e., considering patent applications filed in the five years prior to the focal acquisition deal) as follows:

$$Technological\ similarity = cos\theta = \frac{\vec{A} \cdot \vec{T}}{|\vec{A}| \cdot |\vec{T}|}$$

where $\vec{A}$ and $\vec{T}$ denote a vector space constructed from patent classes of an acquirer and its target, respectively.

3.4.4 Preacquisition alliance

From the SDC Platinum database, we identified whether the two firms had any strategic alliance for the previous five years from the focal acquisition date. We assigned one if the two firms had any strategic alliance relationship during this period, and zero otherwise.

3.4.5 Hostile acquisition

The acquisition attitude is strongly associated with employees' emotions and behaviors in the post-acquisition period (Larsson and Finkelstein, 1999). This variable was coded as one when the focal acquisition deal was the hostile type, and zero otherwise.

3.4.6 Structural integration

When the target is structurally integrated into the acquirer, target employees experience disruption and restructuring processes, thus influencing their perceptions and behaviors (Pablo, 1994; Puranam and Srikanth, 2007; Schweizer, 2005). If the target's name disappeared on the acquirer's subsidiary list within one year from the acquisition date, we coded this variable as one, and zero otherwise.

3.4.7 Inventor's tenure

We counted the number of years from the year of the focal inventors' first patent application in the acquirer to the year of the acquisition (Dokko and Rosenkopf, 2010; Singh and Agrawal, 2011). Due to the skewness, we logged the calculated value.

3.4.8 Inventor's reliance on target knowledge

The exposure to the target knowledge may influence the acquirer inventors' innovation activities after the acquisition deal (Cloodt et al., 2006; Kapoor and Lim, 2007). We counted the ratio of the number of the target's patents cited by the focal acquirer inventor to the total number of patents cited by him or her for the previous five years from the acquisition date.

3.4.9 Inventor's knowledge scope

The focal inventor's broad knowledge is related to the innovation activities (Banerjee and Campbell, 2009). We counted the number of patent classes assigned to the focal inventor's patent applications filed in the USPTO for the previous five years from the acquisition date.

3.4.10 Inventor's number of collaborators

The extent to which the focal inventor has collaborators within an organization is associated with innovation activities (Gomez-Solorzano et al., 2019). We counted the number of collaborators the focal inventor had filed the patent applications with for the previous five years at the time of the acquisition.

3.4.11 Inventor's centrality

The position of the focal inventor within the organization influences his or her influence over others, visibility as attractive collaborators, and access to other inventors and resources, thus influencing innovation activities (Paruchuri, 2010; Singh et al., 2016). We measured the focal inventor's centrality by using the eigen centrality within the acquirer's inventor collaboration networks (Bonacich, 1987; Wasserman and Faust, 1994), which consists of inventors and their collaborative relationships obtained from the patent applications for the five preceding years from the acquisition (Carnabuci and Operti, 2013).

Ⅳ. Results

The descriptive statistics and correlations for all variables are presented in 〈Table 1〉. While most correlations are relatively low, we conducted variance inflation factor (VIF) tests to further address potential concerns about multicollinearity. First, we estimated VIFs using the overall crowding variable along with all other independent variables. This analysis yielded an average VIF of 1.21 and a maximum of 1.52. Second, we repeated the analysis using the three status-differentiated crowding variables instead of the overall crowding measure. In this case, the average VIF was 1.20 and the maximum was 1.52. All values fall well below the conventional threshold of 10 and the more conservative benchmark of 2.5 (Vittinghoff et al., 2012), suggesting that multicollinearity is unlikely to affect the validity of our regression estimates.

Compared to the Similar-status crowding variable, the distribution of the Higher- and Lower-status crowding variable may be measured sparser, as it is theoretically more likely to be influenced by observations at the extreme end of the target inventors' distribution. Upon examining the distribution of the three variables, a comparison of the distributions of the three variables using t-tests indicated that Similar-status crowding exhibited the highest mean, followed by Higher-status crowding, and then Lower-status crowding.

In 〈Table 2〉, the results of the first-stage logit regression are presented. The positive and significant coefficient (β = 0.023, p = .018) of inventor's gender, the instrumental variable, implies that male inventors are more likely to be observed in the post-acquisition phase than female inventor. This satisfies the first-stage criterion that the instrumental variable should be associated with the sample selection (Certo et al., 2016; Heckman, 1979; Kang et al., 2017). 〈Table 3〉 exhibits the second stage OLS regression analysis with industry and year fixed effects. The coefficient of the inverse Mills ratio in Model 1

〈Table 1〉 Descriptive Statistics and Pairwise Correlations

No.	Variables	Mean	S.D.	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.
1.	Productivity growth	-0.07	1.00	1.00																	
2.	Crowding	0.09	0.42	-0.06*	1.00																
3.	Higher-status crowding	0.00	0.05	-0.01*	0.25*	1.00															
4.	Similar-status crowding	0.01	0.06	-0.02*	0.27*	0.31*	1.00														
5.	Lower-status crowding	0.00	0.04	-0.01*	0.18*	0.06*	0.28*	1.00													
6.	Network segregation	1.95	1.20	-0.05*	0.00	-0.02*	0.01*	0.01*	1.00												
7.	Geographical distance	6.50	2.09	0.04*	-0.23*	-0.04*	-0.06*	-0.03*	-0.03*	1.00											
8.	Industry distance	2.75	1.70	0.08*	-0.24*	-0.09*	-0.10*	-0.05*	-0.01*	0.21*	1.00										
9.	Technological similarity	0.49	0.23	-0.06*	0.21*	0.08*	0.09*	0.05*	0.05*	-0.22*	-0.47*	1.00									
10.	Preacquisition alliance	0.08	0.27	0.03*	-0.05*	-0.02*	-0.02*	-0.01*	-0.11*	0.09*	0.13*	-0.21*	1.00								
11.	Hostile acquisition	0.02	0.13	0.00	-0.02*	-0.01*	-0.01	-0.00	0.09*	-0.00	-0.00	-0.12*	-0.04*	1.00							
12.	Structural integration	0.31	0.46	0.07*	-0.13*	-0.05*	-0.06*	-0.04*	-0.26*	0.16*	0.25*	-0.19*	0.27*	0.08*	1.00						
13.	Inventor's tenure	1.62	0.80	-0.29*	-0.02*	0.00	-0.01*	-0.02*	-0.01*	0.03*	0.04*	-0.01*	0.02*	-0.02*	0.03*	1.00					
14.	Inventor's reliance on target knowledge	0.00	0.01	0.00	0.05*	0.04*	0.15*	0.08*	0.03*	-0.04*	-0.05*	0.06*	0.00	0.02*	-0.02*	-0.03*	1.00				
15.	Inventor's knowledge scope	1.32	0.70	-0.21*	-0.12*	-0.02*	-0.01*	0.00	-0.09*	0.06*	0.11*	-0.13*	0.09*	0.05*	0.10*	0.27*	-0.00	1.00			
16.	Inventor's collaborators	8.70	10.05	-0.25*	0.02*	0.01*	-0.01*	-0.01*	-0.04*	-0.02*	-0.01*	0.05*	-0.00	0.01*	-0.01*	0.32*	-0.01*	0.32*	1.00		
17.	Inventor's centrality	0.03	0.11	-0.08*	0.00	0.01*	0.01*	0.04*	-0.04*	-0.02*	-0.10*	0.02*	-0.01*	0.01*	-0.04*	0.08*	0.01*	0.09*	0.44*	1.00	
18.	Inventor's gender	0.82	0.38	-0.01*	-0.03*	-0.00	-0.01*	-0.00	-0.00	0.04*	0.04*	-0.05*	0.00	0.01*	0.05*	0.09*	-0.00	0.07*	-0.00	-0.00	1.00

Note. n = 130,600; *p 〈 .05

〈Table 2〉 First-stage Probit Regression

Dependent Variable	Active Inventor Post-Acquisition
Constant	-0.719*** (0.033)
Geographical distance	-0.010*** (0.002)
Industrial distance	0.019*** (0.003)
Technological similarity	0.190*** (0.016)
Preacquisition alliance	-0.068*** (0.018)
Hostile acquisition	0.068** (0.025)
Structural integration	0.041*** (0.008)
Inventor's tenure	-0.212*** (0.005)
Inventor's reliance on target knowledge	0.360* (0.177)
Inventor's knowledge scope	-0.218*** (0.008)
Inventor's number of collaborators	0.032*** (0.001)
Inventor's centrality	-0.270*** (0.064)
Inventor's gender (male)	0.023* (0.010)
Industry fixed effects	Yes
Year fixed effects	Yes
Pseudo R-Squared	0.068
Log-Likelihood	-269,225.74
N	492,567

Note. Robust standard errors, shown in parentheses, are clustered by inventor; $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

is positive and significant, and this trend remains consistent across the rest of three models (Model 2—Model 4). These positive and significant coefficients provide evidence for the presence of sample selection bias (Certo, et al., 2016; Heckman, 1979). Specifically, unobserved factors influenced both the first-stage selection process (i.e., whether an inventor remained productive and thus was included in the sample) and the second-stage outcome (i.e., the level of productivity growth among those retained). The significant values of the inverse Mills ratio indicate that the violation of random sampling, thus confirming the use of the two-stage model in our analysis (Certo et al., 2016; Heckman, 1979; Kang et al., 2017).

We further conducted the Durbin-Wu-Hausman test to validate whether the estimates of the two-stage models are appropriate and obtained the *p*-value of 0.000, which implies that the two-stage model was appropriate because of endogeneity (Cameron and Trivedi, 2005). Thus, the significance of the instrumental variable at the first stage, that of the inverse Mills ratio at the second stage, and the Durbin-Wu-Hausman test provide the empirical support for the appropriateness of our two-stage model with our instrumental variable.

In 〈Table 3〉, Model 1 reports the baseline specification with only control variables included. The signs and significance levels of the control variables in Model 1 are statistically consistent across all the models, which yields empirical evidence for model stability. Model 2 tested our first hypothesis, which posited that acquirer inventors facing greater crowding by target inventors in their technological niche would be more likely to experience a slowdown in productivity following the acquisition. The coefficient for *crowding* is negative and statistically significant (β = -0.082, *p* = .000). This result supports Hypothesis 1, indicating that increased crowding is associated with diminished productivity growth among acquirer inventors.

Model 3 examined our second hypothesis, which proposed that the negative effects of crowding would be most pronounced when the crowding originates from target inventors of similar status, compared to those of higher or lower status. The coefficient for *higher-status crowding* is negative but not significant (β = -0.018, *p* = .668). In contrast, both *similar-status crowding* (β = -0.230, *p* = .000) and *lower-status crowding* (β = -0.181, *p* = .001) show negative and statistically significant coefficients. While both forms of crowding are associated with a productivity slowdown, the effect of similar-status crowding is more pronounced, supporting Hypothesis 2.

Nonetheless, the findings warrant further exploration of possible underlying mechanisms. The negative impact of lower-status crowding may appear counterintuitive, as lower-status inventors are not direct competitors. However, this pattern can be understood through what we call the upgrade effect. In the post-acquisition context, target inventors benefit from several advantages. First, they gain access to the acquirer's advanced technologies, facilities, and processes, which enhance their innovative capacity (Graebner and Eisenhardt, 2004; Graebner et al., 2010). Second, collaboration with acquirer inventors allows them to more effectively exploit these resources and build complementary capabilities (Lee and An, 2025). Third, acquirers often provide deliberate support to targets in order to unlock value during integration (Puranam and Srikanth, 2007). Together, these benefits elevate the productivity of target inventors relative to their pre-acquisition baseline, effectively "upgrading" even those who previously held lower positions in the status hierarchy.

For acquirer inventors, however, this upgrading process can have adverse consequences. As formerly lower-status target inventors become more capable and better supported, they compete more directly for organizational resources, collaborative opportunities, and managerial attention. The presence of many such "upgraded" inventors can intensify competition, thereby constraining acquirer inventors' ability to maintain their prior productivity levels.

By contrast, crowding from higher-status inventors appears less destabilizing. Two mechanisms help explain this. First, deference norms often shape interactions with higher-status colleagues, making direct competition less salient or psychologically threatening.

〈Table 3〉 Main Results from OLS Models of Productivity Growth

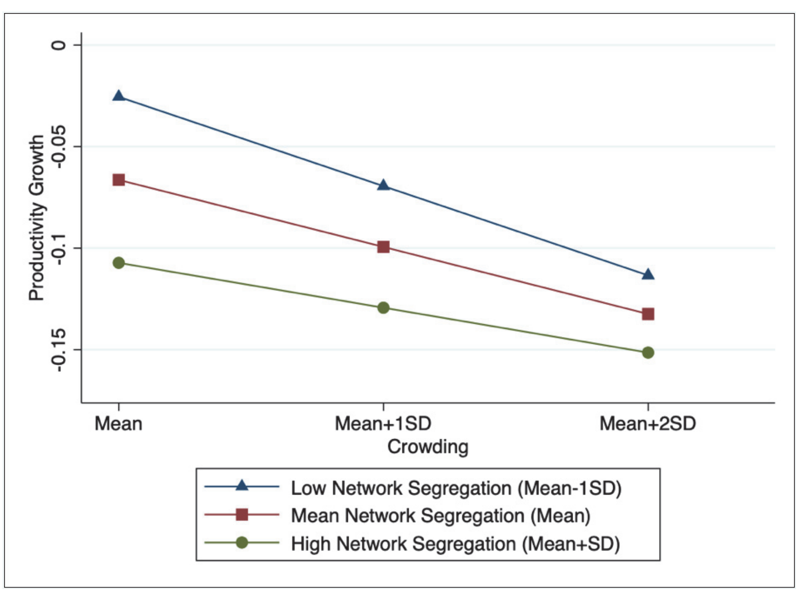
Variables	Model 1	Model 2	Model 3	Model 4
Constant	-1.970***	-1.931***	-1.966***	-1.916***
	(0.136)	(0.135)	(0.135)	(0.135)
Inverse Mills ratio	2.315***	2.309***	2.312***	2.309***
	(0.099)	(0.099)	(0.099)	(0.099)
Geographical distance	-0.020***	-0.023***	-0.020***	-0.023***
	(0.002)	(0.002)	(0.002)	(0.002)
Industrial distance	0.053***	0.051***	0.053***	0.051***
	(0.003)	(0.003)	(0.003)	(0.003)
Technological similarity	0.290***	0.311***	0.296***	0.311***
	(0.022)	(0.022)	(0.022)	(0.022)
Preacquisition alliance	-0.053**	-0.063***	-0.061***	-0.063***
	(0.017)	(0.017)	(0.017)	(0.017)
Hostile acquisition	0.160***	0.156***	0.158***	0.154***
	(0.032)	(0.032)	(0.032)	(0.032)
Structural integration	0.080***	0.075***	0.078***	0.072***
	(0.007)	(0.007)	(0.007)	(0.007)
Inventor's tenure	-0.586***	-0.586***	-0.585***	-0.585***
	(0.015)	(0.015)	(0.015)	(0.015)
Inventor's reliance on target knowledge	0.225	0.296	0.393+	0.307
	(0.209)	(0.210)	(0.210)	(0.211)
Inventor's knowledge scope	-0.623***	-0.624***	-0.623***	-0.625***
	(0.016)	(0.016)	(0.016)	(0.016)
Inventor's number of collaborators	0.034***	0.034***	0.034***	0.034***
	(0.002)	(0.002)	(0.002)	(0.002)
Inventor's centrality	-0.319***	-0.328***	-0.317***	-0.329***
	(0.036)	(0.036)	(0.036)	(0.036)
Network segregation	-0.028***	-0.031***	-0.028***	-0.036***
	(0.003)	(0.003)	(0.003)	(0.003)
H1: Crowding		-0.082***		-0.122***
		(0.006)		(0.010)
H2: Higher-status crowding			-0.018	
			(0.043)	
H2: Similar-status crowding			-0.230***	
			(0.046)	
H2: Lower-status crowding			-0.181***	
			(0.055)	
H3: Crowding × Network segregation				0.022***
				(0.004)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R-Squared	0.185	0.186	0.185	0.186
F-Value	238.67	238.33	230.52	235.63
N	130,600	130,600	130,600	130,600

Note. Robust standard errors, shown in parentheses, are clustered by inventor; $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Second, higher-status inventors typically enjoy segmented access to organizational resources (e.g., preferential allocation of projects, funding, or visibility), which reduces overlap with the resource pools on which most acquirer inventors rely. These buffering mechanisms limit the extent to which higher-status crowding translates into productivity losses.

Taken together, these results suggest that the disruptive impact of crowding hinges not only on its intensity but also on the *direction* and *legitimacy* of status-based threats. Similar-status crowding is most threatening because it directly challenges incumbents' relative standing, while lower-status crowding becomes threatening once those individuals are "upgraded" through acquisition-related benefits. In contrast, higher-status crowding tends to be less disruptive because deference norms and resource differentiation mitigate head-to-head competition.

Model 4 tested Hypothesis 3, which proposed that the negative effects of crowding would be moderated by the segregation of the target firm's collaboration network. As predicted, the interaction effect between *crowding* and *network segregation* is positive and stat-



Note. *We illustrate the effects of crowding on productivity growth across varying levels of network segregation, focusing on the range of crowding values from the mean to two standard deviations above the mean. This range is used because the crowding variable is non-negative, with a mean of 0.09 and a standard deviation of 0.42 (see Table 1).*

〈Figure 1〉 The Impacts of Crowding and Network Segregation on Productivity Growth istically significant (β = 0.022, p = .000), while *crowding* has a negative and significant impact on productivity growth (β = -0.122, p = .000). These findings indicate that higher network segregation reduces the adverse impact of crowding on acquirer inventors' productivity, thereby supporting Hypothesis 3.

To illustrate the economic significance of our findings, 〈Figure 1〉 plots the effects of crowding on productivity growth across varying levels of network segregation, holding all other variables at their mean values. The x-axis represents the level of crowding, ranging from the mean to two standard deviations above the mean. This range is used because crowding, by definition, takes values greater than or equal to zero, and its observed mean and standard deviation are 0.09 and 0.42, respectively (*see* Table 1). As crowding increases from its mean to one standard deviation above the mean, its marginal effect on productivity growth decreases by approximately 50.00% $(=100\times(\frac{(-0.099)-(-0.066)}{|-0.066|}))$, with network segregation held constant at its mean level.

Next, we assess how changes in network segregation influence the marginal effects of crowding. When crowding increases by one standard deviation from its mean, the marginal effect on productivity growth becomes approximately 33.33% $(=100\times(\frac{\{(-0.069)-(-0.025)\}-\{(-0.099)-(-0.066)\}}{|(-0.099)-(-0.066)|}))$ more negative as network segregation decreases by one standard deviation from its mean. Under the same increase in crowding, an increase in network segregation from its mean to one standard deviation above the mean results in an approximately 33.33% $(=100\times(\frac{\{(-0.129)-(-0.107)\}-\{(-0.099)-(-0.066)\}}{|(-0.099)-(-0.066)|}))$ decrease in the negative marginal effect of crowding on productivity growth. These results suggest that greater structural fragmentation in the target firm's network meaningfully reduces the intensity of competitive crowding experienced by acquirer inventors.

〈Table 4〉 presents our analyses using alternative measures of network segregation to assess the sensitivity of our findings. Specifically, we employed a cohesion-based measure, the number of components, and the number of components excluding isolates. To construct these measures, we first built each target's collaboration network, composed of inventors and their co-authorship relationships extracted from patent applications filed within a five-year window preceding the acquisition (Carnabuci and Operti, 2013; Paruchuri, 2010). We measured inverse cohesion by taking the reciprocal of the network's transitivity (Wasserman and Faust, 1994):

$$Inverse\ Cohesion = \frac{1}{Transitivity}$$

$$Transitivity = \frac{3 \times Number\ of\ triangles}{Number\ of\ connected\ triplets}$$

〈Table 4〉 Sensitivity Tests

Variables	Model 1	Model 2	Model 3
Network segregation variables	Inverse cohesion	Number of components	Number of components excluding isolates
Constant	-2.031***	-2.028***	-2.035***
	(0.136)	(0.135)	(0.135)
Inverse Mills ratio	2.282***	2.304***	2.306***
	(0.099)	(0.099)	(0.099)
Geographical distance	-0.023***	-0.023***	-0.023***
	(0.002)	(0.002)	(0.002)
Industrial distance	0.049***	0.046***	0.047***
	(0.003)	(0.003)	(0.003)
Technological similarity	0.318***	0.358***	0.357***
	(0.023)	(0.022)	(0.022)
Preacquisition alliance	-0.058**	-0.041*	-0.041*
	(0.018)	(0.017)	(0.017)
Hostile acquisition	0.185***	0.200***	0.192***
	(0.033)	(0.033)	(0.033)
Structural integration	0.094***	0.081***	0.082***
	(0.007)	(0.007)	(0.007)
Inventor's tenure	-0.579***	-0.584***	-0.584***
	(0.015)	(0.015)	(0.015)
Inventor's reliance on target knowledge	0.214	0.323	0.321
	(0.213)	(0.207)	(0.207)
Inventor's knowledge scope	-0.623***	-0.624***	-0.624***
	(0.016)	(0.016)	(0.016)
Inventor's number of collaborators	0.033***	0.034***	0.034***
	(0.002)	(0.002)	(0.002)
Inventor's centrality	-0.296***	-0.332***	-0.331***
	(0.037)	(0.036)	(0.036)
Crowding	-0.127***	-0.081***	-0.082***
	(0.018)	(0.007)	(0.007)
Network segregation	0.037+	-0.001***	-0.001***
	(0.020)	(0.000)	(0.000)
Crowding × Network segregation	0.106**	0.000**	0.000**
	(0.034)	(0.000)	(0.000)
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
R-Squared	0.186	0.186	0.186
F-Value	244.90	237.20	237.01
N	127,635	130,600	130,600

Note. Robust standard errors, shown in parentheses, are clustered by inventor; $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$; Model 1 includes 127,635 observations. In the analysis, 2,965 observations were dropped because they contained no triplets with two co-inventorship ties.

A triangle refers to three inventors who are all mutually connected, while a connected triplet consists of any group of three inventors with exactly two co-inventorship ties. Higher transitivity reflects stronger cohesion and denser local structures. By inverting this value, the measure captures reduced cohesion, such that higher values indicate more fragmented and less integrated networks.

Model 1 in 〈Table 4〉 shows that the interaction between *crowding* and *inverse cohesion* is positive and significant (β = 0.106, p = .002), while the main effect of *crowding* remains negative and significant (β = -0.127, p = .000). These results suggest that the negative impact of crowding is attenuated in less cohesive networks, providing empirical support for the moderating role of network structure.

To further validate this finding, we examined the number of components in each target's collaboration network. A component is defined as a subgroup of inventors connected directly or indirectly through co-inventorship ties (Carnabuci and Operti, 2013; Wasserman and Faust, 1994). A single component implies a fully connected network, while a greater number of components indicates a highly fragmented network.

In Model 2, we included the total number of components, including isolates (i.e., inventors with no co-inventorship ties). The interaction effect between *crowding* and *the number of components* is positive and significant (β = 0.0001, p = .004), and the main effect of *crowding* remains negative and significant (β = -0.081, p = .000). In Model 3, we used an alternative specification that excludes isolates and considers only connected components. The interaction between *crowding* and *number of components (excluding isolates)* is also positive and significant (β = 0.0002, p = .002), while *crowding* again shows a negative and significant main effect (β = -0.082, p = .000).

Together, these findings reinforce our theoretical claim that greater network segregation weakens the negative effects of competitive crowding, highlighting the buffering role of structural separation in collaborative networks.

Ⅴ. Discussion and Conclusion

5.1 Discussion and Conclusion

This study provides fresh insight into how acquisitions affect the innovation trajectories of acquirer-side employees. While much of the existing literature focuses on firm-level integration processes and outcomes, we shift our attention to the micro-level experiences of acquiring inventors and how their innovation productivity is shaped in the post-acquisition period. Our findings indicate that acquirer inventors experience a decline in innovation output when their technological domains become more crowded by inventors from the target firm. This study complements recent research suggesting that, as crowding intensifies post-acquisition, acquirer inventors collaborate with target inventors to differentiate themselves (Lee and An, 2025). Yet such collaboration entails substantial costs—adapting to new routines, managing interactions, and absorbing unfamiliar knowledge—which can reduce productivity. These temporal, cognitive, and emotional demands can reduce the acquirer inventors' productivity, since human resources such as time, cognitive capability, and emotional energy are finite. Consistent with network theory and with organizational ecology more broadly, such crowding creates localized competition for resources and influence, which in turn shapes individual innovation behavior within the organization.

Importantly, the negative effects of crowding are amplified when they occur in domains shared with inventors of similar status. This finding aligns with established insights from organizational ecology (e.g., Baum and Mezias, 1992) and social comparison theory (e.g., Festinger, 1954; Kilduff et al., 2010), which suggest that rivalry is especially intense among actors who are similarly positioned in terms of status and expertise. Moreover, the decline in innovation is amplified when the incoming inventors are embedded in a more integrated collaboration network. In contrast, when the target's network is more segregated, the adverse effect of crowding is mitigated. Segregated networks reduce opportunities for direct comparison, observation, and interaction, thereby buffering acquirer inventors from competitive pressures.

Our investigation contributes to the acquisition literature by moving beyond aggregate firm-level outcomes to consider how individuals within acquiring organizations respond to organizational change. While prior research has identified key drivers of acquisition performance, including integration strategy, cultural alignment, and resource reconfiguration (e.g., Birkinshaw et al., 2000; Graebner et al., 2017; Pablo et al., 1996), it has struggled to explain the continued underperformance of many acquisitions despite alignment on these dimensions. A growing body of work has begun to address this limitation by focusing on the role of individual actors in shaping post-acquisition outcomes (Meyer-Doyle et al., 2019; Paruchuri and Eisenman, 2012), although much of this research has focused on employees from the acquired firm. Our study highlights that inventors in the acquiring firm also face meaningful changes in their social and technical environments, which in turn influence their capacity to sustain innovation. By examining status dynamics and structural segregation, we identify a social mechanism through which competitive crowding affects individual performance following an acquisition.

More broadly, this research contributes to the network literature by developing and empirically examining the construct of competitive crowding within the context of corporate acquisitions. In network terms, crowding within a niche reflects interdependence among actors competing for similar resources, where localized rivalry shapes outcomes such as performance, survival, and growth (e.g., Baum and Mezias, 1992; Freeman and Hannan, 1983; Hannan and Freeman, 1977). We extend this logic to the intraorganizational context, demonstrating that analogous dynamics unfold within firms when individuals occupy overlapping domains and vie for attention, resources, and recognition. Consistent with network theory, we show that performance is shaped not only by individual capabilities but also by patterns of social structure and comparison (Festinger, 1954; Granovetter, 1985). These dynamics enrich our understanding of post-acquisition integration by illustrating how informal organizational structures, including network cohesion and status positioning, influence individual behavior alongside formal mechanisms such as resource reallocation and structural adjustment (Graebner et al., 2017; Karim and Mitchell, 2000; Puranam et al., 2009). Taken together, our findings underscore the value of a structurally embedded and socially grounded perspective on how acquisitions affect individual-level outcomes.

This research also advances a contingency perspective on crowding and its impact on performance. Our findings indicate that the effects of crowding are not uniform but depend on two key contextual factors: the social status of incoming inventors and the structure of the collaborative network. Crowding by similar-status actors intensifies perceived rivalry, which in turn leads to sharper declines in innovation performance. In contrast, when crowding occurs within more segregated networks, its negative effects are mitigated. Segregation reduces exposure to direct comparisons and limits opportunities for competitive interaction, thereby easing the social pressures associated with crowding. These findings suggest that crowding is a relational phenomenon shaped by the broader social architecture. Identifying when and for whom crowding becomes most disruptive offers a more nuanced understanding of post-acquisition innovation dynamics.

Finally, this study has managerial implications by emphasizing the importance of social dynamics in the acquisition process. From the initial acquisition decision to post-acquisition integration, managers have traditionally focused on firm-level and dyadic factors such as resource complementarity, cultural fit, expected financial synergies, and technological potential (Bauer and Matzler, 2014; Makri et al., 2010; Rao et al., 2016; Zaheer et al., 2013). In addition to these established considerations, our findings emphasize the importance of relational factors within the workforce. Attending to network positioning and structural characteristics can help reduce the risk of integration failure and support the continuity of innovation across the combined firm's technical core.

In practical terms, managers can act on this insight in two ways. First, during target selection, when alternative candidates are otherwise comparable, preference can be given to firms whose inventor networks are organized into smaller, more modular sub-groups rather than a single, tightly integrated cluster. Such a choice reduces the risk that acquirer inventors will suddenly find themselves competing with a large, cohesive bloc of target inventors. Similarly, even when technological domains overlap, attention to whether target inventors possess distinct, complementary expertise—rather than homogenous, interchangeable skills—can help mitigate productivity loss by limiting direct head-to-head competition.

Second, once an acquisition is completed, careful integration design can help preserve or even reinforce these beneficial features. Rather than folding all inventor groups into one centralized R&D unit, managers might maintain semi-autonomous clusters or create modular project teams that allow competition to remain localized while reducing the disruptive force of system-wide rivalries. In this way, managers can buffer acquirer inventors from the full brunt of competitive crowding and sustain innovative performance during a period that otherwise risks significant productivity decline.

5.2 Limitations and Future Research

This study has several limitations that suggest fruitful directions for future research. First, we focused exclusively on the quantitative dimension of innovation performance. Innovation productivity, measured by the number of patent applications, is a widely accepted indicator of individual engagement in innovation (Kapoor and Lim, 2007; Paruchuri et al., 2006). However, this metric does not capture the qualitative aspects of innovation, such as novelty and commercial value. Future research should explore whether individuals working in crowded technological niches respond by shifting their focus from quantity to quality, pursuing more original or economically valuable innovations even if this results in a lower volume of patent output.

Second, although we found that crowding by similar-status inventors has a more pronounced negative effect on innovation productivity, our analysis provided limited insight into how crowding by higher-, similar- or lower-status individuals shapes innovation behavior. Research that examines Formula One racing suggests that lower-status competitors can exert a disproportionate influence on strategic responses (Bothner et al., 2007). Future studies should investigate whether inventors respond differently to crowding depending on the status of those encroaching on their domain. For example, does crowding by lower-status individuals prompt efforts to distinguish oneself through quality enhancement, or by shifting toward more explorative innovation strategies?

Third, our study examined the performance effects of crowding on acquiring inventors, but did not consider how those individuals respond behaviorally to performance decline. Future research should investigate the strategic responses inventors adopt under such pressures. These may include exiting the firm, repositioning themselves in less crowded domains, engaging in more exploratory innovation, or prioritizing high-risk, high-reward projects. Gaining insight into these adaptive behaviors would deepen our understanding of post-acquisition dynamics at the individual level.

Fourth, our study accounted for only one form of status—performance-based status—measured by the number of patent applications filed before and after the acquisition. While this approach is widely used in status research, it does not capture the broader range of status constructs recognized in the literature. Scholars have identified multiple types of status, including deference-based, certification-based, and ranking-based status, each representing a different mechanism of social evaluation (Piazza and Castellucci, 2014). For example, network centrality reflects an individual's structural position and influence within a social structure (Bonacich, 1987; Podolny, 1993). Formal organizational rank or external rankings represent alternative sources of status (Bothner et al., 2007). Future research could examine how competitive crowding operates when status is conceptualized through alternative status dimensions.

Finally, the generalizability of our findings may be limited by the scope of our sample. We focused on acquisitions in high-tech industries and specifically on inventors, whose work is well-suited to patent-based performance metrics. The mechanisms we identified may not extend to other sectors, such as manufacturing or financial services, or to employees in non-technical roles. Future research should investigate whether similar crowding dynamics emerge in different organizational contexts and explore how such effects vary across occupational and industry settings.

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