ORGANIZING KNOWLEDGE PRODUCTION WITHIN A FIRM: HOW THE LOCUS OF KNOWLEDGE DIVERSITY SHAPES FIRM-LEVEL INNOVATION

Abstract. While there is broad acknowledgement among strategy scholars that recombining diverse individual-level knowledge benefits firm-level innovation, prior literature has paid less attention to how variance in intra-firm organization may impact the efficacy of the knowledge recombination process. To this end, we examine the link between how a firm's knowledge production teams are organized and the overall innovation output of the firm. Access to diverse knowledge is known to aid knowledge recombination; yet, the prior literature focuses primarily on only one way of achieving that: diversity of inventor-held knowledge within a given knowledge production team ("within-team knowledge diversity"). We introduce the concept of "across-team knowledge diversity," which captures the extent to which knowledge diversity of a firm's inventors is distributed across, rather than within, knowledge production teams. We propose that these two forms of knowledge diversity differ with respect to the conditions under which they are beneficial for firm-level innovation: within-team knowledge diversity is more beneficial when the firm pursues combinatorially-novel inventions; on the other hand, across-team knowledge diversity is generally beneficial for innovation, although the positive effect of across-team knowledge diversity is attenuated by higher levels of within-team collaborative experience. Using a panel dataset of all venture capital-backed U.S. biotechnology ventures founded over a 21-year period and followed annually from inception, we document supporting empirical patterns.

Keywords. Knowledge recombination; internal organization; firm-level innovation

INTRODUCTION

Over the past two decades, the knowledge-based view (KBV) has emerged as a prominent lens through which strategy scholars have sought to understand the origins of competitive advantage (Grant 1996). The foundational principles of the KBV stem from, and continue to influence, a wide range of intellectual traditions within strategy, including the resource-based view of the firm (Barney 1991, Barney et al. 2001), organizational learning (Levitt and March 1988, Schulz 2001), and strategy microfoundations (Felin et al. 2012). While these theoretical perspectives vary in their central explanatory constructs, they collectively acknowledge the uniquely important role of knowledge—which ultimately resides in the minds and experiences of individuals that make up the firm—in explaining differences in performance among firms (Eisenhardt and Santos 2002). The role of knowledge as a determinant of firm performance is particularly salient for firms in fast-moving technology-based settings, where continued growth and survival often necessitate ongoing innovation.

While strategy scholars broadly acknowledge the link between individual-level knowledge and firm-level performance outcomes, the extant literature has made only limited progress in understanding how within-firm organizational factors might influence the efficacy of knowledge integration when firm-level innovation is the primary outcome of interest. Early foundational work on the KBV argues that the purpose of firms is the *integration* of specialized individual knowledge (Grant 1996). Extensive work on group behavior and dynamics has advanced our understanding of knowledge production in individual teams (Jones 2009, Singh and Fleming 2009, Toh and Polidoro 2013, Wuchty et al. 2007). Yet, we still know little about how the broader knowledge context within which a firm's production teams operate might shape firm-level innovation output, and hence, explain the origins of competitive advantage in technology-based settings.

In this paper, we examine the determinants of firm-level innovation output, with our central focus being the *organization* of diverse knowledge within and across a firm's knowledge production teams. We argue that alternative forms of firm-level organization can explain variation in the overall innovative productivity of a firm. Given the centrality of innovation to competitive advantage in knowledge-based settings, recognizing how differential forms of internal organization lead to variation in firm-level innovation should be an important concern for strategy scholars. In contrast with prior literature that has focused on group-level innovation performance antecedents, which address the role of *within-team* knowledge diversity (Ancona and Caldwell 1992, Bantel and Jackson 1989, Hoisl et al. 2016), we introduce the notion of *across-team* knowledge diversity. This concept captures the degree to which diversity of knowledge exists across, rather than within, particular knowledge production teams inside a firm. Taken together, these two constructs (within- and across-team knowledge diversity) provide a more complete representation of how knowledge diversity within a firm can be organized.

In the following section, we elaborate on the distinction between within-team and across-team diversity in the context of a firm's knowledge-based production teams. Given the relative lack of theory as related in particular to the novel construct of across-team diversity, we propose a set of theoretical mechanisms to guide our empirical study relating a firm's within- and across-team knowledge diversity levels to firm-level innovation under various contingent conditions. We confine our attention to firms in which the production of innovation occurs at the level of teams of collaborating individuals, with multiple teams interacting in close proximity to one another such that their interactions create a broader environment for ongoing knowledge exchange.

Empirically, we draw on a sample of venture capital-backed biotechnology firms observed longitudinally from their date of founding, collecting information on the full career experience of their inventors in order to measure their individual-level knowledge. We document robust evidence that across-team knowledge diversity promotes innovation output, with the effect attenuated under conditions of greater within-team collaborative experience. By contrast, within-team diversity can impair firm-level innovation output, except in cases where the firm is pursuing combinatorially-novel inventions. Our findings are consistent with the theory that semi-permeable team boundaries influence the flow of knowledge within and across teams, shaping the efficacy of organizing a firm's individual inventors into teams with varying levels of within- and across-team knowledge diversity. We discuss, in a concluding section, the implications of our findings for work on innovation, organization design, and the continuing development of the KBV.

THEORETICAL BACKGROUND

Intra-Firm Organizing: Dimensions of Knowledge Diversity

To understand how the organization of knowledge diversity inside a firm influences firm-level innovative output, we distinguish within-team knowledge diversity from across-team knowledge diversity. We define *within-team knowledge diversity* as the degree to which an average production team inside the firm has individuals who differ among themselves with respect to the knowledge embodied in their prior technical experience. By contrast, *across-team knowledge diversity* is the degree to which an average production team inside the firm differs from other teams, with respect to the knowledge embodied in the aggregate technical experience of the team's inventors. In the former case, individuals encounter knowledge diversity among their own team members; in the latter case, knowledge diversity resides across team boundaries. Across-team knowledge diversity can be thought of as characteristic of the firm-level environment in which the production teams are embedded. To ensure that across-team knowledge diversity is meaningful, we confine our conceptual development and empirical analyses to firms organized into multiple production teams (Gerwin and Moffat 1997, Sabbagh 1996).

To intuitively illustrate the contrast between across-team versus within-team knowledge diversity, Figure 1 presents two contrasting "organizational knowledge environments." The top panel illustrates a firm with high levels of within-team knowledge diversity and low levels of across-team knowledge diversity, i.e., an organizational knowledge environment where knowledge about a given technological area can be characterized as "diffuse" throughout the firm. By contrast, the bottom panel illustrates a firm with low levels of within-team knowledge diversity and high levels of across-team knowledge diversity, i.e., an organizational knowledge environment where knowledge can be characterized as "concentrated," in the sense that teams hold unique knowledge relative to the other teams in the firm.

[Insert Figure 1 here]

To understand how these two alternate dimensions of organizing knowledge diversity might have distinct implications for firm-level innovation productivity, we first outline the theoretical premise for metaphorical semi-permeable team boundaries that surround the teams where knowledge recombination occurs. We next explain the implication of that semi-permeable team boundary for the *set* of input knowledge that the team draws upon. The set of knowledge upon which the team's recombination process operates is determined by whether any given team has the requisite knowledge among its own inventors. Relative to this set, *where* the knowledge recombination process occurs is within the particular team performing the recombination act that leads to a novel invention. These considerations provide the analytical foundation linking the organization of knowledge diversity with firm-level innovation outcomes.

Semi-permeable team boundary. We conceptualize a metaphorical boundary around the team that selectively allows input knowledge to cross the boundary for use by the team. Like other informal intra-firm boundaries, the team boundary arises from shared sets of goals and incentives—in this case producing innovation output—which result in within-team routines and norms (Bettenhausen and Murnighan 1985, Gersick 1988, Lawrence and Lorsch 1967). These emergent team-based routines define the organizational "sub-unit" boundary around the team. In the context of the broader firm, a team boundary is "semi-permeable": although shared goals and incentives cause individuals to focus inwards towards the team, individuals can "cross" the semi-permeable boundary by interacting with other teams within the firm. This boundary-spanning activity can have implications for the knowledge used in recombination (e.g., Rosenkopf and Nerkar 2001). As we discuss next, the semi-permeable team boundary may differentially affect the set of input knowledge a given team draws upon when recombining knowledge for inventive outcomes.

Set of input knowledge. The organization of a firm's inventive human capital further influences the set of the input knowledge used by its production teams. Given that the individual inventors embody knowledge accumulated through their past experiences (Gruber et al. 2013), the aggregate inventive human capital inside the firm reflects the available *input* knowledge to draw upon in the knowledge recombination process (Bantel and Jackson 1989, Grant 1996, Simon 1991). Accordingly, a production team can draw on input knowledge from across the firm. In contrast with the internal-to-the-team production process, the plausible set of input knowledge for an invention exists across the firm and can be external to the team. In this sense, the production team can search for input knowledge either internally (contained within the team itself) or externally through boundary-spanning (existing inside the firm but on a different production team).[1] Boundary-spanning search for input knowledge outside the team qualitatively differs from search among knowledge held by the production team members themselves. Past research shows how intra-firm organizational boundaries can affect the relative use of knowledge either internal or external to the boundary: hierarchical boundaries inhibit knowledge sharing (Tsai 2002), while centralized R&D allocation, as compared to decentralized R&D, is associated with a broader search process outside of intra-organizational units than firms with decentralized R&D (Argyres and Silverman 2004). Thus, the location of knowledge relative to an intra-firm boundary affects the set of input knowledge emerging from search.

While we focus on the consequences of the organization of knowledge diversity, a mix of antecedent factors determine the organizational structure of teams within a firm, which in turn results in a particular knowledge diversity organizational structure. The structures and processes of individual agency and managerial fiat lead to patterns of team formation arising as an outcome of the firm's organizational architecture (Joseph and Ocasio 2012). While some determinants of this architecture are ultimately subject to managerial control, numerous other factors beyond managerial control—only a subset of which are observable—are likely to come into play. Abstracting away from the *antecedents* of knowledge diversity organization, we focus on the *consequences* of alternative knowledge diversity structures for firm-level knowledge production.[2]

In summary, the organization of human capital defines the semi-permeable team boundaries, which determine the set of input knowledge used in the recombination process in a knowledge production team. We first discuss the firm-level innovation implications of within-team knowledge diversity, and then of across-team knowledge diversity.

Effects of Within-Team Diversity

Within-team knowledge diversity entails a trade-off between direct internal access to diverse knowledge

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[1] We focus here on input knowledge that is available within the firm. We exclude from consideration input knowledge available from outside the firm. However, in our analyses we empirically control for the firm's use of this external knowledge by including a set of covariates related to firm-level knowledge capabilities, which broadly capture the firm's absorptive capacity (Cohen and Levinthal 1990).

[2] In the Discussion section, we address how follow-on work might more directly study team formation precursors.

and diminished boundary-spanning search for knowledge. We explore this trade-off and propose a condition under which within-team knowledge diversity may be more beneficial for firm-level innovation.

On one hand, within-team knowledge diversity provides accessible input knowledge benefiting the recombination process occurring within teams. Internally accessible diverse knowledge does not require crossing an organizational boundary, as the knowledge resides within the members of the production team. Higher levels of within-team knowledge diversity ensure that there are more possible combinations of prior input knowledge that can result in an innovation (Leiponen and Helfat 2010, March 1991). By this argument, proximal access to appropriate input knowledge facilitates recombination, and as such, within-team knowledge diversity can benefit knowledge production.

On the other hand, within-team knowledge may limit the degree to which a team engages in boundary-spanning search to seek out diverse knowledge. Boundary-spanning activities can promote the beneficial use of higher-quality knowledge that better suits the innovative efforts of a focal production team (Rosenkopf and Nerkar 2001, Stuart and Podolny 1996). However, the inertia of within-firm routines favors knowledge within the team (Bettenhausen and Murnighan 1985, Eisenhardt et al. 1997, Klimoski and Mohammed 1994, Tajfel 1982, Zucker 1977). When diverse knowledge is present within the production team, teams are less likely to seek out input knowledge externally: "slack" excess knowledge diminishes incentives to search and to seek input knowledge outside the focal production team, much in the way that slack resources at the firm level can reduce discipline in innovative projects (Nohria and Gulati 1996). As a result, diverse teams may over-favor the use of within-team knowledge. The tendency toward non-boundary-spanning search for sourcing diverse knowledge may then reduce the efficacy of the team's innovation efforts: as such, within-team knowledge diversity could harm knowledge production.

The implications of the trade-off likely depend on the degree to which the firm and its production teams pursue inventions that are combinatorially novel. Combinatorially-novel inventions recombine technological components not recombined in the past, usually consisting of distant components (Fleming 2001, Fleming and Sorenson 2001). Depending on the degree to which the firm chooses to orient itself toward pursuing more exploratory versus exploitative search, its teams would recombine knowledge from distant or similar domains respectively, with distant recombination being more combinatorially-novel.

Combinatorial novelty can have a moderating effect on the relationship between within-team knowledge diversity and firm-level innovation. In situations where firms are pursuing less combinatorially-novel inventions, the downsides associated with pressure to incorporate (unnecessarily) diverse technological components into an invention will outweigh the benefits of access to diverse knowledge within the team. On the other hand, when firms are pursuing more combinatorially-novel inventions, the benefits of within-team access to the diverse knowledge necessary to realize these novel knowledge outcomes will dominate. Thus, whether within-team knowledge diversity benefits or harms firm-level innovation output is contingent on the combinatorial novelty of the firm's inventions.

This theoretical discussion leaves ambiguous the aggregate general effect of within-team knowledge diversity, but suggests a generalizable moderating effect from combinatorial novelty. The aggregate direct effect depends on the relative context-specific strength of the two mechanisms: within-team diversity benefits the direct internal access to diverse knowledge, but also diminishes boundary-spanning search for knowledge. The aggregate effect may differ across contexts: our particular empirical study consists of early-stage biotechnology firms which value exploratory innovation more than more established firms in other industries (e.g., Gans and Stern 2003). Nevertheless, combinatorial novelty may moderate the balance between these two mechanisms, generalizable across contexts, regardless of whichever dominates.

Effects of Across-Team Diversity

Across-team knowledge diversity enhances the returns to boundary-spanning search by the firm's production teams, but the efficacy of this search is moderated by the extent to which the production teams actually engage in boundary-spanning search.

Boundary-spanning search within a firm, across intra-organizational boundaries, can have innovation-related benefits when production teams are embedded in a rich firm-level environment of across-team knowledge diversity. Higher levels of across-team knowledge diversity expand the scope of possible input knowledge available to a production team, increasing the likelihood of a useful recombination (Leiponen and Helfat 2010). Rosenkopf and Nerkar (2001) propose that there is an interaction between the range of exploratory search in technological space (local versus distant) and whether or not the exploratory search spans an organizational boundary (internal or external). Search that is distant in the technical space and that also spans the boundary is deemed to be "radical" exploration, providing the highest overall impact because the resulting innovations are relevant to a broad cross-section of innovators. Because innovation output is highest when the associated technological exploration crosses both technological and organizational boundaries, greater levels of across-team knowledge diversity will likely increase the efficacy of firm-level innovation by offering production teams the possibility of developing more innovative combinations through distant search.

Given that across-team knowledge diversity resides outside the boundaries of a particular production team, teams must cross a semi-permeable boundary to access across-team knowledge held within the firm but outside the focal production team. Members of the production team engage in a boundary-spanning role (March and Simon 1958, Tushman 1977, Tushman and Katz 1980) and serve as a filter in the boundary-spanning process (Tushman 1977). These individuals involved in the search for input knowledge outside the team boundary do not necessarily need to incorporate the across-team knowledge. Therefore, they can operate with comparative freedom in the process of choosing which across-team knowledge to incorporate than they would for selecting which within-team knowledge to incorporate. The benefits of across-team knowledge diversity when engaging in boundary-spanning search, together with the lack of pressure to incorporate this into inventions, suggest that across-team knowledge diversity should generally be beneficial for firm-level innovation output.

The ability of a particular production team to effectively utilize across-team knowledge depends in large measure on the degree to which the team actually engages in boundary-spanning versus non-boundary-spanning search when seeking out knowledge. To examine this, we consider within-team collaborative experience as a possible determinant of boundary-spanning activity. While within-team experience can have a positive effect on a production team's innovative performance by reducing within-team coordination costs (Kotha et al. 2012), we propose that greater within-team experience may limit valuable boundary-spanning activity. Prior within-team experience in collaborating on the production of innovations may, via greater group identity and cohesion, strengthen the routines that affect the relative balance between local and boundary-spanning search (Leonard-Barton 1992, Levitt and March 1988, Nelson and Winter 1982). In other words, greater levels of within-team collaborative experience make the semi-permeable team boundary more impermeable, restricting a production team's access to knowledge outside of the team. This shift from boundary-spanning to more non-boundary-spanning search reduces the possible benefits a production team can derive from being embedded in an environment of rich across-team knowledge diversity.

Taking these arguments together, we conjecture that across-team knowledge diversity unambiguously benefits firm-level innovation output, while within-team collaborative experience attenuates that benefit.

METHODOLOGY

Industry Setting

To examine the firm-level innovation implications of across- and within-team knowledge diversity, we seek an industry in which innovation output is a key performance metric and the use of multiple teams within a firm is commonplace. The biotechnology industry fits these requirements and also has several other beneficial characteristics for the purpose of this study. First, this setting is one in which knowledge-based resources are an important driver of innovation output, consistent with our objective of studying the link between the organization of knowledge-oriented human capital and firm-level innovation. Patents are a key means of value appropriation in the biotechnology industry (e.g., Levin et al. 1987), and as such we can be more confident in relying on patent data to capture the relevant individual- and team-level characteristics that serve as precursors to the firm's innovative output.

The biotechnology industry is one in which teams generally work independently from one another, and a particular team's production process is not directly dependent on another team's output. At the same time, any given team will likely hold knowledge that may be of use to other teams because teams operate within a shared overall knowledge space. Additionally, focusing on start-up firms in this industry not only avoids issues of left-censoring but also provides a setting in which lower levels of geographic dispersion allow knowledge sharing across teams (as compared to multiproduct, multinational settings).

This setting exposes the structure of the firm's production teams for empirical observation. Firms generally patent all inventions, and the resulting patent records—which contain names of individual inventors—reveal team composition to observers. For empirical purposes, production teams are defined as the set of inventors meriting attribution on a patent team. Patent data therefore has the primary benefit of enabling us to observe staffing in a large sample panel, which would otherwise be difficult to obtain systematically, especially across firms. In addition, the historical patent record allows us to construct detailed inventor career histories, allowing for comprehensive tracking of an inventor's technical experience both before and during their tenure at an in-sample firm. We use this inventive experience as a measure of the inventor's knowledge.

Although we leverage this data in order to observe a large sample of realized team structures, identifying teams in this way does impose some limits to the generalizability of our data. Our data reveal the *ex post* realized team structures associated with inventions, but not necessarily the *ex ante* team structure as imposed by management. As a result, the team structures reflect a combination of managerial design and employee discretion. Thus, our results may not generalize to settings where team structures arise solely through direct managerial fiat. We discuss these issues in more detail in the Discussion section.

Data and Sample

To construct our sample, we seek a set of firms that are as homogeneous as possible, apart from the dimension of team organization, in order to construct comparable and meaningful measures of innovation. Confining the sample to a single industry provides uniformity in interpreting firm-level objectives. Additionally, restricting the sample to venture capital-backed firms increases the commonality of the objectives and time horizons facing firms in our sample. Together, these factors reduce unobserved differences across firms, aside from the desired dimension of heterogeneity in team organization.

Our empirical sample is the universe of 476 venture capital-backed human biotechnology firms (SIC codes 2833–2836) founded between 1980 and 2000, as identified using the VentureXpert database.

Our primary dataset is an unbalanced firm-year panel in which firms are observed from their year of founding through either 2009 or, if sooner, their year of dissolution. (A longer time window facilitates within-firm inference.) In addition to including all years in which the firm is privately held, we also include in our observation window firm-years following an IPO or acquisition by another entity, together with controls for these alternate ownership regimes.[3] We utilize several sources to construct our variables. The IQSS Patent Network database includes all U.S. Patent and Trademark Office data on patents applied for since 1975 (Li et al. 2014), allowing us to uniquely identify inventors associated with patents and to construct various measures of the production teams engaged in the creation of patents. Firm-year level attributes come from Deloitte Recap RDNA, Pharmaprojects, Inteleos, ThomsonOne, Zephyr, and SEC filings.

Dependent Variables

The main dependent variable is the number of *forward citations* received within a four-year post-application window to the firm's patents in the focal firm-year. We use this measure because forward citations are an accepted measure of innovation output (Jaffe and Trajtenberg 2002, Trajtenberg 1990), standing in as a proxy for the economic and social value created by the patented innovations.[4] A fixed citation window also facilitates meaningful comparisons across observation years: without such a window, older patents would be artificially biased upwards in citation count. In supplemental analyses, we include total (non-citation-weighted) *patent count* as an alternate dependent variable.[5]

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[3] In order to collect patent data on a firm's post-M&A years we follow the procedure outlined in Aggarwal and Hsu (2014), which identifies a firm's inventors pre-acquisition and matches them to patenting activity by the same inventors in the acquiring firm post-acquisition.

[4] Our findings using forward citations within a four-year post-application window are robust to the inclusion or exclusion of self-citations to the inventions by the inventors on a patent team and self-citations to patents by the focal firm itself.

[5] Patent count is included as a control in specifications where forward citation count is the outcome variable. Neither *forward citations* nor *patent count* accounts for the activities of the firm that lead to "unsuccessful" innovative output that does not lead to a patentable output, a constraint stemming from the data generation process that affects this and other research utilizing patent data. In the context of our main forward citation-based dependent variable, this data limitation bounds the interpretation of our findings to only the effect of production team diversity on the quality of patented inventions, which reflect the upper part of the quality distribution of all possible inventions.

Independent Variables

Our primary independent variables of theoretical interest are within- and across-team knowledge diversity, which we measure using individual inventors' career patenting experience. The *within-team knowledge diversity* variable captures the diversity of knowledge among different inventors on a particular production team.[6] To create this variable, we first measure the angular distance between the knowledge experience of each pair of inventors on a team (as described in further detail below, as well as in the Appendix), and then take the mean of this value across all pairs of inventors on a team. The *within-team knowledge diversity* variable is then the average of this team-level value for all teams in a firm-year (our level of analysis). The *across-team knowledge diversity* variable captures the degree to which production teams within the firm differ from one another with respect to each team's aggregate knowledge. This variable is constructed as the average of the knowledge experience angular distance between all pairs of teams in the firm-year (as described in further detail below, as well as in the Appendix).[7]

The angular distance between pairs of inventors, used to calculate *within-team knowledge diversity*, and pairs of production teams, used in order to calculate *across-team knowledge diversity*, are both based on Jaffe's (1986) cosine similarity measure. For each inventor at each year of her career, we capture her knowledge experience with a "class experience vector," consisting of the total experience the inventor has had patenting in each technology class. An inventor's total experience includes her entire history, and as such captures experience not only in the context of her current firm, but also in all prior firms. For a particular inventor, a given entry in the class experience vector thus represents the stock count of that inventor's patents in that particular technological class through the focal year, with the dimension of the vector being the total number of primary patent classes used by the USPTO. In the case of any two

[6] We use a dyadically-determined measure of diversity, which, as opposed to a measure based upon concentration (i.e., Herfindahl index) or variance, allows us to take the full range of an inventor's experience into account and provide a complete measure of diversity among all the technological experience dimensions within a production team (i.e., a particular patent).

[7] We organize our empirical analyses with these two forms of knowledge diversity estimated as independent constructs. In unreported results, we find that our theoretical predictions are robust to the inclusion of the interaction effect among the two constructs. We also find that the interaction is not significant in our model specifications; we thus choose to report the more concise model specification (i.e., without the interaction).

inventors, for example, Jaffe's (1986) cosine similarity measure would be calculated as the "angular separation" between the corresponding class experience vectors. Cosine diversity is defined as 1 minus the cosine similarity measure; as such, the two diversity measures range from 0 to 1, where 1 is completely diverse (no overlap among class experience vectors) and 0 is completely homogeneous (full overlap among class experience vectors).

The *within-team knowledge diversity* measure is created by forming all possible dyads between inventors on a particular production team, calculating the cosine diversity for each dyad, averaging this for inventor dyads on a production team, and then aggregating to the firm-year level by taking the average for all patents in the firm-year. The *across-team knowledge diversity* measure is created by first summing the class experience vectors of the inventors on a given production team (i.e., a particular patent) in order to create a single (aggregate) class experience vector for the entire production team. We then take the set of patents of the firm in the firm-year, form all possible dyads among these patents, calculate the cosine diversity measure among patents based on their respective aggregate class experience vectors (in contrast to within-team knowledge diversity where the cosine diversity measure is calculated among dyads of inventors within a team, in the case of across-team knowledge diversity it is calculated among dyads of patents), and then calculate the average over all dyads of patents in the firm-year. We calculate across-team knowledge diversity across teams rather than across individuals (i.e., across the dyads of individuals in the firm) because we want a measure that captures the diversity of the firm in the context of the organization of teams within the firm.[8] We provide a detailed example of how the two knowledge diversity measures are calculated in the Appendix.

Moderators

Our measure of *combinatorial novelty* draws on the measure of complexity in Fleming (2001) and Fleming & Sorenson (2001). Their measure proposes that truly novel inventions recombine technological components, represented by patent subclasses, that have not been frequently recombined in the past. The

[8] The inclusion of a firm-level diversity measure as calculated across all dyads of individual inventors in the firm does not change the sign or significance of the two main independent variables.

combinatorial novelty for a patent is the sum of the "ease of recombination" for all subclasses on the patent at the time of the patent application. Ease of recombination of a particular subclass at a given time is the ratio of the number of other subclasses combined with the subclass and the number of previous patents in the subclass. In other words, the measure captures how often new components are combined with a focal component, normalized by the number of times the focal component appears. The measure gets larger when there are more subclasses combined with each of the subclasses on the focal patent and when the focal patent contains more subclasses, but gets smaller when there are more previous patents in the subclasses on the focal patent. The firm-year measure of *combinatorial novelty* is the average across all patents in a firm-year patent portfolio.

We construct measures of prior *within-team collaborative experience* between different inventors. For any two inventors i and $-i$, joint experience at time t is defined as the stock count of patents for which both inventors were on the same patent team at any point in their career through time t. The measure is constructed by averaging the joint experience between all dyads of inventors on the same patent team, which is then averaged over all patent teams in a firm-year.

Control Variables

We employ a set of time-varying control variables (measured at the firm-year level) to account for residual differences beyond the time-invariant firm-level characteristics addressed by the inclusion of firm fixed effects across all models. There are four categories of controls: production team patenting controls; firm patenting controls; corporate (firm-level) controls; and top management team diversity (TMT) controls.

Production team patenting controls. We account for the aggregate technological experience embodied in the firm's inventors at the level of the production team, averaged across teams in the firm-year. These variables account for the knowledge and experience contained within a firm's teams, and as such implicitly incorporate the implications of how a firm's teams are organized. The "firm patenting controls" discussed next, on the other hand, control for knowledge and experience of the firm as a whole.

The experience of a particular inventor within a team includes not only that which the inventor has gained within the context of the focal firm itself, but also that which the inventor has gained over the course of her entire career. We construct the following variables: *team patenting experience*, which measures the average number of patents collectively held by inventors on a production team; *team forward citation experience*, which similarly measures the average number of forward citations collectively held by inventors on a production team; and *team class experience*, which measures the unique number of patent classes represented by inventors on a production team. All measures are averaged across the firm's production teams in a given firm-year and, as noted above, capture inventors' entire career histories.

Firm patenting controls. These account for characteristics of the firm's overall patent portfolio, and the inventors associated with these patents. In conjunction with the set of "corporate controls" described next, these variables account for various time-varying dimensions of firm scale, scope, and quality, all of which may be correlated with both the knowledge diversity characteristics we use as our core theoretical measures, as well as our main dependent variable capturing innovation output.

The firm patenting controls include *patent count*, which is the total number of patents applied for by the firm in the firm-year; *inventor count*, which is the number of unique inventors in the firm-year; and *class span*, which is the number of unique classes in which the firm patents in the firm-year. These controls thus account for aspects of the firm's innovative capacity separate from the two forms of knowledge diversity that we are concerned with theoretically. *Total collaborative experience* is the average level of joint experience among all dyads formed from the full set of inventors patenting in a firm-year, constructed in a similar matter to within-team collaborative experience, described above. This control serves primarily as a counterpart to the moderator of *within-team collaborative experience*, to ensure that the main moderator measures collaboration only within teams and does not errantly measure all collaboration within the firm, which is a correlated activity and measure.

Corporate (firm-level) controls. These measures further account for time-varying characteristics of the startup firm that could correlate with both knowledge diversity characteristics and innovation. Collectively, these variables capture characteristics of firm quality and development stage that are particularly relevant in our industry setting of early-stage venture capital-backed biotechnology firms.

The variables we create are: *age* of the firm in years since founding (from VentureXpert and public sources); *VC inflows stock*, which measures the cumulative venture capital investment into the firm (from VentureXpert); *strategic alliance stock*, which measures the cumulative stock of alliances in which the firm has been involved to date (from Deloitte Recap RDNA); and *active product*, which is an indicator for whether the firm has at least one active product in the U.S. Food and Drug Administration (FDA) pipeline (from PharmaProjects and Inteleos). While privately-held is the baseline ownership scenario, we also control for the firm's ownership using the *post-IPO* and *post-M&A* variables (hand-collected using archival news sources), as the ownership regime of the firm may influence both knowledge diversity characteristics and innovation (Aggarwal and Hsu 2014). *Post-IPO* indicates that the firm has undergone an initial public offering (IPO) in or before the focal year, and *post-M&A* is an indicator that the firm has undergone a merger or been acquired in or before the focal year.

TMT diversity controls. We capture top management team characteristics that might influence both the organization of knowledge diversity among the firm's inventors, as well as innovation output. Diverse top management teams are associated with greater innovation (Bantel and Jackson 1989), and TMT diversity may also correlate with the two dimensions of diversity at the inventive human capital level that we study. For each firm, we manually collect data from public sources such as publicly viewable LinkedIn profiles and BoardEx to construct a full history of the top management team of each firm, focusing specifically on those holding C-suite titles (CEO, CTO, etc.). From there we construct Herfindahl measures of various characteristics of the management team for each firm-year. For each member of the top management team we capture age, job tenure at the focal firm, and educational duration to construct (using a Herfindahl measure) the level of concentration of these characteristics within the firm-year. These measures of age, job tenure, and educational duration diversity are highly correlated, so we average these three measures into a composite measure of *TMT Diversity*.[9]

Table 1 provides definitions and summary statistics, while Table 2 provides pair-wise correlations of our independent variables.

[Insert Table 1 and Table 2 here]

[9] Our results are also robust to including any one of these measures individually.

Model Specification

We employ conditional fixed effects Poisson models with robust standard errors in our main analyses at the firm-year level. This estimation technique is appropriate because our main dependent variable, *forward citations*, is a non-negative count (Hall and Ziedonis 2001, Hausman et al. 1984). We employ firm and year fixed effects throughout all models in order to control for time-invariant firm qualities and year-to-year changes that might correlate both with our two forms of knowledge diversity and with firm innovation. Together with the set of controls described above, the conditional firm fixed effects model facilitates the interpretation of our results as estimating within-firm, across-time effects.

RESULTS

In Tables 3, 4, and 5, we present estimates of the models used to measure the potential effect of within- and across-team knowledge diversity on firm-level innovation. The coefficients reported in the tables are incidence-rate ratios, which represent the exponentiated form of the regression coefficients in a conditional fixed effects Poisson model. These coefficients can be interpreted as follows: for a unit increase in an independent variable, the incidence rate of the dependent variable would be expected to be scaled (multiplied) by the value of the estimated coefficient. Thus, a coefficient value less than one should be interpreted as a negative effect, while a coefficient value greater than one should be interpreted as a positive effect.

Within-Team Knowledge Diversity

In Table 3, we present estimates of our models of *within-team knowledge diversity*, contingent on the *combinatorial novelty* pursued by the firm. All of the models utilize *forward citations* as the dependent variable, employing Poisson specifications at the firm-year level with conditional firm and year fixed effects, together with robust standard errors. As noted previously, the dependent variable—citations to the focal firm-year filed patents within a four-year window—represents a measure of innovation output. The first three models vary in the sets of control variables included, starting with the production team patenting controls (3-1), adding in the firm patenting and corporate controls (3-2) and the TMT diversity controls (3-

3).[10] Among the control variables, we find a positive significant association between the dependent variable and some measures of the firm's current patenting and past strategic alliances, a negative significant association for an M&A event, and a positive significant association with TMT diversity, consistent with prior findings in the literature.

As a main effect, we find that *within-team knowledge diversity* is negatively associated with innovation outcomes in our context. Our estimates suggest that moving from completely homogeneous (0) to fully diverse (1) with the firm's level of *within-team knowledge diversity* corresponds to approximately 50% fewer *forward citations* across all models, with significant *p*-values of under 5% for models (3-1) to (3-3) and under 1% for models (3-4) and (3-5). In the most fully specified base model (3-3), going from complete homogeneity to fully diverse within-team knowledge is associated with 57% fewer *forward citations* within a four-year window of patenting.

In models (3-4) and (3-5), we test the moderator of combinatorial novelty. The coefficient on *within-team knowledge diversity*, reflecting the condition of low *combinatorial novelty*, continues to have a significant negative effect on the dependent variable. In model (3-5), we find that high *combinatorial novelty* moderates the negative effect of *within-team knowledge diversity*, so much so that under a regime of high *combinatorial novelty*, the coefficient reverses and become positive. The interaction term is significant at the 10% level in this model, and the same result holds at the 5% level in a robustness check presented on Table 5 (model (5-2)). Thus, when the innovations sought by the firm are more complex and novel, having within-team knowledge diversity within the teams can have value. The left panel of Figure 2 graphically represents the moderator effect.

[Insert Table 3 and Figure 2 here]

Across-Team Knowledge Diversity

In Table 4, we present estimates of our models for the main effect of across-team knowledge diversity and the moderator of within-team collaborative experience. These follow the same sequence of empirical

[10] We find (in unreported regressions) that our results are robust to including various combinations of the firm patenting controls of *patent count*, *inventor count*, and *class span*.

models as in Table 3. Across all models (4-1) through (4-5), we find a consistent and stable positive coefficient on the main independent variable of *across-team knowledge diversity*, all significant at below the 1% level. With respect to the economic magnitude of these results, hypothetically shifting the firm's level of *across-team knowledge diversity* from complete homogeneity (0) to fully diverse (1) would yield 90% more *forward citations* in the most parsimonious model (4-1) to 63% more *forward citations* in the fully specified model without the moderator (4-3). This finding suggests that across-team knowledge diversity generally has a positive main effect on innovation output.

In models (4-4) and (4-5), we introduce the moderator of *within-team collaborative experience*. We find that high *within-team collaborative experience* moderates the positive effect of *across-team knowledge diversity*, but not to the point of completely offsetting the main across-team diversity effect. Interpreted through our theoretical framing, this finding suggests that inventors with more prior collaborative experience can make the team boundary less permeable, reducing the benefits of across-team knowledge diversity. The right panel of Figure 2 graphically represents this effect.

[Insert Table 4 here]

Supplemental Analyses

Table 5 presents fully specified models with both *across-team knowledge diversity* and *within-team knowledge diversity* independent variables included, enabling us to run a comparative test between the effects of within- and across-team knowledge diversity. Models (5-1) and (5-2) have forward citations as the dependent variable and contain the full set of controls. Model (5-2) includes both moderators simultaneously, with both moderators interacted with the two dimensions of knowledge diversity. We continue to find significant results on the main independent variables and moderators consistent in direction with the previous tests. To compare the magnitude of the coefficients on within- and across-team knowledge diversity, we perform a Wald test on the equality of coefficients: in each of the models we can reject the null that the coefficients are equal with a *p*-value of less than 0.1%, suggesting that *across-team knowledge diversity* is associated with higher-quality firm-level innovation as compared to *within-team knowledge diversity*.

In models (5-3) and (5-4) we estimate the same models as (5-1) and (5-2), but using *patent count* as the dependent variable instead. While *patent count* does not necessarily demonstrate much about the value of the innovative contributions made, a simple patent count-based measure can be characterized as a measure of the contemporaneous inputs into the R&D process, representing the effort and expenditures going into the process (Jaffe and Trajtenberg 2002). We find that *within-team knowledge diversity* continues to be significant, while the coefficient of *across-team knowledge diversity* is positive and statistically significant in (5-4) but not significant in (5-3). In model (5-4), the interaction between within-team knowledge diversity and combinatorial novelty continues to be positive but is not significant in this case, while the interaction between *across-team knowledge diversity* and within-team collaborative experience continues to be negative and significant. While innovation output as measured by *forward citations* remains the most theoretically relevant outcome variable, our predicted effects also apply, albeit a lesser degree, to *patent count* as a dependent variable.

[Insert Table 5 here]

Robustness Checks

The main effects in Tables 3, 4, and 5, are robust to differing combinations of the various control variables: production team patenting controls; firm patenting controls; corporate (firm-level) controls; and top management team diversity (TMT) controls. All empirical results are also robust to the inclusion of all the various permutations of Herfindahl-based measures of age, job tenure, and education duration measures instead of *TMT Diversity*. The results are also robust to the use of an ordinary least squares model (OLS) with firm fixed effects and the same variable specification.

Endogeneity Considerations

The main endogeneity concern for a study of this type is that there is an omitted variable that relates to firm quality which could correlate both with how knowledge diversity is organized within the firm (either or both of the two main independent variables) as well as with innovation output (the dependent variable). For example, a superior management team may be able to impose a particular structure of knowledge diversity within the firm, while at the same time also exerting a positive influence on the firm's innovation output quality, with this influence occurring *independently* of the effect on the structure of knowledge diversity. More generally, the firm may select a structure due to an unobserved or unmeasurable factor that also drives the innovation outcomes. While we cannot fully exclude this possibility, the inclusion of firm fixed effects mitigates endogeneity resulting from unobserved, time-invariant factors. Furthermore, the set of control variables described above is designed to control for further omitted variables that are time-varying.

The second endogeneity concern is related to simultaneity bias, i.e., reverse causality, between the dependent variable of innovation output and the main independent variables. In other words, the innovation output of the firm drives the across- and within-team knowledge diversity rather than the alternative that we propose. This reverse effect could be the case if firms with more promising innovation possibilities choose to select more or less diverse team structures to implement the innovation. Alternatively, firms with more innovative output may be able to become more diverse because they have greater resources from their innovation and can choose to be diverse while other firms may be constrained from doing so. To examine this type of bias, we ran all our models with one-year lagged versions of the main independent variables relative to the main independent variables. We find consistent signs and coefficients. These models capture the effect of the previous year's diversity structure on the present year's innovation output and other dependent variables. The findings of these models are inconsistent with reverse-causality explanations, presuming that future innovation output cannot affect the past diversity structure. In addition, as in addressing omitted variables bias, the inclusion of firm fixed effects mitigates endogeneity resulting from unobserved, time-invariant factors associated with reverse causality. Nevertheless, the antecedents of production team formation are an important research agenda in their own right, which we touch upon in the concluding discussion.

DISCUSSION

In contrast with much of the extant literature on diversity and innovation, which focuses on the *team- or sub-unit*-level implications of knowledge diversity, we show that knowledge diversity arising from the *firm*-level organization of inventive human capital can play a key role in influencing the efficacy of a firm's knowledge-generation processes. We introduce the novel conceptualization of across-team knowledge diversity, which stands in contrast to the well-developed construct of within-team knowledge diversity. In a longitudinal study of the venture capital-backed biotechnology firms, we find that firms organized with higher levels of within-team knowledge diversity in their production teams are associated with lower levels of firm-level innovation, except when pursuing combinatorially-novel inventions. Across-team knowledge diversity, on the other hand, is generally associated with higher levels of firm-level innovation output, with the positive effect attenuated by greater levels of within-team collaborative experience.

Implications

Our firm-level view of the organization of knowledge diversity has theoretical implications for work on intra-firm networks, organization design, and the knowledge-based view of the firm, as well as practical implications for managers. First, with respect to intra-firm knowledge networks, a large body of work has sought to understand how ties between individuals and between organizational sub-units within the firm influence the sourcing, use, and creation of knowledge (Grigoriou and Rothaermel 2013, Nerkar and Paruchuri 2005, Tsai 2002). A central theme of work in this domain relates to innovation arising from inter-personal ties across sub-units within the firm, which enable workers and sub-units to utilize knowledge developed elsewhere in the firm. Our findings suggest that a key moderating influence on access to such knowledge is the strength of within-team ties: higher levels of within-team collaborative experience influence the extent to which members of a particular team are able to draw upon knowledge from ties with individuals on other teams inside the firm. Another theme in this domain relates to the innovative capacity of peripheral players in the firm, which suggests that players holding weaker intra-organizational ties are relatively unconstrained from social influences, allowing them to be more creative (Perry-Smith 2006). Our findings for the generalized benefits of across-team knowledge diversity complement these insights, which result from the inventive teams being less constrained with respect to their use of diverse knowledge than they would be for within-team knowledge diversity.

Furthermore, this study informs several open questions on the topic of intra-firm knowledge networks. In a recent review article, Phelps, Heidl, and Wadhwa (2012) suggest that a key open question in this domain is how a firm's overall network structure influences knowledge creation at the level of the organizational sub-unit. Our paper helps to address this question by identifying the critical role of intra-organizational (team) boundaries as a component of the firm's overall network structure. Intra-organizational boundaries moderate the use of intra-firm knowledge by shaping the nature and quality of input knowledge used in the inventive process. Another open question concerns the role of knowledge diversity among organizational sub-units in knowledge creation: this paper addresses this precisely in our conceptualization of across-team diversity and its empirical effect on firm-level innovation output.

Second, our study has implications for work on organization design, which is concerned with how knowledge and information should be provisioned across different actors and sub-units within a firm (Puranam et al. 2012, 2014). To engage in effective production—such as of knowledge-related output—individual sub-units need access to requisite knowledge and information which serve as inputs to the knowledge production process. Coordinating and integrating this knowledge across a firm's sub-units allow for the generation of new knowledge. Effective organization design relies upon tools such as physical co-location to mitigate communication and coordination costs and to ensure a free flow of information among productive participants when these flows are appropriate. The permeability of the team boundary conceptualized in this paper can serve in a similar capacity: such a boundary can influence the nature of information flows among organizational sub-units, and hence the nature of knowledge inputs used by a given sub-unit. Thus, the organization design of human capital within the firm can shape the efficacy of information flows and, by extension, the overall efficacy of the firm's pool of inventors.

Third, our results have theoretical implications for the broader knowledge-based view of the firm (KBV). KBV argues that inter-firm performance heterogeneity ultimately stems from the ability of firms to integrate the specialized knowledge of individuals (Grant 1996, Kogut and Zander 1992). This work recognizes the importance of individuals, their knowledge, and the within-firm flow of such knowledge as key component pieces of the innovation puzzle. However, our understanding of the ways in which knowledge is integrated and then influences innovation performance remains somewhat underdeveloped. Firms face challenges in sharing and transferring knowledge internally across barriers at the individual and group levels (Gupta and Govindarajan 2000, Szulanski 1996), and in overcoming these barriers to effectively transfer knowledge, such as through the use of electronic documents (Hansen and Haas 2001). Our study suggests that the organization of inventive human capital within a firm can play a key role in shaping the nature of knowledge flows that do occur, and hence the overall efficacy of the firm as a vehicle for integrating individual-level knowledge.

Finally, our work suggests that the organization of human capital should be a core managerial consideration, particularly given the growing recognition of human capital as a source of competitive advantage (Campbell et al. 2012) and the importance of teams in the innovation process, where innovation is now a central source of firm-level competitive advantage. Managers should pay particular attention to the ways in which the technical and collaborative experience characteristics of a firm's inventors interact with the mechanisms that firms use to shape knowledge flows among different parts of the organization.

Limitations and Future Research

In our conceptual development and empirical analysis, we abstract away from the antecedents of production team formation and instead focus primarily on the innovation consequences of alternate patterns of human capital (and knowledge diversity) organization. Production teams may arise from some combination of managerial fiat and self-organizing activities by the inventors themselves. In hierarchical organizations, managers may explicitly assign formal teams; the organizational behavior literature, and increasingly the strategy literature, document the antecedents to formal team structures. Alternatively, production teams can self-organize: team members may organically search for team members, and then decide to work together of their own volition. There is a limited literature on the process and outcome of self-organization, but such situations can be conceptualized either as informal working relationships that form "at the water cooler," or in a more intentional way, as in agile or scrum development teams, which are common in software industry settings. In a recent paper, Mortensen and Haas (2016) review the changing nature of team boundaries, arguing that teams have become more fluid, with increasingly greater degrees of overlap; other recent papers examine the team performance consequences of such fluid configurations (Edmondson 2012, Valentine and Edmondson 2014).

Our main empirical results are robust to many empirical specifications, including the consideration of many models and control variables, but unobserved factors may bias our empirical estimates. In particular, as discussed above, our setting is certainly one where teams are not static and where factors outside of our study determine the composition of our observed teams. However, endogeneity concerns arising from the team formation process are likely to have a second-order effect relative to the main relationship between firm organization and innovation argued in this paper. First, given that for across-team knowledge diversity (our main novel construct), there is no prior literature or managerial assumptions about the role it might play (particularly relative to within-team knowledge diversity), it is unlikely that managers or inventors would have strong priors regarding how to organize in order to maximize the benefits of knowledge diversity. Accordingly, there is likely no strong *ex ante* basis for intentionally organizing with high or low levels of across-team knowledge diversity. Furthermore, the biotechnology R&D context mitigates possible concerns because the inventive process in this industry is not formulaic: managers themselves are thus unlikely to have strong *ex ante* beliefs regarding optimal knowledge diversity structure and innovation-related outcomes.[11] Future follow-on work might more fully address the team formation process by conducting field experiments in inventive firms, where production teams are randomly assigned with respect to each inventor's patenting experience across technology classes.

Future work, perhaps employing more in-depth qualitative methods, might examine the micro-processes leading to the creation of semi-permeable team boundaries, and in so doing further expand our understanding of the factors that lead to the benefits associated with across-team (versus within-team) knowledge diversity. Our present study also only considers the team boundary, but there are other forms of intra-firm boundaries, such as the laboratory boundary, functional boundary, or department boundary, identified in the literature that may have a similar or different effect as the team boundary for search processes (e.g., Tushman 1977).

Our results also suggest that future work on organization design—particularly work on teams and other intermediate levels of analysis between individuals and the firm (such as production units more

[11] We confirmed this intuition with a series of ten qualitative interviews with biotechnology industry managers, which reflected a wide range of opinion on the issue of production team composition for innovation efficacy.

generally)—can benefit from taking into account the "across-team" dimension of knowledge available to people within the firm. While the dimension of "within-team" diversity has been well-studied, the dimension of "across-team" diversity has been relatively understudied. Paying closer attention to the role of inter-team organization may lead to a potentially fruitful interplay between the rich literatures on teams and on organization design.

CONCLUSION

The prior literature focuses primarily on access to diverse knowledge as an input to the knowledge recombination process. We suggest that when conceptualized at the firm level, knowledge diversity can be characterized along two distinct dimensions: within-team and across-team. The latter captures the extent to which knowledge diversity of a firm's inventors is distributed across, rather than within, production teams, thereby taking into account characteristics of the firm's internal organization. Our theory development and results suggest that the alternate forms of inventive human capital organization can be differentially effective with respect to firm-level innovation: within-team knowledge diversity is beneficial when the firm pursues combinatorially-novel inventions, while across-team knowledge diversity is generally beneficial for innovation, where within-team collaborative experience attenuates its effect. By introducing the distinct dimension of across-team knowledge diversity, and by examining the conditions under which within- and across-team knowledge diversity influence firm-level innovation, we advance our understanding of the link between the organization of inventive human capital and innovation.

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FIGURES & TABLES

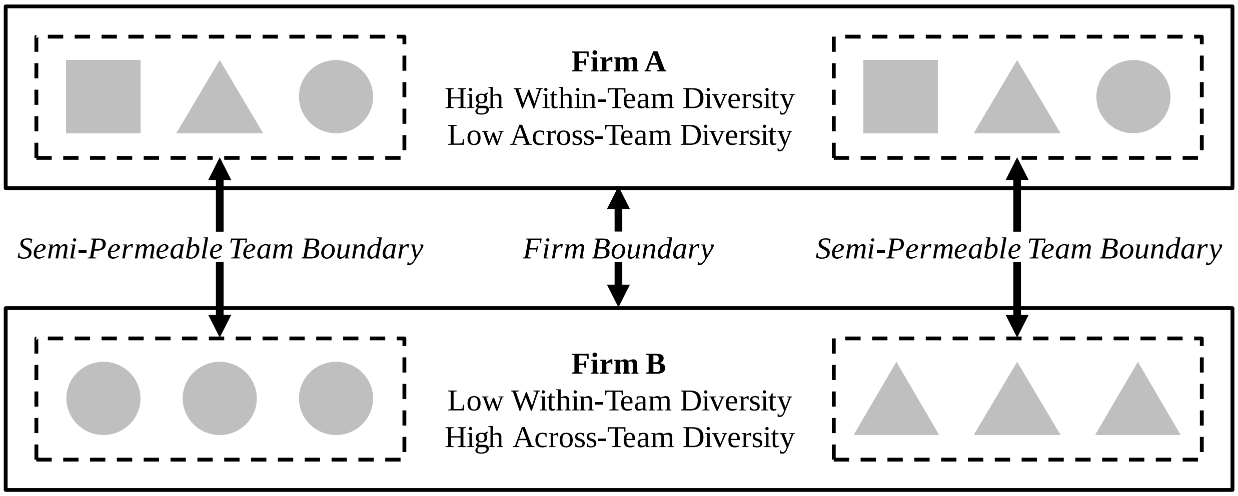

Figure 1. Organizational Knowledge Environments: The Locus of Knowledge Diversity

The dashed lines represent production team boundaries and the solid lines represent firm boundaries. Distinct shapes represent inventors with different technological specializations. Two alternate firm-level approaches to organizing inventors on a team are depicted. Firm A represents a firm with high within-team knowledge diversity and low across-team knoweldge diversity. Firm B represents a firm with low within-team knowledge diversity and high across-team knowledge diversity.

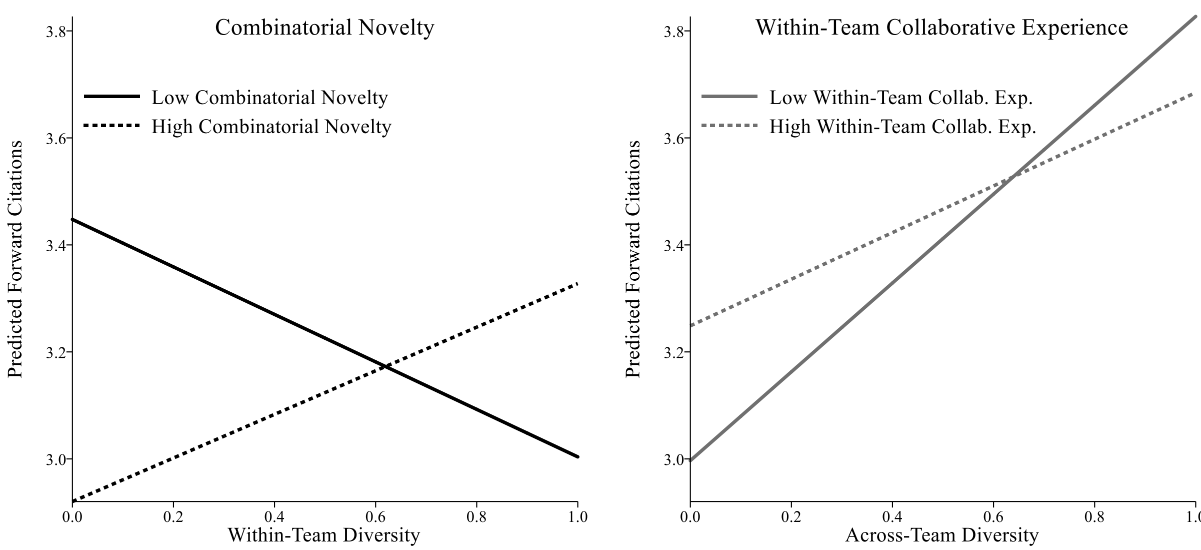

Figure 2. Predicted Forward Citations (4Y) on Moderated Main Independent Variables

This figure graphically portrays the interaction effects, showing the effect of *within-team knowledge diversity* moderated by *combinatorial novelty* on *forward citations (4Y)* in the left panel and the effect of *across-team knowledge diversity* moderated by *within-team collaborative experience* on *forward citations (4Y)* in the right panel. For each figure, we evaluate the predicted values of forward citations for values of the moderators at the fifth- and ninety-fifth percentiles of the distribution of values (referred to as low and high, respectively) of combinatorial novelty and within-team collaborative experience. The y-axis represents predicted forward citations from our model, with a positive (negative) slope indicating a positive (negative) association between the diversity measure and the dependent variable.

Table 1. Summary Statistics and Variable Definitions, Firm-Year Level of Analysis

VARIABLE	DEFINITION	MEAN	S.D.
Dependent Variable			
Forward Citations	Total forward citations within a four-year window to patents filed in the focal firm-year	5.14	21.46
Main Independent Variables and Moderators			
(1) *Across-Team Knowledge Diversity*	Average angular distance in technology class experience between production teams	0.12	0.23
(2) *Within-Team Knowledge Diversity*	Average angular distance in technology class experience between inventors on a production team, averaged over teams	0.20	0.18
(3) *Combinatorial Novelty*	Recombination of infrequently combined technological components (see the text)	0.22	0.30
(4) *Within-Team Collaborative Experience*	Average joint prior patenting experience between dyads of inventors on the same patent team	1.26	2.52
Production Team Patenting Controls			
(5) *Team Patenting Experience*	Average patenting experience of teams in a firm	9.81	10.72
(6) *Team Forward Citation Experience*	Average forward citations within a four-year window to patents by teams in a firm	29.18	70.28
(7) *Team Class Experience*	Average class experience of teams in a firm	4.70	3.30
Firm Patenting Controls			
(8) *Patent Count*	Number of patents in a firm-year	2.24	7.93
(9) *Inventor Count*	Number of inventors in a firm-year	4.46	12.61
(10) *Class Span*	Number of classes in a firm-year	0.80	1.47
(11) *Total Collaborative Experience*	Average joint patenting experience between all inventors	0.74	1.56
Corporate (Firm-Level) Controls			
(12) *Age*	Years since firm founding	8.42	6.09
(13) *VC Inflows Stock*	Cumulative venture capital investment	16.39	27.88
(14) *Strategic Alliance Stock*	Stock count of strategic alliances	10.39	17.91
(15) *Active Product*	Indicator for active product under FDA review	0.65	0.48
(16) *Post-IPO*	Indicator for IPO in firm history	0.32	0.47
(17) *Post-M&A*	Indicator for M&A in firm history	0.15	0.35
TMT Diversity Controls			
(18) *TMT Diversity*	Average of Herfindahl TMT measures based on age, job tenure, and educational duration	0.08	0.19

Table 2. Pairwise Correlation Matrix of Independent Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)	1.00																	
(2)	0.05	1.00																
(3)	0.02	0.02	1.00															
(4)	0.11	-0.11	0.06	1.00														
(5)	-0.03	0.07	0.07	0.60	1.00													
(6)	-0.05	0.03	0.01	0.29	0.57	1.00												
(7)	0.04	0.37	0.01	0.29	0.53	0.25	1.00											
(8)	0.20	-0.04	0.02	0.47	0.36	0.14	0.10	1.00										
(9)	0.30	-0.02	0.02	0.38	0.19	0.04	0.16	0.77	1.00									
(10)	0.45	0.03	0.03	0.55	0.25	0.11	0.19	0.71	0.79	1.00								
(11)	-0.07	-0.08	0.03	0.77	0.31	0.18	0.24	0.08	0.10	0.25	1.00							
(12)	0.02	-0.10	0.11	0.06	0.11	-0.02	0.10	0.08	0.15	0.09	0.02	1.00						
(13)	0.07	0.03	0.06	0.20	0.16	0.00	0.23	0.09	0.14	0.20	0.14	0.11	1.00					
(14)	0.21	-0.05	0.11	0.22	0.15	-0.01	0.11	0.31	0.46	0.40	0.06	0.43	0.15	1.00				
(15)	0.05	-0.11	-0.12	-0.02	-0.11	-0.11	-0.14	0.04	0.07	0.06	-0.04	0.34	-0.14	0.14	1.00			
(16)	0.15	-0.04	0.00	0.21	0.09	-0.05	0.10	0.19	0.24	0.30	0.12	0.39	0.21	0.45	0.27	1.00		
(17)	-0.03	-0.03	0.07	-0.06	0.03	0.00	-0.03	-0.06	-0.06	-0.09	-0.04	0.30	0.06	0.07	-0.09	0.15	1.00	
(18)	0.11	0.00	0.04	0.19	0.09	0.02	0.10	0.16	0.19	0.24	0.11	0.11	0.30	0.29	-0.01	0.24	-0.09	1.00

Table 3. Average Effects of Within-Team Knowledge Diversity

	Conditional Firm Fixed Effects Poisson Estimation Exponentiated coefficients reflect incidence rate ratios.				
DV: Forward Citations (4Y)	**(3-1)**	**(3-2)**	**(3-3)**	**(3-4)**	**(3-5)**
Within-Team Knowledge Diversity	0.551** (0.148)	0.425** (0.143)	0.432** (0.144)	0.430*** (0.140)	0.317*** (0.099)
Combinatorial Novelty				0.546** (0.143)	0.363*** (0.132)
Within-Team Knowledge Diversity × Combinatorial Novelty					5.262* (4.862)
Team Patenting Experience	1.006 (0.005)	0.991 (0.007)	0.992 (0.007)	0.992 (0.007)	0.992 (0.008)
Team Forward Citation Experience	1.000 (0.001)	1.002 (0.001)	1.002 (0.001)	1.002 (0.001)	1.002 (0.001)
Team Class Experience	1.049*** (0.018)	1.061*** (0.019)	1.058*** (0.019)	1.055*** (0.019)	1.058*** (0.019)
Patent Count		1.006*** (0.001)	1.006*** (0.001)	1.006*** (0.001)	1.006*** (0.001)
Inventor Count		0.998 (0.003)	0.998 (0.003)	0.998 (0.003)	0.998 (0.003)
Class Span		1.103*** (0.041)	1.108*** (0.038)	1.108*** (0.037)	1.108*** (0.037)
Total Collaborative Experience		0.916** (0.031)	0.919** (0.031)	0.917*** (0.030)	0.916*** (0.030)
Age		1.482 (0.587)	1.391 (0.549)	1.444 (0.573)	1.442 (0.573)
VC Inflows Stock		1.001 (0.003)	1.001 (0.003)	1.001 (0.003)	1.001 (0.003)
Strategic Alliance Stock		1.009*** (0.004)	1.008** (0.004)	1.008** (0.004)	1.008** (0.004)
Active Product		1.105 (0.153)	1.099 (0.147)	1.078 (0.145)	1.072 (0.142)
Post-IPO		0.999 (0.136)	0.963 (0.133)	0.965 (0.131)	0.954 (0.127)
Post-M&A		0.707** (0.116)	0.808 (0.126)	0.812 (0.127)	0.813 (0.128)
TMT Diversity			1.747** (0.434)	1.783** (0.447)	1.802** (0.454)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	2546	2283	2283	2279	2279
Log Pseudo-likelihood	-15065.4	-11984.5	-11892.7	-11819.5	-11776.5

Note: 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. Robust standard errors are shown in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

Table 4: Average Effects of Across-Team Knowledge Diversity

DV: Forward Citations (4Y)	Conditional Firm Fixed Effects Poisson Estimation Exponentiated coefficients reflect incidence rate ratios.				
	(4-1)	**(4-2)**	**(4-3)**	**(4-4)**	**(4-5)**
Across-Team Knowledge Diversity	1.897*** (0.286)	1.621*** (0.252)	1.627*** (0.242)	1.561*** (0.221)	2.441*** (0.314)
Within-Team Collaborative Experience				1.129*** (0.030)	1.154*** (0.036)
Across-Team Knowledge Diversity *× Within-Team Collaborative Experience*					0.818*** (0.038)
Team Patenting Experience	1.008 (0.005)	0.992 (0.008)	0.992 (0.008)	0.959*** (0.008)	0.958*** (0.008)
Team Forward Citation Experience	1.001 (0.001)	1.002 (0.001)	1.002 (0.001)	1.004*** (0.001)	1.004*** (0.001)
Team Class Experience	1.040** (0.018)	1.041** (0.020)	1.039* (0.020)	1.060*** (0.020)	1.059*** (0.020)
Patent Count		1.008*** (0.001)	1.007*** (0.002)	1.005*** (0.001)	1.004*** (0.001)
Inventor Count		0.998 (0.003)	0.998 (0.003)	1.000 (0.002)	1.002 (0.002)
Class Span		1.084** (0.040)	1.089** (0.036)	1.066*** (0.024)	1.070*** (0.027)
Total Collaborative Experience		0.952* (0.027)	0.954* (0.027)	0.826*** (0.040)	0.812*** (0.043)
Age		1.434 (0.547)	1.345 (0.510)	1.753 (0.679)	1.984 (0.897)
VC Inflows Stock		1.001 (0.003)	1.001 (0.003)	0.999 (0.004)	0.998 (0.004)
Strategic Alliance Stock		1.010*** (0.004)	1.008** (0.004)	1.008** (0.003)	1.007** (0.004)
Active Product		1.081 (0.174)	1.076 (0.168)	1.047 (0.139)	1.040 (0.142)
Post-IPO		1.038 (0.135)	0.997 (0.131)	0.989 (0.134)	0.976 (0.136)
Post-M&A		0.691** (0.110)	0.792 (0.123)	0.748* (0.130)	0.794 (0.122)
TMT Diversity			1.756** (0.419)	1.698** (0.389)	1.706** (0.379)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	2676	2365	2365	2365	2365
Log Pseudolikelihood	-15385.5	-12322.2	-12225.8	-11570.4	-11414.3

Note: 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. Robust standard errors are shown in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

Table 5: Combined Models

	Conditional Firm Fixed Effects Poisson Estimation Exponentiated coefficients reflect incidence rate ratios.			
	Forward Citations (4Y)		*Patent Count*	
	(5-1)	**(5-2)**	**(5-3)**	**(5-4)**
Across-Team Knowledge Diversity	1.563*** (0.232)	2.026*** (0.352)	1.027 (0.134)	1.356*** (0.158)
Within-Team Knowledge Diversity	0.424** (0.144)	0.321*** (0.107)	0.274*** (0.061)	0.360*** (0.068)
Equality: Across vs. Within Diversity [χ2]	**[13.81]*** **	**[23.58]*** **	**[56.61]*** **	**[41.37]*** **
Combinatorial Novelty		0.226*** (0.113)		0.725*** (0.090)
Across-Team Knowledge Diversity *× Combinatorial Novelty*		3.229 (2.376)		1.346 (0.356)
Within-Team Knowledge Diversity *× Combinatorial Novelty*		9.891** (9.701)		1.520 (0.452)
Within-Team Collaborative Experience		1.149*** (0.036)		1.137*** (0.018)
Across-Team Knowledge Diversity *× Within-Team Collaborative Experience*		0.803*** (0.037)		0.872*** (0.031)
Within-Team Knowledge Diversity *× Within-Team Collaborative Experience*		1.071 (0.132)		0.944 (0.092)
Team Patenting Experience	0.992 (0.007)	0.959*** (0.008)	1.014*** (0.002)	0.980*** (0.006)
Team Forward Citation Experience	1.002 (0.001)	1.004*** (0.001)	0.999 (0.001)	1.001** (0.001)
Team Class Experience	1.060*** (0.020)	1.072*** (0.020)	1.020** (0.009)	1.040*** (0.012)
Patent Count	1.007*** (0.001)	1.004*** (0.002)		
Inventor Count	0.998 (0.003)	1.002 (0.002)	1.003** (0.001)	1.003*** (0.001)
Class Span	1.090*** (0.037)	1.071*** (0.028)	1.117*** (0.045)	1.103*** (0.036)
Total Collaborative Experience	0.931** (0.029)	0.792*** (0.041)	0.891*** (0.017)	0.805*** (0.023)
Corporate Controls & TMT Diversity	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2283	2279	2314	2310
Log Pseudolikelihood	-11806.1	-10913.4	-4307.7	-4028.4

Note: 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. Corporate Controls are *Age*, *VC Inflows Stock*, *Strategic Alliance Stock*, *Active Product*, *Post-IPO*, and *Post-M&A*. Robust standard errors are shown in parentheses. Chi-squared test is reported in brackets. * p<0.10 ** p<0.05 *** p<0.01.

APPENDIX

Calculating the Across-Team and Within-Team Knowledge Diversity Measures

Count of Patents in Each Class

	Team 1					Team 2	Team 3
Class	John	Paul	George	Ringo	Total	Total	Total
1	3	3	0	3	9	4	0
2	4	4	0	0	8	3	6
3	0	0	5	4	9	0	2

Within-Team Knowledge Diversity of Team 1		Across-Team Knowledge Diversity of Firm	
Pairings	Dyadic Diversity $1 - \frac{A \cdot B}{\|A\| * \|B\|}$	Pairings	Dyadic Diversity $1 - \frac{A \cdot B}{\|A\| * \|B\|}$
John & Paul	0	Team 1 & Team 2	$1 - \frac{12}{\sqrt{226}}$
John & George	1		
John & Ringo	16/25	Team 2 & Team 3	$1 - \frac{9}{5\sqrt{10}}$
Paul & George	1		
Paul & Ringo	16/25	Team 3 & Team 1	$1 - \frac{33}{2\sqrt{565}}$
George & Ringo	1/5		
Within-Team Knowledge Diversity	0.58	Across-Team Knowledge Diversity	0.31

We illustrate the calculation of *across*- and *within-team knowledge diversity* for a hypothetical firm. The table at the top shows the stock count of patents in each primary patent class for the members of Team 1, and the total amounts for Teams 2 and 3. The lower left table shows the calculation for the *within-team knowledge diversity* of Team 1, where the dyadic diversity, which is 1 minus the cosine similarity of each dyad, is calculated for each dyad of inventors, and then averaged across all dyads. The lower right table shows the calculation of *across-team knowledge diversity* for the firm, where dyadic diversity is calculated for each dyad of teams and then averaged across all dyads.