Inventor Commingling and Innovation in Technology Startup Mergers & Acquisitions*

Qingqing Chen, David H. Hsu & David Zvilichovsky

May 2020

Abstract: How does inventor team "commingling" (containing inventors from the acquiring and acquired firms) in technology startup acquisitions relate to innovation outcomes? Commingling reflects collaboration benefits and costs of integrating human resources across organizational boundaries. Commingled team innovation may also depend on the *form* of inter-organizational R&D, ranging from less (strategic alliance) to more integrated (M&A) structures. M&A control may aid innovation. We study technology startups experiencing a merger, some of which also had a prior alliance with the acquirer. Innovation outcomes (patent counts, forward citations, and patent scope) increase post-merger for firms with more intensive inventor commingling. We exploit direct flights between the M&A parties to instrument for endogenous commingling, and find robust results. Inventor-level commingling is more effective under M&A as compared to alliances.

Keywords: technology acquisitions; inventor commingling.

* We thank audience members at Wharton and MIT for their comments. Stacey Chen and Kenneth Shinn provided outstanding research assistance. We gratefully acknowledge research funding from the Wharton Global Initiatives Research Funding Program, the Mack Institute for Innovation Management at Wharton, and the Henry Crown Institute of Business Research at Tel-Aviv University. Emails: qingch@wharton.upenn.edu; dhsu@wharton.upenn.edu; davidz@tauex.tau.ac.il.

1. INTRODUCTION

Technology acquisitions have been the overwhelmingly dominant mode in which venture capital-backed enterprises achieve liquidity over the past quarter century (Aggarwal & Hsu, 2014). Similarly, established industry incumbents are increasingly reliant on inter-organizational relations with innovative new ventures to develop new lines of business or to advance established ones (e.g., Puranam, Singh & Zollo, 2006). Despite these aligned motivations on both sides of the market, a long-standing literature suggests disappointing post-merger innovation outcomes (e.g., Hitt, Hoskisson & Ireland 1990; Kapoor & Lim, 2007). Two broad explanations have been offered for the performance shortfalls within the management-based acquisitions literature: issues with selecting firms with the most appropriate technological knowledge with which to combine (e.g., Ahuja & Katila, 2001) and post-merger integration and assimilation-based issues (e.g., Haspeslagh & Jemison, 1991).

The first literature finds the empirical regularity of an inverted-U shaped relationship between technology overlap among the acquired and acquiring parties and innovation outcomes, with the interpretation that an intermediate amount of technical novelty is important for recombination-based innovation (and that too much overlap reduces the innovation benefits of acquisition). One common theme of the second literature is that organizational design, such as structural integration, can aid in successful post-merger integration. We aim to contribute to the second literature on post-merger integration (while capitalizing on the central idea from the first literature regarding recombination as a key driver of innovation) by developing the concept that literal recombination of inventive staff from the acquired and acquiring organizations—what we term "commingled" inventor teams—is associated with (and may cause) innovation outcomes.

We believe this advances the literature in two ways. First, while others have recognized the importance of the need to "unstick" tacit information in order to assimilate and exploit knowledge in different domains (e.g., von Hippel, 1994), examining the micro-foundations of that process has not received much attention at the organizational and especially inter-organizational level, particularly in broad sample empirical work (perhaps because of data challenges). Second, the effectiveness of inventor commingling may depend on the organization of R&D collaboration between organizational entities, and so studying inventor output under varied inter-organizational collaborative arrangements represents a window into how the *form* of such collaboration matters.

Starting from individual-level origins, we conceptualize and align our empirical measurement of inventor commingling to address a multi-level conceptualization and dynamic treatment of this organizational investment in human capital integration. We pose the following two linked research question in this study: (1) what are the firm-level innovation implications of inventor commingling following technology M&A, from the standpoint of the acquired firm? (2) how does post-acquisition individual inventor commingling innovation output compare to output by (the same) inventors commingling under a pre-M&A alliance?

Our empirical analysis uses a broad-based sample of technology venture acquisitions (not conditioned on receiving venture capital), which also contains approximately 30% non-US acquisitions. All ventures in the sample have at least one US patent, which we impose in keeping with the concept of a technology acquisition-based rationale for the M&A, as well as a measurement-oriented reason. We find that the degree of post-acquisition firm-level inventor commingling is positively related to innovation output (as measured by granted patents and forward citation weighted patents) and exploration (patents with new-to-the-firm technology classes). We then address the issue that unobserved and unmeasured business policy and managerial choices likely shape the degree of inventor commingling. We investigate whether our main results are overturned once we adjust the estimates by exploiting the exogenous introduction of direct flights between acquirer and acquired entities. Such flights exogenously shift the cost of commingling, allowing us to construct an instrumental variable for commingling (note that the acquisition event itself is still exogenous to our analysis; again we aim to contribute to the literature on post-merger integration rather than the merger selection literature). We find that our results are robust. A further analysis exploits the fact that commingling occurs in our sample prior to some acquisitions, via a less integrated inter-organizational form such as alliances. This allows us to examine innovation outcomes of (the same) inventors under different inter-organizational cooperation structures. We find that firm-level innovation outcomes are higher under the acquisition structure, which suggests an explanation for a puzzle identified by Dyer, Kale & Singh, (2004) regarding targeted cooperative organization.

2. LITERATURE & HYPOTHESES

In this section, we discuss two literatures and topics which inform our theorizing about the relationship between inventor team commingling and organizational innovation outcomes. We first review the literature on knowledge access via inter-organizational collaboration, and particularly the literature on the various modes of organizing cooperative relationships. This allows us to segue into identifying and developing one under-appreciated construct in the literature related to drivers of cooperative R&D form: authority and control. We embed in this discussion a review of the relevant technology M&A literature as applied to the control issue (rather than attempting a review of the much larger M&A literature). A final section connects inventor commingling to the equation, and allows us to pose two empirical predictions.

2.1 Modes of inter-organizational cooperation for innovation. Accessing knowledge outside of an organization's boundaries can be instrumental to its competitiveness (e.g., Cohen & Levinthal, 1990), especially when the requisite knowledge for innovation is not entirely resident in the focal firm. As Rosenkopf & Almeida (2003: 762) succinctly note: inter-firm knowledge transfer can "effectively fill in holes in [the focal firm's] knowledge landscapes." Of course, the form and efficacy of inter-firm knowledge transfer to induce innovation has been the subject of enduring interest in the literature, with arm's length technology licensing, strategic alliances, and mergers/acquisitions representing these modes from least- to most-integrated forms.

However, *comparatively* assessing such modes has only received light attention in the literature. This knowledge shortfall leads Dyer, Kale & Singh (2004) to pose a puzzle: why are inter-organizational collaborations not more "targeted" in the sense of balancing the expected knowledge benefits of each cooperative mode with the costs of organizing and governing each mode? Dyer et al. (2004) report that based on a survey of 200 U.S. companies, managers report that 82% believe that decision makers should consider acquisitions and alliances as two different ways of achieving the same growth goals. Yet, only 14% of managers stated that their company has developed specific policy guidelines or criteria for choosing between forming an alliance with and acquiring a potential partner. While such disparities are only suggestive, we contend that we do not, as a field, have an adequate (and certainly not a fulsome) answer to the original puzzle. It may be the case that disappointing innovation outcomes following technology startup acquisitions may be related to misaligned targeting of cooperative mode (for example, a well-specified alliance arrangement might have been more appropriate given benefits and costs instead of an acquisition).

We do have a framework to begin such an analysis, however. Aggarwal & Hsu (2009) propose that there are two drivers of cooperative mode choice at the organizational (not transactional) level, from the standpoint of the startup venture: appropriation environment and governance capabilities. However, because these authors do not consider the full span of cooperative forms, (acquisitions are not considered in their analysis), they do not examine what we believe has been an overlooked driver of cooperative mode choice: the benefits and costs of control. The role of ownership was analyzed by Villalonga & McGahan (2005) in their study of US Fortune 100 companies. In particular, they relate ownership (by insiders, blockholders, and institutions) to mode choice, but in addition to the incumbent's standpoint, they do not examine the control implications of ownership. Neither paper examines innovation consequences associated with inter-organizational collaborative R&D mode.

2.2 Control and Technology M&As. As compared to other modes of inter-organizational cooperation in R&D, such as arm's length technology licensing and strategic alliances, M&As may be less targeted in the sense that the less integrated alternatives can focus on a particular technology or project, and the cost of reversing or dissolving the cooperation is much lower. Naturally, there is a different profile of cost and benefit associated with increasingly integrated cooperation modes. For example, one key element associated with M&As as compared to the alternative R&D modes is the control and authority element associated with ownership, especially as related to managing human capital. Without full ownership, as would be the case in strategic alliances, the counterparties must contractually specify the boundaries of the joint development in a more targeted manner, and incur transaction and governance/oversight costs in the arrangement. For example, in technology development alliances, contractual covenants specifying technical staff (even the exact identity of such individuals) is relatively common (Ryall & Sampson, 2009).

Interestingly, it is not unusual for alliance contracts to contain unverifiable and unenforceable covenants (such as number of man-hours required, but no mechanisms to monitor or verify). Robinson & Stuart, (2007) found that 20 out of 125 contracts in their sample contained this feature, with the following as an example: "the client should pursue the development of alliance-developed drugs with the same vigor that it shows its own drug candidates…". (pp. 562; 578). In addition, because alliances are often *project*-level collaborations (unlike mergers/acquisitions), no firm-level control rights are typically allocated (Robinson & Stuart, 2007). One consequence of this project-level feature of R&D alliances is the threat of misappropriation of funds and resources from contracted projects to non-contracted ones within the firm. Lerner & Malmendier (2010) analyze contractually-based ways to mitigate these threats (via termination clauses and milestone payments to align incentives). Naturally, mergers and acquisitions reduce the degree of contractually-based control and governance issues due to common ownership.

With the starting point that contracts are inherently incomplete (not all future states of the world can be identified and contracted upon), Grossman & Hart (1986) introduce the notion of residual rights – those control rights which accrue to a party when no covenant in an agreement specifies the allocation of those rights. In their economic analysis, ownership is equated to those residual rights, and their theory makes predictions about who should optimally own a particular asset (ownership should be given to the party making the most non-contractible investment). We are concerned with understanding the efficacy of different collaborative arrangements, particularly in R&D and technology environments in which there may be a great deal of uncertainty. Contractual incompleteness and the associated contracting costs therefore factor into our analysis.

In our next section, we develop the idea that one of the hallmarks of the need for deeper integration such as the M&A channel (as opposed to less integrated forms) is the need to "unstick" knowledge from technical staff. This can best be done with more control (we saw examples of the contractual difficulties in alliance arrangements, which can be particularly severe in unchartered R&D contexts), and will be manifest in inventor commingling. Before we turn to that section, we briefly review the technology M&A literature, which has not explored this terrain.

In the M&A for innovation context, most of the prior work examines either partner selection or partner integration. Overwhelmingly, the perspective in this literature is from the point of view of the acquiring firm. One influential set of studies assesses the pool of organizational knowledge, both the levels and the potential complementarity with the counterparty organization, as key factors in post-merger innovation success (Ahuja & Katila, 2001; Cassiman, et al., 2005; Cloodt, Hagedoorn & Van Kranenburg, 2006; Guadalupe, Kuzmina & Thomas, 2012). This line of literature identifies partner and technology selection (as well as "treatment" effects) as important in post-merger innovation success.

The literature has also examined a wide-range of other organizational characteristics for knowledge assimilation and integration, such as the length and quality of acquirer experience (Puranam & Srikanth, 2007), the structural form of the combined organization (Puranam, Singh, & Zollo, 2006), informal coordination mechanisms (Puranam, Singh, & Chaudhuri, 2009), sustained corporate venturing programs (Benson & Ziedonis, 2009), and the presence of dedicated integration units with codified knowledge (Zollo & Singh, 2004). Neither the partner selection nor partner integration literature links targeted R&D collaboration forms with control and innovation outcomes, however.

2.3 Inventor commingling to "unstick" knowledge in M&A contexts. A separate literature emphasizes the role of individuals and their knowledge, but is less sharp on the role of organizational boundaries. The individual-level process of "unsticking" tacit knowledge is a complex one (e.g., Von Hippel, 1994), and there are important interactions of that process with organizational routines for knowledge storage and recombination, as has been highlighted in the knowledge-based view of the firm (e.g., Kogut & Zander, 1992; Grant, 1996).

Unsticking individual-level knowledge is an important first step to knowledge assimilation, and we argue that one specific means of doing so is by forming commingled inventor teams. Alongside the great benefit of potentially unsticking tacit information in the process of innovative production, inventor commingling is likely to entail a range of costs, and so the net benefits may be uncertain. In the realm of inter-organizational R&D relations, Aggarwal & Hsu (2009) document the negative valuation consequences of switching R&D cooperation modes into one in which the focal organization is less experienced. This suggests the presence of organizational costs associated with reconfiguring operations and/or building competence in identifying, governing, and otherwise implementing alternative forms of inter-organizational cooperative R&D relations.

Control and authority of technical human capital could be an overriding benefit, however, of the M&A channel as compared to alternative R&D cooperation modes, especially in circumstances in which close knowledge sharing may be important for realizing synergies (Dyer, Kale & Singh, 2004). Within this context, the notion of "unsticking" knowledge for both knowledge sharing (Szulanski, 1996) and especially for knowledge creation is important. Von Hippel (1994), building on considerable prior work on tacit knowledge, argues that sticky information is costly to acquire, transfer and use. This is due to the nature of the information itself, the amount of information that must be transferred, and/or attributes of the seekers and providers of the information. Co-locating problem solvers can help unstick such tacit knowledge (Kogut & Zander, 1993; von Hippel, 1994), though there can be tremendous variation in the costs of knowledge transfer across domains (Teece, 1977).

Because of the fluid nature of R&D, it may be difficult or at least very costly to contract on (in an alliance arrangement) all the ex-ante elements which might be important in shaping innovation outcomes. Managerial fiat prevails under common ownership, and so merged organizations in which there are higher degrees of inventor commingling may provide evidence of more targeted inter-organizational arrangements. Our discussion yields two testable hypotheses:

- **Hypothesis (H1).** *acquired firms which commingle more intensively are associated with more favorable innovation outcomes.*
- **Hypothesis (H2).** *commingled inventors will be more innovative under more integrated R&D inter-organizational cooperative modes (post-merger) as compared to less integrated forms*.

3. DATA, VARIABLES AND EMPIRICAL STRATEGY

To test these two predictions about innovation and inventor commingling, we first describe the data construction process. We then preview our main variables, which are at both the firm-year and inventor-year levels of analysis. We end the section with a short discussion of our empirical strategy.

3.1 Data construction. We start with the set of ventures listed in Crunchbase, a crowdsourced platform, which were listed as acquired between the years 1970 and 2014 (since our measure of innovation quality is based on forward patent citations in the 4 years post grant, we stop the analysis window before the data end in 2018). This yields a list of 44,834 acquired companies. Since a Crunchbase listing is not dependent on receiving venture capital funding nor conditional on being US-based, we believe that this database allows us to cover a broader sample of startup firm acquisitions.[1]

We then use the set of acquired firms to build a longitudinal database at both the acquired firm and inventor levels. To do so, we make use of the PatentsView dataset provided by the United States Patent & Trademark Office (UPSTO). If an acquired firm does not have any granted patents between 1976-2014 as listed in PatentsView, we drop those firms. This helps us ensure that the acquired firm is being acquired for technology-centric reasons (while acknowledging that we might miss non-patented knowledge, such as that protected by trade secrecy). There is also a pragmatic reason in that our key empirical variables are derived from patent information, as we discuss below. We fuzzy match (using the Stata 15 built-in "reclink2" software package) acquired firm names from Crunchbase with patent firm assignees listed in PatentsView. We find an overlap of 7,404 firms in both databases. Finally, we exclude multiple acquisition situations of the same firm to ease interpretation. This leaves a final sample of 6,478 acquired firms in our analysis.[2]

---

[1] We compare the Crunchbase data to two datasets to assess coverage quality. First, we examine the overlap between Crunchbase listings of ventures acquired from Israel to an Israeli data source of venture capital-backed startups in Israel, known as the IVC Research Center database. Since Israel is well-represented in technology acquisitions of technology-centric startups, we believe that this comparison is worthwhile. We find that the Crunchbase data is quite comprehensive in its coverage (by comparison, established venture capital data sources such as Thomson One do not systematically cover international transactions). Second, we compare Crunchbase coverage of technology acquisitions to SDC Platinum, a standard dataset used for acquisition data. We find that the SDC coverage skews toward larger firms and misses many smaller firm acquisitions, which is of particular relevance to us. To further compare the quality of these two databases, we examine the listed acquisition data in each database as compared to that contained in the IVC data for the set of Israeli acquisitions (with the assumption that the local data provider, IVC, is most likely to be a "gold standard" on data quality). We find that the CrunchBase dataset dramatically outperforms the SDC dataset in this comparison.

[2] In the interest of space, we do not provide a "thick" description of the overall data, but consider the following facts: (1) acquisition events become much more prevalent as we approach the present; (2) the top three industries of the acquired firms are: communications (23%), health and medical-related (19%), and motor vehicle-related (7%); (3) the top four nations of the acquired firms are: US (71%), UK (6%), Germany (3.6%), and Canada (3.4%); (4) within the US, the top three states of venture location are: California (31%), Massachusetts (8.5%), and Texas (6.1%); and (5) the top three acquiring firms in our sample are: Microsoft (0.58%), IBM (0.57%), and Cisco (0.41%).

We then gather a list of all the inventors whose patents were assigned to the focal acquired companies using the unique inventor identifiers contained in the PatentsView database. This allows us to build a history of patenting of each inventor over her/his career, both before and after patenting in the focal firm, if applicable. These inventor- and patent-level data are crucial for measuring the key constructs, such as inventor commingling (as we explain in the next section). Of course, patent assignment records can only indicate inventors' employers (via the patent assignee or patent owner field) in years where patent applications are observed. In the absence of other intervening assignees, we assume that an inventor continued his or her employment with the same employer during the period spanning consecutive patent applications. An inventor is considered to have switched employers in the year s/he is associated with a patent application assigned to a different employer. In our concluding section, we will discuss some limitations using patent data, but to systematically and empirically study the phenomenon of inventor commingling, we are unaware of alternative data sources available.

3.2 Constructed variables

3.2.1 Outcome variables. *Firm patent stock* is defined as the cumulative number of patent applications which are ultimately successful up to a given year, aggregated to the firm-year or inventor-year level of analysis (*inventor patents stock*). These are measures of innovation quantity commonly used in the literature. To measure innovation quality, we follow the convention in the innovation literature by weighting the patent grants by the number of forward patent citations over the following four years post patent grant (and calculating the stock), resulting in the variable, *firm forward citations stock*.[3] Again, we aggregate this variable to the firm-year level of analysis, and

[3] Our data analysis spans M&A transactions through 2014 and the associated patent data up to 2018, given the time lapse between patent filing and grant, and the four-year moving window used for forward citation tracking. Given the

examine the variable at the inventor-year level as well (*inventor forward citations stock*). Finally, to measure innovative activity broadening, we construct the variable, *firm cumulative patent classes*, which is a cumulative count of the number of main (3-digit) patent classes up to a given year (for analysis at the firm level), or at the inventor level (*inventor cumulative patent classes*). Given the count nature of these outcome variables, our main specifications are fixed effects conditional Poisson regressions (though the results are robust to OLS estimation as well). Variable definitions and descriptive statistics are contained in Table 1, while correlations are in Table 2.

[INSERT TABLES 1 & 2 ABOUT HERE]

3.2.2 Explanatory variables. We define a commingled patent as one which is produced by inventors coming together from the acquired and acquiring firms. While most commingled patents are produced after an acquisition event (6.6% of patents post-acquisition are commingled), commingling can also occur before an acquisition (which we infer arises from inter-organizational collaboration such as an alliance; in our sample, 1.1% of pre-acquisition patents are commingled). *Firm commingling intensity* is the share of the cumulative patent stock invented by commingled teams (*inventor commingling intensity* is similarly constructed).[4] *Post-acquisition* is a dummy variable indicating years after the acquisition. With a difference-in-differences specification, our key variable is *commingling intensity, post-acquisition*, to test the first prediction relating firm-level inventor commingling with our innovation outcomes. This variable is operationalized as the interaction between commingling intensity and an indicator variable for the post-acquisition time

---

fact that there has been a secular rise in technology M&As, suppressing more recent years from our analysis implies disproportionate decreases in sample size and therefore statistical power.

[4] To construct the measure of commingling, we take the pool of patents assigned to the acquired firm (329,504 patents) and compile the associated inventors (a total of 233,011 inventors). We then construct for this total inventor group the history of inventor-employers (using a similarity score of 0.8 as a threshold for matching and uniquely identifying employers). A commingled patent is one in which inventor-employers come together from the acquired and acquiring employers (not necessarily after an acquisition). Using this definition, 7,932 patents are invented by a commingled team in our dataset.

period. To test our second prediction that inventor commingling is more productive with more complete managerial control/authority (as would be the case under a merged form), we narrow our sample to the set of inventors who were at the firm before the acquisition who also stayed with the focal acquired firm at least 5 years after the acquisition and who had coinvented patents with the acquirer before the acquisition. These criteria are guided by the comparison we wish to make, which is inventor innovation in a more integrated regime (post-acquisition) as compared to less integrated pre-M&A cooperative modes (such as alliances). The inventor commingling intensity variable is defined as the share of patents in inventor *j*'s patent stock which were invented by a commingled team. The unit of analysis is an inventor-year.

Recall that our discussion about the possible mechanism at the inventor level of providing innovation benefits under the merged as compared to the alliance collaborative form centers on control and authority. Such control should be particularly impactful under "complex" innovation regimes, in that the recombination being undertaken at the patent level by the given inventor(s) involves patent subclasses which have rarely been recombined in the past.[5]

3.2.3 Control variables. At the firm-year level, two variables control for the acquired firm's investor base and external funding activity: *firm cumulative funding rounds* and *firm cumulative VC investors*, in each case, up to the focal year. Finally, five variables control for various aspects of the acquired firm's patent position and inventor experience. *Firm technology concentration* is

[5] Following Fleming & Sorenson (2001), we define patent complexity as follows. N is the number of reference subclasses assigned to a patent. E_i is the observed ease of recombination of subclass i as compared to all prior patents: $E_i = \frac{\#\, subclasses\ previously\ combined\ with\ subclass\ i}{\#\, previous\ patents\ in\ subclass\ i.}$. K_j is the "interdependence" of patent *j*: $K_j = \frac{\#\, subclasses\ on\ patent\ j}{\sum_{j \in i} E_i}$. Finally, patent complexity is defined as: $C_j = \frac{K_j}{N_j} = \frac{interdependence\ of\ patent_j}{No. of subclasses\ on\ patent\ j}$ (which we then aggregate to the inventor level for analysis).

a Herfindahl index of 3-digit (main) patent classes in the firm's patent stock up to year *t* (higher values indicate more concentration of patent classes). The variable, *firm inventors*, gives a count of the number of distinct inventors at the firm in year *t*. The final three control variables in this series give firm cumulative averages of inventor innovation activity (*firm inventor avg cumulative patent counts*, *firm inventor average cumulative fcitation*, and *firm inventor avg cumulative patent classes*), somewhat akin to lagged outcome variable controls. Acquirer and aquiree firm fixed effects are also included in the specifications.

At the inventor-year level of analysis, aside from acquiree-inventor fixed effects, we control for *inventor co-located*, an indicator for whether the inventor's most recent residential address (as listed in PatentsView) is located within a 100km distance from the acquirer's R&D center (see the next section for method). This variable proxies alternative means of unsticking tacit knowledge.

3.2.4 Instrumental variable. The first step is to determine the R&D locations of the acquired firms. Since our aim is to construct an instrumental variable for firm commingling, we focus on the 719 acquisitions in which commingling ever occurred. If we simply constructed direct flight information from listed firm headquarters, we would miss the geographically distributed R&D activities which are common for many technology-oriented ventures. As a consequence, we take advantage of inventor residential address information (from PatentsView) to examine the geographic location of their firm's R&D activities. For each acquired firm, we gather the list of addresses of the inventors who patented before the acquisition. We first cluster these addresses at the patent level, aggregating to a circle with a radius of 50 kilometers (km). We then group these clusters based on their center so that all circles for which the center can be placed within a circle with a radius of 50 km will be considered part of the same R&D location. We define the center of each of these resulting clusters as an R&D location of the acquired firm. We keep the top 50 R&D

locations of each acquired firm, ranked by innovation intensity. Some acquired firms have multiple (and distributed) R&D locations, which we do not want to miss. Through this process, we identify 7,499 R&D locations associated with the 719 focal acquired companies, spread across 69 countries. Approximately 35% of the acquired companies have a single R&D location; however, some have many locations which are geographically disbursed. On average, each acquired company has 10.4 R&D locations. We use the same procedure to construct the R&D locations of the acquiring firms. Since acquirers are typically larger in size, we keep the top 100 R&D locations for this group. We identify 20,231 R&D locations in 114 countries of 521 acquiring firms.

We then construct a reference dataset in which on a longitudinal basis, we record the number of direct flights which connect R&D centers *a* and *b* for the dyadic pairing of acquirers-acquired firms. We use the Air Carrier Statistics database, also known as the T-100 data bank, from the US Bureau of Transportation Statistics to measure the direct flights (this is a standard data source in the literature which uses direct flights as an instrumental variable to address the endogenous choice of geographic location). The database contains monthly reports from 1980 to 2018 for all flight routes of certified US air carriers which have at least one point of service in the US or its territories. For the 6,519,684 dyads of acquired firm R&D location-acquiring firm R&D location, we first find all airports within 100 km to the center of the focal R&D locations (which rests on an assumption of household commuting distance to the relevant airport). We aggregate the monthly data to the annual level on direct flights, by location dyad. If there is at least one route operating in a given year between the airports serving the focal R&D centers, we say those R&D centers are connected by direct flight.

With that background, we construct at the R&D center level the innovation outcome variables akin to our three main outcome variables: *location patents stock*, *location forward* *citations stock*, and *location cumulative patent classes*. The endogenous variable in this set up is *R&D location commingling intensity*, which is analogous to the other commingling intensity variables, though the unit here is an R&D location. The instrumental variable is *location connectedness* (defined as the number of acquirer's R&D locations which have direct flights to location *l* in year *t*) in the *post acquired* period. Finally, *location knowledge relatedness* is a control variable for the share of knowledge base overlap between the acquirer and location *l*, following Ahuja & Katila (2001).

3.3 Empirical specification. Our main empirical specifications use difference-in-differences (DiD) designs. To test our first prediction that post-merger integration involving a higher degree of commingling will be associated with improved innovation outcomes, we compare firm innovation profiles before and after the merger, as well as stratified by firms which have a higher versus lower level of commingled inventor teams. Our analysis is at the firm-year level of analysis. Since our innovation outcome variables are count variables, our main specifications use Poisson models. In each main specification, in addition to the main DiD variables of interest, we include a host of controls for firm and inventor composition variables, as well as several fixed effects. These specifications are our test of hypothesis 1. Since post-merger integration is certainly not randomly determined, we interpret these results as correlational.

To assess the degree to which the results might be driven by selection (rather than treatment) effects, we exploit an exogenous shift of the costs of firm-level commingling. The introduction or removal of direct flights between the location of the acquiring and acquired firms is a decision outside of managerial control. In a two-stage least squares regression, we use direct flights between the location dyad, post-acquisition, to instrument for the potentially endogenous variable, *R&D location commingling intensity*.

Finally, to examine the prediction that commingled inventors will be more productive post M&A compared to their own commingling outcomes under alliance (pre-M&A) forms, we switch to the inventor-year level of analysis. We examine the inventor-level analogs of the innovation-level outcomes, and use a similar DiD approach, again in a Poisson regression framework given the count nature of the outcomes.

4. RESULTS

Table 3 empirically tests hypothesis 1, in which our expectation is that there will be a positive relation between firm-level inventor commingling and innovation outcomes.

[INSERT TABLE 3 ABOUT HERE]

The unit of analysis is a firm-year in these regressions. For each of our outcome variables, *firm patents stock*, *firm forward citations stock*, and *firm cumulative patent classes*, we present two specifications: one with just the key DiD variables (with fixed effects for year, acquiree and acquiror in all models) and another which adds to the specification the set of firm-level control variables listed in Table 1. The estimation method is a conditional Poisson regression, since the outcomes are all non-negative counts (integers). The reported estimates are all expressed as incident-rate ratios (IRR), which exponentiates the estimated coefficient, and so can be interpreted relative to the number 1.0. Values above 1.0 which are statistically significant (t-statistics are included in parentheses in the tables) correspond to positive effects, while values below 1.0 correspond to negative effects. The IRR helps interpret the economic significance of the estimates: a unit increase in an independent variable scales (multiplies) the dependent variable by the estimated coefficient. Because our key variable, commingling intensity, is expressed as a ratio but does not (in our data) span the entire distribution from zero to one, we express the economic effects throughout this section as the innovation effect of a standard deviation change in commingling intensity from the mean of the variable's distribution. We only report the estimates of the key DiD variables throughout our tables, as those are the theoretical variables of interest (we denote the inclusion or exclusion of control variables and fixed effects in the tables).

In Table 3, in examining the *post-acquisition* dummy, we see that it is significantly negative (IRRs below 1.0) in a few of the specifications, most robustly as related to *firm cumulative patent classes*, but also as related to *firm patents stock* when the set of firm level controls is omitted. This pattern fits with the prior literature: at the organizational level, there are two categories of cost which arise after an acquisition: (1) disrupted team standard operating procedures and routines, and (2) enhanced coordination costs.[6]

Across all the specifications, *firm commingling intensity* is strongly positive, both in statistical and economic significance. The key variable of interest, however, in the DiD specification is *firm commingling intensity * post acquisition*. This variable is also strongly positive in statistical significance (at least $p<0.01$ in all cases). To illustrate the economic significance, when all variables on the right-hand side are kept at their mean after the acquisition, the predicted patent stock = 27.8, forward citation stock = 108.9, and cumulative patent classes = 4.3. For a standard deviation increase in firm commingling intensity after the acquisition, the corresponding increases for each of these innovation outcome variables are: 18.9%, 13.7%, and 5.3%, respectively.

[6] To the first domain, Kogut & Zander (1992) propose organizational capabilities in knowledge sharing and transfer which spans both information and know-how, and transcends the associated individual knowledge. A logical consequence of M&As is comprehensive disruption of these organizational processes and domains (Ranft & Lord, 2002). Kapoor & Lim (2007) find empirical evidence consistent with this notion of disrupted organizational routines at the inventor level following M&A, though this is mitigated with time. The second cost, coordination costs, are due to unfamiliar shared norms (Haspeslagh & Jemison, 1991) and the lack of shared common ground.

We then move to Table 4, where we use an instrumental-variables approach in recognition of the possible endogenous process of firm commingling associated with the results from Table 3. While our approach does not address the firm-level selection of target firm, or the matching process between acquiror and acquired firms (again, our focus is on the post-merger integration literature rather than the M&A partner selection literature), we focus on the introduction (or removal) of direct flight between the two firms as an exogenous shock (outside of managerial control) to the cost of R&D collaboration. Specifically, we use *location connectedness* * *post acquisition* as an instrument for the endogenous commingling variable (*location commingling intensity*).

[INSERT TABLE 4 AROUND HERE]

In the first two columns, we show that there is a positive and significant relation between the instrumental and endogenous variables. This is the first stage of the two stage least squares (2SLS) regression. Over the following three pairs of columns, for each of the three firm-level innovation outcome variables, we compare the OLS (un-instrumented) estimates in the odd columns with the 2SLS estimates in the even ones. The robust positive coefficient of the *location commingling intensity* in the 2SLS estimates suggests that the prior commingling intensity result is not entirely driven by commingling selection effects, but instead points to a commingling treatment effect on innovation.

Having found support for our first hypothesis, we move to testing our second prediction, that inventor commingling intensity post-M&A is associated with higher innovation performance as compared to the effect of commingling under pre-M&A (alliance) organization. The possible mechanism is control and authority in the integrated (post-M&A) form (especially in R&D contexts), though our test of that mechanism is indirect. In Table 5, not only do we shift the analysis to the inventor-year level, we match our sampling strategy to test the hypothesis. Specifically, inventors in our sample are those who stayed at the merged firm at least 5 years after the M&A (following Kapoor & Lim, 2007) from firms which have coinvented patents with their acquirers before the acquisition (and so all of the inventors in the sample worked at firms with commingled patents). In this sample, we can compare inventor innovation profiles under an integrated regime (after the M&A) as compared to their own output under commingling via alliance structure in the pre-M&A regime (3,030 out of the 43,936 inventors in this sample commingled with the acquirer's inventors before acquisition).

[INSERT TABLE 5 AROUND HERE]

Due to the count nature of the innovation outcomes, we return to Poisson estimation with a variety of fixed effects. All estimates are again expressed as IRRs, with values above 1.0 corresponding to positive effects and those below 1.0 associated with negative effects. Each specification in Table 5 contains acquiree-inventor fixed effects as well as year fixed effects. The odd columns omit the control variables, while the even specifications contain those controls.

The key variable of interest, in the DiD specification is *inventor commingling intensity * post -acquisition*. This variable is strongly positive and significantly different than zero statistically (at least $p<0.001$ in all cases). To illustrate the economic significance, when all variables on the right-hand side are kept at their mean after the acquisition, the predicted patent stock = 6.8, forward citation stock = 33.1, and cumulative patent classes =2.7. For a standard deviation increase in inventor commingling intensity after the acquisition, the corresponding increases for each of these variables are: 9.1%, 6.2%, and 4.1%, respectively, in innovation outcomes. These results are consistent with the prediction contained in hypothesis 2.

Recall that the underlying mechanism we put forward relates the organizational form of R&D collaboration (merger versus alliance) to innovative output via control and authority. To operationalize this concept, we investigate the contingent role of patent complexity. A patent is "complex" when it recombines (loosely speaking) relatively uncommon knowledge elements (Fleming & Sorenson, 2001). Managerial authority might be particularly important when the innovative task environment is complex, as the lack of an established map or recipe for innovation implies a high value of control (and especially when complex contingencies are difficult to specify or contract upon ex ante). By contrast, in "simple" innovation task environments, such managerial authority may be less important as the nature of knowledge recombination is less unusual, and therefore more easily governed via contractual (alliance) relationships.

In Table 6, we examine this logic, using the same inventor-year data structure, sample, and outcome variables as in Table 5. In the odd-number specifications in the table, we find that the estimated direct effect of inventor average patent complexity is positive and statistically significant (though in each case, the economic magnitude is not large), which is consistent with the notion that in an M&A setting, more complex patents are associated with innovation outcomes.[7] In the even-number specifications, the key variables of interest are the interactions between low or high complexity (defined as the lowest and highest quartile of *inventor avg patent complexity*) and the *post-acquisition* indicator (the inter-quartile range is the omitted reference group). We interpret the low complexity, post-acquired interaction as a potentially misaligned structure, as less integrated R&D forms (such as licensing or alliances) may have been more effective in fostering innovation. We indeed estimate a negative effect of this structure (the reported coefficients are IRRs) on *inventor patents stock* and *inventor cumulative patent classes* (a six and four percent decline, respectively, as compared to the inter-quartile baseline). In contrast, the regime of high

[7] Consistent with our upfront caveat of leaving the acquisition decision exogenous to our empirical analysis, one interpretational point is the possibility that managers choosing or anticipating a merger may undertake projects and staffing decisions with innovation complexity in mind.

complexity, post-acquisition is positive and significant across all three innovation outcomes, with three to 10% increases, consistent with targeted circumstances for authority and control associated with merged organizations.[8]

[INSERT TABLE 6 AROUND HERE]

5. DISCUSSION & CONCLUSION

We introduce the concept of post-merger inventor commingling as a means of improving innovation outcomes and show that post-M&A commingling increases both patent output and scope. We also provide evidence that especially in M&A settings of technology-oriented ventures, inventor commingling is associated with a more targeted mode of R&D cooperation, in that inventor innovation outcomes improve when a given inventor is in a post-M&A regime as compared to when that inventor is in a less integrated pre-M&A alliance regime. Further analysis is consistent with the interpretation that managerial authority and control under the merged form, especially when the innovation task environment is complex, is an operative mechanism.

Within the broader literature on post-merger integration for innovation, we share the thesis that organizational design choices matter significantly for M&A success. While the prior literature has focused on what might be thought of as centralized corporate policy action such as dedicated alliance integration departments, codifying knowledge via manuals, and more generally when to structurally integrate the target entity with the acquirer (as we briefly reviewed in our literature discussion), our focus is more at the production of innovation level. We believe this focus on literal knowledge recombination at the inventor and production team level is novel to the post-merger integration literature (and is a separate construct from the typical (R&D production) team

[8] In unreported specifications, we analyzed whether there is a further interaction with the degree of inventor commingling on these "aligned" and "misaligned" structures. We estimate relatively precise (statistically) near-zero economic effects.

composition one, e.g., Aggarwal, Hsu & Wu (2020)). Of course, broader corporate policies such as structural integration as well as the mode or form of R&D cooperation certainly influence the degree of post-merger commingling. However, there are likely a number of other channels by which commingling arises.

Because we advance the commingling construct and measurement into two literatures which have had little prior intersection (post-merger integration and targeted form of R&D cooperation), we hope we have laid the groundwork for extensions and new avenues for research. Before we discuss a few such possibilities, we would also like to call attention to a number of limitations and interpretational issues with the study. One set of inherent limitations stem from using patent data. Not only is there the well-known censoring issue associated with not observing patent applications which were not granted (and therefore the distribution of patent inventor composition necessary to measure commingling), there is likely a complex process shaping the antecedents of firm and inventor commingling identified from the patent data. In the present analysis, we take as given inventor stayers and leavers post-acquisition. The process governing this choice is clearly intentional and multifaceted (involving the inventor and/or the acquiring firm), and of course the employment contract(s) are unobserved. Among the stayers, organizations may target certain individuals for commingling in ways which are unobserved and unmeasured. More generally, commingled teams may result from serendipity or from managerially-placed organizational design choices (some of which have been discussed in the literature). Future research in this domain would ideally improve our understanding of the antecedents of inventor commingling. Doing so would also help build a bridge between the two main branches of the technology M&A literature: partner selection versus post M&A integration studies.[9]

[9] More generally, there are a number of selection issues at work on both sides of the acquisition market which makes this bridge work challenging. Consider organizing for innovation from the perspective of the acquirer. There are a

A second area of limitation (and research opportunity) is centered on the research sample for providing evidence of targeted R&D cooperation mode. We compare inventor-level innovation outcomes before and after an acquisition to conclude that certain R&D cooperation forms are higher performing. However, the sample of inventors all ultimately experienced an acquisition event, which limits the generalizability of the results.[10] To understand possible selection effects or boundary conditions, future research would ideally draw from a broader sample of inventors to better understand the role of commingling. Doing so may entail matching individuals and firms on observables to build counterfactual samples for comparison.

More generally, future studies to further elaborate the consequences of startup R&D cooperation mode (and how they interact with incumbent firm choices) would be particularly welcome. The obstacles of such examinations are formidable, however, including appropriate outcome counterfactuals as well as empirical strategies to address selection on both sides of the market. Notwithstanding these limitations, our hope is that the concepts developed here will open new avenues for subsequent work on both post-merger technology integration, as well as more broadly on modes of R&D cooperation.

host of internal conditions and choices which shape the degree to which the potential acquirer looks to the external environment for R&D collaboration of any sort (including acquisitions). Some of these conditions are unobserved and unmeasured, such as incumbent manager expectations about the pace of innovation in a given domain, the value of control under different states of the world (e.g., Forbes & Lederman, 2009) and more generally the rationale for undertaking inter-organizational R&D work in the first place (e.g., Cunningham, Ederer & Ma, 2019).

[10] Note, however, that our empirical set-up is likely conservatively estimated since inventors with productive inventive output under an alliance structure are likely to be the ones who are retained in an acquisition. Inventor retention selection forces therefore likely work against the positively-estimated post-acquisition innovation effect.

References

Aggarwal, VA, Hsu, DH. 2009. Modes of cooperative R&D commercialization by start-ups. *Strategic Management Journal* **30**(8): 835-864.

Aggarwal, VA, Hsu, DH. 2014. Entrepreneurial exits and innovation. *Management Science* **60**(4): 867-887.

Aggarwal, VA, Hsu, DH, Wu A. 2020. Organizing knowledge production teams within firms for innovation. *Strategy Science* **5**(1): 1-16.

Ahuja, G, Katila, R. 2001. Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal* **22**(3): 197-220.

Benson, D, Ziedonis, RH. 2009. Corporate venture capital as a window on new technologies: Implications for the performance of corporate investors when acquiring startups. *Organization Science* **20**(2): 329-351.

Cassiman, B, Colombo, MG, Garrone, P, Veugelers, R. 2005. The impact of M&A on the R&D process: An empirical analysis of the role of technological-and market-relatedness. *Research Policy* **34**(2): 195-220.

Cloodt, M, Hagedoorn, J, Van Kranenburg, H. 2006. Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries. *Research Policy* **35**(5): 642-654.

Cohen, WM, Levinthal, DA. 1990. Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly* **35**: 128-52.

Cunningham, C, Ederer, F, Ma, S. 2019. Killer acquisitions. London Business School working paper.

Dyer, JH. Kale, P. and Singh, H. 2004. When to ally & when to acquire. *Harvard Business Review* July-August.

Fleming, L, Sorenson, O. 2001. Technology as a complex adaptive system: evidence from patent data. *Research Policy* **30**(7): 1019-1039.

Forbes, SJ, Lederman, M. 2009. Adaptation and vertical integration in the airline industry. *American Economic Review* **99**(5): 1831-49.

Graebner, ME. 2004. Momentum and serendipity: How acquired leaders create value in the integration of technology firms. *Strategic Management Journal* **25**(8-9): 751-777.

Grant, RM. 1996. Toward a knowledge-based theory of the firm. *Strategic Management Journal* **17**(S2): 109-122.

Grossman, SJ, Hart, OD. 1986. The costs and benefits of ownership: A theory of vertical and lateral integration. *Journal of Political Economy* **94**(4): 691-719.

Guadalupe, M, Kuzmina, O, Thomas, C. 2012. Innovation and foreign ownership. *American Economic Review* **102**(7): 2594-3627.

Haspeslagh, PC, Jemison, DB. 1991. *Managing acquisitions: Creating value through corporate renewal*. New York: Free Press.

Hitt, MA, Hoskisson, RE, Ireland, RD. 1990. Mergers and acquisitions and managerial commitment to innovation in M-form firms. *Strategic Management Journal* **11**(4): 29-48.

Kapoor, R, Lim, K. 2007. The impact of acquisitions on the productivity of inventors at semiconductor firms: A synthesis of knowledge-based and incentive-based perspectives. *Academy of Management Journal* **50**(5): 1133-1155.

Kogut, B, Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science* **3**(3): 383-397.

Kogut, B, Zander, U. 1993. Kwoledge of the firm and the evolutionary theory of the multinational corporation. *Journal of International Business Studies* **34**(6): 516-529.

Makri, M, Hitt, MA, Lane, PJ. 2010. Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. *Strategic Management Journal* **31**(6): 602-628.

Lerner, J, Malmendier, U. 2010. Contractibility and the design of research agreements. *American Economic Review* **100**(1): 214-246.

Puranam, P, Srikanth, K. 2007. What they know vs. what they do: How acquirers leverage technology acquisitions. *Strategic Management Journal* **28**(8): 805-825.

Puranam, P, Singh, H, Chaudhuri, S. 2009. Integrating acquired capabilities: When structural integration is (un) necessary. *Organization Science* **20**(2): 313-328.

Puranam, P, Singh, H, Zollo, M. 2006. Organizing for innovation: Managing the coordination-autonomy dilemma in technology acquisitions. *Academy of Management Journal* **49**(2): 263-280.

Ranft, AL, Lord, MD. 2002. Acquiring new technologies and capabilities: A grounded model of acquisition implementation. *Organization Science* **13**(4), pp.420-441.

Robinson DT, Stuart TE. 2007. Financial contracting in biotech strategic alliances. *Journal of Law and Economics* **50**(3): 559–595.

Rosenkopf, L, Almeida, P. 2003. Overcoming local search through alliances and mobility. *Management Science* **49**(6): 751-766.

Ryall, MD, Sampson, RC, 2009. Formal contracts in the presence of relational enforcement mechanisms: Evidence from technology development projects. *Management Science* **55**(6): 906-25.

Szulanski G. 1996. Exploring internal stickiness: impediments to the transfer of best practice within the firm. *Strategic Management Journal* **17**(S2): 27-43.

Teece, DJ. 1977. Technology transfer by multinational firms: The resource cost of transferring technological know-how. *The Economic Journal* **87**(346): 242-61.

von Hippel, E. 1994. 'Sticky information' and the locus of problem solving: Implications for innovation. *Management Science* **40**(4): 429-39.

Wuchty, S, Jones, BF. and Uzzi, B. 2007. The increasing dominance of teams in production of knowledge. *Science* **316**(5827):1036-1039.

Villalonga B, McGahan AM. 2005. The choice among acquisitions, alliances, and divestitures. *Strategic Management Journal* **26**(13): 1183–1208

Zollo, M. and Singh, H., 2004. Deliberate learning in corporate acquisitions: post-acquisition strategies and integration capability in U.S. bank mergers. *Strategic Management Journal* **25**(13): 1233-1256.

Table 1: Descriptive statistics and variable definitions

Firm-year level of analysis			
VARIABLE NAME	***DEFINITION***	***MEAN***	***SD***
Firm patents stock	Stock of patents of acquired firm *i* in year *t* (PatentsView/Crunchbase). A patent will be included in firm *i*'s patent stock if (i) the patent was directly assigned to firm *i* and filed before year *t*, or (ii) the patent was filed after the acquisition before year *t* under the name of firm *i*'s acquirer, and had at least one inventor working for firm *i*.	32.44	393.1
Firm forward citations stock	Forward citations to firm *i*'s stock of patents within 4 years since patent grant (PatentsView)	99.95	1315.1
Firm cumulative patent classes	Number of distinct 3-digit (main) technology classes for firm *i*'s patent stock (PatentsView)	4.224	6.763
Firm commingling intensity	Share of patents which were invented by commingling teams in firm *i*'s patent stock (PatentsView/Crunchbase) $Firm\ commingling\ intensity = \frac{cumulative\ \#\ of\ patents\ invented\ by\ commingling\ teams\ in\ year\ t}{firm\ i's\ patent\ stock\ in\ year\ t}$	0.0132	0.0756
Post-acquisition	Dummy=1 if *t* >= acquired year (Crunchbase)	0.288	0.453
Firm cumulative funding rounds	Cumulative # of funding rounds the firm has received up to year *t* (Crunchbase)	0.440	1.150
Firm cumulative VC investors	Cumulative # of venture capitalists who have invested in the firm up to year *t* (Crunchbase)	0.441	1.296
Firm technology concentration	Herfindahl index of firm *i*'s patent distribution among 3-digit (main) patent technology classes (PatentsView) $Firm\ technology\ concentration_{it} = \sum_{s=1}^{N}(percent\ of\ patents\ in\ technology\ class\ s\ in\ firm\ i's\ patent\ stock\ in\ year\ t)^2$	0.451	0.337
Firm inventors	Number of inventors working for firm *i* in year *t* (PatentsView/Crunchbase)	17.54	129.8
Firm inventor avg cumulative patent counts	Average patenting experience (cumulative patent counts) among firm *i*'s inventors (PatentsView/Crunchbase)	5.368	6.264
Firm inventor avg cumulative fcitation	Average patenting experience (cumulative patent counts weighted by forward citation) among firm *i*'s inventors (PatentsView/Crunchbase)	33.53	69.15
Firm inventor avg cumulative patent classes	Average patenting experience (cumulative patent class counts) among firm i's inventors (PatentsView/Crunchbase)	2.759	1.709
Inventor-year level of analysis			
Inventor patents stock	Inventor *j*'s patent stock in year *t* (PatentsView/Crunchbase)	5.741	12.22
Inventor forward citations stock	Forward citations to inventor *j*'s patents stock within 4 years since patent grant(s) (PatentsView/Crunchbase)	30.04	112.1
Inventor cumulative patent classes	Number of distinct 3-digit (main) technology classes to inventor *j*'s patent stock (PatentsView/Crunchbase)	2.634	2.230
Inventor commingling intensity	Share of patents in inventor *j*'s patent stock which were invented by a commingling team (PatentsView/Crunchbase) $inventor\ commingling\ intensity = \frac{Cumulative\ \#\ of\ patents\ coinvented\ by\ inventor\ j\ and\ inventors\ from\ the\ acquirer}{Inventor\ j's\ patent\ stock}$	0.0220	0.125
Inventor co-located	Dummy=1 if the inventor's current address (registered on the most recent patent document) is located within 100km of the acquirer's R&D center.	0.235	0.424

Table 1 (Continued)

Inventor avg patent complexity	Average complexity of patents in the inventor's current patent stock. For each patent, the complexity is constructed following Fleming & Sorenson (2001).	515.8	408.0
R&D location-year level of analysis			
Location patents stock	A R&D location is defined as a 100km-radius cluster of inventors (addresses) who worked for firm *i* before the deal. Inventor *j* works in location *l* if her residential address locates in the range of the 100km-radius of location *l*. Location *l*'s patent stock is the pool of patents which are invented by inventors working in location *l* and filed before year *t*. (PatentsView/Crunchbase)	17.25	111.3
Location forward citations stock	Forward citations to location *l*'s patent stock within 4 years since patent grant(s) (PatentsView/Crunchbase)	56.72	458.4
Location cumulative patent classes	Number of distinct 3-digit (main) technology classes for location *l*'s patent stock (PatentsView/Crunchbase)	3.939	4.700
Location commingling intensity	Share of patents in location *l*'s patent stock which were coinvented by inventors of firm *i* working in location *l* and inventors from the acquirer. (PatentsView/Crunchbase) $\mathit{Location\ commingling\ intensity} = \frac{\mathit{Cumulative\ \#\ of\ patents\ coinvented\ by\ inventors\ of\ the\ R\&D\ location\ l\ and\ those\ from\ the\ acquirer}}{\mathit{Location\ ls\ patent\ stock}}$	0.0383	0.157
Location connectedness	Number of acquirer's R&D locations which have direct flights to location *l* in year *t*. (PatentsView/Crunchbase/T-100 data bank)	18.99	19.96
Location knowledge relatedness	Share of overlap between location *l* and the acquirer's knowledge base. (PatentsView/Crunchbase) Firm knowledge base is defined following Ahuja & Katila (2001) as the pool of patents that are either acquired by the firm within a 5-year window before year *t* or cited by these acquired patents. (i) R&D location's knowledge base is defined similar to firm knowledge base (ii) $\mathit{center\ knowledge\ relatedness} = \frac{\mathit{overlap\ in\ location\ l\ and\ the\ acquirer's\ knowledge\ base}}{\mathit{absolute\ size\ of\ R\&D\ location\ l's\ knowledge\ base}}$	0.127	0.286

Notes:
1. This table reports variable definitions and summary statistics for variables used in the analyses. Each section of the table focuses on one of the three levels of analysis employed: firm-year, R&D location-year, and inventor-year.
2. Firms in the firm-year panel are target companies in the Crunchbase M&A database who also have patent records in the PatentsView database and was acquired before 2014. To avoid the mixed effects from multiple deals, we exclude firms who experienced more than one acquisition.
3. Inventors in the inventor-year panel were employed by acquired firms which allied with their acquirers before the acquisition. Inventors in the sample started to patent for the focal acquired firm before the deal and remained for 5 years after the acquisition (following Kapoor & Lim, 2007).
4. A firm's R&D location is defined as a 100km-radius cluster of the residential addresses of inventors who patented for the firm before the acquisition. Only the top 50 R&D locations of each acquired company which have commingling teams are included in the sample.

TABLE 2: Correlation matrix

FIRM YEAR LEVEL VARS		1	2	3	4	5	6	7	8	9	10	11	12
1	*Firm patents stock*	1.000											
2	*Firm forward citations stock*	0.934	1.000										
3	*Firm cumulative patent classes*	0.467	0.406	1.000									
4	*Firm commingling intensity*	0.002	0.004	0.014	1.000								
5	*Post-acquisition*	0.016	0.012	0.137	0.096	1.000							
6	*Firm cumulative funding rounds*	-0.015	-0.007	-0.032	0.057	0.120	1.000						
7	*Firm cumulative VC investors*	-0.013	-0.006	-0.028	0.049	0.105	0.793	1.000					
8	*Firm technology concentration*	-0.033	-0.020	-0.181	0.003	0.181	0.146	0.136	1.000				
9	*Firm inventors*	0.824	0.713	0.568	-0.002	0.027	-0.022	-0.019	-0.037	1.000			
10	*Firm inventor avg cumulative patent counts*	0.044	0.050	0.073	0.083	0.027	0.097	0.089	-0.035	0.019	1.000		
11	*Firm inventor avg cumulative fcitation*	0.024	0.062	0.008	0.081	0.023	0.146	0.134	0.045	-0.000	0.664	1.000	
12	*Firm inventor avg cumulative patent classes*	0.009	0.005	0.173	0.011	-0.045	-0.031	-0.032	-0.389	0.002	0.553	0.266	1.000

INVENTOR YEAR LEVEL VARS		1	2	3	4	5	6
1	*Inventor patents stock*	1.000					
2	*Inventor forward citations stock*	0.567	1.000				
3	*Inventor cumulative patent classes*	0.512	0.278	1.000			
4	*Inventor commingling intensity*	0.056	0.054	0.039	1.000		
5	*Inventor co-located*	-0.021	-0.021	-0.012	-0.068	1.000	
6	*Inventor avg patent complexity*	0.060	0.058	-0.213	0.058	-0.100	1.000

TABLE 3: Estimated effects of commingling on firm innovation

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm patents stock		Firm forward citations stock		Firm cumulative patent classes	
Firm commingling intensity * post-acquisition	2.423*** (8.39)	2.000*** (7.74)	2.063*** (4.47)	1.575** (3.04)	1.319*** (5.73)	1.220*** (6.23)
Post-acquisition	0.962*	1.002	0.966	0.999	0.987***	0.994*
	(-2.17)	(0.18)	(-1.51)	(-0.03)	(-3.80)	(-2.06)
Firm commingling intensity	5.630***	4.973***	4.694***	3.475***	1.469***	1.630***
	(12.20)	(12.37)	(6.37)	(4.95)	(5.65)	(10.77)
Firm level controls	N	Y	N	Y	N	Y
Acquiree Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Acquirer Fixed Effects	Y	Y	Y	Y	Y	Y
Observations	101,250	84,711	91,685	77,811	101,250	84,711

Notes:
*1. This table reports exponentiated coefficients in incidence-rate ratios and t-statistic (in parentheses) from conditional Poisson regressions at the firm-year level. Standard errors are robust. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.*
2. For conditional Poisson models, the reported exponentiated coefficients are incidence-rate ratios: a unit increase in an independent variable scales (multiplies) the dependent variable by the estimated coefficient. A coefficient value less (greater) than one represents a negative (positive) effect.
3. The control variables are listed in Table 1.
4. Firms in the firm-year panel are target companies in the Crunchbase M&A database who are also listed in the PatentsView database and were acquired before 2014.

TABLE 4: Estimated effects of team commingling on innovation - IV regressions at the R&D location level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1st stage regression		OLS versus 2SLS IV regressions					
	Location commingling intensity		Log (location patents stock+1)		Log (location forward citations stock+1)		Log (location cumulative patent classes)	
Regression model			OLS	IV	OLS	IV	OLS	IV
Location connectedness * post-acquisition	0.000194*** (3.85)	0.000148** (2.95)						
Location connectedness	-0.0000634 (-0.48)	-0.000135 (-0.99)						
Post-acquisition	0.00209 (1.77)	-0.00115 (-0.95)	-0.00169 (-0.24)	-0.0140 (-1.33)	-0.0157 (-1.68)	-0.0272* (-2.23)	-0.00733 (-1.90)	-0.0165* (-2.48)
Location commingling intensity			0.805*** (7.70)	7.898* (2.45)	1.035*** (6.47)	7.627* (2.23)	0.205*** (3.46)	5.492** (2.64)
Controls	N	Y	Y	Y	Y	Y	Y	Y
Location fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	102,864	80,419	80,419	80,452	80,419	80,452	80,419	80,452

Notes:
*1. This table reports coefficients and t-statistic (in parentheses) from OLS/2SLS regressions at the R&D location-year level. Standard errors are robust. * p<0.05, ** p<0.01, *** p<0.001.*
2. The control variables are listed in Table 1.
3. A firm's R&D location is defined as a 100km-radius cluster of the residential addresses of inventors who patented for the firm before the acquisition. Only the top 50 R&D locations of each acquired company which had commingling teams are included in the sample.

TABLE 5: Estimated effects of commingling (by collaborative organizational structure) on inventor innovation

	(1)	(2)	(3)	(4)	(5)	(6)
	Inventor patents stock		Inventor forward citations stock		Inventor cumulative patent classes	
Inventor commingling intensity * post-acquisition	1.880***	1.632***	1.735***	1.422***	1.168***	1.165***
	(17.00)	(14.76)	(12.63)	(8.68)	(8.85)	(8.54)
Post-acquisition	1.028***	1.042***	0.944***	0.957***	1.011***	1.018***
	(10.91)	(17.90)	(-7.97)	(-6.26)	(13.56)	(22.84)
Inventor commingling intensity	4.347***	3.449***	2.731***	2.332***	1.968***	1.894***
	(27.92)	(25.03)	(15.30)	(14.27)	(26.89)	(23.29)
Firm and inventor controls	N	Y	N	Y	N	Y
Acquiree-Inventor fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Observations	634,079	589,671	568,510	529,672	627,429	583,508

Note:
*1. This table reports exponentiated coefficients in incidence-rate ratios and t-statistics (in parentheses) from conditional Poisson regressions at the inventor-year level. Standard errors are robust. * p<0.05, ** p<0.01, *** p<0.001.*
2. For conditional Poisson models, the reported exponentiated coefficients are incidence-rate ratios: a unit increase in an independent variable scales (multiplies) the dependent variable by the estimated coefficient. A coefficient value less (greater) than one represents a negative (positive) effect.
3. The control variables are listed in Table 1.
4. Inventors in the sample worked for the acquired companies under two regimes: a less integrated, business alliance regime (pre-acquisition) and in a formally integrated, post-acquisition regime. They are from 493 acquired companies which allied with the acquirer before the acquisition. Inventors in the sample started to patent for the focal companies before the acquisition and stayed at least 5 years post acquisition.
5. The composition of inventors of the 493 acquired firms are: total number of inventors = 54,559; joiners, those who started to patent for the firm after the M&A = 7,118; leavers, those who started to patent for another company within 5 years after the M&A = 3,515; and stayers, those included in the sample = 43,936.

TABLE 6 Estimated effects of patent complexity and collaborative organizational structure on inventor innovation

	(1)	(2)	(3)	(4)	(5)	(6)
	Inventor patents stock		Inventor forward citations stock		Inventor cumulative patent classes	
Inventor commingling intensity * post-acquisition	1.405***	1.385***	1.154***	1.126**	1.143***	1.125***
	(12.69)	(12.16)	(3.89)	(3.16)	(7.57)	(6.67)
Post-acquisition	1.029***	1.023***	0.961***	0.933***	1.016***	1.024***
	(13.80)	(9.18)	(-7.97)	(-11.02)	(20.41)	(23.31)
Inventor commingling intensity	1.956***	1.963***	1.333***	1.363***	1.727***	1.729***
	(14.15)	(14.25)	(4.76)	(5.12)	(19.72)	(19.73)
Inventor avg patent complexity	1.002***	1.002***	1.002***	1.002***	1.000***	1.000***
	(67.22)	(62.12)	(47.19)	(44.96)	(37.44)	(31.87)
Low complexity * post-acquisition		0.944***		1.001		0.955***
		(-14.99)		(0.09)		(-31.11)
High complexity * post-acquisition		1.054***		1.102***		1.027***
		(13.07)		(10.93)		(15.65)
Firm and inventor controls	Y	Y	Y	Y	Y	Y
Acquiree-Inventor fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Observations	589,671	589,671	529,672	529,672	583,508	583,508

Note:
*1. This table reports exponentiated coefficients in incidence-rate ratios and t-statistics (in parentheses) from conditional Poisson regressions at the inventor-year level. Standard errors are robust. * p<0.05, ** p<0.01, *** p<0.001.*
2. For conditional Poisson models, the reported exponentiated coefficients are incidence-rate ratios: a unit increase in an independent variable scales (multiplies) the dependent variable by the estimated coefficient. A coefficient value less (greater) than one represents a negative (positive) effect.
3. The control variables are listed in Table 1.
4. Inventors included in the sample are the same as ones included in Table 5.
5. High/low complexity is a dummy variable, which equals 1 if the inventor's avg patent complexity is ranked among the highest/lowest quartile.

Appendix: Difference-in-differences parallel trends plots

To examine the parallel trends assumption, we compare the innovation performance (expressed as innovation incident rate ratios, IRRs) between ever-commingled acquired firms and inventors with those who were never involving in commingling. The time trends are listed as below, with the horizontal red line in each panel indicating the prevailing estimated IRR as of the year prior to the acquisition event (recall that values below 1.0 are associated with a negative effect, with values above 1.0 corresponding to a positive effect). The vertical bars around each point estimate designate the 95% confidence interval.

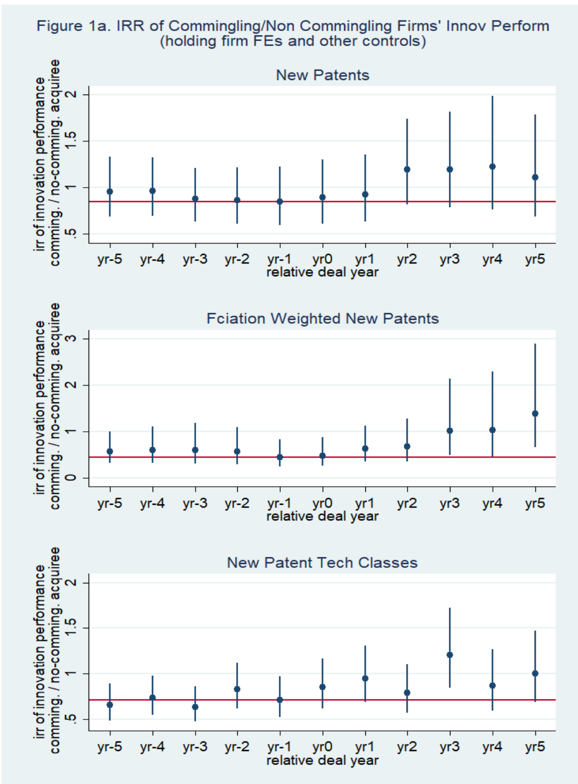

Figure 1a. IRR of Commingling/Non Commingling Firms' Innov Perform (holding firm FEs and other controls)

Figure 1b. IRR of Commingling/Non Commingling Inventors' Innov Perform (holding inv FEs and other controls)