External Technology Sourcing and the Dark Side of Open Innovation

by

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ABSTRACT

Firms in high-technology industries face a complex set of challenges to innovate successfully and continuously, to gain a sustainable competitive advantage. At the top of this list of challenges lies the choice firms must make regarding project sourcing in their pursuit of innovation. This research makes a significant and novel contribution to this discourse and examines the sourcing decision in the context of new product development. Specifically, we apply a project-level typology along the dimensions of new R&D project source and project familiarity. Drawing from transaction cost economics and knowledge-based view theories, we empirically test our theoretically-developed hypotheses on a dataset of 2,971 biopharmaceutical R&D projects. Results from these analyses show that both R&D project source and project familiarity have significant direct effects on focal project performance outcomes. We also determine that focal project familiarity has a significant moderating effect on the relationship between project source and performance outcome.

DEDICATION

To my family and loved ones, who never doubted me even when I doubted myself. And to myself, for persevering.

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"If I have seen further, it is by standing on the shoulders of giants."

– Sir Isaac Newton

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List of Acronyms

CDF	Cumulative distribution function
FDA	United States Food and Drug Administration
IPO	Initial public offering
IV	Instrumental variable
IV-2SLS	Instrumental variable two-stage least-squares
KBV	Knowledge-based view
MFT	Markets for technology
NBER	National Bureau of Economic Research
NPD	New product development
OI	Open innovation
OLS	Ordinary least squares
R&D	Research and development
SME	Small-to-medium enterprise
TCE	Transaction cost economics
USPTO	United States Patent and Trademark Office

Chapter 1. Introduction

For almost two decades, both scholars (e.g., Gassmann et al., 2010) and practitioners (e.g., PricewaterhouseCoopers, 2017) have witnessed a shift of firms' internal strategies toward an increasingly open mode of governing research and development (R&D) and innovation activities. PricewaterhouseCoopers' 2017 Innovation Benchmark report stated that 61% of surveyed organizations used an open innovation model to drive innovation in their firms, while 35% of companies said customers are their most important innovation partners (PricewaterhouseCoopers, 2017) – a key mechanism of open innovation strategy. Coined by Chesbrough in 2003, Open Innovation (herein, OI) describes the strategic opening of firms' organizational boundaries to the flow of both inbound and outbound technology and knowledge in order to exploit new and different knowledge to provide solutions to critical innovation needs or "problems" (i.e., Felin and Zenger, 2014). Turning to OI has allowed high-tech firms, in particular, to innovate more efficiently and at higher performance levels, therefore improving overall competitive positioning due to the improved ability to exploit a broader and more diversified alliance portfolio (Faems et al., 2005), leading to more diversified resources.

OI is most often defined as 'the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and to expand the markets for external use of innovation, respectively' (Chesbrough et al., 2006, p. 1) and it has been argued to contribute to a firm's dynamic capabilities (Hutton et al., 2021). Studies have highlighted the perceived far-reaching benefits of OI which include reducing research costs, risks, and time to market (West et al., 2014), licensing revenues as a new revenue stream, and the ability to access new markets via licensing (Lichtenthaler, 2007), increased value

capture capabilities (Rothaermel and Alexandre, 2009), and increased innovative performance (Chesbrough et al., 2006).

One particular stream of research has examined the differences between open versus closed innovation strategies (e.g., Almirall and Casadesus-Masanell, 2010; Hsieh and Tidd, 2012; Heimstadt and Friesike, 2021; Morgan et al., 2021). At the same time, another area of research has considered the benefits and risks of both open and closed (i.e., external and internal, respectively) R&D innovation and technology sourcing in new product development (NPD) in high-tech industries (e.g., Bae and Chang, 2012; Wang and Li-Ying, 2014). However, the extant literature does not presently agree on a united 'best practice' outcome for the classical 'make or buy', or internally-source or externally source[1], decision. Relying on the Transaction Cost Economics (TCE) theory, Borah and Tellis (2014) found support for make and 'ally', as did Geyskens et al. (2006), while Berchicci (2013) and Wang and Li-Ying (2014) found support for 'buy'.

In contrast to recent studies highlighting the benefits of OI, this paper builds on the emerging literature on the dark side of OI (e.g., Trott and Hartmann, 2009; Coad et al., 2021; Stefan et al., 2022); that is, the negative consequences of externally-sourcing or 'buying' an OI strategy and the negative effects of openness on new product development (NPD; Knudson and Mortensen, 2011). Relying primarily on the theoretical support of TCE (i.e., Williamson, 1985), we argue that transaction-related costs and risks pose substantial and unavoidable threats to firms in terms of their new R&D project outcomes,

[1] Herein these terms are used interchangeably, and this research takes the classic 'make versus buy' decision as a metaphor for the internal versus external sourcing approach to NPD.

especially if externally-sourced knowledge cannot be effectively or efficiently appropriated (i.e., within an unfamiliar knowledge or technology area). In this context, we define focal project performance outcomes as the likelihood of termination. Uncertainty mounts for firms, especially when projects are new, and in knowledge areas previously unknown to the focal firm (Arend et al., 2014). The OI paradigm inherently relies on the multi-level, multi-partner alliances that are required for technology/knowledge inflow and outflow (Brunswicker and Chesbrough, 2018) and thus presents a multi-faceted challenge to firms and their managers that we believe warrants a more thorough investigation of the dark side of OI.

In this study, we propose and empirically examine how firms' decisions regarding technological sourcing of, as well as familiarity with, R&D projects may help prevent firms from experiencing the dark side of OI. In this regard, the vast majority of published studies have focused on firm-level outcomes as their unit of analysis (e.g., Berchicci, 2013; Borah and Tellis, 2014; Lee et al., 2017). While insightful and valuable to the literature, the results of these studies provide aggregated insights. We believe by taking the project-level of analysis in this study (as Bagherzadeh et al. (2021) deems rare), we can reveal more complex and fine-grained effects occurring at the project-level of analysis. In addition, this viewpoint allows a clearer analysis of costs, risks, and implications of the technology sourcing decision and along the rigorous NPD process. At the same time, projects within a firm's portfolio are fraught with intricate interdependencies (Delerue and Sicotte, 2020) which we would be remiss in overlooking. This more appropriate level of analysis (see Hoang and Rothaermel, 2010) allows us to

account for these complex project-related interactions and make more specific and actionable recommendations.

To our knowledge, there is a paucity of research that examines the possible dark side of the seemingly evergreen trend of OI in innovation management and R&D project performance. With this research, we aim to address this surprising gap in the literature and present the plausible dark side of the sourcing-via-OI paradigm. More specifically, in this study we answer the following questions: 1) whether and how R&D project source is associated with that focal project's NPD performance, 2) whether and how R&D project familiarity is associated with that focal project's NPD performance, and 3) how project familiarity affects the possible relationship between source and project performance outcome. To do this, we apply a two-dimensional source/familiarity typology to a longitudinal sample of 2,971 biopharmaceutical R&D projects owned by publicly-traded firms. Our conceptualized typology considers the technology sourcing choice firms must make (i.e., open or closed innovation) when sourcing a new focal R&D project (i.e., fulfilling an innovation need) and the subsequent effect of the specific knowledge domain (i.e., drug therapeutic area) on that project's performance outcome.

Considering the differences among firms' project performance, we argue that the source of new R&D projects becomes a critical factor. Employing a TCE lens (Williamson, 1985), we must question why certain projects are abandoned (i.e., terminated) prior to commercialization, while others are not. The source of the technology not only defines the path of the project through the NPD process (i.e., project management strategy) (Barney, 1999), but also affects the project-level interdependencies at play within an NPD portfolio (i.e., Delerue and Sicotte, 2020). The choice that firms

must make when sourcing new technology and/or knowledge may have different implications for new R&D projects within the TCE theory. Consequently, the risks, costs, uncertainties, and benefits of sourcing internally versus externally must be thoroughly considered by technology managers. In addition to project sourcing, we build on Arend et al. (2014) regarding a firm's proprietary knowledge base as an asset in innovative R&D project development and propose the moderating effect of project familiarity on focal project performance outcomes. Borrowing also from Diestre and Rajagopalan (2012), we consider knowledge areas prior to introducing a new R&D project to examine how the familiarity of the R&D project developer (i.e., firm) with the focal project can affect that project's subsequent performance outcomes. Accordingly, this represents the potential absorptive capacity (i.e., ability to appropriate value from externally-sourced technology) of the firm in regard to each new project.

Our results provide support for our hypothesized associations between both new R&D project source and new project familiarity with focal project performance, demonstrating that both project source and project familiarity present a direct effect on that focal project's performance outcome (i.e., termination or otherwise). We also find significant support for our hypothesized interaction effect[2] between project sourcing and focal project familiarity, demonstrating that knowledge area (familiarity) does indeed lessen the risks and costs of sourcing via OI. By taking the project-level of analysis in

[2] This study uses the term 'interaction effect' to refer to a base method comparison between four mutually exclusive and collectively exhaustive categories, discussed later in this paper. We use the term to refer to the comparative analysis of the relationship between the two binary variables of interest, project source and project familiarity (see section 5.1. Main results).

this paper, we are enabled to make more fine-grained practical recommendations, and this also serves to open the black box of the complicated and nuanced NPD process.

This paper proceeds with the contextual background of our study and hypotheses, the methods used and our findings, followed by insights into these results in the ensuing discussion section. We conclude with research limitations and potential future research opportunities.

Chapter 2. Literature Review

2.1. Open versus closed innovation

For almost two decades, Open Innovation (OI) has received growing scholarly attention in the innovation and management literatures. Chesbrough's introduction of OI in his 2003 book garnered the attention of managerial and academic audiences alike. In the years since, OI has been the focus of countless conferences, special issues, books, and papers (West et al., 2014). Mostly, scholars have painted OI theory in a positive light (i.e., Chesbrough, Lettl, and Ritter, 2018; Chesbrough, 2020; Xie and Wang, 2020) including both the manufacturing (Obradović et al., 2021) and biopharmaceutical sectors (Johnson, 2020; Wikhamn and Styhre, 2020; Yeung et al., 2021) with relatively little cautionary research suggesting a dark side of OI (i.e., Trot and Hartmann, 2009) except within the context of the 'paradox of openness' which denotes "the contradictory role of knowledge as a key resource that creates value when shared, but also as a source of appropriability challenges" (Ritala and Stefan, 2021, p. 281).

The notion of 'open' innovation implies the existence of its inverse (i.e., 'closed' innovation). In contrast, Chesbrough (2003) denotes closed innovation as the classical and controlled hierarchical business model (i.e., vertical integration). This model was

long believed to best capture the value of firm-level knowledge and many firms during this time deployed vast amounts of capital on in-house R&D efforts. It was secrecy and design complexity that signified the height of attaining competitive advantage (Foege et al., 2019). However, due to an expansion of the market for technologies (Bianchi et al., 2011), the need to collaborate to exploit complementary resources (Lo Nigro et al., 2014), and rapid technological change and complexity (Hill and Rothaermel, 2003), firms have seemingly migrated to a more dynamic and open business model, turning their attention outside of their organizational boundaries to exploit both inbound and outbound technology transfers. This approach is especially evident in the biopharmaceutical sector (Forster, 2013; Gillespie et al., 2019; Lee et al., 2019).

2.2. Inbound versus outbound OI

On the one hand, inbound OI is related to exploration and leveraging technology/knowledge from parties external to the firm and requires the opening of boundaries to access technical and scientific competencies. Governance modes providing the inbound OI mechanism for high-tech firms include in-licensing, acquisitions, joint ventures and R&D contracts, among others (Bianchi et al., 2011). Specifically, inward licensing agreements refer to the purchase of the right to another firm's technology upon payment (Watler, 2012). This paper takes a narrowed focus on inbound innovation (and more specifically, the licensing mechanism), as our interests lie in the effects of the external sourcing of technology/knowledge on project termination. Demonstrating a recent interest in the literature for the inward licensing mechanism, Padula et al. (2015) singularly focus on and discuss the licensing mechanism in markets for technology

(MFT), as well as Cabaleiro-Cervino and Burcharth (2020), who found inward licensing announcements to be negative signals on market value.

On the other hand, outbound OI is comprised of the opposite yet complimentary action, that is, still the practice of establishing interorganizational relationships, but with the purpose to transfer *out* proprietary knowledge and/or technologies for commercial exploitation (Bianchi et al., 2011). While outbound OI activities do not fall within the scope of this research study, their prevalence and the validity of future research in this area cannot be overlooked (Cheah and Ho, 2021), particularly in the context of biopharmaceuticals (Osta and Maamari, 2020; Torres and Poulsen, 2020; Kim et al., 2021), and also in the context of inbound and outbound OI and engaging simultaneously in managing knowledge inflows and outflows involving having appropriate absorptive and desorptive capacities (Aliasghar and Haar, 2021).

2.3. The importance of OI

The advantages of embracing OI have been studied extensively and reported throughout the past two decades. Laursen and Salter (2006) discussed the important role that the network of relationships between a firm and its external environment plays in shaping overall firm performance. In addition, Du et al. (2014) found that OI-based partnerships are associated with improved financial performance, while van de Vrande et al. (2009) found that many of their sample SMEs (small-to-medium enterprises) were engaging in OI behaviours to manage customer demands and competitive threats. Further, Keil et al. (2008) examined alliance governance mode effects on innovative performance and found that, increasingly, more open governance forms led to increased

innovation results for firms. In looking at moderators of OI on firm performance, Liao et al. (2020) demonstrated that technological capability and market information management capability act as moderators and enhance the impact of inbound OI on firm performance. Among many others, these studies represent the significant depth and breadth in which scholars have explored the OI concept. Of late, academic researchers have adopted a wider scope of OI, researching its prevalence and characteristics in not just large, high-tech firms but turning their attention to SMEs and other, lower-tech industries where a more organic and incremental adoption of OI as occurred (i.e., Chesbrough and Crowther, 2006). Moreover, a recent meta-analysis focused on the past, present, and future of OI concludes that there are nine thematic areas in which OI is being investigated including: (1) context-dependency of OI, (2) collaborative frameworks, (3) organizational dimensions of OI, (4) performance and OI, (5) external search for OI, (6) OI in small and medium-sized enterprises, (7) OI in the pharmaceutical industry, (8) OI and intellectual property rights, and (9) technology (Bigliardi et al., 2021). In addition, another recent meta-analysis qualifies the extent to which OI enhances innovation output and concludes that: "1) OI has a stronger effect on innovation output in coupled OI (a combination of inbound and outbound OI) than the inbound or outbound OI alone; 2) OI has a stronger effect on innovation output in developing than developed countries; 3) OI has a stronger effect on innovation output at subfirm than firm level; and 4) OI has a stronger effect on innovation output in service than manufacturing industries" (Nguyen et al., 2021, p. 1).

Further, the advantages of licensing-in external R&D technology (a primary inbound mechanism of OI, (Huizingh, 2011)) on the R&D process have been studied

(i.e., Cesaroni, 2004; Fukugawa, 2009; Kim, 2009), but it is seemingly not without risk as many contradictory viewpoints exist (i.e., Atuahene-Gima, 1993; Cassiman and Veugelers, 2006; Cohen and Levinthal, 1990). The same contradictory literature exists for the benefits of sourcing R&D technology in-house (i.e., 'closed' innovation) (i.e., Huang et al., 2009) as well as the opposing viewpoint (i.e., Hurry et al., 1992). Thus, the choice of technology source that firms must make becomes unclear yet remains an important variable to consider. Borah and Tellis (2014) considered firms' options to make, buy, or ally, and established specific implications for innovation and NPD. We further this body of literature as to how modes of technology source have implications for project performance outcomes. Table 1, below, demonstrates relevant empirical research and how this study fits in the extant literature.

Table 1: Relevant empirical research

Study	Question	Empirical context	Research perspective	Level of analysis	Covariate(s)	Outcome(s) assessed	Key findings
Arend et al. (2014)	How do the dimensions of knowledge source and familiarity affect post-IPO firm performance?	United States IPOs, high-tech manufacturing firms, KBV theory	Consequences of choice	Firm-level	Knowledge source, Knowledge familiarity in 4 dimensions	Firm failure proclivity (survival), Return on assets (RoA), Tobin's *q*	Focused, internal knowledge correlated with higher performance.
Berchicci (2013)	How do R&D configuration and internal R&D capacity affect a firm's innovative performance?	Italian manufacturing firms, TCE theory	Consequences of choice	Firm-level	External R&D, Internal R&D capacity, Size, Age	Share of innovative sales	Firms that rely on external R&D have better innovative performance, to a point (inverse U-shape), which is moderated by R&D capacity.
Borah and Tellis (2014)	How does the choice of innovation strategy (make, buy, or ally) affect payoff?	Firms in 108 industries (global), TCE theory	Consequences of choice	Firm-level	Strategic choice, type of make/buy/ally, financial diversification	Cumulative abnormal returns (CAR)	Make or ally generate positive and higher payoffs than buy (negative payoffs).
Hoang and Rothaermel (2010)	How do alliance exploration and exploitation affect R&D project performance?	43 global pharmaceutical firms and their projects, KBV and TCE theories	Consequences of choice	Project-level	External experience, Internal experience	Project approval, Project termination	Exploitation positively affects project performance; exploration has negative effects.
Delerue and Sicotte (2020)	How do resource interdependencies affect project termination?	25 U.S. biopharmaceutical SMEs RBV and KBV theories	Consequences of choice	Project-level	Pooled interdependence, Longitudinal interdependence, Reciprocal interdependence	Project termination	Only certain types of interdependencies have a significant effect on drug development projects.

Study	Question	Empirical context	Research perspective	Level of analysis	Covariate(s)	Outcome(s) assessed	Key findings
Thakur-Wernz, et al. (2020)	How do sourcing choices affect project performance?	Global biopharmaceutical industry, TCE theory	Antecedents & consequences of choice	Project-level	Sourcing choices (consequences model), Org. boundaries, Project complexity, Project uncertainty, Prior experience	Sourcing choices, Project cost and duration	Greater complexity, prior stage uncertainty, and prior sourcing experience determine the sourcing choices. Sourcing choices vary in their ability to minimize project costs vs. duration.
This study	How do focal project source and familiarity affect focal project performance?	257 biopharmaceutical firms & 2,971 projects, TCE and KBV theories	Consequences of choice	Project-level	Project source, Project familiarity	Likelihood of project termination	Internal projects are less likely to be terminated. Familiar projects are less likely to be terminated and mitigate the negative effects of external projects.

2.4. Project-level outcomes

We noted a tendency in the literature toward studying firm-level (as opposed to project-level) performance. In terms of projects, we find it important to investigate the possibility of a dark side for internally- versus externally-sourced R&D projects and the impact this may have on project-level outcomes while further addressing if and how this relationship may be aggravated or possibly mitigated. Further, we posit that the extant literature's inconclusive stance on the make or buy decision warrants a more fine-grained approach with the important addition of such a variable that may further differentiate the performance of R&D projects. Moreover, the introduction of an additional variable (i.e., familiarity, in this study) would help provide impactful strategic insights for firms and further determine specifically where and how to initiate new R&D projects to capture a higher likelihood of project success.

2.5. Two-dimensional typology

In this study, we present a mutually exclusive and collectively exhaustive typology along two dimensions relating to the imperative choices made by firms engaging in R&D projects (with outcomes assessed as likelihood of termination in this paper). The first dimension concerns the source of R&D projects and considers whether a firm has initiated the focal project in-house (i.e., via closed innovation) or has in-licensed the project from an external source (i.e., via open innovation). The second dimension considers the extant tacit knowledge base of the firm and the familiarity (via prior experience) that a firm may have within the technology area of new focal projects. The combination of these dimensions allows a finer analysis of the interplay between R&D

project sourcing and familiarity during the NPD process; both of which hold strong support in the current literature. See Figure 1 below for a visual representation of the typology to be discussed in this section.

Figure 1: Two-dimensional, mutually exclusive, typology for R&D projects.

		Project Source	
		In-house (closed innovation)	**In-licensed (open innovation)**
Project Familiarity	**Familiar Area**	In-house, familiar	In-licensed, familiar
	Unfamiliar Area	In-house, unfamiliar	In-licensed, unfamiliar

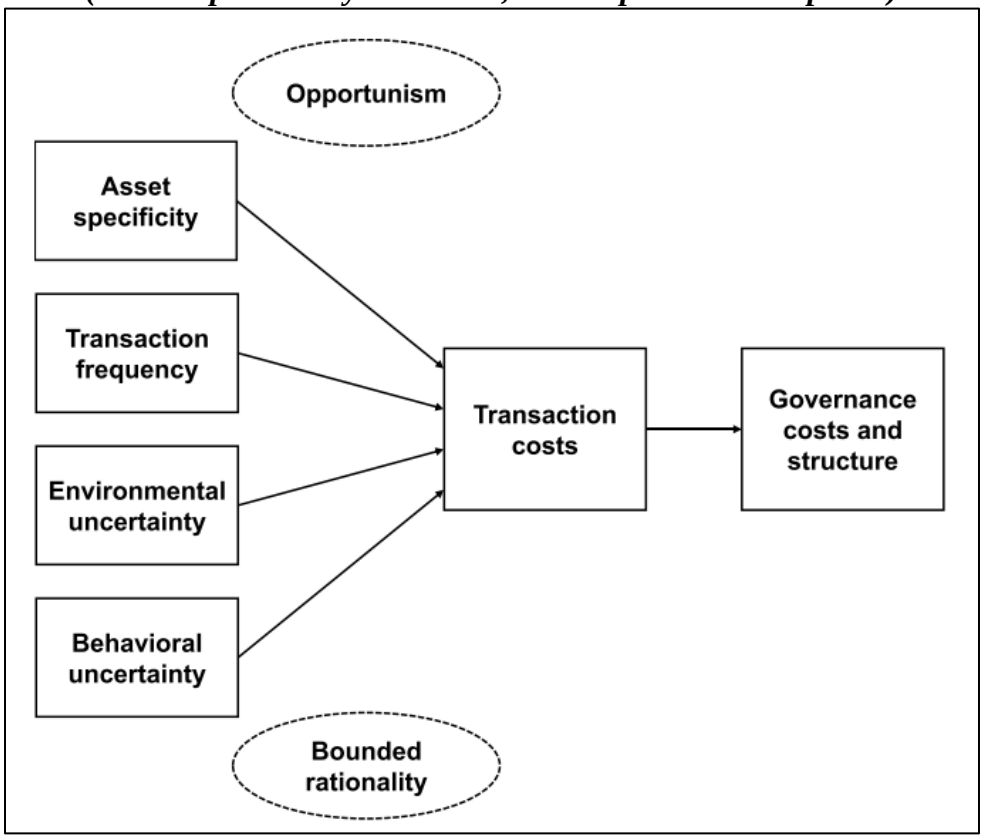
2.5.1. Transaction cost economics

Transaction costs economics (TCE) identifies firms on a spectrum based on whether they transact in the marketplace (one end of the spectrum), facilitate vertical integration (the opposing end of the spectrum), or prefer a hybrid approach (somewhere in between). Further, TCE focuses on the organizational governance modes of firm-level contractual relations (Williamson, 2007) and the benefits, risks and costs of doing business in the marketplace. The theory looks at the firm as a governance structure (rather than a production function as in classic economic theory) (Rindfleisch and Heide, 1997) and considers the *ex ante* choice of governance mode that firms must make, as well as the *ex post* hazards of partnering (Williamson, 1998). Transaction-related costs, specifically, can be separated into four distinct groups: search costs (gathering

information about potential partners), contracting costs (costs associated with negotiating and drafting agreements), monitoring costs (costs associated with monitoring partners to ensure fulfillment of obligations), and enforcement costs (costs associated with *ex post* actions in the case that a partner does not act according to the agreement) (Williamson, 1985; Dyer, 1997).

Williamson first outlined bounded rationality (the limits of individuals to gain and process information without error), opportunism (an effort to realize individual gains through a lack of honesty in a transaction), and atmosphere (institutional design) as the key 'human' factors of the theory, while he lists uncertainty (in the form of information asymmetry), small numbers (of market traders), and information impactedness (the costs of achieving information symmetry) as key 'transactional' factors affecting firms in markets (Williamson, 1973). He later contended that asset specificity is perhaps the most crucial factor with the potential to raise transaction costs (Williamson, 1998). This is supported by much research spanning decades since then (e.g., Simonin, 1999; Geyskens, et al., 2006; Kermani and Ma, 2023). Asset specificity refers to the specialization or level of tailoring of assets to the transaction in question. High asset specificity indicates that transacted assets cannot be re-deployed outside of the dyadic alliance or partnership (Geyskens, et al., 2006) and thus increases transactional costs.

Figure 2. The transaction cost theory framework
(Boxes represent key constructs, ovals represent assumptions)



Source: Schmidt and Wagner (2019)

More broadly, the underlying theory of transaction cost economics proposes that firms participating in a marketplace are subject to numerous transaction-related costs in the form of partner opportunism, asymmetric information (including asset specificity) and other forms of uncertainty (largely due to bounded rationality and opportunism). It focuses on these firms' endeavours to reap the benefits of forming alliances (via a selected governance mode) while at the same time, attempting to minimize the (pecuniary and otherwise) costs/risks/hazards of doing so.

We conclude this section by presenting and briefly discussing three example studies from management research which employed and contributed to TCE theory:

Mukherjee et al. (2013) employed TCE theory in their investigation on small to medium-sized enterprise (SME) alliance formation. Their findings supported and contributed back to TCE theory – that knowledge-intense firms benefit less from alliances (information asymmetry), and that partner trust plays a role in SME alliance formation (potential opportunism/bounded rationality affecting *ex ante* choices).

In their 2005 study, Santoro and McGill applied TCE to their study of alliances created by biotechnology firms. They found that firms select governance modes based on the differing types of uncertainty present at the time of partnering. More specifically, they found that firms use more hierarchical governance modes (e.g., joint ventures in which risk is equalized) to control higher levels of uncertainty in terms of the alliance partner (e.g., their intentions, capabilities or opportunity for knowledge appropriation).

Lastly, Penney and Combs (2020) examined firms' alliance portfolio diversity through a transaction cost lens. In this study, the authors wanted to investigate the effects of a diverse alliance portfolio specifically, departing from the extant literature which had mainly looked at the costs of doing business across diverse industries. They posit that transaction costs at the alliance portfolio level (a firm's set of ongoing partnerships with different kinds of partners such as suppliers, competitors, etc.) encourage integration into alliance partners' industries. That is, as alliance portfolio's diversity and subsequent transaction costs increase (Goerzen and Beamish, 2005), firms reach a decision point whereby it is deemed cheaper to expand into the alliance partner's industry themselves. The authors find support for this using data on S&P 500 firms.

2.5.2. Project source

The innovation source of R&D projects has been established as the classic dilemma for firms with Williamson's transaction cost economics (TCE) theory (Williamson, 1998). In the case of innovative R&D projects, we view OI or licensing alliances to be a prerequisite for innovation and commercialization (Lin et al., 2012), and in line with Mukherjee et al. (2013), we contend that the attractiveness of OI (i.e., the trading off of capital for time-savings) cannot be denied. Berchicci (2013) discussed the motivations for firms to outsource external R&D knowledge; one of these motives closely relates to TCE theory as firms increasingly attempt to minimize the risks of doing business in the market by sharing with others.

For example, firms in the biopharmaceutical industry are not immune to the seemingly evergreen phenomenon of OI. Baum et al. (2000) predicted that startup firms could improve early performance by establishing an open alliance network. More recently, Delerue and Sicotte (2020) found that 49% of their sample projects (n=451) were developed with one or more pharmaceutical firm partners (i.e., via alliance). Therefore, we conclude that OI alliances cannot be avoided in the current competitive, innovative and fast-moving market landscape, regardless of the inherent risks they pose.

Uncertainty (both partner- and knowledge-related) and asymmetric information (as discussed in the previous section) also hold a vital role in the challenges faced when managing licensed projects from external sources (van de Vrande et al., 2011). Arend et al. (2014) note the differing, yet comparable costs and risks associated with interorganizational relationships (e.g., spillovers to potential rivals) as opposed to in-

house R&D sourcing, which ultimately renders the choice of knowledge sourcing nontrivial (Gopalakrishnan and Bierly, 2001), as mentioned previously. In light of these arguments, we propose that the sourcing decision is a critical choice that firms must not take lightly, and while sourcing R&D projects externally may appeal to technology managers, this decision carries potentially detrimental transaction-related risks and costs to both the focal project (in terms of performance) and potentially the firm itself in terms of overall firm innovative performance.

2.5.3. Knowledge-based view

The overarching theory, the resource-based view (RBV), closely relates to the above-discussed transaction cost theory and provides secondary theoretical support to this study. Together, KBV and TCE are two of the most frequently used theoretical lenses employed in firm-level governance research (Carayannopoulos and Auster, 2010), including alliance-related studies such as this. The resource-based view as presented by Wernerfelt (1984), considers firms in terms of their internal resources rather than their products. Often referred to as an evolution of RBV, the knowledge-based view (KBV), specifically, extends this viewpoint and takes a focus on the specific knowledge-based resources of the firm (Grant, 1996).

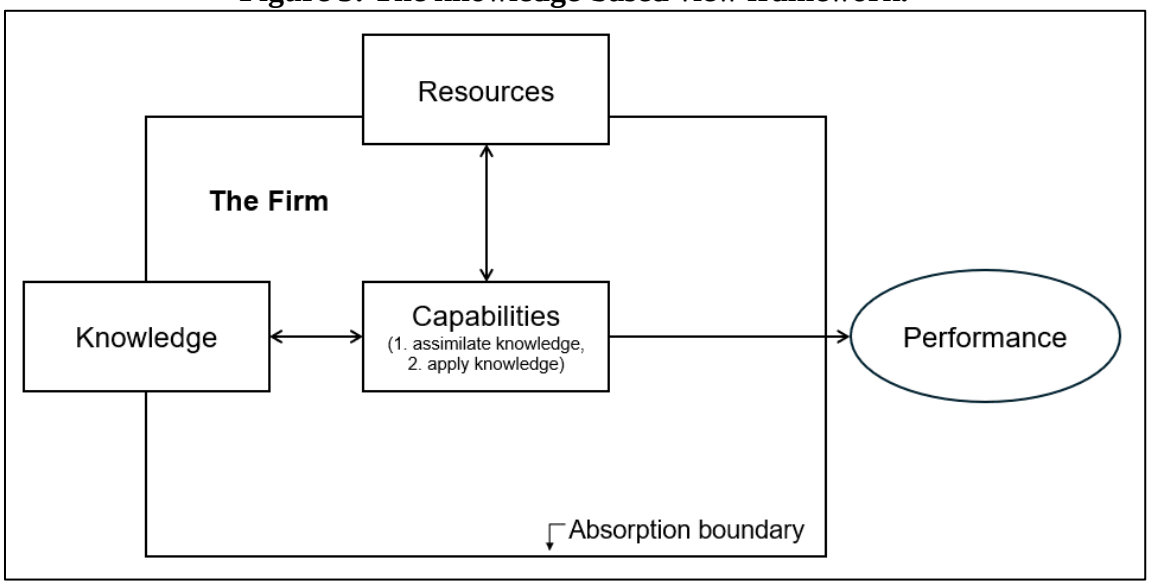
Further, KBV considers how a firm may gain (via exploration) and/or use (via exploitation) specific knowledge assets to create value (Grant and Baden-Fuller, 2004). The distinction between these two modes should be noted: knowledge exploration entails the use of alliances for learning purposes as the focal firm absorbs knowledge from the alliance partner into its base of organizational knowledge. On the other hand, knowledge

exploitation, or access, is deployed when knowledge sharing is desired to take advantage of firm-level synergies. In this case, the focal firm retains its original knowledge base (Grant & Baden-Fuller, 2004).

Further, researchers have long considered and researched firms' capacity to innovate via external knowledge (Zou et al., 2018). Absorptive capacity, a principal topic within KBV research, is key to this area of study. Firms who possess absorptive capacity are more enabled to learn and solve problems via assimilating external knowledge and creating new knowledge (Cohen and Levinthal, 1990). Absorptive capacity is determined by several factors like internal resources, routines and processes (Zahra and George, 2002) and has been claimed to be key to gaining a competitive advantage (Lane & Lubatkin, 1998). George et al. (2001) discussed how accumulated knowledge can enhance a firm's ability to acquire and recognize the importance of new information, citing Lindsay & Norman, 1977, specifically. Further, the same study proposes that firms who have strong capabilities to value and apply knowledge (i.e., absorptive capacity), would have superior innovation and performance, and finds partial support for this as the ability to value knowledge was a significant predictor of products on the market in their study (George et al., 2001).

It therefore becomes evident that knowledge begets knowledge and so on, in the case of absorptive capacity and the knowledge-based view. See Figure 3 for an adapted framework of the knowledge-based view.

Figure 3: The knowledge-based view framework.



Source: Adapted from Kaplan et al. (2012)

2.5.4. Project familiarity

The second dimension in our typology, familiarity, considers a firm's prior experience in a particular knowledge domain. Closely following Arend et al. (2014) regarding their familiarity variable, we use a measure of proprietary knowledge which had been accumulated by the firm through prior R&D project experience that could be subsequently applied to a new focal R&D project[3]. Considering the knowledge-based view (KBV), they argue that patenting activity involving previously explored technology classes (i.e., patent classes) will be more likely to increase a focal firm's absorptive capacity (i.e., the ability to assimilate and appropriate value from externally sourced knowledge) (Arend et al., 2014). In addition, Cohen and Levinthal (1990) discussed the

[3] In this paper we use this project-level method to measure familiarity. However, we acknowledge that we assume no other unobserved events are at play (i.e., hiring of scientists to generate familiarity). We control for this partially with our Instrumental Variable method, discussed in Chapter 4. Method and Analysis. We were unable to find an alternate method to address this assumption in the extant literature.

cumulative nature of learning, and that learning performance is optimal when the new object is related to what is already known (i.e., familiar). The incrementally growing knowledge base of the focal firm can then be applied to current pipeline and future innovative R&D projects. In essence, externally sourced knowledge is augmented and can be better appropriated (i.e., value capture) by way of extant internal capabilities (Tzabbar et al., 2013).

Relying on the knowledge-based view, we consider therapeutic area as a moderating factor for R&D project performance (Diestre and Rajagopalan, 2012). Taking the project level of analysis, we use therapeutic area as a more fine-grained proxy for prior innovative knowledge experience. Considering the composition of a firm's project portfolio in terms of therapeutic area[4] allows a precise measure of that focal firm's diversity (or lack thereof) across knowledge domains as well as their capacity to internalize new knowledge. For example, Switzerland-based biotech firm, Addex Therapeutics' project portfolio is made up of 62.5% psychiatric-related projects (5 of 8 projects from 2002 through 2012, from our data). In this case, a new psychiatric-related project is considered familiar to the firm as they already have knowledge and experience in this area. In contrast, the Washington state-based firm, Alder Biopharmaceuticals, has experience in the autoimmune/inflammatory and dental/oral areas (8 of 10 projects from 2008 through 2014, from our data), but not in the cancer therapeutic area. In this instance,

[4] The National Cancer Institute (2024) defines therapeutic area as, "A knowledge field that focuses on research and development of treatments for diseases and pathologic findings, as well as prevention of conditions that negatively impact the health of an individual".

a new cancer-related project is considered diversifying for (or unfamiliar to) this focal firm. This conceptualization stems from Arend et al.'s 2014 study of knowledge-based theory and post-IPO firm-level performance.

We argue that this marked difference between projects moderates a focal project's performance through the NPD process due to experience curve effects (Arend et al., 2014) and internal capacity for knowledge appropriation (Tzabbar et al., 2013), i.e., absorptive capacity. Combining this measure with the work of Diestre and Rajagopalan (2012), we created and operationalized a measure to determine the presence of experience (or not) in a particular therapeutic area for each focal project in our sample. We argue that diversifying new focal projects are more often associated with project termination. Drawing on the KBV theory, firms without a prior knowledge base may be left with added risks and costs in terms of knowledge uncertainty and negative knowledge transfer (Arend et al., 2014), partnered with a lack of internal capability to assimilate externally sourced knowledge and/or technology.

2.6. Direct effects of R&D project source

Due to the inherently external nature of in-licensed projects sourced via OI with interorganizational relationships, we argue these projects (as opposed to internally sourced R&D projects) will be subject to higher transaction costs, specifically in terms of absorptive capacity (knowledge base inconsistencies, from KBV), and partner uncertainty (from TCE).

Geyskens et al.'s (2006) valuable meta-analysis of TCE theory provides strong support for both make (versus buy), and ally (versus buy) decisions. Considering this

analysis, we view R&D projects that have been in-licensed via OI (which Park and Russo (1996) assigned as a "market-like solution" and the 'buy' mechanism) to be the equivalent of a 'buy-like' decision. Costs (financial, risk, and otherwise) of in-licensing may arise in terms of absorptive capacity or the focal firm's ability to assimilate the knowledge and prior alliance experience of the focal firm (Carayannopoulos and Auster, 2010).

Nonetheless, we expect that internally-sourced R&D projects will also be subject to transaction costs, however considerably less than their external (in-licensed via OI) counterparts, and not from the outset of the project (i.e., are not the subject of an OI/licensing agreement with one or more partner). Thus, projects initiated internally to the focal firm are not exposed to such risks as knowledge spillovers, opportunistic behaviour of partners, or performance uncertainty stemming from partners during the sourcing period (i.e., drug discovery). Kessler et al. (2000) discussed how internally-sourced knowledge could easily flow within an organization due to the synergies of background and experience, commonalities, and mutual understandings of employees. These authors found a reliance on external knowledge sourcing was associated with rising development costs, lower competitive success, and slower innovation speed.

Accordingly, we posit that all these factors have the potential to elicit a higher likelihood of termination (i.e., the dark side), and thus hypothesize:

***Hypothesis 1*.**

There is a positive association between in-licensed projects (via open innovation) and the likelihood of focal project termination.

2.7. Direct and moderating effects of project familiarity

Prior experience at the firm-level has been employed in numerous studies to represent a focal firm's capabilities in a specific domain (i.e., prior alliance experience for project performance in Hoang and Rothaermel, 2010). Repeated innovation and NPD experience in, for example, a specific knowledge domain, would allow a firm to establish a tacit knowledge base that may be exploited for current pipeline and future new R&D projects. Extant research establishes that a firm's absorptive capacity plays a significant role in the relationship between outside-in OI and innovation performance (Roldán Bravo et al., 2021).

In addition, the accumulated general (internal) knowledge base allows for the improved assimilation and appropriation activities for the counterpart externally sourced technologies (Cohen and Levinthal, 1990). As a result of this general base of knowledge stemming from project-level specific knowledge experience, unintended but positive learning spillovers may enhance a firm's innovative performance at the project level, as projects may benefit from the tacit knowledge obtained from previous experience (i.e., lessened likelihood of focal project termination in this paper) (Delerue and Sicotte, 2020).

It is important that we consider a firm's prior knowledge experience in this study as it would directly influence a firm's current ability to innovate both internally- and externally-sourced technology projects via the development of a firm-level absorptive

capacity which relates to each new R&D project initiated. This ability is critical to project performance and undoubtedly relates to the likelihood of termination of focal projects as firms continuously "learn by doing" (Tzabbar et al., 2013)

Considering the project level of analysis, we posit that a familiar knowledge base (i.e., previous and recent therapeutic area experience) facilitates a firm's level of absorptive capacity for externally sourced technology, and thus enhances project performance, subsequently reducing the likelihood of focal project termination. Tzabbar et al. (2013) discuss the importance of familiarity for firms to recognize, assimilate, and exploit external knowledge, which is also supported by the absorptive capacity theory presented by Cohen and Levinthal (1990) who developed a model regarding organizational learning based on extant (at the time) psychological and sociological theories and discussed the prerequisite complementariness (for performance) of inward-looking and outward-looking absorptive capacities.

We therefore expect that new projects (whether internally- or externally-sourced) initiated in a familiar therapeutic area will benefit from the firm's optimized and experiential knowledge base and the likelihood of termination will be reduced. We thus hypothesize:

***Hypothesis 2*.**

There is a negative association between projects initiated in familiar knowledge domains and the likelihood of focal project termination.

Next, we consider the potential interactive effects between a focal project's knowledge source and the firm's familiarity with the associated knowledge domain. Firms may choose to open their organizational boundaries to externally source an R&D project, in which a trade-off is made between capital and time (Teece, 1986). Often, in-licensed projects have already been developed past the development or preclinical stages (Nishimura and Okada, 2014), which subsequently allows firms to jumpstart and/or expedite their NPD innovation process. However, we suggest that this seemingly evergreen strategy is not without significant risks. As discussed above (Hypothesis 1), we posit that externally sourced projects are subject to relatively higher transaction costs and the associated inherent risks. In this more detailed model, we posit a moderating effect of project familiarity on the effects of the knowledge sourcing decision. In this regard, we hypothesize that selecting a familiar therapeutic domain may have a mitigating effect on the negative transaction costs and risks of sourcing a new NPD project via OI (i.e., externally) in which a tacit and relatively familiar knowledge base allows the firm to appropriate and assimilate the new project more effectively.

In addition, we further present the interaction effect that may occur when a project is sourced externally and also lies within an unfamiliar knowledge domain. In this case, we posit that externally sourced projects that fall within an unfamiliar knowledge domain will be subject to amplified risks and costs due to not only the negative transaction-related effects (i.e., partner/knowledge uncertainty) of sourcing, but also the firm's potential inability or lessened ability to assimilate new (unfamiliar) knowledge. We thus hypothesize:

Hypothesis 3a.

The familiarity of new R&D projects amplifies the negative association between internally sourced projects and the likelihood of focal project termination.

Hypothesis 3b.

The lack of familiarity of new R&D projects lessens the positive association between externally sourced projects and the likelihood of focal project termination.

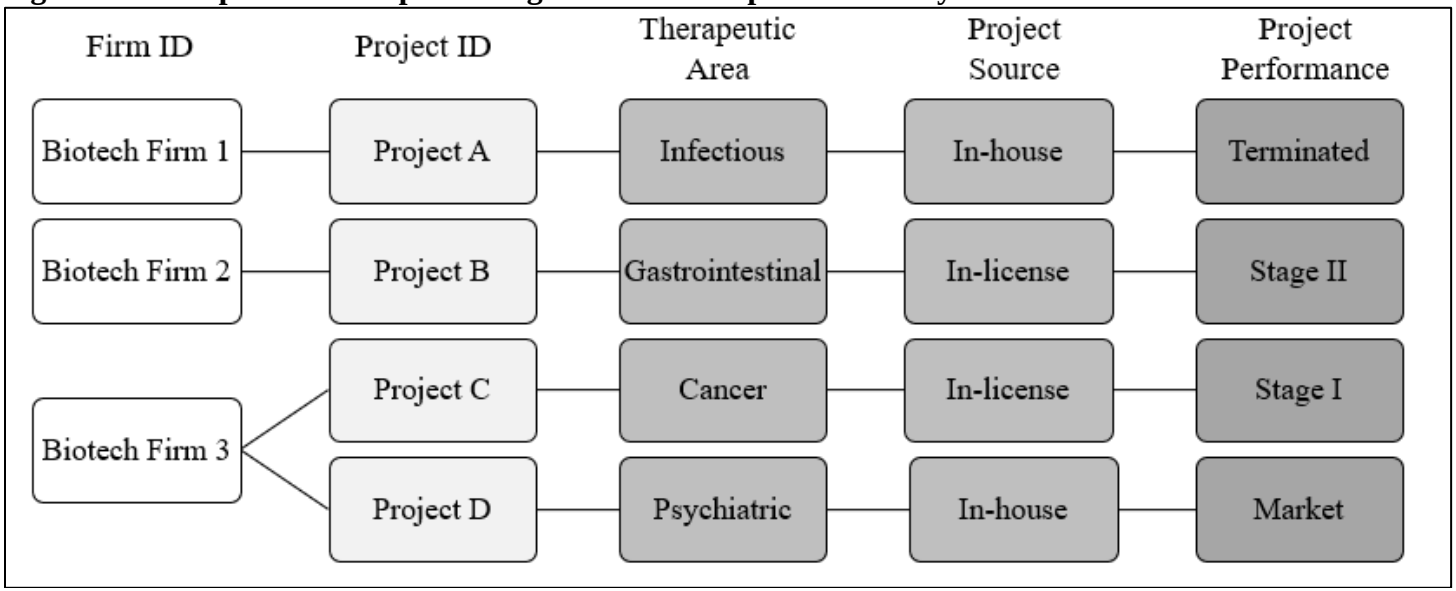
Chapter 3. Data and Measures

3.1. Dataset and sources

To test our hypotheses, we use a nested, cross-sectional dataset of 3,839 R&D projects owned by 386 biotechnology firms between 1985 and 2016 (up to December 31, 2015). Due to the intrinsic lack of financial information for privately-owned firms within our dataset[5], our final sample consisted of 257 publicly traded firms and 2,971 R&D projects, which we use in our analysis. First, we obtained our primary data points from Recombinant Capital (ReCap) and Lexis-Nexis (now Nexis-Uni). Then, publicly available firm-level financial information (i.e., R&D expenditure) was sourced from Compustat and matched with firms in our abovementioned sample. Figure 4, below, visually represents a sample of data and the relationships between the independent and dependent variables.

[5] This, of course, presents a limitation of this study in that privately-owned firms could not be included in the dataset and thus, not studied. It should be noted that results may only be generalized to publicly traded firms in the biopharmaceutical industry.

Figure 4. A sample of data representing the relationships between key variables of interest.



3.2. Variables

Our analyses lie at the project level, and we consider variation in the characteristics of projects owned by the firms in our sample. These variables include therapeutic area, project start date, and current status (i.e., clinical phase at the time of data collection, approval, or termination). We also used firm-level variables to control for the clustering of projects among firms of differing capacities, and a recession indicator variable for each project to account for the economic landscape over time. Table 2, below, demonstrates our primary variables with modes of operationalization and data sources, to be discussed further in the remainder of this chapter.

Table 2: Operationalization of variables

Variable	Operationalization	Data source(s)
Current status (project)	A binary variable that takes a value of 0 for an ongoing or not terminated project, value of 1 for a terminated project.	ReCap, LexisNexis (now Nexis-Uni)
Source	A binary variable that takes a value of 0 for internal source, value of 1 for external (OI) source.	ReCap, LexisNexis
Familiarity	A binary variable that takes a value of 0 for unfamiliar (i.e., the firm had no experience in the prior five years), value of 1 for familiar.	ReCap, LexisNexis
Therapeutic area	A binary variable that takes a value of 0 for a non-cancer area, value of 1 for cancer related.	ReCap, LexisNexis
Total development time	Time in months between project start and project approval/termination/end of research window.	Calculated measure (Dates from ReCap, LexisNexis)
Firm R&D expenditure	Average R&D expenditure per firm per project per year	Compustat
Recession	A binary variable that takes a value of 0 for a non-recession start date, value of 1 for a start date with a financial recession period.	National Bureau of Economic Research (NBER)

3.2.1. Dependent variable

In line with the studies by Hora and Dutta (2013) and Rothaermel and Deeds (2006), we employ project performance as the variable of interest in this study. Our operationalized outcome variable, current status, indicates whether the focal project was terminated, had obtained Food and Drug Administration (FDA)[6] market approval, or was ongoing if the project was still active at the end of the data collection period (i.e., Dec. 31, 2015). Using a binary methodology and following Delerue and Sicotte (2020), a project was assigned '0' if it had been approved by the FDA or was ongoing, and '1' if it had been terminated.

3.2.2. Independent variables

The source of innovation and focal project familiarity are the explanatory variables of interest in this study. Project data obtained from ReCap and Nexis-Uni disclosed whether each project within our sample was initiated in-house (by the focal firm) or licensed-in via OI. Our operationalization of the project source variable followed the method of Blindenbach-Driessen and van den Ende (2014); we assigned a value of '0' for an internal (in-house) project and '1' for an external (in-licensed via OI) project.

Focal project familiarity was also used as an independent variable. Following the methods of Diestre and Rajagopalan (2012) and Arend et al. (2014) we calculated the

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[6] In the context of this study, the American Food and Drug Administration (FDA) is responsible for regulating the prescription and non-prescription drug manufacturing and development industry. The FDA also regulates biological products (including vaccines), some cosmetics, medical devices, animal drugs, food products and additives, and tobacco (U.S. Food & Drug Administration, 2023).

familiarity of each focal project in our sample. A project was considered focused by identifying if the firm had experience in the associated therapeutic area during the five years prior to the introduction of the project (*t* - 5 to *t* - 1), otherwise, the project was considered new, or diversifying, to the firm. A diversifying focal project is either in a therapeutic area that is new to the firm or has not been explored by the firm in the five years prior to the new project, and subsequent knowledge in that area has depreciated or been lost (Ahuja and Lampert, 2001; Hall et al., 2005; Leten et al., 2011).

3.2.3. Control variables

Firm-level information was used to control for clustering effects. We sourced yearly R&D expenditure for each firm in the sample from Compustat and calculated the average R&D expenditure per year over the firm's lifetime within the timewise bounds of our analysis. Following Berchicci (2013), we expected that, to a point, firms with a higher R&D expenditure on average would have improved project performance.

Total development time was also used as a control variable to ensure projects were evaluated and compared against one another in an equal manner. This measure was calculated as the time in months between the project start date and either the date of FDA approval, the date of project termination, or the data collection cutoff date for ongoing projects (December 31, 2015). Informed by Gassmann & Reepmeyer (2010), we anticipated that projects with a higher development time would have a higher rate of success through the NPD process. The authors report that attrition rates in the pharmaceutical industry, specifically, decrease as projects move past the pre-clinical stage into clinical phases II and III (p.4, para. 5). We also controlled for therapeutic area

(knowledge domain) in two broad categories. Projects were assigned a value of ‘0’ if they did not target cancer, and a ‘1’ for drug projects targeting cancer (43% of the sample). We expected projects in the cancer area to be more likely to be terminated due to the complicated nature of cancer-related drugs as discussed by Safavi et al. (2016). Lastly, to control for fluctuations over the span of time of the study, we employed a recession binary for each project to account for changes in the economic climate when the project was initiated. This data was sourced from the National Bureau of Economic Research (NBER). We anticipated that projects started within a period of recession would be more likely to be terminated; possibly due to lack of resources or project portfolio downsizing/prioritizing. Table 3 demonstrates the descriptive statistics and correlations among our variables of interest.

Table 3: Variable descriptive statistics and correlations

Variables	Obs.	Mean	Std. Dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Current Status	2,971	.408	.491	1.000						
(2) Source	2,971	.245	.430	0.025	1.000					
(3) Familiarity	2,971	.604	.489	0.007	-0.029	1.000				
(4) R&D Exp.	2,971	242.121	388.584	0.063	-0.086	0.189	1.000			
(5) Recession	2,971	.167	.373	0.026	-0.042	0.043	0.048	1.000		
(6) Thera. Area	2,971	.444	.497	0.003	0.010	0.371	-0.015	0.007	1.000	
(7) Total Dev.	2,971	59.965	41.508	-0.282	0.066	-0.071	-0.017	0.068	0.062	1.000

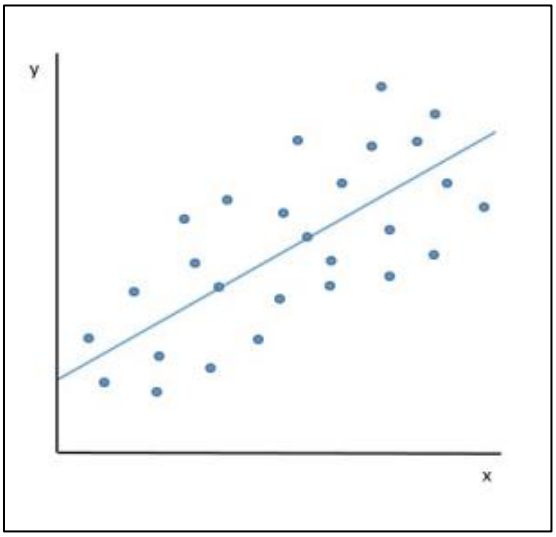
Chapter 4. Method and Analysis

4.1. Method selection and endogeneity

The ordinary least squares (OLS) method is widely used to estimate unbiased parameters in a linear regression model. Its name, ordinary least squares, comes from the fact that the generated estimates minimize the sum of squared residuals (Wooldridge, 2012). Regression analysis, an OLS technique, results in a line of best fit through data points (minimizing the sum of squared residuals), illustrated in Figure 5.

As characterized in Wooldridge (2012), OLS has several key assumptions that must be met to ensure unbiased estimators: 1) the model is linear in parameters, 2) random sampling, 3) variation in the explanatory variable, 4) zero conditional mean (i.e., $E(u|x) = 0$), 5) homoskedasticity (i.e., constant variance). Due to the strong assumption of a zero conditional mean (i.e., that there are no omitted variables), we were unable to employ the common OLS method.

Figure 5: Theoretical OLS results.



Source: University of New Brunswick STAT4703 course material. Used with permission.

Next, considering the binary nature of the dependent variable (i.e., the focal project is terminated or otherwise), we then planned to employ a logistic or logit model. However, our two main independent variables (project source and familiarity) introduce the same estimation challenge as in OLS above. We further recognized that the choice of sourcing and familiarity by the focal firm could be affected by some unobservable factors (i.e., omitted variables), and these choices are seemingly not random. In addition, these seemingly unobservable choices could be a function of the firm's experience and other firm characteristics. This unfortunately violates the assumption of independent error terms for logistic regression.

Keeping mindful of the commentary by Zaefarian et al. (2017) regarding the proclivity of endogeneity present in recent marketing and strategic management research (Semadeni et al., 2014), we therefore determined that our two main independent variables are endogenous, and we needed to correct for endogeneity before proceeding. The ensuing challenge was due to the complex nature of these endogenous variables.

Specifically, endogeneity bias occurs when an independent variable correlates with the error term in a model. This may lead to biased estimators and thus creates issues in claiming causal inferences (Zaefarian et al., 2017) or lead to potentially spurious findings. One form of endogeneity is the omission of variables. Zaefarian et al. (2017) give the example of organizational governance mechanism choices as an example of an omitted variable leading to endogeneity – i.e., firms self-select into certain relationships based on factors that are not observable and therefore cannot be included in the model.

In this study, the source and familiarity variables are both binary variables. Considering this, and due to the forementioned nature of endogeneity, we could have employed a 2SLS (two-stage least squares[7]) approach to address the issue, however, alone, it is not an efficient model when endogenous variables are present. Therefore, after further searching for a method to better suit the unique requirements of our data, we chose to employ the cmp (conditional mixed process) method to test our hypotheses. In the presence of endogenous variables, the cmp method can estimate a recursive set of regression equations that have different models for the dependent and endogenous variables (Roodman, 2011; Sande and Ghosh, 2018). This method is based on the maximum likelihood[8] class of estimators and allows for a flexible error structure; it also allows the use of different dependent variables with unique distribution properties (Malshe et al., 2020; Roodman, 2011). Due to the binary nature of our dependent variable in question (i.e., current project status – terminated or otherwise) and also the presence of endogenous covariates (namely project source and familiarity), we deemed the cmp method to be appropriate for our study. Since the introduction of the method by Roodman in 2011 and the availability of this method in Stata 17, this procedure has been used in

[7] The two-stage least squares (2SLS) method is an extension of OLS and may be used when the error terms of the dependent variable are correlated with the independent variables (an assumption of OLS). In the first stage of 2SLS, the problematic variable is substituted by an instrumental variable. Next, an OLS model is computed using the estimators from stage one in place of the values of the problematic variable.

[8] Maximum likelihood estimation (MLE) is a method of parameter estimation that seeks the probability distribution that makes the observed data most likely (Myung, 2003). MLE is the foundation for chi-square tests, Bayesian methods, random effects models, and more established estimation methods.

many studies in the marketing and management fields (e.g., Antia et al., 2012; Kashyap et al., 2012; Kashyap and Murtha, 2017; Malshe et al., 2020).

4.2. Model specification

We estimate the following three equations using cmp:

Equation 1: CMP estimation for project status

$$Prob(Current\_status_{ij} = 1|\boldsymbol{x}) = \Phi_1\big(\beta_{10} + \beta_{11}Source_i + \beta_{12}Familiarity_i + \beta_{13}Source_i \times Familiarity_i + \beta_{14}Avg.R\&D_j + \beta_{15}Total\ dev_i + \beta_{16}Therapeutic_i + \beta_{17}Recession_i + \sum_{j=1}^{257}\tau_j \mathrm{Firm_j}\big) + \mu_{1i}$$

Equation 2: CMP estimation for project source

$$Prob(Source_i = 1|\boldsymbol{x}) = \Phi_2\Big(\beta_{20} + \beta_{21}N_{ext_{term\,j}} + \beta_{22}N_{int_{term\,j}} + \beta_{23}N_{fami_{term\,j}} + \beta_{24}N_{unfami_{term\,j}} + \beta_{25}Avg.R\&D_j + \beta_{27}Therapeutic_{ij}\Big) + \mu_{2i}$$

Equation 3: CMP estimation for project familiarity

$$Prob(Familiarity_{ij} = 1|\boldsymbol{x}) = \Phi_3\Big(\beta_{30} + \beta_{31}N_{ext_{term\,ij}} + \beta_{32}N_{int_{term\,ij}} + \beta_{33}N_{fami_{term\,ij}} + \beta_{34}N_{unfami_{term\,ij}} + \beta_{35}Avg.R\&D_j + \beta_{37}Therapeutic_{ij}\Big) + \mu_{3i}$$

where:

Φ_1, Φ_3, and Φ_3 = standard normal CDFs,
$\mathrm{Firm_j}$ = the firm fixed-effect,
μ_{1i}, μ_{2i}, and μ_{3i} = error terms,
N_int_term$_{ij}$ = the number of previous internally sourced projects that had been terminated by firm *i*,
N_ext_term$_{ij}$ = the number of previous externally sourced projects that had been terminated by firm *i*,

$N\_fam\_term_{ij}$ = the number of previous familiar projects that had been terminated by firm *i*,
$N\_unfami\_term_{ij}$ = the number of previous unfamiliar projects that had been terminated by firm *i*.

The four latter variables impact the firm's strategic choices (in-house vs. licensing and familiar vs. unfamiliar) while not necessarily influencing the likelihood of project success or termination. We therefore use them in Eq. (2) and Eq. (3). All other control variables and their operationalizations are reported in Table 2 in Chapter 3 (Data and Measures).

Due to the cross-sectional nature of the study and following Xu (2015) we created two models: the first (Model 1) incorporates the direct effects hypothesized in *H1* and *H2* (namely, the direct effects of project source and project familiarity) (see Figure 6, below). The second (Model 2) includes the interaction effects hypothesized in *H3* (see Figure 7, below). To control for time in terms of the presence of recession and the difference among firms in the sample, we added an additional indicator variable ('Recession'). We also control for multiple observations at the firm-level by clustering the error term to ensure robust results.

Figure 6. Visualization of Model 1 (direct effects)

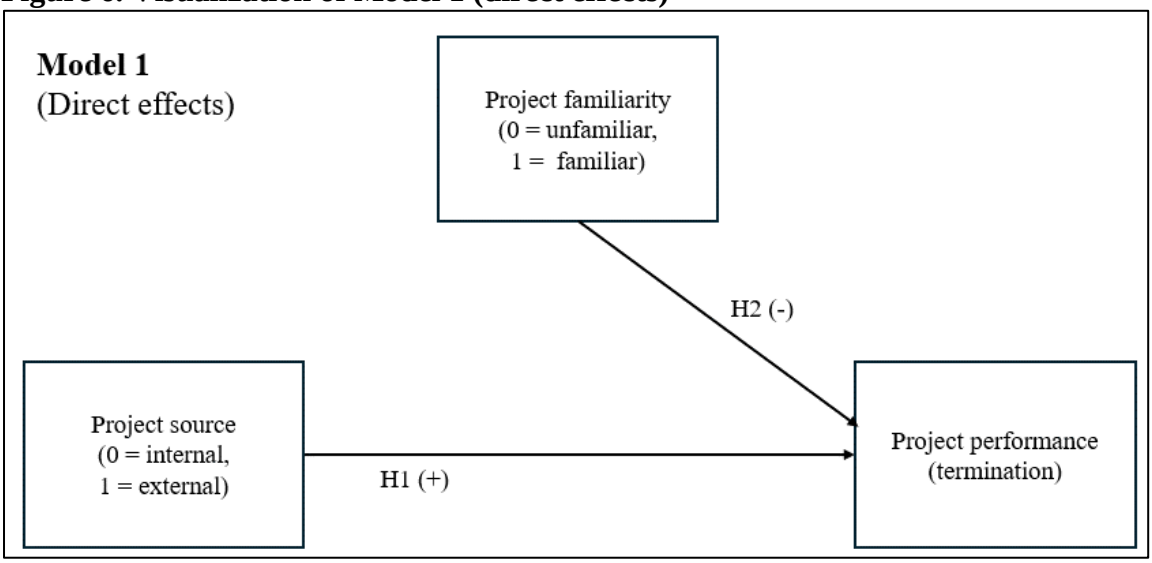
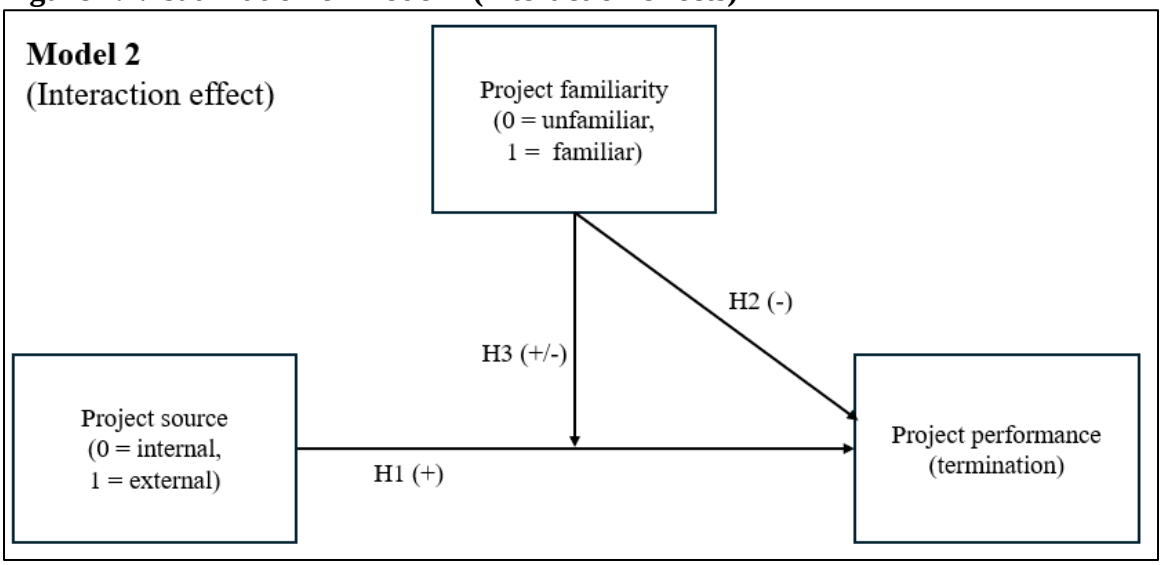


Figure 7. Visualization of Model 2 (interaction effects)



Chapter 5. Results

5.1. Main results

We found significant support for all hypotheses as demonstrated in our estimation results in Table 4, below. First, we created a direct effect model to test *H1* and *H2*, for which we found support. Then, we added the interaction variable (Model 2) to test *H3*. Following Yip and Tsang, 2007, we took the base approach (versus the partition approach) to interpret the findings of the interaction effect. More specifically, we employ internal, familiar projects as the base to which we compare the other three types of projects (i.e., internal, unfamiliar; external, familiar; and external, unfamiliar).

Table 4: Empirical results

	DV	Current status							
	Model	Dir. Effects (Model 1)		Inter. Effects (Model 2)		Eq. (2) (Source)		Eq. (3) (Fam.)	
Variables		**Coefficient**	**RSE[a]**	**Coefficient**	**RSE[a]**	**Coefficient**	**RSE[a]**	**Coefficient**	**RSE[a]**
Intercept		-.1089	.5752	-1.6251**	.5763	-.7211**	.0424	-.5952**	.0414
Controls									
Recession		.1558	.0638	.1544	.0639				
Avg. R&D exp/yr		.0150	.0075	.0153	.0075	.0001	.0001	-.0001	.0001
Total dev.		-.0140**	.0009	-.0140**	.0009				
Therapeutic area		.5286**	.0764	.5327**	.0754	.1244	.0518	1.1155**	.0542
Prior Ext. Term.						.0478**	.0145	.1247**	.0146
Prior Int. Term.						-.0070	.0106	.0718**	.0105
Prior Fam. Term.						-.0336	.0139	-.0559**	.0139
Direct effects									
Source	(H1)	.8933**	.2416						
Familiarity	(H2)	-1.4731**	.1012						
Interaction effect [b]	(H3)								
Internal × Unfam.				1.5102**	.1048				
External × Unfam.				2.3060**	.2026				
External × Fam.				0.9423**	.2410				
Wald χ^2		1953.42**		1955.03**		1955.03**		1955.03**	
Model log likelihood		-4452.390		-4451.586		-4451.586		-4451.586	
Firm fixed effect		Yes		Yes					

N = 2,971 projects.

*p ≤ .1, **p ≤ .01.

[a] Robust standard errors.

[b] Base = Internal × familiar projects. Thus, the interpretation is such that all other types of projects are significantly more likely to lead to termination.

H1 posits that there is a positive association between in-licensed projects and the likelihood of focal project termination. In support of this, we found a significant result (β_{11} = .89, p < .001) in Model 1. This demonstrates that R&D projects that are externally sourced have a significantly higher likelihood of being terminated. This empirically demonstrates the potential dangers and risks of OI in terms of focal R&D project performance.

Next, *H2* hypothesizes that familiar projects are negatively associated with the likelihood of focal project termination. More specifically, projects in a knowledge domain familiar to the firm are more likely to be successful. We found significant support for this hypothesis as well (β_{12} = -1.47, p < .001).

H3a and *3b* address the typological relationships between familiarity and project source on focal project performance. We found that, in comparison to internal, familiar projects (the comparative base), all other types of projects (internal, unfamiliar; external, familiar; and external, unfamiliar) demonstrate a positive and significant interaction in this regard and are associated with a higher likelihood of termination (β = 1.51, p < .001; β = 2.31, p < .001; β = 0.94, p < .001, respectively). Projects that are both internal and familiar to a firm have significantly lower transaction cost risks in terms of alliance and knowledge asymmetries and thus are less more likely to be terminated. Auxiliary analysis indicates that in comparison to internal, unfamiliar projects, only external, unfamiliar projects are associated with a higher likelihood of termination (β = 0.80, p < .01). We, however, did not get significant results in comparing external, familiar projects. Lastly, when comparing with external, unfamiliar projects, external familiar projects are

associated with a lower likelihood of termination at a statistically significant level ($\beta = -1.36$, $p < .001$).

Upon analysing our control variables, we found some significant results. While we did not find significant results for the average R&D expenditure and recession indicator variables, we found that the therapeutic area variable, which controls for cancer-related projects, significantly increases the likelihood of termination ($p < .001$). Total development is also significant ($p < .001$) and is negatively associated with the likelihood of termination.

5.2. Robustness check

To ensure our results are robust and mindful of existing robustness studies on inbound OI and performance (Ebersberger et al., 2021), we also employ an additional approach to address potential endogeneity (a type of omitted variable bias) introduced in Chapter 4.

Wooldridge (2012) outlines four options to tackle omitted variable bias: (1) ignore the problem and accept biased and/or inconsistent estimators; (2) try to find a suitable proxy variable for the unobserved variable(s); (3) assume the omitted variable does not change over time and use the fixed effects or first-differencing methods; and (4) an instrumental variable method. As we were unable to accept biased estimators or to find a suitable proxy variable and could not assume that the omitted variable(s) did not change over time [choices made by firms are subject to new and changing information such as organizational learning (Thakur-Wernz et al., 2020)], we were left with an instrumental variables approach. This approach leaves the unobserved variable in the

error term and uses an estimation method that recognizes the presence of the omitted variable (Wooldridge, 2012). Additionally, the IV approach does not have any assumption on the nature of endogenous regressors (Papies et al., 2017), therefore it is appropriate to use this method to address endogeneity when binary endogenous regressors are present.

When considering the choice of project source that firms must make, we cannot reject that the firm's previous experience influences this decision. Thus, we operationalized several "exclusion" variables that satisfied the criteria to act as explanatory instrumental variables: the IVs must be correlated with the interdependent variable(s) (i.e., relevant) and must be uncorrelated with the dependent variable (i.e., exogenous) (in the case of this study: likelihood of focal project termination). We employ previous experience as our exogenous IVs: the number of previous internally- and externally-sourced projects that had been terminated by the firm, and the number of previous familiar and unfamiliar projects that had been terminated by the firm. We also include average R&D expenditure per project per firm, total project development time, and whether the project was cancer-related or not in our analyses similar to Eq. (2) and Eq. (3). We use the predicted source and familiarity in the main equation, Eq. (1). The results from this method were similar to the cmp method discussed in section 4.1.

Chapter 6. Discussion and Conclusions

Innovative R&D projects are an important source of competitive advantage in high-technology industries. Previous literature has long debated the various costs, risks, uncertainties, and possible benefits of the different sources of technology; however, a

united viewpoint on the various benefits and disadvantages of OI has not yet been achieved. The findings of this study support a more contextualized approach to and consideration of OI since (at least in the context under examination) open innovation is not as consistently beneficial as the extant literature assumes. These findings differ significantly from traditional assumptions in different, low- and medium-tech settings, mainly in traditional sectors, where OI is perceived as a non-R&D means of addressing specific firm limitations due to firms' weak internal innovation and dependency on external sources (Hervás-Oliver et al., 2021). Relying on licensing as a formal means of technology sourcing (formal planning of innovation), findings of the present study reflect a context of more formal OI cooperation; compared to more common informal mechanism such as non-technological and non-R&D activities used in low tech industries (Hervás-Oliver et al., 2021). The point to be made is that although the biopharmaceutical industry is an appropriate setting to examine the performance effect on formal R&D technology sourcing (i.e., licensing), significant differences regarding the complexity and innovation mechanisms between high- and low-tech industries encourage researchers to explore new research avenues and validate our findings in different contexts/setting (Caner and Tyler, 2015).

Laursen and Salter (2006) alluded to a dark side of innovation (i.e., over-search in their study) that may hinder innovation performance, indicating that if not managed well, OI could present a range of challenges, risks, and costs. In support of this indication, our results provide support for our hypothesized associations between both new R&D project source and new project familiarity with focal project performance, demonstrating that both project source and project familiarity present a direct effect (positive and negative,

respectively) on that focal project's performance outcome (i.e., termination or otherwise). We also find significant support for our hypothesized interaction effect between project sourcing and focal project familiarity, demonstrating that knowledge area (familiarity) does indeed minimize the negative risks and costs of sourcing via OI. By taking the project-level of analysis in this paper, we are able to make more fine-grained practical recommendations, and this also serves to open the black box of the complicated and nuanced NPD process in the highly competitive NPD arena. This research denotes that in the current era of high-technology, volatile environments, and strong competitive forces, strategic firms cannot avoid the dark side of OI. However, understanding the OI sourcing strategies presented in this paper may help them mitigate such effects. Thus, it is important for firms to know how their project sourcing strategies can create favourable project outcomes in this regard and, additionally, how they may mitigate the risks and costs of opening up their innovation processes if they choose to do so. This is especially relevant in the highly competitive and high-tech biopharmaceutical sector, in which it may initially seem beneficial for SME (small-to-medium enterprise) biotech firms to open their firm boundaries to external knowledge, technology, and to access new markets. However, we have demonstrated that this may not necessarily be the case.

This study theoretically and empirically sheds light on a potential dark side of OI, thus supporting cautionary arguments in the literature (Coad et al., 2021), and if such a phenomenon exists, how firms can understand and apply this knowledge to potentially mitigate the possible negative effects of such a strategy. In general, we found that externally sourced projects via OI have a higher likelihood of being terminated during the expensive and challenging NPD process, which falls in line with the work of Jones et al.

(2001). We also found that knowledge familiarity has a similar effect on focal project performance, namely that unfamiliar or new (knowledge area) projects also exhibit a higher likelihood of being terminated. This finding is akin to the findings of Arend et al. (2014), who found alliance-based knowledge development to be associated with reduced post IPO-performance.

Lastly, we found that a moderating effect exists between our two variables of interest as well. By applying a unique project-level typology, our results show that projects in a familiar knowledge area may be subject to diminished negative effects of being externally sourced and that a manager's best choice would be to choose an internal and familiar new R&D project. Subsequently, according to our results and in comparison to internal, familiar projects, the next best choice for managers is projects that are external and familiar. These projects presumably benefit from the tradeoff of capital for time as well as are further benefitted by the mitigating effect of the familiar knowledge domain, which may help to reduce the negative effects of any external risks associated with OI. In other words, these projects can be better managed and supported by leveraging the firm's internal base of knowledge. Internal, unfamiliar projects are the next best choice in terms of likelihood of success (or non-termination). Last are external, unfamiliar projects which were the most likely to be associated with project termination in comparison to internal, familiar projects. These projects face the highest level of risks associated with OI, and because they lie in an unfamiliar knowledge area, would not benefit from the associated mitigating effects. The results of this study would suggest that managers should avoid sourcing these types of projects if possible.

The findings of this study go beyond prior research by taking the less-often studied project-level scope of analysis, while also addressing the endogeneity concerns of a seemingly non-arbitrary choice made by firms. We also include a much-needed additional variable to the common 'open vs. closed' decision (i.e., familiarity), providing further fine-grained clarity to the results. In actuality, our data and analyses support the idea of a dark side of OI strategy. While on the surface, it might be argued that our results support the notion of 'not invented here' (Katz and Allen, 1982; Hussinger and Wastyn, 2016), we would, however, argue that 'not invented here' has more to do with the tenure and communications between insiders and outsiders and the inherent negative attitude of employees toward externally-developed knowledge (especially if the knowledge being acquired is from competitors) as opposed to the level of familiarity of the drug development project and the associated ability to integrate this outside knowledge and the fact that we have essentially focused on in-licensing external knowledge. As discussed earlier in this paper, costs (financial, risk, and otherwise) associated with in-licensing may arise in terms of absorptive capacity or the focal firm's ability to assimilate the knowledge and prior alliance experience of the focal firm (Carayannopoulos and Auster, 2010). Thus, we again note that despite in-licensing often entailing bringing in products from competitors (Fitzgerald, 1992), which raises the issue of 'not invented here', we have focused on project familiarity and absorptive capacity as contextual factors associated with the dark side of open innovation as opposed to an attitudinal 'not invented here' perspective.

6.1. Theoretical implications

The findings of this study have significant theoretical implications. Our findings are consistent with the theories we employed to conceptualize and construct our hypotheses. Specifically, we see both TCE and KBV empirically at play within our longitudinal dataset and models as suggested in H1 and H2. The empirical results confirm that both new R&D project source and familiarity have a direct positive and negative (respectively) effect on a project's likelihood of termination.

H1 posits that externally sourced projects were more likely to be associated with project termination. We find support for this hypothesis. Considering a TCE perspective, this empirically demonstrates that, in comparison to internally initiated projects, externally sourced (via OI) projects face higher risks, costs, and otherwise associated with transactions in the marketplace (in this case, licensing).

H2 posits that unfamiliar projects were more likely to be associated with project termination. That is, when a project is initiated in an unfamiliar knowledge area, the firm lacks a base of knowledge, including prior experience, to apply to this project. Thus, the project is subject to higher risks along the NPD process. We find support for this hypothesis as well. From a KBV standpoint, this demonstrates absorptive capacity empirically at play.

Most importantly, we find support for the moderating/interactive effect that familiarity poses on project source, demonstrating that the potentially harmful effects of an externally sourced project may be somewhat mitigated by familiarity and an appropriate internal knowledge base. Our results highlight the importance of using and

further contributing to the theoretical arguments TCE and KBV for OI at the project level of analysis.

6.2. Managerial implications

By examining the direct effects of technology source and project familiarity, we offer empirically tested results that provide theoretically supported fine-grained insights into the new R&D project selection process (i.e., fulfilling an innovation need). In practice, technology managers may use the insights provided by this research to make more informed and educated technology sourcing and knowledge type (i.e., therapeutic area) decisions. Based on our empirical results, ideally managers would prioritize internally sourced projects in a familiar (to the firm) knowledge domain. Moreover, if managers decide to turn to or are limited to external (OI) sourcing, our results suggest that selecting a project in a familiar domain may mitigate the associated risks. Also, by benefitting from additional insights into the moderating effects of familiarity on the project source selection type, managers have more information at their fingertips to recognize when and why they may be facing project-level performance challenges.

6.3. Limitations and future research

A limitation of this research is the lack of generalizability of these findings beyond the focal context under investigation, thus we are unable to conclude that these findings hold true for all settings/industries, and we wish to emphasize that our results reflect a focus on inbound open innovation; largely manifesting as in-licensing. Publicly traded biopharmaceutical firms and their R&D projects are not completely generalizable to all firms engaged in R&D due to the highly regulated and high-tech nature of this

sector. However, we believe the application of the 'make versus buy' decision demonstrated in this paper still applies, and we encourage future researchers to explore this phenomenon in other attractive sectors (i.e., low-tech, etc.).

In terms of future research, it would be fruitful to gather project-level patent data for our sample firms. Patent data (from the USPTO database[9]) would allow us to better understand the knowledge generation, accumulation, and potential spillover from one project to another. Further, future studies could employ a hazard model to account for the survival/attrition rates of projects over time and the right-censored nature of our ongoing NPD projects. This would allow a closer examination of the NPD process over time and consideration of the associated nuances of each clinical trial stage and the effects on projects within them. Further research requires the examination of project portfolio-level measures of diversity and source to determine how this may affect the decisions firms make regarding sourcing future projects. Given the significance of knowledge flow in NPD projects, it would be interesting to expand the study to include additional constructs deemed to be important in driving firms' inbound and outbound innovation such as the structural and relational embeddedness of their collaboration networks (Lyu et al., 2020; Shi et al., 2021), the paradox of openness (Stefan et al., 2022), firm age, and patent registration and citations (Filiou, 2021). These various analyses and methods would provide further insights and value to the results of this study.

[9] The United States Patent and Trademark Office (USPTO) issues patents and trademark registrations to inventors and businesses. The searchable online database provides electronic copies of issued patents and applications.

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Conference Presentations:

Purdy, L., Eslami, H., Eshghi, K., & Rod, M. (2021). Leveraging Familiarity Experience: Technology Sourcing and R&D Project Performance. At PDMA JPIM Research Forum 2021, *Virtual*, January 15, 2021.

Academic awards:

2021 Recipient of the Lieutenant Governor of New Brunswick Silver Medal - Business
2021 UNB Saint John Graduating Student Leader Award
2020/21 Dr. Colin B. Mackay Scholarship
2020/21 Ed and Muriel Maher Scholarship
2020/21 Erskine Ireland Carter Memorial Prize in Business Admin.
2020/21 UNB Saint John Campus Scholarship
2020/21 Dean's List Student
2019/20 Dean's List Student