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Missed chances and unfulfilled hopes: Why do firms make errors in evaluating technological opportunities?

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Abstract

Research Abstract: This study examines commission and omission errors in the evaluation of technological opportunities. Integrating structural and cognitive perspectives, we propose that inventors with more cohesive collaboration networks within the firm or geographically closer to the corporate headquarters exert greater influence on the dominant representations shaping opportunity evaluation within the firm. Thus, their inventions are more likely to be positively assessed, even if quality considerations suggest otherwise. Conversely, even when superior in quality, inventions from individuals with less cohesive collaboration networks within the firm or located far from the corporate headquarters are less likely to be positively evaluated, leading to omission errors. The study provides evidence based on 22 interviews and archival data from the mobile phone and personal digital assistant industry between 1990 and 2010.

Managerial Abstract: This study examines commission and omission errors in decision-making about technologies. Studying patent renewal decisions of 42 firms in the mobile phone and personal digital assistant industry between 1990 and 2010, we show that inventors with

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more cohesive collaboration networks within the firm or located close to the corporate headquarters have their inventions positively assessed even when of lower quality, leading to commission errors. On the other hand, inventors with less cohesive collaboration networks within the firm or located far away from the corporate headquarters have their inventions disregarded even when of higher quality, causing omission errors. These findings call for managerial vigilance in technology evaluation decisions, ensuring valuable ideas are not overlooked due to an inventor's network position or location.

KEYWORDS

commission and omission errors, decision-making biases, inventor networks, opportunity evaluation, patent renewal

1 | INTRODUCTION

Evaluating technological opportunities is difficult in fast-paced industries (Criscuolo et al., 2017; Eggers, 2012). Consequently, firms often make errors in selecting and retaining technological opportunities (Garud et al., 1997; Klingebiel, 2018). Such errors may erode firms' competitive advantage (Reitzig & Sorenson, 2013). For example, Nokia lost its leadership in the global mobile phone market between 2007 and 2013 due to its persistent commitment to the Symbian operating system, despite its inferiority to iOS and Android (Lamberg et al., 2021; Vuori & Huy, 2016, p. 18). Similarly, Motorola initially developed camera technology for mobile phones before its competitors but failed to recognize its value leading the chief product architect and lead engineers to pursue the project elsewhere.[1] Later, when Sanyo launched the first camera phone in the United States, Motorola suffered severe losses due to this missed feature (Klingebiel et al., 2022).

Why do firms make commission and omission errors in evaluating technological opportunities? Scholars have addressed this question taking two perspectives. The first line of research examined the impact of organizational structure on the incidence of each type of error. For instance, prior studies examined the effect of hierarchy on information aggregation within an organization, revealing that centralized decision-making increases omission errors while distributed decision-making increases commission errors (Csaszar, 2012; Csaszar & Eggers, 2013; Sah & Stiglitz, 1986). The second perspective offered a cognitive view on errors (Burgelman, 1983, 1994; Kaplan, 2008; Kaplan & Tripsas, 2008; Ocasio, 1997). This approach suggests that organizations may have competing representations of technologies, shaped by political and social factors, which can trigger inaccurate information interpretation and induce decision-making biases (Criscuolo et al., 2017; Gavetti, 2005; Kaplan, 2008).

Although the structural and cognitive perspectives emerged independently, some scholars integrated them to study decision-making (Gavetti, 2005; Lee & Csaszar, 2020). In this view,

[1]The episode was reported by Andrea Cuomo (Executive Vice President at STMicroelectronics) during his keynote speech at the SMS Special Conference in Rome in 2016.

structural factors, such as an actor's position within the hierarchy, affect the representations used to assess technological opportunities (Dearborn & Simon, 1958; Gavetti, 2005, p. 603), thereby inducing decision-making errors (Greenwood & Hinings, 1993; Siggelkow & Rivkin, 2005). Our article extends this approach to examine how inventors' network interactions with collaborators (Carnabuci & Operti, 2013; Nerkar & Paruchuri, 2005) and with key decision-makers located at the corporate headquarters (Bouquet & Birkinshaw, 2008; Monteiro, 2015) affect commission and omission errors in the evaluation of their inventions.

We propose that inventors who can mobilize more cohesive collaboration networks within the firm or who can frequently interact with key decision makers at the corporate headquarters are better positioned to influence the dominant representations guiding decision-making about technologies within an organization. Therefore, their inventions are more likely to be selected and retained, even when objective quality criteria suggest dismissing such inventions (commission error). In contrast, inventors with less cohesive collaboration networks within the firm or limited interactions with key decision makers at the corporate headquarters are less effective in influencing the dominant representations used to evaluate technologies within the organization. Therefore, the inventions they generate are less likely to be selected and retained even if they are of higher quality (omission error).

We tested our hypotheses in the mobile phone and personal digital assistant (PDA) industry between 1990 and 2010, combining 22 qualitative interviews and data on patents, inventors, products, and financial performance of a sample of 42 firms. We operationalized technological opportunities available to a firm in terms of its patented innovations. We study patent renewal decisions (Bessen, 2008; Serrano, 2010) to measure commission and omission errors. Specifically, we determined optimal renewal decisions based on objective patent quality indicators (Griliches, 1990; Lanjouw & Schankerman, 2004). We then coded renewal decisions that deviated from the optimal decisions as errors. We used inventors' co-patenting and location records to track collaboration networks within firms and interactions with the corporate headquarters (e.g., Monteiro, 2015; Nerkar & Paruchuri, 2005). Mindful of concerns regarding the use of patent data (Jaffe & Rassenfosse, 2017), we interviewed 7 R&D scientists and 15 IP professionals to validate our approach and gain insights into decision-making about technologies.

Our article contributes to research on commission and omission errors (Csaszar, 2012; Dye et al., 2014; Garud et al., 1997; Klingebiel, 2018; Klingebiel et al., 2022). While earlier studies have documented the interplay between "cognitions" differently situated in the hierarchy (Gavetti, 2005; Lee & Csaszar, 2020), they remained confined to the analysis of a few archetypes of organizational forms (Gavetti, 2005, p. 603; Greenwood & Hinings, 1993; Siggelkow & Rivkin, 2005). We broaden this line of research by focusing on networks, which can shape decision-making above and beyond formal hierarchies (Krackhardt & Hanson, 1993). We show that inventors' interactions with their peers and the key decision makers influence which representations prevail and are used to evaluate technological opportunities, thus determining commission and omission errors.

The study also contributes to a long-standing debate in network scholarship regarding the relative benefits of cohesive versus boundary-spanning network positions. Prior work has highlighted that ties bridging disconnected actors (e.g., Reagans & McEvily, 2003; Tortoriello & Krackhardt, 2010) and geographic boundaries (e.g., Dahlander & Frederiksen, 2012; Monteiro, 2015) bring advantages and shortcomings. Our findings suggest that such inconsistencies may arise because boundary-spanning may promote technology generation while exerting opposing effects on technology evaluation within the organization.

2 | THEORY AND HYPOTHESES

2.1 | Commission and omission errors in the evaluation of technological opportunities

Organizations generate technological opportunities through distant and local search (Levitt & March, 1988). Subsequently, they select and retain some technologies while abandoning others (Burgelman, 1983, 1994; Criscuolo et al., 2017; Knudsen & Levinthal, 2007). Decision makers should rationally pursue high-quality opportunities and discard low-quality ones (McGrath, 1997; Zardkoohi, 2004). However, boundedly rational actors may deviate from decisions based on objective quality dimensions (Adner & Levinthal, 2004; Knudsen & Levinthal, 2007; Reitzig & Sorenson, 2013). Following prior research (Csaszar, 2012; Garud et al., 1997), we classify such deviations as errors. A commission error occurs when an organization pursues a low-quality technological opportunity that should have objectively been rejected, while an omission error arises when an organization rejects a high-quality technological opportunity that should have objectively been pursued.

To some extent, errors are unavoidable. Organizations operating under uncertainty must balance the costs of failing big or foregoing hits (Dye et al., 2014; Garud et al., 1997; Klingebiel et al., 2022). Structure determines the prevalence of distinct types of errors by shaping information aggregation in the organization. While hierarchical structures reduce the risk of accepting inferior alternatives, they increase the incidence of omission errors. Similarly, polyarchies minimize the risk of rejecting superior alternatives but increase commission errors (Csaszar, 2012; Csaszar & Eggers, 2013; Sah & Stiglitz, 1986).

Research adopting a cognitive perspective also provides insights into organizational decision-making. Actors' representations of technologies (also known as frames) help them understand what a technology is, how it works, what problems it solves, and how it performs vis-à-vis its alternatives (Kaplan, 2008). Consequently, these representations influence technology evaluation decisions (Kaplan & Tripsas, 2008). Decision makers often fail to foresee ways to exploit a technological opportunity incongruent with their cognitive representations (Ocasio, 1997). Hence, they are more likely to abandon it. Conversely, if an opportunity aligns with their existing representations, they are more likely to perceive it as relevant and pursue it.

Representations of technologies at the organizational level are heterogeneous, with multiple and often competing representations coexisting within the same organization (Kaplan, 2008). In such cases, technology evaluation can be viewed as contests in which structure, processes, and interactions determine which representations prevail (Burgelman, 1983, 1994; Kaplan, 2008). Consistent with the view of organizations as patterns of communications and interactions between members (Simon, 1947, pp. 18–19), we contend that the dominant representations of technological opportunities in organizations emerge through inventors' interactions with their peers (Nerkar & Paruchuri, 2005) and key decision makers (Burgelman, 1983; Monteiro, 2015). Through these interactions, inventors can influence firm's selection decisions at the time of technology emergence, and retention decisions in the long run, thanks to the path-dependent nature of firm's R&D and commitment persistence to past choices (Guler, 2007; Klingebiel & Esser, 2020). However, inventors vary in their influence based on their position within the organization. Such heterogeneity can create distinct types of errors in technology evaluation decisions.

2.2 | Interactions with peers: Intraorganizational collaboration networks, commission and omission errors

In an organization, scientists innovate by collaborating on multiple projects, forming a network structure (Nerkar & Paruchuri, 2005; Tortoriello & Krackhardt, 2010). This study focuses on the co-patenting network of inventors (e.g., Carnabuci & Operti, 2013; Nerkar & Paruchuri, 2005), where each node represents an inventor and the ties between nodes indicate collaboration in generating a patent. We characterize an inventor's position using the well-established distinction between cohesive[2] and boundary-spanning positions within the intraorganizational network (Burt, 1992; Coleman, 1990). Cohesion offers numerous advantages. Inventors whose contacts are directly and indirectly connected can benefit from increased knowledge depth, superior mobilization, and influence. Common connections encourage individuals to "invest time, energy, and efforts in sharing knowledge with others" (Reagans & McEvily, 2003, p. 240), facilitating information triangulation within their local network (Tortoriello & Krackhardt, 2010). On the other hand, boundary-spanning inventors connect alters that are not directly connected (Burt, 1992). These connections provide access to a more diverse range of information, potentially enhancing the invention process (Fleming et al., 2007).

Based on these mechanisms, we expect network cohesion to be associated with a higher rate of commission errors and a lower rate of omission errors. Inventors with more cohesive collaboration networks within the organization can exert more influence on the dominant representations, defending their ideas from skeptics and shaping information interpretation to their advantage (Dahlander & Frederiksen, 2012; Hargadon, 2006). As a result, even if cohesion may result in lower quality ideas (Burt, 1992; Fleming et al., 2007), these inventions are more likely to be favorably assessed during technology evaluation decisions, such as patenting, commercialization, and patent renewal.

In contrast, boundary-spanners connect several disconnected individuals within the organization but lack shared third-party connections with their collaborators. As a result, they have access to a rich and diverse range of information (Fleming et al., 2007). However, they are less effective at mobilizing their peers (Tortoriello & Krackhardt, 2010) to influence decision-making to their advantage when competing representations emerge. The absence of triangulation in closed triads may lead to reduced comprehension of the inventions generated by boundary-spanners (Burt, 1992; Fleming et al., 2007), resulting in less favorable decisions concerning the inventions they generate.

These expectations resonate with the data from the fieldwork. In all the settings where we conducted interviews, R&D personnel could directly or indirectly influence technology evaluation decisions by shaping the views of their peers and key decision makers in their organizations. Groups of connected inventors can proactively disseminate their representations within the firm. IP professional #1 explained, "Different people [in the company] see the value of technologies in different ways, depending on divisional interests and strategic priorities [...]. Groups in the company have their preferred designated use and share it with others so that they come to see things alike." These efforts can introduce short-term and long-term biases in decision-making about technologies, primarily when a large, cohesive group supports the focal inventors. In the words of IP professional #8, "Inventors can be biased towards certain inventions or certain parties or groups in the company." The role of network connections is well described by

[2]A high level of cohesion implies that an inventor has a tightly knit ego-network of collaborators within the firm, where direct and indirect contacts are also linked to one another.

Scientist #1: "If a project crosses the decision-making threshold of yes, and many scientists say this product needs to go, then decision-making follows a bottom-up approach." Similarly, Scientist #3 suggested that it is tough to shut down a project when inventors have cohesive peer support: "They publish papers, they build groups within the company, they go to conferences, they get talks, so their social identities are wrapped up in these projects. It's a delicate thing."

Inventors can leverage early support through the invention lifecycle, from the patent application to the follow-up maintenance decisions, through various mechanisms, such as shaping roadmaps and evaluation board appointments, designing path-dependent decision processes, and following up with peers and scientists. IP professional #6, for instance, gave us an example of how an inventor with a larger and more cohesive collaboration network within the firm can utilize social influence so that objective data on the future value of a technology is disregarded in patent maintenance decisions: "Analytics helped [decision-making] a lot. But, this kind of decision had pushback because you decide on projects and people, and in real life, people come back to you if they do not like the decision. If they do not like the decision, a scientist with a large following may ask to kill the Patent Intelligence unit that produced the report or to outsource expert evaluation until they get an advisor that says that their project is good." Along these lines, Scientist #7, a boundary-spanner at Nokia according to our data, shared that he was less able to shape firm's decisions about technologies than "regular scientists" working in cohesive units of specialists, despite his high productivity in the UX area. Scientist #6 suggested that inventors backed by more cohesive peer networks might induce long-term bias in patent renewal decisions. This occurs as they are more likely to be appointed to the teams responsible for crafting the company's technology roadmaps. Consequently, even if the inventors who developed a technology depart the organization, these roadmaps—to which they contributed—persist in influencing the perception of which technologies are deemed vital over the next 5–10 years. IP Professional #11 likewise observed that early evaluation decisions leaning towards inventors with more cohesive networks could bear long-term implications, as early-stage resource allocations are instrumental in determining future selection and retention. "When approved, some technology projects in client firms come with a budget allocation. That budget may cover publishing, IP, and legal expenses, so the project will not go through the corporate pruning process later on but use its own budget."

Based on the discussions above, we formulate the following hypotheses:

Hypothesis 1a. The more cohesive the intraorganizational network of an inventor, the higher the likelihood of commission error in the evaluation of the technological opportunities that the inventor generates.

Hypothesis 1b. The more cohesive the intraorganizational network of an inventor, the lower the likelihood of omission error in the evaluation of the technological opportunities that the inventor generates.

2.3 | Interactions with key decision makers: Colocation, commission, and omission errors

The internationalization of firms' R&D activities has increased the geographic distance between headquarters and R&D laboratories while reducing the interactions between key decision makers located at the company headquarters and inventors working at remote locations

(Bouquet & Birkinshaw, 2008; Monteiro, 2015). Conducting R&D in distant regions with unique knowledge resources is beneficial because inventors at distant locations are embedded in their local innovation ecosystems and can access diverse information (Funk, 2014). Inventors in peripheral subsidiaries are better equipped to pursue exploratory research projects, identify diverse, novel knowledge, and overcome the "local search" constraints often imposed by the dominant representations at the headquarters (Monteiro, 2015).

Distant locations offer unique advantages, but they also pose challenges, primarily due to the reduced influence of inventors on the dominant representations used to evaluate technologies. Geographical proximity engenders face-to-face interactions, which are crucial for effective information transfer and interpretation (Catalini, 2017; Choudhury, 2017). Such interactions facilitate argumentation, contestation, sense-making, and sense-giving processes, reducing information asymmetry and fostering alignment of divergent representations (Daft & Weick, 1984). Balsmeier et al. (2023) provides substantial insights into the effects of these interactions. They observed a discernible drop in regional patent citations when a co-inventor of a patent dies between application and grant. This finding reveals that the inventor's physical presence in a particular region amplifies the influence and use of their technology. However, the impact of such championing efforts does not extend beyond the deceased inventor's immediate geographic region, suggesting that these efforts are geographically bound. Similarly, in a corporate context, distant inventors often secure more R&D funding following a visit to the headquarters (Choudhury, 2017), and decision makers have been observed to favor inventors sharing their geographic location or unit affiliation (Criscuolo et al., 2017; Reitzig & Sorenson, 2013). To summarize, inventors collocated with key decision makers have more opportunities to generate inventions aligned with the headquarters views or to influence the dominant representations to their advantage. Conversely, geographically distant inventors face more significant challenges interacting with the decision makers (Burgelman, 1983), making it harder to secure their support, even for high-quality inventions.

Our interviews substantiate this reasoning. In all the firms we contacted, technology decisions with medium to long-term consequences required input from decision makers at the headquarters. In the words of IP professional #7: "If you have to choose, you have to pick the ones that are best for the interests of the whole company [...]. If you move up in the chain, close to the headquarters, there is usually more judgment to do so." However, distance can penalize remote R&D locations. Scientist #1, who serves as the head of an Asian R&D lab for a European firm, suggested that "the biggest challenge when you are managing a remote subsidiary is to convince the headquarters." He further explained that the main difficulty stemmed from differences in interpretations: "It's a matter of different perspectives between people sitting in headquarters and people sitting here, plus the kind of information which may be missing or seen differently, due to limited interactions. They have access to information, right? But not all see the same idea. Even the same idea may be interpreted differently by India or, say, Europe or by the United States. There are chances of seeing it differently." IP professional #14 reported a similar cognitive discrepancy: "[referring to the Asian R&D subsidiary of a U.S. firm] There was a newer, younger engineering group, and they didn't always understand the technology as the senior people here were looking at it." Scientist #4 suggested that colocation can reconcile diverging views: "If you are championing an idea here [at the headquarters], you would probably speak to several different people to promote the idea." Distance from headquarters can also impact the evaluation of technologies in the long run. IP professional #14 indicated that engineers from the headquarters lab were more likely to serve on the company patent review board, potentially disadvantaging distant inventors in patent portfolio decisions, including pruning.

Scientist #7 suggested that inventor close to the headquarters would be more aware of what kinds of technologies are likely to be seen as "easy wins" and be retained. IP professional #15 proposed that when considering renewal of patents generated at the headquarters, decision makers may be more aware of the project sunk cost, and less open to let such investment lapse even after several years.

Based on these considerations, we hypothesize:

Hypothesis 2a. The higher the geographical proximity of an inventor to the key decision makers located at the corporate headquarters, the higher the likelihood of commission error in the evaluation of the technological opportunities that the inventor generates.

Hypothesis 2b. The higher the geographical proximity of an inventor to the key decision makers located at the corporate headquarters, the lower the likelihood of omission error in the evaluation of the technological opportunities that the inventor generates.

3 | DATA AND METHODS

3.1 | Setting and sample

We tested our hypotheses in the mobile phone and PDA industry, a technology-intensive sector characterized by high uncertainty (Lamberg et al., 2021; Vuori & Huy, 2016). Several incumbent firms in the industry led the development of new technologies and product features but made substantial errors in selecting and retaining them, subsequently losing market dominance (Klingebiel et al., 2022). For instance, Microsoft developed an electronic reader in 1998 and acquired Danger, a company with a working smartphone prototype, in 2008. Likewise, Nokia developed a touchscreen smartphone prototype in 1996. However, both companies were unable to compete with Apple and Google a decade later (Vuori & Huy, 2016). Understanding why firms dismiss certain technologies and commit to low-quality ones is critical in this context.

Our work combines qualitative and quantitative data. We conducted 22 interviews with IP professionals and R&D scientists,[3] inquiring about the evaluation of technological opportunities in their organization, the actors and units involved, and how firm's technology evaluation decisions related to patent portfolio management. Interviews were conducted in person or by phone/video conference by at least one of the authors, recorded and transcribed. We also attended a 1-day seminar and a webinar on the topic, organized by the MIP European Patent Reform Forum and Questel (an IP consulting firm). We coded the transcripts using Nvivo 12. The qualitative data helped us construct the measures and interpret the results. Tables A1 and A2 (Supporting information) summarize the characteristics of the informants and present the interview protocols.

We used patent data to conduct quantitative analyses of errors, in line with interviews suggesting that patent portfolios reflect short- and long-term decisions about technologies.

[3]We contacted IP professionals working in electronics firms or in IP law and consulting firms whose clients operate in the mobile phones and PDA industry. Where possible, we asked them to share with us the contact details of an inventor or an R&D scientist to enable us to validate their views. We also sent out requests to prominent inventors identified by industry sources and in our data.

Mobile phone firms proactively patent inventions, manage IP portfolios in line with their technology strategy, and protect IP assets from infringement (Reidenberg et al., 2015). Patent portfolio maintenance is a critical decision in this context. To construct the sample, we retrieved a list of firms that launched at least five products (mobile phones or PDAs) from PDAdb.net, the world's largest online repository of data regarding mobile devices, and we retrieved all patents in each mobile phone US Patent and Trademark Office (USPTO) technology class granted between 1990 and 2010, using Google patents and the disambiguated Harvard patent database (Li et al., 2014).[4] For each patent, we retrieved data regarding the size of its patent family—the collection of patent documents covering the same technology in different countries—using the European Patent Office (EPO) INPADOC database. The sample includes firms that launched at least 5 mobile devices or appeared in the top 10 patent assignees in the mobile phone and PDA industry during at least 1 year between 1990 and 2010. This step returned a list of 59 firms. We collected financial data from the Compustat database and excluded firms with missing financial data, no errors of either type during the observed timeframe, and those making fewer than a hundred renewal decisions. The final sample included 42 firms meeting these criteria.[5]

3.2 | Dependent variables

Research on commission and omission errors face serious hurdles. As Csaszar (2012, p. 618) underlines, operationalizing errors requires the following information: (1) the choice-set of opportunities that a firm has at any given time, (2) information regarding which opportunities the firm selected and retained, and which ones it dismissed, and (3) a measure of the underlying quality of each opportunity. To address the first challenge, we operationalized technological opportunities available to a firm in terms of its patented inventions. Collecting information regarding (2) and (3) proved more challenging. Firms rarely document the projects they reject, making it difficult to observe decisions on technologies for a large sample of firms (Csaszar, 2012).[6] We used publicly available data on patent renewal (Bessen, 2008; Serrano, 2010) as proxies of firms' evaluation of technological opportunities. The USPTO requires an assignee to renew its patent rights over the invention in the 4th, 8th, and 12th year after the patent was granted. At each stage, the assignee must pay a gradually increasing maintenance fee. With each renewal request, the firm that owns the patent rights (the assignee) must decide whether to pay the maintenance fee and retain the patent rights over the protected innovation. Firms devise dedicated processes to identify the most valuable technological assets while controlling costs by allowing some patents to lapse (Hanel, 2006).

Our interviews suggest that renewal decisions reflect long-term selection and retention of technological opportunities within firms. According to IP professional #14, firms typically evaluate their portfolios in alignment with their strategic and business goals. The decision-making

[4]According to Reidenberg et al. (2015), the USPTO technology classes that are relevant to the mobile phone and PDA industry are 320, 341, 349, 361, 370, 375, 379, 398, 455, 704, 706, 707, 715, and 719.

[5]Excluding these firms allows us to maintain the same number of observations across our models of commission and omission errors, adhering to a reviewer's recommendations. Including these firms would result in varying sample compositions depending on the specification. For instance, firms with no error of commission or of omission would be excluded when estimating a logit with firm fixed effects. Moreover, firms with a small number of decisions may be dropped due to multicollinearity with other sets of fixed effects. Results using all possible observations for each model align with those displayed in the article (Table B4, Supporting information).

[6]Most studies on the evaluation of technological opportunities within organizations build on primary data from a single firm for a short-time window (Criscuolo et al., 2017; Monteiro, 2015; Reitzig & Sorenson, 2013).

process entails periodic internal reviews that involve IP professionals and senior managers with technical and commercial backgrounds supervised by corporate managers. The process typically starts with a quantitative assessment that combines technology, market, and strategic considerations, as described by IP professional #5: "We look at the patents coming up for renewal over the next six months and we put together a number of different metrics [...]. Then we tell you whether we recommend that you renew, get rid of, or somewhere in between. Sometimes we give you just a numerical rating." Following the initial screening, the review board makes decisions on controversial cases, striving to balance the interests of multiple actors. In the words of IP professional #4, "We make sure that decisions are not taken in isolation, but after having discussed and obtained the views of various stakeholders."

Inventors champion their innovations during the initial stages of technology development. Nevertheless, the interviews reveal a noteworthy persistence of these championing efforts through the technology lifecycle, which can be discerned in patent renewal decisions even after substantial time has elapsed. Table A3 (Supporting information) delineates the short-term (direct) and long-term (indirect) mechanisms through which early-stage interactions with peers and with key decision makers influence renewal decisions.

We define errors as renewal decisions that depart from an objective assessment of the quality of the underlying patent. Quality assessments are often firm-specific, and it is challenging to ascertain the quality of inventions that the firm did or did not pursue. In the words of IP professional #1, "Very few patents make up the value of the whole portfolio. But it is not clear which ones matter early on. You will find out when you see it, often when it is too late." Similarly, IP professional #8 reasoned: "The nature of the patent system is such that filing a patent application always carries, within a certain degree, speculation." IP professional #5 suggested that ascertaining patent quality entails three related questions: "The first is how important is the underlying invention. Is it terrific or an incremental little toy? Second, has the value of the invention been captured in a legal document? That is, how good is the patent document? How well-written is it? And third, what do you do with it? Because if it is a great invention and a great legal document, and you don't have a strategy, or a market, still you have no value."

We employed a three-step method to identify renewal decisions that diverge from the objective quality considerations. Based on past studies and on the approach developed by a consulting company in which we conducted interviews, we first collected 11 indicators used to objectively assess patent quality. These indicators capture the technological quality of the invention and of the technology trajectory to which the patent belongs, the strength of the patent document and an estimate of the market scope of the associated patent family and technology trajectory, in line with the remarks of IP professional #5. Tables 1,3 presents these dimensions, their data sources, the rationale for inclusion, and related studies.

To determine whether a patent should be renewed based on objective criteria, we built a logit model estimating the probability of a patent's renewal at a given point in time based on its quality dimensions, and technology, geographical and maintenance year fixed effects, using all patents filed in the technology classes relevant to mobile phones:

$$\ln[p/(1-p)] = b_0 + b_1 Q + \text{Geographic dummies} + \text{Technology Dummies} + \text{Year dummies}$$

Two key decisions arise when building a classification model: the choice of the dimensions included in the model and the definition of a threshold predicted probability τ, which best discriminates patents that should be renewed from patents that should not be. We use the ROC (receiver operating characteristic) curve, an evaluation metric for binary classification problems

TABLE 1 Patent objective quality dimensions.

Indicator	Measure	Rationale	Validating literature	Data source
Technological value	Count of the forward citations received by a patent (normalized by year)	Forward citations indicate that the underlying technology is adapted and builds upon the invention	(Griliches, 1990)	USPTO
Firm specific technological value	Share of forward citations received by a patent originated by the focal firm	Self-forward citations indicate that the firm has reabsorbed its spilled knowledge in later inventions and has higher appropriability of value from invention/technology	(Hall et al., 2005)	USPTO
Inclusion in a patent thicket	Share of a patent's backward citations originated by the focal firm	Self-backward citations suggest that the technology builds on other inventions owned by the firm and may be part of a thicket	(Reitzig, 2004)	USPTO
Originality	Herfindahl index of diversification of a patent's backward citations across technology classes	High originality indicates newer and breakthrough technologies; low originality characterizes more incremental innovations	(Hall et al., 2001)	USPTO
Generality	Herfindahl index of diversification of a patent's forward citations across technology classes	High generality indicates a wider scope of application across various technologies; low generality indicates application that is more specific	(Hall et al., 2001)	USPTO
Technology scope	Number of patent claims in a patent document	More claims indicate a wider scope of protection	(Harhoff et al., 2003)	USPTO
Market scope	Size of the INPADOC patent family: number of different patent jurisdictions where the patent has been filed	Large family size indicates that the invention is protected across markets and the firm has invested greatly to protect it	(Harhoff et al., 2003)	USPTO, EPO
Inclusion in a technology standard	Patent is part of a standard or is meant to become part of a standard	Being part of a standard indicates greater scope for licensing and market scope, esp. in downstream industries	(Lerner & Tirole, 2015)	Private source (Questel)

TABLE 1 (Continued)

Indicator	Measure	Rationale	Validating literature	Data source
Opposition	Whether the patent had been opposed or re-examined, and the validity of the patent stood in court	If validity has been re-affirmed, the patent value increases because it guarantees strong protection	(Harhoff et al., 2003)	USPTO
Litigation	Whether the patent has been litigated	If litigation has occurred, the patent value is challenged	(Lanjouw & Schankerman, 2001)	Private source (Questel)
Presence of a shark	Dummy equal to 1 when a minimum of 3 and at least 30% of the forward citations are from a single entity (not being the assignee itself)	The presence of a shark indicates the presence of an active licensing market/ market for technology	(Reitzig et al., 2010)	USPTO

Abbreviation: EPO, European Patent Office; USPTO, US Patent and Trademark Office.

(Capponi et al., 2022; Hajian-Tilaki, 2013), to inform the first decision. It plots, for any given model, the true positive rate (TPR) against the false positive rate (FPR) at various threshold values and essentially separates the "signal" from the "noise."[7] The area under the curve (AUC) summarizes the ROC curve, measuring the ability of a classifier to distinguish between classes.[8] To determine the variables that provide the best prediction, we opted for the most parsimonious model with the highest AUC. Results are presented in Table 2. Starting with the most basic model comprising only the fixed effects (Model 1) and the full model using all quality indicators (Model 2), we added one by one each quality dimension and retained the most parsimonious

TABLE 2 Probability of patent renewal as a function of quality dimensions.

	DV: Probability of patent renewal		
	Model 1	**Model 2**	**Model 3**
Technological value		0.162 (.000)	0.165 (.000)
Firm specific technological value		0.002 (.192)	
Inclusion in patent thicket		−0.014 (.000)	−0.014 (.000)
Originality		−0.230 (.000)	−0.231 (.000)
Generality		−0.297 (.000)	−0.296 (.000)
Technology scope		0.018 (.000)	0.018 (.000)
Family size		0.073 (.000)	0.073 (.000)
Inclusion in a technology standard		1.551 (.000)	1.552 (.000)
Opposition		0.394 (.000)	0.394 (.000)
Litigation		1.117 (.000)	1.118 (.000)
Presence of a shark		−0.001 (.960)	
Technology class fixed effects	Y	Y	Y
Maintenance Year fixed effects	Y	Y	Y
Geographic fixed effects	Y	Y	Y
Constant	2.861 (.000)	2.579 (.000)	2.579 (.000)
Log likelihood	−144856.4	−140467.2	−140468.6
Wald chi^2	8790.9	11375.9	11368.4
Pseudo R^2	0.0511	0.0799	0.0799
Observations	302,688	302,688	302,688

Note: *p*-Values in parentheses.

[7]From the confusion matrix, we can define four parameters: (i) Sensitivity or True Positive Rate TPR = True Positive/(True Positive + False Negative); (ii) False Negative Rate (FNR) = False Negative/(True Positive + False Negative); (iii) Sensitivity or True Negative Rate = True negative/(True Negative + False Positive); (iv) False Positive Rate = False Positive/(True Negative + False Positive).

[8]When AUC = 1, then the model is able to perfectly distinguish between Positive and the Negative points. When 0.5 < AUC <1, there is a high chance that the model will be able to distinguish the positive class values from the negative class values. When AUC = 0.5, then the model is not able to distinguish between Positive and Negative class points (it is predicting random class or constant class for all the data points). In other words, the higher the AUC value, the better the model's ability to distinguish between positive and negative classes.

model that provides an AUC comparable to the full model. The selected specification is presented in Model 3.

To define the predicted probability threshold that should discriminate between patents that should be renewed from patents that should not, we examined the ROC curve of the selected model and the sample distribution of the predicted renewal probability. Specifically, we selected a threshold corresponding to the median predicted renewal probability in our sample based on Model 3.[9] This threshold then defines which patents should be renewed based on objective quality and contextual factors.

We operationalized errors as patent renewal decisions that deviate from decisions based on quality indicators, technology, geographical, and year-fixed effects. A renewal decision is classified as a commission error if the patent was renewed at a given point in time, but it should not have been renewed based on Model 3 and the selected threshold. Conversely, a renewal decision is classified as an omission error if the patent was not renewed at a given point in time, but it should have been renewed based on Model 3 and the selected threshold.

3.3 | Independent variables

We used inventors' collaboration networks within the firm and locations at the time of the patent grant to construct the independent variables. This choice aligns with the view that dominant representations of technological opportunities are formed at the organizational level when new technologies emerge (Eggers, 2012; Kaplan, 2008). The interactions that an inventor has at this point shape future technology selection and retention decisions in a path-dependent fashion due to commitment persistence through the project's lifecycle (Guler, 2007; Klingebiel & Esser, 2020). This expectation aligns with the view that firms continue a line of R&D and renew patents even after the inventors have left the firm at the time of maintenance decisions (Goossen & Carnabuci, 2020; Wang & Zheng, 2022). Table A3 (Supporting information) presents further qualitative evidence in this direction.

We measured an inventor's ability to influence decision-making about technologies by looking at the constraint of the inventors in the intraorganizational co-patenting network. In line with past research (Carnabuci & Operti, 2013; Nerkar & Paruchuri, 2005), two inventors are connected by a collaboration tie if they coauthored at least one patent within the last 3 years. We operationalize *Cohesion* as the average network constraint of the inventors associated with a given patent (Burt, 1992; Reagans & McEvily, 2003). The network constraint score of each inventor was computed as follows:

$$C_i = \Sigma\, c_{ij}\; i \neq j,$$

where $c_{ij} = (p_{ij} + \Sigma p_{iq}p_{qj})^2$ is a measure of contact-specific constraint that varies with the extent to which inventor i's collaboration investment is directly (p_{ij}) or indirectly ($\Sigma p_{iq}p_{qj}$) spent on inventor j. The ego network constraint C_i of inventor i is given by the sum of c_{ij} over all the contacts in the inventor's network and measures the extent to which an inventor is embedded in a

[9]We tried three thresholds: the median predicted probability of renewal ($\tau = 0.807$), the mean predicted probability of renewal ($\tau = 0.797$), and the exact value derived from the ROC curve ($\tau = 0.784$). They return consistent results across specifications (see Table B5, Supporting information).

single group of interconnected colleagues, or brokers between weakly connected groups. We used the igraph R-package software to compute all network measures.

Our fieldwork and prior research on scouting (Monteiro, 2015) suggested that the key technology evaluation decisions reflect strategic directives formulated at the corporate headquarters. Thus, we measured the *Geographic distance* between inventors and key decision makers for each patent by examining the average geodesic distance of each inventor's location from the corporate headquarters in thousands of kilometers using the command "geodist" in STATA (Picard, 2010).[10] We divided these distances by the mean distance between headquarters and inventors for all patents of the assignee firm that were granted in the same year, allowing for comparison across firms with varying degrees of geographic diversification. We retrieved inventors' locations from the Harvard Patent Database. We ascertained the headquarters' locations using Compustat and Factiva.

3.4 | Control variables

We compiled a comprehensive list of factors affecting errors in technology evaluation decisions, drawing on previous research and information provided by the interviewees. This process aimed to address concerns of endogeneity due to omitted variables.

First, we considered alternative sources of social influence within the firm. To separate the effect of cohesion from simple connectivity (Burt, 1992), we control for the normalized average network centrality of inventors listed on a patent (*Average degree*). Star scientists are more likely to receive corporate attention (Tzabbar, 2009) and can influence the evaluation of technologies. Accordingly, we controlled for the *Proportion of stars* in the inventor team, defining stars as those in the top 5% of the productivity distribution in the sample.

Second, we accounted for the novelty of the underlying technology (Criscuolo et al., 2017) by including a proxy of *Technological maturity*, captured by the average age of a patent's backward citations (Ahuja & Lampert, 2001).[11] Technologies with broader applicability tend to receive greater scrutiny (Fleming et al., 2007). We accounted for patent scope using the *Number of subclasses* assigned to each patent. We also controlled for the strength of the patent document using the count of *Backward citations* listed in a patent.

We also included some firm-level controls that may directly affect errors in technology evaluation decisions. We accounted for the impact of organizational structure on decision-making (Csaszar, 2012) using three variables. The first variable, *R&D network centralization*, captures the centralization of a firm's intraorganizational network using Freeman's centralization index. The second control measures *Formal R&D centralization*. Using data from the Directory of

[10]We performed further analyses using the minimum distance between inventors and headquarters for each patent, postulating that even one nearby inventor could influence key decision makers (Table B3, Supporting information). Results align with the findings presented below. We also tried to study location effects by identifying inventors who relocated within the same firm, but who kept working on similar technologies. Yet, relocations were rare events (<6% of the inventors change location at least once) and typically associated with a change in employer (83%) and/or in technology domain (46%). Matching the same employer with the same technology, while considering a change in location as a treatment, yielded an insufficient sample size for analysis.

[11]The logic behind the measure is well-articulated by Ahuja and Lampert (2001, p. 533). Every patent must legally disclose all prior art, which refers to the previous patents that laid the groundwork for the current patent. If a firm primarily focuses on older technologies, the average age of the patents it cites is likely to be high. Conversely, if a firm cites very recent patents, its inventions are likely to be related to emerging and uncertain technologies.

American Research and Technology and publicly available sources for non-US companies, we follow Argyres and Silverman (2004) and track the location of R&D labs/facilities of each firm. Firms are categorized as centralized if they solely have corporate-level R&D labs. Decentralized and hybrid structures denote business/division level R&D presence or combined corporate and divisional R&D activities.[12] We also control for *Firm R&D internationalization*, using the count of countries where the firm has active inventors (Di Minin & Bianchi, 2011).

R&D-intensive firms are more likely to renew their patents than others (Bessen, 2008; Harhoff et al., 2003) and establish appropriate processes to improve IP portfolio management decisions. Accordingly, our models included firms' *R&D intensity* (i.e., expenditure normalized by total assets). To account for the cognitive burden affecting decision-making quality, we control for a firm's *Patent portfolio size*, a good proxy of the firm's renewal decisions at a given time. We controlled for *Firm age*, as old firms often favor incremental innovation and omit emerging technologies (Tripsas & Gavetti, 2000). We included the *Firm's return on assets* (ROA) to account for the effect of organizational performance on risk-taking in technology evaluation decisions.

3.5 | Data structure and estimation method

Our unit of analysis is the patent renewal decision. For each patent, one may observe up to three decisions during the 4th, 8th, and 12th year after the patent is granted. We used two separate logit models with maintenance Year, primary Technology class, and Firm fixed effects to estimate the probability of commission or omission errors as a function of the independent and control variables. Maintenance year and primary Technology class fixed effects help address time trends and time-invariant technology factors affecting errors. Firm fixed-effects reduce endogeneity concerns due to firm-level omitted factors that can affect both the relational patterns of key actors and the process of opportunity evaluation, such as firm-specific R&D organization policies, including practices regarding the assignment of projects to subsidiaries, and stable differences in patent portfolio management practices. We clustered standard errors at the patent level to account for the relationship between decisions on the same technology. We used the software STATA 17 to estimate the models.

4 | RESULTS

Table 3 displays descriptive statistics and correlations between variables. The mean variance inflation factor for the full model is 1.47, below the recommended multicollinearity threshold of 5. Table 4 presents the main results. Models 1–3 estimate the likelihood of commission errors, with Model 1 as the baseline. Model 2 introduces the variable *Cohesion*, which positively affects the probability of commission errors ($\beta = .205$, $p = .000$), corroborating Hypothesis 1a. In Model 3, we add the variable *Geographical distance*, which negatively affects the probability of commission errors ($\beta = -.045$, $p = .000$), in line with Hypothesis 2a. Based on Model 3, a one-unit increase in *Cohesion* raises the odds of commission errors by a factor of 1.24. A one-unit increase in *Geographical distance* decreases the likelihood of commission errors by a factor of 0.96.

[12]We combine the hybrid and decentralized categories into one category because the boundary between the two is found to be ambiguous for the firms in our sample.

TABLE 3 Descriptive statistics and correlations.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Commission error	1															
Omission error	−0.18	1														
Cohesion	0.04	0.01	1													
Geographical distance	−0.02	0.03	0.02	1												
Average degree (norm)	−0.04	−0.01	−0.16	0	1											
Proportion of stars	−0.07	−0.01	−0.46	−0.01	0.12	1										
Technological maturity	0.02	0.01	0.05	−0.01	0.01	−0.02	1									
Backward citations (ln)	−0.02	0.00	−0.12	0.04	0.05	0.10	0.21	1								
Number of subclasses (ln)	0.04	−0.01	−0.01	0.01	0.00	0.01	0.04	0.11	1							
Formal R&D centralization	−0.06	0.07	−0.06	0.00	−0.05	0.03	−0.03	0.10	−0.01	1						
R&D network centralization	0.05	0.02	−0.02	0.00	−0.67	−0.02	−0.01	−0.02	0.00	0.08	1					
Firm R&D internationalization	−0.02	0.04	−0.18	0.00	−0.15	0.04	−0.04	0.12	−0.01	0.36	0.26	1				
R&D intensity	−0.14	−0.01	−0.07	0.00	0.02	0.04	−0.01	0.05	−0.06	−0.26	−0.01	0.31	1			
Patent portfolio size	0.05	0.02	−0.21	0.00	−0.16	0.05	−0.10	0.09	0.00	0.38	0.27	0.70	0.00	1		
Firm age	0.05	0.03	0.08	0.00	−0.15	−0.07	0.04	−0.07	−0.03	−0.12	0.21	0.17	−0.09	0.03	1	
Firm ROA	−0.04	0.01	−0.05	0.00	0.02	0.04	0.00	0.06	0.00	0.15	−0.04	0.13	−0.13	0.17	−0.07	1
Mean	0.35	0.06	0.75	1.00	0.01	0.12	5.33	2.04	1.34	0.18	0.98	9.56	8.47	0.42	85.53	−0.00
SD	0.48	0.23	0.32	2.39	0.02	0.28	3.10	0.75	0.61	0.39	0.03	6.40	4.74	0.35	39.26	9.76
Min	0.00	0.00	0.03	0.00	0.00	0.00	−1.00	0.00	0.00	0.00	0.00	1.00	0.01	0.00	4.00	−100.99
Max	1.00	1.00	1.13	94.25	1.00	1.00	33.00	6.72	4.01	1.00	1.00	27.00	33.16	1.89	167.00	27.39

TABLE 4 Logit with firm fixed effect (DV: probability of commission and omission errors).

	DV: Commission error			DV: Omission error		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Geographical distance (norm)			−0.045 (.000)			0.058 (.000)
Cohesion		0.205 (.000)	0.213 (.000)		−0.105 (.016)	−0.128 (.003)
Average degree (norm)	−3.499 (.000)	−0.991 (.201)	−0.909 (.237)	−2.247 (.056)	−3.204 (.019)	−3.391 (.015)
Proportion of stars	−0.398 (.000)	−0.316 (.000)	−0.321 (.000)	0.008 (.856)	−0.035 (.465)	−0.030 (.532)
Technology maturity	0.004 (.024)	0.004 (.052)	0.003 (.133)	0.011 (.010)	0.011 (.008)	0.012 (.004)
Backward citations (ln)	−0.107 (.000)	−0.104 (.000)	−0.096 (.000)	0.085 (.000)	0.083 (.000)	0.078 (.000)
Number of subclasses (ln)	−0.033 (.001)	−0.032 (.001)	−0.031 (.001)	0.033 (.116)	0.032 (.127)	0.028 (.171)
Formal R&D centralization	0.058 (.203)	0.049 (.281)	0.051 (.265)	−0.372 (.000)	−0.367 (.000)	−0.364 (.000)
R&D network centralization	0.513 (.176)	0.950 (.015)	0.958 (.014)	0.534 (.536)	0.300 (.721)	0.235 (.778)
Firm R&D internationalization	−0.015 (.000)	−0.015 (.000)	−0.015 (.000)	0.033 (.000)	0.032 (.000)	0.032 (.000)
R&D intensity	−0.007 (.053)	−0.007 (.058)	−0.007 (.051)	0.027 (.001)	0.027 (.001)	0.027 (.001)
Patent portfolio size	0.046 (.170)	0.068 (.044)	0.068 (.044)	0.596 (.000)	0.591 (.000)	0.594 (.000)
Firm age	1.107 (.000)	1.108 (.000)	1.110 (.000)	0.099 (.000)	0.098 (.000)	0.100 (.000)
Firm ROA	−0.001 (.087)	−0.001 (.093)	−0.001 (.094)	−0.004 (.003)	−0.004 (.003)	−0.004 (.003)
Second renewal	−0.281 (.000)	−0.287 (.000)	−0.288 (.000)	1.097 (.000)	1.100 (.000)	1.102 (.000)
Third renewal	−0.773 (.000)	−0.782 (.000)	−0.785 (.000)	1.728 (.000)	1.734 (.000)	1.737 (.000)
Technology class fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y	Y	Y
Constant	−42.587 (.000)	−43.349 (.000)	−43.380 (.000)	−9.088 (.000)	−8.694 (.000)	−8.747 (.000)
Log likelihood	−145014.9	−144950.0	−144700.1	−48500.4	−48496.0	−48363.3
Wald chi^2	27812.5	27893.7	27782.4	7142.9	7146.8	7473.1
Pseudo R^2	0.1500	0.1554	0.1569	0.1080	0.1080	0.1105
Observations	259,284	259,284	259,284	259,284	259,284	259,284
Number of firms	42	42	42	42	42	42

Note: *p*-Values in parentheses.

Models 4–6 estimate the likelihood of omission errors. Model 4 is the baseline model. Model 5 introduces the *Cohesion* variable, which has a negative coefficient ($\beta = -.105$, $p = .016$). This finding aligns with the expectation that the likelihood of omission errors decreases with *Cohesion* (Hypothesis 1b). Model 6 introduces the variable *Geographical distance*, which positively affects the probability of omission errors ($\beta = .058$, $p = .000$). This finding suggests that when inventors are located farther from the firm's headquarters, the chances of omission errors increase substantially, in line with Hypothesis 2b. According to Model 6, a one-unit in *Cohesion* decreases the odds of an omission error by a factor of 0.88. As for *Geographical distance*, the odds of omission errors increase by a factor of 1.06 for every unit of distance.

All control variables enhance our understanding of the drivers of commission and omission errors in technology evaluation decisions. First, the Proportion of star inventors in the invention team decreases the likelihood of commission error ($\beta = -.321$, $p = .000$), while its effect on omission errors is also negative but not different from zero ($\beta = -.030$, $p = .532$). This result may seem counter-intuitive, as research indicates that ideas generated by high-status actors are perceived to have higher potential value and are less likely to be rejected regardless of quality (Reitzig & Sorenson, 2013). Yet, existing research suggests that star employees produce higher quality output, which may amplify their internal influence while also calling for greater scrutiny (Tzabbar, 2009).

The effects of patent-level covariates suggest that mature technologies engender more omission errors ($\beta = .012$, $p = .004$). Patents disclosing an extensive list of prior arts or classified in multiple technology areas are less prone to commission errors ($\beta = -.096$, $p = .000$, $\beta = -.031$, $p = .001$) and more prone to omission errors ($\beta = .078$, $p = .000$; $\beta = .028$, $p = .171$). These variables may capture firms' difficulties in detecting novel valuable applications in technology domains, which are more mature or crowded, which results in lower renewal rates regardless of quality considerations.

Findings on the role of formal hierarchy depart from prior research: centralized structures decrease omission errors ($\beta = -.364$, $p = .000$).[13] As expected, evaluating inventions in a geographically dispersed firm poses more significant challenges, with firms with inventors in multiple countries less likely to make commission errors ($\beta = -.015$, $p = .000$) and more likely to make omission errors ($\beta = .032$, $p = .000$). Corroborating the notion that organizational inertia increases with firm size and age, we find that older firms ($\beta = 1.110$, p = .000; $\beta = .100$, $p = .000$) and larger portfolios ($\beta = .068$, $p = .044$; $\beta = .594$, $p = .000$) display higher error rates of both kinds. We expected better-performing firms to make fewer errors of either type because they can establish structured decision processes due to their positive economic outlook. The effect of Firm ROA is indeed negative ($\beta = -.001$, $p = .094$; $\beta = -.004$, $p = .003$), corroborating these expectations.

4.1 | Robustness analyses

4.1.1 | Evaluation of technological opportunities: Unit of analysis

In the article, we used patent renewal decisions as the unit of analysis. Yet, technologies do not necessarily map one-to-one with patents. To determine the appropriate unit of analysis for

[13]This finding seems to contradict previous research (Csaszar, 2012; Sah & Stiglitz, 1986). Yet, the models reported here include firm fixed effects. Thus, the coefficient only captures the effect of within-firm reorganizations occurring in this time interval (e.g., shifts from hybrid to centralized). We record few changes of this nature, and the measure simply captures the announcement of a reorganization (not its implementation).

studying renewal decisions, we consulted our informants during interviews. Their responses varied. Some referred to patents, patent families, or US Patent Classification (USPC) patent subclasses, providing examples of how these units of aggregation map to (un)successful products, technological trajectories, and downstream markets. These considerations validate the decision to model errors at the patent level while assessing objective quality based on some technology-level metrics, such as inclusion in a thicket, inclusion in a standard and patent family size.

Another approach would be to use a different level of aggregation for the analyses, assuming that evaluation occurs at the patent family or the USPC subclass level. Table 5 presents the results obtained using the (a) firm—patent family—maintenance year (Models 1 and 6), and (b) firm—USPC subclass—maintenance year (Models 2 and 7), as units of analysis. The effects of the covariates of interest remain consistent with the main findings.

4.2 | Strategic citations and changes in patent ownership

Some quality dimensions in Table 1 are based on patent citations, which may be biased due to the selective disclosure of prior art (Jaffe & Rassenfosse, 2017). The use of several indicators, in which only a few dimensions are citation-based, mitigates these concerns. As explained by IP professional #10: "if you strategize along one dimension, you may have unintended consequences in another line. A document where prior art is not properly listed can sooner or later be opposed or litigated." However, we tried to address strategic disclosure in each patent by considering the subset of patents granted after 2001[14] and computing the proportion of backward citations provided by the reviewer. We include this variable as a control (Table 5, Models 3 and 8). The control is positively related to commission errors ($\beta = .388$, $p = .000$) while negatively to omission errors ($\beta = -.295$, $p = .000$). The results remain consistent with the main findings.

Patent ownership changes can complicate the identification of decision makers responsible for renewal decisions. We used the Patent Assignment Dataset (Graham et al., 2018) to identify assignment transactions between distinct assignees and we removed from the sample all renewal decisions that occurred after these transactions. Results based on the subsample of patents not subject to ownership transactions align with the main findings presented in the article (Table 5, Models 4 and 8).

4.3 | Inventor's state at the time of patent renewal

This article explores how inventors' interactions with peers and key decision makers during technology emergence affect errors in renewal decisions. This choice is based on theoretical grounds, and on qualitative evidence of short- and long-term consequences of inventors' interactions (see Table A3, Supporting information) . However, one may still wonder whether the state of the inventor at the time of renewal decisions affects errors. We computed a set of variables that account for the number of inventors in the original team still active in the firm and the number of inventors active at a competitor at the time of renewal. Results including these controls align with those discussed in the previous paragraphs (Table 5, Models 5 and 10). Interestingly, both variables reduce the likelihood of errors of commission ($\beta_{\text{Active at firm}} = -.022$,

[14]2001 is the first year where citations added by the patent examiner can be distinguished from those provided by the author using USPTO data.

TABLE 5 Robustness analyses.

	DV: Commission error					DV: Omission error				
	Model 1 Patent family	Model 2 Subclass	Model 3 Examiner check	Model 4 Ownership change	Model 5 Inventor at renewal	Model 6 Patent family	Model 7 Subclass	Model 8 Examiner check	Model 9 Ownership change	Model 10 Inventor at renewal
Geographical distance (norm)	−0.045 (.000)	−0.042 (.000)	−0.049 (.000)	−0.057 (.000)	−0.046 (.000)	0.057 (.000)	0.058 (.000)	0.097 (.000)	0.067 (.000)	0.057 (.000)
Cohesion	0.210 (.000)	0.107 (.000)	0.241 (.000)	0.074 (.011)	0.157 (.000)	−0.125 (.000)	−0.200 (.000)	−0.170 (.009)	−0.195 (.000)	−0.176 (.000)
Average degree (norm)	−0.032 (.953)	−0.186 (.744)	0.068 (.951)	−2.856 (.011)	−0.698 (.353)	−3.108 (.003)	−3.421 (.002)	0.009 (.997)	−4.050 (.035)	−3.276 (.017)
Proportion of stars	−0.244 (.000)	−0.200 (.000)	−0.343 (.000)	−0.195 (.000)	−0.303 (.000)	−0.076 (.057)	0.052 (.215)	0.066 (.346)	−0.007 (.889)	−0.024 (.618)
Technology maturity	0.002 (.174)	−0.006 (.002)	0.011 (.000)	−0.005 (.043)	0.003 (.130)	0.015 (.000)	−0.000 (.931)	0.004 (.478)	−0.001 (.769)	0.012 (.004)
Backward citations (ln)	−0.076 (.000)	−0.080 (.000)	−0.049 (.000)	−0.076 (.000)	−0.095 (.000)	0.056 (.000)	0.096 (.000)	0.067 (.012)	0.086 (.000)	0.079 (.000)
Number of subclasses (ln)	−0.033 (.000)	−0.049 (.000)	−0.030 (.009)	−0.030 (.015)	−0.029 (.002)	0.027 (.120)	−0.002 (.921)	0.057 (.066)	0.084 (.000)	0.031 (.137)
Formal R&D centralization	0.055 (.173)	0.001 (.988)	0.176 (.002)	0.077 (.281)	0.055 (.233)	−0.429 (.000)	−0.376 (.000)	−0.613 (.000)	−0.034 (.780)	−0.366 (.000)
R&D network centralization	0.878 (.014)	0.846 (.020)	1.183 (.022)	0.617 (.154)	0.974 (.013)	0.661 (.365)	0.633 (.404)	0.529 (.672)	−0.110 (.917)	0.239 (.775)
Firm R&D internationalization	−0.016 (.000)	−0.006 (.036)	−0.010 (.006)	−0.014 (.000)	−0.014 (.000)	0.037 (.000)	0.037 (.000)	0.006 (.525)	0.037 (.000)	0.032 (.000)
R&D intensity	−0.006 (.085)	−0.004 (.218)	−0.014 (.015)	−0.031 (.000)	−0.008 (.041)	0.029 (.000)	0.025 (.000)	0.005 (.736)	0.066 (.000)	0.027 (.001)
Patent portfolio size	0.071 (.018)	0.200 (.000)	−0.034 (.442)	−0.025 (.661)	0.052 (.127)	0.579 (.000)	0.891 (.000)	1.542 (.000)	−0.056 (.570)	0.590 (.000)
Firm age	1.117 (.000)	1.134 (.000)	−0.117 (.001)	1.167 (.000)	1.109 (.000)	0.094 (.000)	0.112 (.000)	0.083 (.285)	0.165 (.000)	0.100 (.000)
Firm ROA	−0.001 (.037)	−0.001 (.092)	−0.001 (.452)	−0.001 (.555)	−0.001 (.105)	−0.004 (.000)	−0.003 (.008)	−0.001 (.479)	−0.006 (.001)	−0.004 (.003)
Second Renewal	−0.305 (.000)	−0.297 (.000)	−0.258 (.000)	−0.532 (.000)	−0.289 (.000)	1.147 (.000)	1.081 (.000)	0.716 (.000)	0.928 (.000)	1.102 (.000)
Third Renewal	−0.812 (.000)	−0.828 (.000)	−0.636 (.000)	−1.181 (.000)	−0.790 (.000)	1.805 (.000)	1.697 (.000)	1.083 (.000)	1.340 (.000)	1.735 (.000)
Technology class fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

TABLE 5 (Continued)

	DV: Commission error					DV: Omission error				
	Model 1 Patent family	**Model 2 Subclass**	**Model 3 Examiner check**	**Model 4 Ownership change**	**Model 5 Inventor at renewal**	**Model 6 Patent family**	**Model 7 Subclass**	**Model 8 Examiner check**	**Model 9 Ownership change**	**Model 10 Inventor at renewal**
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Ratio examiner			0.388 (.000)					−0.295 (.000)		
No. of inventors active in firm at renewal					−0.022 (.000)					−0.029 (.001)
No. of inventors active in rival firm at renewal					−0.081 (.000)					−0.005 (.848)
Constant	−43.800 (.000)	−44.100 (.000)	2.473 (.053)	−45.367 (.000)	−43.334 (.000)	−8.937 (.000)	−9.492 (.000)	−7.550 (.006)	−10.074 (.000)	−8.702 (.000)
Log likelihood	−137889.8	−105996.5	−89847.3	−86661.1	−144637.4	−46041.1	−40814.1	−20743.4	−37275.8	−48356.1
Wald chi^2	36479.6	28126.1	13418.7	20047.7	27918.1	9983.0	9796.2	3220.6	8064.6	7503.8
Pseudo R^2	0.1597	0.1653	0.1195	0.1866	0.1572	0.1153	0.1240	0.0846	0.1526	0.1106
Observations	247,426	186,339	148,424	165,737	259,284	247,426	186,339	148,424	165,737	259,284
Number of firms	42	42	41	41	42	42	42	41	41	42

Note: *p*-Values in parentheses.

$p = .000$; $\beta_{\text{Active at rival}} = -.081$, $p = .000$) and the number of inventors still active at the firm reduces omission errors ($\beta_{\text{Active at firm}} = -.029$, $p = .001$).[15] This may be due to the lower uncertainty entailed in the evaluation of old-timer inventors, or to the fact that quality is easier to verify for these actors.

4.4 | Alternative model specifications and operationalization of key variables

In a set of additional analyses, we used alternative model specifications to test the robustness of the findings. Results are presented in Table B1 (Supporting information). First, we used bootstrap to assess how much coefficient variation is due to extreme data values or to sampling decisions. This entailed resampling the data in memory 200 times with replacement and running the full model each time. Second, given that logit models are harder to interpret (Hellevik, 2009), we present additional estimates based on a fixed effect panel linear probability model. Third, we fit a rare-event logit (King & Zeng, 2001), to address the fact that only 5.4% of renewal decisions are coded as omission errors.

Results align with the main findings. The only exception is the effect of Cohesion on omission errors, which does not support Hypothesis 1b in the fixed effects panel linear probability model ($\beta = -.006$, $p = .145$). However, the linear probability approximation is considered a good fit when the modeled probabilities range between .20 and .80 (Hellevik, 2009), while the incidence of omission error is much lower in our sample. A rare event logit seems to be a more appropriate fit for variables in this range.

We also used an alternative operationalization of commission error and omission errors. We used factor analysis to create a unidimensional quality indicator based on the dimensions listed in Table 1. We then measure omission errors as patents belonging to the top decile of the index quality index distribution and not renewed. Commission errors are defined as patents, which were renewed but belong to the bottom decile of the quality index distribution. The results (Table B2, Supporting Information) are aligned with those presented in the previous tables.

4.5 | Economic implications of commission and omission errors

Our analyses revealed biases in the evaluation of technological opportunities, raising questions about the consequences of these errors for managerial practice. To address this question, we analyzed the effects of the cumulative numbers of commission and omission errors on future sales at the firm level, while controlling for factors previously linked to market success in this industry. We present the results of these analyses in Table 6, with Models 1–3 using a 1-year lag between the independent and dependent variable and Models 4 and 5 using a 2 and 3 years lag, respectively.

Results show that commission errors decrease short- and long-term sales ($\beta = -.140$, $p = .010$; $\beta = -.121$, $p = .019$; $\beta = -.092$, $p = .042$). Omission errors are also negatively related to sales, although the confidence interval includes zero ($\beta = -.086$, $p = .101$; $\beta = -\ .128$,

[15] We also checked whether the presence of active inventors within the firm at the time of renewal exacerbates biases resulting from cohesion and geographical distance. The results corroborate these expectations (refer to Table B6, Supporting information). In three cases the results align with the prediction, while in the Omission error model the confidence interval of the interaction between No. of inventors in firm and Geographical distance includes zero.

TABLE 6 Economic effects of commission and omission errors on firm performance.

	Model 1 ln sales ($t + 1$)	Model 2 ln sales ($t + 1$)	Model 3 ln sales ($t + 1$)	Model 4 ln sales ($t + 2$)	Model 5 ln sales ($t + 3$)
Cumulative commission errors (ln)			−0.140 (0.010)	−0.121 (0.019)	−0.092 (0.042)
Cumulative omission errors (ln)		−0.142 (0.034)	−0.086 (0.101)	−0.128 (0.094)	−0.154 (0.085)
Number of products (ln)	0.137 (.009)	0.155 (.009)	0.158 (.007)	0.132 (.024)	0.103 (.090)
Number of patents (ln)	0.267 (.000)	0.249 (.000)	0.239 (.000)	0.171 (.022)	0.111 (.166)
Number of design patents (ln)	0.047 (.350)	0.049 (.318)	0.078 (.110)	0.087 (.067)	0.083 (.078)
Network density	−1.741 (.047)	−1.559 (.085)	−1.103 (.211)	−1.088 (.207)	−1.396 (.120)
Network centralization	−1.476 (.188)	−1.436 (.171)	−1.406 (0.150)	−1.315 (0.160)	−0.873 (.343)
R&D intensity	−0.067 (.000)	−0.062 (.001)	−0.064 (.000)	−0.053 (.008)	−0.039 (.074)
Firm age	−0.195 (.079)	−0.182 (.106)	−0.123 (.201)	0.146 (.417)	0.035 (.666)
Firm fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
Constant	24.740 (.005)	24.074 (.008)	20.012 (.011)	−0.649 (.962)	8.197 (.189)
R^2	0.537	0.558	0.576	0.532	0.485
Observations	606	606	606	601	593
Number of firms	42	42	42	42	42

Note: p-Value in parenthesis.

$p = .094$; $\beta = -.154$, $p = .085$). Moreover, the effect of omission errors seems more pronounced in the long run, while commission errors have more significant consequences in the short run. Such considerations align with anecdotal evidence from the fieldwork. Despite substantial R&D investments and extensive patent holding, leading mobile phone and PDA companies lost their sales leadership, partly due to commission and omission errors.

In the opening example, Motorola's Arizona R&D laboratory (located far from the company's headquarters in Schaumburg, Illinois) developed sensors for mobile phone cameras. The failure to utilize this invention marked a critical omission error for the firm. Eventually, the team moved to STMicroelectronics through a partnership, significantly contributing to Nokia's surging market share in the 1990s. The two inventors responsible for the project were on the periphery of the organization, and their efforts to persuade top managers of the invention's potential proved unsuccessful. This research offers valuable insights for identifying and preventing similar errors in other firms.

5 | DISCUSSION AND CONCLUSION

This article aims to understand why firms make commission and omission errors in technology evaluation decisions. Extending prior research on the joint effect of organizational structure and cognition on decision-making (Gavetti, 2005; Lee & Csaszar, 2020), we focused on how interactions with peers and key decision makers at the company headquarters influence commission and omission errors. We hypothesized that an inventor with more cohesive collaboration networks within the firm or geographical proximity to key decision makers at the corporate headquarters could more effectively sway the dominant representations that guide decision-making about technologies, leading to more commission errors. Conversely, boundary-spanning inventors or located distant from the corporate headquarters have a reduced ability to influence the dominant representations, leading to more omission errors in the evaluation of their inventions. Qualitative and quantitative data from the mobile phone and PDA industry between 1990 and 2010 support the hypotheses.

5.1 | Theoretical contribution

We contribute to two research streams. First, we add to research on the organizational sources of commission and omission errors (Csaszar, 2012; Dye et al., 2014; Garud et al., 1997; Klingebiel, 2018; Klingebiel et al., 2022). Studies in this area established the distinct effect of structure and cognition on commission/omission errors (Csaszar, 2012; Kaplan, 2008; Sah & Stiglitz, 1986). Recent research combined structure and cognition (Gavetti, 2005, p. 603; Lee & Csaszar, 2020) to document the interplay between "cognitions" differently situated in the hierarchy. Yet, these studies remain confined to analyzing a few archetypes of organizational forms (Gavetti, 2005; Greenwood & Hinings, 1993; Siggelkow & Rivkin, 2005). In line with Simon's (1947, pp. 18–19) view of organizations as the pattern of interactions between members, we examined the role of network forms of organizing (Podolny & Page, 1998), demonstrating that networks within a firm can induce biases beyond those stemming from its formal structure. These insights offer fertile ground for future research on the interplay between the formal and informal structure within organizations (Krackhardt & Hanson, 1993; McEvily et al., 2014).

Our findings also advance studies on R&D project evaluation within established firms (Criscuolo et al., 2017; Klingebiel et al., 2022; Reitzig & Sorenson, 2013). Currently, two lines of research have developed in this area. One focuses on strategies employees can devise to champion their projects in the firm (see Wooldridge et al., 2008; for a review). The other focuses on key decision makers, studying factors that affect their decisions to promote or terminate innovation initiatives (Criscuolo et al., 2017; Monteiro, 2015; Reitzig & Sorenson, 2013). By providing evidence that interactions between inventors and key decision makers at the company headquarters may trigger errors, we highlight the benefits of bringing these two lines of research together when analyzing technology evaluation decisions.

Our approach also challenges the traditional models of technology-related decisions under uncertainty based on real-options theory (McGrath, 1997; Zardkoohi, 2004). These models assume that uncertainty resides primarily in the environment and that objective decisions are possible when uncertainty is resolved. In contrast, our findings indicate that organizational factors can impede an objective assessment of alternatives, even when environmental uncertainty is resolved. The observation that deviations from objective quality considerations occur when evaluating technologies backed by inventors with more cohesive collaboration networks within the firm or located close to the corporate headquarters confirms the existence of "option traps" (Adner & Levinthal, 2004, p. 80). This finding urges caution when applying real-options theory to organizations.

The second contribution of this article lies in advancing the understanding of intraorganizational collaboration within the context of R&D activities (Dahlander & Frederiksen, 2012; Nerkar & Paruchuri, 2005; Reagans & McEvily, 2003), which has yielded mixed evidence on the relative benefits of cohesion and boundary-spanning. We offer new insights by shifting the focus from positive outcomes, like innovation impact, to negative consequences, such as errors. We highlight that commission and omission errors might stem from a misalignment between the two phases of innovation—typically described as idea generation and selective retention in creativity research (Simonton, 2010) or as alternative generation and alternative evaluation in strategy (Knudsen & Levinthal, 2007). The type of network structure beneficial for one phase may be detrimental for the second phase. Further research should explore how other dimensions of informal networks impact other types of negative outcomes, such as the intensity of failure (e.g., Khanna et al., 2016) and other types of errors (e.g., Klingebiel et al., 2022).

5.2 | Limitations

This study presents several limitations. First, we measure errors as deviations from renewal decisions based on objective quality. However, biases in errors might occur earlier, during filing decisions. This concern is somewhat mitigated in this context, due to the high patenting propensities in the mobile phone industry. Future studies may use detailed records of patent filing boards within firms (e.g., Criscuolo et al., 2019) to investigate commission and omission errors in earlier stages of the patent lifecycle. Second, the measures used in this study are imperfect proxies of the underlying constructs. We do not observe interactions directly, but infer them through collaboration ties and colocation. Although we focus on a single industry and use technology and firm fixed effects, unobserved practices in assigning projects to teams or locations may confound the results we attribute to interactions. Similarly, researchers with access to detailed records of project commercial returns (e.g., Criscuolo et al., 2017; Reitzig & Sorenson, 2013) can further improve the measure of patent quality. Third, we examine how inventors' interactions with their peers and key decision makers in the early stages of technology emergence affect errors in patent renewal decisions, several years after these interactions. Although this approach is validated by the interviews and with research on commitment persistence in decision-making (Guler, 2007; Klingebiel & Esser, 2020), it does not allow to observe championing efforts occurring through the invention lifecycle. Further academic research is required to improve our understanding of the influence of social processes on technology evaluation decisions after patents are granted, connecting inventor careers and patent filing, renewal, and termination (e.g., Goossen & Carnabuci, 2020; Khanna et al., 2016; Wang & Zheng, 2022).

5.3 | Managerial implications

Our results carry significant managerial implications, particularly in light of the substantial economic penalty resulting from commission and omission errors, as demonstrated in Table 6. Managers should remain mindful of the biases engendered by interactions within the organization. While errors are inevitable, especially in fast-changing and uncertain environments (Dye et al., 2014; Garud et al., 1997), these findings provide insights into factors associated with commission and omission errors, with direct practical implications. To minimize commission errors, managers should enforce deadlines and abandonment triggers against inventors with more cohesive networks or located at the corporate headquarters. To reduce omission errors, resources and discretion should be paid to projects in remote locations or by boundary-spanning individuals. Managers should also proactively foster interactions within the firm in ways that compensate for the biases identified by this article. While the top-down design of informal organizational networks presents more significant challenges than structuring hierarchies, both elements demand prioritized consideration in the management agenda, particularly in rapidly evolving environments.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from sources listed in Table 1 and in Section 3.1 of the article. Some restrictions apply to the availability of data from certain vendors (COMPUSTAT, Questel).

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SUPPORTING INFORMATION

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

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