

Knowledge sourcing by multidivisional firms

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Research Summary: Research on knowledge sourcing has generally treated firms as monolithic entities, even though firms most active in knowledge sourcing often comprise heterogeneous divisions, each possessing specialized knowledge and facing unique market prospects. This study examines how heterogeneity across divisions affects knowledge sourcing by multidivisional firms. We argue that firms source more early-stage knowledge, whose market prospects are highly uncertain, for low-performing divisions; by remaining active in the relevant markets, firms keep the flexibility to tap favorable market opportunities should they arise in the future. In contrast, firms source more late-stage knowledge, whose market prospects are largely revealed, for high-performing divisions so as to maximize current returns. The *intra-firm* heterogeneity, in turn, explains *inter-firm* differences in knowledge sourcing. Data from the pharmaceutical industry support these arguments.

Managerial Summary: Firms that source external knowledge often span multiple technological areas and markets, and hence it is not immediately clear what to source and how much to source. This study examines how multidivisional firms tailor their knowledge-sourcing strategies to differences in performance across their divisions. We find that firms source more early-stage knowledge, whose market prospects are uncertain, for divisions with low innovation performance. This helps firms prop up those divisions and remain active in the related markets. In contrast, firms source more late-stage knowledge, whose market prospects are more certain, for divisions with high sales performance. This helps firms leverage the strengths of those divisions and realize immediate gains. Performance differences across divisions inside firms, therefore, can explain differences in knowledge-sourcing strategies across firms.

KEY WORDS

corporate strategy, knowledge sourcing, market dynamics, multidivisional firms, specialized knowledge

1 | INTRODUCTION

In 2002, two pharmaceutical firms, Novo Nordisk and Schering AG, were granted a similar number of drug patents. Yet, Schering had twice as many alliances to source external knowledge in the drug discovery stage as Novo Nordisk. In the same year, Eli Lilly and Novartis had similar sales, but Novartis had four times as many knowledge-sourcing alliances in the commercialization stage as Eli Lilly. It is puzzling that firms with similar firm-level attributes exhibited markedly different patterns of external knowledge sourcing.

A closer look inside these firms reveals that drug patents were distributed more unequally across therapeutic areas in Schering than in Novo Nordisk. Similarly, drug sales were distributed more unequally across therapeutic areas in Eli Lilly than in Novartis. The implications of such intra-firm heterogeneity have not been examined in the knowledge-sourcing literature, which has otherwise provided important insights on knowledge sourcing as an integral part of firm strategy (Eisenhardt & Santos, 2002; Eisenhardt & Schoonhoven, 1996; Kale, Dyer, & Singh, 2002; Lavie, Stettner, & Tushman, 2010; Nickerson & Zenger, 2004; Oxley & Sampson, 2004).

In this study, we seek to understand how intra-firm heterogeneity influences a firm's overall knowledge-sourcing strategy, beyond the effect of firm-level characteristics. This question is important for several reasons. First, with the growing prominence of knowledge-intensive activities, the market for knowledge has flourished in recent times (Arora & Gambardella, 2010) and is especially salient in industries such as pharmaceuticals, chemicals, biotechnology, semiconductors, and software (Arora, Fosfuri, & Gambardella, 2001). Second, the major players in the market for knowledge are often multidivisional firms (Argyres & Silverman, 2004; Arora et al., 2001) that comprise divisions spanning distinct markets and technological areas. Third, insofar as knowledge sourcing entails a significant commitment of resources (Liebeskind, Oliver, Zucker, & Brewer, 1996), it directly impacts resource allocation within the firm, a topic of enduring interest to strategy scholars (Bower, 1970; Burgelman, 1983; Levithal, 2017; Rumelt, Schendel, & Teece, 1994; Sengul, Costa, & Gimeno, Forthcoming). Therefore, to understand knowledge-sourcing strategies of multidivisional firms at the firm level, we need to understand knowledge-sourcing strategies at the division level.

Accordingly, we present our arguments in two steps. First, we theorize how a firm tailors knowledge sourcing to its heterogeneous divisions, with heterogeneity defined based on the divisions' innovation and sales performance. Second, we build on the logic at the division level to theorize how heterogeneity among divisions explains knowledge sourcing at the firm level.

Critical to our arguments about the knowledge-sourcing strategies of multidivisional firms are the ideas of market uncertainty and specialized knowledge of divisions. In dynamic markets, it is difficult for the firm to predict which specific market will show promise in the future (Eisenhardt & Brown, 1999; Helfat & Eisenhardt, 2004). However, knowledge is often specialized to each division in a multidivisional firm (Macher & Boerner, 2006). Thus, to take advantage of market opportunities when they materialize, the relevant division in the firm has to possess a minimum level of specialized

knowledge. Otherwise, the cost of re-entering a market after having exited it can be high (DiMasi, Hansen, & Grabowski, 2003; Lieberman, Lee, & Folta, 2017; O'Brien & Folta, 2009). By keeping a division active in the present, the firm has the flexibility to tap opportunities in the future, should the relevant market show promise.

How the above considerations translate into firms' knowledge-sourcing strategies depends on how far a technology (an application of the sourced knowledge) is from commercialization. In the early-stages of a technology's development, it is not immediately clear whether the relevant market will show promise by the time the technology is ready to be commercialized. Exogenous shocks, for instance, can rapidly change the prospects of dynamic markets (Helfat & Eisenhardt, 2004). External knowledge can then be a means to prop up a division with low innovation performance and keep the firm active in that market. In contrast, in the later stages of a technology's development, the firm has a more precise estimate of the relevant market's immediate potential. Hence it would seek to maximize current returns from commercializing the technology by leveraging divisions with high sales performance. This logic leads to two hypotheses at the division level. First, a firm will source more early-stage knowledge for divisions with low innovation performance. Second, the firm will source more late-stage knowledge for divisions with high sales performance.

Building on these arguments at the division level, we develop two hypotheses at the firm level. First, a firm with greater inequality in innovation performance across divisions will source more early-stage knowledge at the firm level, primarily to prop up the large number of divisions with low innovation performance. Second, greater inequality in sales performance across divisions will lead to less late-stage knowledge sourcing at the firm level. This is because, with greater inequality in sales, the firm will source late-stage knowledge for a smaller number of divisions with high sales, and these divisions face diminishing returns from each additional alliance. In sum, differences in knowledge-sourcing strategies *across firms* are a function of heterogeneity among divisions *inside* firms, beyond the effect of firm-level attributes.

To test these hypotheses, we use data on knowledge-sourcing alliances of the top 50 firms in the pharmaceutical industry from 1999 to 2004. Large pharmaceutical firms routinely source external knowledge for their therapeutic areas that span distinct markets. The lengthy R&D process in this industry allows us to classify external knowledge as early-stage or late-stage based on time to commercialization (Arora, Gambardella, Magazzini, & Pammolli, 2009; Rothaermel & Deeds, 2004). To better understand the knowledge-sourcing phenomenon, we supplement the quantitative analyses with interviews of scientists and managers representing companies in our sample.

The results at both the division and firm levels support the idea that heterogeneity among divisions is an important determinant of firms' knowledge-sourcing strategies. To address alternative explanations for our results, such as the not-invented-here bias (Katz & Allen, 1982), power dynamics (Pfeffer & Salancik, 1974), and agency behavior (Meyer, Roberts, & Milgrom, 1992; Scharfstein & Stein, 2000), we examined whether the presence of a corporate-level coordination function has a differential impact on knowledge sourcing within and across firms. We find that the results for the four hypotheses are stronger for firms that have a coordination function, thus confirming that the corporate headquarters can play an important role in a multidivisional firm's knowledge-sourcing strategy (Kale et al., 2002).

This study contributes to the knowledge-sourcing literature by introducing the idea of intra-firm heterogeneity in multidivisional firms and theorizing about its implications for firms' knowledge-sourcing strategies. One implication of intra-firm heterogeneity is that when knowledge is specialized to each division, it may be beneficial for the firm to sustain certain divisions for their future value. That is, in a dynamic environment, maintaining a broader scope than that determined solely by

considerations of economies of scope at a point in time can help multidivisional firms realize benefits over time. Relatedly, this is the first study, to our knowledge, that uses large sample data to show how intra-firm heterogeneity among divisions helps to uncover inter-firm variations in knowledge-sourcing strategies. A decade ago, scholars observed that organizational research had moved away from examining internal processes that influence choices (Gavetti, Levinthal, & Ocasio, 2007). By exploring how intra-firm heterogeneity impacts knowledge sourcing, this study complements recent qualitative research on the phenomenon (Monteiro & Birkinshaw, 2017) and brings our attention back to intra-firm characteristics.

2 | THEORY

In this section, we first review the literature on external knowledge sourcing. We argue that the bulk of the literature has treated firms as monolithic entities, even though the major players that source knowledge are often multidivisional firms that are internally complex. We therefore introduce the idea of intra-firm heterogeneity to this literature and theorize about its relation with multidivisional firms' knowledge-sourcing strategies, both at the division and firm levels.

2.1 | External knowledge sourcing

Sourcing knowledge from external sources is an important mechanism for firms to remain competitive (Cohen & Levinthal, 1990; Helfat et al., 2007). Knowledge sourcing is an especially important facet of firm strategy in knowledge-intensive industries as it allows firms to stay at the frontiers of developments in their industry (Brown & Eisenhardt, 1997; Eisenhardt & Santos, 2002). In one of our interviews, a manager at a large pharmaceutical firm highlighted the importance of external knowledge sourcing:

“All the units had a very positive view of external knowledge. Even scientists in the big therapeutic areas were equally positive because it was very clear from the company strategy that we need to look outside for external deals.”

A rich body of research has examined why and how firms source knowledge (Eisenhardt & Santos, 2002; Eisenhardt & Schoonhoven, 1996; Henderson & Cockburn, 1994; Lavie et al., 2010; Nickerison & Zenger, 2004; Powell, Koput, & Smith-Doerr, 1996). Categorized broadly, these questions have been analyzed at three levels: the transaction, the firm, and the population. At the transaction level, studies have examined the governance mechanisms, alliance experience, and inter-organizational routines in the formation of individual alliances between two firms (Gulati & Singh, 1998; Zollo, Reuer, & Singh, 2002). At the firm level, research has examined portfolios of transactions (Ozcan & Eisenhardt, 2009; Wassmer, 2010). This work has highlighted the corporate center's active role in forming alliances (Sarkar, Aulakh, & Madhok, 2009), ensuring greater accountability in managing alliances (Dyer, Kale, & Singh, 2001), assimilating and sharing knowledge within the firm (Kale et al., 2002), and defining routines to enhance the firm's knowledge-sourcing capability (Lavie & Singh, 2012). Finally, at the population level, the open innovation literature (Chesbrough, 2003) views knowledge sourcing as an outside-in process (Enkel, Gassmann, & Chesbrough, 2009). Laursen and Salter (2006) highlight that firms source knowledge by adopting an open search strategy that involves a wide range of external actors. Therefore, the focal firm—a node in a network of organizations—can source knowledge from customers, suppliers, competitors, and private and public research organizations. Leiponen and Helfat (2010) argue that given uncertainty, a firm that places

multiple bets in sourcing knowledge can improve its chances of success. The open innovation perspective is especially relevant to knowledge-intensive industries such as software, electronics, pharma, and biotech (Gassmann, Enkel, & Chesbrough, 2010).

Whether focusing on individual or a portfolio of transactions, or viewing the firm as an isolated entity or part of a population, research on knowledge sourcing has largely assumed that the firm is a monolithic entity (Bos, Faems, & Noseleit, 2017). This assumption, however, does not adequately capture the internal complexities of firms which, we argue next, have important implications for their knowledge-sourcing strategies.

2.2 | Specialized knowledge and market uncertainty

The major players in the market for knowledge are often multidivisional firms (Argyres & Silverman, 2004; Arora et al., 2001), which are complex (Adner & Levinthal, 2004) and polylithic entities (Bos et al., 2017) comprising heterogeneous divisions. In such firms, a division's assessment of the prospects of a project (or of a portfolio of projects) can differ from that of the corporate center, which seeks to balance firm-level risk and return. Thus, the corporate center may choose to invest in projects that, examined in isolation, do not offer the best expected returns. Given the prominence of multidivisional firms in the market for knowledge, we believe that it is important to acknowledge two of their key attributes that are relevant to the knowledge-sourcing phenomenon.

First, knowledge is often specialized to each division in a multidivisional firm, which means that knowledge sourcing is specific to each division. Even though there may be some degree of relatedness across divisions, the core knowledge underlying a division is often unique. For example, while different therapeutic areas in a pharmaceutical company share some common knowledge that can result in knowledge spillovers (Henderson & Cockburn, 1996), the knowledge core to each area is unique as each area spans a different technological field and product market (Macher & Boerner, 2006). A manager echoed this point in an interview:

“Even when R&D was organized in one unit, there were groups specialized in different therapeutic areas.”

Second, knowledge sourcing is a decision made under uncertainty, and different divisions face different levels of market uncertainty at any point in time. By sourcing external knowledge, the firm is placing bets on different markets, knowing that in the future, some markets will turn out to be more profitable than others. Unexpected shifts in market conditions (Miller & Yang, 2016), revisions in regulations (Hannah, Bremner, & Eisenhardt, 2016), and technological discontinuities (Lee & Parachuri, 2016)—changes that are often beyond any single firm's control—alter the value of a technology. A veteran in the pharmaceutical industry commented:

“It is very difficult to estimate the sales potential of a particular drug candidate. For individual companies working on their pipelines, the market can shift quickly. For example, Pfizer did not expect *Lipitor* or any statin products to be such a big success; aggressive marketing by competitors helped educate the market. Also, the fast growth of the emerging market propelled the demand for diabetes drugs, and a couple of court cases quickly cooled down the market for anti-depressant drugs.”

The above discussions suggest that sourcing external knowledge is essentially a resource allocation decision. In a dynamic market, a firm must determine the best possible use of its limited resources

across divisions, each of which possesses specialized knowledge and faces different market prospects. Corroborating this idea, a manager at a large pharmaceutical company told us:

“If a dollar invested in an oncology project is a better investment than a dollar invested in the respiratory project, somebody has to be at a very high level to understand the tradeoffs across the whole company.”

Therefore, we need to go beyond firm-level characteristics and take intra-firm heterogeneity into consideration when studying knowledge sourcing by multidivisional firms. In the next two subsections, we first theorize on how a multidivisional firm tailors knowledge sourcing to its heterogeneous divisions. We then build on the logic at the division level to theorize how heterogeneity among divisions explains knowledge sourcing at the firm level.

2.3 | Division-level knowledge sourcing

To lay the groundwork for our hypotheses about how intra-firm heterogeneity is related to knowledge sourcing, we distinguish between early- and late-stage knowledge to capture differences in market uncertainty associated with the sourced knowledge, and use the innovation and sales performance of divisions to capture intra-firm heterogeneity.

With respect to market uncertainty, we argue that externally-sourced knowledge varies substantially in the uncertainty associated with its market prospects.¹ To capture this variation, we distinguish between early- and late-stage knowledge. Early-stage knowledge involves invention or experimentation with new ideas that, by nature, have a longer gestation period (Arora et al., 2009). When a firm sources early-stage knowledge, it may not know *a priori* whether the market will show promise when the technology is ready to be commercialized (Granstrand, Patel, & Pavitt, 1997). Thus, an investment in an unpromising market early in the innovation cycle may yield high returns if and when the tide of the market turns. In contrast, market uncertainty is largely resolved when firms source late-stage knowledge.²

With respect to intra-firm heterogeneity, we argue that the relative performance of individual divisions is an important criterion in the knowledge-sourcing strategies of multidivisional firms. Prior research has used performance-based criteria to capture differences among firms affiliated with a business group (Lincoln, Gerlach, & Ahmadjian, 1996) or among divisions within a firm (Scharfstein & Stein, 2000). We capture heterogeneity among divisions based on their innovation and sales performance. We assume that a division's innovation performance relates more closely to early-stage knowledge sourcing, given the emphasis on research and creation of new ideas. In this stage, the eventual application of the technology is often unclear (Rothaermel & Deeds, 2006). Likewise, a division's sales performance relates more closely to late-stage knowledge sourcing, given the emphasis on commercialization of ideas. Technologies in the late stage are more readily converted to commercially feasible products (Rothaermel & Deeds, 2006).

Note that we are agnostic about the antecedents of performance differences across divisions. A division could perform well because of stronger capabilities, more effective learning processes, or more prior investments by the firm. Exogenous shocks can also affect the relative performance of divisions. For instance, the discovery of gene-editing tools has profoundly changed oncology (cancer) research, and changes in consumer lifestyles have increased sales of antidiabetic drugs.

¹Note that market uncertainty is distinct from the technological uncertainty inherent in early-stage knowledge. The latter can be managed by using a portfolio strategy akin to making multiple bets that reduce overall risk. Similar intuition underlies the parallel path strategy (Nelson, 1961) and sampling models (Baldwin & Clark, 2006; Leiponen & Helfat, 2010).

²The different degrees of uncertainty in market prospects of early-stage and late-stage knowledge closely relates to the notion of inducements in research on resource redeployment within firms (Sakhartov & Folta, 2015).

We now present the hypotheses for how multidivisional firms tailor their knowledge-sourcing strategies to divisions with heterogeneous performance.

2.3.1 | Sourcing early-stage knowledge

Crucial to our arguments about early-stage knowledge sourcing is the idea that sustaining a division requires a minimum scale of operations (Binenbaum, 2008; Graves & Langowitz, 1993). For instance, each division may need to hire scientific and technical personnel with specializations, develop a sales force that understands the specific products and customers, or have a team to lobby regulators and lawmakers. Below a minimum scale, the division may not be able to leverage the resources allocated to it and fail to tap market opportunities. Alternatively, below a minimum scale, the division may become financially unviable on a standalone basis (Helfat & Eisenhardt, 2004).

The alternative to maintaining a minimum scale is to leave the market. However, with specialized knowledge at the division level, the cost of re-entering a market after having exited is not trivial (DiMasi et al., 2003; Lieberman et al., 2017).³ Consider the case of the British pharmaceutical company GlaxoSmithKline. The company sold its oncology drugs to Novartis in 2014 and dismantled its oncology sales force, only to start rebuilding its pipeline of oncology drugs a few years later. Analysts noted that rebuilding the oncology infrastructure was a “tough challenge” (Ward, 2016). The upshot is that in dynamic markets, sustaining a division in the present may mitigate re-entry costs and provide the flexibility to leverage favorable market opportunities in the future.

We argue that when knowledge is specialized to each division and the cost of re-entering the relevant market is high, early-stage knowledge sourcing is a means for the firm to prop up divisions with low innovation performance and retain the specialized knowledge inside the firm. Divisions with low innovation performance risk falling short of the minimum level of specialized knowledge required to sustain their operations (Binenbaum, 2008; Graves & Langowitz, 1993). Sourcing external knowledge sustains such divisions and allows continuity of routines (Feldman, 2014; Helfat & Eisenhardt, 2004), thereby keeping the firm active in the relevant markets. In case these markets show promise in the future, the firm retains the flexibility to allocate additional resources to these divisions.

Our arguments do not imply that multidivisional firms source early-stage knowledge only for divisions with low innovation performance; divisions with high innovation performance can also benefit from early-stage knowledge. Instead, we argue that multidivisional firms have greater incentive to prop up divisions facing survival risks so as to remain active in those markets. This tilts the balance in early-stage knowledge sourcing towards divisions with low innovation performance. Thus, we hypothesize:

Hypothesis 1 (H1) *Multidivisional firms source more early-stage knowledge for divisions with low innovation performance than for divisions with high innovation performance.*

2.3.2 | Sourcing late-stage knowledge

When a firm sources late-stage knowledge, commercial considerations assume significance because the firm has a more precise estimate of the technology's market prospects compared to when it sources early-stage knowledge. The firm's goal then would be to maximize returns from commercializing the knowledge in the immediate future. We argue that, with lower uncertainty in the market, the

³The concept of re-entry costs is similar to that of sunk costs (Dixit, 1989; O'Brien & Folta, 2009) or upfront costs (Helfat & Eisenhardt, 2004).

firm would source more late-stage knowledge for divisions with high sales performance, which reflects robust market conditions and strong internal capabilities.

When a division has high sales, the relevant market is likely doing well. Using the pharmaceutical industry as an example, such a market may be a therapeutic area with consistently strong sales, such as cardiovascular and anti-infectious drugs, or an area witnessing favorable market conditions, such as immunology or antidiabetic drugs in recent years. A robust market allows firms to recoup the costly investments in late-stage knowledge.

High sales performance also reflects the division's strong capabilities to commercialize the knowledge. Again using the pharmaceutical industry as an example, even sizable market demand will be futile without the relevant division's capability to conduct clinical trials, obtain regulatory approvals, and mobilize an effective sales force, all of which are division-specific to varying degrees. The existence of such capabilities increases the potential value of externally-sourced knowledge. In the alliance literature, prior research shows that high-performing firms have more partnership opportunities (Ahuja, 2000). This argument can be extended to divisions within a firm. From the firm's perspective, sourcing knowledge for divisions with high sales performance would ensure better selection of partners and greater leverage of the divisions' capabilities. Thus, we hypothesize:

Hypothesis 2 (H2) *Multidivisional firms source more late-stage knowledge for divisions with high sales performance than for divisions with low sales performance.*

2.4 | Firm-level knowledge sourcing

A key objective of strategy research is to explain heterogeneity across firms (Rumelt et al., 1994). Thus, from a strategy perspective, it is valuable to understand how the composition of heterogeneous divisions *within* a firm can explain differences in knowledge-sourcing strategies *across* firms. In that sense, division-level knowledge-sourcing patterns serve as "proximate causes" (Felin, Foss, & Ployhart, 2015, p. 586) for firm-level knowledge-sourcing strategies.

There are many ways to characterize the composition of heterogeneous divisions within a firm. We focus on the concept of inequality (Harrison & Klein, 2007), which is an important dimension of heterogeneity. Specific to multidivisional firms, a small number of divisions can account for the bulk of patents or sales, which is consistent with the Pareto Principle.⁴ Comparing two firms with similar overall patents or sales, greater inequality across divisions is most likely to occur when a smaller number of divisions account for the bulk of patents or sales within the firm. Thus, greater inequality in sales implies a smaller number of high-performing divisions that the firm can leverage in the late stage, and greater inequality in patents implies a larger number of low-performing divisions that the firm needs to prop up in the early stage.⁵

We first discuss early-stage knowledge sourcing at the firm level. Recall that for the firm to remain active in a particular market, the relevant division must maintain a minimum level of specialized knowledge. If we compare two firms with the same aggregate innovation performance, the one with greater inequality in innovation performance across its divisions tends to have a larger number of divisions with low innovation performance, *ceteris paribus*. In the example mentioned in the introduction, Schering has greater inequality in patents across its divisions than Novo Nordisk. And

⁴The Pareto Principle (Pareto, 1964)—80% of the wealth is concentrated with 20% of the population—applies to a wide range of organizational and social phenomena. For example, 20% of the products generate 80% of sales across several industries (Brynjolfsson, Hu, & Simester, 2011).

⁵We acknowledge that different distributions can lead to different predictions, but the broader point remains that the distribution of performance across divisions matters for firm-level knowledge sourcing.

indeed, there are several more divisions with relatively few patents in Schering than in Novo Nordisk. Using external knowledge, Schering will have to prop up a larger number of divisions, and therefore source more early-stage knowledge at the firm level than Novo Nordisk. Thus, we hypothesize:

Hypothesis 3 (H3) *Multidivisional firms with greater inequality in innovation performance across divisions source more early-stage knowledge at the firm level.*

With respect to late-stage knowledge sourcing, there is relatively less market uncertainty. As discussed in Hypothesis 2, the firm will source more late-stage knowledge for divisions with high sales performance. However, for any division, there are diminishing returns from each additional knowledge-sourcing alliance (Rothaermel, 2001; Sampson, 2005; Schweizer, 2005). As the number of alliances of a division increases, the marginal cost of adding an alliance can increase due to coordination costs (Grigoriou & Rothaermel, 2017) or managerial costs (Leiponen & Helfat, 2010), while the marginal benefit can decrease due to the diminishing supply of low-hanging fruit. Thus, high-sales divisions have a lower marginal propensity to source knowledge, similar to the logic in the context of wealth and consumption that the rich have a lower marginal propensity to consume (Carroll, Slacalek, Tokuoka, & White, 2017; Khan, 1987).

Therefore, as inequality in sales performance across divisions increases, late-stage knowledge sourcing will be concentrated in a few high-sales divisions. Again using the example of Eli Lilly and Novartis mentioned in the introduction, Eli Lilly has greater inequality in sales across its divisions than Novartis. Indeed, we observe only two divisions with very strong sales in Eli Lilly. Since the high-performing divisions have a lower marginal propensity to source more knowledge, the number of additional alliances formed by the high-sales divisions will be less than those forgone by the low-sales divisions. The net effect is that Eli Lilly has less late-stage knowledge sourcing at the firm level than Novartis. Thus, we hypothesize:

Hypothesis 4 (H4) *Multidivisional firms with greater inequality in sales performance across divisions source less late-stage knowledge at the firm level.*

2.5 | Role of the centralized coordination function

We have assumed that the firm's incentive to retain a division's specialized knowledge and remain active in the relevant market outweighs the divisions' competitive incentives to garner more resources from the corporate center (Birkinshaw, 2001; Hill, Hitt, & Hoskisson, 1992; Song, Lee, & Khanna, 2016; Tsai, 2002). However, this assumption may not hold in all multidivisional firms. In a firm where the corporate center does not actively coordinate the divisions' knowledge-sourcing activities, high-performing divisions will likely overshadow the low-performing ones in sourcing both early-stage and late-stage knowledge.

An indication of the firm's ability to coordinate across divisions is the presence of a centralized coordination function at the corporate level. The premise here is that the firm's choices regarding knowledge sourcing can differ from those of individual divisions because the former seeks to optimize opportunities across divisions, while the latter focuses only on its own perspective. Related to this study, prior research highlights the role of the centralized function in coordinating the formation and management of knowledge-sourcing transactions and sharing the learning thereof (Dyer et al., 2001; Kale et al., 2002; Lavie & Singh, 2012; Rothaermel & Deeds, 2006). Firms that institutionalize such a mechanism are likely to use it as an instrument to actively influence knowledge sourcing. A manager at a large pharmaceutical company said the following about the corporate center's role:

“You [divisions] really are fighting for resources. And they [managers in the corporate center] realize that and are trying to rebalance it.”

A manager in the alliance management function of another pharmaceutical company remarked:

“We allocate the money across therapeutic areas according to the strategic priority, that is, which area is the future. If cardiovascular is the priority but is weak right now, we may allocate more resources for them to secure external technologies.”

These quotes resonate with the idea that some degree of centralization significantly affects the firm's innovation activities (Argyres & Silverman, 2004). In the context of knowledge sourcing, the existence of a centralized coordination function in firms is consistent with our assumption that the corporate center can scan external opportunities across the board and allocate resources accordingly. For example, in 2001, the Japanese pharmaceutical company Takeda established a Corporate Product Planning Committee presided over by its CEO. This committee enabled Takeda “to realize even more appropriate resource allocation and rapid R&D processes by improving the speed and strategic focus of decision-making through comprehensive evaluation of each project on the basis of compound novelty, market needs, investment risk, profitability, and other factors” (Takeda Annual Report, 2002, p. 12). The arguments leading to our earlier hypotheses would hold if there exists a centralized coordination function for managing knowledge sourcing in the firm. Thus, we hypothesize:

Hypothesis 5 (H5) *The predicted patterns of Hypotheses 1–4 will be stronger for multi-divisional firms with a centralized coordination function than for those without.*

3 | METHODS

3.1 | Context, sample, and data

The pharmaceutical industry is a pertinent context to test our hypotheses for two reasons. First, knowledge sourcing is critical for large pharmaceutical firms, most of which are multidivisional. Second, the knowledge sourced is often specialized to a therapeutic area (our proxy for a division). Our sample includes the global top 50 pharmaceutical firms in 1999–2004 per *Pharmaceutical Executive*, an annual industry publication. Except for a few generic drug makers (e.g., King and Teva), these large pharmaceutical firms are actively engaged in the discovery and development of new drugs.⁶ Our data do not constitute a balanced panel due to frequent mergers and acquisitions (M&As) among pharmaceutical companies. In case of an acquisition or a merger, we assigned the acquiring firm's name to the acquired firm (after an acquisition) or the surviving legal entity's name to both firms (after a merger).

We obtained data on the knowledge-sourcing alliances of large pharmaceutical firms from *Recombinant Capital*, a database used extensively in academic research (Schilling, 2009), and supplemented these data with records from *SDC Platinum*. We focused on alliances in which the flow of knowledge was from the small firm to the large firm, thereby removing ambiguity about the direction of knowledge flow when two large firms collaborate.⁷ Furthermore, to exclude sporadic observations,

⁶Removing these generic drug makers from the sample does not qualitatively change the results.

⁷In this study, a knowledge-sourcing alliance covers a broad range of governance mechanisms, including co-development, minority equity stakes, and licensing. Parsing alliances into different types and theorizing about each of them separately would be an avenue for further research.

we focused on alliances valued at more than \$1 million. Our final sample comprises 2,239 alliances in which our focal firms sourced specific technologies from small firms. We randomly selected and validated 10% of the records using *Factiva* newswires.

The unit of analysis is a division–firm–year for Hypotheses 1 and 2, and a firm–year for Hypotheses 3 and 4. We used therapeutic areas as a proxy for divisions. Admittedly, business divisions do not always overlap with actual therapeutic areas in large pharmaceutical firms; administrative lines in these firms can be complicated, especially after M&As. Moreover, the actual organizational structures vary widely across firms and across time. However, using therapeutic areas as a proxy for divisions served our analytical purpose well. First, the knowledge sourced is often specific to a therapeutic area. Second, therapeutic areas are subject to resource allocation by the corporate center. In our interviews, managers often used therapeutic areas as the frame of reference when discussing resource allocation inside firms. We also found support for the use of therapeutic areas as a proxy for divisions in strategy research (Nerkar & Roberts, 2004). We defined therapeutic areas based on 17 areas identified in the *PharmaProjects* database, which tracks R&D pipelines in the industry. Collectively, the firms in our sample exhibited high variation in the number and types of therapeutic areas.

We measured a division's innovation performance by its patents, given the close association between pharmaceutical R&D and patenting (Cohen, Nelson, & Walsh, 2000; Henderson & Cockburn, 1996; Levin, Klevorick, Nelson, & Winter, 1987). We extracted all pharmaceutical patents⁸ filed with the US Patent and Trademark Office (USPTO) between 1997 and 2004 and granted between 1999 and 2006 (with a 2-year lag), and matched the patent assignees to the top 50 firms. In some cases, the USPTO assigned patents to a firm's branches or subsidiaries. We used *CorporateAffiliations* by LexisNexis to consolidate a subsidiary's patents into the parent firm. In all, the top 50 firms were granted 8,148 pharmaceutical patents during the sample period. We linked these patents to therapeutic areas using pipeline data from *PharmaProjects*. For patents that did not show up in the pipelines, we constructed a probability table between patent classes/subclasses and therapeutic areas, and used it to create the patent portfolios of divisions.

To measure a division's sales performance, we collected data from *Med Ad News* on the annual sales of the top-selling drugs. With sales ranging from \$0.38 billion to \$11 billion in 2004, these drugs represented a large fraction of industry sales.⁹ We matched a drug's name to its corresponding record in the *PharmaProjects* database to classify each drug into a therapeutic area. For a drug co-developed by two firms, we split its annual sales between the firms.

Finally, we used *Compustat* for firm-level financial metrics such as assets, profits, and R&D expenditures. Since the firms are listed in different countries, we standardized the financial data to US dollars using the average exchange rates of the respective currencies in the focal year.

We also interviewed managers and scientists in 8 large pharmaceutical companies. From a mixed methods perspective, the objective of using both the quantitative and qualitative approaches was to seek complementarity (Greene, Caracelli, & Graham, 1989; Molina-Azorín, 2007, 2012). To preserve confidentiality, we cannot reveal the names of the companies or of the interviewees. Collectively, our interviewees represented different functions and seniority levels including directors of business development, R&D managers, a director of alliance management, a vice president of geographical operations, an intellectual property lawyer, and junior and senior scientists. The interviews were

⁸Our definition of pharmaceutical patents follows the categorization in Hall, Jaffe, and Trajtenberg (2001), wherein a "drug" patent is one for which the first 12 primary classes include 514.

⁹While data from 2001 onward were available for the top 200 drugs, data for 1999 and 2000 were available for the top 50 drugs only, which created noise for our drug-sales-based measure in the earlier years.

semi-structured with a few pre-determined questions. Conducted over phone, most interviews lasted between 30 and 60 minutes. Some of the topics discussed included the importance of external knowledge sourcing, the role of the corporate center, and how firms determine strategic priorities and allocate resources amidst market uncertainty.

3.2 | Variables

3.2.1 | Hypotheses 1 and 2: Division-level knowledge sourcing

Dependent variables

The dependent variables for Hypotheses 1 and 2 are the *number of early-stage alliances* and *number of late-stage alliances*, respectively, at the division level. Early-stage alliances involve knowledge sourcing in the discovery, pre-clinical, and formulation stages, while late-stage alliances involve knowledge sourcing during and after clinical trials. This categorization is consistent with prior research (Arora et al., 2009; Rothaermel & Deeds, 2004; Zhang, Baden-Fuller, & Mangematin, 2007) and industry norms (Ohlsson, 2007).

The authors and a doctoral student in pharmacy independently mapped the alliances to their stages and primary therapeutic areas using the *Recombinant* and *Factiva* data. The *Recombinant* data clearly stated the stage of the sourced knowledge for 75% of alliances in the sample. For example, an alliance in 2001 between GlaxoSmithKline and BioFocus on asthma was categorized as “Discovery,” which we labeled as early-stage. Similarly, an alliance in 2002 between Pfizer and Neurocrine Biosciences for the treatment of insomnia was categorized as “Phase III,” which we labeled as late-stage (see Table A.1 in the online appendix for representative examples). For the remaining alliances, we used *Factiva* newswires to determine their respective stages. Alliances with ambiguous information were mostly in general-purpose technologies such as bioinformatics, diagnostics, and gene sequencing and were not included in the sample.

With regard to mapping an alliance to a therapeutic area, some alliances were simple to map based on the descriptions. For example, an alliance between Amgen and Tularik in 2003 on “Oncology target collaboration” was classified under oncology. For an alliance with limited information, we used the detailed description in *Factiva* to map the alliance to a therapeutic area. The inter-rater reliability to code the alliance stage and therapeutic area was 93% and 83%, respectively, well above the recommended norm of 70% (Cohen, Cohen, West, & Aiken, 2003).

Independent variables

We developed a binary classification of strong and weak divisions based on their innovation and sales performance. We defined a *strong division (per patents)* as a division whose patents were greater than the mean number of patents in the firm–year. Similarly, we defined a *strong division (per sales)* as a division whose sales were greater than the mean in the firm–year. To overcome idiosyncrasies in a particular year's numbers, we used the 3-year moving average of patents and sales. We chose binary variables because strong and weak divisions serve very different strategic objectives for the firm, so their impact on knowledge-sourcing decisions is not linear. Furthermore, our interviews suggested that managers had a clear sense of strong divisions in their respective companies: oncology in Novartis, cardiovascular in Pfizer, and endocrinology in Eli Lilly. In contrast, they often referred to weak divisions as “others.” For a robustness check, we also used the continuous 3-year moving averages of patents and sales at the division level.

Control variables

We included several control variables at the division, firm, and therapeutic-area levels. At the division level, we controlled for a division's *prior alliances*. Since experience gained via prior alliances facilitates future alliances (Gulati, 1999), we extended the sample period back to 1995 to construct a 3-year moving average of prior alliances. Including prior alliances also controls for unobserved division-level characteristics that may affect the tendency to source external knowledge.

We controlled for the possibility that a division expecting a declining product pipeline is more desperate to source external knowledge (Higgins & Rodriguez, 2006). Using data from *PharmaProjects* and US Food and Drug Administration (FDA), we tracked each drug's data exclusivity period and patent expiration date, and then calculated its expected future sales by multiplying its average annual sales in the past 3 years with the remaining years of exclusivity. A division's *drop in expected sales* is defined as the negative of the change in the aggregated expected future sales across all drugs in the division. For example, if a division's expected future sales were \$1.2 billion in 2001 and \$1 billion in 2002, then the drop in expected sales was \$0.2 billion. We used logarithmic values of the variable due to its skewed distribution.

We also used data from *PharmaProjects* to control for the *number of early-stage projects* and *number of late-stage projects* of each division in estimating the number of early-stage alliances and late-stage alliances, respectively. Doing so accounts for the possibility that a division's internal pipeline may substitute or complement externally-sourced knowledge (Cassiman & Veugelers, 2006). Whether an internal project was in the early or late stage in a focal year was determined by the milestones before and after that year. In case a clear termination event for a project was not identified in the dataset, we used 3 years after the last recorded event as the cutoff to define the termination year.

At the firm level, we used the logarithmic values of *firm patents* and *firm sales* to control for firm size. Furthermore, since most knowledge-sourcing alliances are investments in future technologies, we controlled for *firm R&D intensity*, i.e., R&D expenditure divided by sales. We also used *firm return on assets* to control for financial performance. We removed three firms—Boehringer Ingelheim, Otsuka Pharmaceutical, and Purdue Pharma—because their financial data were not publicly available.

At the therapeutic-area level, we used three variables to control for intrinsic differences across areas. First, we controlled for *therapeutic area sales* by including logarithmic values of total drug sales for all sample firms at the therapeutic-area-year level. This variable accounts for the current state of the market for a particular therapeutic area. Second, we controlled for *therapeutic area newness* by calculating the average citation lags of patents in the therapeutic area. In an area with emerging technologies, patents tend to cite more recent prior arts. That is, the time gap between citing and cited patents is smaller. Including this variable alleviates the concern that divisions with low innovation performance may form more early-stage alliances because they are in newer therapeutic areas. Third, we used data from *PharmaProjects* to control for overall *therapeutic area market size*. In an area with large market potential, firms should have a stronger incentive to fill their pipelines, especially with late-stage drug candidates. Since the distribution of market size is highly skewed, we used logarithmic values for this variable.

We used random effects at the division–firm level and clustered standard errors at the division–firm–year level to allow for serial correlation. Using random effects has limitations because one cannot precisely identify every factor that influences the dependent variable at the division–firm level. However, we chose this approach because the number of panels (at the division–firm level) is much larger than the number of years per panel. In such cases, a fixed-effects estimator is inconsistent, while a random-effects estimator is not (Hsiao, 1986). Given a data structure similar to ours, the

random effects approach has been used in other strategy papers as well (Barnett & Salomon, 2006; Leiblein & Madsen, 2009; Yin & Zajac, 2004).

Finally, to control for unobserved heterogeneity across firms, we included dummy variables for firms. We also included dummy variables for years to capture factors that similarly influence all firms in a year. To mitigate concerns of simultaneity, we lagged the independent and control variables by 1 year.

3.2.2 | Hypotheses 3 and 4: Firm-level knowledge sourcing

Dependent variables

To examine differences in knowledge-sourcing strategies across firms, we aggregated the number of early-stage and late-stage alliances to the firm level.

Independent variables

To measure inequality in performance across divisions within a firm, we used the Gini coefficient, a measure commonly used to calculate inequality (Bos et al., 2017; Harrison & Klein, 2007; Little, 2004). A value of 0 denotes complete equality across divisions, while a value of 1 denotes complete inequality across divisions. We calculated the *Gini coefficient (per patents)* to measure inequality in innovation performance across divisions (to test Hypothesis 3) and the *Gini coefficient (per sales)* to measure inequality in sales performance across divisions (to test Hypothesis 4).

Control variables

We calculated firm-level values of several control variables in the division-level specifications and included them in the firm-level specifications. We also included year dummies and clustered standard errors at the firm-year level to account for serial correlation. Similar to the division-level specification, we lagged the independent and control variables by 1 year to mitigate concerns of simultaneity.

3.2.3 | Hypothesis 5: Effect of centralized coordination function on knowledge sourcing

In Hypothesis 5, we theorized about the effect of a *centralized coordination function* on sourcing external knowledge at the division and firm levels. We argued that the presence of a coordination function may indicate active coordination by the corporate center in a multidivisional firm. To construct the variable for a *centralized coordination function*, we searched for words such as “alliance,” “licensing,” “business development,” and “office” in the annual reports and 10K statements of our sample firms. Based on descriptions in these documents, we generated a binary variable for whether a firm had a dedicated function for knowledge sourcing (see Table A.2 in the appendix for more details). The coding was cross-verified between two coders, including one of the authors. The inter-rater reliability was 89%, again above the recommended 70% level (Cohen et al., 2003). We then tested Hypotheses 1–4 by dividing the sample into firms with and without a *centralized coordination function*. We adopted this approach, instead of treating *centralized coordination function* as a moderating variable, because insufficient within-firm temporal variation in this variable meant that its effect was largely absorbed by the firm dummies. Our use of sub-samples is also consistent with prior research (Dewan & Kraemer, 2000; Miller & Yang, 2016; Nickerson & Silverman, 2003).

3.3 | Empirical model

Since the dependent variables at both the division and firm levels are non-negative integers, the specifications belong to the class of count models. One option is to use the negative binomial (NB) model since it does not necessitate the (conditional) mean–variance equality. But the conditional fixed-effects

NB model (Hausman, Hall, & Griliches, 1984) does not condition out the fixed effects (Allison & Waterman, 2002). Thus, for our data, a panel comprising relatively few years of observations, the NB model may have an incidental parameter problem (Lancaster, 2000; Neyman & Scott, 1948), which the Poisson model does not have (Greene, 2005). We therefore used the Poisson model.

4 | RESULTS

Table 1 provides the descriptive statistics and correlation matrix of the variables used in the division-level specifications. We highlight several observations related to our research questions. First, divisions vary significantly in their propensity to form alliances. The standard deviations of early-stage alliances and late-stage alliances are more than two and three times their corresponding mean values, respectively. Such variance also persists over time. Both early- and late-stage alliances of a division positively correlate with its prior alliances, confirming results of prior research that the propensity to form alliances increases with experience (Gulati, 1999). Second, within a firm, the binary variable for a *strong division (per patents)* is negatively correlated with early-stage alliances, while the binary variable for a *strong division (per sales)* is positively correlated with late-stage alliances. These results are consistent with the hypothesized relationships. Finally, the characteristics of the therapeutic areas matter. Therapeutic area newness is positively correlated with early-stage alliances, which is expected in an emerging area. Therapeutic area market size is positively correlated with late-stage alliances, suggesting that larger markets offer more opportunities for downstream collaborations.

4.1 | Main results

4.1.1 | Hypotheses 1 and 2: Division-level knowledge sourcing

At the division level, we have two hypotheses: multidivisional firms source more early-stage knowledge for divisions with low innovation performance (Hypothesis 1), and they source more late-stage knowledge for divisions with high sales performance (Hypothesis 2). Table 2 presents results for the relationship between a division's innovation (sales) performance and the number of early-stage (late-stage) alliances. Accordingly, there are two dependent variables: the number of early-stage alliances (Models 1–4) and the number of late-stage alliances (Models 5–8). Within each set of models, the first two columns present results for the full sample, while the next two columns split the full sample into firms with and without a centralized coordination function (to test Hypothesis 5). We discuss results for Hypothesis 5 in a later subsection.

Models 1 and 2 present results for early-stage alliances for the full sample. Model 1 includes only the control variables. Model 2 includes *strong division (per patents)*, the binary measure of a division's innovation performance. The coefficient estimate is negative ($-0.449; p = 0.003$), thereby supporting Hypothesis 1. All else equal, firms form 56% more early-stage alliances for divisions with weak innovation performance than the strong ones.

Models 5 and 6 present results for late-stage alliances for the full sample. Model 5 includes only the control variables. Model 6 includes *strong division (per sales)*, the binary measure of a division's sales performance. The coefficient estimate is positive ($0.547; p = 0.011$), thus supporting Hypothesis 2. All else equal, firms form 73% more late-stage alliances for divisions with strong sales performance.

We turn to the results for the control variables in Table 2. With regard to division-level variables in the full sample, we find evidence that past experience leads to more alliances for early-stage alliances (Models 1 and 2) but not for late-stage alliances (Models 5 and 6). In Model 2 for early-stage alliances, a *drop in expected sales* is negative ($-0.150; p = 0.015$), suggesting that divisions expecting a large drop in sales have less inclination for early-stage knowledge. The coefficient estimate for

TABLE 1 Descriptive statistics and correlation matrix for knowledge sourcing at the division level

S. No.	Variables	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Early-stage alliances	0.382	0.924	0	8	1																		
2	Late-stage alliances	0.110	0.398	0	4	0.120	1																	
3	Dummy: Strong division (per patents)	0.622	0.485	0	1	-0.199	0.071	1																
4	Continuous: Strong division (per patents)	2.870	1.065	0	4.980	0.056	0.115	0.414	1															
5	Dummy: Strong division (per sales)	0.146	0.353	0	1	0.006	0.156	0.175	0.249	1														
6	Continuous: Strong division (per sales)	1.258	2.625	0	9.475	0.019	0.155	0.211	0.353	0.892	1													
7	Prior alliances	0.567	1.072	0	9.667	0.611	0.223	-0.185	0.086	0.074	0.077	1												
8	Drop in expected sales	9.682	0.240	0.405	10.405	-0.015	0.025	-0.008	0.008	0.048	0.060	0.016	1											
9	Early-stage projects	0.011	0.103	0	1	0.005	0.046	0.061	0.044	0.027	0.042	0.017	0.033	1										
10	Late-stage projects	0.392	0.968	0	10	0.201	0.136	0.142	0.213	0.173	0.198	0.261	-0.060	0.194	1									
11	Firm sales	6.551	3.408	0	10.516	0.196	0.095	0.009	0.554	0.244	0.314	0.216	0.003	0.017	0.124	1								
12	Firm patents	5.482	1.332	0	7.442	0.175	0.071	0.065	0.812	0.118	0.194	0.197	0.010	0.024	0.143	0.514	1							
13	Firm return on assets	0.088	0.068	-0.094	0.233	0.148	0.002	0.012	0.298	0.090	0.141	0.084	0.012	0.019	0.072	0.420	0.262	1						
14	Firm R&D intensity	0.144	0.089	0	0.744	0.043	0.032	0.001	0.064	0.001	0.009	0.068	-0.002	-0.025	0.020	0.193	0.076	-0.012	1					
15	Centralized coordination function	0.475	0.500	0	1	0.036	0.037	-0.027	-0.045	-0.013	0.005	0.042	-0.007	0.000	-0.042	0.007	-0.022	0.038	0.038	1				
16	Therapeutic area sales	6.980	3.874	0	10.680	-0.238	0.019	0.379	0.168	0.288	0.335	-0.274	0.055	-0.015	-0.062	0.035	-0.033	-0.038	-0.004	-0.008	1			
17	Therapeutic area newness	-9.174	1.938	-15.812	-5.244	0.195	0.062	0.005	-0.038	0.048	0.043	0.251	-0.011	-0.007	0.081	0.047	-0.019	-0.026	0.008	0.031	0.043	1		
18	Therapeutic area size	0.924	0.643	-0.539	1.701	-0.034	0.130	0.456	0.191	0.697	0.120	0.039	-0.009	0.058	0.253	-0.027	-0.047	-0.007	-0.022	0.002	0.135	0.196	1	
19	Year	2001	1.056	2000	2003	0.020	0.023	0.015	-0.014	0.114	0.150	0.081	0.026	0.029	-0.010	0.264	-0.091	-0.131	0.069	-0.039	0.168	0.023	0.049	1

Notes. N = 1,952; Variables 1–10 are at the division level; Variables 11–15 are at the firm level; Variables 16–18 are at the therapeutic area level; Variables 3–18 are lagged by 1 year; Variables 3–7 are based on 3-year moving averages; Variables 4, 6, 8, 11, 12, 16, and 18 are expressed in natural logarithms; Variables 3, 5, and 15 are binary.

TABLE 2 Knowledge sourcing at the division level

Dependent variable: Number of alliances	Early stage				Late stage			
	1	2	3	4	5	6	7	8
	Full sample		Firms with CCF	Firms with no CCF	Full sample		Firms with CCF	Firms with no CCF
<i>Division-level variables</i>								
Dummy: Strong division (per patents)		-0.449 (0.003)	-0.469 (0.002)	-0.192 (0.243)				
Dummy: Strong division (per sales)						0.547 (0.011)	0.558 (0.058)	0.652 (0.107)
Prior alliances	0.263 (0.005)	0.248 (0.010)	0.292 (0.000)	0.341 (0.000)	0.163 (0.154)	0.164 (0.140)	0.228 (0.030)	0.282 (0.093)
Drop in expected sales	-0.135 (0.026)	-0.150 (0.015)	-0.063 (0.131)	-0.551 (0.004)	0.884 (0.279)	0.556 (0.339)	0.289 (0.860)	0.877 (0.114)
Early-stage projects	-0.051 (0.910)	-0.037 (0.932)	-1.284 (0.212)	-0.011 (0.974)				
Late-stage projects					0.154 (0.014)	0.121 (0.044)	0.041 (0.622)	0.155 (0.020)
<i>Firm-level variables</i>								
Firm sales	0.108 (0.045)	0.102 (0.056)	0.032 (0.738)	0.154 (0.252)	0.320 (0.067)	0.301 (0.065)	0.552 (0.172)	-0.222 (0.400)
Firm patents	-0.138 (0.227)	-0.140 (0.229)	-0.016 (0.957)	-0.392 (0.055)	-0.061 (0.739)	-0.054 (0.767)	-0.242 (0.645)	-0.101 (0.660)
Firm return on assets	2.390 (0.060)	2.378 (0.056)	6.305 (0.086)	2.900 (0.043)	1.252 (0.534)	1.306 (0.515)	0.121 (0.981)	1.849 (0.479)
Firm R&D intensity	0.206 (0.843)	0.229 (0.821)	3.632 (0.264)	-0.788 (0.457)	1.842 (0.334)	1.977 (0.297)	-12.661 (0.006)	5.995 (0.014)
Centralized coordination function	0.100 (0.508)	0.086 (0.562)			0.338 (0.147)	0.357 (0.124)		
<i>Therapeutic-area-level variables</i>								
Therapeutic area sales	-0.062 (0.000)	-0.042 (0.003)	-0.039 (0.031)	-0.040 (0.015)	0.061 (0.012)	0.036 (0.180)	0.066 (0.054)	0.022 (0.597)
Therapeutic area newness	0.134 (0.001)	0.116 (0.002)	0.099 (0.023)	0.127 (0.024)	0.069 (0.211)	0.062 (0.249)	-0.000 (0.998)	0.093 (0.222)
Therapeutic area market size	-0.086 (0.216)	0.038 (0.637)	0.094 (0.376)	-0.095 (0.295)	0.832 (0.000)	0.824 (0.000)	0.908 (0.000)	0.602 (0.064)
Constant	0.714 (0.488)	0.735 (0.473)	-1.527 (0.303)	5.098 (0.032)	-14.462 (0.073)	-11.152 (0.057)	-8.834 (0.601)	-10.117 (0.077)
Observations	1,952	1,952	928	1,024	1,952	1,952	928	1,024
Number of firm-divisions	664	664	427	478	664	664	427	478
Log-likelihood	-1,228	-1,222	-605	-587	-561	-558	-292	-239
Chi-square	34,696	31,711	19,143	36,569	48,894	49,703	37,607	85,039
Degrees of freedom	57	58	42	46	57	58	42	46

Notes. CCF stands for ‘Centralized Coordination Function’; All models include year and firm dummies, and firm–division random effects; Robust standard errors clustered at the firm–division level; *p*-values reported in parentheses; All tests are two-tailed.

a division's internal pipeline of *early-stage projects* is negative ($-0.037; p = 0.932$). In contrast, in Model 6 for late-stage alliances, we find a positive relationship (0.121; $p = 0.044$) between a division's internal pipeline of *late-stage projects* and late-stage alliances. The firm-level variables mostly have high p -values, which is not surprising given that the specification includes firm dummies in a sample spanning only a few years. With respect to therapeutic-area-level variables, *therapeutic area sales* has a negative association with early-stage alliances ($-0.042; p = 0.003$; Model 2), and *therapeutic area market size* has a positive association with late-stage alliances (0.824; $p = 0.000$; Model 6). These results suggest that both current and potential market opportunities tend to draw resources to knowledge that can generate immediate benefits. The relation between *therapeutic area newness* and early-stage alliances is positive (0.116; $p = 0.002$; Model 2), presumably because there exist many potential collaborators early-stage technologies. In sum, the results for *strong division (per patents)* and *strong division (per sales)* support Hypotheses 1 and 2 regarding early-stage and late-stage knowledge sourcing, respectively, at the division level.¹⁰

4.1.2 | Hypotheses 3 and 4: Firm-level knowledge sourcing

At the firm level, we have two hypotheses: firms with a more unequal distribution of innovation performance across divisions source more early-stage knowledge in the aggregate (Hypothesis 3), and firms with a more unequal distribution of sales performance across divisions source less late-stage knowledge in the aggregate (Hypothesis 4).

The results in Table 3 based on the full sample confirm Hypothesis 3 but not Hypothesis 4. Recall that we use the Gini coefficient to measure within-firm inequality in innovation and sales performance, based on division-level patents and sales, respectively. Model 1 includes the control variables to estimate the number of early-stage alliances. A firm's sales, return on assets, and R&D intensity have a positive association with early-stage alliances.

In Model 2, the estimate for the *Gini coefficient (per patents)* is positive (1.208; $p = 0.009$). All else equal, firms form 11.4% more early-stage alliances in the aggregate for a one-standard-deviation increase in the patent-based Gini coefficient. Indeed, within-firm inequality in innovation performance explains the example in the introduction: Schering AG formed two times more early-stage alliances than Novo Nordisk in 2002, despite similar firm-level patent outputs. A closer inquiry reveals a difference in the patent-based Gini coefficients between Schering (0.26) and Novo Nordisk (0.18). As inequality in innovation performance across divisions increases, firms form more early-stage alliances overall, primarily for divisions with low innovation performance.

Model 5 includes the control variables for estimating the number of late-stage alliances. Model 6 includes the *Gini coefficient (per sales)*. While the coefficient estimate for this variable is negative (-1.886) as predicted, the p -value is 0.111, which does not support Hypothesis 4. However, the hypothesis is supported for the sub-sample of firms that have a centralized coordination function (see results for Hypothesis 5 next).

4.1.3 | Hypothesis 5: Effect of centralized coordination function on knowledge sourcing

We theorized how the presence of a centralized coordination function in a firm impacts knowledge sourcing. The division-level results in Table 2 are consistent with our predictions in Hypothesis 5. There is a negative relation between *strong division (per patents)* and early-stage alliances ($-0.469; p = 0.002$ in Model 3 for firms with a centralized coordination function and $-0.192; p = 0.243$ in Model 4 for firms without this function). There is a positive relation between *strong*

¹⁰We have used the number of alliances as a proxy for resource allocation within a firm. However, our division-level (and firm-level) results are robust to the smaller subset of alliances that report a value (see Table A.3 in the appendix).

TABLE 3 Knowledge sourcing at the firm level

Dependent variable: Number of alliances	Early stage				Late stage			
	1 Full sample		3 Firms with CCF	4 Firms with no CCF	5 Full sample		7 Firms with CCF	8 Firms with no CCF
	Poisson model							
<i>Firm-level variables</i>								
Gini coefficient (per patents)	1.208 (0.009)	3.006 (0.001)	-2.680 (0.309)					
Gini coefficient (per sales)					-1.886 (0.111)	-5.711 (0.016)	1.621 (0.244)	
Centralized coordination function	0.047 (0.749)	0.006 (0.966)			0.254 (0.348)	0.246 (0.334)		
Number of divisions	0.200 (0.036)	0.175 (0.072)	0.069 (0.504)	0.316 (0.005)	-0.039 (0.729)	-0.050 (0.601)	-0.060 (0.612)	1.662 (0.011)
Prior alliances	-0.003 (0.908)	0.001 (0.969)	0.052 (0.024)	0.001 (0.973)	-0.010 (0.865)	-0.015 (0.804)	-0.011 (0.848)	0.037 (0.492)
Drop in expected sales	0.034 (0.166)	0.023 (0.307)	-0.057 (0.169)	0.050 (0.095)	-0.058 (0.214)	-0.058 (0.207)	-0.004 (0.951)	-0.071 (0.223)
Early-stage projects	-0.020 (0.861)	-0.043 (0.665)	0.142 (0.571)	-0.084 (0.654)				
Late-stage projects					-0.022 (0.582)	-0.026 (0.530)	-0.027 (0.424)	-0.016 (0.676)
Firm sales	0.076 (0.055)	0.066 (0.088)	0.036 (0.279)	0.121 (0.010)	0.408 (0.336)	0.621 (0.169)	0.895 (0.207)	0.581 (0.147)
Firm patents	0.055 (0.718)	0.041 (0.781)	0.120 (0.500)	0.085 (0.671)	0.218 (0.218)	0.256 (0.101)	0.168 (0.562)	-0.256 (0.430)
Firm return on assets	2.619 (0.024)	2.867 (0.014)	5.069 (0.014)	1.516 (0.201)	-0.889 (0.689)	-0.856 (0.664)	-0.319 (0.916)	-0.536 (0.811)
Firm R&D intensity	1.403 (0.017)	1.358 (0.022)	2.465 (0.180)	1.295 (0.026)	0.177 (0.815)	0.279 (0.694)	-0.030 (0.995)	0.354 (0.601)
Constant	-3.087 (0.020)	-2.835 (0.024)	-2.102 (0.148)	-4.858 (0.002)	-3.570 (0.251)	-5.062 (0.136)	-6.492 (0.130)	-31.406 (0.007)
Observations	225	225	94	131	177	177	82	95
Number of firms	58	58	34	50	45	45	31	34
Log-likelihood	-462	-459	-190	-255	-247	-245	-103	-119
Chi-square	21,020	22,086	6,289	8,182	14,409	15,166	12,985	6,353
Degrees of freedom	14	15	14	14	14	15	14	14

Notes. CCF stands for 'Centralized Coordination Function'; All models include year dummies; Robust standard errors clustered at the firm level; *p*-values reported in parentheses; All tests are two-tailed.

division (per sales) and late-stage alliances (0.558; *p* = 0.058 in Model 7 for firms with a centralized coordination function and 0.652; *p* = 0.107 in Model 8 for firms without such a function). With similar sample sizes for firms with and without the centralized coordination function, the notable differences in the *p*-values indicate that our hypothesized patterns manifest themselves when coordination by the corporate center plays a decisive role.

The firm-level results in Table 3 also support Hypothesis 5. The *Gini coefficient (per patents)* has a positive relation with early-stage alliances for firms with a centralized function (3.006; *p* = 0.001;

Model 3) but not for firms without such a function ($-2.680; p = 0.309$; Model 4). With respect to late-stage alliances, the *Gini coefficient (per sales)* is negative for firms with a centralized coordination function ($-5.711; p = 0.016$; Model 7) but not for firms without such a function ($1.621; p = 0.244$; Model 8). The coefficients are also statistically different across the two subsamples based on seemingly unrelated estimation.¹¹

All else equal, firms with a centralized function form 64% fewer late-stage alliances overall for a one-standard-deviation increase in the sales-based Gini coefficient. In the introduction, we noted that Novartis formed more late-stage alliances than Eli Lilly in 2002. We can now explain this observation by the fact that Eli Lilly had a sales-based Gini coefficient of 0.48, compared with 0.32 for Novartis.¹² Thus, as inequality in sales performance across divisions increases, firms form fewer late-stage alliances overall, mainly by concentrating them in the few high-sales divisions that also have a lower marginal propensity to form alliances.

The results for Hypothesis 5 also help to address alternative explanations. Sure enough, middle managers can use influence tactics (Meyer et al., 1992; Scharfstein & Stein, 2000) and their entrenched interests can create distortions (Shleifer & Vishny, 1989). Further, power dynamics among divisions can also influence resource allocation (Pfeffer & Salancik, 1974). Finally, scientists may develop a not-invented-here (NIH) bias (Katz & Allen, 1982). All these considerations can influence knowledge sourcing at the division level. However, if agency, NIH, and power-based explanations were swaying the observed patterns, then we should expect a stronger effect of internal heterogeneity in firms without the centralized coordination function—the opposite of what we find. Thus, while these alternative explanations are relevant, they cannot fully explain the results in this study.

Another noteworthy result is that in firms without a centralized coordination function, the coefficient estimate for the number of divisions in a firm is positively related to both early-stage alliances ($0.316; p = 0.005$; Model 4) and late-stage alliances ($1.662; p = 0.011$; Model 8). That is, in firms with no active coordination by the corporate center, more divisions translate into more alliances at the firm level, most likely due to the competition for resources among the divisions (Birkinshaw, 2001; Hill et al., 1992; Song et al., 2016; Tsai, 2002). Put differently, active coordination of knowledge sourcing by the corporate center can blunt the competitive incentive of divisions.

4.2 | Robustness tests

We conducted several robustness tests for the results in Tables 2 and 3.

4.2.1 | Continuous variables for performance of divisions

We re-estimated the specifications by using continuous rather than binary variables for a division's innovation and sales performance. The results presented in Table 4 are consistent with those using the binary measures in Table 2. For early-stage alliances, the coefficient estimate for a division's patents is negative ($-0.596; p = 0.004$) for the full sample (Model 1). The results for firms with and without a centralized coordination function in Models 2 and 3, respectively, are similar to those in Table 2. Similarly, for late-stage alliances, the coefficient estimate for a division's sales is positive ($0.079; p = 0.016$) for the full sample (Model 4). Furthermore, this coefficient estimate is positive for firms with and without a centralized coordination function (0.093 in both Models 5 and 6, respectively). However, the *p*-value is smaller in Model 5 ($p = 0.039$) than in Model 6 ($p = 0.115$).

¹¹Here we used the *suest* command in Stata.

¹²Both companies had centralized coordination functions around that time: Strategic Planning and Business Development in Novartis and Office of Alliance Management in Eli Lilly (Source: Company Annual Reports).

TABLE 4 Knowledge sourcing at the division level using continuous measures for performance

Dependent variable: Number of alliances	Early stage			Late stage		
	1 Full sample	2 Firms with CCF	3 Firms with no CCF	4 Full sample	5 Firms with CCF	6 Firms with no CCF
Poisson model						
<i>Division-level variables</i>						
Continuous: Strong division (per patents)	-0.596 (0.004)	-0.647 (0.001)	-0.204 (0.289)			
Continuous: Strong division (per sales)				0.079 (0.016)	0.093 (0.039)	0.093 (0.115)
Prior alliances	0.201 (0.087)	0.248 (0.001)	0.330 (0.000)	0.169 (0.133)	0.238 (0.026)	0.272 (0.064)
Drop in expected sales	-0.154 (0.013)	-0.075 (0.105)	-0.545 (0.005)	0.561 (0.340)	0.164 (0.874)	0.869 (0.122)
Early-stage projects	-0.091 (0.820)	-1.253 (0.230)	-0.059 (0.862)			
Late-stage projects				0.118 (0.051)	0.031 (0.721)	0.152 (0.018)
<i>Firm-level variables</i>						
Firm sales	0.099 (0.068)	0.034 (0.721)	0.153 (0.252)	0.310 (0.059)	0.562 (0.164)	-0.203 (0.427)
Firm patents	-0.066 (0.595)	0.226 (0.441)	-0.356 (0.072)	-0.050 (0.780)	-0.234 (0.653)	-0.108 (0.634)
Firm return on assets	2.052 (0.088)	6.331 (0.078)	2.938 (0.040)	1.234 (0.539)	0.016 (0.997)	1.677 (0.525)
Firm R&D intensity	0.312 (0.746)	3.347 (0.258)	-0.689 (0.506)	1.830 (0.341)	-12.917 (0.005)	5.748 (0.016)
Centralized coordination function	0.102 (0.467)			0.351 (0.135)		
<i>Therapeutic-area-level variables</i>						
Therapeutic area sales	-0.035 (0.012)	-0.029 (0.094)	-0.038 (0.025)	0.032 (0.242)	0.059 (0.092)	0.015 (0.734)
Therapeutic area newness	0.110 (0.002)	0.089 (0.029)	0.127 (0.025)	0.061 (0.251)	-0.001 (0.990)	0.095 (0.198)
Therapeutic area market size	0.148 (0.171)	0.219 (0.073)	-0.071 (0.488)	0.804 (0.000)	0.879 (0.000)	0.593 (0.048)
Constant	1.055 (0.311)	-1.970 (0.176)	5.124 (0.031)	-11.228 (0.057)	-7.602 (0.495)	-10.056 (0.086)
Observations	1,952	928	1,024	1,952	928	1,024
Number of firm-divisions	664	427	478	664	427	478
Log-likelihood	-1,216	-600.3	-586	-558	-291	-239
Chi-square	39,823	15,165	39,353	50,659	40,035	79,567
Degrees of freedom	58	42	46	58	42	46

Notes. CCF stands for ‘Centralized Coordination Function’; All models include year and firm dummies, and firm–division random effects; Robust standard errors clustered at the firm–division level; *p*-values reported in parentheses; All tests are two-tailed.

4.2.2 | Include measures of both innovation and sales performance

We included measures for both a division's innovation and sales performance in the same specification to estimate the number of early-stage alliances and late-stage alliances at the division level. In Table 5, the binary variable for *strong division (per patents)* is negative for early-stage alliances (-0.467 ; $p = 0.002$; Model 1) and positive for late-stage alliances (0.570 ; $p = 0.017$; Model 3). The binary variable for *strong division (per sales)* is positive for both early-stage alliances (0.310 ; $p = 0.018$; Model 1) and late-stage alliances (0.516 ; $p = 0.016$; Model 3). The results using the continuous variable for a division's innovation performance in Model 2 (for early-stage alliances) and Model 4 (for late-stage alliances) are consistent with those using the binary variable. Similarly, we included both the patent-based and sales-based Gini coefficients in specifications for early-stage and late-stage alliances at the firm level. The results, presented in Table 6, are consistent with those in Table 3 for early-stage alliances (Models 1–3) but not for late-stage alliances (Models 4–6).

4.2.3 | Alternative termination year for internal projects

In the results presented above, we defined the termination year for a project using a 3-year cutoff after the last recorded event (unless the last event is a successful launch). We used an alternative cutoff of 5 years and re-estimated all the specifications. These results, presented in the appendix, are similar to those in Tables 2–6.

4.2.4 | Zero-inflated models

We used the zero-inflated Poisson (ZIP) model, given the preponderance of zeroes in the value of the dependent variables. The results (see appendix) are broadly consistent with our main results for both early- and late-stage alliances. The only exception in the ZIP model is that the *p*-values for *Gini coefficient (per patents)* in predicting firm-level early-stage alliances are higher. But the positive coefficients for the subsample of firms with a centralized coordination function still support the idea that in

TABLE 5 Knowledge sourcing at the division level (both patent- and sales-based measures of performance)

Dependent variable: Number of alliances Poisson model	Early stage		Late stage	
	1	2	3	4
<i>Division-level variables</i>				
Dummy: Strong division (per patents)	−0.467 (0.002)		0.570 (0.017)	
Dummy: Strong division (per sales)	0.310 (0.018)		0.516 (0.016)	
Continuous: Strong division (per patents)		−0.658 (0.001)		0.865 (0.011)
Continuous: Strong division (per sales)		0.067 (0.000)		0.065 (0.046)
Observations	1,952	1,952	1,952	1,952
Number of firm–divisions	664	664	664	664
Log-likelihood	−1,220	−1,211	−555	−552
Chi-square	31,398	33,078	3.698e + 06	54,651
Degrees of freedom	59	59	59	59

Notes. Results for the control variables not reported; All models include year and firm dummies, and firm–division random effects; Robust standard errors clustered at the firm–division level; *p*-values reported in parentheses; All tests are two-tailed.

TABLE 6 Knowledge sourcing at the firm level (both patent- and sales-based Gini coefficients)

Dependent variable: Number of alliances	Early stage			Late stage		
	1 Full sample	2 Firms with CCF	3 Firms with no CCF	4 Full sample	5 Firms with CCF	6 Firms with no CCF
<i>Firm-level variables</i>						
Gini coefficient (per patents)	1.412 (0.007)	3.493 (0.009)	1.629 (0.666)	1.727 (0.097)	2.628 (0.003)	-2.830 (0.345)
Gini coefficient (per sales)	0.070 (0.928)	1.400 (0.136)	0.135 (0.871)	-1.420 (0.258)	-4.061 (0.154)	1.746 (0.212)
Observations	159	70	89	159	70	89
Number of firms	41	26	32	41	26	32
Log-likelihood	-347	-143	-193	-229	-93	-119
Chi-square	17,858	6,177	14,421	10,981	24,149	7,761
Degrees of freedom	16	15	15	16	15	15

Notes. CCF stands for 'Centralized Coordination Function'; Results for the control variables not reported; All models include year dummies; Robust standard errors clustered at the firm level; *p*-values reported in parentheses; All tests are two-tailed.

such firms, greater within-firm inequality in innovation performance is associated with more firm-level alliances.

4.2.5 | Exclude marginal divisions

Divisions may have been included in our sample because of a few sporadic observations of patents or sales. For example, a firm may not have major projects in oncology but may show up in our sample as having an oncology division simply because the firm owns a few oncology-related patents. To address the concern that such observations may impact the results, we removed marginal divisions, i.e., those with patent counts fewer than 10% of those of the firm's largest division. The results, presented in the appendix, are similar to those in Tables 2 and 4.

4.2.6 | Fractional dependent variables

To reflect the relative balance between early- and late-stage alliances within a division, we tested the division-level hypotheses using a fractional dependent variable: early-stage alliances divided by (early-stage plus late-stage alliances). The results using the Tobit, generalized linear, and generalized least squares models are presented in the appendix.

4.2.7 | Alternative inequality indices

For the firm-level hypotheses, we used the Theil index (Theil, 1967) and Atkinson's index (Atkinson, 1970) as alternative measures of inequality. The results, presented in the appendix, are consistent with those using the Gini coefficient in Table 3.

4.2.8 | Citation-based measures for a division's innovation performance

In Tables 2 and 3, a division's innovation performance is measured by the simple count of patents in each division. For robustness, we created an alternative measure of innovation performance by weighting the patent counts with the number of forward citations that each patent receives. Such citation-weighted patent counts reflect both the quality and quantity of innovation. In the appendix, we present the division- and firm-level results based on citation-weighted patent counts using data from two alternative sources:

USPTO bibliography data (2016) and Li et al. (2014). Both the division- and firm-level results are consistent with those in Tables 2 and 3, and support our hypotheses.

5 | DISCUSSION AND CONCLUSION

Building on the premise that knowledge is often specialized to divisions, we examine how a multidivisional firm tailors its knowledge-sourcing strategy to its heterogeneous divisions and how a firm's composition of heterogeneous divisions affects firm-level knowledge sourcing. The results show that at the firm level, firms with greater inequality in innovation performance across divisions source more early-stage knowledge. In contrast, firms with greater inequality in sales performance across divisions source less late-stage knowledge, especially for firms with a centralized coordination function. Underlying these firm-level patterns is the idea that firms source early- and late-stage knowledge with different strategic goals in mind: They source more late-stage knowledge for divisions with high sales performance to maximize immediate returns, but they source more early-stage knowledge for divisions with low innovation performance to remain active in the relevant markets for the future. The stronger results for firms with a centralized coordination function suggest that strategic coordination within the firm plays an important role in knowledge-sourcing decisions. Thus, our findings underscore the idea that *intra-firm* heterogeneity can help to explain differences in *inter-firm* knowledge-sourcing strategies, beyond the effect of firm-level characteristics.

The principal contribution of this study is to introduce the idea of intra-firm heterogeneity in multidivisional firms to the literature on external knowledge sourcing. One implication of intra-firm heterogeneity is that when knowledge is specialized to each division, firms have an incentive to source early-stage knowledge for divisions with low innovation performance in order to keep them active in the present. In a dynamic environment, external knowledge sourcing gives a firm the flexibility to tap a promising market in the future, as opposed to eliminating the division now and paying high re-entry costs later (DiMasi et al., 2003; Lieberman et al., 2017; O'Brien & Folta, 2009). On a related note, the current study is the first to our knowledge that uses large sample data to relate intra-firm heterogeneity to inter-firm differences in knowledge sourcing. In emphasizing that intra-firm heterogeneity matters, our study joins the endeavor to unpack the relation between a firm's internal organization and its R&D strategy (Argyres & Silverman, 2004; Arora, Belenzon, & Rios, 2014; Grigoriou & Rothaermel, 2017; Monteiro & Birkinshaw, 2017). In doing so, it brings attention back to the importance of intra-firm characteristics for firm strategy (Gavetti et al., 2007).

This study also speaks to the real options literature, which has made significant progress in analyzing strategic investment decisions under uncertainty (McGrath & Nerkar, 2004). While the real options literature has recognized that firms are complex and non-monolithic entities (Adner & Levinthal, 2004), most studies have not considered its implications. Our focus on firms comprising divisions with specialized knowledge suggests that single-business and multi-business firms may view the option value of a project differently. While a single-business firm may assess a project's prospect on its own merit, a multi-business firm would assess the project based on the firm's potential to allocate resources to it in the future.

Our effort to look inside the firm also relates to research on the micro-foundations of strategy (Barney & Felin, 2013; Felin et al., 2015; Lippman & Rumelt, 2003; Teece, 2007). While some scholars associate micro-foundations research with the actions of individuals (Felin & Hesterly, 2007), others view "micro-foundations as a levels argument" (Felin et al., 2015, p. 578). In the spirit of the second interpretation, our study theorizes how division-level patterns aggregate to firm-level strategies, given a certain composition of heterogeneous divisions in a firm. Looking inside the firm also helps us unpack the role of the corporate center in the strategies of multidivisional firms

(Markides, 2002; Rumelt et al., 1994). Specifically, our results highlight that a centralized coordination function can play an active role in a firm's knowledge-sourcing strategy.

Finally, this study also has implications for managers of multidivisional firms. Classical theories prescribe a fit between a firm and its external environment (Lawrence & Lorsch, 1967). The implication is that in uncertain environments, firms adapt by entering and exiting businesses to reposition their portfolios (Eisenhardt & Brown, 1999; Helfat & Eisenhardt, 2004). Yet, continuously changing a firm's scope can disrupt routines (Feldman, 2014) and create restructuring costs (John, Lang, & Netter, 1992). Our study suggests that in uncertain environments, knowledge sourcing can help to maintain stability in firm scope. Although retaining a division can impose short-term costs, these costs should be weighed against the potential long-term benefit of avoiding future re-entry costs.

Contributions notwithstanding, the study is not without limitations. First, while we use knowledge sourcing as a proxy for resource allocation inside a multidivisional firm, the corporate center can also allocate other types of resources—human, technical, and physical—to divisions. Future research can offer deeper insights if data on the allocation of specific types of resources can be matched with external knowledge sourcing at different stages.

Second, we used therapeutic areas as a proxy for divisions. Based on prior research and our conversations with managers in the pharmaceutical industry, we believe this proxy matches well with our theoretical concepts of specialized knowledge and distinct markets. However, the proxy does not capture all attributes of a multidivisional firm's formal structure. For instance, an important aspect of the formal structure is the degree of autonomy for divisions in strategic decision-making (Williamson, 1975, 1991) and the degree of information- and resource-sharing among them (Hornstein & Zhao, 2011). In some firms, divisions may be profit centers with significant autonomy; in others, they may be cost centers with much less latitude. While we have analyzed the role of the centralized coordination function, future research can incorporate more fine-grained attributes of a multidivisional firm's formal structure.

Finally, we analyzed early- and late-stage sourcing independently and did not account for the possibility that knowledge sourcing at both these stages may be a joint decision. We made this choice for analytical simplicity, although we recognize that a more comprehensive theory of knowledge sourcing by multidivisional firms would require examining the interdependence between early- and late-stage knowledge sourcing within and across divisions.

To conclude, we revisit the observation that "strategic management is about coordination and resource allocation *inside the firm*" [italicized in original] (Rumelt, Schendel, & Teece, 1991, p. 19). We built on the concepts of market uncertainty and specialized knowledge to present arguments about the knowledge-sourcing strategies of multidivisional firms. Our findings underscore the idea that intra-firm heterogeneity can help explain differences in inter-firm strategies, beyond the effect of firm-level characteristics. We believe that further investigation of how intra-firm heterogeneity influences other aspects of a multidivisional firm's strategy is a fruitful agenda for future research.

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