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Technological complexity and the creation of impactful technologies: The role of inventors' international diversity and expertise

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ABSTRACT

Given that highly impactful technologies can generate immense value and build competitive advantages for MNEs, it is crucial to understand how they can successfully create them. This study's overarching contribution lies in explaining how MNEs can assemble inventor teams and optimize their composition to overcome the challenges of technological complexity and create highly impactful technologies. Analyzing a sample of 2.3 million technologies created by 183,833 firms across 139 countries, the study reveals that MNEs with teams that are internationally diverse (multi-country) and possess greater technological expertise are better equipped to leverage complex knowledge in technology creation. Importantly, it also indicates that while international diversity is less effective in making teams more innovative across all levels of complexity, its value lies in delaying the point at which extreme complexity hinders technology creation. In contrast, technological expertise helps team create more impactful technologies at any level of complexity but is less effective in postponing the point where extreme complexity becomes overwhelming. These insights underscore that international diversity and technological expertise are complementary, supporting MNE teams in distinct but synergistic ways.

1. Introduction

A large body of research in international business and management (IB&M) has explored how MNEs combine and integrate knowledge (Frost and Zhou, 2005; Gupta and Govindarajan, 2000; Tzabbar et al., 2022), emphasizing its significance in technology creation (Berry, 2023; Kogut and Zander, 1993, 1995; Martin and Salomon, 2003). This literature highlights the role of inventors, showing that mobile inventors who worked in other countries prior to joining a firm improve knowledge integration (Castellani et al., 2022; Choudhury and Kim, 2019; Useche et al., 2020) and create more value (Cassiman et al., 2018). Moreover, it recognizes that not all new technologies are equally valuable to MNEs (Kafouros et al., 2022), with only few becoming *impactful technologies*—those that significantly influence future discoveries across fields, often becoming breakthrough technologies. Given that impactful technologies contribute to the development of competitive advantages and generate immense value, understanding how MNEs can successfully

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develop them is essential.

Impactful technologies are difficult to create because they involve greater *technological complexity*—their creation relies on a complicated process that requires inventors combining highly interdependent technological components (Maggitti et al., 2013). While low to moderate levels of technological complexity create new opportunities for novelty and may enhance the impact of technologies (Keijl et al., 2016), extreme complexity has a negative effect, as it strains inventors' cognitive capacity and hinders their ability to identify novel technological combinations (Fleming and Sorenson, 2001). Therefore, managing technological complexity becomes very difficult beyond a certain point, resulting in an inverted U-shaped relationship with the creation of impactful technologies. Motivated by the key premise that innovation is driven by the integration of geographically dispersed knowledge (Cano-Kollmann et al., 2018; Rossi et al., 2023), this study demonstrates that IB&M research can offer new insights into how certain firms and MNEs can outperform their rivals in creating impactful technologies by assembling internationally diverse inventor teams capable of managing complexity more effectively. *International diversity* of an inventor team refers to the variety of countries where the inventors on a team are located. While some technologies are created by teams of inventors all located within the same country, others are created by internationally diverse (multi-country) teams (Berry, 2014). A team's international diversity therefore captures inventors from different national contexts, partly reflecting the breadth of the team's knowledge.

Combining insights from the IB&M literature on knowledge recombination (Berry, 2014; Kogut and Zander, 1993; Kafouros et al., 2022) and innovation (Fleming and Sorenson, 2001; Maggitti et al., 2013; Xiao et al., 2022), we develop the premise that a team's international diversity increases its recombinant potential and learning, enhancing its ability to handle complexity and create highly impactful technologies. To empirically examine this premise, rather than focusing on the MNE and subsidiary levels (Frost and Zhou, 2005; Gupta and Govindarajan, 2000), our analysis encompasses a sample of 2.3 million patented technologies and all the teams of inventors who created them, spanning 183,833 MNEs and non-MNEs across 139 countries. Capturing the characteristics of inventor teams is theoretically important, as not all inventors are cognitively alike, and not all inventor teams within firms have a similar composition (Conti et al., 2014).

Moreover, this study captures that teams and their inventors differ not only in terms of international diversity but also in their *technological expertise*—their knowledge, skill and competence in a field. While some inventor teams have a strong track record of influential inventions due to a deep understanding of their core area of expertise (Conti et al., 2014), others have been less successful (Boh et al., 2014). International diversity and technological expertise are complementary, representing different dimensions of knowledge. While international diversity reflects the geographic breadth of a team's knowledge, technological expertise—by capturing a team's prior competence—reflects the depth of its knowledge. By incorporating both international diversity and technological expertise, our model allows us to conceptually and empirically disentangle their effects on teams' ability to handle technological complexity and create impactful technologies.

To understand the mechanisms through which international diversity and technological expertise help teams, we explore two interrelated effects. First, we examine whether inventor teams with greater international diversity and technological expertise create more impactful technologies at any level of complexity—low, moderate, or high. This prediction suggests that the two team characteristics enhance the positive effects of technological complexity while mitigating its negative effects on technology creation. Thus, they shift upwards the point at which the effects of complexity start to turn negative. Second, although extreme complexity will eventually have a negative effect on all teams, we examine whether this tipping point occurs later (i.e., at a higher level of complexity) for teams with greater international diversity and technological expertise. This prediction suggests that such teams will be better equipped to handle greater complexity, shifting the inflection point at which the effects of complexity turn negative to the right.

The study contributes to IB&M research (Berry, 2014; Castellani et al., 2022; Useche et al., 2020) and knowledge recombination theory (Arts and Veugelers, 2015; Kogut and Zander, 1993; Kafouros et al., 2022) by demonstrating how MNEs can optimize team composition to manage complexity more effectively and enhance their ability to create impactful technologies. While prior research emphasizes that MNEs must possess a strong technology portfolio (Berry, 2014) and recognizes the role of inventors (Cassiman et al., 2018; Castellani et al., 2022; Shukla and Cantwell, 2018), this study shifts the focus to how they can optimize team composition. Its contribution lies in showing that MNEs capable of assembling internationally diverse (multi-country) teams with the necessary expertise can transform complexity from a challenge to an opportunity and enhance their innovativeness even in highly complex environments. Rather than viewing complexity as an inherent static characteristic of the technology (Fleming and Sorenson, 2001), the study highlights the role of international teams and strategic coordination in overcoming these challenges.

The study also contributes to the IB&M literature on the role of migrant inventors (Cassiman et al., 2018; Castellani et al., 2022; Shukla and Cantwell, 2018) by clarifying why the impact of complexity on technology creation varies across inventor teams, depending on their international diversity and technological expertise. While international diversity is valuable in delaying the negative impact of extreme complexity, technological expertise makes teams more innovative across all levels of complexity but is less effective in postponing the point at which complexity becomes counterproductive. These insights suggest that international diversity and expertise support teams in distinct but synergistic ways and should be treated as complementary rather than interchangeable constructs in IB&M theory. The findings also have strategic implications for MNEs, highlighting the need to tailor team composition to the specific complexity level of each project. This may provide MNEs with a potential advantage over non-MNEs due to their global reach and capacity to hire employees in different countries.

2. Theoretical background

2.1. Knowledge recombination in firms and MNEs and the role of technological complexity

A key premise in IB&M research is that global competitiveness stems from firms' ability to become an effective vehicle for accessing and combining knowledge from different locations that can, in turn, facilitate technology creation within and across national borders (Berry, 2014; Cano-Kollmann et al., 2018). Although not all technologies are beneficial, highly impactful (and breakthrough) technologies generate immense value, opening new opportunities and technological trajectories and serving as platforms for future technological discoveries (Conti et al., 2014). Hence, they result in a major technological impact (Keijl et al., 2016), are utilized heavily in future inventions, and generate considerable economic rents (Kafouros et al., 2022). Their role is strategically important not only for MNEs but also for other firms that increasingly manage knowledge and technology creation internationally, engage in international collaborations, and assemble international teams of inventors (Choudhury and Kim, 2019; Tzabbar et al., 2022).

Within the literature, technology creation is conceptualized as 'recombinant search', which is a process through which firms identify useful combinations of knowledge and optimize configurations of technological components (Arts and Veugelers, 2015; Fleming, 2001; Fleming and Sorenson, 2001; Kauffman, 1993; Kogut and Zander, 1992). Particularly when knowledge recombination involves heterogeneous knowledge and different collaborators, it can have a profound effect on MNEs' ability to create new technologies and achieve superior performance (Kafouros et al., 2022). For instance, prior research shows that migrant inventors provide social networks and cross-border connections that help R&D-performing firms integrate relevant knowledge when choosing locations for foreign acquisitions (Useche et al., 2020). It also shows that inventors, especially those who worked in other countries in the past, provide various other advantages that assist in knowledge recombination and integration (Castellani et al., 2022; Choudhury and Kim, 2019) and value creation (Cassiman et al., 2018).

Nevertheless, despite the benefits of knowledge recombination and technology creation, they also pose challenges for MNEs and non-MNEs alike as they can stretch the cognitive capacity of teams of inventors, who may not always be able to understand and process complex knowledge and combinations (Zahra and George, 2002). The key reason for these challenges is that although the creation of any technology involves a certain degree of difficulty, the creation of highly impactful technologies is even more demanding due to greater *technological complexity*.

Technological complexity is defined as the level of interdependence (K) between the technological components combined within a technology relative to the number (N) of these components (Fleming and Sorenson, 2001; Kauffman, 1993). Interdependence refers to the functional sensitivity a given component exhibits to changes in another constituent component (Fleming and Sorenson, 2001; Keijl et al., 2016). When it is high, recombining components becomes more difficult because changes in one component require significant adjustments in others (Ethiraj and Levinthal, 2004). In such situations, an invention is highly susceptible to even minor changes in its underlying components (Sanchez and Mahoney, 1996). Furthermore, technological complexity also depends on the number (N) of technological components that inventors must combine to create a technology (Fleming, 2001; Keijl et al., 2016; Zhang and Yang, 2022). A smaller number of highly interdependent components constrains inventors' opportunities to discover new solutions. Hence, technological complexity becomes particularly high when the invention includes only few, but highly interdependent, technological components (i.e., when K is much higher than N).

2.2. Multi-country inventor teams

Although IB&M literature has acknowledged the increasing value of knowledge as a key megatrend in the global economy (Cano-Kollmann et al., 2018), early research focused primarily on the MNE and subsidiary levels (e.g., Gupta and Govindarajan, 2000). Our analysis shifts the focus to the team level and the role of inventors (Castellani et al., 2022; Useche et al., 2020), examining how knowledge recombination—and, consequently, the creation of impactful technologies—is influenced by the composition of inventor teams and the characteristics of each individual within them. Indeed, while it has been established that MNEs act as cross-border orchestrators of teams and activities (Berry, 2014; Cano-Kollmann et al., 2018) and that various team characteristics and leadership styles affect innovation performance (Capponi et al., 2022; Conti et al., 2014; Deng et al., 2023; Taylor and Greve, 2006), team composition and its effects remain a complex and unsolved puzzle (Huo et al., 2019). Specifically, the literature often presumes that complexity is an inherent characteristic of the technology, paying limited attention to the fact that not all inventor teams have the same capacity to manage the complexity involved in the development of impactful technologies. We posit that two key dimensions of a team's composition – international diversity and inventor expertise – can profoundly impact how teams manage complexity and, in turn, influence the creation of impactful technologies.

International (or multi-country) Team Diversity as defined in our study differs from studies that capture the nationality of inventors, their migration or whether they have been internationally mobile (Castellani et al., 2022; Choudhury and Kim, 2019; Shukla and Cantwell, 2018; Useche et al., 2020). In our study, international team diversity refers to cases in which the inventors of the team are located in different countries, i.e., they are multi-country teams (Berry, 2014). Such multi-country teams differ from teams that are not internationally diversified, and all their inventors are located in the same country. International diversity therefore reflects the rather broad and diverse experiences, capabilities, perspectives, and ideas that arise from the different institutional and technological contexts of the countries in which the inventors of the team are located (Kafouros et al., 2022). It also reflects the key premise that MNEs as organizations generate value by integrating knowledge across national borders (Cano-Kollmann et al., 2018). In the context of creating impactful technologies, a team's inventors working across national borders can provide significant advantages, including access to heterogenous ideas and knowledge (Kogut and Zander, 1993), as well as benefits in consolidating various approaches to knowledge recombination (Berry, 2014).

Inventor Team Expertise is another team-specific characteristic that can profoundly influence knowledge recombination (Conti et al., 2014). Inventors' expertise within a team reflects their competence and the depth of their understanding in their fields, which can help them develop a track record of influential inventions (Boh et al., 2014). This expertise is shaped by various factors including inventors' prior training, education and experience that together equip them with the skills and competencies required to understand key ideas and principles related to their specialization (Conti et al., 2014). Teams and inventors with greater expertise are also characterized by stronger technical skills and problem solving capabilities (Boh et al., 2014). Incorporating team expertise into our model also enables us to evaluate the effects of team international diversity that occur beyond the effect of expertise. The independent effects of these two constructs suggest that a team's international diversity provides unique benefits, such as diverse perspectives and problem-solving approaches, that extend beyond the advantages of expertise.

3. Hypotheses development

3.1. Technological complexity and the creation of impactful technologies

The starting point of our analysis is the baseline prediction that when inventor teams in firms and MNEs create new technologies, there is an inverted U-shaped relationship between technological complexity and how impactful the new technology becomes. While low to moderate levels of technological complexity can help teams to create impactful technologies, extreme levels of complexity impose significant cognitive constraints and consequently have a negative effect. To explain this relationship, our reasoning relies on how technological complexity influences two key mechanisms: 1) knowledge recombination and the unique opportunities for combining technological components (Singh and Fleming, 2010; Zhang and Yang, 2022) and 2) the learning curve within a team i.e., the rate at which the team learns when it performs activities for a specific project (Argote, 1993; Schilling and Green, 2011; Schilling et al., 2003).

First, a lower degree of interdependence decreases the downside risk, improves the chances that the technology will function and enables inventor teams to be more flexible and responsive to technological changes (Baldwin and Clark, 2003). However, it also decreases the probability of a highly successful breakthrough because it affects the upside potential (Fleming and Sorenson, 2001). In other words, a very low degree of interdependence implies less uncertainty and makes it easier for the team to create a new technology, but it also limits opportunities for novelty and creativity. By contrast, as technological complexity increases from lower to moderate levels, interdependence between technological components also increases (Arts and Veugelers, 2015; Fleming and Sorenson, 2001; Keijl et al., 2016), providing teams with unique opportunities for identifying novel technological combinations and creating impactful technologies (Keijl et al., 2016). This higher recombinant potential also enhances the ability of the team not only to rearrange existing components in novel ways, but also identify better and highly imaginative solutions. Overall, the availability of unique opportunities induces variation and helps the team to come up with more radical and useful configurations, thus increasing the potential impact of new technologies (Conti et al., 2014; Mun and Chung, 2017).

Second, prior research shows that although the decoupling of components may increase adaptability and decrease costs (Baldwin and Clark, 2003), inventors' efforts become more useful when they combine components with an intermediate degree of interdependence (Fleming and Sorenson, 2001). Following this logic, we expect that as technological complexity increases from low to moderate levels, it enhances learning within the inventor teams (Schilling et al., 2003). By striking the right balance between creative uncertainty and overwhelming complexity (Baldwin and Clark, 2003), a moderate level of technological complexity improves the team's learning rate, enabling inventors to identify and understand the potential of novel combinations. It also helps teams to become more effective in co-exploiting their collective knowledge, which is crucial for discovering valuable configurations and impactful technologies. This is particularly important because, as the number of components in a system decreases, it becomes increasingly difficult to find novel combinations from a limited set of components (Ahuja and Lampert, 2001; Fleming, 2001; Yayavaram and Chen, 2015). Overall, low to moderate levels of complexity enhance the team's recombinant potential and learning, thereby increasing the potential for creating impactful technologies.

However, while moderate levels of technological complexity are beneficial, extreme levels are detrimental, hindering the creation of impactful technologies. Extreme technological complexity means that teams experience a low degree of familiarity and recognizability (Keijl et al., 2016). In such situations, teams must manage interdependence with a limited range of potential solutions. Unfamiliarity and high interdependence place cognitive constraints on inventors, diminishing the recombinant potential and learning within teams (Ahuja and Lampert, 2001; Arts and Veugelers, 2015). Indeed, when there are very few technological components and the interdependence between them is extremely high, predicting the outcomes of these interactions can strain and exhaust a team's cognitive resources (Fleming and Sorenson, 2001). These cognitive restrictions also make it particularly difficult for the team to effectively identify and test the most promising technological combinations (Keijl et al., 2016).

Furthermore, a low degree of familiarity at extreme levels of complexity means that inventors must combine highly interdependent components without easily recognizing their interactions. These challenges, in turn, decrease the likelihood of identifying novel opportunities (Yayavaram and Chen, 2015). At extreme levels of complexity, a team's cognitive limitations become more pronounced because replacing one component with another can significantly alter the functionality of the resulting technology due to the high level of interdependence. Extreme levels of complexity also make the learning process more challenging. Trying to understand highly interdependent interactions can slow the pace of learning and, consequently, hinder technology development given the already high risk of failure when dealing with unfamiliar components.

Put differently, although complexity is beneficial at low to moderate levels, learning slows down at extreme levels of complexity, making it more challenging for teams to identify useful combinations, thus decreasing the opportunities for creating impactful technologies. Accordingly, we expect an inverted U-shaped relationship between technological complexity and teams' creation of impactful technologies. The above discussion can be summarized in the following baseline expectation:

While inventor teams benefit from low to moderate levels of technological complexity in creating impactful technologies, extreme levels of technological complexity negatively affect their ability to do so.

3.2. International (multi-country) team diversity

Our first two interrelated hypotheses suggest that international team diversity moderates the inverted U-shaped relationship between technological complexity and the creation of impactful technologies in two ways: (1) at any given level of complexity (low, moderate or extreme), we expect internationally diverse teams in firms and MNEs to create more impactful technologies than teams that are less internationally diverse. This means that international team diversity will shift the inverted U-shaped curve *upwards*; (2) although extreme levels of complexity will eventually begin to negatively affect the creation of impactful technologies for all teams in firms and MNEs, this will occur later (i.e., at a higher level of complexity) for teams that are internationally diversified, as they are better equipped to manage higher levels of complexity. Hence, the inflection point of the inverted U-shaped curve (i.e., the point at which the effects of complexity begin to turn negative) will shift not only upward but also *to the right*. We discuss the reasoning for these predictions below.

We argue that international team diversity is beneficial at both low to moderate levels of complexity as well as extreme levels of complexity. In internationally diverse teams, the varied experiences, cultures, knowledge and ideas of inventors from different backgrounds enable teams to identify combinations that may not be apparent to less internationally diverse teams (Deng et al., 2023; Xie and Li, 2015). The value of diversity is further underscored in the IB literature on inventors' inter-organizational and cross-border mobility (Cassiman et al., 2018; Castellani et al., 2022), which highlights how diverse perspectives and problem-solving approaches can profoundly impact innovation. As a result, team diversity increases the likelihood of creating impactful technologies that typically require heterogeneity in thought, ideas and inputs.

Moreover, international diversity enhances a team's ability to exploit the range of potential combinations arising from moderate or extreme levels of complexity. It does so by enhancing learning and recombinant potential in the team, as inventors can draw on a broader knowledge pool and a diverse array of perspectives to identify creative and novel combinations (Gray et al., 2022; Zhang et al., 2010). By facilitating learning and knowledge exchange among team members from different countries, international diversity not only accelerates how quickly teams learn, but also the way in which they learn by enhancing their ability to share, understand and adapt to various ways of combining components (Gray et al., 2022). Prior research supports this reasoning, suggesting that diversity can help teams overcome cognitive biases that occur when inventors share similar ideas and perspectives from the same country (Zhang et al., 2010). These cognitive similarities may hinder conceptual blending and a team's learning by causing inventors to perform similar searches and overlook alternative combinations (Aggarwal and Woolley, 2019), ultimately leading to redundant and unimaginative solutions.

We further expect international team diversity to remain beneficial even at extreme levels of complexity. Due to these benefits, the negative effects of extreme levels of complexity on the impact of technologies will be less pronounced and occur later in internationally diverse teams than in less diverse ones. Thus, international diversity enables teams to be able to manage a greater level of complexity before it overwhelms their cognitive capacity, ultimately hindering negatively their ability to develop impactful technologies. In other words, international diversity helps extend the upward phase of the inverted U-shaped relationship. Although interdependence between components increases exponentially at high levels of complexity (Henard et al., 2014), the benefits of diversity may again help inventors navigate these challenges more effectively (Stahl and Maznevski, 2021). Diverse learning perspectives and approaches enhance problem solving (Cassiman et al., 2018; Kumar, 2014) and accelerate the pace of learning, thereby supporting the development of impactful technologies. International diversity also encompasses cultural diversity, which fosters increased creativity, adaptability (Minbaeva et al., 2021) and a greater capacity to handle a broader range of information (Stahl and Maznevski, 2021; Stahl et al., 2010). Furthermore, it encourages divergent thinking (Stahl and Maznevski, 2021; Stahl et al., 2010), which is strongly linked to the generation of novel ideas, as well as with convergent thinking that enables teams to focus on ideas with the greatest potential.

Accordingly, we introduce the following hypotheses, proposing that international diversity shifts the inverted U-shaped relationship between technological complexity and the creation of impactful technologies upwards (H1a) and to the right (H1b):

H1a. Inventor teams with greater international (multi-country) diversity create more impactful technologies at any level of technological complexity—low, moderate or extreme.

H1b. Inventor teams with greater international (multi-country) diversity can manage extreme levels of technological complexity more effectively, delaying its negative effects on the creation of impactful technologies.

3.3. Inventor team expertise

Our next two hypotheses (H2a & H2b) suggest that inventor team expertise moderates the inverted U-shaped relationship between technological complexity and the creation of impactful technologies. Specifically, we expect teams with greater expertise to a) create more impactful technologies at any level of complexity (low, moderate or extreme) and b) manage extreme complexity more effectively, experiencing its negative effects much later. These predictions suggest that the inverted U-shaped curve will shift upward and its inflection point to the right. We discuss the reasoning for these predictions below.

Inventor team expertise is beneficial not only at low to moderate levels of technological complexity but also at extreme levels. At low to moderate complexity, team expertise enhances the creation of impactful technologies by improving the identification of the most useful combinations (Fleming and Sorenson, 2004). Expertise helps teams navigate the challenges of complexity by facilitating the parallel processing of multiple problems related to technology development (Nonaka, 1994) and generating insights that are shared and iterated among team members, thereby increasing the potential for generating and recombing ideas (Singh and Fleming, 2010).

The above reasoning is consistent with the idea that inventors with greater expertise are more capable of leveraging their own expertise and use their domain-specific knowledge to find broader and potentially more novel solutions (Boh et al., 2014; Mastrogiorgio and Gilsing, 2016). Specifically, inventors with greater expertise, by definition, have a proven track record of creating novel solutions (Conti et al., 2014), along with a deep understanding of scientific principles and the necessary skills and analogical abilities (Mastrogiorgio and Gilsing, 2016) to comprehend and analyze technological knowledge (Gruber et al., 2013). This, in turn, enables them to make inferences and extrapolate beyond the obvious (Boh et al., 2014) while drawing on prior useful combinations to develop new ones (Mastrogiorgio and Gilsing, 2016). Hence, while teams with greater expertise are particularly well-equipped to benefit from moderate levels of complexity, teams with lower levels of expertise are less capable of doing so.

Furthermore, prior expertise enables teams to adopt more rigorous screening processes when evaluating different options (Singh and Fleming, 2010). As team members assess prior knowledge and technologies (Boh et al., 2014), their expertise enables them develop better technological combinations (Conti et al., 2014; Zhang and Yang, 2022) by predicting which configurations are likely to succeed and which may lead to dead ends. This enables them to pursue the most promising technological trajectories while avoiding those that are potentially less fruitful (Fleming and Sorenson, 2004; Singh and Fleming, 2010).

Moreover, greater expertise can accelerate learning within a team and lead to unique insights, which is particularly important as complexity increases. Prior research suggests that learning can be either implicit or be more specific to a solution (Schilling et al., 2003). We expect these benefits to create a synergistic effect, enabling inventors to better manage the unpredictability associated with technological complexity and develop impactful technologies. A faster learning pace is also advantageous when teams face extreme complexity, as component interdependence increases considerably (Fleming and Sorenson, 2001; Keijl et al., 2016), making recombination more difficult (Yayavaram and Chen, 2015). While greater expertise helps teams improve the process of identifying the most useful combinations and opportunities, teams with limited expertise have a reduced capacity to avoid mistakes and correct errors during technology creation (Fleming and Sorenson, 2004). Hence, we expect inventor teams with greater expertise to create more impactful technologies at both low to moderate and extreme levels of technological complexity, pushing both the increasing and decreasing phase of the inverted U-shaped curve upwards.

We further hypothesize that team expertise shifts the inflection point of the inverted U-shaped curve to the right, indicating that the negative effects of extreme complexity will occur much later for teams with greater expertise. The rationale behind this prediction is that expertise enables inventors to manage much higher levels of complexity more effectively compared to teams with limited expertise, by helping them cope with cognitive challenges and coordinate complex routines and processes. They can also handle high levels of detail and possess a greater capacity to navigate the uncertainty involved in identifying useful combinations and making decisions that determine the most effective solutions for developing an impactful technology. Teams with greater expertise are also better equipped to manage cognitive challenges, as their prior expertise helps them stay focused when interdependence among components is high, anticipate less promising technological trajectories, and filter out unproductive combinations. Consequently, expertise helps teams avoid mistakes throughout the process, ultimately leading to successful combinations and impactful technologies.

Accordingly, we expect inventors' expertise to shift the inverted U-shaped relationship between technological complexity and the creation of impactful technologies upwards (H2a) and to the right (H2b):

H2a. Inventor teams with greater expertise create more impactful technologies at any level of technological complexity—low, moderate or extreme.

H2b. Inventor teams with greater expertise can manage extreme levels of technological complexity more effectively, delaying its negative effects on the creation of impactful technologies.

4. Data, variables and methods

4.1. Data

To test the hypotheses, we initially collected data on the technologies (inventions) developed by firms using patent data from the OECD REGPAT database (Maraut et al., 2008). This includes patent applications filed in the European Patent Office (EPO) since 1977, including those filled under the Patent Cooperation Treaty (PCT). We matched EPO and PCT priority numbers and excluded duplicate patent applications. One limitation of the REGPAT patent data is that inventor names are provided as registered in the patents, and inventor ID numbers are assigned based on exact spellings. This may create issues because the same inventor may appear with different name spellings or titles across different patents. To overcome this problem, we used patent numbers to merge the patent data with the patent inventor data provided by Morrison et al. (2017). This approach relies on precise geo-location data for inventor disambiguation that ensures the correct matching of inventors across patents. This study covered all EPO patents filed until the end of 2011. Therefore, our dataset includes patents that were filed until 2011.

Furthermore, we collected patent citation data from the OECD Patent Quality Indicators database (Squicciarini et al., 2013) to measure patent impact and account for various patent-specific characteristics. The OECD Citations database draws data from the Worldwide Statistical Patent Database (PATSTAT), providing a comprehensive coverage of citations globally. We considered a 5-year forward citation window for our analysis, and thus, the citation data we collected includes citing patents until the end of 2016. We used the ORBIS-IP database by Bureau van Dijk (BvD) to identify patents filed by firms. By matching patent numbers, we linked the OECD patent data with ORBIS-IP data, and excluded patents attributed to individuals. Consequently, our sample comprised 2,343,712 EPO and PCT patents that were matched with 183,833 firms recorded in ORBIS-IP, spanning from 1977 to 2011. The sample of firms covers 139 countries, including developed and emerging economies.

4.2. Variables

4.2.1. Dependent variable

The dependent variable of the study requires us to capture how *impactful the creation of each invention is*. Following established practice in prior research, we operationalize such impact using the number of forward citations that each invention (patent) receives within a 5-year window (Fleming and Sorenson, 2001; Hall et al., 2005; Kaplan and Vakili, 2015; Lanjouw and Schankerman, 1999; Trajtenberg, 1990). Given that some inventions were created more recently than others, the 5-year window normalizes the measure to avoid a time-related bias. The number of forward citations captures how influential a technology becomes and reflects the intensity of future references to the patent by other inventors as well as its impact on the development of future technologies.

4.2.2. Independent variables

To operationalize the measure of *technological complexity* for a given invention, we followed a method developed by prior studies (Fleming and Sorenson, 2001). For illustration purposes, the formula for complexity is reproduced from Fleming and Sorenson (2001, p.1027). This measure is calculated in three steps. First, the ease of recombination (E) for each patent sub-class is calculated as $E_i =$ (number of sub-classes previously combined with sub-class i) / (number of previous patents in sub-class i). Second, the interdependence of patent l (K_l) is calculated as $K_l =$ (number of sub-classes on patent l) / $\sum_{l \in i} E_i$. Third, interdependence K is divided by the number (N) of components in the patent. Hence, *technological complexity* is estimated as K/N. This is a well-established method of measuring technological complexity through recombinant search (Fleming, 2001; Keijl et al., 2016). A higher K/N ratio is indicative of higher complexity because of the increased interdependence relative to the number of components.

To measure each *team's international diversity* of inventors, we needed to capture the variety of countries represented in the team. Therefore, we first identified the number of countries where the inventors listed on the patent were located. We did so for each team separately. We then operationalized the measure of each team's international diversity by estimating the total number of different countries the inventors of each team are located. For example, if a team has five inventors who are located in three different countries, the measure will take the value of three. Hence, a higher value indicates greater international diversity within a team. This measure differs from measures that capture inventor mobility (i.e., in how many countries the inventor has been located in the past) (Castellani et al., 2022), and whether the patent of a firm has mobile inventors (Cassiman et al., 2018) or migrant inventors (Useche et al., 2020).

As discussed earlier, an *inventor team's expertise* refers to their knowledge, prowess and competence in an area that can drive their ability to create impactful technologies. This measure is suitable for our study because a team's prior citations reflect how effective the team and its members have been in exploiting their knowledge and expertise. Hence, this measure captures not only a team's knowledge in various technological areas, but also its impact. This measure follows established practice, such as the study of Melero and Palomeras (2015), that uses the cumulative number of inventors' prior patent applications to capture the extent of inventors' expertise and the cumulative number of citations of past patents to measure the quality of inventor expertise (Melero and Palomeras, 2015). Given that our aim is to capture both the extent and quality of a team's expertise, we calculate a measure that uses each team's average number of past patent applications weighted by their forward citations (standardized within a 5-year forward window). This measure is based on the rationale that systematically producing several high-quality impactful patents reflects both the extent and quality of the inventor team expertise.

Accordingly, we collected data on the previous patents of each inventor within a team and traced how many forward citations their patents received within a 5-year window. Specifically, we calculated the cumulative number of patents filed and the standardized citations per year for each inventor in the dataset. We assigned these counts based on the patent filing date, until the year preceding the filing year of the focal patent (i.e., the cumulative patents and citations of inventors until, and including, year *t-1* for a patent filed in year *t*). Given that patent citation patterns vary across technology classes and change over time, we follow prior studies and standardize citation counts as the nominal 5-year window citations divided by the cohort mean, where the cohort is defined as the IPC 4-digit average citations in each year (Hall et al., 2001; Melero and Palomeras, 2015). We then calculated the patent average for each team by taking the sum for the team and dividing it by its number of inventors.

4.2.3. Control variables

In addition, following prior patent-level studies (Fleming and Sorenson, 2001; Singh and Fleming, 2010), we included several patent- and firm-level control variables. First, the patterns of invention impact and forward citations received by patents may vary across different technological domains. Following Fleming and Sorenson (2001), we control for technology-specific characteristics by including *technology mean control* and *technology variance control*. These controls account for differences in citation rates observed across technology classes. We follow the calculation procedure outlined in the formulas by Fleming and Sorenson (2001, p. 1027). This process involves several steps. First, we calculated the average of forward citation in each technology class. This average represents a technology-specific tendency to receive citations. Given that each patent belongs to multiple technology classes, we assigned patent-specific technology control by calculating the weighted average of the technology classes assigned to the patent. The weights are calculated based on the share of sub-classes (full IPC code) within each class (IPC4 code), i.e., classes with more sub-classes assigned to the patent receive higher weights. Similarly, the technology variance control is calculated in a similar manner with the calculated technology class-specific citation variance assigned to each patent as the weighted average of technology class variances.

Furthermore, following prior studies, we incorporate several control variables that can influence technology creation. Specifically, we control for *prior art citations* using the number of backward citations in a patent made to other patents. We also control for *science citations* as the number of non-patent references made in the patent (Singh and Fleming, 2010). Furthermore, following prior research (Fleming and Sorenson, 2001), we controlled for technological diversity in the patent with a number of variables. We included a *single class dummy* that equals 1 if a patent has only one technology class reference, and 0 otherwise. We also included the *number of classes* (technology class references) as an additional control. Moreover, we controlled for the number of *trials*, which captures the number of previous patents that combine the same technology classes.

Next, given that our data covers both ordinary and PCT patents, we included a dummy variable that equals one if the patent is filed under PCT. This control variable captures potential differences of PCT filings and other factors associated with the firms' selection of this filing route. Furthermore, we controlled for the *number of claims* made by patents, because the claims represent the scope of novelty and boundaries of property rights represented by the patent (Singh and Fleming, 2010; Squicciarini et al., 2013).

We further controlled for several team-specific characteristics. First, to differentiate between patents that are developed by a team and those that are not, our model incorporates a dummy variable that equals 1 if a patent is developed by a team (i.e., when it has two or more inventors). Second, following (Singh and Fleming, 2010), we calculated *inventor network size (log)* as the number of inventors within a distance of two or less in the team's past collaborative network, based on collaborative patents in our dataset. Third, inventors differ in their experience and ability to leverage the benefits of working in international teams. To control for such differences, our model incorporates a control variable for *inventors' international team experience*, which is operationalized as the cumulative sum of each inventor's experience of working in international teams. Third, to further capture variations in the team size (that might not be captured by the team dummy), we included a control variable for the *size of the team,* which is operationalized as the number of inventors in the team. This control variable is important because it isolates the team size effect from the effect of the team's international diversity.

Furthermore, our model controls for three important firm-level characteristics. First, the creation of impactful inventions might be affected by the firm's portfolio (stock) of past patents. To account for this effect, our model includes a *firm-level patent stock* variable (in log) to account for the firm's patent portfolio and knowledge base. We calculated the variable as a cumulative patent stock using the perpetual inventory method (Arora et al., 2018; Hall et al., 2005). Formally, $S_t = P_{t-1} + (1-\delta)S_{t-2}$, where S is the stock of patents in time t, P represents the number of patents of the firm filed in the year. δ is the depreciation rate accounting for knowledge devaluation over time, assumed to be 0.15 following the previous studies (ibid.). To calculate the patent stock for a patent filed in year *t*, we use the stock of the firms' patents up to and including year *t-1*.

Second, firms with greater international experience (typically, MNEs) may exhibit a higher propensity to use international teams compared to firms with limited international experience. This firm-specific characteristic may lead to potential correlation with patent-level variables. To control for such variations, our model incorporates a variable for *firm-level international experience*, operationalized as the number of different countries involved in a firm's patents over the past five years. Third, the impact of a technology might also be affected by the fact that some patents are co-developed by multiple firms, rather than by a single firm. We have therefore included an additional control variable to capture *the number of assignee firms*. Finally, all models include year-specific dummy variables to control for temporal shifts in technological development and citation rates.

4.3. Estimation method

Given that the dependent variable is a count-based variable, we use a Poisson-type estimation method. In addition, due to the overdispersed nature of the distribution of forward citations, these models are traditionally estimated using the negative binomial estimation method (Fleming and Sorenson, 2001; Singh and Fleming, 2010). Accordingly, we estimate all the models using negative binomial regression. In all regressions, we monitored the dispersion parameter (ln (Alpha)). Every model returned a value significantly higher than zero, verifying the suitability of using negative binomial regression over the regular Poisson regression.

5. Results

Table 1 reports summary statistics and correlations. We estimated the variance inflation factor (VIF) for the variables and the mean VIF for each model. In model 1, the highest VIF was 5.67 (for the squared term of complexity). However, models that included interaction terms returned VIFs exceeding the threshold value of 10. To address this, we conducted a robustness check using mean-centered versions of the variables. In this test, the VIFs for all the variables, including the interaction terms, decreased below the threshold of 10. The significance levels of the coefficients remained unchanged, indicating that interaction-driven multicollinearity did not affect the results. Table 2 reports the results of the regression analysis, with *p*-values calculated from robust standard errors.

Model 1 in Table 2 validates the baseline effect of technological complexity on the impact of technologies. The coefficient for the first order term is positive, while the squared term is negative. Both coefficients are highly statistically significant, indicating that the initially positive marginal effect of complexity gradually weakens and eventually turns negative as complexity becomes extreme. This confirms the presence of an inverted U-shaped relationship between technological complexity and the creation of impactful technologies. To verify whether this relationship holds within the range of complexity in our dataset, Fig. 1 depicts this relationship across

Table 1
Descriptive statistics.

	Variable	Mean	Std.dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Impact of technology (Fwd cit.s; 5 yr)	1.03	2.93																	
2	Technology mean control	0.99	0.31	0.10																
3	Technology variance control	0.00	0.00	−0.01	−0.06															
4	Prior art citations	5.29	7.72	0.09	0.02	0.01														
5	Science citations	2.38	8.33	0.13	0.09	−0.03	0.39													
6	Single class dummy control	0.46	0.50	−0.07	−0.16	−0.03	−0.03	−0.06												
7	Number of classes control	1.97	1.22	0.11	0.17	0.03	0.04	0.09	−0.73											
8	Trials	48.94	374.93	−0.01	−0.02	−0.03	−0.01	0.04	0.14	−0.10										
9	PCT dummy	0.45	0.50	−0.06	0.08	−0.03	0.07	0.02	−0.06	0.07	0.02									
10	Number of claims made by the patent	13.20	10.04	0.04	0.08	−0.02	0.03	0.04	−0.07	0.11	0.02	0.18								
11	Team dummy	0.68	0.46	0.06	0.18	−0.03	0.03	0.06	−0.07	0.09	0.01	0.09	0.08							
12	Inventor network size (log)	467.93	3045.98	0.09	0.32	−0.05	0.08	0.08	−0.09	0.11	0.02	0.15	0.09	0.54						
13	Inventors' international team exp.	0.36	1.57	0.04	0.11	−0.01	0.06	0.06	−0.02	0.02	0.01	0.07	0.04	0.06	0.26					
14	Firm-level patent stock (log)	718.81	1468.74	0.03	0.28	−0.05	−0.02	−0.01	−0.02	0.00	0.02	−0.02	−0.06	0.16	0.40	0.10				
15	Assignee firm international exp.	6.75	8.16	0.02	0.26	−0.06	−0.01	0.03	−0.02	0.02	0.04	0.06	0.00	0.16	0.38	0.17	0.88			
16	Size of inventor team	0.76	0.63	0.09	0.23	−0.04	0.06	0.09	−0.09	0.12	0.01	0.11	0.11	0.83	0.69	0.08	0.18	0.18		
17	Number of assignee firms (NoA)	1.23	0.49	0.02	0.03	0.00	0.02	0.04	−0.04	0.05	−0.01	0.06	0.00	0.06	0.04	0.00	0.09	0.01	0.08	
18	Technological complexity (TC)	1.04	1.44	−0.02	−0.05	−0.07	−0.03	0.01	0.44	−0.37	0.60	0.01	0.02	−0.02	0.00	0.02	0.09	0.09	−0.03	−0.03
19	Inventor team intern-l diversity (ID)	11.67	32.60	0.08	0.18	−0.03	0.07	0.04	−0.03	0.04	0.00	0.06	0.04	0.15	0.65	0.35	0.31	0.29	0.18	−0.01

Table 2
Negative binomial regression results.

	MODEL 1 Coef.	MODEL 1 p-values	MODEL 2 Coef.	MODEL 2 p-values	MODEL 3 Coef.	MODEL 3 p-values	MODEL 4 Coef.	MODEL 4 p-values
Constant	−1.6079	(0.000)	−1.6163	(0.000)	−1.6029	(0.000)	−1.6129	(0.000)
Technology mean control	0.5882	(0.000)	0.5880	(0.000)	0.5903	(0.000)	0.5900	(0.000)
Technology variance control	−17.0188	(0.000)	−16.9934	(0.000)	−17.3132	(0.000)	−17.2859	(0.000)
Prior art citations	0.0224	(0.000)	0.0224	(0.000)	0.0224	(0.000)	0.0224	(0.000)
Science citations	0.0066	(0.000)	0.0066	(0.000)	0.0066	(0.000)	0.0066	(0.000)
Single class dummy control	−0.0928	(0.000)	−0.0930	(0.000)	−0.0927	(0.000)	−0.0929	(0.000)
Number of classes control	0.1478	(0.000)	0.1478	(0.000)	0.1474	(0.000)	0.1474	(0.000)
Trials (similar technology combinations in the past)	−0.0001	(0.000)	−0.0001	(0.000)	−0.0001	(0.000)	−0.0001	(0.000)
PCT dummy	−0.4026	(0.000)	−0.4026	(0.000)	−0.4025	(0.000)	−0.4025	(0.000)
Number of claims made by the patent	0.0077	(0.000)	0.0077	(0.000)	0.0077	(0.000)	0.0077	(0.000)
Team dummy	−0.1281	(0.000)	−0.1279	(0.000)	−0.1290	(0.000)	−0.1288	(0.000)
Inventor network size (log)	−0.0166	(0.000)	−0.0166	(0.000)	−0.0168	(0.000)	−0.0168	(0.000)
Inventors' international team experience	0.0081	(0.000)	0.0081	(0.000)	0.0079	(0.000)	0.0079	(0.000)
Firm-level patent stock (log)	−0.0115	(0.000)	−0.0115	(0.000)	−0.0116	(0.000)	−0.0116	(0.000)
Assignee firm international experience	0.0100	(0.000)	0.0100	(0.000)	0.0104	(0.000)	0.0104	(0.000)
Size of inventor team	0.3353	(0.000)	0.3352	(0.000)	0.3362	(0.000)	0.3361	(0.000)
Number of assignee firms (NoA)	0.0775	(0.000)	0.0775	(0.000)	0.0770	(0.000)	0.0770	(0.000)
Baseline: Technological complexity (TC)	0.1611	(0.000)	0.1745	(0.000)	0.1456	(0.000)	0.1608	(0.000)
Baseline: TCˆ2	−0.0102	(0.000)	−0.0114	(0.000)	−0.0096	(0.000)	−0.0109	(0.000)
Inventor team international diversity (ID)	0.1381	(0.000)	0.1381	(0.000)	0.1297	(0.000)	0.1295	(0.000)
H1a&b: TC x ID			−0.0123	(0.011)			−0.0142	(0.003)
H1a&b: TCˆ2 x ID			0.0011	(0.018)			0.0012	(0.013)
Inventor team expertise (log) (ITE)	0.1072	(0.000)	0.1155	(0.000)	0.1073	(0.000)	0.1173	(0.000)
H2a&b: TC x ITE					0.0087	(0.000)	0.0089	(0.000)
H2a&b: TCˆ2 x ITE					−0.0003	(0.009)	−0.0003	(0.006)
Observations	2,343,712		2,343,712		2,343,712		2,343,712	

Dependent Variable: Impact of technology (Forward citations; 5-year window).
P-values are calculated from robust standard errors. Year specific dummy variables are included.

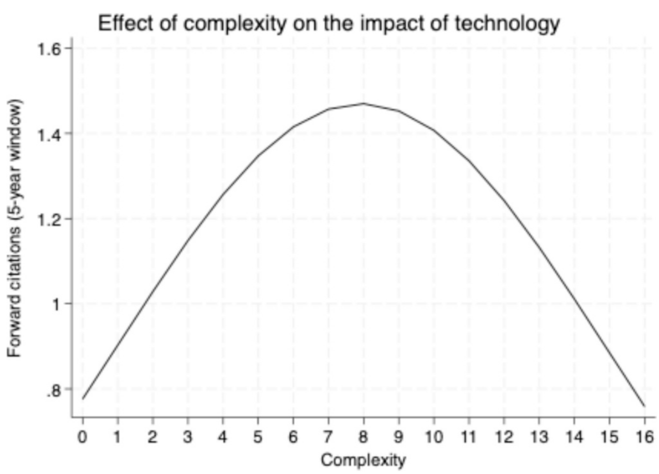


Fig. 1. Effects of technological complexity on the impact of technologies.

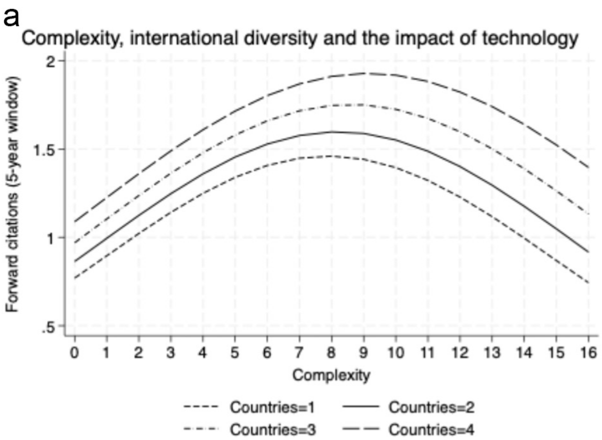
the entire sample, supporting the inverted U-shape pattern.

Model 2 tests Hypotheses H1a and H1b. The coefficient for inventor team international diversity is positive and statistically significant, indicating that it has a positive effect even at low levels of complexity. The moderating effects of international diversity on the first order and squared terms of technological complexity are positive and negative, respectively. The results of Model 2 indicate a positive and statistically significant interaction between technological complexity and international diversity. However, interpreting moderation effects in nonlinear relationships is complex, as the overall effect depends on four different coefficients with opposing signs. Moreover, whether the moderating effect shifts the inflection point to the right or left depends on the relative strength of the moderation effects on both sides of the inverted U-shaped relationship.

To facilitate a more accurate interpretation, Fig. 2a depicts the relationship between complexity and technological impact at four different levels of international diversity. Hypothesis H1a suggests that internationally diverse teams create more impactful technologies across all levels of technological complexity—low, moderate or extreme. As shown in the figure, higher levels of international diversity shift the curve upward at all levels of complexity, with no intersection of the curves, supporting Hypothesis H1a. The figure also shows that the inflection point shifts considerably to the right, supporting H1b and indicating that internationally diverse teams are better equipped to handle higher levels of complexity before experiencing its negative effects.

Fig. 2b depicts the marginal effects of this relationship. When the line of the marginal effects is above 0, it indicates a positive effect; 0 is the inflection point, and below 0 reflects negative effects. The long-dashed line remains above the other lines, indicating that the positive marginal effect is stronger when international diversity is higher. On the right side of the graph, the long-dashed line remains above the others, suggesting that the negative effects are weaker. This figure also confirms that higher levels of international diversity shift the inflection point to the right. This shift to the right appears to be the dominant effect, as it is considerably stronger than the corresponding upward shift of the curve.

Model 3 and Fig. 3a and b test Hypotheses H2a and H2b. Hypothesis H2a proposes that teams with greater expertise create more impactful technologies at any level of technological complexity—low, moderate or extreme. The coefficient of the direct effect of inventor team expertise is positive and statistically significant, validating that the effect of team expertise is positive even at the lowest levels of complexity. This is also reflected in Fig. 3a, which shows that at higher levels of inventor team expertise, the curve shifts upwards at all levels of complexity, again with no intersection of the curves. This finding shows that the effect of team expertise is positive across all levels of complexity, supporting Hypothesis H2a. Furthermore, Fig. 3a shows that greater team expertise strengthens both the positive and negative phases of the relationship, leading to a more pronounced (steeper) inverted U-shaped relationship. This shift intensifies the effect of complexity on technological impact and raises the inflection point to a higher level. Interestingly this shift



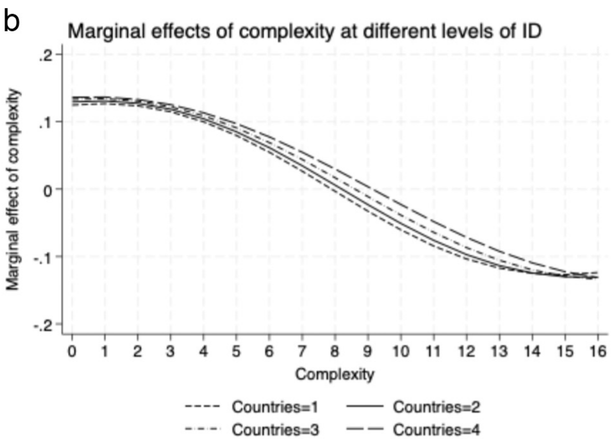


Fig. 2. a: Effects of technological complexity on the impact of technologies at different levels of international diversity.
b: Marginal effects of complexity at different levels of international diversity (ID).

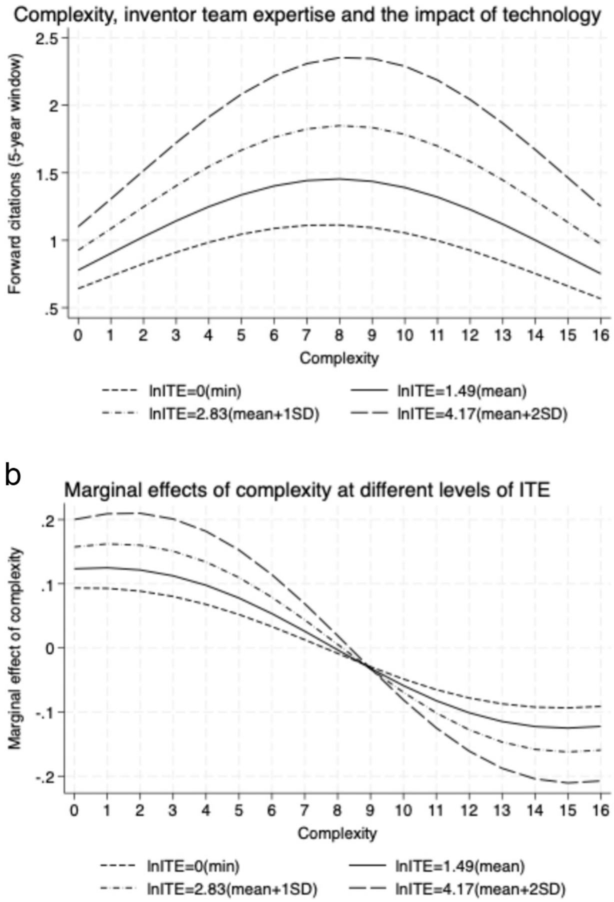


Fig. 3. a: Effects of technological complexity on the impact of technologies at different levels of inventor team expertise (ITE).
b: Marginal effects of technological complexity at different levels of inventor team expertise (ITE).

is considerably stronger than the shift observed for international diversity.

Furthermore, the moderation effect shifts the inflection point to the right, supporting H2b and showing that team expertise strengthens the increasing phase of the inverted U-shaped relationship. This is also visible in Fig. 3b that depicts the corresponding marginal effects. At low to moderate levels of complexity, the positive marginal effect is stronger at higher levels of expertise, as indicated by the long-dashed line initially appearing above all others. The points where the lines cross 0 on the vertical axis represent the inflection point. At higher values of expertise, the inflection point occurs at higher complexity levels. However, although the inflection point shifts to the right, supporting H2b, the magnitude of this move is not a big as it is in the case of international diversity.

Overall, although the above results and figures support the hypotheses, they also reveal an interesting pattern of effects, highlighting that the benefits of international diversity and expertise are distinct yet complementary. Specifically, while international diversity does not considerably shift the inverted U-shaped relationship between complexity and technological impact upwards, it is highly effective in shifting the curve to the right, delaying the point at which the negative effects of extreme complexity emerge. In contrast, team expertise exhibits the opposite pattern of results. It effectively shifts the inflection point upwards, enabling teams to create more impactful technologies at any level of complexity, but it does not play an important role in shifting the inflection point to the right.

6. Discussion

6.1. Theoretical contributions

Given the strategic importance of possessing strong technology portfolios, it is crucial to understand how MNEs can successfully create highly impactful technologies. The study’s overarching contribution lies in demonstrating how MNEs can assemble internationally diverse teams with greater technological expertise to both leverage the benefits and overcome the challenges of complexity, thereby enhancing their ability to create impactful technologies. Accordingly, it makes several theoretical contributions to the IB&M literature (Berry, 2014; Castellani et al., 2022; Choudhury and Kim, 2019; Useche et al., 2020), as well as to theory on knowledge recombination in international business (Berry, 2023; Kogut and Zander, 1993; Kafouros et al., 2022) and innovation research (Arts and Veugelers, 2015; Fleming and Sorenson, 2001).

First, the study enables us to understand why certain characteristics in team composition within MNEs are beneficial when dealing with different levels of technological complexity (Conti et al., 2014; Taylor and Greve, 2006). Prior studies often assume that technological complexity influences all inventor teams in a similar way. The study shows that its effects on the creation of impactful technologies are not uniform across teams but depend on their international diversity and technological expertise. Its contribution to research on how firms combine and integrate knowledge (Berry, 2023; Gupta and Govindarajan, 2000; Tzabbar et al., 2022) lies in theorizing how these two boundary conditions alter the dynamics of knowledge recombination and learning within teams, enabling them to benefit from low to moderate levels of complexity while mitigating the negative impact of extreme complexity.

The study not only underscores the importance of international diversity and expertise in creating impactful technologies, but also deepens our understanding of their distinct effects. By showing that these team characteristics do not have a similar linear pattern of effects on technology creation, it suggests that they should not be viewed as purely beneficial or detrimental. Specifically, although international diversity does not considerably steepen the inverted U-shaped relationship between complexity and technological impact, it delays the point at which extreme complexity hinders teams' ability to benefit, effectively shifting the tipping point to the right. In contrast, technological expertise plays a crucial role in shifting the inverted U-shaped relationship upwards, making the curve steeper. Interestingly, while expertise helps teams increase the benefits of low to moderate complexity and reduces the negative effects of extreme complexity, it is less effective in delaying the point at which the negative impact of extreme complexity comes into effect.

The above insights enrich prior explanations about technology creation in MNEs (Kafouros et al., 2022) by establishing that international diversity and technological expertise are complementary, supporting teams in MNEs in different yet synergistic ways. The study deepens understanding of how multi-country teams (Berry, 2014) function in complex technological environments, offering a more nuanced approach to managing international diversity and expertise in MNEs. It also clarifies how and when international diversity and technological expertise provide a competitive advantage for MNEs, highlighting that their roles in innovation should be differentiated, as they operate through distinct mechanisms. This contribution suggests that IB&M theory should not treat international diversity and technological expertise interchangeably. Instead, MNEs should strategically either integrate both elements or prioritise one based on the specific challenges posed by technological complexity and the level of complexity of a given project.

Furthermore, these findings highlight how MNEs can manage knowledge flows and collaboration in multi-country teams, extending prior studies that emphasize the value of knowledge gained through mobile and migrant inventors (Castellani et al., 2022; Cassiman et al., 2018; Useche et al., 2020) and cultural diversity (Kumar, 2014; Stahl et al., 2010). Adding to studies on the role of geographically dispersed knowledge (Cano-Kollmann et al., 2018; Rossi et al., 2023), our analysis reveals that because internationally diverse teams are better equipped to navigate complex knowledge, the benefits of technological complexity persist for longer for these teams, particularly when complexity reaches extreme levels. In contrast, the negative influence of complexity kicks in earlier for less internationally diverse teams. This contribution enriches IB&M research by suggesting that we should focus not only on the locational advantages MNEs exploit when operating in foreign markets but also on the advantages gained through employing internationally diverse staff and actively managing team composition.

The study also contributes to the literature on the role of inventors in MNEs (Castellani et al., 2022; Cassiman et al., 2018; Useche et al., 2020) and innovation studies on breakthroughs (Conti et al., 2014; Zhang and Yang, 2022) by demonstrating that technological expertise produces a distinct pattern of effects compared to international diversity. Inventor team expertise increases the benefits of low to moderate complexity and reduces the negative effects of extreme complexity. A key implication is that, for any given level of complexity, teams with greater expertise are better equipped to create impactful technologies. However, expertise plays a less important role in delaying the inflection point where extreme complexity becomes overwhelming for the team. From a theoretical point of view, this finding suggests that although a team's expertise is a crucial boundary condition on the effects of complexity, its impact manifests in two different ways depending on how complex a given project is.

Finally, the study contributes to theory on knowledge recombination in international business (Kogut and Zander, 1993; Kafouros et al., 2022) and innovation (Fleming and Sorenson, 2001; Keijl et al., 2016). Prior research acknowledges that technological complexity, depending on its level, can either aid or hinder the creation of impactful technologies (Fleming and Sorenson, 2004). By clarifying how international diversity and technological expertise influence learning and recombinant potential within inventor teams (Argote, 1993; Conti et al., 2014; Schilling and Green, 2011), the study introduces a more dynamic perspective, explaining how different team characteristics affect technology creation at various levels of complexity. This nuanced explanation contributes to theory on knowledge recombination by asserting that team characteristics and composition should align with the complexity level of a given technology project. Unlike prior conceptualizations that rest on the assumption of a static optimal level of complexity (beyond which it always becomes detrimental), this approach offers new insights into how MNEs can optimize the effects of complexity through team management. For instance, a project involving extreme complexity may benefit more from an internationally diverse team, while a moderately complex project might lead to better outcomes with a team possessing greater expertise.

6.2. Managerial implications

One of the key implications for MNE managers is that adjusting certain characteristics of inventor teams can enhance their ability to manage technological complexity, thereby improving their success in creating impactful technologies. Hence, our analysis offers guidance to MNE managers seeking to build effective teams for managing complexity and driving innovation, particularly in high-tech industries where complexity is more pronounced. Although both international diversity and technological expertise should be incorporated into team composition to unlock the full potential of innovation efforts, these team characteristics drive the creation of impactful technologies differently, as they help teams navigate complexity in distinct ways.

This insight is crucial for designing strategies that enable teams to function more effectively in complex technological environments. Although strategies fostering both international diversity and technological expertise in teams can extend the limits of complexity they can handle, an optimal strategy should tailor team composition to the specific complexity levels of each project. For example, teams with high technological expertise may excel in projects with moderate complexity, whereas teams with greater international diversity are better suited for highly complex projects. Managerial strategies that recognize that these two characteristics are complementary and synergistic are likely to yield the strongest innovation outcomes.

6.3. Limitations and future research

Our study has several limitations that present opportunities for future research. First, it focuses on patents and their forward citations to measure impactful technologies. A common shortcoming is that some technologies cannot be fully captured by patents (Schilling and Green, 2011). While patents are widely used in prior research (Arts and Veugelers, 2015; Mun and Chung, 2017; Singh and Fleming, 2010), future research could explore how technological complexity influences other forms of innovation and non-patentable technologies. This would provide a more comprehensive understanding of how MNEs can optimize the creation of different types of impactful technologies.

Second, we operationalized technological complexity by using the interdependence and number of components (Fleming and Sorenson, 2004; Maggitti et al., 2013; Singh and Fleming, 2010). However, we did not examine how other dimensions of complexity, such as functional complexity at the organization level, impact the creation of impactful technologies. For instance, diverse functional complexity at the organizational level—pertaining to the coordination and management of multiple functions across various units—may also play a role in technology creation. This type of complexity may have different effects compared to the knowledge recombination of technological components. For example, interactions and interdependencies between different organizational units could influence the development of impactful technologies in distinct ways.

CRediT authorship contribution statement

Mario Kafouros: Writing – original draft, Project administration, Conceptualization. **Eva Mavroudi:** Writing – review & editing, Writing – original draft, Conceptualization. **Murod Aliyev:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Junjie Hong:** Writing – review & editing, Supervision, Conceptualization.

Data availability

The authors do not have permission to share data.

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