Mergers and Acquisitions (M&A), Inventor Turnover, and Network Properties

ABSTRACT

The acquisition of high-technology acquisitions often triggers significant inventor turnover, jeopardizing the knowledge assets acquirers seek to obtain. Yet, our knowledge of the conditions that accelerate or ameliorate inventor turnover is limited. In this study, we examine how the target inventors' pre-acquisition productivity and network position shape their post-acquisition mobility decisions. Using data from 139 U.S. technology acquisitions, we find that highly productive inventors and those occupying brokerage positions are less likely to leave. Furthermore, community density, the cohesiveness of a broker's collaborative community, strengthens this retention effect. We also argue and show that inventor productivity mediates the relationship between brokerage and departure. Our findings advance understanding of post-acquisition human capital retention by specifying individual-level predictors and the mechanisms linking social structure to inventor mobility.

INTRODUCTION

Acquisitions serve as a key mechanism through which firms access external knowledge to enhance their innovative capabilities and sustain a competitive advantage (Ahuja & Katila, 2001; Makri, Hitt, & Lane, 2010). The strategic value derived from M&As, however, is critically dependent on the successful utilization of the target firm's key human capital, particularly its inventors (Haspeslagh & Jemison, 1991). Yet, post-acquisition environments are fraught with uncertainty and disruption, often leading to a significant exodus of valuable talent. Recent evidence underscores the severity of this challenge: acquisitions can increase inventor turnover by as much as 80% (Seru, 2014), with some studies showing that fewer than a quarter of a target's inventors remain with the acquirer in the long term (Cunningham, Ederer, & Ma, 2021). This loss of human capital not only represents a direct erosion of the knowledge assets the acquirer sought to obtain but also jeopardizes the dynamic capabilities required for future innovation (Paruchuri, Nerkar, & Hambrick, 2006).

While existing research has identified several firm- and deal-level factors that create pressures for departure, such as integration strategies (Bresman, Birkinshaw, & Nobel, 2010), geographic relocation (Kim, 2022), and cultural misfit (Schweiger, 2005), we have a less developed understanding of the individual-level attributes that differentiate inventors who stay from those who leave. To further this line of inquiry, we shift the theoretical lens from organizational context to the individual inventor, specifically examining how their pre-acquisition characteristics and social embeddedness shape their mobility decisions.

To understand which inventors are most at risk of departure, we focus on two fundamental and distinct individual-level characteristics: their performance and social embeddedness. First, an inventor's pre-acquisition productivity serves as the most salient indicator of their human capital and intrinsic value (Palomeras & Melero, 2010). It directly affects the decision-making process of both the acquirer, who may offer specific incentives to avert a costly loss, and the inventor, who encounters different costs of switching, making it a key factor in the choice of turnover. Second, we examine an inventor's network position, which captures their social capital and structural influence within the firm's innovation production function

(Nahapiet & Ghoshal, 1998). The disruption of these established social structures is a key source of post-acquisition friction (Paruchuri et al., 2006). An inventor's specific position within the firm shapes their access to resources and perceived value, thereby influencing their likelihood of departure. By analyzing both productivity and network structure, we can disentangle the effects of individual performance from those of social embeddedness on inventor turnover.

We first establish a baseline argument rooted in human capital theory, positing that an inventor's pre-acquisition productivity powerfully shapes their decision to depart. While acquirers may extend significant incentives to prevent the departure of highly productive inventors (Groysberg, Lee, & Nanda, 2008), these inventors also face higher switching costs, as their performance is often tied to firm-specific resources and collaborations that are difficult to replicate elsewhere, creating a strong disincentive to leave (Palomeras & Melero, 2010).

We then extend beyond individual performance to argue that an inventor's structural position within the target firm's pre-acquisition collaboration network is a critical predictor of their mobility. Specifically, we focus on brokerage, which refers to the extent to which an individual spans structural holes by connecting otherwise disconnected colleagues (Burt, 1992, 2004). We theorize that inventors in brokerage positions are less likely to depart because their unique access to diverse knowledge flows makes their potential departure particularly costly for the acquirer. Furthermore, the context-specific nature of their brokerage advantage creates a powerful disincentive to depart, as their structural position is not likely to be easily portable to another organization (Stovel & Shaw, 2012).

However, we contend that the factors mitigating turnover for brokers are not uniform. The social context in which a broker is embedded also matters. To understand these dynamics, we introduce community density, the degree of interconnectedness within the broader network community to which a broker belongs, as a key contingency. Community density is particularly important because it captures the collaborative infrastructure of the broader group within which the broker operates, creating a social context that facilitates knowledge-sharing and collective problem-solving (Coleman, 1988; Uzzi & Spiro, 2005). We argue that when a broker operates within a dense, tightly knit community, the factors inhibiting their departure are strengthened. In such environments, brokers occupy a uniquely valuable position that combines the informational advantages of spanning structural holes with the relational advantages of being embedded in a cohesive, trusted network (Burt, 2005; Tortoriello et al., 2012). This dual position makes them particularly valuable to the acquirer as effective integrators and coordinators. Moreover, the deep social investments and context-specific advantages accumulated within dense communities create substantial switching costs that would be difficult to replicate elsewhere, further anchoring these brokers to the firm (Granovetter, 1985; Reagans & McEvily, 2003).

Finally, and central to our theoretical contribution, we propose that the influence of an inventor's network position on their turnover is not direct but is mediated by their productivity. We argue that a brokerage position enhances an inventor's productivity by facilitating access to novel information (Fleming, Mingo, & Chen, 2007). This enhanced productivity, in turn, becomes the potential reason inhibiting their departure. We further examine if productivity serves as a mediating pathway linking brokerage to inventors leaving. This framework allows us to unpack the causal mechanisms linking social structure to individual mobility outcomes in a post-acquisition context.

Our analysis of 139 U.S. technology acquisitions offers robust support for our theoretical model. We find that a one standard deviation increase in inventor productivity is associated with a 6.81% decrease in the probability of inventor departure ($\beta = -0.04$, $p < 0.001$ Model 2 Table 4), and one standard deviation increase in the brokerage is associated with a 3.47% decrease in the probability of inventor departure ($\beta = -0.48$, $p < 0.001$, Model 3 table 4) after an M&A.

This study makes several contributions. We advance the literature on post-acquisition integration by developing a multi-level model that connects an inventor's individual performance, their network position, and the social context of their community to explain the critical outcome of turnover. In doing so, we respond to calls for a more granular, individual-level perspective on the dynamics of human capital turnover in M&A (Nyberg, Moliterno, Hale, & Lepak, 2014). Furthermore, by theorizing and testing the mediating role of productivity, we illuminate *how* social structure influences mobility, offering a more nuanced causal story and providing practical guidance for managing turnover post-acquisition.

THEORY AND HYPOTHESES

In this section, we develop hypotheses explaining the determinants of inventor turnover following acquisitions. We build our theoretical model in two stages. First, we examine direct effects of pre-acquisition productivity and network brokerage position on departure likelihood, along with the moderating effect of community density. Second, we propose a mediation model specifying *how* network position influences departure through its effect on productivity.

Individual and Structural Determinants of Inventor Departure

We posit that an inventor's risk of post-acquisition departure is a function of two fundamental characteristics: their performance (human capital) and their structural position within the firm's collaboration network (social capital). These distinct but complementary sources of value are likely to shape both the acquirer's retention strategy and the inventor's mobility decision.

Inventor Productivity and the Decision to Leave. An inventor's pre-acquisition productivity serves as the most visible and credible signal of their value to the acquiring firm (Palomeras & Melero, 2010; Hoisl, 2007). From a human capital perspective, highly productive inventors embody the valuable, often inimitable knowledge assets that acquirers seek to obtain and leverage for future innovation (Campbell, Ganco, & Agarwal, 2012). The departure of these productive inventors triggers a "knowledge drain," representing a particularly significant loss of strategic resources that directly undermines the acquisition's rationale (Groysberg, Lee, & Nanda, 2008; Tzabbar & Kehoe, 2014).

Acquirers recognize this risk and likely respond with targeted retention strategies. High-productivity inventors typically receive substantial financial packages, enhanced autonomy, leadership roles in critical projects, and greater access to resources (Hess & Rothaermel, 2011; Coff & Kryscynski, 2011). These retention mechanisms increase the opportunity cost of departure, making alternative employment less attractive. Recent evidence suggests that acquirers increasingly use tactics akin to "golden handcuffs", including deferred compensation, equity vesting schedules, and performance bonuses, specifically designed to retain key technical talent during the critical post-acquisition integration period (Bena & Li, 2014; Ouimet & Zarutskie, 2014).

From the inventor's perspective, high productivity is deeply intertwined with firm-specific resources, routines, and collaborative relationships. This firm-specific human capital is not easily portable (Campbell et al., 2012; Carnahan & Somaya, 2013). Departing inventors face the substantial challenge of rebuilding the context-specific advantages that underpinned their past success, leading to high switching costs and performance uncertainty in new organizations. The transferability of performance is particularly low for highly productive employees whose success depends on the unique organizational environment in which it was cultivated (Groysberg et al., 2008; Campbell, 2013). For example, empirical evidence shows that star inventors who move to new firms experience significant productivity declines, particularly when their knowledge is deeply embedded in their former organization's routines and collaborative networks (Palomeras & Melero, 2010; Ge, Huang, & Png, 2016).

The combination of strong retention incentives from the acquirer and high personal switching costs creates strong disincentives for departure. Therefore, we expect a negative relationship between an inventor's past performance and their likelihood of post-acquisition turnover.

Hypothesis 1: Inventors with higher pre-acquisition productivity are less likely to depart the acquiring firm post-acquisition.

Network Brokerage and Inventor Departure. We also argue that beyond individual performance, an inventor's position within the firm's social structure is likely to significantly influence their value and mobility decisions. Social capital, embodied in network relationships, is distinct from human capital and provides access to resources that enhance performance and influence (Adler & Kwon, 2002; Nahapiet & Ghoshal, 1998). We focus on brokerage, a structural position characterized by spanning *structural holes* that separate otherwise disconnected individuals or groups (Burt, 1992, 2004). Inventors acting as brokers serve as crucial conduits for novel and diverse information, facilitating the combination and synthesis of disparate knowledge streams, a process critical for successful innovation (Fleming, Mingo, & Chen, 2007; Tortoriello & Krackhardt, 2010).

But why are brokers uniquely valuable in the post-acquisition context? We identify three distinct reasons. First, they are uniquely positioned to bridge knowledge and social gaps between acquiring and target firms, facilitating smoother integration and mitigating the "us-versus-them" mentality that often plagues such transitions (Paruchuri et al., 2006; Ranft & Lord, 2002). Their boundary-spanning capabilities enable them to translate knowledge across organizational boundaries, identify complementarities, and facilitate coordination, all of which are particularly valuable during the turbulent post-acquisition period (Tushman & Scanlan, 1981; Tortoriello, Reagans, & McEvily, 2012).

Second, acquirers recognize that brokerage positions are difficult to substitute. Unlike individual skills or knowledge that can potentially be replaced by hiring, structural positions emerge from path-dependent processes that unfold over years (Stovel & Shaw, 2012; Soda, Usai, & Zaheer, 2004). The departure of a broker creates a structural hole that cannot be easily filled, potentially fragmenting the knowledge network and disrupting information flows critical for innovation (Zaheer & Soda, 2009; Kleinbaum, Stuart & Tushman, 2013). This recognition should lead to targeted retention efforts.

Third, inventors in brokerage roles recognize that their structural advantage is context-specific and embedded within particular organizational architectures. The potential loss of this firm-specific social capital creates high switching costs, discouraging departure (Groysberg et al., 2008; Carnahan, Agarwal, & Campbell, 2012). Therefore:

Hypothesis 2: Inventors who occupy brokerage positions in the pre-acquisition network are less likely to depart the acquiring firm post-acquisition.

The Moderating Role of Community Density. While brokerage positions generally create disincentives for departure, we argue that the strength of this retention effect depends on the social context in which the broker is embedded. We focus on the density of a broker's community, which we identify from the structure of the firm's internal collaboration network. A dense community is characterized by high closure, where a broker's collaborators also frequently work together, creating a tightly knit social structure (Soda, Usai, & Zaheer, 2004; Reagans & McEvily, 2003). We focus on density given the classic tension in network theory between the benefits of brokerage (spanning structural holes) and those of network closure (Coleman, 1988; Burt, 2005).

We theorize that high community density amplifies the negative relationship between brokerage and departure through two complementary mechanisms. First, dense communities enhance the broker's strategic value to the acquiring firm. When a broker is embedded in a dense community, they serve not merely as information conduits but as critical integrators who can mobilize cohesive teams and coordinate collective action (Obstfeld, 2005; Reagans & Zuckerman, 2001). The combination of brokerage (access to diverse knowledge) and closure (ability to mobilize trusted collaborators) creates a uniquely valuable position that is particularly difficult to replicate (Burt, 2005; Tortoriello et al., 2012). Dense communities provide the broker with a stable, trusted base from which to span boundaries, making their bridging activities more effective and their coordination role more critical (Fleming, Mingo, & Chen, 2007). From the acquirer's perspective, losing such a broker would disrupt not only information flows but also the cohesive collaborative infrastructure they anchor, making their retention especially valuable.

Second, dense communities increase the broker's embeddedness and switching costs. Brokers in dense communities have invested heavily in building and maintaining relationships within a cohesive social structure characterized by high trust, shared norms, and mutual obligations (Coleman, 1988; Uzzi, 1997). This deep social embeddedness creates high psychological and relational costs to departure (Granovetter, 1985). Departure would mean forgoing not just individual relationships but an entire collaborative ecosystem in which the broker holds a central, trusted position (Podolny & Baron, 1997). The dense community also provides the broker with social support and collective identity that protects against the uncertainty and disruption of acquisition (Krackhardt & Stern, 1988). Furthermore, the broker's effectiveness in their role depends on the trust and shared understanding developed within this dense community, advantages that would be difficult to recreate in a new organizational context (Reagans & McEvily, 2003). The combination of high relational investment, social support, and context-specific advantages creates powerful disincentives for departure.

Together, these mechanisms suggest that brokers embedded in dense communities face a "double lock-in": they are more valuable to the acquirer (increasing retention incentives) and more embedded in their social context (increasing personal switching costs). This dual dynamic makes departure particularly unlikely for brokers in dense communities.

Hypothesis 3: The negative relationship between an inventor's brokerage position and their likelihood of departure is strengthened (i.e., becomes more negative) when the inventor is embedded in a high-density community.

The Mediating Role of Productivity in the Departure Decision

In this section, we extend the direct and moderated effects argued earlier to propose a more fine-grained causal pathway. We argue that the effect of an inventor's network position on their departure is not merely direct but is fundamentally channeled through their productivity. This specification allows us to explain *how* social structure translates into mobility outcomes, responding to calls to unpack the mechanisms linking different forms of capital to strategic outcomes (Nyberg, Moliterno, Hale, & Lepak, 2014; Ployhart & Moliterno, 2011).

Brokerage, Productivity, and the Likelihood of Departure. The theoretical link between brokerage and performance operates through information access and recombination mechanisms. By bridging structural holes, brokers gain access to a diverse array of non-redundant information, ideas, and resources (Burt, 1992, 2004). This privileged access enables them to act as knowledge entrepreneurs, identifying novel opportunities for recombination and synthesis that are unavailable to those embedded in more constrained, cohesive networks (Fleming et al., 2007; Obstfeld, 2005).

The productivity advantage of brokers stems from three specific mechanisms. First, brokers access diverse knowledge pools that enable them to recognize novel combinations and opportunities (Hargadon & Sutton, 1997; Tortoriello & Krackhardt, 2010). Second, they benefit from early access to information, learning about new developments, techniques, and opportunities before others in more constrained network positions (Burt, 2004; Kleinbaum, Stuart & Tushman, 2013). Third, brokers develop integrative capabilities, the ability to synthesize disparate knowledge streams into coherent innovations, through repeated practice of boundary-spanning activities (Hargadon, 2002; Fleming et al., 2007).

Empirical evidence consistently shows that this structural advantage directly enhances innovative output, leading to higher productivity and creativity (Burt, 2004; Guler & Nerkar, 2012; Kwon, Rondi, Levin, De Massis, & Brass, 2020; Carnabuci & Dioszegi, 2015). Connecting this to our prior arguments creates a clear causal chain: if brokerage enhances productivity, and higher productivity reduces the likelihood of departure, then productivity serves as a key mediating mechanism. In this view, one of the reasons brokers are less likely to depart is that their network position enables them to be more productive, and it is this superior performance that ultimately anchors them to the firm. The social structure influences the mobility decision by first shaping the inventor's performance, which is the more proximate determinant of their value and switching costs.

This mediation model extends beyond a simple association between social capital and retention to specify a causal chain in which social capital is converted into human capital (performance), which in turn drives the turnover decision. This specification presents a more comprehensive theoretical model by identifying two distinct mechanisms that link network position to retention. It posits that a direct effect, driven by the switching costs of social embeddedness, operates in parallel with an indirect effect, channeled through the productivity gains that network positions facilitate.

Hypothesis 4: Inventor productivity mediates the negative relationship between an inventor's brokerage position and their likelihood of departure.

METHODS

Sample Construction

The data for this study comes from multiple sources (1) mergers and acquisitions (M&A) transactions data from SDC Platinum (2) data on target inventors and their patenting activity from United States Patent and Trademark Office's (USPTO) Patentsview database and (3) data made available by Kogan et al., (2017), from hereon called KPSS dataset, that links granted patents to U.S. public firms. Using data from the sources mentioned above, we construct our dataset by applying the following steps. First, we create a sample of M&A deals using a set of criteria. Second, we identify the inventors who worked in the target firms around the announcement of the M&A deals. Third, we utilize patent data from Patentsview to document the inventing career of these inventors. We discuss these steps in detail below.

Identifying the M&A Deals:

Our initial sample of M&A deals includes completed transactions between U.S. public acquirer and U.S. public target firms between 1986 and 2015. Our choice of this time period is driven by the need to be able to track an inventor's inventing activity 5 years before the M&A announcement date and 5 years after the deal is completed. Defining the 5-year pre-window is a key step to reliably identify all the inventors that worked in the target firm around the M&A announcement date. The post-window is needed to determine whether the inventor continued to stay in the organization after the merger completion. We discuss the method for inventor-tracking later in this section. Following prior literature (Seru, 2014; Li & Wang, 2023, Testoni et al., 2022), we used the following selection criteria to build our final sample of M&A deals (1) we retain all the deals classified as "acquisition of majority Interest" or "acquisition of assets" or "mergers" or "acquisition" (2) we include those M&A deals where the acquirer acquires more than 50% of the target firm's shares and ultimately own 100% of the shares (3) since our objective is to study technology-driven acquisitions, we exclude deals from the finance, real estate, or insurance sectors, i.e., we exclude target firms that have primary 3-digit SIC code with first two digits belonging to the range of 60 and 67 (4) to keep our focus on deals that are economically significant for the acquirer firms, we include the deals with a minimum value of USD 1 million (in 2020 constant dollars) and deals where the relative size of the transaction (i.e., the ratio of the transaction value to the acquirer firm's total assets) is at least 1% (5) finally, since we are focused on patenting-active firms, we limit the selection of the deals where both the target and the acquirer firms have patented at least once in the five years before the deal's announcement. We identify an initial set of 949 deals that meet these criteria discussed above.

Inventor Identification and Career Tracking:

Following prior work (Li & Wang, 2023; Marx, Strumsky & Fleming, 2009; Palomeras & Melero, 2021), we utilize patenting records to identify active inventors of the target firms and track their mobility. An inventor is considered in the target firm before the M&A announcement if the inventor is employed with the target firm in the year before the M&A announcement. Similarly, the target inventor is considered to have been retained in the acquirer firm after the M&A if she files at least one patent with the acquirer firm or the target firm after the M&A completion date. The detailed procedure is documented in Appendix 2. Through this process, our initial sample comprises 9,382 target inventors that are part of the 524 M&A deals (refer to Table 1 for the drop-off in the number of deals at each step). An inventor is referred to as a *stayer inventor* if the inventor's firm is determined to be either the acquirer firm or the target firm in the year after the completion of the deal. An inventor is referred to as a *leaver inventor* if the inventor's firm is determined to be neither the acquirer firm nor the target firm in the year after the announcement of the deal. An inventor is referred to as an *exit inventor* if the inventor has not patented with any firm after the last patent with the target firm. Stayers, leavers and exit inventors comprise 48%, 27% and 24% of the sample respectively.

[Insert Table 1]

The final sample selection exercise we do is to filter on the target firm's network size. For each firm in our sample, we build a collaboration network of inventors based on the co-inventorship of patents filed by the target firm five years before the M&A announcement. Each inventor is considered as a node of the network, and the patent filed by the firm is the edge. The inventors relate to each other through the patents, and their relationship is determined by whether they have worked together on a patent. All patents have equal weights in the network in our specification. The network size of the firms in our sample ranges from 1 to 571. We limit our sample to firms that have a network size of 10 or more since firms with smaller network sizes are not meaningful contexts to study the phenomenon of interest. Since the distribution of network size is highly skewed, we restrict the network size to the 99th percentile (i.e. network size of 236).

Our final sample consists of 149 deals completed between 1985 and 2015 and 6508 inventor-deal pairs (6460 unique target inventors) with a network size between 10 and 236 (refer to Table 1 for the drop-off details about the deals at each step).

Measures

Dependent Variable:

The outcome variable, *leaver*, is a binary variable equal to 1 if the inventor is identified as a leaver inventor or an exit inventor and equal to 0 if the inventor is identified as a stayer inventor.

Independent Variables:

Productivity, is the count of the number of patents filed by the inventor in the five years period before the deal announcement.

Brokerage, operationalized as Burt's (1992) measure of effective size, captures the extent of redundancy in an actor's network (Soda, Tortoriello, and Iorio, 2018). We follow the approach of Borgatti (1997), Tortoriello et al., (2015), and Khanna (2021) to calculate the effective size of the inventor and then normalise it with the degree of the inventor to measure the *brokerage* of the inventor (Paruchuri & Awate, 2017; Quintane et al., 2022). This measure therefore depicts the proportion of non-redundant ties within the inventor's network.

$$Brokerage = \frac{n - \frac{2t}{n}}{degree} \tag{1}$$

where t is the number of ties in the inventor's network (not including ties to the inventor) and n is the total number of inventors excluding the inventor (i.e., network size – 1). This measure varies between 0 and 1 in our sample, with a higher value indicating greater number of non-redundant ties.

Control variables:

We use the *Community Density* measure to quantify the level of cohesion within an inventor's community. It is defined as the ratio of the number of actual ties among the inventors in a community to the maximum number of ties that could exist among them:

$$Community\ Density = \frac{2E}{N(N-1)} \tag{2}$$

Where E is the number of actual ties and N is the number of inventors in the community.

The measure of community density varies between 0 and 1 in our sample, with a higher value indicating that there is greater connectedness among inventors in the focal inventor's community.

Following prior literature, we account for the *tenure* of the inventor, defined as the number of years since the inventor filed his / her first patent (Kapoor & Lim, 2007) and *Specialization*, measured as the Herfindahl index (Palomeras & Wehrheim, 2021 and Jain & Mitchell, 2022). The Herfindahl index captures the concentration of the inventor's patents across different technological classes, specifically within USPTO Cooperative Patent Classification (CPC) subclasses over the past 10 years.

$$Specialization = \Sigma p_i^2 \quad (3)$$

where, p_i is the proportion of the patents filed by the inventor in i^{th} CPC subclass in the last 10 years. Following Paruchuri, Nerkar & Hambrick (2006), We also control for the *Social Embeddedness* of the inventor, measured as the average number of co-authors the inventor has patented with in the five years before the M&A ; the inventor's potential *Loss of Relative Standing*, defined as the difference in the standing of the inventor (percentile ranking of the inventor based on his productivity) among the inventors of both the acquirer firm and target firm and the standing of the inventor among the inventors of the target firm alone; and the *Inventor's divergence*, constructed by identifying the top three CPC subclasses the acquirer firm has patented frequently in the five years before the M&A and counting how many of these subclasses the inventor has not patented. This results in the divergence score ranging from 0 to 3, where 0 indicates that the inventor has patented in all three subclasses and 3 indicates that the inventor has not patented in any of the three subclasses.

Since we are interested in understanding why some inventors stay after the acquisition whereas others leave, we are able to include deal fixed-effects in all our regressions. Including deal fixed effects allows us to account for any time-invariant target- or acquirer-level characteristics (measured at the time of the deal announcement) that may impact the inventor's decision to stay or leave.

METHODOLOGY

The unit of analysis in our sample is at the inventor-deal level. We utilize a logit model since the outcome variable, stayer, is dichotomous in nature. We estimate the parameters using maximum likelihood (MLE) approach with deal fixed-effects. The general specification is of the form:

$P(Y) = 1/(1 + e^{-z})$,

$$Z = \beta_0 + \beta_1 X_1 + \beta_1 X_2 + \cdots + \beta_1 X_n + Deal\ Fixed\ Effects + \epsilon_i, \quad (4)$$

Where P(Y) is the probability of the target inventor staying in the acquirer or the target firm after the M&A, and Z is the linear combination of explanatory variables (e.g., productivity, brokerage etc.), including interaction terms and control variables.

We test whether inventor productivity mediates the relationship between inventor brokerage and inventor staying in the firm after the M&A, and whether this mediation is dependent on the community density.

We estimate a two-stage moderated mediation model, in which community density moderates the relationship between inventor brokerage and productivity, and productivity in turn affects the probability of inventor staying after an M&A. In the first stage (mediator model), inventor productivity is regressed on inventor brokerage, community density, interaction of brokerage and community density, controls, and deal fixed-effects.

$$\begin{aligned} Inventor\ Productivity_i &= \alpha_1 Inventor\ Brokerage_i + \alpha_2 Community\ Density_i \\ &+ \alpha_3 (Brokerage\ X\ Community\ Density)_i + Controls_i + Deal\ FE \quad (5) \end{aligned}$$

In the second stage (outcome model), inventor leaving is regressed on inventor productivity and controlling for brokerage, community density, including other controls and Deal Fixed Effects.

$$\begin{aligned} Leaver_i = {} & \beta_1 Inventor\ Productivity_i + \beta_2 Brokerage_i + \beta_3 Community\ Density_i + Controls_i \\ & + Deal\ FE \quad (6) \end{aligned}$$

To assess the moderated mediation, we compute conditional indirect effect of brokerage on inventor staying via productivity at low community density (mean – SD) and high community density (mean + SD). Statistical inference is based on a non-parametric bootstrap procedure with 1000 replications, clustered at deal level.

RESULTS

Our sample consists of 6508 inventor-deal pairs belonging to 149 target firms. The average proportion of leavers in each firm is 0.49 with a standard deviation of 0.5. Figure 1a shows that the high-productive (inventor's productivity is in the top quartile of the firm) inventors are less likely to leave on average. Figure 1b shows that the inventors with a high brokerage (the inventor's brokerage is in the top quartile of the firm) are less likely to leave on average. Table2 and Table 3 provide the descriptive statistics and correlation matrix for all our variables. The average inventor in our sample had 5.5 granted patents in the five-year window before the M&A announcement year, had a tenure of 10.8 year in the profession, and was moderately specialized (i.e., the specialization index was 0.43). Table 3 shows that the correlation between key variables is not high. We confirmed that multicollinearity is not a problem as VIF is less than 10 for all the regressions.

[Insert Tables 2 and 3 and Insert Figures 1a and 1b]

Table 4 presents the result of regressing the likelihood of leaving on the key explanatory variables. Model 1 is a controls-only specification. We note that *inventor divergence* has a negative effect on staying ($\beta = 0.36$, $p < 0.001$ Model 1 Table 4), whereas inventor's social embeddedness, potential loss in relative standing, inventor specialization, and inventor tenure have no statistically significant effect. Model 2 is the test for H1, which posits that more productive inventors are less likely to leave. The coefficient of inventor *productivity* is negative and statistically significant ($\beta = -0.04$, $p < 0.001$ Model 2 Table 4), thus providing support for H1. We find that that one standard deviation increase in inventor productivity is associated with approximately 6.81 percent decrease in the probability of leaving for the target inventors. H2 concerns the effect of inventor brokerage on the probability of leaving after M&A. Inventor brokerage is negatively associated with leaving ($\beta = -0.48$, $p < 0.001$, Model 3 table 4), with a one standard deviation increase in brokerage linked to 3.47 percent decrease in leaving likelihood. H3 predicts that community density positively moderates the negative effect of brokerage on leaving. Model 3 (table 4) shows that the main effect of community density is positive and significant ($\beta = 1.02$, $p < 0.001$, Model 3 table 4), suggesting that inventors belonging to dense communities are, on average, more likely to leave. One standard deviation increase in community density is associated with 7.05 percent increase in the likelihood of leaving. To test

H3, we interact community density with inventor brokerage and the coefficient is negative and significant (β = -0.50, $p < 0.1$, Model 4 table 4). This indicates that while dense communities increase baseline departure risk, they simultaneously strengthen the retention effect of brokerage: brokers embedded in dense communities are less likely to leave than brokers in sparse communities. Figure 3 illustrates this pattern by showing that the decline in departure probability associated with brokerage is steeper at higher levels of community density.

To test hypothesis 4, we estimate a two-stage mediation model in which brokerage predicts inventor productivity in the first stage, and productivity predicts departure in the second stage. Table 5a Model 1 shows that brokerage has positive and significant effect on productivity (β = 2.31, $p < 0.001$, Model 1 Table 5), consistent with the argument that brokers benefit from access to diverse, non-redundant knowledge and occupy advantageous positions for recombination. Table 5 Model 3 shows that productivity has negative and significant effect on the probability of an inventor leaving (β = -0.04, $p < 0.001$, Model 3 table 5), indicating that more productive inventors are less likely to leave after an M&A. Taken together, these results establish the two core conditions for mediation: brokerage is positively related to productivity, and productivity is negatively related to departure. Consistent with Hypothesis 4, these findings indicate that part of the retention advantage associated with brokerage operates through productivity. Inventors in brokerage position enhances their productivity, which increases their value to the acquiring firm and raises their personal switching costs. This mediating pathway complements the direct effect of brokerage on departure shown in Table 4, suggesting that brokerage influences inventor retention through both performance-based and structural mechanisms.

[Insert Tables 4 and 5 and Figures 2 and 3]

Robustness Checks

We perform several robustness checks to validate our main findings. These results are presented in the Appendix 1. First, we relaxed the restriction that the network size of the firms needs to be less than or equal to 99 percentile. The sample size increased to 8,612 after relaxing this constraint, but our key results remain consistent (Table A1). Second, our results are robust to considering a bigger window for calculating productivity (10-year pre-M&A) (Table A2). We re-ran all the models with an alternative regression specification, the linear probability model (LPM) and found robust results.

Addressing selection issues

We do not have a control group in our sample. All the inventors in our sample belong to the target firm. We conduct further analysis to understand whether M&A has a differential effect on the likelihood of an inventor leaving over and above a normal situation where there is no M&A. To investigate this differential effect, we construct a counterfactual set of firms: firms that are similar to the target firms on key observables but didn't get acquired.

We create our hypothetical target firms using the Coarsened Exact Matching (CEM) procedure. We followed the method outlined by Chow et al. (2001) to match our treatment and control firms on the following variables: announcement year, industry, market-to-book ratio, and total assets. We describe this procedure in detail in the appendix 3. We create the binary variable, *treatment*, that is 1 if the target firm is an acquired firm and 0 if the firm is a hypothetical target firm. To calculate the differential effect of M&A, we interact the treatment variable with our key explanatory variables separately.

[Insert Table 6 and Figure 6]

Table 6 presents the logistic regression results, with the dependent variable being stayer. Model 1 shows the main effect of treatment (M&A) on leaving while controlling for productivity. Figure 6 shows that the likelihood of leaving is higher in case of an M&A. The coefficient of treatment is positive and statistically significant ($\beta = 0.44$, $p < 0.001$). Model 2 shows the interaction effect of treatment variable and productivity on leaving. We find that the coefficient of interaction term is negative and significant ($\beta = 0.03$, $p < 0.01$), showing that in case of an M&A the probability of leaving decreases as the productivity of the inventor increases. Model 3 shows that the interaction treatment and brokerage negative and significant effect on leaving ($\beta = -0.18$, $p < 0.1$). In other words, brokers are less likely to leave, in the event of an M&A. Model 4 shows that the effect of the interaction of treatment with brokerage and community density is statistically insignificant ($\beta = 0.30$, $p > 0.1$).

Discussion

In this study we answer the fundamental question: which inventors are most likely to leave after an M&A, and why? While prior literature has discussed about the post-acquisition integration, our focus is on how the per-acquisition productivity and the network position of the inventor influence the post-acquisition mobility decision. In this paper, we not only discuss who leaves, but also the mechanisms through which human capital and social structure jointly influence the inventor's decision.

This study makes three theoretical contributions. First, it advances research on post-acquisition integration by shifting attention from firm-level averages to individual-level heterogeneity among inventors. Second, it integrates human capital and social capital perspectives by showing that productivity and network position operate as distinct but complimentary determinants of inventor retention. Third, our findings challenge a purely performance-based account of retention. Although brokerage increases productivity and productivity reduces departure, the strongest retention effects for brokers embedded in dense communities appear to operate though mechanisms other than productivity. This highlights the importance of social and structural lock-in as a distinct source of retention, extending classic debates on brokerage versus closure in network theory.

Our findings open several avenues for future research. First, future studies could directly examine alternative mechanisms such as identity, status, influence, etc. that may explain why brokers embedded in dense communities are particularly likely to stay despite lower productivity gains. Second, research could explore how these dynamics vary across different types of acquisitions, such as technology versus market-driven. Third, future work could examine longer-term outcomes, such as whether the retention of brokers in dense communities ultimately enhances post-acquisition performance or organizational integration.

This study has several limitations. Our reliance on patent data means that we observe inventor activity only through patenting outcomes, which may not capture all forms of inventive contributions. Our sample focuses on U.S. public firms in technology intensive industries, which may limit generalizability to other contexts.

In conclusion, this study shows that who stays and who leaves after an acquisition depends not only on how productive inventors are, but also on where they sit within the firm's social structure and the communities that surround them. By demonstrating that brokerage and community density jointly shape inventor retention through both performance based and social mechanisms, we offer a more nuanced understanding of post-acquisition human capital dynamics, underscoring the importance of not just individual talent, but also the social structures that sustain it.

Table 1: Deals drop-off due to applying selection filters

Step	Number of Deals
Number of Deals initially selected	949
Number of Deals after tracking inventors	524
Number of Deals after limiting the network size to 10 and 236	149

Table 2 Descriptives:

VARIABLES	Mean	Standard Deviation	Minimum	Maximum
Tenure	10.84	7.61	2.00	43.00
Productivity	5.50	6.89	0.00	164.00
Specialization	0.43	0.27	0.06	1.00
Loss in Relative Standing	-5.70	9.91	-53.28	30.72
Inventor Divergence	1.99	0.93	0.00	3.00
Social Embeddedness	3.17	2.70	0.00	26.00
Community Density	0.49	0.39	0.00	1.00
Brokerage (Efficiency)	0.42	0.35	0.00	1.00
Leaver	0.49	0.50	0.00	1.00

Note: Number of observations is 6508

Table 3 Correlation Matrix

Variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Productivity	1	1.00							
Brokerage	2	0.15	1.00						
Community Density	3	0.04	0.51	1.00					
Social Embeddedness	4	0.04	-0.21	0.15	1.00				
Loss in Relative Standing	5	0.15	0.06	0.06	0.01	1.00			
Inventor Divergence	6	-0.27	0.01	-0.01	-0.20	-0.10	1.00		
Specialization	7	-0.24	-0.08	0.00	-0.06	-0.03	0.28	1.00	
Tenure	8	0.23	0.10	0.03	-0.01	0.07	-0.05	-0.24	1.00

Table 4: Effects of Productivity, Brokerage and Ego-Density on likelihood of leaving

VARIABLES	(1) Leaver	(2) Leaver	(3) Leaver	(4) Leaver
Inventor Productivity		-0.04***		
		(0.01)		
Brokerage (efficiency)			-0.48***	-0.24
			(0.11)	(0.17)
Community Density			1.02***	1.21***
			(0.11)	(0.15)
Brokerage X Community Density				-0.50+
				(0.27)
Social Embeddedness	0.01	0.01	-0.03	-0.03*
	(0.01)	(0.01)	(0.02)	(0.02)
Loss in Relative Standing	-0.00	0.01*	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Inventor Divergence	0.36***	0.31***	0.35***	0.35***
	(0.05)	(0.05)	(0.05)	(0.05)
Specialization	0.11	0.07	0.11	0.11
	(0.13)	(0.13)	(0.14)	(0.14)
Tenure	-0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	5,565	5,565	5,565	5,565
Number of Deals	139	139	139	139
Fixed effect	Deal	Deal	Deal	Deal
Chi-square	82.36	116.7	178.1	181.5
Log Likelihood	-3146	-3129	-3098	-3096

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 5: Mediating Role of Productivity

VARIABLES	(1) Productivity	(2) Productivity	(3) Leaver	(4) Leaver
Inventor Productivity			-0.04*** (0.01)	-0.04*** (0.01)
Brokerage (efficiency)	2.31*** (0.29)	4.88*** (0.44)	-0.41*** (0.11)	-0.08 (0.17)
Community Density	-1.12*** (0.28)	0.88* (0.38)	0.98*** (0.11)	1.24*** (0.15)
Brokerage X Community Density		-5.40*** (0.70)		-0.69* (0.27)
Social Embeddedness	-0.02 (0.04)	-0.10* (0.04)	-0.03+ (0.02)	-0.04* (0.02)
Loss in Relative Standing	0.43*** (0.01)	0.42*** (0.01)	0.01 (0.01)	0.01 (0.01)
Inventor Divergence	-1.68*** (0.12)	-1.66*** (0.12)	0.29*** (0.05)	0.29*** (0.05)
Specialization	-1.19*** (0.35)	-1.13** (0.35)	0.06 (0.14)	0.07 (0.14)
Tenure	0.12*** (0.01)	0.12*** (0.01)	0.00 (0.00)	0.00 (0.00)
Constant	10.33*** (0.35)	9.90*** (0.35)		
Observations	5,748	5,748	5,565	5,565
R-squared	0.29	0.29		
Number of Deals	149	149	139	139
Fixed effect	Deal	Deal	Deal	Deal
Chi-square			208.6	214.9
Log Likelihood			-3083	-3080

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 6: Effect of an M&A on the likelihood of inventor staying, compared to firms not involved in an M&A

VARIABLES	(1) Leaver	(2) Leaver	(3) Leaver	(4) Leaver
treatment = 1	0.44***			
	(0.05)			
Productivity	-0.01**	-0.01**	-0.01***	-0.01***
	(0.00)	(0.01)	(0.00)	(0.00)
Productivity X treatment (=1)		-0.03**		
		(0.01)		
Brokerage (efficiency-degree)			-0.37***	-0.14***
			(0.03)	(0.04)
Brokerage X treatment (=1)			-0.18+	-0.41*
			(0.09)	(0.18)
Community Density			0.90***	1.09***
			(0.02)	(0.03)
Community Density X treatment (=1)				0.04
				(0.15)
Brokerage X Community Density				-0.50***
				(0.06)
Brokerage X Community Density X treatment (=1)				0.30
				(0.28)
Social Embeddedness	0.02*	0.04**	-0.03***	-0.04***
	(0.01)	(0.01)	(0.00)	(0.00)
Specialization	0.10	0.07	-0.12***	-0.11***
	(0.08)	(0.11)	(0.03)	(0.03)
Tenure	0.01***	0.01**	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.85***			
	(0.07)			
Observations	9,697	8,792	127,253	127,253
Chi-square	93.71	44.96	1654	1723
Log Likelihood	-6248	-4180	-64329	-64294
Number of Deals		520	3,222	3,222

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Appendix 1:

Table A1a: Robustness for Effects of Productivity, Brokerage and Ego Density on the likelihood of leaver after an M&A (Network size greater than 10)

VARIABLES	(1) Leaver	(2) Leaver	(3) Leaver	(4) Leaver	(5) Leaver
Inventor Productivity		-0.04***			
		(0.01)			
Brokerage (efficiency-degree)			0.18*	-0.39***	-0.19
			(0.08)	(0.10)	(0.14)
Community Density				0.94***	1.13***
				(0.09)	(0.13)
Brokerage X Community Density					-0.45+
					(0.23)
Social Embeddedness	0.00	-0.00	0.01	-0.03*	-0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Loss in Relative Standing	-0.01	0.01*	-0.01+	-0.01*	-0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Inventor Divergence	0.28***	0.21***	0.28***	0.25***	0.25***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Specialization	0.13	0.07	0.13	0.15	0.15
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Tenure	-0.00	0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	6,951	6,951	6,951	6,951	6,951
Number of Deals	144	144	144	144	144
Fixed effect	Deal	Deal	Deal	Deal	Deal
Chi-square	73.14	125.6	78.02	186.1	189.9
Log Likelihood	-4063	-4037	-4061	-4007	-4005

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table A1b: Robustness for Mediating Role of Productivity (Network size greater than 10)

VARIABLES	(1) Productivity	(2) Productivity	(3) Leaver	(4) Leaver
Inventor Productivity			-0.04***	-0.04***
			(0.01)	(0.01)
Brokerage (efficiency-degree)	2.41***	5.10***	-0.31**	-0.01
	(0.26)	(0.38)	(0.10)	(0.14)
Community Density	-1.15***	1.25***	0.91***	1.18***
	(0.25)	(0.35)	(0.09)	(0.13)
Brokerage X Community Density		-6.02***		-0.67**
		(0.62)		(0.23)
Social Embeddedness	-0.01	-0.09**	-0.03*	-0.04**
	(0.04)	(0.04)	(0.01)	(0.01)
Loss in Relative Standing	0.48***	0.46***	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Inventor Divergence	-1.79***	-1.76***	0.19***	0.19***
	(0.11)	(0.11)	(0.04)	(0.04)
Specialization	-1.43***	-1.41***	0.10	0.10
	(0.32)	(0.32)	(0.12)	(0.12)
Tenure	0.12***	0.12***	0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.00)
Constant	10.88***	10.33***		
	(0.32)	(0.33)		
Observations	7,134	7,134	6,951	6,951
R-squared	0.29	0.30		
Number of Deals	154	154	144	144
Fixed effect	Deal	Deal	Deal	Deal
Chi-square			234.1	242.5
Log Likelihood			-3983	-3978

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table A2: Robustness for Effects of Productivity in the 10 years prior to M&A

VARIABLES	(1) Leaver	(2) Productivity	(3) Productivity	(4) Leaver	(5) Leaver
Productivity (10 years)	-0.02***			-0.01***	-0.02***
	(0.00)			(0.00)	(0.00)
Brokerage (efficiency-degree)		4.07***	8.00***	-0.43***	-0.13
		(0.49)	(0.75)	(0.11)	(0.17)
Community Density		-3.10***	-0.03	0.98***	1.21***
		(0.47)	(0.64)	(0.11)	(0.15)
Brokerage X Community Density			-8.27***		-0.62*
			(1.19)		(0.27)
Social Embeddedness	0.01	0.03	-0.09	-0.02	-0.03*
	(0.01)	(0.07)	(0.07)	(0.02)	(0.02)
Loss in Relative Standing	0.01	0.58***	0.57***	0.00	0.00
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Inventor Divergence	0.32***	-2.48***	-2.44***	0.31***	0.31***
	(0.05)	(0.20)	(0.20)	(0.05)	(0.05)
Specialization	0.08	-1.92**	-1.82**	0.08	0.08
	(0.13)	(0.60)	(0.60)	(0.14)	(0.14)
Tenure	0.00	0.38***	0.38***	0.00	0.00
	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)
Constant		13.27***	12.60***		
		(0.59)	(0.60)		
Observations	5,565	5,748	5,748	5,565	5,565
R-squared		0.27	0.28		
Number of Deals	139	149	149	139	139
Fixed effect	Deal	Deal	Deal	Deal	Deal
Chi-square	104.1			193.4	198.4
Log Likelihood	-3135			-3091	-3088

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Figure 1: a) Relation Between Productivity and Leavers and (b) Relationship between Brokerage and Leavers

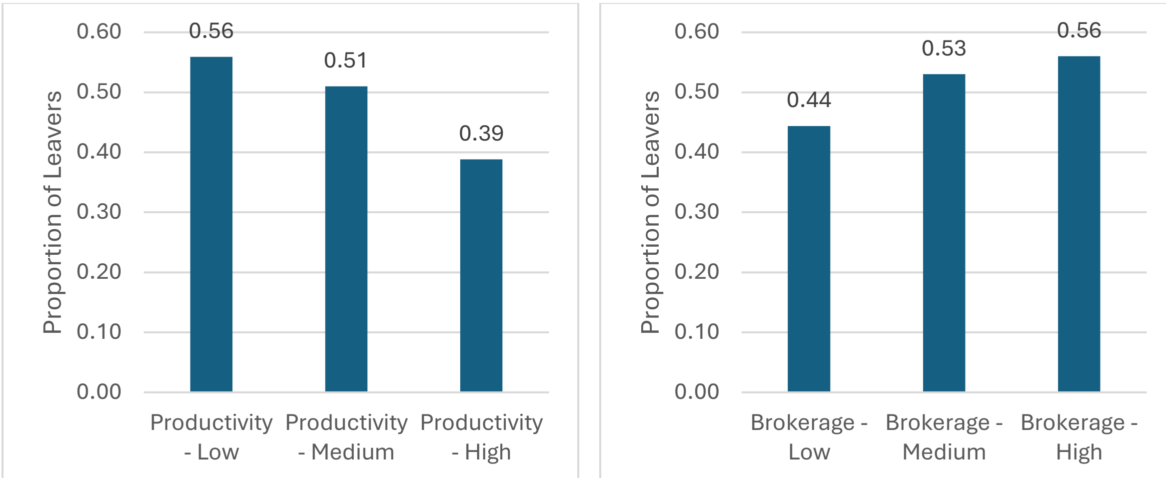


Figure 2: Effect of the interaction of Brokerage and Ego Density on the Productivity of the inventor

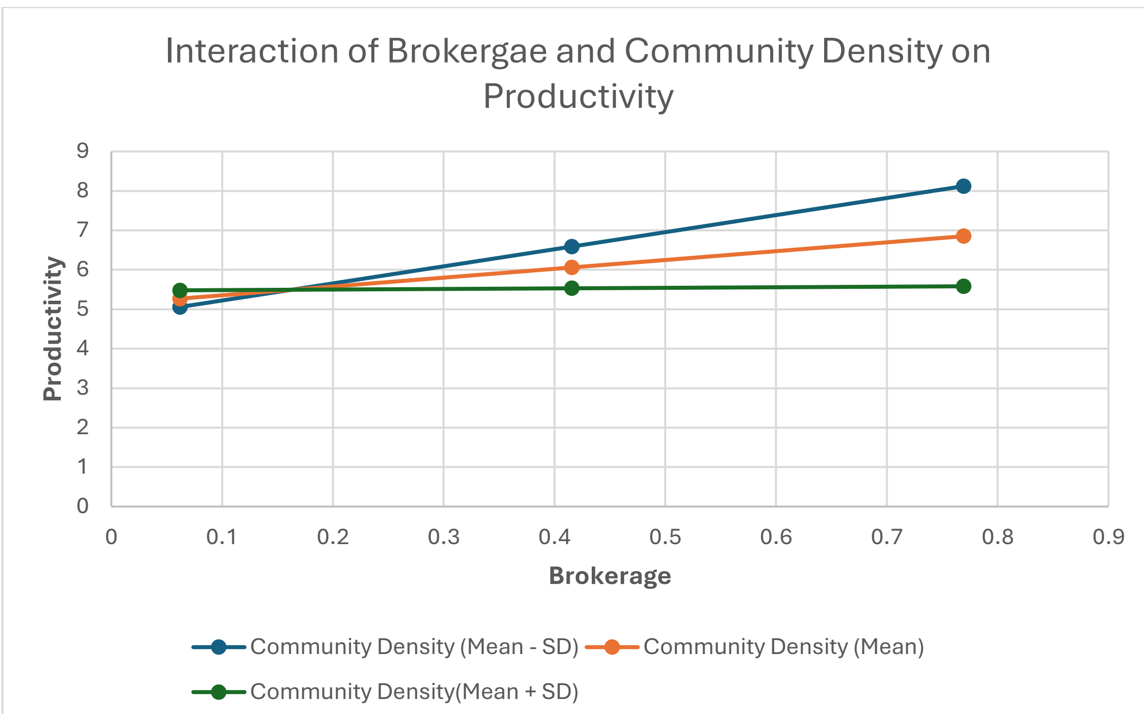


Figure 3: Effect of interaction of Brokerage and Ego Density on the probability of inventor leaving after an M&A

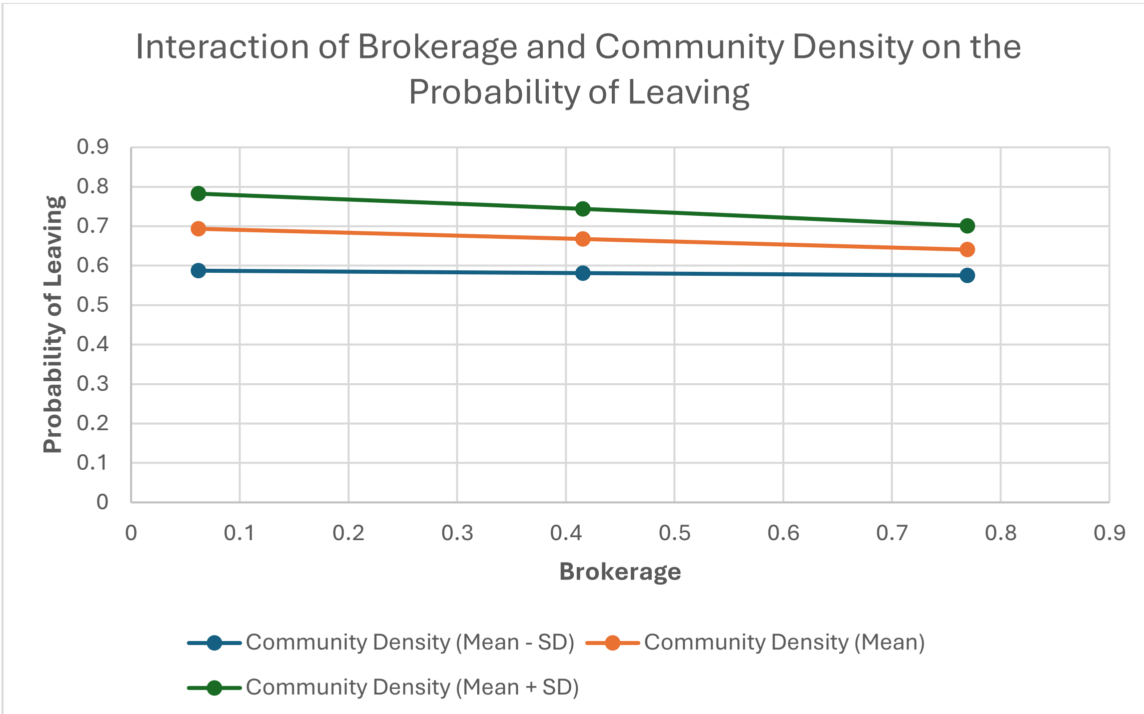
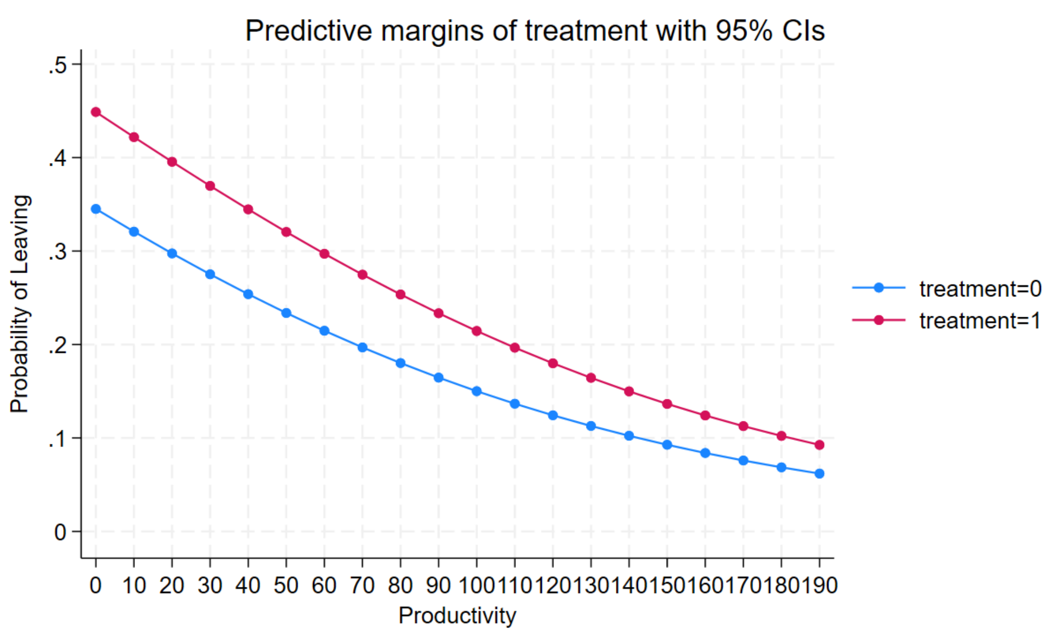


Figure 4: Effect of Productivity on the Probability of Inventor Leaving in the firm in case of an M&A compared to when the inventor is not in an M&A



Appendix 2: Detailed procedure to track inventors

Step 1: Using the KPSS database, we identify the patents filed by the target firm five years before the deal announcement and those filed by the acquirer firm[1] five years after the deal completion. *Step 2*: From USPTO's Patentsview database, we identify the inventors of the target and acquirer firms' patents obtained from step 1. *Step 3*: We compute an inventing career history of the inventors identified in step 2. To create the inventor's career history (i.e., the period between the inventor's first and the last year of filed patents), we identify all the patents that have been filed by the inventor (and subsequently granted). This process allows us to compute the patenting productivity of the inventor during his/her career. It also allows us to track the mobility of the inventor from one organization to other (Agarwal, Ganco & Ziedonis, 2009; Kim & Steensma; 2017). To determine an inventor's employer for a particular year, we utilize information about the assignee of the granted patent. We follow the approach proposed by Li and Wang (2023) to identify the employer of the inventor for any particular year. First, we identify all the inventor-year pairs in which the inventor has patented at least one patent in that particular year. We identify the assignees associated with the inventor's patents for each inventor-year pair. This step provides us with two sets of inventor-year pairs: those linked to a unique assignee (UA) and those associated with multiple assignees (MA). Inventor-year pairs with multiple assignees comprised 7.11% of our sample. If all the patents filed by the inventor in a particular year are assigned to a single assignee (i.e., belongs to the UA set), that assignee is considered the inventor's employer for that year. In cases where the patents filed by the inventor in a particular year belong to different assignees (i.e., belongs to the MA set), then the assignee to which the inventor filed for the highest number of patents in that particular year is considered as the inventor's employer. In situations, where we are still not able to unambiguously identify the assignee for that year (for e.g., the inventor has filed an equal number of patents with two or more firms), we implement the following process. We match an assignee to an inventor-year pair in the set MA if the inventor has the same assignee for the year prior

[1] Considering only the acquirer firm will not cause any issue because we use the post M&A data only to track the inventors. When we drop the patents filed under the target firm, we find that there is a drop of approximately 6% of the patents filed after the M&A

in the set UA. If the assignee cannot still be determined for an inventor-year pair based on matched information in set UA, we choose the assignee that is a U.S. corporation to be the inventor's employer for that particular year. If the assignee cannot still be determined for an inventor-year pair, we randomly pick one of the assignees (random allocation done for 1.81% of assignee-year pair).[2] This process results in linking the inventor-assignee-year (I-A-Y) observations for the years the inventor has applied for the patents. We still need to determine the inventor's employer for the years he/she didn't apply for the patents. We fill the gap years in which an inventor is not matched to an assignee using the following steps (Li & Wang, 2023; Marx, Strumsky, and Fleming, 2009; Hombert & Matray, 2017): if the inventor has the same assignee, A, between years Y1 and Y2 then the employer of the inventor is the assignee A from year Y1 to Y2. If the assignee is A1 in year Y1 and A2 in year Y2, we assume that the job change occurs at the midpoint of years Y1 and Y2. The assignee will be A1 from year Y1 to the integer value of the mean of Y1 and Y2, and assignee A2 from the subsequent year of the integer value of the mean of Y1 and Y2 to year Y2. Using the patent-PERMCO link provided by KPSS, we match assignees to U.S. public corporations.

[2] In such a situation, Li & Wang (2023) randomly picked one of the assignee. We modified this rule because in our sample we were able to uniquely identify a US corporation as one of the assignees for 1.8% of inventor-year pair.

Appendix 3: Detailed Procedure for Creating the Hypothetical Target Firms

We require that the control firms (i.e., the hypothetical target firms) should not have engaged in an M&A in the 3-year window prior to the announcement year and a 3-year window post the announcement year. This results in a sample of 496 treated target firms and 11,976 hypothetical control firms (with a multivariate distance of 0.461). We further refined this sample by matching on network size. To match on the network size we consider only the firms that have a network size between 10 and 236. This reduces the number of treated firms to 144 and hypothetical firms to 3313. The final sample consists of 90 treated firms and 513 control firms (with a multivariate distance of 0.332) (refer to table (a) for the drop of the deals at each step of CEM)

[Insert Table (a)]

Step 1: We begin by compiling a list of all the public firms for each year in which we have an M&A deal in our dataset using the Compustat database.

Step 2: Next, we ensure that the hypothetical target firms were not involved in any M&As in the three years before or after the announcement year of the actual target firms' deals. We used SDC Platinum dataset to achieve this.

At this stage, we have 114,334 hypothetical target firm-year observations and 500 actual target firms in our sample, with a multivariate distance of 0.99.

Step 3: We now apply the CEM algorithm to match the hypothetical target firms with the actual target firms. Matching is based on exact announcement year, exact industry (Standard Industrial Classification (SIC) code), market-to-book ratio, and the total assets of the firms as covariates.

Step 4: We further refine the sample by retaining only the firms with a network size between 10 and 236, and then apply CEM algorithm again, using network size as a covariate.

Table (a): Deals drop-off due to applying selection filters for Hypothetical Target Firms

Step	Number of Treated Deals	Number of Hypothetical Deals
Initial number of Deals	524	114,334
Number of deals with financial data	500	114,334
Number of Matched deals when matched on announcement year, industry, market-to-book ratio, and total assets	496	11,976
Number of Deals when limiting the network size to 10 and 236	144	3,313
Number of deals after coarsened matching on network size	90	513

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