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When Do Expert Teams Fail to Create Impactful Inventions?

Simon J. D. Schillebeeckx, Yimin Lin and Gerard George

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ABSTRACT We investigate the salience of expertise in creating high impact inventions and question experts' ability to deploy novel ideas. Specifically, we examine the relationships between expertise, component originality, and a team's structural holes' position in the collaborative network and propose that, in relative terms, expert teams create lower impact inventions if they deploy more original components and if they occupy structural holes. We test and confirm our hypotheses in a sample of semiconductor firms. In post-hoc analyses, we find a three-way interaction where the negative effect of structural holes almost disappears when an expert team experiments with original components whereas an increase in non-redundancy is detrimental when teams with high expertise use familiar components. Our findings inform a foundational view of the invention process and provide novel insights into the contingent benefits of domain expertise.

Keywords: component originality, expertise, inventor teams, patents, structural holes

INTRODUCTION

During their careers, inventors acquire knowledge, make discoveries, develop new ideas, and create inventions. In doing so, they develop expertise within and across domains. In general, multi-level research findings have established positive effects of expertise on invention-related outcomes. For individual actors, experience with specific technologies or products is positively linked to learning (Christensen et al., 2001; Johnson and Russo, 1984), for team actors, experience with patenting positively influences the likelihood that a patent is a breakthrough invention (Kaplan and Vakili, 2015; Singh and Fleming, 2010), for organizational actors, prior experience boosts likelihood of engaging

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in impactful technology development (Stuart and Podolny, 1996), and for industry actors, experience with technological components relates positively to the impact of inventions that recombine those components (Fleming, 2001).

Such findings provide support for the so-called ‘foundational view’ which proffers that inventing requires the identification of anomalies or inconsistencies in a knowledge domain and that this identification is almost impossible without a foundational understanding of a domain’s underlying assumptions, weaknesses, and strengths (Kaplan and Vakili, 2015; Weisberg, 1999). An opposing view of invention however suggests that deep expertise may ‘entrench’ actors into narrow ways of thinking, limiting creativity, and eventually reducing novelty and/or impact (Audia and Goncalo, 2007; Dane, 2010; George et al., 2008; Kaplan and Vakili, 2015). This problem may be exacerbated for teams, especially if team members work together on multiple projects because repeated prior collaboration may further entrench their ways of working, limit perspective-taking, and reduce creative abrasion, thus undermining the ability to generate truly novel ideas (Hoever et al., 2012; Skilton and Dooley, 2010). Given these opposing schools of thought, our research questions whether it is possible for there to be too much expertise and if so, whether teams can avoid such competency traps by integrating original ideas in their inventions (Siggelkow and Levinthal, 2005)? Our theoretical arguments suggest that expert teams underperform when they are strongly exposed to original content, either in terms of the knowledge components they use, or in terms of non-redundancy in the collaboration network. We examine this issue in a sample of over 40,000 patents of 105 US semiconductor firms and make three contributions to the literature.

First, we ask whether teams with high domain expertise are better or worse at deploying original knowledge components, a form of exploration, than teams with less expertise. While some have claimed that ‘near consensus exists on the need for balance’ between explorative and exploitative search (Gupta et al., 2006, p. 967), the entrenchment view stipulates that distant search is needed to break out of the narrow trenches of expertise and avoid competency traps (Leonard-Barton, 1992; Siggelkow and Levinthal, 2005). For instance, Jung and Lee (2016) established a strong link between original search and invention impact. The foundational view on the other hand posits that local search, through its strong relation with the likelihood of cognitive breakthroughs, positively affects invention impact (Kaplan and Vakili, 2015). Unlike Jung and Lee (2016), we find a negative effect of knowledge originality and postulate that teams with high domain expertise benefit less from using original knowledge than teams with less expertise. Our findings confirm this hypothesis.

Our second contribution establishes non-redundancy in the social network as a boundary condition for expertise’s effect on invention impact. In doing so, we contribute to a growing literature on the contingent effects of inventor networks on invention outcomes (Guan and Liu, 2016; Paruchuri and Awate, 2017; Wang et al., 2014). We investigate how a team’s structural holes’ position in the inventor network influences the contribution of expertise to the generation of impactful inventions. While such a position has typically been found to boost search and exploration, its effect on invention impact is less clear-cut (Ahuja, 2000; Guan and Liu, 2016). Stepping away from the purely ‘structuralist’ perspective (Carnabuci and Diószegi, 2015), we proffer that structural holes may be considered substitutes for domain expertise, consequently we anticipate an antagonistic

relationship between both predictors (Andersson et al., 2014), which is confirmed in our findings.

A third contribution stems from a post-hoc analysis that focuses on how both contingencies interact. Because both original components and structural holes can be interpreted as sources of novelty, it may be so that combining them imposes excessive cognitive difficulty on teams, making them substitutes, or that they can complement one another, e.g., when a non-redundant prior collaborator can help illuminate the use cases of an original knowledge component. We find empirical evidence of this three-way interaction and discuss how this finding adds boundary conditions to our focal hypotheses. Expert teams that are connected to non-redundant ties in the social network and use highly original components significantly underperform those that are either less connected or those that use more familiar components. Overall, expert teams that use familiar components and are not connected to non-redundant ties create the highest impact inventions. As such, our paper provides strong support for the foundational view that sees creativity and successful invention as processes that require both high levels of expertise and a within-domain search focus, rather than as an outcome of boundary-spanning, multi-disciplinary search.

THEORETICAL BACKGROUND

Through a combination of deliberate practice, implicit and explicit learning, inventors amass significant knowledge in a domain. Accumulating such knowledge takes time and is susceptible to time compression diseconomies, which makes it valuable and hard to imitate (Barney, 1991; Dierickx and Cool, 1989). Once sufficient knowledge in a particular domain is mastered, we can say the inventor has become an expert and her expertise, defined as ‘a high level of domain-specific knowledge acquired through experience’, sets her apart from others (Dane, 2010, p. 580). Domain experts have a broad knowledge scope, in terms of the quantity of diverse components within a focal domain that they master, and have an in-depth understanding of the variety of ways and the intensity with which these components are interlinked (Dane, 2010). But scope alone is not enough for true expertise, for inventors to be truly successful, they also require significant knowledge depth (Boh et al., 2014). By combining deep and broad knowledge, expertise underpins absorptive capacity and architectural competence that enable teams to recombine components to achieve inventive success (Henderson and Clark, 1990). Given these strengths of domain expertise, we question whether there are constraints to experts’ abilities to recombine knowledge components into impactful inventions.

Specifically, because novelty creation is essential to the inventive process, our focal research question asks whether expert teams are better or worse at turning original knowledge into successful inventions. Because firms, teams, and inventors are embedded in collaborative and knowledge component networks within which they search for ideas and solutions to problems (Guan and Liu, 2016; Kotha et al., 2013; Wang et al., 2014), we conceive of original knowledge in two complementary ways: original knowledge components taken from the knowledge component network, and original ideas accessed through their structurally advantageous position in the collaboration network. Teams can focus on reusing familiar components that are well-understood in the industry and

for which each new use case creates new information flows and enhances the recombinatorial potential (Fleming and Sorenson, 2001; Kok et al., 2018). Alternatively, they can engage in more distant search and deploy original components, thereby introducing new ideas to the industry which could boost impact as well (Kaplan and Vakili, 2015). Within the social network, teams can occupy more or less advantageous positions. Burt (2004) stipulated that actors in structural hole positions are better positioned for good ideas but they might struggle with the implementation of those ideas, what Obstfeld (2005) referred to as the action problem of structural holes. We ground our theory in the foundational view and develop hypotheses on conditions when expert teams fail to generate impactful inventions.

HYPOTHESES

Team domain expertise captures the domain knowledge that team members acquire during their inventive history. Knowledge is organized in the form of schemas. Compared to novices, experts have larger schemas consisting of more domain-specific knowledge components as well as a stronger relationships between those components (Dane, 2010). Expertise thus implies a historically built-up knowledge stock and cognitive structure in which inventors can look for previously deployed and developed ideas and reuse them. It is generally easier to invent within a familiar domain, as these inventions fit into existing cognitive structures and can leverage established channels of communication (Normann, 1971; Zander and Kogut, 1995). An expert inventor can then recycle mechanical representations and concepts because a 'creative technologist possesses a mental set of stock solutions from which he draws in addressing problems' (Jenkins, in Gorman et al., 1990, p. 141). The path-dependent nature of intra-domain knowledge accumulation (Dierickx and Cool, 1989) and the unique rules and heuristics by which the firm interacts with the knowledge domain (Normann, 1971) are valuable, rare, and hard to imitate, creating a potential advantage (Barney, 1991).

More experienced inventors have knowledge schemas that more accurately reflect (a part of) the knowledge landscape, making it easier to locate new knowledge in the vicinity of their own idiosyncratic existing knowledge. Expertise helps inventors create new knowledge and to create new recombinations and this requires both an in-depth understanding of the focal domain as well as significant breadth within this domain which exposes inventors to new ideas that can be meaningfully integrated (Boh et al., 2014).

High expertise is also associated with a reduction in the probability of making mistakes in the selection of components or combinations (Fleming, 2001; Levinthal and March, 1981). Moreover, because expertise improves understanding about which components are tightly coupled, experts have a lower risk of making mistakes in the recombination of those components or combination, thus reducing experimentation failure (Katila and Ahuja, 2002; Yayavaram and Chen, 2015). Expert teams heightened abilities in finding, selecting, and recombining components (or their combinations) are the essence of absorptive capacity, the ability to recognize, assimilate, and apply new external knowledge (Zahra and George, 2002; Zou et al., 2018), which in turn is susceptible to time compression diseconomies, making it both valuable and hard to substitute (Dierickx and Cool, 1989).

In addition, more knowledgeable inventors have a better perspective on what is required to create a successful product. They know the necessary steps and can envision plausible solutions thanks to a forward-thinking orientation (Dane, 2010). This enables expert teams to decompose a problem set into more manageable problems that can be worked on in parallel or in an efficient sequence (Eisenhardt and Tabrizi, 1995). This *capacity to envision* a future invention during the invention process is rooted in the actor's position in the knowledge landscape. Each position is idiosyncratic and provides a unique vantage point, a platform for future inventive activity. Inventors or teams with more expertise have access to more diverse knowledge components, each of which forms a possible stepping stone from which to start another invention process. Thus, teams that invent in domains in which they have high expertise are likely to see unique opportunities: 'The more distinctive the view, the more likely that such a view can encompass valuable opportunities not similarly visible to other firms – implying at least a temporary advantage for the firm that identifies the opportunity' (Denrell et al., 2003, p. 988).

Yet, expertise has potential downsides. Dane (2010) argues a trade-off exists between expertise and flexibility because experts may become cognitively entrenched in specific schemas and ways of thinking that reduce their ability to come up with creative solutions. In addition, high experience in one domain may result in core rigidities and induce teams to rely on historically established ideas and routines, thereby decreasing their chances of novelty and impact (Audia and Goncalo, 2007; Leonard-Barton, 1992; Singh and Fleming, 2010). Also, while Boh et al. (2014) find that the combination of breadth and depth has a very small negative influence on impact generation, we believe this is more likely to hold at the individual than at the team level, because teams can consist of generalists and specialists, rather than their elusive 'polymaths', and thus benefit from the best of both worlds. Also, given that technological domains are broad and malleable knowledge areas that are continually being reinvented, not only by inventors but also by patent officers who can assign new inventions to existing domains by broadening the domain's boundaries, it is unlikely that individual inventors will ever reach domain saturation, suggesting that the recombinant potential of extant knowledge need not decrease over time (Fleming and Sorenson, 2001). This is because new inventions not only take up space within a domain but also enlarge it, creating new possibilities for invention through further recombination (Normann, 1971). Because of the combined benefits of the accumulated knowledge stock, the superior ability to find, select, and use components, the ability to envision objectives clearly, and because knowledge breadth and depth need not be embodied in a single inventor when considering team expertise, we propose that:

Hypothesis 1: Team domain expertise exhibits a positive relationship with invention impact

Domain expertise and component originality

Knowledge components that have been used frequently are more reliable (Fleming, 2001). They have gone through extensive testing and verification which makes them useful to actors with sufficient absorptive capacity to understand and deploy them (Zou

et al., 2018), such that teams with high domain expertise should have a natural advantage when reusing them. Due to the path dependent nature of knowledge accumulation (Nelson and Winter, 1982), teams with strong domain expertise are likely to be well aware of how knowledge components can be used and have been used before. If they rely on components that have been used extensively in the industry, they are engaging in a form of local search by reusing components with an established track record. This reduces the risk of experimentation and increases the chances of success. Kaplan and Vakili (2015) have found that local search leads to cognitive novelty which in turn leads to impact. For expert teams, engaging in local search requires sticking to what they know best and thus using common knowledge components.

Yet, it is possible that frequently used components edge closer to a technological frontier and thus have a lower recombination potential (Dosi, 1982). This would diminish the probability of detecting novel and impactful combinations, simply because there is less novelty to detect (Galunic and Rodan, 1998). Such a view aligns with the entrenchment effect of invention which suggests that search beyond the familiar helps firms overcome path dependency (Ahuja and Katila, 2001; Rosenkopf and Nerkar, 2001). However, other authors have proposed that with every component recombination, new information flows emerge that actually broaden the future recombination potential (Katila and Chen, 2008). If it is indeed true that prior recombination increases the potential for future recombination opportunities (Yang et al., 2010), expert teams' superior absorptive capacity should enhance their ability to learn from these new information flows and their higher architectural competence, rooted in past experimentation and learning from failure, should improve their ability to recombine familiar components. One could think of the new information embedded in each component recombination as having public good characteristics. It is only through the complementarity between that public good and expertise that teams can synergistically use these knowledge flows to achieve superior impact. Non domain-experts and novices would thus be at a disadvantage.

Even if a higher incidence of past recombination reduces the future recombination potential (Dosi, 1982; Galunic and Rodan, 1998), teams with high domain expertise should be less susceptible to these dynamics, because their position in the technological landscape gives them a unique perspective on the latent recombinative possibilities, enhancing their chances of discovering even narrow pathways to high peaks (Fleming and Sorenson, 2004). In addition, even if the technological potential of components decreases with increased use (Dosi, 1982), the process of historical component selection is not random such that frequently used components are likely to have inherently higher recombination potential. Capaldo et al. (2017) therefore state that components that have not been taken up by the industry are likely to have lower technological applicability.

As expertise increases, the relative benefit of deploying commonly used components goes up because more experienced teams are also more likely to be familiar with these components that have been used before in the industry. This benefit however disappears when expert teams deploy original components which are generally as unfamiliar to them as they are to inexperienced teams. Finally, we have also acknowledged that expertise may have a downside, especially because it may reduce flexibility and impose mental blockades, which may make experts less receptive to new ideas. This cognitive entrenchment may drive expert teams to deploy tried and tested schemas when using original

components even if they are poorly suited for the novel knowledge (Audia and Goncalo, 2007; Dane, 2010). Non-expert teams should not have these problems and therefore should be relatively better at deploying original knowledge. In line with the foundational view (Kaplan and Vakili, 2015), these arguments lead to the following hypothesis:

Hypothesis 2: The positive effect of team domain expertise on invention impact is negatively moderated by component originality such that experienced teams create lower impact inventions when they recombine original components.

Social network position: the downside of structural holes

Knowledge creation is influenced by the composition and structure of collaborative networks (Schilling and Phelps, 2007) within which individuals, teams, or firms can take up positions that are associated with diverging performance (Savino et al., 2017). Like original components, structural holes are associated with access to information and could provide an alternative source of novelty that improves recombination potential (Burt, 2004; Schillebeeckx et al., 2019). Two complementary explanations drive this effect. First non-redundant ties could facilitate early access to novel information and dynamic, tacit, transient, and social knowledge such that the team may have an advantage in learning about recent developments and trends, and may know more about the distribution of knowledge within the inventor community (i.e., who knows what) (Wang et al., 2014). Secondly, researchers whose social networks are rich in structural holes may have *more autonomy* during their inventive activities because they are typically able to work free from interference (Burt, 1992, 2004; Guan and Liu, 2016).

While recent work has established a positive relation between structural holes and various invention-related outcomes (Guan and Liu, 2016; Paruchuri and Awate, 2017; Wang et al., 2014), these authors have so far not yet investigated the influence of invention impact. Moreover, Ahuja (2000) established a negative relation between a firm's structural holes and its inventive output, leading to further questions about the causal logic. Furthermore, most network studies remain agnostic about the quality of the node, evidencing a lack of synthesis between attribute and relation-based approaches to the team-performance relationship (Balkundi and Harrison, 2006). While collaborative ties are 'conduits for the flow of interpersonal resources' (Balkundi and Harrison, 2006, p. 50), the provenance of these interpersonal resources that can flow through ties is often ignored. Rodan and Galunic (2004) for instance argue that it is essential to consider 'the knowledge held by actors in the network' above and beyond the structure itself. While the connectionist perspective presumes that the ability of an actor to succeed in some endeavour 'is a function of the quality and quantity of resources controlled by the actor's alters' (Borgatti and Foster, 2003, p. 1004), we would be remiss to ignore the resources controlled by the focal actor.

Thus, if we consider the ego to be a team with high domain expertise, non-redundant ties may add limited value in the form of knowledge access because the team already has direct access to unique knowledge from its members. Also teams of domain experts tend to receive autonomy within their organizations by virtue of their expertise, irrespective of their social network position. In addition, recent findings suggest that individuals with

an invention-oriented cognitive style do not benefit from their structural hole position (Carnabuci and Diószegi, 2015). While experts do not know everything, one can question whether the added value of information provided by non-redundant ties can reliably lead to high impact inventions? Wang et al. (2014) for instance fail to confirm that a structural holes' position in the collaboration network improves researcher productivity, suggesting that the information provided may not be actionable.

In this light, Obstfeld (2005) suggested that while structural holes represent an opportunity structure for idea generation, they may create an action problem as well, making harder to mobilize resources and turn an idea into a successful invention. This problem may be particularly salient for expert teams for two reasons. First, expert teams are likely to be constrained by mental models and schemas that determine their way of thinking about specific problems. Because individuals work within cognitive frames, they are bound to think about problems along relatively consistent lines, forcing them into local search habits and limiting exploration (March, 1991). Access to diverging information may then create some form of cognitive dissonance that experts fail to resolve in the recombinatorial process. In addition, expert teams have worked along a specific technological trajectory, developing their expertise over time. This creates expectations of continuity within the firm, making it easy for experts to mobilize resources, but only if they stick to what they know.

Finally, at the impact side, structural holes in the collaboration network could facilitate idea diffusion which heightens the probability of receiving more attention. However, social attention can also be driven by expertise rather than by network structure. Put differently, the attention network can be much thicker than the collaboration network, making the latter largely redundant in terms of idea diffusion, and this effect is likely to increase with expertise. On the other hand, being connected, even indirectly, to others may increase the network's reliance on you, especially if you are an expert. This may divert attention away from your own inventive work, leading to lower quality and eventually lower impact.

Thus, as team expertise increases, the commonly cited benefits of structural holes' non-redundancy in the collaboration network – access to novel, often tacit, information, structural autonomy, and increased diffusion of ideas – may be respectively redundant and distracting, driven by expertise rather than the collaboration network, and embedded in a much thicker attention network. We therefore anticipate an 'antagonistic interaction' where both predictor and moderator are assumed to contribute to impact but their interaction is in the opposite direction (see Andersson et al., 2014). This leads us to propose:

Hypothesis 3: The positive effect of team domain expertise on invention impact is negatively moderated by the team's structural holes' position in the collaboration network such that expert teams create lower impact inventions when they have access to more diverse non-redundant ties.

DATA AND METHODS

We envisage invention as the end result of a problem-solving exercise conducted by an inventor or, more commonly, a team of inventors (Wuchty et al., 2007). A patent is a

formal representation of an externally validated and novel solution to a problem and therefore is a useful proxy for successful inventive activity (Katila, 2002; Walker, 1995). Patent documents provide ‘a reasonably complete description of the invention’ which makes them especially useful in answering research questions around the antecedents of inventive success (Griliches, 1998, p. 291). Patent examiners assign technological classes and subclasses to each invention and these serve as fine-grained identifications of the technological domains within which the invention is situated. A number of prior studies has used patent subclasses as proxies for experience, recombination of technological components, and the relationships between various technological domains (Carnabuci and Operti, 2013; Fleming, 2001; Fleming and Sorenson, 2001, 2004; Schillebeeckx et al., 2019; Sorenson et al., 2006). In line with these and many other patent studies, we will use the rich information captured in patents to proxy technological domains (patent classifications), knowledge components and their age (prior art citations and their grant dates), impact (received forward citations), and team information.

The empirical setting for this study is the US semiconductor industry. We chose a single industry because dominant paradigms of ‘things that work’ are likely to exist within the same industry but differ across industries such that using multiple industries could have caused unrelated variation (Kaplan and Vakili, 2015). In comparison to other industries, US semiconductor firms have been noted to have exceptionally high invention rates, as well as high propensities to patent most of these inventions, especially since the 1980s (Hall and Ziedonis, 2001; Schillebeeckx et al., 2019; Stuart, 2000). Therefore, patents serve as an appropriate proxy for invention in this context.

Data Sources

We began by combining the list of US semiconductor firms used in Hall and Ziedonis (2001) with all other US semiconductor firms that are available via COMPUSTAT (SIC code = 3674). This additional source was required since Hall and Ziedonis (2001) only consider firms which were active between 1975 and 1995, whereas our data extends to 2004, and our forward citations to 2015. To ensure that no major semiconductor firm was left out of our dataset, we supplemented our list with those firms listed on the annual publication by iSuppli Corporation which ranks semiconductor firms (Schillebeeckx et al., 2019). Following these methods, we compiled a list of 171 US semiconductor firms, all of which have a COMPUSTAT record. We limited ourselves to US firms to avoid variation in institutional context and patenting behaviour, which would have been hard to control for in a meaningful way (Alnuaimi and George, 2016).

Next, we retrieved the patents assigned to these firms by comparing our list of 171 firms to the 247,309 assignees that were granted a USPTO patent during the time-period 1975–2008. A simple name-matching algorithm would have not been accurate because of the various ways in which many firms are named on a patent document. For example, the firm’s name may appear in full or as an acronym, or a subsidiary. To ensure that each firm’s patents were aggregated as accurately as possible, first, we used the unique numerical identifiers¹ available from the NBER patent project which groups unique firms. Then, we used the Directory of American Firms Operating in Foreign Countries, which lists each variation in the names of the subsidiaries associated with US

firms. These variations were compared against the 247,309 assignees that were granted a USPTO patent during the time period spanning 1975 and 2008.

We excluded patents that were applied for after 2004 to avoid right censoring of the forward citation data. Thus, our main sample spanned the time period 1975 and 2004, and contained 92,252 patents assigned to 159 firms. It is notable that inventive activity was rather slow for these firms in the first 15 years as 83,786 patents were applied for since 1990. We therefore chose to build our sample using only the 1990–2004 period, which is useful because it excludes exogenous variation following a number of important institutional changes in the 1980s (Hall and Ziedonis, 2001; Mody and Wheeler, 1986). Because we require team historical information to measure experience, our focal sample is limited to the 2000–04 period, which gives us 10 years of historical data about firm inventions. The number of patents in the five-year period is 40,138.

Dependent Variable

Invention impact. We define the impact as the number of forward citations received by the focal patent during a ten-year period following its application date. Hence, for a patent applied for on 17/08/2000, we measure all forward citations until 17/08/2010. Forward citations have been shown to be correlated with the economic importance of inventions and expert evaluation of their value (Albert et al., 1991; Hall et al., 2005; Jaffe et al., 2002), making them an appropriate and frequently used measure of impact. Using a sliding ten year window improves comparability of the results as citation frequency tends to decrease over time. E.g. for patents applied for in 2000, the average number of citations in the first five years is 6.51. This goes up to 12.02 if we extend the window to ten years and then further rises to only 14.04 if we extend the window until 2015.

Explanatory Variables

Team Domain Experience (TDE) captures the experience of each individual team member in the four digit CPC subclasses to which the focal invention is assigned. Our sample contains 448 distinct four digit CPC subclasses, while there are a total of 705 such subclasses (Leydesdorff et al., 2017).² The most frequently occurring one is H01L ‘semiconductor devices; electric solid state devices not otherwise provided for’. The second most used class is G06F ‘electric digital data processing’. We follow Fleming and co-authors (Fleming, 2001; Fleming and Sorenson, 2004; Fleming et al., 2007; Singh and Fleming, 2010) in arguing that patent classifications are appropriate measures for technological combinations. Classifications are assigned by the USPTO ‘thus, unlike patent citations, they are not biased by firms’ strategic considerations’ (Carnabuci and Operti, 2013, p. ev. 9). We create a measure that considers depth, breadth, and domain relevance and operationalize a domain as a subclass in the cooperative classification, e.g., H01L.

The depth of inventor experience in a subclass is the number of patents assigned to that subclass in the inventor’s portfolio (p_{it}). For a specific subclass (e.g., H01L) it can thus range from zero (inventor has never patented in this class before) to the number of patents the inventor has applied for before (if every single one of them is assigned to H01L). The breadth of knowledge is the number of different subgroups within a subclass in which a focal inventor has invented during her invention history (s_{it}). If an inventor has

only one prior patent and this one is assigned to five distinct subgroups within a subclass of H01L, the breadth count will thus be 5. Finally, we determine the relevance of this domain experience to the focal invention as the fraction of subclasses of the focal patent that are within $CPC_i = f_j$. This measure is summed across all CPC_i classes (k) to which the focal patent is assigned and then aggregated for all team members (t). Because expertise builds up over time and is susceptible to time compression diseconomies (Dierickx and Cool, 1989), we chose to include all inventor knowledge in our extended sample, so going back to 1975 and until the day before the focal patent application. To reduce skewness we use the natural logarithm in the regression.

$$\text{Team domain experience (TDE)} = \ln \left(1 + \sum_{t=1}^t \sum_{i=1}^k \frac{\sqrt[2]{pit.sit}}{1/f_i} \right)$$

As an example, consider the Corning (now Dow Silicones Corp) patent US6177071B1, which is assigned to three inventors (Lin, Schulz, and Smith) and has eight different classifications. Of those eight, five are within A61K (preparations for medical, dental, or toilet purposes) and three are within A61Q (specific use of cosmetics or similar toilet preparations). If we assume, Lin has 10 patents assigned to A61K (depth) for a total of 17 distinct groups (breadth) and 0 expertise in A61Q, his domain expertise would be $5/8 * \sqrt{(10 * 17)}$. Assume Schulz has only expertise in different areas his domain expertise be zero. Then, consider that Smith has two prior patents in A61K (with a breadth of seven) and six prior patents in A61Q with a total breadth of four. Her domain expertise would then be $5/8 * \sqrt{(2 * 7)} + 3/8 * \sqrt{(6 * 4)}$. The team's domain expertise would then be calculated as $\ln[1 + 5/8 * (\sqrt{(170)} + 0 + \sqrt{(14)}) + 3/8 * (0 + 0 + \sqrt{(24)})] = 2.589$.

Component Originality (CO). The limitations of using prior art citations are well known. Many of them are added by the USPTO which makes them poor proxies for direct knowledge transfers (Alcacer and Gittelman, 2006; Alcacer et al., 2009; Giuri et al., 2007). But, because prior art chiefly serves to demarcate ownership of previous inventions, they are a useful proxy for the components upon which a focal patent implicitly or explicitly builds. We measure the average number of times a prior art citation has been cited before in the industry by counting its incidence between 1975 when our database starts and the focal patent's application date. Component originality then equals $CO = 1 / (\text{count} + 1)$.

Team Structural Hole Position (TSH). Using a static, undirected network of collaborative ties between inventors in the 1990–99 period, we determine team structural holes as the aggregated structural holes' value of each team member. Following Burt (2004), we first calculate the node constraint value for each team member in the collaboration network and then determine the structural holes' value for each node as two minus the constraint value. The average of this value per team is then used as the structural holes value. The node's constraint value C is determined by $C_i = \sum_{j \in EG_i \setminus \{i\}} (p_{ij} + \sum_{q \in EG_i \setminus \{i,j\}} p_{iq} p_{qj})^2$ and $\sim p_{ij} = \frac{a_{ij} + a_{ji}}{\sum_{k \in EG_i \setminus \{i\}} (a_{ik} + a_{ki})}$, where EG is node i 's ego network, and 'a' is the weight of an edge, i.e., the number of prior collaborations of two inventors in the 10-year collaboration network.

Control Variables

We add controls at the firm, team, and patent level to capture different sources of variance that help explain invention impact. At the firm level, we control for *size* (# employees / 1,000), *debt/asset ratio* (annual firm liabilities / firm assets), *absorptive capacity* (annual R&D spending/ annual sales), *search* (# subclasses / # 4-digit CPC classes of firm invention portfolio in five years before focal patent application year), and *mean inventor productivity* (firm's total patent count divided by number of different patenting inventors in prior 5 years). We used the inventor database, which identifies unique USPTO inventors and matches them to their respective patents (Lai et al., 2011), to create this last variable.

At the team level, we control for *team size* because patents developed by larger teams composed typically receive more forward citations, as size correlated with knowledge breadth and diversity, which enhance the usefulness of inventions (Singh and Fleming, 2010). We control for *non-domain experience*, which is construed in the same way as domain experience but then for all CPCi classes in which the team members have invented before that are not assigned to the focal patent. We add further controls for the *number of first time inventors* because new team members lack experience but could bring in fresh ideas, the *number of non-directional prior direct ties* between the team members and their collaborators in the five years before the application date, and the *team's collaboration experience* in the prior five years. We operationalized the latter as the sum of direct and indirect prior ties among team members, with all direct ties weighted twice as strongly as indirect ties. Finally, we add a control for the aggregate structural holes value for the team's inventors' knowledge components (defined as 4-digit CPC classes).

Then, at the patent level, we control for the number of claims, prior art citations, subclasses and 4-digit CPC classes which have all been found to positively correlate with invention impact (Fleming and Sorenson, 2001; Stuart and Podolny, 1996). In addition, we add a count variable for the number of 4-digit CPC classes that occur for a first time in our sample which suggests teams bridging into unfamiliar knowledge domains.

We use the same approach used to determine component originality to construct a standard-normalized measure for the average age gap (in days) between the focal patent's priority dates and the priority dates of the prior art citations. Unlike Nerkar (2003), we use priority dates rather than grant dates as these are more proximate to the time during which the inventive activity took place and during which the knowledge was novel. *Component age (CA)* is an important control because even a standardized measure of component originality, grouped by application year, is still not independent of the relative age of the cited art because more recent backward citations have had less time to be cited. We also control for the age variation of the prior art by controlling for the *time spread* in days between the 75th and the 25th quantile of the prior art citations, divided by 365. We prefer this measure over the standard deviation because of the lower correlation with component age.

We added *technology dummies* for six technological categories Hall et al. (2001), because the number of citations received by patents may differ across technological fields (Hall et al., 2005). However, none of these dummies were significant so we omitted them from the analysis regression. Finally, we control for the *age profile* of the patent by including dummies for both application and grant year. We also add a variable that measures the

time difference in years between the application and the priority date of the focal patent because this suggests that the patent has probably been applied for before in another jurisdiction, meaning its antecedent patent may have absorbed some forward citations already.

Analysis

Most patent research uses negative binomial (NB) regressions in Stata to analyse count data because invention impact (proxied by a count of forward citation) tends to be highly skewed leading to overdispersion (mean impact \ll standard deviation impact). In our sample, overdispersion is moderate ($\mu = 9.71$, $\sigma = 14.48$), suggesting Poisson regression may be more efficient. Using `xtnbreg` in Stata comes at the price of lower robustness, as unconditional fixed effects and clustering of standard errors around the firm identifier are problematic, which is not the case for the Poisson regression. We therefore present the conventional Negative Binomial and perform robustness checks using other regression techniques. We deploy a Hausman (1978) specification test which was significant ($p < 0.001$), suggesting that fixed effects are required. This confirms the suspicion that some of our independent variables are likely to be correlated with the individual effects. To check for collinearity, we ran an OLS regression without indicator variables, quadratic terms, and interactions as they artificially inflate the variance inflation factors (Allison, 2012). Two strongly correlated control variables (firm search and firm mean inventor productivity) have VIF above 4 (Wooldridge, 2014). We checked the stability of their sign and significance by excluding either one, both, or none, and found the results to be entirely consistent, so we chose to leave in both variables.

RESULTS

Descriptive statistics and correlations are displayed in Table I. Despite some high correlation coefficients, multicollinearity should not be problematic as the variance inflation factors were low enough (Wooldridge, 2014). Table II presents a stepwise inclusion of the variables to investigate potential spurious effects or sign shifts. Column 1 in Table II contains only the control variables. A team's non-domain expertise and the team's position in the knowledge network are both insignificant. We report three decimals in the text (to provide additional detail) and two decimals in the table. Team collaboration experience has a positive effect ($\beta = 0.003$, $\sigma = 0.001$) and so do patent technical breadth (both patent subclasses and the number of distinct 4-digit CPC classes have a positive effect), number of claims ($\beta = 0.005$, $\sigma = 0.000$) and search breadth in terms of prior art citations ($\beta = 0.002$, $\sigma = 0.000$). We also see a strong negative coefficient for average component age ($\beta = -0.090$, $\sigma = 0.008$) suggesting that more recent knowledge components are associated with higher impact. However, inventions that span temporal boundaries correlate positively with impact ($\beta = 0.007$, $\sigma = 0.002$). The effect of the time gap between application and priority year is significantly negative ($\beta = -0.051$, $\sigma = 0.004$) as anticipated.

Model 2 introduces the focal variables and finds a strong positive coefficient for team domain expertise ($\beta = 0.018$, $\sigma = 0.004$) which supports hypothesis 1. As expected, teams

Table I. Correlation matrix and descriptive statistics

	Mean	SE	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	
1 Impact	9.77	14.53	0	383																								
2 ImpactSN	0	0.76	-0.8	3	0.88																							
3 TIDE	2.03	1.69	0	6.88	0.07	0.07																						
4 TSH	1.13	0.65	0	1.95	0.02	0.02	0.38																					
5 CO	0.32	0.27	0	1	-0.05	-0.05	-0.31	-0.3																				
6 Comp age	0	0.89	-2.36	3.49	-0.06	-0.06	-0.12	-0.04	-0.11																			
7 Firm size	29.6	29.18	0	86.1	-0.03	-0.04	-0.07	-0.04	0.17	-0.08																		
8 Firm acap	0.2	0.22	0	6.31	0	0.01	-0.07	-0.06	-0.02	-0.01	-0.22																	
9 Firm D/A	0.04	0.08	0	4.2	-0.02	-0.02	0.1	0.05	-0.03	0.01	-0.12	0.08																
10 Firm search	172	131.1	0.5	589.5	-0.02	-0.04	0.37	0.27	-0.3	-0.04	0.07	-0.05	0.16															
11 Firm inv prod	3	2.59	0.17	9.41	-0.01	-0.03	0.39	0.31	-0.39	0	-0.23	-0.06	0.15	0.86														
12 Team size	2.3	1.5	1	19	0.06	0.07	0.28	0.05	0	-0.03	0.02	-0.01	0	-0.13	-0.14													
13 Non-domain exp	1.17	0.9	0	5.15	0.03	0.04	0.65	0.55	-0.19	-0.05	-0.05	-0.04	0.06	0.32	0.34	0.36												
14 KN str. hole	1.44	0.52	0	1.91	0.02	0.02	0.35	0.61	-0.22	-0.02	-0.07	-0.01	0.03	0.17	0.21	-0.04	0.34											
15 # 1st timers	0.56	0.94	0	12	0.01	0.01	-0.34	-0.47	0.14	0.04	0.01	0.03	-0.03	-0.21	-0.21	0.44	-0.33	-0.48										
16 Collaboration exp.	15.5	25.58	0	561	0.04	0.05	0.59	0.41	-0.13	-0.09	-0.05	-0.03	0.07	0.09	0.1	0.51	0.59	0.18	-0.17									
17 Team col exp.	15.3	47.81	0	635	0.01	0.01	0.3	0.24	-0.19	0.03	-0.09	-0.03	0.07	0.3	0.35	-0.2	0.25	0.12	-0.17	0.05								
18 Pat classes	5.76	7.67	1	156	0.11	0.11	0.21	0.1	-0.16	0.03	-0.06	0	0.06	0.15	0.14	0.04	0.07	0.06	0.02	0.04	0.12							
19 # dif. CPC	1.52	0.86	1	14	0.04	0.04	-0.05	0.03	-0.01	0.1	-0.03	0.01	0.03	0.04	0.05	0.02	0.01	0.02	0.04	-0.01	0.05	0.35						
20 # 1st CPC	0	0.05	0	6	0	0	-0.02	-0.01	0.02	0.04	0.01	-0.01	0	-0.01	-0.01	0	-0.01	0.01	-0.01	-0.01	0.01	0.04						
21 # prior art	17.4	29.13	0	525	0.05	0.07	0.16	0.11	-0.28	0.18	-0.06	-0.01	0.04	0.2	0.23	0.05	0.11	0.08	0.01	0.04	0.18	0.19	0.09	0				
22 # claims	22.3	15.59	1	418	0.09	0.11	0.06	0	-0.07	-0.02	-0.06	0.05	0.02	0.16	0.18	0.01	0.08	0.01	-0.01	0	0.05	0.02	0.02	0	0.11			
23 app-prior year	1	1.59	0	14	-0.05	-0.06	0.13	0.29	-0.33	0.13	-0.12	-0.03	0.04	0.17	0.32	-0.01	0.1	0.2	0.01	-0.02	0.22	0.21	0.15	0	0.2	-0.07		
24 Comp age spread	4.48	3.84	0	74.92	-0.04	-0.04	-0.1	-0.05	-0.03	0.72	-0.05	-0.02	0.01	-0.06	-0.01	-0.02	-0.03	-0.03	0.04	-0.07	0.01	0.02	0.10	0.05	0.1	-0.01	0.08	

All correlations above |0.02| are significant at p ≤ 0.01.

Table II. The influence of team domain experience, component originality and structural holes on invention impact

<i>DV: invention impact</i>	(1)	(2)	(3)	(4)	(5)
Firm size	-0.00*** (0.00)	-0.00*** (0.00)	-0.00*** (0.00)	-0.00*** (0.00)	-0.00*** (0.00)
Firm Absorptive Capacity	0.04† (0.03)	0.04† (0.03)	0.04† (0.03)	0.04† (0.03)	0.04 (0.03)
Firm Debt/Asset Ratio	0.06 (0.06)	0.06 (0.06)	0.06 (0.06)	0.06 (0.06)	0.06 (0.06)
Firm search	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Firm Mean Inventor Productivity	-0.04*** (0.01)	-0.05*** (0.01)	-0.05*** (0.01)	-0.05*** (0.01)	-0.05*** (0.01)
Team size	0.03*** (0.00)	0.03*** (0.01)	0.03*** (0.01)	0.02*** (0.01)	0.02*** (0.01)
Team Non-domain Expertise	-0.00 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Team Str. holes in knowledge network	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
# 1 st time inventors	-0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)
# Non-directional Prior ties	-0.00 (0.00)	-0.00† (0.00)	-0.00* (0.00)	-0.00 (0.00)	-0.00 (0.00)
Team Collaboration Experience	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
Patent subclasses	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Distinct 4-digit CPC classes	0.03*** (0.01)	0.03*** (0.01)	0.04*** (0.01)	0.03*** (0.01)	0.03*** (0.01)
1 st Occurrences of CPC class	-0.03 (0.08)	-0.01 (0.08)	-0.01 (0.08)	-0.01 (0.08)	-0.01 (0.08)
Prior Art Citations	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
Claims	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
App year – Priority Year	-0.05*** (0.00)	-0.06*** (0.00)	-0.06*** (0.00)	-0.06*** (0.00)	-0.06*** (0.00)
Component Age	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Time spread					

Table II. *Continued*

<i>DV: invention impact</i>	(1)	(2)	(3)	(4)	(5)
Component Age	-0.09***	-0.09***	-0.09***	-0.09***	-0.09***
Average	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Team Domain		0.02***	0.03***	0.04***	0.05***
Expertise (TDE)		(0.00)	(0.01)	(0.01)	(0.01)
Component		-0.12***	-0.07**	-0.12***	-0.06*
Originality (CO)		(0.02)	(0.03)	(0.02)	(0.03)
Team Social Network		-0.01	-0.01	-0.00	0.01
Structural Holes (TSH)		(0.01)	(0.01)	(0.01)	(0.01)
TDE x CO			-0.03**		-0.04***
			(0.01)		(0.01)
TDE x TSH				-0.01*	-0.02**
				(0.01)	(0.01)
Chi square	6,417	6,482	6,491	6,489	6,504
Log Likelihood	-128,493	-128,459	-128,455	-128,456	-128,451

Constant, application and grant year dummies unreported; firm FEs, SEs in parentheses. Observations = 40,138, Firms = 105.

†p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001. Invention impact (the dependent variable (DV)) is operationalized as 10-year forward citations.

that have access to a larger domain-specific knowledge stock can benefit from their knowledge breadth and depth and are capable to create higher impact inventions. We find no main effect for a team's structural hole position ($\beta = -0.015$, $\sigma = 0.011$) and a strong negative effect of component originality ($\beta = -0.119$, $\sigma = 0.019$), suggesting that using original components generally does not improve impact. Model 3 tests hypothesis 2 by adding the interaction effect between team domain expertise and component originality. The interaction between team domain expertise and component originality is negative ($\beta = -0.033$, $\sigma = 0.011$), providing support for H2: teams with high domain expertise seem to be less able to deploy original knowledge than teams lacking such domain expertise.

We note that our measure for component originality is distinct from the "original knowledge" measure used by Jung and Lee (2016). These authors find a strong positive effect of original knowledge whereas we find the opposite. Our measure captures the average number of times the prior art has been cited since it was patented which proxies how familiar the industry currently is with a specific component. Jung and Lee (2016) on the other hand define original knowledge as a component combination that appeared for a first time in a specific patent, and argue that original knowledge 'is typically underdeveloped and in uncertain condition' (p. 1730) which is surely true at the time of invention. However, this is not necessarily true anymore at the time of citing as it is possible this such component combination has enjoyed refinement over time and been used often since the original invention. We contend that uncertainty about knowledge is driven primarily by how many times it has been used since its invention, not by how novel

a combination was at the time of invention. This difference in interpretation of original knowledge may explain why our results differ from theirs.

Model 4 then tests hypothesis 3 by adding the interaction between team domain expertise and the team's structural hole value, which is also found to be negative and significant ($\beta = -0.013$, $\sigma = 0.005$) in support of H3: Teams with high domain expertise do not seem to successfully exploit their structurally advantageous network position and fail to absorb and implement the original ideas they may extract as a consequence of their structural hole position. Model 5 includes both interaction effects and find consistent and significant results, providing support for our three hypotheses. We depict the marginal effects in Figures 1 and 2.

Robustness checks

We discuss alternative regression techniques, model specifications, variable operationalization and an instrumental variable approach. First, we repeat the above analyses using negative binomial regression without fixed effects but with firm dummies and clustered standard errors as well as using Poisson regression on a response variable, winsorized at 3 standard deviations to reduce skewness. Support for hypotheses 1 and 2 remains strong but the significance of the interaction between team domain expertise and team structural holes disappears, suggesting the support for hypothesis 3 is perhaps not as robust as Table II indicated. We dive deeper into this question below.

Second, we checked the quadratic specification of our independent effects. This is important because there are reasons to believe that excessive expertise may damage the invention process by narrowing the team's collective mindset and create some form of collective cognitive entrenchment as it does for individuals (Dane, 2010). Authors that hypothesized quadratic effects of familiarity have typically relied on arguments that

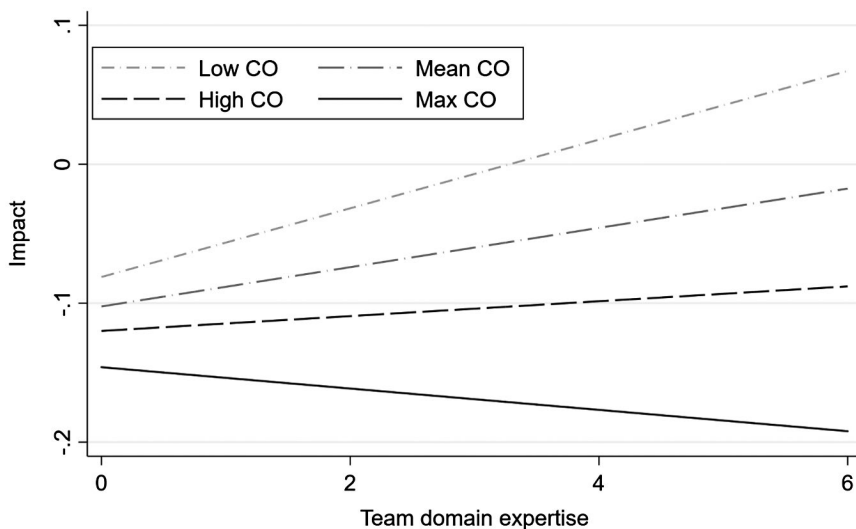


Figure 1. Marginal effect of team domain expertise on invention impact at different levels of component originality (CO)

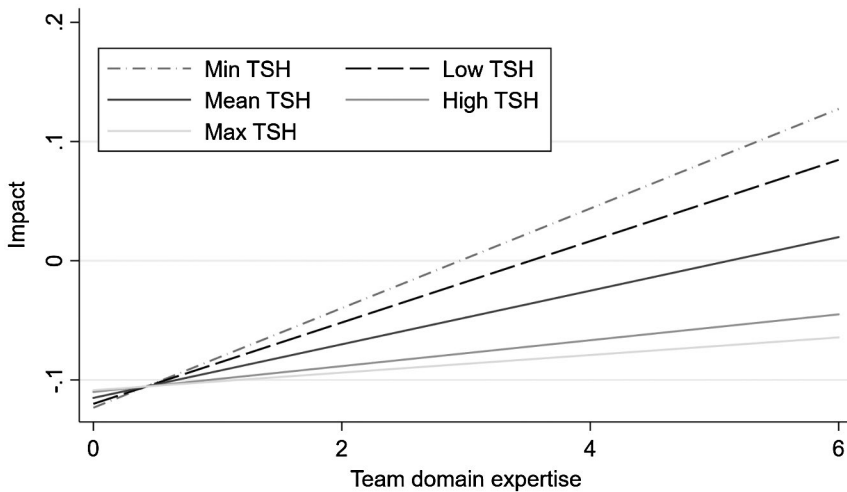


Figure 2. Marginal effects of team domain expertise on invention impact at different structural hole positions

relate to aging knowledge (e.g. older knowledge may be harder to recombine because it may be poorly remembered or because it may fit poorly in the current technological paradigm), but we capture these dynamics with a control for knowledge age (Heeley and Jacobson, 2008; Katila, 2002; Katila and Ahuja, 2002; Nerkar, 2003). Capaldo et al. (2017) for instance investigate the effects of knowledge maturity (component age) and use a measure of component familiarity at the firm level as a robustness check, finding identical results for both.

Table III presents four regression results in which our three focal independent variables are included with their quadratic effects. We can see that in all cases the main effect of team domain expertise is not significant anymore while the quadratic term is, suggesting that expertise ostensibly becomes increasingly valuable as it grows. So rather than diminishing returns to expertise, we see somewhat increasing returns to expertise for the logged measure. Using proper tests for the statistical significance, we find that no support for a U-shape because the Fieller interval includes the lowest value of team domain expertise, suggesting there is no statistical certainty there is an initial downward slope (Lind and Mehlum, 2010). When using the original, non-logged measure we find a significant and positive independent effect and a negative quadratic effect, but the 95 per cent Fieller interval includes the highest value of domain expertise, suggesting this is not a real inverted U-shape but merely slowly diminishing returns (Haans et al., 2016; Lind and Mehlum, 2010) which is consistent with our theory. These tests convince us that the expertise does not relate curvilinearly to impact, supporting H1. For network structural holes, inclusion of the quadratic term eliminates the significance of both terms in three of the four models: the quadratic term does not improve the model.

Looking at component originality, we find ostensibly significant curvilinear results across all models. When conducting Lind and Mehlum's (2010) curvilinearity tests, we find that these significant quadratic relationships do not create actual U-shaped effects, except for the cluster-robust negative binomial regression (Table III, column 2). For the

Table III. Quadratic effects of main explanatory variables

	(1)	(2)	(3)	(4)
	<i>NB-FE</i>	<i>NB-robust</i>	<i>Poisson</i>	<i>OLS</i>
Team Domain	-0.01	-0.02	-0.01	-0.01
Experience (TDE)	(0.01)	(0.01)	(0.01)	(0.01)
TDE ²	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Team Social Network	0.06†	0.01	0.05	0.04
Structural Holes (TSH)	(0.03)	(0.04)	(0.05)	(0.03)
TSH ²	-0.03*	-0.00	-0.03	-0.02
	(0.02)	(0.02)	(0.03)	(0.02)
Component Originality (CO)	-0.23***	-0.65***	-0.59***	-0.38***
	(0.07)	(0.11)	(0.13)	(0.09)
CO ²	0.11†	0.46***	0.40**	0.26**
	(0.06)	(0.10)	(0.12)	(0.08)
Chi square	6,512	7,640	45,900	R ² = 7.94%
Log likelihood	-128,447	-130,114	-239,075	-43,760

All non-focal variables unreported but included. Firm fixed effects (except model 2 which has firm dummies), Robust, clustered standard errors in parentheses (except model 1). Observations = 40,138, Firms = 105.

Models 1-2 use 10-year forward citations as DV. The Poisson model (column 3) uses 10-year forward citations, winsorized at 3 standard deviations to reduce skewness. Model 4 uses the 10-year forward citations, standard-normalized per application year and winsorized at 3 standard deviations.

†p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001.

three other models, the Fieller interval includes the extreme values so that we can rule out a real U-shape. While component originality ranges between 0.005 and 1, for model 2 the extreme point is at 0.70 with the 95 per cent Fieller interval [0.62 0.87] and a t-value of 2.67 (p < 0.01). With almost 12 per cent of observations higher than the extreme value, the curvilinear effect seems to represent an authentic effect in this regression, suggesting that very original components may overturn the negative effect of originality. To check how salient this would be, we repeated the regressions from Table II with an additional dummy variable that took on the value 1 if component originality was higher than the extreme point. The dummy's coefficient was significant and positive but did not affect the other results. We also ran the regression with the quadratic term for component originality included and all ensuing interactions included. While the significance of the interactions with team domain expertise disappeared, the marginal effects and the graphical representation were almost identical to the ones presented, suggesting the linear approximation captures the underlying relationship quite well.

Third, we conduct some checks regarding the operationalization of our focal measures. We repeat the analysis presented in Table II but operationalize our focal variables differently. Table IV, model 1 operationalizes team domain expertise as the non-logged measure described above. Model 2 replaces our component originality measure with a

Table IV. Robustness checks: alternative variable operationalizations

	<i>(NB1)</i>	<i>(NB2)</i>	<i>(NB3)</i>	<i>(NB4)</i>	<i>(NB5)</i>	<i>(IV regression)</i>
DV: Invention impact		<i>10-year forward citations</i>			<i>No self-citations</i>	
Team Domain	0.00***	0.04***	0.07***	0.00***	0.03*	0.26**
Experience (TDE)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.09)
Team Social Netw.	0.01	0.01	0.01	0.02†	-0.01	0.10
Structural Holes	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.07)
Component	-0.12***	<u>0.00</u>	-0.06*	<u>0.03***</u>	-0.03	-0.07
Originality (CO)	(0.02)	<u>(0.01)</u>	(0.03)	<u>(0.01)</u>	(0.03)	(0.03)
TDE x TSH	-0.00**	-0.02**	-0.02**	-0.00**	-0.01†	-0.15**
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.06)
TDE x CO	-0.00	<u>0.01**</u>	-0.04**	-0.00	-0.02*	-0.07**
	(0.00)	<u>(0.00)</u>	(0.01)	(0.00)	(0.01)	(0.03)
Constant	0.51***	0.46***	0.47***	0.46***	0.45***	-0.45***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.09)
Chi square	6,540	6,486	6,502	6,511	5,171	Root MSE = 0.76
Log Likelihood	-128,443	-128,460	-128,451	-128,453	-121,117	Residual SS = 21,254

All non-focal variables unreported but included. Coefficients in italics reflect alternative variable operationalizations (respectively team domain expertise, component originality, and structural holes value in models NB1, NB2, and NB3). Note that the alternative operationalization for component originality is mean adjusted component familiarity and should thus have opposite effects (we underline the coefficients for which opposite effects are expected because of this change). Finally, in model NB4, coefficients in **bold** are the result of an interaction between two alternative variable operationalizations.

Model 5 has non-self forward citations as response variable. Observations = 40,138, Firms = 105.

The IV regression has as dependent variable the natural logarithm of the 10-year forward citation measure.

† p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001.

mean-adjusted measure of component familiarity. Specifically, we average the number of times a prior art citation has been cited before in the industry across all prior art cited in the focal patent and then we standard-normalize this measure, grouped by the application year of the focal patent. This gives us a measure that increases with prior component use. To reduce skewness, we right-winsorize this variable at the 99th percentile. A low (negative) value reflects the fact that most prior art has rarely been used while a high value reflects industry familiarity with the cited prior art. The results of using this measure for component familiarity rather than originality are consistent with Table II. The sign of the interaction between domain expertise and component familiarity is predictably opposite to the sign in Table II, further providing support for hypothesis 2. In column 3, we replace our measure for team average structural holes' position in the collaboration network with the maximum individual team member structural holes' value. If structural holes are indeed conduits of original ideas (Burt, 2004), then using the maximum value of a single team member rather than the average over all team members

may make more sense. Results remain consistent. Model 4 uses all the alternative operationalizations together and still finds similar results, although the significance of the interaction with component familiarity disappears. Finally, column 5 depicts the results for the number of non-self-citations as response variable.

Instrumental Variable Approach

A final validity check acknowledges the possibility that domain expertise and a team's network position are both driven by an omitted variable such as talent and/or are determined contemporaneously, created by endogeneity problems. To see if our main results are robust to potential endogeneity bias we instrument our measure for team structural holes with three measures that may influence the likelihood that teams within the firm would occupy structural hole positions but are unlikely to influence the impact of single patent (i.e., the instruments are presumed to be exogenous). We use a measure for the breadth of firm knowledge (log of total number of firm portfolio subclasses in the last five years), a measure for team knowledge concentration (Herfindahl index of the team's portfolio subclasses in the last five years), as well as the total number of team collaborators over the last five years. These three measures are checked for exogeneity by including them in the original regressions from Table II and verifying that both indeed do not significantly impact the response variable.

We run an instrumental variable regression (see Table IV) with the above three instruments and their interactions with team domain expertise, to instrument for team social network structural holes and its interaction with team domain expertise. We can reject the Hansen J statistic at the 5 per cent level, suggesting over-identification is not a significant issue, despite the inclusion of the interaction effects. The under-identification and weak identification tests are both strongly rejected ($p < 0.001$) and the F-tests for excluded instruments take on acceptable values of above 10. Although the instruments are not perfect – the Anderson-Rubin Wald test suggests over-identifying restrictions are not valid – the overall results of the instrumental variable regression supports our initial findings. Moreover, via Stata's implementation of the endogeneity test we cannot reject the conclusion that our endogenous network variable can be treated as exogenous ($p = 0.59$). Irrespectively, we see in Table IV, final column that the instrumented team structural hole variable is not significant but the interaction with team domain expertise is significant and negative ($\beta = -0.147$, $\sigma = 0.056$) and the interaction effect between team domain expertise and component originality also remains significant ($\beta = -0.074$, $\sigma = 0.027$) providing additional support for hypotheses 2 and 3.

A three-way interaction

Because it is important to 'understand when the pattern of social ties is most influential' (Balkundi and Harrison, 2006, p. 50) and because structural holes and original components could be considered substitute sources of new information, it is not unlikely that a three-way interaction would manifest among our three focal variables. If structural holes indeed provides access to novel information and good ideas (Burt, 2004), this may be more valuable when the team seeks to deploy original components which are characterized by uncertainty and recombinant challenges. Under these circumstances,

even a team with high domain expertise may still benefit from access to new and non-redundant information.

On the other hand, the structural hole position may also add to the cognitive difficulty of processing original knowledge components because there is noise in the information that is being obtained and it may be incorrect (Guan and Liu, 2016). Intuitively, one could presume that expert teams would benefit from their structural hole position when they deploy familiar components and not vice versa, while expert teams that are far away from structural hole positions could benefit more from original components. However, it may also be true that structural holes provide added value when using original components. To see if such a three-way interaction indeed exists, we present Table V. Column 1 displays the regression results from Table II, this time including the triple interaction term. Note that we have to add the interaction term between component originality and team structural holes as well for statistical purposes and that this term is negative, suggesting that on average teams in structural hole positions do better when they refrain from using original components.

In Table V, we provide alternative analyses methods to verify whether our finding of a triple interaction is robust to model specification. Model 2 depicts a negative binomial regression without fixed effects but with firm dummies and robust standard errors. We then repeat the analysis in columns 3 and 4 where we use the more robust Poisson regression with firm-clustered standard errors. Although the dependent variable is over-dispersed, the Poisson model provides a good fit and the results are confirmed in model 3. The second Poisson model we run repeats the analysis but uses a response variable that is winsorized at 3 standard deviation to reduce skewness. Finally, we run the analysis as a simple OLS regression on the number of yearly standard-normalized response variable, winsorized at 3 standard errors. These results are depicted in column 5 in Table V and are also consistent with the main findings. We repeat all these analyses for a shorter (5 years) and longer yet uneven (all data until 2015) forward citation window and find consistent results (not reported). The triple interaction term is positive while the interaction between component originality and team structural hole position is negative, suggesting a complex net effect of the three focal terms on invention impact. Unlike the unreported models discussed previously, the findings here across all models are highly consistent, suggesting that ‘the true model’ may indeed be better approximated by this model that includes a triple interaction.

In order to provide clarity about how to interpret the interaction effect we provide two complementary graphical representations (Aiken and West, 1991). Figure 3 depicts the marginal effect of domain expertise at low and high values of both component originality and team structural holes. The figure clarifies that domain expertise makes its largest marginal contribution to invention impact when teams are not in structural holes’ positions *and* when they use familiar components. When using original components, the effect of structural holes barely alters the slope of domain expertise’s marginal contribution to invention impact, although the net effect remains higher for low values of structural holes. Inexperienced teams do best when they have access to non-redundant information in their social network and when they use familiar components. Under these conditions, inexperienced teams may even outperform more experienced ones.

Table V. Robustness Checks – Alternative Regression Analyses

<i>DV: invention impact</i>	<i>1. NB FE</i>	<i>2. NB Robust</i>	<i>3. Poisson</i>	<i>4. Poisson</i>	<i>5. OLS</i>
Firm Size	−0.00*** (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Firm Absorptive Capacity	0.04 (0.03)	0.11* (0.04)	0.06 (0.06)	0.04 (0.05)	0.04 (0.05)
Firm Search	0.00 (0.00)	0.00* (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Firm Mean Inventor Productivity	−0.04*** (0.01)	−0.07*** (0.02)	−0.06* (0.03)	−0.06* (0.03)	−0.04* (0.02)
Team size	0.02*** (0.01)	0.02* (0.01)	0.03** (0.01)	0.02** (0.01)	0.02** (0.01)
Team Non-domain Expertise	−0.01 (0.01)	−0.03* (0.01)	−0.04† (0.02)	−0.02 (0.02)	−0.01 (0.01)
Team str. holes in knowledge networks	0.01 (0.01)	0.03† (0.02)	0.04 (0.02)	0.02 (0.02)	0.01 (0.01)
1 st time inventors	0.01 (0.01)	0.02† (0.01)	0.02 (0.02)	0.02† (0.01)	0.01 (0.01)
Team Collaboration Experience	0.00*** (0.00)	0.00* (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
Patent subclasses	0.01*** (0.00)	0.02*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Distinct 4-digit CPC classes	0.03*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.06*** (0.01)	0.03*** (0.01)
Prior art citations	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
Claims	0.00*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.00*** (0.00)
App year – Priority Year	−0.06*** (0.00)	−0.08*** (0.01)	−0.09*** (0.01)	−0.08*** (0.01)	−0.05*** (0.01)
Component Age	0.01*** (0.00)	0.01** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Time spread	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Component Age	−0.09*** (0.01)	−0.13*** (0.01)	−0.14*** (0.02)	−0.14*** (0.01)	−0.08*** (0.01)
Team domain Expertise (TDE)	0.07*** (0.01)	0.09*** (0.02)	0.12** (0.04)	0.10*** (0.03)	0.07** (0.02)
Component Originality (CO)	−0.02 (0.04)	−0.03 (0.06)	−0.03 (0.06)	−0.04 (0.05)	−0.01 (0.03)
Team social network	0.02 (0.02)	0.04 (0.03)	0.04 (0.03)	0.04 (0.02)	0.02 (0.02)
Structural holes (TSH)					

Table V. *Continued*

<i>DV: invention impact</i>	<i>1. NB FE</i>	<i>2. NB Robust</i>	<i>3. Poisson</i>	<i>4. Poisson</i>	<i>5. OLS</i>
TDE x CO	-0.09** (0.03)	-0.12* (0.05)	-0.16* (0.08)	-0.13* (0.06)	-0.10** (0.04)
TDE x TSH	-0.03*** (0.01)	-0.03† (0.01)	-0.04 (0.03)	-0.04† (0.02)	-0.03† (0.02)
CO x TSH	-0.04 (0.04)	-0.12* (0.06)	-0.13* (0.07)	-0.10* (0.04)	-0.06* (0.03)
TDE x CO x TSH	0.04* (0.02)	0.07* (0.03)	0.10† (0.05)	0.07† (0.04)	0.05† (0.03)
Chi square	6,512	7,964	229,834	41,835	R ² = 7.87%
Log likelihood	-128,449	-130,143	-278,213	-239,278	-43,777

Constant, application and grant year dummies and insignificant variables unreported. Observations = 40,138, Firms = 105. (Robust) standard errors in parentheses.

Models 1-3 use 10-year forward citations as response, model 4 uses the same DV, winsorized at 3 standard deviations to reduce skewness. Model 5 uses the standard-normalized DV per application year, also winsorized at 3 standard deviations.

†p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001.

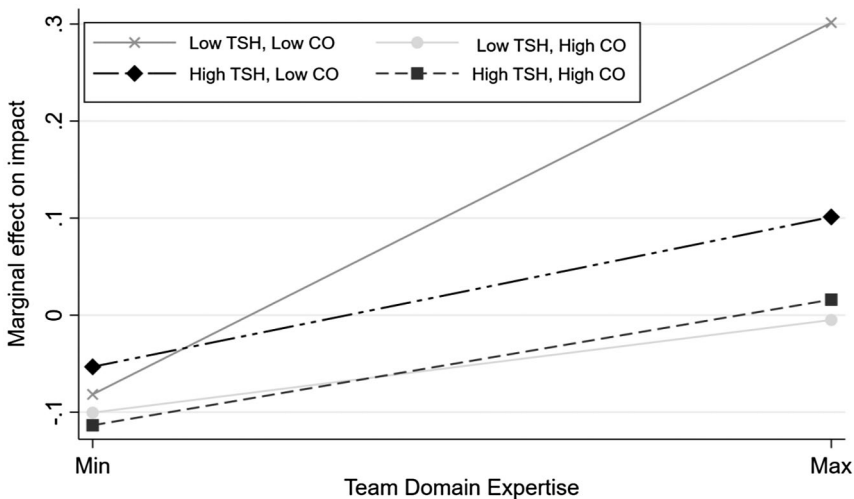


Figure 3. 2D visualization of threeway interaction

Figure 4 provides another perspective. The dark lines represent marginal effects of a change in domain expertise on forward citations, for increasing levels of component originality at five distinct levels of structural holes. At minimal and mean values of structural holes, domain expertise’s marginal effect on impact reduces as the team uses more original components. At high structural hole values, the effects are however positive, although the significance of the effect disappears as originality crosses its mean value.

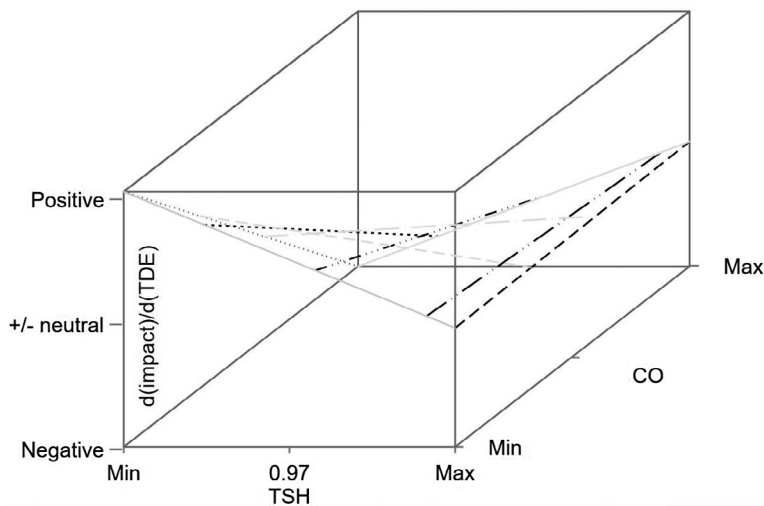


Figure 4. 3D visualization - Marginal effects of a change in team domain expertise on the standard normalized number of forward citations. The 3D graph is based on the results obtained from the full OLS regression with fixed firm effects, and standard errors clustered around firms, using the Stata command 'surface'

The presence of the three-way interaction provides boundary conditions for hypotheses 2 and 3. While the average effect of structural holes indeed reduces the impact of expert teams, this is chiefly so when the teams use more familiar components and less so if the team uses very original components. It seems that the structural holes indeed provide non-redundant information that help the expert team make sense of original components. Looking at it differently, the average effect of component originality is negative for experienced teams, but this reverses as the team becomes increasingly connected to non-redundant ties.

Finally, we provide some additional clarity on the economic significance of the effects by running a simple OLS regression (unreported) on the 10-year forward citation count. While this model has poorer overall fit due to the poor alignment between the distribution of the dependent variable and the assumptions of the OLS model, it facilitates the interpretation of the economic significance of the effects. Because we are interested in the impact of the focal variables on the number of forward citations only, we put all control variables and fixed effects to zero. Looking at the interaction of team domain expertise and component originality at mean team structural holes, we see that low team domain expertise (mean - 1 standard deviation) combined with highly original components (mean + 1 standard deviation), results in a 10.6% decrease in invention impact (liken to a mean impact of 9.77), whereas the opposite (high team domain expertise and low component originality) is associated with a 44 per cent increase in impact. The latter effect decreases to + 21 per cent when component originality increases from low to high. Looking at the interaction of team domain expertise with team structural holes' value at mean component originality, we see that at low team domain expertise, an increase from low to high structural holes' value leads to an 11 per cent decrease in impact (from -1 per

cent to -12 per cent), whereas at high domain expertise the effect is opposite, increasing from +29 per cent to +36 per cent as the structural hole value evolves from low to high.

DISCUSSION AND FUTURE RESEARCH

Our findings shed new light on the relation between expertise and invention impact. Expertise results from path-dependent investments that create domain-specific absorptive capacity, which in turn helps develop an idiosyncratic perspective on the knowledge space that creates competitive advantage (Dierickx and Cool, 1989). Our findings suggest this advantage is quite persistent: even if teams build up enormous reservoirs of domain expertise, the worst effect we witness is perhaps decreasing marginal returns but no statistical support for negative returns. This finding aligns with the foundational view and goes against the entrenchment perspective which suggests that individuals or teams can become 'too expert' in such a way that it constrains their exploration and future success (Kaplan and Vakili, 2015; Singh and Fleming, 2010).

Empirically, we do observe a negative correlation between component originality and domain expertise but rather than arguing in favour of entrenchment, we posit that this reduced distant search is actually a rational strategy for expert teams, as they are better able to turn familiar components into impactful inventions than their non-expert counterparts. Thus, we proffer that the foundational and entrenchment views may not be contradictory nor incompatible (Kaplan and Vakili, 2015). Specifically, our results imply that experts should stick to what they know, exploiting anomalies in the knowledge structure and identifying sources of invention through a deep and foundational engagement with the knowledge. Because experts have high absorptive capacity in this domain and because acquiring this knowledge is subject to time compression diseconomies (Dierickx and Cool, 1989), they possess a unique advantage in this space. However, non-experts may benefit more from non-local search, experiments with original components, and novelty creation through unexpected component combinations rather than through architectural recombination of existing components.

The results also provide support for a non-structuralist perspective in network research (Carnabuci and Diószegi, 2015; Obstfeld, 2005). While prior research has looked at the effects of network structure at the level of the actor (either a firm or individual), our focus on the unit level (i.e. an invention) presents diverging results. Firstly, because we focus on the patent-level (see also Schillebeeckx et al., 2019), network characteristics do not provide the significant main effects found at the actor-level of analysis (see Guan and Liu, 2016; Paruchuri and Awate, 2017; Wang et al., 2014). Thus, while structural holes in an actor's social network may create an opportunity structure that enhances the actor's exploration, it is not so this automatically translates into higher impact at the invention level. We contend that much of the benefits associated with structural holes provide less of a differential when a team has significant expertise as experts possess substitute resources that more directly influence their inventive success.

While we do not address questions of diversity directly, our finding that non-domain expertise has no significant effect is of interest. Most of the literature has argued that experience diversity is positively associated with inventive outcomes such as individual

team member creativity (Shin et al., 2012), invention breadth (Choudhury and Haas, 2018), and likelihood of breakthrough success (Singh and Fleming, 2010). Yet, these findings are not universal either as Nerkar (2003) for instance does not find a significant relationship between his team diversity measure and impact. In unreported regressions, we investigated whether there would be a positive interaction effect between domain expertise and non-domain expertise but we did not find such a relation. This adds further credence to the foundational view of invention. If teams can combine deep domain knowledge with sufficient knowledge breadth within that domain, they have the necessary expertise to create high impact inventions (Boh et al., 2014).

This raises the question of how managers can best organize their firm's capacity to invent and innovate. Our findings support more focus on local search and specialization, and less on boundary-spanning – possibly reopening avenues for research on these important determinants of invention impact. One consideration in such research should be a meaningful theorization about the boundaries of localness. If Dane (2010) is right in arguing that expertise is a combination of the quantity and diversity of knowledge components as well as the connections between them, it could be so that diversity of knowledge within a domain is preferable over diversity across domains. Within domain diversity then allows for cohesive yet complex schemas to develop in the mind of the inventor whereas beyond domain diversity may inevitably be associated with insufficient specialization.

Next, the strong empirical support for our post-hoc analysis of a three-way interaction among expertise, non-redundancy in the social network, and component originality gives us pause. While domain expertise positively influences invention impact, this effect was found to be contingent on both team position in the collaborative network and on the industry's familiarity with used knowledge components. Inventors' non-redundant social ties and used original components can operate as substitutes or complements, depending on team expertise. For inventors that are not located near structural holes, the marginal effect of expertise decreases as they deploy more original components. For inventors with many non-redundant ties however, using original components may actually improve the effect of expertise on invention impact. Looking at it differently, inventors experimenting with original components will benefit more from domain expertise as they have more non-redundant ties in their social network but the effect is very small. The differential effect of low versus high structural ties is negligible when the team deploys highly original components. However, when expert teams use familiar components, they create the highest impact when they are not occupying structural positions.

If we can consider network structural holes or original components VRIN resources for a team of inventors, our findings suggest these resources do not automatically lead to higher performance. One could potentially argue that network non-redundancy and component originality are not 'valuable' – a contentious concept in the resource-based view (Priem and Butler, 2001a, 2001b; Schmidt and Keil, 2013). The negative interaction effects points to the importance of not strictly the resources themselves, but rather how that resource is deployed to create value (Costa et al., 2013; Sirmon et al., 2011). Our findings suggest that VRIN resources may not always be performance-enhancing as it depends on the context in which they are used, to whom they are accessible, and whether they are 'actionable' or whether they can be effectively orchestrated with the rest

of the firm's resource base. Tacit knowledge embedded in networks comes with strings attached and may be time-consuming to maintain, divert attention processes, and be largely redundant. While our results suggest this may be true for structural holes, it would be interesting to see if the same holds of network centrality. Network researchers could further investigate how the historically acquired (knowledge) resources of a specific node in a network and its position interact in various contexts to improve our understanding of the relative contributions of network structure versus node characteristics like expertise. In addition, more research could focus on what types of resources networks provide and to what extent these can be substituted.

Finally, our findings add to the literature on the effects of time on inventive success. While we focused on component originality, we also controlled for knowledge component age and the time spread in the age of deployed knowledge components. It is noteworthy that our results do not always align with prior research. We proffer these divergences may be explained by a frequently occurring conflation of arguments around knowledge maturity in terms of temporal lapse or recency (e.g., fit, nascent capability-building, risk of retaliation), familiarity (e.g., reliability, uniqueness, search costs), and time spread (combinatorial difficulties), as well as the transference of findings across units of analysis (e.g., Capaldo et al., 2017; Heeley and Jacobson, 2008; Katila, 2002; Katila and Ahuja, 2002; Katila and Chen, 2008; Kok et al., 2018; Nerkar, 2003). Researchers could clarify the confusion by investigating knowledge age, recency of use, time spread, and repeated use across units of analysis and across contexts to identify possible universal or contingent effects between time and invention outcomes.

CONCLUSION

Teams with high domain-specific expertise are generally able to create more impactful inventions. We establish this baseline hypothesis and then investigate whether such expert teams are also more capable at integrating novelty successfully. We look at both expert teams' ability to deploy original components and their ability to benefit from non-redundant structural holes in their collaboration networks, as both are possible sources of novelty. We posit and find that relatively speaking, experts are not good at integrating these sources of novelty and identify a complex three-way interaction between expertise, component originality, and structural holes. Overall, our findings provide an alternative viewpoint to a commonly held belief that boundedly rational individuals search excessively in familiar domains (Cyert and March, 1963; Simon, 1982). Unlike Rosenkopf and Almeida's (2003) submission, we find that teams, especially those with high expertise, may actually spend too much time searching in distant landscapes. Jung and Lee (2016) found that those who search locally are more likely to develop cognitive breakthroughs that are antecedents to high impact inventions. Biologist Jennifer Owen spent the better part of 30 years studying her own garden, identifying over 2,500 species, and discovering four new ones. With additional expertise the total tally could have reached about 8,000 (Brown, 2010). Perhaps the real takeaway is that once people have developed domain expertise, moving beyond that in order to engage in cross-disciplinary research simply does not pay for the majority, which is why it is so hard to find researchers willing to do it.

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NOTES

- [1] This data is available from two sources: <https://sites.google.com/site/patentdataproject/Home> and <http://www.nber.org/patents/>. The first source is used for this research as it is a more up to date version.
- [2] The Cooperative Patent Classification was adopted officially on the first of January 2013 by both USPTO and its European counterpart EPO. CPC is largely based on the European Classification System (ECLA) and very consistent with the International Patent Classification (IPC) schema. It however differs significantly from the USPC and there is no straightforward conversion between the CPC and the USPC schemas, although the USPC makes the concordance available. For the semiconductor class 438 for instance almost all its subclasses are assigned to H01L (see <https://www.uspto.gov/web/patents/classification/uspc438/us438toipc8.htm>). H (electricity), H01 (basic electric elements), H01L (semiconductor devices; electric solid state devices not otherwise provided for). The CPC system is more logically and more hierarchically structured such that components co-occurrence and linkages and knowledge accumulation within domains should be better captured by the CPC system than by the USPC system. This is why the collaboration of the USPC and the EPO that created the CPC has chosen to use the European system as the baseline for the CPC and not the USPC. As more and more countries are starting to use the CPC schema, it will facilitate global comparability of patents. Additional info can be found on <http://www.cooperativepatentclassification.org>. A detailed description of the USPC classification is available via <https://www.uspto.gov/sites/default/files/patents/resources/classification/overview.pdf> Leydesdorff et al. (2017) provide a statistical comparison of different categorization schema.

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