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Organizing for innovation: A contingency view on innovative team configuration

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Abstract

Research Summary: While innovation has increasingly become a collaborative effort, there is little consensus in research about what types of team configurations might be the most useful for creating breakthrough innovations. Do teams need to include inventors with knowledge breadth for recombination or do they need inventors with knowledge depth for identifying anomalies? Do teams need overlapping knowledge to integrate insights from diverse areas or does this redundancy hamper innovation by creating inefficiencies? In this article, we offer evidence that the answers to these questions may depend on the characteristics of the technologies. Focusing on the degree of modularity and the breadth of application in patent data, we identify empirical patterns suggesting that differing team configurations are associated with different technological domains.

Managerial Summary: While innovation has increasingly become a collaborative effort, there is little guidance for managers about how you can construct teams to create novel breakthroughs. Who should be on the team? Some have suggested that inventors should have broad knowledge in order to facilitate the recombination of ideas, which is at the heart of creativity. Others suggest that only deep knowledge in an area can lead to

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novel solutions. How much diversity in backgrounds is useful? Some find that inventors need to have common knowledge in order to integrate their insights. Others worry that this redundancy will lead to inefficiencies that slow down innovation. In this article, we resolve these conflicting recommendations by showing that the team you pick depends on the type of technology.

KEYWORDS

breakthrough innovation, general purpose technologies, knowledge, modularity, patents, recombination, team configuration

1 | INTRODUCTION

Innovation has increasingly become a collaborative effort (Wuchty, Jones, & Uzzi, 2007). Data from United States Patent and Trademark Office (USPTO) patents shows that the average size of innovative teams grew from 1.7 in 1975 to more than 2.5 inventors in 2010. As knowledge domains advance and individuals become more specialized, inventors need to engage in more collaborative efforts to advance the knowledge frontier (Agrawal, Goldfarb, & Teodoridis, 2016; Jones, 2009). Such teams may also be better at filtering out low-quality ideas and thus are likely to produce more impactful innovations than lone inventors (Singh & Fleming, 2010). Accordingly, a long stream of studies has argued that there is an important relationship between the configuration of innovative teams and their innovation outcomes (Bercovitz & Feldman, 2011; Dahlin, Weingart, & Hinds, 2005; Kogut & Zander, 1992; Perry-Smith & Shalley, 2014; Taylor & Greve, 2006).

Yet, research to date offers inconsistent insights. While a large body of studies claim that teams that combine distant and diverse knowledge are associated with innovation novelty (Fleming, 2001; Gittelman & Kogut, 2003), others have reported that it is more important that team members have deep knowledge in order to identify anomalies (Kaplan & Vakili, 2015). Similarly, whereas some have shown a positive relationship between a team's knowledge breadth and creative output because it increases the potential for recombination (Burt, 2004; Hargadon & Sutton, 1997; Uzzi & Spiro, 2005), others have found a team's knowledge breadth to stymie creativity by lowering productivity (Leahey, 2007; Leahey, Beckman, & Stanko, 2017).

In this article, we conduct an exploratory empirical exercise to identify one possible explanation of these contradictory findings about team configurations: differences in technological domains. From the days of Joan Woodward (1958), Woodward, 1970), we have known that organizational form should depend on the types of technologies the organization pursues. Yet, prior research on team configurations for innovation either cover innovations drawn from a wide set of technological domains, often the whole population of patents (e.g., Arts & Veugelers, 2015; Fleming et al., 2007; Singh & Fleming, 2010) while simply controlling for technological differences, or they focus on a single technological domain such as biotechnology (Phene, Fladmoe-Lindquist, & Marsh, 2006), optical disks (Rosenkopf & Nerkar, 2001) or carbon nanotubes (Kaplan & Vakili, 2015). In both cases, the claims about organizational form are generally agnostic to the technological domain in which the innovation takes place. That is, average effects in a broad range of technological domains might disguise opposing effects within specific domains. Alternatively, specific effects identified in one technological domain might not be applicable elsewhere. In most of these studies, acknowledgement of the boundary conditions that technological domains might impose is not central to the theorizing.

In this article, we suggest that this non-replicability may be a “feature” and not a “bug” (see Levinthal & Rosenkopf, 2020 for a detailed argument on non-replicability), and we offer some empirical evidence to suggest that generalizations that abstract away from the role of technological domain can lead to theoretical and empirical confusion. The insights and practical implications drawn from one domain could potentially lead to undesirable outcomes if applied in another domain with different underlying characteristics. In our analysis, we take a step towards addressing these issues by comparing the relationship between team configuration and innovation outcomes in different technological domains.

In this cross-domain analysis, we focus specifically on two underlying factors or what Levinthal and Rosenkopf (2020) call “basis variables” driving variations in impacts on innovation: differences in the degree of modularity and the breadth of application, each of which relate to important streams of research on technological characteristics. Using two different measures of innovative outcomes—patents that represent novel breakthroughs and those that represent economic breakthroughs—we look at how different team configurations might be associated with each in different technological domains. To characterize the configuration of innovative teams, we examine the knowledge breadth and depth of the main inventors as well as the overlap in their knowledge.

Examining a theoretical sample of four different domains that vary according to modularity and breadth of application—magnetic resonance imaging (MRI), radio frequency identification (RFID), stem cells, and nanotubes—we find that different team configurations map onto the production of novel breakthroughs in each. Our exploration suggests that in modular technological domains (MRI and RFID), the production of novel breakthroughs is associated with teams having less overlap between their inventors' knowledge scope, while in non-modular domains (stem cells and nanotubes), it is associated with teams in which the most experienced inventor can act as the knowledge integrator. Further, novel breakthroughs in technologies with broad applications (RFID and nanotubes) are associated with teams in which the second most experienced inventor has wide knowledge breadth, presumably to seek out a wide range of applications. In contrast, novel breakthroughs in narrow technologies (MRI and stem cells) are associated with teams in which the second inventor has more knowledge depth, presumably to seek out anomalies. Using our cross-domain research design, we then examine how the interaction of modularity and application breadth can moderate the relationship between different team configurations and the odds of producing breakthroughs. Our analysis gives support to the idea that team design might be contingent on the technological domain, which offers a productive pathway for future research into the role of team configurations for innovation.

2 | BACKGROUND

2.1 | Innovative team configuration

Past research has highlighted the tradeoffs associated with knowledge depth versus breadth at individual (Leahey et al., 2017), technological (Kaplan & Vakili, 2015), team (Bercovitz &

Feldman, 2011), and organizational (Ahuja & Lampert, 2001) levels. On the one hand, scholars highlight the importance of a team's knowledge diversity for developing innovations (Jeppesen & Lakhani, 2010; Leiponen & Helfat, 2011; March, 1991; Powell, Koput, & Smith-Doerr, 1996). The argument relies on the idea that innovation is a recombination process (Audia & Goncalo, 2007; Hargadon & Sutton, 1997). New ideas are combinations of previously disconnected ideas. Hence, more breadth in knowledge input can lead to more novel knowledge recombinations and consequently more impactful innovations (Burt, 2004; Fleming, 2001; Hargadon & Sutton, 1997; Schilling & Green, 2011).

On the other hand, research highlights the importance of knowledge depth (Kuhn, 1962; Taylor & Greve, 2006; Weisberg, 1999). This research argues that specialists have a better understanding of the fundamental gaps in their domain of specialty (Weisberg, 1999), can absorb and use the knowledge at the frontier more effectively (Jones, 2009; Teodoridis, Bikard, & Vakili, 2019), and have superior domain-specific memory and problem-solving skills (Larkin, McDermott, Simon, & Simon, 1980; Sweller, Mawer, & Ward, 1983). From this standpoint, teams and organizations should invest in domain-specific expertise to maximize their impact.

The effect of knowledge overlap for innovation output is also similarly debated in the literature. On the one hand, knowledge overlap helps facilitate knowledge integration by bridging their individual knowledge stocks (Dahlin et al., 2005; Dougherty, 1992). A lack of common language can increase the communication costs between team members and lead to undesirable frictions (Cramton, 2001; Krauss & Fussell, 1990), especially when there is a need for cross-boundary knowledge integration. The coordination costs are higher when individuals have different knowledge and when links between knowledge domains are less established.

On the other hand, research also points out that redundancies in knowledge bases for innovation may be undesirable (Burt, 2004). All things being equal, an increase in overlap in individuals' knowledge bases comes at the expense of a decrease in the total diversity of knowledge at the team level. Hence, while knowledge overlap can facilitate the knowledge integration process, it can nevertheless lead to lower diversity in knowledge input.

A few scholars have pointed to contingencies in these relationships. Leahey et al. (2017) show that scientists who engage in more interdisciplinary projects (i.e., rely on wider knowledge breadth) are more likely to produce very impactful innovations, but they experience a decline in their productivity. In contrast, they show that specialization is associated with higher innovation rate, but lower impact. Others have explored the non-linear effects of knowledge breadth and overlap, suggesting that while both are necessary for the production of innovations, too much of either can lead to negative effects (Berman, Down, & Hill, 2002; Katz, 1982).

2.2 | Technological domain

The idea that technology characteristics might be associated with different team configurations has long roots in innovation research. Going back to early contingency theory (Perrow, 1967; Thompson, 1967; Woodward, 1958), scholars have highlighted the importance of the match between technology and organization design. Woodward (1958) specifically distinguishes between three types of technological features—large batch and mass production, unit and batch production, and continuous processing—and argues that while centralized bureaucratic decision-making structures are more effective for the first, organizations with decentralized decision-making structure are better fit to the latter two types of technology. In this article, we build on this legacy of insights from contingency theory and demonstrate that different team configurations are more likely to be associated with producing novel and impactful innovations depending on different technological characteristics. We especially focus on two features, or "basis variables" (Levinthal & Rosenkopf, 2020), of a technological domain: modularity and application breadth. Such basis variables offer a means for defining the generalizability of findings such that any conclusions to be drawn about the configuration of innovative teams must be constrained by these features.

2.2.1 | Modularity

Modularity is defined as the extent to which a technology can be decomposed to a set of components with standardized interfaces between them (Brusoni & Prencipe, 2001; Langlois, 2002), such as in electronics and computer programming. In modular technologies, there is usually a one-to-one mapping between physical components and functional elements (Ulrich, 1995). In contrast, non-modular technologies such as chemistry or biology usually cannot be decomposed into their sub-components and involve complex mapping between their physical and functional elements (Ulrich, 1995). This is highly related to the original distinction that Woodward (1958) drew between batch and process manufacturing.

There has been a growing interest in the implications of modularity or non-modularity for organization design. The research, however, has predominantly focused on product-level modularity and its impact on organizational design choices such as vertical integration (Brusoni & Prencipe, 2001; Langlois, 2002) and hierarchical coordination (Sanchez & Mahoney, 1996). At the team level, we expect technological modularity to substitute for knowledge overlap in the integration process. A one-to-one mapping between components and functionalities allows individual inventors to focus on components, relying on the standardized interfaces between components for team-level integration. For modular technologies, teams with lower levels of overlap can achieve higher levels of knowledge diversity while avoiding the inefficiency of redundancy, hence producing more novel innovations. While there is usually a need for a lead inventor to design the system at the top level, the lead does not need to have extensive knowledge about each component and its intricacies.

By corollary, for non-modular technologies, knowledge overlap will be needed to integrate insights with the team leader playing a more significant role in team-level knowledge integration. Though most research on organizing for modularity is at the organizational rather than team level, it implies that in non-modular domains, knowledge overlap plays a crucial role in knowledge integration (Grant, 1996). In short, in non-modular technologies, we expect teams in which the lead inventor has more knowledge breadth and more overlap with other inventors will be more likely to produce novel and impactful innovations.

2.2.2 | Breadth of application

The breadth of application of a technology can also moderate the performance of innovative teams. Technologies vary substantially in their range of application areas. At one extreme, technologies such as electricity and computer chips can find applications across a very large range of domains (general purpose technologies; Helpman & Trajtenberg, 1994). At the other extreme, some technologies such as coronary stents and electrocardiography are developed for narrow applications. Most broadly applied technologies have their roots in a specific technological domain, but innovations based on them usually bridge the technology to new application domains. For example, many novel innovations based on nanotubes involve exploiting a specific mechanical, chemical, or electrical property in new applications. Hence, when the technology is broadly applied, we expect inventors' knowledge breadth to be essential for discovering new applications. By implication, too much overlap between the top inventors in such domains can limit the team's ability to explore new applications. In contrast, when technologies are only narrowly applied, we expect knowledge breadth to be less helpful.

Our goal in this article is to explore how the team configurations that produce breakthrough innovations might differ based on the nature of the technological domain in which they operate—modular versus non-modular and broad versus narrow application. We use this cross-domain exploration to shed light on the contrasting findings in extant research about whether breadth or depth of knowledge matters and how much knowledge overlap would be required for an innovation team. In our analysis, we observe that the association of different team configurations with innovative outcomes depends on the technological domain. While these results are only descriptive, they should be useful for advancing the conversation in future research studies that consider organizational design principles for innovation. To the question, "What team configurations work best for innovation?" scholars would be well advised to append, "given the features of the technological domain."

3 | METHODOLOGY

3.1 | Data sample

We use evidence from teams listed in patents from the US Patent and Trademark Office for this analysis. Patents, despite their shortcomings as a measure of innovation (Mansfield, 1968), provide evidence of successful innovations and document clearly the team members who participated in the innovation process. Patent data also allow us to measure the depth and breadth of experience of each listed inventor by tracing features of their other granted patents.

To explore the role of modularity and technological breadth in moderating the association of team configuration on innovation output, we need patents from a theoretical sample of four technological domains that represent each unique combination of modularity and breadth of application from Table 1. Moreover, we should be able to trace the history of each technological domain: technologies should not be so recent as to have few patents and not so old as to have a bulk of patents prior to 1976 which is the cutoff for the digitization of patent data. Finally, we need to focus on technological domains that have a roughly identifiable boundary to be able to categorize the set of innovations that belong to each domain.

Given these requirements, we identified a comprehensive sample of patents in four technological domains—MRI, RFID, stem cells, and nanotubes—each of which represent one box in a two-by-two of modularity and breadth of application (Table 1). MRI is a (modular and narrowly applied) medical imaging technology used to scan internal organs and physiological processes

TABLE 1 Characteristics of the selected four technologies

	Broadly-applied	Narrowly-applied
Modular	RFID	MRI
Non-Modular	Nanotube	Stem Cell

of humans and animals. RFID is a (modular and broadly applied) technology based on electromagnetic fields used to identify and track pre-programmed tags in a certain physical range. Stem cells are a (non-modular and narrowly applied) technology based in undifferentiated cells that have the capability to develop into specialized cell types. Nanotubes are a (non-modular and broadly applied) technology made of cylindrical materials made of carbon molecules with nanometer scale diameters and special properties such as superconductivity and high levels of elasticity. These four technologies vary substantially across the two technological dimensions of interest.

Our sample consists of all patents granted by the United States Patent Office (USPTO) in each domain 1970–2010. For patents prior to 1976, we hand searched the patent database because fully digitized records are not available. The cut-off year 2010 was used because of our reliance on the NBER Patent Dataset and the Harvard Patent Dataverse (Lai, D'Amour, Yu, Sun, & Fleming, 2014) for complementary data, both of which only cover patents granted until 2010. Moreover, ending our sample in 2010 allows us to trace the impact of the patents on follow-on innovations (forward citations) over subsequent years. Given that we use granted patents to measure innovation, our results are conditioned on the success of teams in producing patentable inventions.

We used several complementary methods to identify patents in each technological domain. Table A1 in the Appendix lists the set of search terms used for each technology, the number of patents retrieved from each search, and the total number of patents resulting from all searches for each technology after collapsing all patents belonging to the same family into one. Our final sample includes 9,230 MRI patents, 3,521 RFID patents, 1,775 stem cell patents, and 2,384 nanotube patents. There are small overlaps between the four groups of patents: four patents belong to both RFID and nanotubes categories; six patents belong to both MRI and RFID; 14 patents are classified in both MRI and nanotubes; seven patents are classified in both MRI and stem cells; and three patents belong to both stem cells and nanotubes. The overlaps are small, and all results are robust to excluding the patents belonging to more than one category.

3.2 | Technological modularity and application breadth

Importantly for the purposes of this analysis, each of these four technological domains are positioned differently with respect to the two technological characteristics of interest: application breadth and modularity (Table 1 above). In our empirical analysis, we use two independent variables associated with these two characteristics of technologies. The *Broadly_applied* variable is equal to 1 for RFID and nanotube patents and is 0 otherwise. The *Modular* variable is equal to 1 for MRI and RFID patents, and 0 for stem cell and nanotube patents. Though not all patents in a technological domain share the typical characteristic of the domain, our simplifying assumption is aligned with the purpose of our analysis which is to show how team configurations behind breakthrough innovations vary at the technological domain.

3.2.1 | Breadth of application

Whereas innovations in RFID and nanotubes domains have a wide range of applications, MRI and stem cells innovations are much narrower in their application. Variants of RFID technology have found applications in numerous domains such as physical tracking of materials through the supply chain, item-level monitoring in the manufacturing process, queue optimization in hospitals and amusement parks, race timing, production of robbery-proof chips for casinos, library management systems, interactive marketing, and attendee tracking in large conferences. Similarly, nanotubes have found applications from producing new semiconductor materials to developing reinforced golf balls to improving fuel performance. In Table A2 in the online Appendix, we discuss our procedure for eliminating 128 patents in the RFID domain and 115 patents in the nanotube domain that are not about application and show that our results are robust to their inclusion or exclusion. MRI and stem cells have more limited application areas. To date, stem cells have been only used for specific therapeutic applications in animals and humans. MRI technology has, since the 1970s, been used predominantly for non-invasive medical imaging purposes. Table A3 in the online Appendix shows that these characterizations of each technology are supported by evidence of the relative breadth of the range of 3-digit patent classes in forward citations for each.

3.2.2 | Modularity

The technologies can also be categorized based on their level of modularity. MRI and RFID are more modular than stem cells and nanotubes. MRI and RFID both have their roots in electronics. A standard MRI device is composed of an external magnetic field, a set of gradient coils, RF equipment, a power supply, a display unit, a computing unit and computer programs to analyze and display the data collected from imaging. The interactions between these components are highly standardized. An improvement in one component does not require a system change. RFID technology is similarly composed of a set of standard components with standardized interfaces. The system includes tags, a reader, antenna, and a computing unit with application software. There are two large standards bodies, ISO RFID and EPCglobal, that specify and supervise the standardization of RFID systems and elements.

In contrast, stem cell and nanotubes have their roots in biology and chemistry respectively, and have much less modular designs. They are not produced by putting a set of sub-components together and it is difficult to map their functions to specific physical elements. Stem cells are generally extracted from animal or human tissues and then grown through cell culture in a laboratory. None of the constituent components of stem cells such as protein, DNA, and RNA can function in the absence of other components, nor can they be assembled using standard interfaces. The same is largely true for nanotubes. They are produced through (electro)chemical and, depending on the production process, they may end up with different properties such as superconductivity or physical resistance. While it is possible to produce nanotubes separately and combine them with other materials, nanotubes themselves cannot be manufactured by putting their constituent components (i.e., carbon molecules) together; at least not yet.

3.3 | Innovative team's knowledge composition

Our analysis focuses on how team configurations might differ for each of these different technological domains. A fundamental question in organization design is the deployment of specialists and generalists and the degree of coordination required between people (Brusoni, Prencipe, & Pavitt, 2001; Stan & Puranam, 2017). Specialists have deep knowledge in one domain: they are needed when there are economies of scale for knowledge and integration across multiple domains is less essential. Generalists have broad knowledge across multiple domains but may not be as deep. They are needed when cross-boundary knowledge integration is essential for creating and capturing value.

In the case of inventive teams, we are concerned about the knowledge depth and breadth of the main inventors and the overlap in their knowledge. For our analyses, we focus on the two inventors of each team with the greatest amount of experience during the 5 years prior to their focal innovation (hereafter 5-year patenting experience) (not the first two listed in the document). The median innovative team in our sample has only two inventors. The average team size is 2.6. We gain very little information by expanding beyond the first two team members. For teams that have more than two inventors, the median five-year patenting experience of the third, fourth, and fifth inventor (ranked by their 5-year experience) is zero. Moreover, their average five-year patenting experience is less than two patents. Finally, their knowledge scope has more than 80% overlap with the lead inventor. Nevertheless, we control for their experience and the total number of inventors in a team in all specifications. In the Appendix, we show that our results and their interpretations are robust to the inclusion of the knowledge composition of these inventors as separate variables (Tables A4 and A5 in the Appendix).

For each of the two top inventors in a team, we include two variables indicating their knowledge breadth and depth. These are based on technology classes of the patents for which they are listed as inventors. Following prior research (Boh, Evaristo, & Ouderkirk, 2014; Fleming, Mingo, & Chen, 2007), we use the number of unique technology classes in which an inventor had successfully filed patents during the five years prior to the focal patent as a proxy for the inventor's *knowledge breadth*. Here, we measure "successfully filed" at the application date of patents that were eventually granted. *Knowledge depth* is measured as the maximum number of patents the inventor had successfully filed in a single technology class during the same five-year period, a measure similar to that used by Boh et al. (2014) and Mannucci and Yong (2018). The two measures together explain more than 90% of the variance in the inventor's 5-year patenting experience. Because that the mean and variance of inventors' knowledge depth and breadth differs across the four technological domains we study, we de-mean all variables and normalize them based on the mean and standard deviation of each variable in each technology class.

We also measure the overlap between the knowledge of the two top inventors by calculating the ratio of technology classes in which they both successfully filed patents in the 5 years prior to the focal patent over relative to the number of unique technology classes in which either successfully filed patents (i.e., overlap over union). Figures A1 and A2 in the online Appendix show two examples illustrating how these measures are constructed.

3.4 | Outcome measures: Innovation output

We focus on two types of the innovation output: economic and novel breakthroughs in knowledge. A standard measure of breakthroughs in patent studies is based on future (forward) citations to the patent. While the measure is imperfect, several studies have shown strong correlations between the number of forward citations and the economic value of a patent (Hall, Jaffe, & Trajtenberg, 2005; Trajtenberg, 1990). We use the number of citations received by a patent in a fixed window of time—here, five years since application date—as a proxy for its economic impact. Following past research (Ahuja & Lampert, 2001; Hall et al., 2005; Singh & Fleming, 2010), we define economic breakthroughs as the 10% most cited patents in the sample.

Because research has suggested that there are important differences between the citation-based measure of (economic) impact and the cognitive novelty of the patent (Kaplan & Vakili, 2015), we include a measure of novel breakthroughs as a second measure of innovative outcomes. We might imagine that team configurations could have different relationships to cognitive novelty compared to the economic impact of a patent because these are produced through different processes. Cognitively novel patents are defined as those that introduce a new knowledge trajectory in a technological domain. The measure is based on Kuhn's (1962)/1996) notion that shifts in ideas are reflected in shifts in language. Thus, the novelty in the vocabulary used to describe an idea can be used to assess the cognitive novelty of the idea itself.

Following Kaplan and Vakili's (2015) approach, we use topic modeling, an unsupervised automatic textual analysis method, to identify the set of topics present in the four sets of patents associated with the four selected technologies and identify which patents initiate each topic. Topic modeling is an increasingly used method in strategic management for studying large bodies of texts, particularly as associated with technologies (Croidieu & Kim, 2018; Hannigan et al., 2019; Wilson & Joseph, 2015). Using the Stanford Topic Modeling Toolbox, we identified the 100 main topics represented by the abstracts of patents associated with each technology in our sample. Patent abstracts provide a summary of the novel aspects of an invention, are largely drafted by the inventors rather than patent lawyers, and are of approximately similar length, thus providing a useful basis of comparison across patents. The topic modeling algorithm produces a matrix that contains the association between each abstract and each of the 100 identified topics. Most patents contain only a few key topics, with the remaining topics having nearly no weight. Figure A3 in the Appendix shows a sample RFID abstract and the top two topics.

Most topics are easy to recognize and interpret (see Tables A6–A9 in the Appendix for the top terms for the 100 topics identified in patents associated with MRI, RFID, stem cells, and nanotubes, respectively). For each technological domain, we also find a few topics that are not easily interpretable. For the sake of simplicity and reproducibility of results, we keep these topics in our sample. The inclusion of these topics can potentially increase the noise in our measure of cognitive novelty which would work against us finding significant effects. Once the topics are identified for each set of patents, we select all patents over a 0.2 weighting threshold for each topic filed in the first 12 months since the first appearance of the topic. Using this approach, we identify 101, 153, 154, and 135 topic-originating patents in MRI, RFID, stem cells, and nanotubes respectively. Based on this information, we construct the *TopicOriginating* variable which is equal to one for topic-originating patents and 0 otherwise.

While we use both cognitive novelty (topic origination) and economic impact (top cited patents) as dependent variables in our estimations, it is important to note a gap between theoretical arguments concerning the role of knowledge recombination and measures of innovative output in prior studies. These studies have largely estimated the impact of knowledge recombination on economic impact (as proxied by forward citations), but theorize about how knowledge recombination creates novelty, which in turn leads to economic impact (Fleming, 2001; Gittelman & Kogut, 2003). However, the relationship between recombination, novelty, and economic impact is not so straightforward. Scholars have documented many sources of tension created between pursuing novelty versus pursuing impact (Boudreau, Guinan, Lakhani, & Riedl, 2016; Fleming et al., 2007). While novelty appears to be positively associated with economic impact, mechanisms that lead to novelty may not necessarily align with mechanisms that lead to economic impact (Kaplan & Vakili, 2015). Therefore, we should expect different relationships between team configuration and each of the two dependent variables we use.

3.5 | Estimation model

Because both dependent variables (novel breakthroughs and economic breakthroughs) are binary, we use a logistic model to estimate the association of team configuration with them. Our results are robust to using a linear model. In all estimations, we include a full set of interactions between technology and year fixed effects to control for the change in the opportunity landscape for each technology assuming that each technology might evolve at a different pace from the others. The interaction dummies ensure that each patent is compared to other patents in the same technology category and filed in the same year. We also control for the number of claims on each patent and the number of references to prior patents as these have been shown to positively predict forward citation counts. For models with economic breakthrough as the dependent variable, we include the topic-originating patent indicator as an additional independent variable to examine whether novelty would be associated with economic impact.

In the first set of estimations, we interact the team configuration variables with each of the characteristics of technological domain—modularity and application breadth—separately. In the second set of regressions, we interact team configuration variables with indicators for each of the four technologies to understand how the combination of the two characteristics is associated with the relationship between the team configuration variables and the innovation outcomes. For all estimations, we report the odds ratios. Several scholars have pointed out that the estimated interaction terms in non-linear models such as logits do not equal the marginal effects of interaction terms (Ai & Norton, 2003; Cornelißen & Sonderhof, 2009; Norton, Wang, & Ai, 2004). However, here we report the multiplicative effects of interaction terms in terms of odds ratios. Though multiplicative interpretations do not suffer from the issues raised by these scholars (Buis, 2010), we have also replicated our results using a linear probability model.

4 | RESULTS

Table 2 shows the summary statistics. Slightly fewer than 10% of patents are highly cited economic breakthroughs (due to the discrete nature of citation measures, the percentage of patents in the top 10% of citations for each technology is smaller than 10% overall) and approximately 3% of patents are novel breakthroughs (topic-originating). The average team size is 2.6, ranging from 2.4 to 3.1 across the four technological domains. In the 5 years prior to each focal patent, first inventors on average have filed patents in approximately 4.3 unique technology classes (the measure of knowledge breadth) and approximately 4.6 patents in the technology class in which they have the greatest number of patents (knowledge depth). Second inventors are substantially less experienced: they have on average filed patents in about 1.5 unique technology classes (breadth) and about 1.7 patents in the technology class in which they have the greatest number of patents (depth). In the regressions, we normalize measures of knowledge breadth and depth for the two top inventors within each technology class. The normalized measures have a mean of 0 and a standard deviation of 1. On average, the two top inventors have approximately 17% overlap in the set of technology classes in which they have filed patents. Third, fourth, and fifth inventors have on average 1.5, 0.6, and 0.3 patents filed in the 5 years prior to the focal patent. Patents in our sample list on average 20 claims and cite approximately 13 other patents as prior art.

TABLE 2 Descriptive features of four technologies

	All patents	MRI	RFID	Stem cells	Nanotubes
Economic breakthroughs (top 10% cited)	0.079 (0.270)	0.098 (0.297)	0.096 (0.295)	0.086 (0.281)	0.094 (0.292)
Novel breakthroughs (topic-originating patents)	0.026 (0.161)	0.011 (0.104)	0.043 (0.204)	0.087 (0.282)	0.057 (0.231)
Number of inventors	2.623 (1.751)	2.443 (1.618)	2.517 (1.795)	2.991 (1.955)	3.082 (1.991)
First inventor's knowledge breadth (non-normalized)	4.284 (5.949)	3.504 (4.602)	4.219 (6.773)	3.325 (4.517)	7.424 (8.562)
First inventor's knowledge depth (non-normalized)	4.603 (13.450)	4.247 (6.553)	4.120 (13.384)	3.422 (5.960)	7.688 (31.333)
Second inventor's knowledge breadth (non-normalized)	1.508 (2.900)	1.219 (2.360)	1.437 (3.520)	1.172 (2.119)	2.816 (4.121)
Second inventor's knowledge depth (non-normalized)	1.709 (4.951)	1.591 (4.165)	1.337 (5.094)	1.237 (3.259)	2.883 (8.335)
Overlap in the knowledge scope of the first and second inventors	0.167 (0.290)	0.175 (0.303)	0.101 (0.228)	0.180 (0.314)	0.198 (0.288)
Number of claims	19.860 (16.709)	18.935 (16.024)	22.291 (15.775)	19.977 (19.528)	21.237 (19.250)
Number of backward references to patents	13.366 (33.642)	11.008 (25.414)	23.505 (54.928)	11.822 (29.993)	15.999 (37.325)
Third inventor's 5-year patenting experience	1.504 (6.713)	1.183 (5.181)	1.438 (8.007)	1.181 (5.248)	3.131 (11.271)
Fourth inventor's 5-year patenting experience	0.601 (4.100)	0.462 (3.057)	0.406 (2.959)	0.436 (2.938)	1.523 (7.435)
Fifth inventor's 5-year patenting experience	0.255 (2.498)	0.202 (1.821)	0.165 (1.853)	0.213 (2.382)	0.743 (5.359)

4.1 | Team configurations for innovation by technological domain

We start by comparing the association between team configuration and outcomes for broad versus narrow application (Table 3), then modular versus non-modular (Table 4) before showing the combined effects in Table 5. Table 3 presents the estimated relationship between team configurations and each of the dependent variables in the case of a broadly applied (RFID and nanotubes) or narrowly applied (MRI or stem cells) technological domains. The results in the first column indicate that—other than a negative association between knowledge depth for narrowly applied technologies—there is little association between the first inventor's knowledge breadth or depth and the degree to which broadly or narrowly applied technologies are novel breakthroughs. However, the effects for the second inventor are intriguing. For broadly applied technologies, we see a strong positive association between the knowledge breadth of the second inventor and the likelihood that the team's invention is cognitively novel (becomes a topic-originating patent). A standard deviation increase in the second inventor's knowledge breadth is associated with approximately 1.5 times increase in the chance of the team producing a topic-

TABLE 3 Impact of team configurations on innovation outcomes: Broadly and narrowly applied technologies

Estimation model: DV:	Logistic (odds ratios reported) Novel breakthrough (1)	Economic breakthrough (2)
Novel breakthroughs		1.356 (0.014)
First inventor's knowledge breadth ×		
Narrowly applied (stem cell and MRI)	1.289 (p = .102)	1.050 (p = .087)
Broadly applied (nanotubes and RFID)	1.022 (p = .892)	1.211 (p = .000)
First inventor's knowledge depth ×		
Narrowly applied (stem cell and MRI)	0.841 (p = .038)	1.054 (p = .164)
Broadly applied (nanotubes and RFID)	0.815 (p = .656)	0.959 (p = .150)
Second inventor's knowledge breadth ×		
Narrowly applied (stem cell and MRI)	0.724 (p = .024)	0.984 (p = .746)
Broadly applied (nanotubes and RFID)	1.470 (p = .000)	0.986 (p = .607)
Second inventor's knowledge depth ×		
Narrowly applied (stem cell and MRI)	1.364 (p = .005)	0.992 (p = .821)
Broadly applied (nanotubes and RFID)	0.586 (p = .000)	0.982 (p = .784)
Overlap in the knowledge scope of the first and second inventors ×		
Narrowly applied (stem cell and MRI)	0.720 (p = .728)	1.038 (p = .713)
Broadly applied (nanotubes and RFID)	1.008 (p = .941)	0.909 (p = .337)
Full set of controls	Yes	Yes
Technology-time fixed effects	Yes	Yes
Number of observations	4,001	16,744
R^2	0.269	0.182

Note: All models are logistics regressions with robust standard errors clustered at the technology level. Reported estimates are odds rations. *p*-values are reported in parentheses.

originating patent in a broadly applied technological domain. In contrast, in narrowly applied technologies, the second inventor's knowledge depth rather than the breadth is more important when producing cognitively novel patents. A standard deviation increase in the second inventor's knowledge depth is associated with approximately 1.4 times increase in the likelihood of producing a topic-originating patent in a narrowly applied technological domain.

The results are consistent with the idea that, for broadly applied technologies, producing cognitively novel patents often involves seeking new application domains for the technology. The results suggest that second inventors—that is, the inventors with the second most amount of experience on each patent—may be the ones who act as the bridge between the technology and a new application domain. In contrast, in narrowly applied technologies, the second inventor's knowledge depth is more crucial to identify novel technological paths. Here, the novelty is generally associated with finding new methods of producing the technology or modifying the

TABLE 4 Impact of team configurations on innovation outcomes: Modular and non-modular technologies

Estimation model: DV:	Logistic (odds ratios reported) Novel breakthrough (1)	Economic breakthrough (2)
Novel breakthroughs		1.322 (0.033)
First inventor's knowledge breadth ×		
Non-modular (stem cells and nanotubes)	1.369 (p = .007)	1.239 (p = .000)
Modular (MRI and RFID)	0.908 (p = .002)	1.045 (p = .039)
First inventor's knowledge depth ×		
Non-modular (stem cells and nanotubes)	0.722 (p = .000)	0.855 (p = .000)
Modular (MRI and RFID)	0.986 (p = .863)	1.066 (p = .002)
Second inventor's knowledge breadth ×		
Non-modular (stem cells and nanotubes)	0.802 (p = .464)	1.028 (p = .507)
Modular (MRI and RFID)	1.294 (p = .013)	0.978 (p = .322)
Second inventor's knowledge depth ×		
Non-modular (stem cells and nanotubes)	1.318 (p = .040)	1.149 (p = .001)
Modular (MRI and RFID)	0.786 (p = .069)	0.974 (p = .584)
Overlap in the knowledge scope of the first and second inventors ×		
Non-modular (stem cells and nanotubes)	1.612 (p = .069)	1.131 (p = .368)
Modular (MRI and RFID)	0.248 (p = .064)	0.965 (p = .197)
Full set of controls	Yes	Yes
Technology-time fixed effects	Yes	Yes
Number of observations	4,001	16,744
R^2	0.271	0.183

Note: All models are logistics regressions with robust standard errors clustered at the technology level. Reported estimates are odds rations. p-values are reported in parentheses.

technology itself to be capable of new functionalities. Knowledge depth can provide insight into the fundamentals of the technology and its attributes, potentially increasing the chance of finding novel breakthroughs. It is therefore not surprising that, in either case, the estimates for the overlap between the first and second inventors are not significant. It is the second inventor that provides a bridge to new domains when needed.

Turning to the economic impact in column 2, the results suggest that topic-originating patents are 1.4 times more likely to be economic breakthroughs compared with non-topic-originating patents. Moreover, the chances of producing an economic breakthrough increases with the first inventor's knowledge breadth in both broadly and narrowly applied technologies. The effect is significantly larger for broadly applied technologies. Very little else in team configuration matters for creating economic breakthroughs beyond the indirect effects mediated through producing topic-originating patents. Dropping the topic-originating patent variable from the regression in column 2 has a minimal effect on the team configuration variables.

One interpretation is that first inventors with wider knowledge breadth may be able to diffuse the patented invention among a wider and more diverse audience. In other words, our measure of the inventor's knowledge breadth is simply a proxy for the breadth of the inventor's audience and reach. To the extent that this interpretation is accurate, we should expect that the first inventor's knowledge breadth would have a positive relationship with the chance of producing economic breakthroughs across any technological domain including all four we study here, which is what we find in the technological domain-level results in Table 5 below.

Table 4 presents the results for technological modularity: comparing modular technologies (RFID and MRI) with non-modular technological domains (stem cells and nanotubes). The estimates in column 1 suggest an interesting difference in the role of knowledge breadth for modular versus non-modular technological domains. In modular domains, teams producing cognitively novel patents have first inventors with knowledge depth, and little overlap between the first inventor and the second inventor is needed. Here, the standardized protocols that exist in modular technologies can facilitate the knowledge integration between the team members. One might infer that too much knowledge overlap would lead to undesirable knowledge redundancy and reduce the chance of producing novel breakthroughs.

However, in non-modular technologies, teams with a first inventor who has a greater knowledge breadth and substantial overlap in knowledge with the second inventor are significantly associated with producing cognitively novel breakthroughs. The estimates are consistent with the idea that in non-modular domains, the lead inventor acts as the knowledge integrator. Hence, it is important for the first inventor to cover a wider knowledge scope and have more overlap in knowledge with other inventors to be able to facilitate communication and knowledge integration at the team level. Comparing these findings suggests that technological modularity may be a substitute for the first inventor's role as knowledge integrator.

The estimates for the association of team configuration with economic breakthroughs in the second column are similar to those reported previously in Table 3. Again, an increase in a first inventor's knowledge breadth is associated with a higher chance of producing economic breakthroughs in both modular and non-modular technological domains. The estimated effect is larger in non-modular technologies.

Finally, in Table 5, we test how the combination of the two technological characteristics moderate the relationship between each team configuration and each innovation outcome. Each interaction represents the effect of a particular team configuration variable in each of the four technological domains we study. That is, the four technological domains in our sample each represent a theoretical interaction between modularity and broad application. For example, the RFID technological domain represents the theoretical interaction term between modular and broad application. Hence, each interaction between a particular technological domain and each of the team configuration variables identifies what type of team configuration is more associated with novel or economic breakthroughs in that domain. Table A10 in the Appendix presents the same estimates in a summary format to ease the comparison across the four technological domains.

Column 1 shows the relationship with novel breakthroughs (topic-originating patents) which varies significantly across each technological domain. A Wald test comparison of estimated coefficients in shows significant differences on the main five dimensions of team configuration across the four domains at the .05 level. In the case of the MRI technologies, a narrow application and modular domain, the inventors' knowledge breadth has little effect on the chance of producing topic-originating patents. Given the narrow application domain of the technology, there is little that inventors can gain from having a greater breadth of knowledge. Meanwhile, since the technology is modular, standardized protocols can facilitate knowledge

TABLE 5 Impact of team configurations on innovation outcomes: All four technologies

Estimation model: DV:	Logistic (odds ratios reported) Novel breakthrough (1)	Economic breakthrough (2)
Novel breakthroughs		1.332 (0.027)
First inventor's knowledge breadth ×		
MRI (modular & narrowly applied)	1.002 (p = .704)	1.032 (p = .000)
RFID (modular & broadly applied)	0.853 (p = .000)	1.139 (p = .000)
Stem cells (non-modular & narrowly applied)	1.556 (p = .000)	1.162 (p = .000)
Nanotubes (non-modular & broadly applied)	1.413 (p = .000)	1.292 (p = .000)
First inventor's knowledge depth ×		
MRI (modular & narrowly applied)	0.932 (p = .000)	1.080 (p = .000)
RFID (modular & broadly applied)	1.224 (p = .000)	0.996 (p = .641)
Stem cells (non-modular & narrowly applied)	0.745 (p = .000)	0.880 (p = .000)
Nanotubes (non-modular & broadly applied)	0.189 (p = .000)	0.884 (p = .000)
Second inventor's knowledge breadth ×		
MRI (modular & narrowly applied)	0.788 (p = .000)	0.974 (p = .938)
RFID (modular & broadly applied)	1.383 (p = .000)	0.981 (p = .441)
Stem cells (non-modular & narrowly applied)	0.600 (p = .000)	1.094 (p = .058)
Nanotubes (non-modular & broadly applied)	1.531 (p = .000)	1.010 (p = .410)
Second inventor's knowledge depth ×		
MRI (modular & narrowly applied)	0.949 (p = .375)	1.002 (p = .938)
RFID (modular & broadly applied)	0.680 (p = .000)	0.914 (p = .019)
Stem cells (non-modular & narrowly applied)	1.536 (p = .000)	1.002 (p = .948)
Nanotubes (non-modular & broadly applied)	0.378 (p = .000)	1.200 (p = .000)
Overlap in the knowledge scope of the first and second inventors ×		
MRI (modular & narrowly applied)	0.158 (p = .000)	0.973 (p = .506)
RFID (modular & broadly applied)	0.898 (p = .014)	0.762 (p = .011)
Stem cells (non-modular & narrowly applied)	2.289 (p = .000)	1.360 (p = .000)
Nanotubes (non-modular & broadly applied)	1.164 (p = .000)	0.994 (p = .849)
Full set of controls & technology-time fixed effects	Yes	Yes
Number of observations	4,001	16,744
Pseudo R^2	0.279	0.184

Note: All models are logistics regressions with robust standard errors clustered at the technology level. Reported estimates are odds rations. p-values are reported in parentheses. Each coefficient shows the odds-ratios of producing novel or economic breakthroughs associated with a team characteristic variable in each domain.

integration at the team level, reducing the need for knowledge overlap between inventors' knowledge scope. Indeed, the estimates suggest that teams with lower levels of knowledge overlap are significantly more associated with producing topic-originating patents.

In the case of RFIDs, a broadly applied and modular technological domain, the estimated effect of the second inventor's knowledge breadth on the likelihood of producing topic-originating patents is positive and significant. A standard deviation increase in the second inventor's knowledge breadth is associated with a 1.4 times increase the chance of producing novel breakthroughs. At the same time, since the technology is modular, standardized protocols can facilitate knowledge integration at the team level. The estimated effect of knowledge overlap is negative and significant. That said, the negative effect of knowledge overlap is not as large as the effect we find for MRI patents. In the case of RFID, because of the large breadth of applications, inventors may find themselves in new application domains where the standardized interfaces are not adequate. In such situations, knowledge overlap may play an important role in knowledge integration at the team level.

In the case of stem cells, a narrowly applied and non-modular technological domain, three effects stand out. Teams in which first inventor has more knowledge breadth are more associated with producing cognitively novel (topic originating) patents. The second inventor's knowledge depth is also significantly associated with the chance of producing topic-originating patents. Moreover, the effect of overlap between the first and second inventors' knowledge scope on the likelihood of producing cognitively novel patents is positive, large, and significant. Overall, the estimates suggest that, in the absence of a modular design with standardized interfaces, an experienced inventor with wider knowledge breadth that overlaps with other team members is essential for knowledge integration at the team level. Meanwhile, due to the narrow-purpose range of integration, the team does not benefit much from the second inventor's knowledge breadth. Instead, an inventor with more knowledge depth is more likely to help the team produce cognitively novel innovations.

The results for nanotubes highlight the importance of both knowledge breadth and knowledge overlap in a broadly applied but non-modular technological domain. The estimates suggest that teams in which both top inventors have more knowledge breadth are more likely to produce novel breakthroughs. This is consistent with the idea that for broadly applied technologies, broader knowledge helps teams navigate a larger knowledge landscape and find new application areas. Meanwhile, because the technology is not modular, it is important for the top inventors to have knowledge overlap to be able to successfully integrate their diverse knowledge stocks. However, the estimated effect of knowledge overlap here is smaller than that in the stem cell domain. Knowledge overlap may be a double-edge sword in non-modular domains with broad applications. Some level of knowledge overlap may be necessary for knowledge integration. However, too much knowledge overlap may limit the effective level of knowledge breadth at the team level.

For economic breakthroughs (column 2 in Table 5), we find that cognitive novelty is positively associated with economic impact. Further, we find exactly what was anticipated by the earlier analyses: the first inventor's knowledge breadth is key for achieving future citations, and this holds across all types of technology. The mirror effect is that the depth of knowledge of the first inventor is largely negatively associated with economic breakthroughs, though the size of the effect is small. There are few other consistent results for team configuration across the different domains, either for the second inventor's knowledge or for knowledge overlap. Because economic breakthroughs are measured by the number of forward citations, this finding suggests that, regardless of technological domain, inventors with more breadth of experience are more likely to garner more future citations to their patents. An implication is that breadth of experience may capture other social processes such as inventor networks or inventor prominence that might contribute to the uptake of particular ideas.

Thus, the variation in desirable team configurations appears to matter more when generating novel breakthroughs than when simply going for economic impact, though this claim comes with an important caveat: cognitive novelty contributes to the future economic impact of a patent. To summarize the findings on novel breakthroughs, we show first in Table 6 the different effects of the types of technologies (broad vs. narrow, modular vs. non-modular) and how, in combination the effects are either reinforcing or offsetting. Figure 1 graphically compares the average de-meaned team configuration for the first two authors behind cognitively novel breakthroughs to the average de-meaned team configuration behind non-novel patents to visualize the differences in team configurations associated with novel breakthroughs relative to the average de-meaned team configuration (that does not produce a novel breakthrough).

Our key insight is that different team configurations may be useful in the case of both modular versus non-modular technologies and broadly applied versus narrowly applied technologies. Interestingly, some of these effects are amplified when they are combined, and some are offsetting. For example, for nanotubes, the inventors' knowledge breadth is important to bridge to new application domains given that the technology is broadly applied. At the same time, due to the non-modular nature of technology, knowledge overlap allows inventors to integrate their diverse knowledge backgrounds. In contrast, in RFID which is also a broadly applied, there is less need for such knowledge overlap since standardization can substitute the need for overlap as a facilitator of knowledge integration at the team level. In stem cells, again we see the importance of knowledge overlap in the absence of a modular technological design. However, since the technology is narrow-purpose, second inventors with deeper knowledge are more likely to contribute to the production of cognitively novel (topic-originating) patents. Meanwhile, a first inventor who has the necessary knowledge breadth and overlap with the second inventor can

TABLE 6 Team configuration for novel breakthroughs

		Broadly-applied	**Narrowly-applied**
		• 2nd inventor acts as a bridge to new applications	• 2nd inventor's knowledge depth helps identify novelty
Modular	• Standard interfaces between components substitute for knowledge overlap in facilitating team-level knowledge integration	**RFID** • 2nd inventor acts as a bridge to new applications • Little knowledge overlap required to integrate	**MRI** • 2nd inventor's knowledge depth helps identify novelty • Little knowledge overlap required to integrate
Non-Modular	• Knowledge overlap is essential to coordinate across inventors • 1st inventor's knowledge breadth is needed for team-level knowledge integration	**Nanotube** • All inventors need knowledge breadth to identify new applications and facilitate team-level knowledge integration • Some degree of knowledge overlap required to coordinate across inventors	**Stem Cells** • 1st inventor's knowledge breadth is in facilitating team-level knowledge integration • 2nd inventor's knowledge depth helps identify novelty • Knowledge overlap is essential to coordinate across inventors

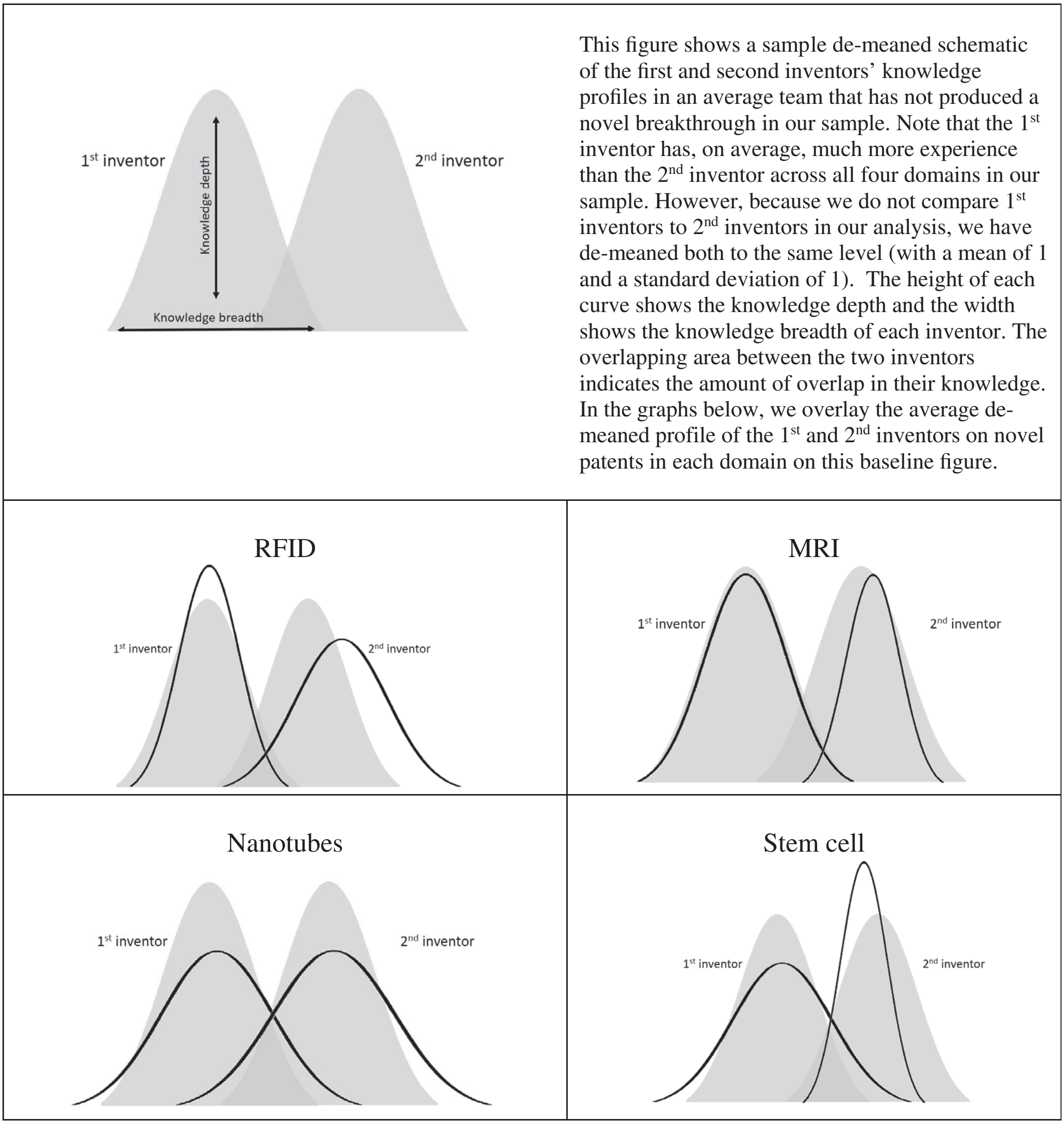

FIGURE 1 Illustrating the results graphically: first and second inventor knowledge breadth, depth, and overlap as associated with novel breakthroughs

facilitate the knowledge integration at the team level. Finally, we see that in the modular MRI domain, knowledge overlap is again negatively associated with the chance of producing novel breakthroughs. Here, the second inventor's knowledge breadth is also not helpful due to the narrow-purpose nature of the technology.

4.2 | Robustness tests

We performed several additional analyses to test the robustness of our results. First, given that our results are based on interactions in a nonlinear estimation models, we have also tested the sensitivity of our findings to using a linear probability model instead of a logistic model and find our results are consistent (Table A11 in the Appendix).

Second, one may be concerned that the effects we have attributed to the breadth of application might instead be driven by the difference between technology used purely as an input to an invention versus further development of a technology In other words, unlike patents for stem cell and MRI that largely involve some further development of the technologies themselves, patents for RFID and nanotube technologies may simply document pure inputs into the innovation process without additional modification to the technologies themselves. Therefore, the effect of application breadth may be confounded. While technologies as inputs or as development can be positively correlated, they are theoretically distinct.

To address this concern, we selected a random subsample of patents in the nanotube and RFID domains and coded them under "pure input/use" and "development/modification." Our coding suggests that approximately 85% of the nanotube patents involve some development or modification of the nanotube technology. Using the same coding procedure, we found very similar figures for the MRI (82% are for development) and stem cell (84%) domains. For the RFID patents, the figure is lower at 55%. However, the coding revealed that within the RFID domain, there is a clear distinction between patents that mention the RFID technology in their titles or abstract versus those that mention the technology only in the claims section. In the former category, more than 90% of the patents involve some development of the RFID technology. To make sure our results are not driven by the variance in input versus development, we did an additional robustness check excluding the latter category of RFID patents—that is, the ones mentioning the technology only in the claims section. The results for this subset of patents in each domain are reported in Table A12 in the Appendix and are in line with those reported in Table 5. It is thus very unlikely that our results regarding application breadth are driven by variation in input patents versus development patents.

Finally, we also repeated our regressions in Table 5 on the full sample of patents included the 128 and 115 patents from the RFID and nanotubes samples that do not conform to the idea that the input technological domain and output technological domain are different for wider-ranging technologies. The results are reported, as mentioned above, in Table A2 and Figure A4 in the Appendix and are in line with those reported in Table 5.

5 | DISCUSSION AND CONCLUSION

While innovation has increasingly become a collaborative effort (Wuchty et al., 2007), studies conflict in their findings about what types of team configurations might be the most useful for creating innovative outputs. Do teams need to include inventors with knowledge breadth (Fleming, 2001; Gittelman & Kogut, 2003; Hargadon & Sutton, 1997; Uzzi & Spiro, 2005) or knowledge depth (Kaplan & Vakili, 2015; Kuhn, 1962/1996; Taylor & Greve, 2006; Weisberg, 1999)? Do teams need overlapping knowledge in order to integrate insights from diverse areas (Dahlin et al., 2005; Dougherty, 1992) or do overlaps create inefficiencies (Burt, 2004)? We wondered if the conflicting conclusions in prior research might come from differences in the characteristics of technologies studied, as these prior arguments have generally not foregrounded the impact of the technological domain for innovation, either drawing from a wide set of technological areas while controlling for technology (e.g., Arts & Veugelers, 2015; Singh & Fleming, 2010) or focusing on a single technological domain, which may not generalize to other contexts (e.g., Phene et al., 2006; Rosenkopf & Nerkar, 2001).

Our empirical analysis explores these tensions by focusing on two underlying factors or basis variables (Rosenkopf & Levinthal, 2020) that might constrain associations with different innovative outcomes—degree of modularity and breadth of application—in a theoretical sample of four different technologies: MRI (modular and narrowly applied), RFID (modular and broadly applied), stem cells (non-modular and narrowly applied), and nanotubes (non-modular and broadly applied). Using two different measures of innovative outcomes—patents that represent either novel breakthroughs or economic breakthroughs—we found that different team configurations are indeed associated with different technological characteristics. Thus, generalizations about team configurations should be limited by the constraints imposed by modularity and application breadth.

5.1 | Team configurations for novel breakthroughs

For cognitively novel breakthroughs, we find that modularity is a substitute for knowledge overlap in integrating diverse insights, while, for technologies that are not modular, the first inventor serves as the integrator. In comparing broadly and narrowly applied technologies, we find that second inventors have a crucial role to play: for broadly applied technologies, they provide knowledge breadth, presumably to seek out a wide range of applications, and for narrowly applied technologies they provide greater knowledge depth, presumably to seek out anomalies. We also find that the interaction of modularity and application breadth moderates the effect of team configuration on the chance of producing novel breakthroughs.

These findings have three implications for theory and empirical analysis concerning organizing for innovation. First, we may not be able to create a general theory for team configurations that works in all settings. Attending to the different technological domains would be essential not only theoretically but also empirically: simply controlling for technological classes may be inadequate because the average effects in a broad range of technologies might disguise opposing effects within specific technologies.

Second, breadth and depth of knowledge serve different creative functions, and the degree to which they are either reinforcing or offsetting depends on the nature of the technology. For example, for broadly applied technologies, the second inventor's breadth of knowledge may be crucial for identifying new applications and depth of knowledge may reduce her ability to find these insights. For narrowly applied technologies, the second inventor's depth of knowledge may be precisely what allows for the new insights in the narrow domain and breadth of knowledge may hinder the ability to seek out those anomalies.

Third, creativity depends on recombinations of insights; however, this integration process can be accomplished in different ways depending on the nature of the technology. In non-modular technologies, inventors may need breadth of knowledge and substantial overlap in team experience in order to integrate ideas. However, in modular technologies, standards may be able to substitute for the human integration function.

5.2 | Team configurations for economic breakthroughs

We show that novel breakthroughs are positively associated with economic impact across all four technological domains. Much of the patent literature on creating breakthroughs has hypothesized but not measured this effect directly (e.g., Phene et al., 2006; Singh &

Fleming, 2010; Trajtenberg et al., 1997). We are able to show empirically that having more novel ideas is associated with the likelihood of creating an economic breakthrough as measured by forward citations no matter the domain (at least in the four we have studied).

When we turn to examining which team configurations contribute to these economic impacts, we find that the breadth of experience of the first inventor matters most, and this holds for all of the technological domains we studied. These results may suggest that measuring the breadth of inventor experience may also capture something about the social processes of diffusion in which more highly connected inventors are more likely to get cited. The inventor's knowledge breadth may act as a proxy for the breadth of the inventor's audience and reach. The fact that, in our analyses, the first inventor's knowledge breadth has a positive relationship with the chance of producing economic breakthroughs across the four very diverse technologies we study here offers some support for this conclusion. However, we do not have a strong theoretical lens to interpret these results pertaining to the relationship between team knowledge composition and the economic impact of their innovations. Since we have drawn our theoretical arguments from a literature that most directly theorizes about the relationship between the knowledge composition of teams and the novelty of their innovations, our interpretations with regard to the economic impact of team configurations are speculative and call for future research to clarify the relationship between team configuration, novelty and economic impact.

5.3 | Limitations

We should emphasize that, given our empirical design, our estimations only show the association between team configuration and innovation output and may not necessarily be based on causal relationships. On the one hand, it is possible that our results do reveal a causal relationship between team configuration and each innovation type. On the other hand, our results might be driven by some selection mechanism in which inventors with certain specialization profiles might be more likely to collaborate for certain type of outcomes (novelty or impact). For example, it is possible that in the RFID domain, inventors with deep knowledge seek out inventors with wider knowledge breadth if they plan to work on more novel ideas. Or, alternatively, managers who put teams with such a profile together may also task them with pursuing cognitively novel innovations. Such selection mechanisms may themselves reflect the underlying causal effects: that because deep knowledge needs to be combined with knowledge breadth to produce novelty in the RFID domain, inventors or their managers try to select on such team profiles if their aim is to produce novelty. Alternatively, such selection mechanisms might be driven by other omitted factors unrelated to the underlying causal effects at work.

However, any such explanation would have to be consistent with the variation we see in the relationship between team configuration and innovation output across all four technological domains. In other words, such an omitted factor should, on the one hand, lead to the formation of teams with complementary and non-overlapping breadth and depth between the first and second inventors in the RFID domain while at the same time increase the chance of such teams producing novel innovations, and, on the other hand, lead to the formation of teams with overlapping knowledge profiles (more depth than breadth) in the stem cell area while, again, at the same time increase the likelihood of producing novel innovations by such teams in that domain. While we cannot think of a plausible selection mechanism that would provide such an alternative explanation, we cannot rule out all such selection mechanisms given our empirical design and believe that this question provides a useful avenue for future research.

In conclusion, we find that team configurations for innovation may be contingent on the technological domain in which an organization operates. Though early continency theory (Woodward, 1958; Woodward, 1970) highlighted that organizational form should depend on the types of technologies an organization pursues, much of the existing literature on team configurations for innovation has not addressed these contingencies directly. Our cross-domain exploratory analysis offers insight into how those contingencies might operate and offers a path towards resolution of some of the prior inconsistent findings about the nature of the relationships between team design choices and innovative outcomes.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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