Internal and External Antecedents of the Adaptive Search of Firms: The Multiplex Influence of Politics on Innovation

by

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DEDICATION

To my grandmother, Fan Cuichan.

ACKNOWLEDGMENTS

In the early summer of 2015, I was packing up my room in Tilburg, Netherlands. I had just finished a two-year research master's program at Tilburg University and had taken all the seminar courses in strategy and organization theory. I felt more than ready to start my PhD at the University of Michigan. I had every step planned out, including which courses to take and what research agenda to pursue. I had even picked out my dissertation topic—the nonmarket strategies of firms.

As it will be clear from this dissertation, my actual PhD life turned out very differently. Six years ago, I had no idea of how many pleasant surprises awaited me on this ride. I am glad to have discovered so many "unknown unknowns" that have enriched my intellectual perspectives and methodological skill set. Gladly, I'm still fascinated by the nonmarket strategies of firms, but I've come to learn more beyond this topic. I became intrigued by both the internal and external politics of firms, and was able to situate politics within the much broader theory of the Carnegie School, which resonated with me deeply. I am grateful for this important six-year journey at the University of Michigan, where I had the luxury to be exposed to the full spectrum of academic disciplines—sociology, political science, economics, complex systems, to name a few—and where I have met so many amazing scholars who inspired me and became my role models.

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ABSTRACT

Innovation by firms is often conceptualized as an adaptive search process. While a large body of research has examined what leads to effective search, it largely abstracts away the heterogeneous preferences and goals of the actors involved in this process. As a result, much less is understood about the role of heterogeneous preferences and the resultant political processes in search. This dissertation tackles this understudied area, exploring how politics—both within firms and between firms and their stakeholders—influence various aspects of search.

The first study looks at an important stage of adaptive search—the evaluation of proposals—and shows how politics can be influenced by the interdependence structure inside an organization and, in turn, influence the effectiveness of proposal evaluation. More specifically, I distinguish between proposals that target activities central in the interdependence structure and proposals that target peripheral activities. I argue that, compared to the latter, proposals targeting central activities tend to be evaluated *less* effectively, as they involve both greater informational challenges and greater political biases. I find support for my theory using over 110,000 proposal evaluations collected from GitHub, a large online platform for developing software projects. I also identity two organizational design levers—the knowledge breadth of the evaluators and the knowledge overlap across the evaluators—that help mitigate the informational challenges and political biases brought by interdependence.

The second study examines how firms' search behavior may be influenced by industrial policy, an important means through which the government imposes its preferences on firms. A computational model is developed to examine this question. The results show that the influence of industrial policy on search crucially depends on government ability, policy type,

policy stability, and environmental complexity. One important finding is that firms may not always be harmed when a less able government imposes its preferences on them. Instead, when a government with moderate ability periodically reshuffles what its policy incentivizes, it may improve firms' innovation outcomes by allowing firms to dislodge from local peaks.

The third study examines firms' search behavior during their participation in production communities, which have become an important source of innovation for firms and feature divergent goals among participants. In particular, I argue that, compared to the hobbyists, firm-affiliated participants tend to be more goal constrained (i.e., required to focus on the specific needs of their firm) but less resource constrained (e.g., more time and access to their firm's knowledge repertoire). As a result, firm participants may be less exploratory during problem search but more exploratory during solution search than the hobbyists. Analyses of over one million contributions made by participants in 290 software development projects on GitHub provide evidence generally consistent with this theory.

Overall, this dissertation shows the prevalent influence of divergent preferences and politics on innovation. The findings also show that, while the presence of divergent preferences can lead to political struggles that harm decision effectiveness, there are also channels through which it benefits innovation. By studying politics and innovation, this dissertation contributes to a more comprehensive and behaviorally realistic understanding of search.

CHAPTER I

Introduction

An enduring question for both managers and policy makers is how firms discover new possibilities for value creation. These new possibilities include new technologies, new product designs, and new ways of organizing production. The process of finding new possibilities is often viewed as an adaptive search process of firms. More specifically, under the conceptualization of the behavioral approach in strategy and organization literatures—which is often termed the "Carnegie School" (Simon 1947, March and Simon 1958, Cyert and March 1963)—firms are not omniscient optimizers with a well-specified choice set, but are boundedly rational actors who need to search for potential alternatives. Such conceptualization has stimulated a large body of research that examines what leads to effective search. Factors that have been explored include (i) different search strategies such as exploration vs. exploitation (e.g., March 1991, Gupta et al. 2006), local vs. distant search (e.g., Katila and Ahuja 2002, Leiponen and Helfat 2010), and problemistic vs. slack search (e.g., Greve 2003, Iyer and Miller 2008); (ii) the characteristics of firms, such as their decision making structure (e.g., Csaszar 2012, Knudsen and Levinthal 2007) and resource composition (e.g., Wu et al. 2014); and (iii) the characteristics of the environment, such as complexity (e.g., Levinthal 1997, Csaszar and Siggelkow 2010) and uncertainty (e.g., Siggelkow and Rivkin 2005, Posen and Levinthal 2012).

While the existing literature has generated rich insights on what affects firms' adaptive search, it oftentimes abstracts away the heterogeneous goals and preferences involved in the process. In other words, existing research tends to focus on the informational aspect of search rather than the political aspect. Much less is understood about how search may be influenced by the political conflicts among actors with different preferences. However, as Thompson (1967:134) has pointed out, both beliefs about causal relationships (i.e., information) and preferences are important dimensions of decision making. Assuming away heterogeneous preferences risks an incomplete understanding of the actual search process in firms and provides insufficient insights regarding ways to improve search effectiveness. As a result, Gavetti et al. (2007:528) refer to politics as one of the "forgotten pillars" of the Carnegie School and call for more scholarly attention on it. Along similar lines, Puranam (2018:82) calls for more research on the crossover effects between information and politics.[1]

This dissertation consists of three studies (Chapter II–Chapter IV) that tackle this understudied aspect of search and explore how politics may influence firms' search at various levels. I define politics broadly, as any actions taken by actors to influence decision making in favor of their own goals and preferences. In particular, the politics studied in this dissertation involve both internal and external politics—both those that arise from divergent preferences within a firm and those that arise from divergent preferences between the firm and its external stakeholders. The first study focuses on internal politics, where I examine how political biases may arise from the interdependence structure inside organizations and, in turn, influence decision quality during a key stage of firms' adaptive search—the evaluation of proposals. The second and third studies examine external politics. In the second study (joint work with Felipe Csaszar), we look at a crucial type of firms' stakeholders—the government—and examine how firms' search process may be influenced when the government imposes its preferences on firms through industrial policy. In the third study, I look at another set of stakeholders that have become increasingly important to firms—production communities that produce high-quality innovations used by firms and where firms pay their employees to participate. I specifically examine how firm-affiliated participants vs. hobbyists exhibit different search behaviors during their joint innovation process, due to their different goals and resources.

[1]Puranam (2018:82) labels information and politics as the knowledge-related and motivation-related challenges in organizations, respectively.

In the remainder of this chapter, I will first provide a short overview of each of the three studies and then discuss the overall insights and contributions of this dissertation.

Internal politics and adaptive search

The decision making in organizations is often a political process. In contrast to the prevailing economic assumption that organizations are unitary entities that share a common goal, strategy and organization researchers recognize that organizations are collections of individuals and subgroups with potentially conflicting interests and goals (Knight 1921, March 1962, Cyert and March 1963, Salancik and Pfeffer 1974). As a result, politics—actions taken by individuals to influence organizational decision making toward their own goals—can be pervasive (e.g., Pettigrew 1973, Pfeffer and Salancik 1974, Morrill 1995). Some of the forms politics can take include forming coalitions (e.g., Eisenhardt and Bourgeois 1988), controlling agendas (e.g., Hammond 1994), distorting communication (e.g., Crawford and Sobel 1982), and manipulating personnel appointments (e.g., Westphal and Zajac 1995). Although often viewed negatively and associated with organizational dysfunction (e.g., Mintzberg 1983), politics have been highlighted as a central process in organizational life that must be recognized (March and Simon 1958, Jensen and Heckling 1995, Pfeffer 1992).

In stark contrast with the rich literature that recognizes politics as a central theme in organizational life is the team-theoretical assumption often adopted in research about firms' adaptive search. Yet, scholars have recently begun to pay more attention to the role of politics in the search process. For example, Ganz (2018) examines the influence of political conflicts on learning, showing how politics can cause organizations to ignore useful information in some cases but engage in unnecessary information collection in others. Levinthal and Rerup (2020) discusses how, when there is ambiguity during search, divergent interests inside a firm can lead to political contestation over how best to interpret ambiguous feedback.

The first study of this dissertation joins this emerging line of research on internal politics during adaptive search. In particular, the study looks at a specific stage of search—the evaluation of proposals—and shows how politics can be influenced by the interdependent activity system within the organization and, in turn, influence the effectiveness of proposal evaluation. More specifically, I distinguish between proposals that target activities central in the interdependence structure of the organization and proposals that target peripheral activities. I contend that, compared to the latter, proposals targeting central activities tend to be evaluated *less* effectively, as they involve not only greater informational challenges (where the evaluators fail to assess the global impact of the proposal due to limited knowledge) but also greater political challenges (where the evaluators favor a proposal that increases their power within the organization). I find support for my theory using over 110,000 proposal evaluations collected from GitHub, a large online platform for developing software projects.

One important insight from this chapter is that it is important to pay attention to the political implications of interdependence in organizations. While the adaptive search literature seems to focus on the technological and informational aspects of interdependence (e.g., Ethiraj and Levinthal 2004a, Rivkin and Siggelkow 2007), this study shares the viewpoint of Albert (2018) for viewing interdependence through a political lens. The study also contributes to the literature by proposing an organizational design level—knowledge overlap across the evaluators—that can help reduce the political conflicts caused by interdependence.

External politics and adaptive search: The context of industrial policy

Firms also need to deal with politics outside their boundaries, as they face the pressure to attend to stakeholders who have divergent preferences and may make various claims to them (Freeman 1984, Neville and Menguc 2006, de Bakker and den Hond 2008). Arguably, one of the most important stakeholders firms face is the government. Considerable scholarly attention has been paid to firm–government relationships, including research on firms' nonmarket strategy (e.g., Hillman 2005), state ownership (e.g., Inoue et al. 2013), and the broad institutional environment (e.g., Martin et al. 2010, Chang and Wu 2014). One form of governmental influence that has received limited attention in the strategy literature is the government's industrial policy, but as I will discuss below, industrial policy provides an important context to study the influence of heterogeneous preferences on firms' search.

More specifically, industrial policy refers to government intervention that seeks to promote certain sectors or practices to facilitate economic growth in a way that would not occur in a market free of such intervention (Lazzarini 2015). A defining feature of industrial policy is its specificity and attention to substantive matters (Johnson 1982:19); that is, unlike other ways of government intervention that target the broad business environment, industrial policy targets the micro-level practices of firms. As such, industrial policy represents an important means for the government to express and impose its preferences for particular practices on firms. Moreover, by setting up external incentive structures (such as subsidies) and regulatory prescriptions (such as pollution control acts), industrial policy infiltrates firms' everyday decision making and, hence, unavoidably influences firms' adaptive search process. Yet, a good understanding of how exactly industrial policy influences firms' search and how firms could cope with the influence is still lacking.

The second study of this dissertation, joint work with Felipe Csaszar and published in *Strategy Science*, speaks to this gap in the literature. More specifically, we develop a formal model to study the influence of industrial policy on firms' adaptive search. The model builds on previous work on NK models, which conceptualize firms as searching for high "peaks" on a "fitness landscape" (Levinthal 1997). Our model augments that literature by allowing the firms' search landscape to be modified when the government imposes its preferences through two main types of industrial policy: regulations and incentives. In a nutshell, regulations are modeled as restricting the search area and incentives as deforming the landscape. One of the interesting results of this chapter is that firms may not always be harmed when a less able government imposes its preference on firms. Instead, when a government with moderate ability periodically reshuffles what its policy incentivizes, it may improve firm performance by allowing firms to dislodge from local peaks. More broadly, managers can use insights from this chapter to devise better means of coping with and leveraging the effects of industrial policy. The insights can also be applied to within-organization contexts in which managers impose their preferences on their employees during R&D activities through incentives and regulation-like rules.

External politics and adaptive search: The context of production communities

Another increasingly important stakeholder group firms face is production communities, where participants voluntarily collaborate to create goods or services (von Hippel and von Krogh 2003, O'Mahony and Ferraro 2007). Production communities represent an important source of high-quality product and innovation today, with open-source software development communities and Wikipedia being two notable examples (O'Mahony and Lakhani 2011, West and Bogers 2014, Bogers et al. 2017). Recently, more and more firms have become not only users of community-developed products (Dahlander and Magnusson 2008) but also participants who pay their employees to contribute to these communities in order to gain control over the quality of their products (von Hippel and von Krogh 2003, Dahlander and Wallin 2006).

As firms become more engaged in the joint innovation process of production communities, they unavoidably face the heterogeneous preferences and goals of the involved parties. It is important to have a good understanding of how divergent goals influence firms' innovation behavior during their community participation, which in turn can influence the output of joint innovation. However, researchers have only begun to examine firm participation in production communities, focusing on why firms participate, who they interact within the communities, and how much they contribute (von Hippel and von Krogh 2003, Dahlander and Wallin 2006, Nagle 2018, Zhang et al. 2019). Despite the valuable insights from existing research, there is still a lack of understanding of *what* firms contribute during the joint innovation process, and how their contributions are influenced by heterogeneous goals.

The third study of this dissertation speaks to this gap in the literature. Specifically, I examine how firm-affiliated participants differ from hobbyists in their search behavior in production communities, by looking at what they each contribute. Drawing upon research that distinguishes between exploration and exploitation (e.g., March 1991, Gupta et al. 2006) and research that distinguishes between problem search and solution search (e.g., Nickerson and Zenger 2004, Nickerson et al. 2012), I argue that firm participants and hobbyists exhibit different exploration tendencies during problem search and solution search, due to their different goals and resources. More specifically, compared to hobbyists, firm participants are more goal constrained (i.e., required to focus on the specific needs of their firm) but less resource constrained (i.e., having more time, financial resources, and access to their firm's knowledge repertoire). As a result, firm participants may be less exploratory during problem search but more exploratory during solution search.

The theory is tested in the context of the software development communities on GitHub. Analyses of over one million contributions made by participants in 290 open source development projects produce results consistent with the theory. In particular, the findings show that, as the firm's prior commitment to the community increases, firm participants increasingly engage in less problem exploration but more solution exploration than hobbyists.

One interesting implication of this chapter is that it suggests one potential upside of having heterogeneous goals during innovation. The findings show that, as firms become more involved in the community, there seems to be a "division of labor," where firm participants focus on finding novel solutions to existing problems and hobbyists focus on applying existing solutions to novel problems. In other words, the different goals and resources that firms and hobbyists have cause them to explore on different fronts. This implies that a community mixed with firm participants and hobbyists may achieve a better balance of exploration and exploitation than a community dominated by either one type.

Overall insights and contributions

While research on firms' adaptive search has predominantly abstracted away the heterogeneous preferences involved in the search process, this dissertation joins an emerging line of research (e.g., Ganz 2018, Levinthal and Rerup 2020) to study the influence of heterogeneous preferences and politics on search. The three studies of this dissertation show the ubiquitous role of politics in innovation. First, innovation takes place in a web of preferences, both within and beyond the boundary of firms. Therefore, politics can influence innovation through various channels—including the divergent interests within the company (Study 1), the imposed preferences from external actors such as the government (Study 2), and the heterogeneous goals in the production communities (Study 3). Additionally, different aspects of innovation can be influenced, including the decision quality during proposal evaluation (Study 1), the chance of finding high "peaks" during search (Study 2), and the tendency to engage in exploration vs. exploitation (Study 3).

The three studies also reveal both the harms and the benefits brought by heterogeneous preferences. On the one hand, politics are often viewed negatively and linked to organizational dysfunction (Mintzberg 1983). Resonating with this traditional view of politics, Study 1 shows that evaluating proposals with higher centrality within the interdependence structure tends to be associated with greater political struggle, which in turn leads to lower evaluation effectiveness. On the other hand, there is a group of studies that recognize the functional value of politics. A notable example is Rerup and Zbaracki (2021), who highlight divergent interests and political contestation as essential features of effective learning. Study 2 and Study 3 provide insights along this line, showing different ways through which divergent preferences can benefit innovation. More specifically, Study 2 shows that externally imposed preferences, such as those proscribed through industrial policy, can sometimes be beneficial by influencing firms to deviate from their search routine and dislodge from local peaks. It is worth noting that externally imposed preferences do not require high accuracy to be beneficial—a government with moderate ability that periodically reshuffles its policy can improve firms' search. Study 3 shows that, in production communities, the different goals of firm-affiliated participants and hobbyists may cause them to explore on different fronts. As a result, a balance of exploration and exploitation may be achieved through their joint effort.

Overall, the major contribution this dissertation seeks to make is to enhance our understanding of how divergent preferences and politics influence the important process of firms' adaptive search. In doing so, this dissertation helps build one of the "forgotten pillars" of the Carnegie School (Gavetti et al. 2007) and contributes to a more comprehensive and more behaviorally realistic understanding of search, which takes into account not only bounded rationality but also divergent preferences.

The rest of this dissertation is structured as follows. Chapter II presents Study 1, which examines the role of internal politics and interdependence during a specific stage of adaptive search—proposal evaluation. Chapter III presents Study 2, which examines how industrial policy, an important means for the government to express and impose its preferences on firms, may influence the performance of firms' adaptive search. Chapter IV presents Study 3, which examines how firm-affiliated participants in production communities exhibit different search behaviors from hobbyist participants, due to their different goals and resources. A conclusion is provided in Chapter V.

CHAPTER II

Seeing the Full Picture:
How Interdependence Affects Proposal Evaluation

II.1 Introduction

Almost all important decisions in organizations involve a proposal evaluation stage, where managers assess whether it is worthwhile to pursue a proposed idea—be the idea resources to acquire (e.g., Barney 1986, Makadok 2001), markets to enter (e.g., Porter 1980, Helfat and Lieberman 2002), or technologies to develop (e.g., Christensen 1997, Ahuja et al. 2013). Achieving a competitive advantage requires firms to effectively evaluate proposals. Evaluating proposals is particularly challenging when making strategic decisions, as these decisions are typically highly complex, uncertain, and ambiguous (Mintzberg et al. 1976, Schwenk 1988). Thus, the question of what makes evaluation effective has attracted increasing attention from strategy and organization scholars (e.g., Knudsen and Levinthal 2007, Csaszar and Eggers 2013, Luo et al. 2020). Factors examined include organizational attributes such as hierarchy and divisionalization (e.g., Csaszar 2012, Reitzig and Sorenson 2013, Keum and See 2017) and individual attributes such as knowledge and social networks (e.g., Boudreau et al. 2016, Teplitskiy et al. 2018).

While research on proposal evaluation has yielded valuable insights, it typically abstracts away the interdependent activity system of an organization. As a result, a key dimension of proposals is overlooked—their centrality in the activity system. More specifically, organizations are systems of interdependent activities (e.g., Milgrom and Roberts 1990, Levinthal 1997, Rivkin 2000), where some activities occupy a more central position in the interdependence structure and influence a greater number of other activities (Baldwin and Clark 2000, Siggelkow 2002, Ghemawat and Levinthal 2008). Therefore, proposals, depending on which activities they target, can have varying levels of influence and cause different dynamics during evaluation. For instance, a proposal to reduce the weight of a car's body, which influences myriad other decisions such as engine design and the branding, may be evaluated differently from a proposal to change the color of car seats, which does not influence as many decisions.

In this chapter, I study how a proposal's centrality in the interdependence structure influences evaluation effectiveness. I argue that proposals with high centrality may be evaluated *less* effectively due to two types of evaluation challenges: informational and political. The informational challenge refers to the case where, due to the high interdependence between a central proposal and other activities, evaluators lack the knowledge needed to accurately assess the proposal's overall impact (Ethiraj and Levinthal 2004a, Khanna et al. 2018). For instance, when evaluating the proposal to reduce the car's body weight, managers have often underestimated the associated costs on the rest of the manufacturing system (Baron 2016:18). The political challenge refers to the case where central proposals—due to their greater impact on the power relationships in the organization—increase the evaluators' tendency to distort decisions to increase their power (Mintzberg 1979, Pfeffer 1981, Fligstein 1987). For instance, the proposal to reduce the car's body weight might be evaluated more favorably by the person in charge of sourcing lightweight materials, as accepting the proposal may significantly enhance this person's importance to the firm.

My goals in this chapter are to examine (i) whether central proposals are indeed evaluated less effectively, and if so, (ii) how organizations can improve the evaluation effectiveness of these proposals by employing evaluators with certain knowledge characteristics. Arguably, these questions have not been investigated due to the steep data challenges of observing the evaluation process, the interdependence structure, the knowledge of the evaluators, and the effectiveness of the decisions for a large number of organizations and evaluators.

To overcome these challenges, I use the unique setting of GitHub, a large online platform for software development projects. The evaluation process I examine involves core developers accepting or rejecting proposals from contributors, a process similar to that in firms where managers review proposals. For the purpose of this study, GitHub allows for measuring all relevant constructs in extreme detail. Interdependence is measured using the function calls in the source code of the software. Knowledge is measured using the code editing history of the developers. Decision effectiveness is determined by comparing project quality under the actual decision vis-à-vis the counterfactual, opposite decision (e.g., for rejected proposals, I can recreate the project history to determine what would have happened to project quality had the proposals been accepted). Project quality is captured using an established measure of architectural health from the software engineering literature (e.g., MacCormack et al. 2006, Nord et al. 2012). The final sample consists of 290 software projects, involving over 3,000 decision makers evaluating over 110,000 proposals during the 2010–2018 period. This large number of repeated observations allows me to include both project and evaluator fixed effects to deal with various kinds of unobservable heterogeneity.

The results show that proposals with greater centrality in an organization's interdependence structure indeed are associated with less effective evaluations. Moreover, the negative impact of proposal centrality on evaluation effectiveness can be mitigated by employing evaluators whose knowledge is spread out in more domains and whose knowledge overlaps with the knowledge of others. This is because broader knowledge gives the evaluators a better understanding of the linkages across components, which alleviates the informational challenge, and higher knowledge overlap lowers the decision makers' incentives to seek power, which alleviates the political challenge. Overall, these findings provide a better understanding of what leads to effective evaluation when interdependence is taken into account. The findings also provide practical implications on how organizations can be designed, in terms of knowledge distribution, to improve proposal evaluation.

More broadly, this chapter contributes to strategy and organization research in three main ways. First, it contributes to the nascent literature on proposal evaluation (e.g., Knudsen and Levinthal 2007, Csaszar and Eggers 2013, Keum and See 2017) by fleshing out the role of interdependence. In particular, this chapter shows the harmful impact of a proposal's centrality on evaluation effectiveness, explores the informational and political mechanisms behind the impact, and suggests factors that mitigate the negative impact. Second, I provide insight on the bottom-up process of innovation, where decisions on individual proposals accumulate to shape organizational performance. This contrasts with previous studies, which have mainly examined innovation as resulting from the deliberate, top-down design process (e.g., Baldwin and Clark 2000, Karim and Kaul 2014). Finally, by elaborating on the political challenge during proposal evaluation, this chapter contributes to one of the "forgotten pillars" of the Carnegie School—politics during decision making (Gavetti et al. 2007:528).

The chapter proceeds as follows. In Section II.2, I bring together literatures on proposal evaluation, interdependence, and organizational power and propose a theory of how proposals with different levels of centrality in the organization's interdependence structure may be evaluated differently. In Section II.3, I describe the empirical setting and the methodology. Section II.4 presents the main findings. In Section II.5, I discuss the theoretical and managerial implications and avenues for future research.

II.2 Theory

In this section, I first summarize key insights about proposal evaluation in the literature, focusing on two major types of evaluation challenges. I then discuss how the two types of evaluation challenges can be influenced by a proposal's centrality in the interdependence structure of an organization. Finally, for each type of challenge, I propose how it can be mitigated by employing evaluators with particular characteristics.

II.2.1 Existing insights on proposal evaluation

Almost all decisions in organizations involve evaluating proposals and selecting alternatives (Simon 1947:3). Effective evaluation—accurately determining the value of the alternatives—

thus serves as a necessary condition for high-quality decisions. At the same time, evaluating proposals is challenging. The nascent proposal evaluation literature (e.g., Knudsen and Levinthal 2007, Csaszar 2012, Csaszar and Eggers 2013, Boudreau et al. 2016) highlights two major types of challenges that typically prevent effective evaluation: informational and motivational challenges.

The first type of evaluation challenge is informational, where the evaluators' limited information prevents them from accurately estimating a proposal's value. Rooted in the notion of bounded rationality (Simon 1947, March and Simon 1958, Cyert and March 1963), the informational challenge is twofold. First, decision makers may not have all the information they need to make an effective decision, as information is often dispersed across the organization and costly to transfer (Dougherty 1992, Milgrom and Roberts 1992, Grant 1996, Dessein 2002). Second, provided the necessary information, decision makers may not be able to process it in a way that accurately predicts the consequences of the proposal. This challenge has been underscored by research on mental models, which shows that decision makers often have an inaccurate understanding of the causal relationship between the alternatives and the value they create (Csaszar and Levinthal 2016, Martignoni et al. 2016). As a result, Csaszar and Eggers (2013) and Li (2017) suggest that evaluators with expertise closer to the proposal are more able to accurately predict its quality.

The second type of evaluation challenge is political, where evaluators distort their evaluation in pursuit of their own interests. Organizations are collections of individuals with potentially conflicting goals and interests (Knight 1921, March 1962, Salancik and Pfeffer 1974, Fama and Jensen 1983, Eisenhardt and Zbaracki 1992). Decision makers may pursue private interests at the cost of the organizations by distorting communication (e.g., Crawford and Sobel 1982), exerting suboptimal effort (e.g., Holmstrom and Milgrom 1987), gaming the incentive scheme (Obloj and Sengul 2012), or manipulating personnel appointments (e.g., Westphal and Zajac 1995). When it comes to the proposal evaluation literature, while existing research mostly builds on the team-theoretical assumption that evaluators share a common goal, two notable studies look at self-interested evaluators. Studying proposal evaluation in a large multinational firm, Reitzig and Sorenson (2013) show that decision makers tend to favor ideas from their own divisions. Keum and See (2017) discuss how evaluators tend to promote their own ideas to improve their status or advance their career.

II.2.2 How interdependence heightens the informational and political challenges during proposal evaluation

While the literature on proposal evaluation has generated important insights, studies tend to focus on the evaluation of proposals in isolation and abstract away the interdependence structure inside the organizations. However, viewing organizations as complex systems with interdependent activities has a long tradition in organization studies (e.g., Thompson 1967, Milgrom and Roberts 1990, Levinthal 1997). More specifically, interdependence refers to the situation where the value generated from one activity varies as other activities change (Puranam 2018:47). Due to interdependence, the impact of a proposal can go well beyond its original intention and cause immense challenges for evaluation. Notably, Khanna et al. (2018) show that the interdependence of patents creates cognitive challenges for evaluating invention projects and reduces the likelihood of project termination. While their study provides an important first step to introduce the role of interdependence to evaluation, a direct examination on how interdependence influences evaluation effectiveness is still lacking. Moreover, the theory I propose extends Khanna et al. (2018) by (i) examining how interdependence would increase both informational and political challenges and (ii) exploring how these challenges can be mitigated by employing evaluators who have certain knowledge characteristics.

Studies have examined interdependence at two different levels: the organization and the activity. While the former focuses on the overall complexity or modularity of the organization (e.g., Sanchez and Mahoney 1996, Levinthal 1997, Ethiraj and Levinthal 2004b), the latter looks at interdependence around each activity and distinguishes between the central and the peripheral activities (Siggelkow 2002, Rivkin and Siggelkow 2007, Sosa et al. 2013, Baldwin et al. 2014). Central activities locate at the core of the interdependence structure and correspond to the major functions of a product; peripheral activities are only loosely connected to the other activities and correspond to secondary functions. In this study, I follow the second approach and examine how the activities targeted by the proposals interact with the rest of the activities in the organization. More specifically, I distinguish between proposals that target the central and the peripheral activities and argue that proposals targeting the central activities may cause greater evaluation challenges.

First, evaluating proposals that target the central activities may be associated with a greater informational challenge. This is because proposals located at the center of the interdependence structure cause more widespread changes in the organization. However, fully assessing the impacts of these proposals can be difficult—individuals may not have sufficient knowledge to go beyond the local consequences of a proposal to consider its global impacts (Ethiraj and Levinthal 2004a, Khanna et al. 2018).

Second, evaluating proposals that target the central activities may also be associated with a greater political challenge. This is because changes to the central activities of an organization can cause major changes to the power relationships among decision makers (Fligstein 1987, 1990). Pfeffer (1981:85) points out that the intensity of power seeking increases with the importance of the decisions. More specifically, power seeking comes with costs: it takes additional time and cognitive effort and decision makers may put their reputations at risk when they distort decisions to increase power. As a result, decision makers are more likely to engage in power-seeking behavior when the decisions are important enough that the potential benefits outweigh the costs. Hence, when a proposal relates to the central activities, evaluation effectiveness may be hampered due to intensified political behavior.

Given that proposals targeting the central activities are associated with greater informational and political challenges during evaluation, I propose the following hypothesis:[2]

[2]One may argue that greater centrality may be associated with greater effectiveness, as organizations may spend more time and resources on evaluating central proposals. However, it is worth noting that the

Hypothesis 1*: The more a proposal targets a central activity of the organization, the less effectively it is evaluated.*

II.2.3 How knowledge breadth mitigates the informational challenge

When proposals with greater centrality create a tunnel-vision challenge for evaluation, the knowledge breadth of the evaluators becomes particularly relevant. Evaluators with diverse knowledge will often have a better understanding of the linkages across domains (Taylor and Greve 2006, Mannucci and Yong 2017), which allows them to better grasp how a change at one domain will influence other domains. For example, in their case study of a tire company, Brusoni and Prencipe (2006) highlight how the decision makers' global knowledge played a crucial role as the company transitioned to a more modular technological system. In contrast, when the evaluators' knowledge is concentrated, their attention would be constrained to only those domains they are familiar with (Audia and Goncalo 2007, Leiponen and Helfat 2010, Piezunka and Dahlander 2015). Such narrow focus prevents the evaluators from effectively assessing the impact of a proposal on the rest of the organization. For this reason, in software engineering, software development teams often assign a few individuals, who are not associated with any specific component of the software, to oversee the project and ensure global consistency during the development process (Brooks 1995:46). Thus,

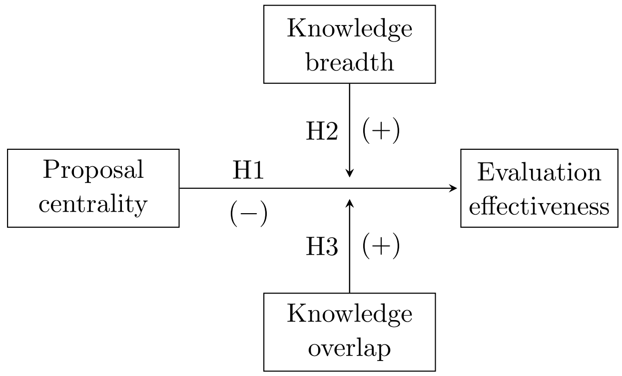
Hypothesis 2*: Knowledge breadth mitigates the negative impact of proposal centrality on evaluation effectiveness.*

II.2.4 How knowledge overlap mitigates the political challenge

When the high centrality of a proposal intensifies the power struggle during evaluation, the role of knowledge overlap becomes salient. An important form of power seeking during

informational and political challenges discussed above can not be easily solved by simply investing more time and resources. In terms of the informational challenge, the cognitive limitation for processing information is hard to be dealt with by spending more time on it. More importantly, the informational challenge often entails not realizing more resources need to spent on information collection (Baron 2016). In terms of the political challenge, a decision maker's political bias is hard to be changed by devoting more resources to the decision making, unless the underlying power structure is altered.

Figure II.1: Summary of the hypotheses



proposal evaluation is for evaluators to favor proposals that increase the importance of their knowledge (Mintzberg 1979:199–200, Nickerson and Zenger 2004:622). This power-seeking process may be mitigated by a higher knowledge overlap, for the following reason. A high knowledge overlap means that, when the importance of the evaluator's knowledge increases, it increases the power of others who have knowledge in the same domain. In other words, while the *absolute* power of the focal evaluator might increase, this person's *relative* power compared to others—which often matters more than absolute power (Dahl 1957, Pfeffer 1981)—might not increase as much. Consequently, the more the evaluators' knowledge overlaps with others', the lower their incentive to manipulate the evaluation decisions. Therefore,

Hypothesis 3*: Knowledge overlap mitigates the negative impact of proposal centrality on evaluation effectiveness.*

In Figure II.1, I provide a summary of the hypotheses. In short, I argue that proposals that are central in the interdependent activity system of the organization create greater challenges during evaluation, leading to lower evaluation effectiveness (Hypothesis 1). The heightened evaluation challenges—one informational and one political—can be mitigated, respectively, by increasing the knowledge breadth (Hypothesis 2) and knowledge overlap (Hypothesis 3) of the evaluators.

II.3 Methodology

This section presents my empirical strategy. I first describe the empirical setting and the sampling criteria, then explain the measurement of the variables, and finally present the estimation model.

II.3.1 Setting and sample

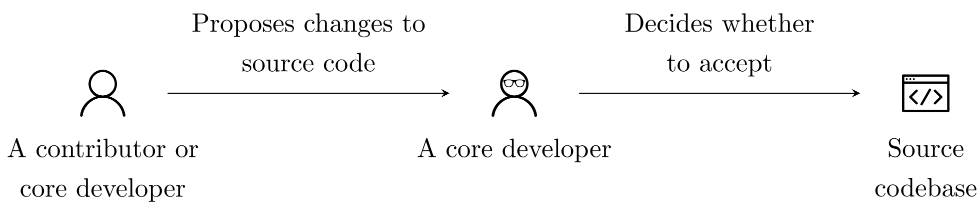
The empirical setting is GitHub (github.com), an online platform hosting the largest number of open source software development projects. GitHub allows developers to collaboratively work on the source code of the software. Such collaboration often involves two types of actors: core developers and general contributors. While core developers have access to directly modify the source code, general contributors do not. Due to the different levels of access, software changes usually go through a review process, as illustrated in Figure II.2. Namely, the contributors, and sometimes core developers as well, propose changes[3] and the core developers decide whether or not to accept them. This evaluation process is similar to the process in traditional organizations where employees or lower-level managers submit proposals to be approved by higher managers.

GitHub provides three unique advantages that makes it an idea "fruit fly" type of setting to study the impact of interdependence on proposal evaluation and the moderating role of the evaluators' knowledge characteristics.[4] Because many of the projects on GitHub are open source software, the development history of these projects is publicly visible. This allows me to collect detailed information on the entire proposal evaluation process, including the submitters, the reviewers, the content of the proposals, and the final decisions. A second advantage is that GitHub records all historical versions of the source code, allowing the evolution of the software's interdependence structure to be tracked over time. The long-

[3] In GitHub's lingo, this process of proposing changes is called a "pull request."

[4] Note that I am not suggesting GitHub as an appropriate setting for any type of organizational questions, as GitHub projects do not belong to traditional forms of organizations after all. However, as I explain below, I posit that GitHub is a suitable setting for the purpose of studying how interdependence influences evaluation effectiveness and for studying the effect of knowledge distribution.

Figure II.2: The evaluation process on GitHub



tracked history also allows for the fixed effects at the project, evaluator, and year levels to be included during estimation to account for multiple sources of unobservable heterogeneity. The third advantage is that GitHub allows me to generate the counterfactuals of the evaluation decisions. Namely, it is possible to simulate what the software would be like had a different decision been made on a proposal and to calculate the effectiveness of the actual decision.

I employed four sampling criteria to filter out projects unsuitable for this study. First, only open source software projects were included because their source code and development process are publicly observable. Second, projects were excluded if they did not have test files or had fewer than 10 core developers along its history. This exclusion ensures that only serious software engineering projects were sampled, not amateur projects for the purpose of experimentation or learning. Third, only projects with at least 200 proposals were included to ensure that the projects had sufficient history to track. Finally, only projects whose major language was Python, C#, or Java (i.e., one of these languages account for at least 75% of the code) were included. This language constraint was due to the limitation of the software used to analyze the interdependence of the source code, which is discussed below. The final sample consists of 290 software development projects involving 3,686 core developers and 110,397 proposals during the years 2010–2018.

It is worth noting that open source projects—especially large ones, like those in my sample—resemble traditional organizations in several aspects. First, facing fierce competition, core developers on GitHub need to make strategic decisions such as positioning their software to attract users, similar to when firm managers seek to maximize profits (Gousios et al. 2015).

Second, the authority relationships observed in firms are also present on GitHub and arise from the expertise and the decision rights to accept and reject others' contributions (Puranam et al. 2014). Finally, decisions on GitHub may also involve politics, as software features may result from negotiation among different parties (Tsay et al. 2014). At the same time, GitHub provides a conservative setting for studying the political challenge, as proposal evaluators may have a lower tendency to seek power due to the lower financial stakes; thus, GitHub provides a lower bound for the effect of the political challenge in traditional organizations.

II.3.2 Measures

The gist of my measurement approach is to measure interdependence based on the function calls between files in the source code (Myers 2003, de Souza et al. 2005, MacCormack et al. 2006, Baldwin et al. 2014), measure knowledge based on the frequencies at which an individual coder has edited a source file in the code (Mockus and Herbsleb 2002, Bird et al. 2011), and measure decision effectiveness based on how the decision influences the quality of the projects (MacCormack et al. 2006, 2012). These measures are well rooted in the literatures on software engineering and strategy. Below, I describe the measurement of each variable in detail.

Dependent variable

The dependent variable is whether the evaluation decision on a proposal is effective or not. I deem a decision to be effective if a "good proposal" (i.e., one that improves the quality of the project) is accepted, or a "bad proposal" (i.e., one that hurts the quality of the projects) is rejected. In other words, effective decisions include cases of both true positives and true negatives, as represented by the shaded areas in Figure II.3.

Project quality is captured using the propagation cost of the software, a measure of quality often used in the software engineering literature (Brown et al. 2011, Nord et al. 2012). Propagation cost measures the extent to which the software is ill-structured (colloquially known as "spaghetti code"). Having simple and well-structured code ensures high reliability, maintainability, and evolvability of the software (Hoare 1981:81, McConnell 2004:80, Mac-

Figure II.3: The intuition behind the dependent variable

		Quality of the proposal	
		Good	Bad
Decision	Accept	True positive	False positive
	Reject	False negative	True negative

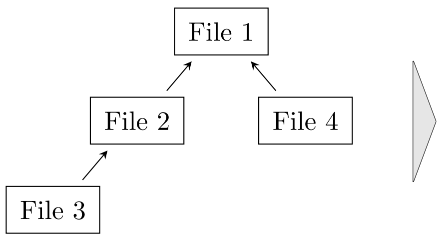
Cormack and Sturtevant 2016) and has been highlighted by Turing Award winner Edsger W. Dijkstra as the "crucial matter that decides between success and failure" (Dijkstra 1982:347). For open source software, well-structured code is even more critical, as it enables coordination among distributed developers (Lee and Cole 2003, Aberdour 2007). Apart from propagation cost, a major alternative measure of software quality is the cyclicality of the software (i.e., the prevalence of circular dependencies in the code; Oyetoyan et al. 2013, Sosa et al. 2013), which I use later as a robustness check.

To be more specific, propagation cost measures the percentage of the source files that can be affected when a random source file is changed (MacCormack et al. 2006, 2012). It is calculated as the density of a visibility matrix that contains all the direct and indirect interdependence across files. More formally,

$$PropagCost_t = \frac{1}{N^2} \sum_{f=1}^{N} \sum_{g=1}^{N} v_{f,g,t}, \tag{1}$$

where N denotes the total number of source files and $v_{f,g,t}$ denotes whether source file f makes source file g visible by calling a function from (i.e., depends on) g through path length 0 or up to $N-1$ at time t. Figure II.4 provides an example. Suppose a software has the function call network shown in Figure II.4a. On the right of the function call network is the derived visibility matrix, where a 1 in a cell means the row file calls a function in the column file through path length 0 or up to 3. The propagation cost thus equals the sum of the 1's in the visibility matrix divided by 4^2, which equals 0.5 (= 8/16), meaning that on average 50% of the files in the software will be impacted when a file is changed.

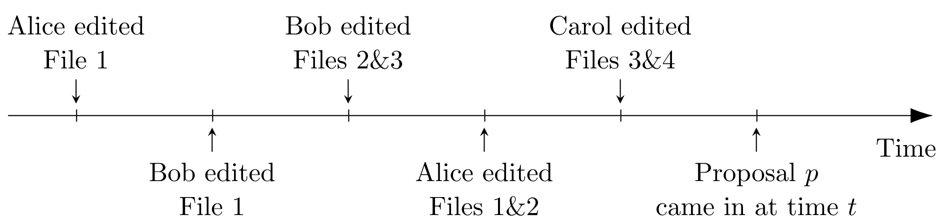
Figure II.4: Illustrative example of a software development project



	File 1	File 2	File 3	File 4
File 1	1			
File 2	1	1		
File 3	1	1	1	
File 4	1			1

$PropagCost = 8/(4^2)$

(a) Function call network, visibility matrix, and propogation cost



(b) Editing history

	Knowledge vector	Knowledge breadth	Knowledge overlap
Alice	$(2,1,0,0)$	$-\big[(2/3)^2+(1/3)^2\big]\times 4=-20/9$	$(Alice, Bob)=1$; $(Alice, Carol)=0$
Bob	$(1,1,1,0)$	$-\big[(1/3)^2+(1/3)^2+(1/3)^2\big]\times 4=-4/3$	$(Bob, Alice)=2/3$; $(Bob, Carol)=1/3$
Carol	$(0,0,1,1)$	$-\big[(1/2)^2+(1/2)^2\big]\times 4=-2$	$(Carol, Alice)=0$; $(Carol, Bob)=1/2$

(c) Knowledge profiles of evaluators

	File 1	File 2	File 3	File 4	Power
Alice	2/3	1/2	0	0	$\big[(2/3)\times 2+(1/2)\times 1\big]/2=11/12$
Bob	1/3	1/2	1/2	0	$\big[(1/2)\times 1+(1/2)\times 0\big]/2=1/4$
Carol	0	0	1/2	1	$\big[(1/2)\times 0+1\times 0\big]/2=0$

(d) File ownership and power of evaluators

Finally, the exact measure of decision effectiveness is denoted by *GoodDec*. Consistent with the intuition in Figure II.3, *GoodDec* is a dummy variable that equals 1 if an evaluator accepts a proposal that does not increase the propagation cost or rejects a proposal that increases the propagation cost, and equals 0 otherwise. In other words, a good decision is one that keeps the code simple and well structured, which is considered "the primary technical imperative" during software development (McConnell 2004:77). Formally, this dependent variable is defined as:

$$GoodDec_p = \mathbb{1}\left[Accept \;\&\; \mathit{\Delta} PropagCost_p \leq 0\right] + \mathbb{1}\left[Reject \;\&\; \mathit{\Delta} PropagCost_p > 0\right], \qquad (2)$$

where $\Delta PropagCost_p = PropagCost^p_{if\ accepted} - PropagCost^p_{if\ rejected}$; that is, the difference between the propagation cost of a project had proposal p been accepted and that had the proposal been rejected. This calculation requires simulating counterfactual decisions, which is made possible by GitHub's feature that allows for local experimentation with the source code.

Independent variables

I hypothesize that evaluation effectiveness would be influenced by proposal centrality and its interactions with the evaluators' knowledge breadth and knowledge overlap. In this subsection, I describe the measurement of these three constructs.

Proposal centrality. The centrality of a proposal is calculated as the degree centrality of the source file that was changed by the proposal in the function call network of the software. More specifically, the centrality of a source file is operationalized as the file's weighted in-degree centrality (Newman 2010:169); that is, the total number of times the functions in the focal source file are called by another file. In the example in Figure II.4, File 1 has a centrality of 2, File 2 has a centrality of 1, and Files 3 and 4 have a centrality of zero. When a proposal induces changes in multiple source files, the average centrality across the changed files is used as the measure of proposal centrality.

Knowledge breadth. Knowledge breadth is operationalized as the Herfindal Index (HHI) of an evaluator's knowledge domains. The knowledge domains of an evaluator are represented by a knowledge vector, where each element is the evaluator's knowledge of a source file (proxied by the number of times the evaluator edits that file). For instance, Figure II.4b depicts the editing history of software with four source files. Since Alice has edited File 1 twice, File 2 once, and has never edited Files 3 and 4, she has a knowledge vector of $(2, 1, 0, 0)$. When measuring the breadth of the knowledge vectors, the traditional HHI measure suffers from a comparability problem: the vectors' dimensionality (i.e., the total number of files) varies across projects and over time, but HHI cannot be compared across different dimensionalities.[5] To adjust for dimensionality, I multiply the HHI by the number of dimensions N, an approach common for dealing with the comparability problem in high-dimensional spaces (Sun et al. 2011, Zimek et al. 2012:380).[6] Note that the HHI measures concentration and thus is a reverse measure for breadth. For ease of interpretation, a negative sign is added to the measure so that a larger value represents a higher knowledge breadth. Formally, knowledge breadth is defined as follows:

$$KnBreadth_{e,t} = -HHI(\mathbf{k}_{e,t}) \cdot N_t, \tag{3}$$

where $\mathbf{k}_{e,t}$ represents the knowledge vector of evaluator e at time t. For illustration, Figure II.4c presents the *KnBreadth* for each evaluator.

Knowledge overlap. Knowledge overlap is measured using the average similarity between the focal evaluator's knowledge vector and the knowledge vectors of others in the organization. Similarity is operationalized as an adaptation of Jaccard similarity (Zaki and Meira 2014:88), which is a common measure of the overlap between two sets. More specifically, the knowledge

[5] For instance, for a vector with two dimensions, the possible HHI values fall within the range of $[0.5, 1]$; for a vector with 20 dimensions, the possible HHI values fall within $[0.05, 1]$. As a result, an HHI that equals 0.5 would denote a highly diverse vector in the former case but a relatively concentrated vector in the latter case.

[6] The rationale behind the multiplication is that it equals dividing HHI by $1/N$, which is the smallest value HHI could take for a knowledge vector with N dimensions.

overlap of an evaluator with another is calculated as the number of files they both have knowledge in divided by the number of all files the focal evaluator has knowledge in. Formally,

$$KnOverlap_{e_1,e_2,t} = \frac{|\mathcal{K}_{e_1,t} \cap \mathcal{K}_{e_2,t}|}{|\mathcal{K}_{e_1,t}|}, \tag{4}$$

where $\mathcal{K}_{e,t}$ denotes the set of files that evaluator e has non-zero knowledge in at time t.[7] For instance, in Figure II.4, Alice and Bob commonly own File 1 and File 2. Therefore, $KnOverlap_{Alice,Bob}$ equals 1 (= 2/2), and $KnOverlap_{Bob,Alice}$ equals 2/3 (see Figure II.4c). This asymmetry of *KnOverlap* accounts for the fact that the same amount of overlap may matter more for an evaluator with a smaller knowledge set.

With the knowledge overlap between a pair of evaluators defined, the knowledge overlap of an evaluator in the whole organization is aggregated by taking the average of the evaluator's knowledge overlap with all other evaluators in the organization. Note that because the organizational boundary of GitHub projects is fluid and not as well defined as in traditional organizations, I define active evaluators as the core developers who have made at least one evaluation decision for the project within the last 365 days of the proposal submission date.

Control variables

I include a set of control variables at the proposal, the evaluator, and the project levels. Definitions of the control variables are in Table II.1. At the proposal level, I control for the number of changes proposed (*nFilesChanged*), the number of evaluators involved, and the number of participants who commented in the discussion section of the proposal (*nReviewers* and *nDiscusants*). Since a proposal can be submitted by a general contributor or a core developer, which could influence the quality of the proposal and the evaluation, I control for whether the submitter was a contributor or a core developer (*ByContributor*). At the evaluator level, I control for knowledge proximity, measured as the average knowledge the evaluator had in the files changed by the proposal (*KnProximity*). Since the evaluator's

[7] To avoid having zero as the denominator in Equation (4), one additional element is added to the knowledge set of each evaluator. This additional element could be understood as some basic knowledge an evaluator has about the project even if the evaluator has not yet edited a source file.

cognitive capacity also may influence evaluation, I control for how busy the evaluator was while evaluating the proposal (*Workload*). I measure this as the number of code edits the evaluator made in all GitHub projects from 10 days before to 10 days after the proposal decision date. Furthermore, since the social network between the evaluator and the submitter might influence the evaluation of the proposal (Teplitskiy et al. 2018), I also control for the prior collaborations between the evaluator and the proposal submitter (*Acquaintance*). At the project level, I control for project age (*Age*) and size (*nCoreDevelopers*).

Table II.1: Definitions of controls and fixed effects

Variable	Definition
Control variables	
Proposal level	
$nFilesChanged_p$	Number of files changed by proposal p
$nReviewers_p$	Number of evaluators involved in proposal p
$nDiscussants_p$	Number of participants who commented in the discussion section of proposal p
$ByContributor_p$	Equals one if proposal p was submitted by an external contributor and zero otherwise
Evaluator level	
$KnProximity_{e,t}$	Average amount of knowledge of evaluator e across the files changed by a proposal at proposal submission time t
$Workload_{e,t}$	Number of code edits evaluator e made across all GitHub projects from 10 days before to 10 days after proposal submission time t
$Acquaintance_{e,t}$	Number of previous interactions between the author of the proposal and evaluator e by proposal submission time t
Project level	
Age_t	Number of months since the creation of the project at proposal submission time t
$nCoreDevelopers_t$	Number of core developers who were active in the past 365 days of proposal submission time t
Fixed effects	
Project	The software project to which the proposal was submitted
Evaluator	The decision maker(s) of the proposal
Year	The year of the proposal submission

II.3.3 Model specification

I estimate the following linear probability model to test the three hypotheses. To account for unobservable heterogeneity of the projects, the evaluators, and the macro-environment that could confound the results, the estimation includes project, evaluator, and year fixed effects:

$$\begin{aligned}\mathbb{P}\left[GoodDec = 1\right] = \beta_0 &+ \beta_1 ProposalCentrality + \beta_2 KnBreadth + \beta_3 KnOverlap \\ &+ \beta_4 ProposalCentrality \times KnBreadth + \beta_5 ProposalCentrality \\ &\times KnOverlap + Controls + ProjectFE + EvaluatorFE \\ &+ YearFE + \varepsilon,\end{aligned} \tag{5}$$

where ε is an error term. The main effect of proposal centrality (Hypothesis 1) is captured by coefficient β_1 and the mitigating role of knowledge breadth and overlap (Hypotheses 2 and 3) is captured by coefficients β_4 and β_5, respectively.

II.4 Results

This section begins with a description of the summary statistics of the variables. Next, I discuss the main regression results. Finally, I present several additional analyses, including a mechanism test and the robustness checks.

II.4.1 Descriptive statistics

Table II.2 reports the summary statistics of the variables. The table suggests that there are sufficient variations in the key variables of interest. Overall, around 95% of the proposals are accepted and 80% of evaluation decisions can be viewed as good decisions. On average, the projects in the sample are slightly more than 29 months old (the mean of *ProjectAge*) and involve 13 active decision makers (the mean of *nCoreDevelopers*). The proposals on average touch 8 files (the mean of *nFilesChanged*) and involve 1 participant in the discussion section (the mean of *nDiscusstants*). These descriptive statistics are similar to those reported in

Table II.2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
Accept	0.95	0.22	0.00	1.00
Δ*PropagCost*	0.00	0.01	−0.04	0.02
GoodDec	0.80	0.40	0.00	1.00
ProposalCentrality	39.80	121.47	0.00	889.00
KnBreadth	−22.44	48.12	−340.92	−1.70
KnOverlap	0.25	0.21	0.00	1.00
KnProximity	15.75	29.77	0.00	181.33
nReviewers	4.31	4.11	1.00	20.00
nDiscussants	0.91	1.10	0.00	5.00
nFilesChanged	8.11	17.77	1.00	127.00
Acquaintance	94.68	202.37	0.00	1606.00
Workload	0.13	1.00	0.00	9.00
ByContributor	0.62	0.49	0.00	1.00
ProjectAge	29.34	27.44	0.00	164.96
nCoreDevelopers	12.86	10.11	1.00	56.00
Year	2015.97	1.42	2010.00	2018.00

other research using GitHub data (Gousios et al. 2014). Note that, although the average number of evaluators involved in a proposal (*nReviewers*) is 4.3, the majority of the proposals involve only one evaluator (around 69% involve one and 80% involve no more than two). Moreover, the values of *KnBreadth* are negative because a negative sign is added to the HHI to ensure that a higher value of *KnBreadth* indicates the knowledge of an evaluator is more diverse. Finally, for *ProposalCentrality* and *Workload*, the two most skewed variables, I use their natural logarithm transformation in the regression analyses, with 1 added before the transformation to avoid undefined values.

Table II.3 reports the correlations of the variables. Overall, the low correlations do not seem to pose multicollinearity problems. The average variance inflation factor (VIF) across the variables used in the regressions is 1.12, which is well below the common threshold of 10 for multicollinearity concerns (Hair et al. 2009:193).

Table II.3: Variable correlations

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
1. *Accept*	1.00														
2. Δ*PropagCost*	0.01***	1.00													
3. *GoodDec*	0.36***	−0.22***	1.00												
4. *KnBreadth*	0.04***	0.01*	0.02***	1.00											
5. *ProposalCentrality*	0.00	0.01*	−0.03***	0.02***	1.00										
6. *KnOverlap*	−0.00	−0.03***	0.00	−0.20***	0.06***	1.00									
7. *KnProximity*	0.04***	0.02***	0.06***	0.11***	0.26***	−0.03***	1.00								
8. *nReviewers*	−0.01***	−0.01***	−0.06***	−0.03***	0.02***	−0.02***	0.00	1.00							
9. *nDiscussants*	−0.20***	−0.03***	−0.10***	−0.06***	−0.02***	0.01**	−0.07***	0.20***	1.00						
10. *nFilesChanged*	−0.05***	−0.08***	−0.12***	−0.00	−0.02***	0.03***	−0.09***	−0.04***	0.08***	1.00					
11. *Acquaintance*	0.09***	−0.00	0.04***	0.09***	0.06***	−0.07***	0.15***	0.13***	−0.16***	−0.03***	1.00				
12. *Workload*	0.01***	0.00	0.02***	−0.06***	−0.02***	−0.03***	−0.02***	−0.01***	−0.01***	−0.01***	−0.01***	1.00			
13. *ByContributor*	−0.06***	−0.02***	−0.02***	−0.04***	0.05***	−0.06***	−0.04***	−0.00	0.01***	−0.04***	−0.05***	0.00	1.00		
14. *ProjectAge*	−0.04***	0.01***	0.01*	−0.09***	0.00	0.02***	0.11***	0.05***	0.04***	−0.02***	−0.02***	0.02***	−0.04***	1.00	
15. *nCoreDevelopers*	−0.04***	0.04***	−0.08***	−0.14***	−0.00	−0.22***	−0.11***	0.29***	0.17***	−0.03***	−0.04***	−0.02***	−0.02***	0.09***	1.00
16. *Year*	0.01***	0.01***	−0.03***	−0.01**	0.08***	−0.12***	−0.02***	0.11***	0.07***	0.01***	−0.07***	−0.03***	−0.07***	0.13***	0.32***

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

II.4.2 Main results

Table II.4 reports the main results. Model 1 includes only the main effects of the variables. Models 2, 3, and 4 include the interactions between knowledge breadth and proposal centrality and between knowledge overlap and proposal centrality. Project and evaluator fixed effects are added in steps in Models 3 and 4; this ensures that the final results are not driven by certain projects or evaluators. In all models, I standardize the non-dummy variables to ease the interpretation of the coefficients.

Before delving into the test of the hypotheses, it is worth noting that the effect of knowledge proximity ($KnProximity$) is significantly positive. This is consistent with Csaszar and Eggers (2013) and Li (2017), who suggest that evaluation effectiveness increases as the evaluators' knowledge gets closer to that of the proposals. Next, I discuss the test for each hypothesis.

In Hypothesis 1, I argue that proposal centrality would have a negative main effect on evaluation effectiveness. Consistent with this prediction, the coefficient of $ProposalCentrality$ is significantly negative ($p < 0.001$), even when year, project, and evaluator fixed effects are included in Model 4. In Hypothesis 2, I propose that knowledge breadth mitigates the negative impact of proposal centrality, which is also supported by the results. More specifically, in Model 4, the coefficient of the interaction term between proposal centrality and knowledge breadth is significantly positive ($p < 0.01$), suggesting that knowledge breadth reduces the negative impact of proposal centrality on evaluation effectiveness. Finally, in Hypothesis 3, I propose that knowledge overlap mitigates the negative impact of proposal centrality. Consistent with this prediction, the coefficient of the interaction term between proposal centrality and knowledge overlap is significantly positive ($p < 0.01$), meaning that knowledge overlap alleviates the negative impact of proposal centrality on evaluation effectiveness.

To further unpack the mitigating effects of knowledge breadth and knowledge overlap, Figure II.5 presents the marginal effects of knowledge breadth and knowledge overlap when

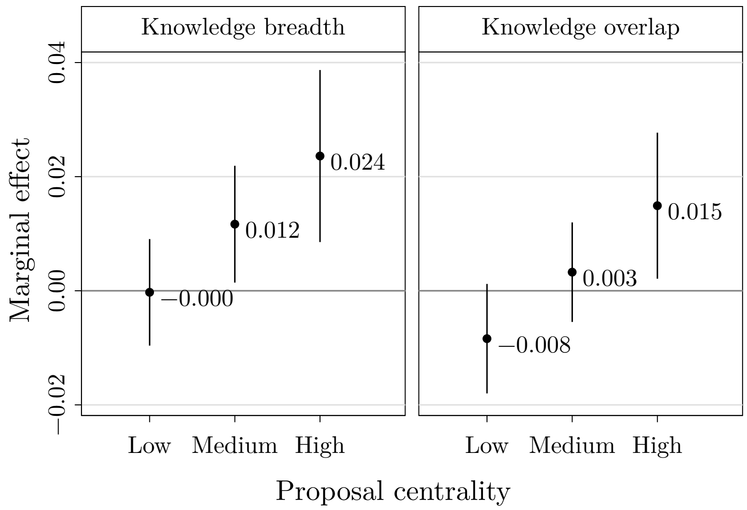
Table II.4: Main results

	Model 1	Model 2	Model 3	Model 4
	GoodDec	*GoodDec*	*GoodDec*	*GoodDec*
Independent				
ProposalCentrality (log)	-0.082^{***}	-0.088^{***}	-0.075^{***}	-0.071^{***}
	(0.009)	(0.008)	(0.006)	(0.006)
KnBreadth	0.010	0.013^{+}	0.010^{*}	0.012^{+}
	(0.007)	(0.007)	(0.004)	(0.006)
KnOverlap	0.013	0.012	0.014^{*}	0.003
	(0.008)	(0.008)	(0.006)	(0.005)
ProposalCentrality (log)×KnBreadth		0.023^{***}	0.011^{**}	0.012^{**}
		(0.005)	(0.004)	(0.004)
ProposalCentrality (log)×KnOverlap		0.028^{***}	0.014^{**}	0.012^{**}
		(0.006)	(0.005)	(0.004)
Controls				
KnProximity	0.023^{***}	0.022^{***}	0.018^{***}	0.016^{***}
	(0.006)	(0.006)	(0.004)	(0.004)
nReviewers	-0.025	-0.025	0.016	-0.005
	(0.022)	(0.021)	(0.027)	(0.018)
nDiscussants	-0.026^{**}	-0.025^{**}	-0.034^{***}	-0.031^{***}
	(0.009)	(0.009)	(0.005)	(0.004)
ByContributor	-0.010	-0.013	-0.014^{*}	-0.010
	(0.014)	(0.013)	(0.007)	(0.007)
nFilesChanged	-0.046^{***}	-0.045^{***}	-0.042^{***}	-0.042^{***}
	(0.005)	(0.005)	(0.005)	(0.004)
Acquaintance	0.014	0.013	0.014^{***}	0.007
	(0.015)	(0.014)	(0.004)	(0.008)
Workload (log)	0.006	0.006	0.003^{+}	0.007^{**}
	(0.004)	(0.004)	(0.002)	(0.002)
ProjectAge	0.005	0.003	0.011	-0.013
	(0.010)	(0.009)	(0.055)	(0.035)
nCoreDevelopers	-0.034	-0.033	0.004	0.001
	(0.022)	(0.021)	(0.015)	(0.013)
Fixed effects				
Year	Y	Y	Y	Y
Project	N	N	Y	Y
Evaluator	N	N	N	Y
Observations	58,635	58,635	58,630	58,377
R-squared	0.072	0.077	0.182	0.228

Notes. Two-way cluster robust standard errors by project and year in parentheses. All models include an intercept, which is not reported to save space.

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

Figure II.5: Marginal effects of knowledge breadth and knowledge overlap on proposal evaluation effectiveness, conditional on proposal centrality



Note. The bars denote the 90% confidence intervals.

proposal centrality is at low, medium, and higher levels (cut-off points at one standard deviation below and above the mean) based on Model 4, which includes year, project, and evaluator fixed effects. Figure II.5 shows that both knowledge breadth and knowledge overlap have a positive impact on evaluation effectiveness when proposal centrality is high. In terms of the effect sizes, when evaluating proposals located at the core of the project, a one standard deviation increase in knowledge breadth and knowledge overlap would increase the chance of good evaluation decisions by 2.4% and 1.5%, respectively. These effects are meaningful, especially considering that there is a 50% chance of making a correct random decision, which could go up to 54% with these two levers.

Overall, the results in Table II.4 provide support for my three hypotheses. The results highlight the increasing challenges to effective evaluation when a proposal targets a more central part of the organization. The findings also demonstrate how knowledge breadth and knowledge overlap would significantly mitigate the challenges to effective proposal evaluation.

II.4.3 Testing the power-seeking mechanism of knowledge overlap

To directly test whether knowledge overlap influences the effectiveness of a decision by influencing the power-seeking tendency of the evaluators, I measure whether a decision increases the power of the evaluator. Consistent with existing literature, I define the power of the evaluators based on the importance of their knowledge in the organization (e.g., Tushman 1977, Pfeffer 1981, Robbins 1990). This is calculated as the weighted average of the centrality of the source files an evaluator "owns" (Bird et al. 2011, Thongtanunam et al. 2016). Owning a file means that the evaluator edited at least 50% of all the changes made to the file, and I use the exact amount of ownership as the weight when calculating power. Formally, the power of evaluator e at time t is defined as follows:

$$Power_{e,t} = \frac{1}{|\mathcal{O}_{e,t}|} \sum_{f \in \mathcal{O}_{e,t}} \big(Ownership_{f,e,t} \cdot Centrality_{f,t} \big), \tag{6}$$

where f denotes the source file and $\mathcal{O}_{e,t}$ denotes the set of source files owned by evaluator e at time t. The centrality of a file is defined the same way as used for *ProposalCentrality*. In the example shown in Figure II.4d, Alice's power depends on the centrality of Files 1 and 2 (of which she owns 2/3 and 1/2, respectively); her power thus equals 11/12 ($= [(2/3) \times 2 + (1/2) \times 1]/2$).

With the power of an evaluator defined, the power impact of a decision is calculated as the difference between the evaluator's power before and after the decision on the proposal. Based on the decision's power impact, I define a new dependent variable of whether the decision indicates power-seeking behavior (*PowerSeekingDec*). Among all decisions that hurt the project quality, *PowerSeekingDec* equals one if the decision increases the evaluator's power and equals zero if it does not. The following linear probability model is estimated to test the power-seeking mechanism of knowledge overlap:

$$
\begin{aligned}
\mathbb{P}\left[PowerSeekingDec = 1\right] = \alpha_0 &+ \alpha_1 ProposalCentrality + \alpha_2 KnBreadth \\
&+ \alpha_3 KnOverlap + \alpha_4 ProposalCentrality \times KnBreadth \\
&+ \alpha_5 ProposalCentrality \times KnOverlap + Controls \\
&+ ProjectFE + EvaluatorFE + YearFE + \varepsilon,
\end{aligned} \tag{7}
$$

where ε is an error term. The coefficients of interest are α_1 and α_5, which capture how proposal centrality influences the power-seeking tendency of the evaluators and how knowledge overlap moderates the influence of proposal centrality. Table II.5 reports the results, where all non-dummy variables are standardized for ease of interpretation. Supporting the power-seeking mechanism, the results show that higher proposal centrality significantly increases the likelihood of power-seeking decisions ($p < 0.01$) and that knowledge overlap negatively interacts with proposal centrality ($p < 0.01$). This suggests that high knowledge overlap helps to mitigate the power struggle during the evaluations of central proposals, providing further support for Hypothesis 3.[8]

II.4.4 Robustness checks

I conduct a series of tests as robustness checks, which are summarized in Table II.6. First, to ensure the results are not sensitive to model specification, I include controls and fixed effects sequentially, cluster standard errors alternatively by projects, and use a Logistic model to replicate the estimation. These analyses generate robust results (see Tables A.1 and A.2). Second, I employ several alternative measures of the key variables. To determine decision effectiveness, software quality is alternatively measured using the cyclicality of the code (i.e., the percentage of the source files involved in circular dependencies; Sosa et al. 2013,

[8] It is also interesting to note that knowledge breadth has a positive main effect and an insignificant interaction with proposal centrality. This shows that, unlike knowledge overlap, knowledge breadth tends to increase power-seeking decisions in general. Yet, the negative interaction between knowledge breadth and proposal centrality in the main results (Table II.4) suggests that the informational benefit of knowledge breadth outweighs its political harm during the evaluations of central proposals.

Table II.5: Testing the power-seeking mechanism of knowledge overlap

	Model 5	Model 6
	PowerSeekingDec	*PowerSeekingDec*
ProposalCentrality (log)	0.023^{**}	0.022^{**}
	(0.008)	(0.007)
KnBreadth	0.098^{***}	0.098^{***}
	(0.022)	(0.022)
KnOverlap	-0.001	0.007
	(0.017)	(0.017)
ProposalCentrality (log)×KnBreadth		0.003
		(0.006)
ProposalCentrality (log)×KnOverlap		-0.021^{**}
		(0.007)
Other controls	Y	Y
Observations	9,472	9,472
R-squared	0.476	0.477

Notes. Two-way cluster robust standard errors by project and year in parentheses. Year, project, and evaluator fixed effects are included in both models. The intercept is not reported to save space.

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

Oyetoyan et al. 2013). I alternatively measure knowledge overlap using cosine similarity across individuals' knowledge.[9] I also alternatively measure proposal centrality using the centrality of the most central file, rather than averaging the centrality of all files changed by a proposal. This is to rule out the possibility that auxiliary file changes may downwardly bias the measure of proposal centrality. The results using the alternative measures remain robust (see Table A.2). Third, to account for potential biases caused by the unobservable heterogeneity of the proposal submitters and the submitter–evaluator pairs, I include the submitter fixed effects and the submitter–evaluator pair fixed effects. I also include the year–project pair fixed effects to account for the unobservable heterogeneity of a project within a specific year. In terms of potential biases caused by the time-varying capability of the

[9] Another commonly used measure of similarity is the Euclidean distance between two vectors (a reverse measure of similarity). I do not use Euclidean distance because the knowledge vectors tend to have many zeros and Euclidean distance overrates similarity when there are many common zeros. In other words, I'm interested in the similarity in the knowledge that people have, not in the knowledge that they do not have.

evaluators, I additionally control for the accumulated total knowledge and decision experience of the evaluators. The results are consistent with my main findings (see Table A.3).

Fourth, since my theory focuses on individual decision making, I carry out several tests to ensure that the results are not influenced by proposals involving more than one evaluator, including re-running the analysis in the subsample of only one-evaluator proposals and additionally controlling for whether the decisions were made by one or multiple evaluators. The results remain robust (see Table A.4). Fifth, to explicate the contingent effect of knowledge breadth and knowledge overlap, I split the sample into low-centrality and high-centrality proposals, using the median of centrality as the cut-off. The results, reported in Table A.5, are consistent with my theory: knowledge breadth and overlap significantly improve evaluation effectiveness in the latter subsample but not the former. Finally, I run several additional tests to rule out the alternative explanations for my findings. These tests include using the incidence of omission and commission errors, the duration of decision making, and the incidence of acceptance as the dependent variables (for a summary of the alternative explanations and the rationale behind the tests, see Table II.6; for a more detailed discussion, see Appendix B).

II.5 Discussion

In this chapter, I investigate the challenging process of evaluating proposals that interact with other parts of the organization. Using unique data from 290 software development projects on GitHub, I show that proposals located at the center of the interdependence structure are subject to greater evaluation challenges. I also show that these challenges can be mitigated by increasing the knowledge breadth and the knowledge overlap of the evaluators.

II.5.1 Theoretical contributions

This study contributes to strategy and organization research in five ways. First, it adds to the growing body of literature on proposal evaluation by fleshing out the role of interdepen-

Table II.6: Summary of robustness checks

Empirical Concern	**Robustness Test**	**Results**
The results may be sensitive to or driven by ...	To validate the robustness of the results, I ...	See ...
... model specification		
- inclusion of certain controls or fixed effects	... sequentially add controls and fixed effects	Table A.1
- how standard errors are clustered	... alternatively cluster standard errors by project	Table A.2 Panel A
- the choice of the estimation model	... replicate estimations using a Logistic model	Table A.2 Panel B
... the measurement of	... alternatively measure it by	
- project quality	- the cyclicality of the source code	Table A.2 Panel C
- knowledge overlap	- the cosine similarity across individuals' knowledge.	Table A.2 Panel A
- proposal centrality	- the degree centrality of the most central file	Table A.2 Panel A
... other omitted variables	... additionally include	
- unobservable heterogeneity of the submitters	- the submitter fixed effects	Table A.3 Panel A
- unobservable heterogeneity of the submitter–evaluator pairs	- the submitter–evaluator pair fixed effects	Table A.3 Panel A
- unobservable heterogeneity of the projects in a given year	- the project–year pair fixed effects	Table A.3 Panel A
- the time-varying capability of the evaluators	- the accumulated knowledge of an evaluator of all files	Table A.3 Panel B
	- the accumulated number of evaluated proposals of an evaluator	Table A.3 Panel C
... whether the decisions were made by one or multiple evaluators	... replicate estimations using the subsample of only one-evaluator proposals	Table A.4 Panel A
	... replicate estimations by averaging across rows of multiple evaluators	Table A.4 Panel B
	... control for whether the decisions were made by one or multiple evaluators	Table A.4 Panel C
... the interpretation of the interaction coefficients	... explicate the contingent effect of knowledge breadth and overlap by splitting the sample into low-centrality and high-centrality proposals	Table A.5
... alternative explanations		
- central proposals tend to increase the propagation cost of the software, which, given the high acceptance rate in general, leads to the negative effect of proposal centrality on decision effectiveness (H1)	... use two new dependent variables: the incidence of commission and omission errors; the alternative hypothesis suggests that proposal centrality would increase commission errors but not omission errors	Table A.6 Panel A; proposal centrality increases both commission and omission errors
- evaluators with higher knowledge breadth and knowledge overlap may be more conservative when evaluating proposals, which leads to the mitigating effect of knowledge breadth and overlap (H2 and H3)	... use a new dependent variable: the incidence of proposal acceptance; the alternative hypothesis suggests that knowledge breadth and overlap would reduce the likelihood of accepting a proposal	Table A.6 Panel B; knowledge breadth and overlap do not influence the likelihood of acceptance
- greater knowledge overlap increases other's ability to monitor decisions, which leads to the mitigating effect of knowledge overlap (H3)	... use a new dependent variable: the duration of decision making; the alternative hypothesis suggests that evaluators with greater knowledge overlap may try to make good decisions by spending more time evaluating the proposals	Table A.7 Panel A; knowledge overlap does not increase the duration of decision making
	... include a three-way interaction among knowledge overlap, proposal centrality, and the number of files changed in a proposal; the alternative hypothesis suggests that the number of files changed in a proposal, which increases the monitoring cost, would reduce the mitigating effect of knowledge overlap	Table A.7 Panel B; the number of files changed in a proposal does not moderate the mitigating effect of knowledge overlap

dence. Extending insights by Khanna et al. (2018), this chapter directly measures proposal evaluation effectiveness and explores how interdependence influences evaluation effectiveness through both informational and political channels. The results also show that the impact of interdependence crucially depends on two knowledge characteristics of the evaluators: knowledge breadth and knowledge overlap.

Second, this chapter shows the importance of paying attention to the political implications of interdependence in organizations. While the technological and informational aspects of interdependence seem to be a focus in the organization design literature (e.g., Baldwin and Clark 2000, Ethiraj and Levinthal 2004a, Rivkin and Siggelkow 2007), this chapter shares the viewpoint of Albert (2018) for a political lens on interdependence and brings in insights from the organizational power literature (e.g., Emerson 1962, Tushman 1977, Pfeffer 1981, Mintzberg 1983). In doing so, this chapter also answers the call by Puranam (2018:82) to study the crossover effects between knowledge and politics and contributes to one of the "forgotten pillars" of the Carnegie School (i.e., conflicts and politics during organizational decision making; Gavetti et al. 2007:528).

Third, I provide insight on how interdependence can shape innovation through a bottom-up process. Existing research on the role of interdependence in innovation tends to take a top-down approach, focusing on how managers can design the interdependence relationships in an organization to facilitate innovation (e.g., Baldwin and Clark 2000, Aggarwal and Wu 2014, Karim and Kaul 2014). In this study, however, I consider a bottom-up process where interdependence affects innovation by influencing individual proposal evaluation decisions. In particular, the findings show that, for proposals that are highly interdependent with other parts of the organization, assigning evaluators with high knowledge breadth and overlap helps to mitigate the challenges during the evaluation decisions, which when aggregated, can lead to a better performance of the organization.

Fourth, by studying the mitigating role of knowledge breadth, this study adds to the discussion on specialists and generalists. Extensive research has explored the benefits and costs of being a specialist or a generalist (e.g., Custódio et al. 2013, Toh 2014, Aldén et al. 2017). To reconcile the trade-offs, researchers identify several contingencies under which one outperforms the other, such as environmental characteristics (Teodoridis et al. 2019) and the types of performance outcomes (Kaplan and Vakili 2015, Leahey et al. 2017). In this study, I show that the specialist–generalist trade-offs also crucially depend on interdependence in organizations. The results demonstrate that generalists (i.e., evaluators with broad knowledge) outperform specialists (i.e., evaluators with narrow knowledge) when evaluating proposals located at the center of the interdependence structure, in which case a good understanding of linkages across activities becomes particularly valuable.

Finally, this chapter has implications for venture capital (VC) research, by showing that VCs' evaluation of investment opportunities may be influenced by their internal political processes. While the evaluation process in VC firms has attracted much attention, existing research mainly looks at the informational aspect of the process, focusing on the evaluation criteria or the cognitive biases of the evaluators (e.g., Macmillan et al. 1987, Franke et al. 2006). There is a limited understanding of how the social dynamics inside the VC firms play a role (Drover et al. 2017:1839). One notable exception is that of Guler (2007), who looks at the political processes inside VC firms as they decide whether to terminate an investment. My study, instead, provides insight on the political processes during the decisions of whether to select an investment opportunity. The findings suggest that VC partners may make biased decisions to increase their power in the firm and that increasing the expertise overlap among the VC partners may help mitigate such power-seeking behavior.

II.5.2 Managerial implications

The findings of this study suggest that interdependence in organizations matters during proposal evaluation and that organization designers should be mindful of the full picture of a proposal's impact. In particular, organization designers should take extra care when dealing with a proposal that targets the center of the interdependence structure, as the evaluators' ability to accurately assess the proposal's value can be hampered due to informational and political challenges. For instance, the evaluators may have "tunnel vision" and overlook the proposal's impact on other parts of the organization, or the evaluators may favor some changes over others to increase their power.

This study also provides a toolbox for organization designers to address these challenges of proposal evaluation in an interdependent organization. More specifically, for a proposal that targets the central part of the organization, employing and assigning an evaluator that is a generalist rather a specialist would likely curb tunnel vision and yield a better evaluation outcome. Employing an evaluator who is not the sole owner of his or her knowledge also improves proposal evaluation, by mitigating the power-seeking tendency of the evaluator. More generally, the chapter suggests that building some redundancy into the knowledge distribution of an organization can be beneficial, as it reduces knowledge differentiation and hence the power struggle around shaping the importance of the different knowledge.

II.5.3 Limitations and future work

This study has some limitations that provide opportunities for future research. First, the setting of GitHub may not be representative of other settings. For instance, the role of knowledge overlap requires knowledge to be an important source of power in the organization, which is more common in some industries (e.g., those that are knowledge intensive and feature horizontal authority; Dahlander and O'Mahony 2011) than others. Future research could investigate other settings and explore, for example, how knowledge overlap interacts with vertical authority during proposal evaluation. Second, I focus on individual decision making. While my findings carry implications for group decision making—as less biased individual evaluations mean better opinions to be aggregated in groups—future research could directly examine how various aggregation rules interact with interdependence to shape evaluation (e.g., Knudsen and Levinthal 2007). Third, among good evaluation decisions, I do not distinguish between true positives and true negatives due to their unbalanced distribution on

GitHub. Future research could employ a more suitable setting to explore how interdependence influences these two types of good decisions differently (e.g., Csaszar 2012). Finally, I only look at one evaluation criterion—a proposal's impact on code quality, whereas recent studies show that multiple evaluation criteria may be at work in organizations (Polidoro 2020, Vinokurova and Kapoor 2020). Future research could explore how the trade-offs among various evaluation criteria are influenced by interdependence and the knowledge of the evaluators.

II.5.4 Conclusion

In this chapter, I examined the challenging process of evaluating proposals that intensively interact with other parts of the organization. The chapter unveils both the informational and political challenges that prevent evaluators from effectively evaluating proposals. The chapter also provides two important organization design levers that help mitigate these evaluation challenges—knowledge breadth and knowledge overlap. In doing so, this chapter increases the behavioral realism of research on proposal evaluation and provides tools for managers to improve proposal evaluation, the high effectiveness of which is the cornerstone for almost all important decisions that shape firms' competitive advantage.

CHAPTER III

Government as Landscape Designer: A Behavioral View of Industrial Policy

Joint work with Felipe Csaszar

III.1 Introduction

Industrial policy—government intervention that aims to facilitate economic growth by promoting selective sectors or practices (Lazzarini 2015)—has resurged in the past decade (Stiglitz et al. 2013). Widely observed examples of this resurgence include: the World Bank, once a strong promoter of free markets, hosting round tables on "New Thinking in Industrial Policy" (Stiglitz et al. 2013); Germany, historically known for its liberal investment climate, increasing government intervention in foreign investments (Ulmer 2018); and McKinsey expanding to offer governments consulting services on policy making (Rodrik 2010).

Examples of the influence of industrial policy on firms include Denmark's wind energy subsidies, which promoted the development of wind turbines as efficient as coal plants (Cooke 2017), and Massachusetts' regulations on toxic chemical disposal, which spurred firms to discover cost-saving process innovations (King 1999, Lenox and Chatterji 2018:81). Of course, industrial policy does not always produce positive outcomes. For instance, US agricultural subsidies have induced farmers to plant crops that fit poorly with their land (Winters 2016).

The growing prevalence of industrial policy and its prominent influence on firms suggest it is increasingly important for managers to understand how exactly industrial policy would affect firms. Only then can firms properly prepare for, cope with, and benefit from industrial policy, thereby creating a source of competitive advantage.

The scholarly literature features several approaches to addressing industrial policy. Welfare economists analyze it as a solution to market failures, political economists delve into the motivations behind it, and political scientists examine the games played between firms and government. Even though these approaches have yielded fruitful insights, caution must be exercised when translating them into firm-level implications.

Such caution stems from the micro-level assumptions employed in the existing industrial policy literature. More specifically, while research from the various approaches has proposed refined perspectives on government—questioning its intention (e.g., Stigler 1975a), recognizing its bounded rationality (e.g., Lindblom 1959), and dissecting its structure (e.g., Lieberthal and Oksenberg 1988)—it has paid limited attention to the behavioral nuances of firms, typically assuming firms to be omniscient optimizers operating in a simple environment. Such view of firms contrasts with the behavioral conceptualization of firms adopted by the strategy and organizations literatures, which incorporates more realistic assumptions about firms and is rooted in the Carnegie tradition (Simon 1947, March and Simon 1958, Cyert and March 1963). Under this latter conceptualization, firm behavior results not from optimization but rather from a boundedly rational and adaptive search process that depends strongly on the complexity of the firm's environment (Simon 1996:53). In short, the micro-level assumptions underlying the macro-level predictions of the industrial policy literature are at odds with the assumptions of other literatures that study firm behavior. That mismatch has motivated calls by Coen et al. (2010:14) and Ostrom (2010:659) to advance the industrial policy literature by improving its micro-level realism.

In this study we adopt micro-level assumptions customary in the strategy and organizations literatures toward the end of improving our knowledge of how industrial policy affects firms. We develop a parsimonious yet behaviorally realistic model of how industrial policy affects firm behavior and performance, and we explore how results common to the industrial policy literature depend on micro-level mechanisms. Our model builds on previous work addressing firm search (Levinthal 1997) and subsequent research on NK models (for a review, see Ganco and Hoetker 2009). We augment that literature by allowing the firms' search landscape to be modified by the two main types of industrial policy: regulations and incentives. In a nutshell, we model regulations as restricting the search area and incentives as deforming the landscape.

We study the effect of industrial policy on firm behavior and performance under three main contingencies: (i) government ability (i.e., how likely is the government to identify and enact the optimal policy), (ii) policy stability (how frequently the government changes its policy), and (iii) complexity (how interdependent firm decisions are). The first two contingencies have been highlighted by the industrial policy literature as fundamental conditions for beneficial intervention (Alesina and Perotti 1996, Kohli 2004). Complexity, the third contingency, is the main contingency in the literature on boundedly rational search but has received scant attention in the industrial policy literature (Colander and Kupers 2014:6).

Our study contributes three novel findings. First, we identify conditions under which policy instability is not harmful, but can improve firms' chance of identifying high-performing new possibilities. We find two mechanisms at work in this dynamic, which we term "training" and "dislodging." Second, we characterize situations in which the industrial policy promulgated by an imperfect government can yield better outcomes (for the firm) than no intervention at all, as when such policy spurs firms' exploration. Third, we find that environmental complexity is a strong moderator of industrial policy effects: increasing complexity raises the intervention intensity required for a government intervention to be effectual and also limits the detrimental effects of an inept government. By bringing insights from the strategy and organizations literatures to the study of industrial policy, we answer calls in the industrial policy literature to increase micro-level realism and develop insights unlikely to be derived under the neoclassical view of firms that has prevailed in the industrial policy literature.

This research also offers four more general contributions to the strategy and organizations literatures. First, we contribute to a better understanding of how government affects firms. Despite extensive research on firms' nonmarket strategy (e.g., Hillman 2005), state ownership (e.g., Inoue et al. 2013), and the broad institutional environment (e.g., Martin et al. 2010, Ahuja and Yayavaram 2011), the strategy literature has paid limited attention to the influence of a government's industrial policy. We help fill this gap by identifying situations where industrial policy can benefit (or harm) firm performance and by suggesting when firms should follow (or ignore) government incentives. Second, we describe a new way of thinking about how government and firms interact. By interpreting regulations and incentives as (respectively) restricting where firms can search and deforming the search landscape, our work expands the search literature to start capturing the influence of the government on firms' search and innovation activities. Third, we further the idea that government can act as an exploration booster (Porter 1991) by fleshing out the factors—including policy type, frequency of policy change, and environmental complexity—that affect the success of such initiatives. Fourth, we advance the literature on landscape design (Levinthal and Warglien 1999) by suggesting levers that a landscape designer can use to improve search. In particular, our insights can be applied to within-organization contexts in which managers use incentives and regulation-like rules to guide R&D. Our results inform how managers can improve R&D effectiveness by choosing the rules' type, intensity, and frequency of change.

The chapter proceeds as follows. We begin by briefly reviewing the industrial policy literature and the boundedly-rational search literature, focusing on how the latter offers new considerations regarding commonly-held results in the former. Next, we describe how the model is set up. This is followed by presenting our main results and findings. Finally, we discuss broader implications of our results and suggest possible areas for future research.

III.2 Theoretical Motivation

This section sets the stage for our theory by: (i) defining industrial policy, (ii) summarizing commonly-held results in the industrial policy literature, and (iii) introducing considerations from the boundedly-rational search literature into the discussion of industrial policy.

III.2.1 Defining industrial policy

Industrial policy refers to government intervention that attempts to promote certain sectors or practices to facilitate economic growth in a way that would not occur in a market free of such intervention (Lazzarini 2015). The ultimate goal of industrial policy is to increase social welfare (Amsden 1989:49). A defining feature of industrial policy is its specificity and attention to substantive matters (Johnson 1982:19); that is, unlike other ways of government intervention that target the broad business environment, industrial policy targets the micro-level practices of firms.[10] It follows that industrial policy has pervasive effects on the firm: in addition to expressing government's preferences for particular practices, it also infiltrates firms' everyday decision making by setting up external incentive structures and regulatory prescriptions.

There are two main types of industrial policy: incentives and regulations (Vedung 1998). *Incentives* are economic inducements—such as subsidies, taxes, and tariffs—that make some choices cheaper (or more expensive) for firms. *Regulations* are rules stipulating what firms can and cannot do; examples include antitrust laws, pollution control acts, and production standards. A key difference between incentives and regulations is their level of coerciveness: although a firm need not take advantage of government incentives, it is required to follow all laws and regulations.

Industrial policy can differ not only in terms of its type, as just described, but also in terms of its intensity of intervention. That intensity can be of two forms, which we call "span" and "premium." *Span* captures how broadly the government intervenes in firm decisions. Its variation is illustrated by contrasting South Korea during the rule of Park Chung Hee (1963–1979) with Brazil during the Old Republic (1889–1930): whereas intervention extended throughout South Korea's entire economy, intervention in Brazil was restricted to only parts

[10] Other types of government intervention include macroeconomic policies and neo-corporatism (Coen et al. 2010:22–24). Macroeconomic policies such as Keynesian demand management focus on maintaining long-term financial stability of the whole economy; neo-corporatism such as in Scandinavian countries in the 1960s and 1970s focuses on fostering social partnerships between unions and firms. Unlike macroeconomic policies and neo-corporatism, industrial policy is "designed to be specific" (Landesmann 1992:245).

of the economy (Kohli 2004). *Premium* captures how strongly the government encourages firms to enact its preferences. Its variation is illustrated by the size of government subsidies, where larger amounts correspond to stronger encouragement. Thus, for example, subsidies in Austria and Denmark are nearly 10 times larger than US and UK subsidies (Buigues and Sekkat 2009). Note that while span applies to both incentives and regulations, premium applies only to incentives (since regulations are presumably nonnegotiable).

III.2.2 Commonly held results in the industrial policy literature

The industrial policy literature tends to agree that performance-enhancing industrial policy requires that the government be an able one and that policy instability be avoided. We discuss these two results next.

First, it is widely believed that the economy will suffer from intervention formulated by a low ability, inept government. The notion of government ability—also referred to as "governmental capability" (Lazzarini 2015) or "capacity" (Guillén and Capron 2016, Skocpol 1985)—broadly refers to the extent to which a government can identify and enact the optimal policy. This ability encompasses two aspects of the government: its competence and its benevolence. The competence of a government is its ability to identify the optimal policy, which depends on how well-educated and informed is its bureaucracy (see Pack and Saggi 2006 for a discussion of the information challenges faced by governments). In turn, the benevolence of a government depends on its ability to resist the influence of self-interested politicians and special interest groups (e.g., to avoid regulatory capture attempts effected through lobbying, bribery, and threatening; Dal Bó 2006, Krueger 1990). Large-sample studies have documented wide variation in government ability around the world (see, e.g., La Porta et al. 1999, Hanson and Sigman 2013).[11]

[11] While there is concern about governments being incompetent and nonbenevolent, it is incorrect to make the sweeping assumption that all governments share these problems. In terms of competence, Chang (1994) points out that governments have the capacity to establish sophisticated information networks (e.g., statistics bureaus) and to access more information that is less subject to local biases. In terms of benevolence, Kohli (2004) shows that some governments are much more successful than others in committing to economic development.

A government with limited ability is generally presumed to be detrimental. For instance, Kohli (2004) contrasts the wide disparity across civil servants in South Korea and Nigeria and argues that successful intervention requires an able government. The "government failure" argument (e.g., Stigler 1975b), which posits that incompetent or nonbenevolent governments should *refrain* from industrial policy interventions, also implicitly assumes that intervention can be beneficial only when government ability is high.

The second commonly held result in this literature is that policy instability stunts economic growth, where by "policy instability" is meant the frequency with which government policies change. A medium or high level of policy instability can result from political turbulence and social upheaval (as in Brazil from the 1930s until the 1980s; Banuri and Amadeo 1991), from policy re-definition due to periodic shifts in political regimes and agendas (as in the United States; Baumgartner and Jones 1993), and from the deliberate alternation of development priorities (as in South Korea during 1962–1991; Chang 1994). The industrial policy literature tends to agree that a highly unstable policy is detrimental to the economy, arguing that instability increases uncertainty and so deters investment. In their examination of more than 50 countries worldwide, Alesina and Perotti (1996) and Roe and Siegel (2011) document the negative effects of high political instability on both investment and development.

III.2.3 Considerations from the literature on boundedly rational search

Despite the rich insights generated, the industrial policy literature has focused on characterizing the government and the broad economy, paying limited attention to the nuances in firm behavior. In contrast, the literature on boundedly rational search (as advanced in the strategy and organizations literatures) *has* developed a nuanced understanding of firm behavior. Here we summarize how the literature on boundedly rational search views the firm and then discuss how considerations from that literature may alter commonly held results in the industrial policy literature.

The boundedly-rational search literature posits that decision making within firms is the result not of optimization but rather of adaptive search. Works in this tradition often conceptualize firms as searching for high “peaks” on a “fitness landscape” (Levinthal 1997). This literature has devoted considerable attention to three factors that affect search performance: environmental complexity, decision-maker accuracy, and environmental instability.

Environmental complexity refers to the level of interdependence among firm decisions. Complexity determines the “ruggedness” of the landscape and thus has a strong effect on search: higher complexity corresponds to more peaks on the search landscape, which increases the likelihood of firms getting “stuck” on a local peak. Research in this area has shown that complexity is a key contingency that influences almost every aspect of firm behavior, including organizational structure (Rivkin and Siggelkow 2003), imitation (Csaszar and Siggelkow 2010, Rivkin 2000), and industry shakeouts (Lenox et al. 2007). So notwithstanding the limited attention it has received in the industrial policy literature (Colander and Kupers 2014:6), the search literature suggests that complexity—by affecting firms’ search process—should also affect the relation between industrial policy and firm performance.[12]

The second key factor highlighted by this literature, *decision-maker accuracy*, refers to the decision maker’s correct perception of that landscape. Research in this area has shown that inaccuracy can actually be beneficial (Knudsen and Levinthal 2007, Csaszar and Levinthal 2016, Martignoni et al. 2016). For example, using simulations, Csaszar and Levinthal (2016) find that managers’ inaccurate understanding of the strategic context prevents firms from locking on local peaks and increases their chance of finding the global peak. Thus, the search literature suggests something that runs counter to the conventional wisdom in the industrial policy literature: that when the firms’ bounded rationality and the environment’s complexity are considered, there may be cases where policy by a low ability, inept government can produce favorable outcomes.

[12] In the industrial policy literature, a concept related to complexity is cross-industry linkages (Hirschman 1958), which refer to transactions across industries (e.g., between the tire and the automobile industries). In the search literature, complexity stems from *any* interdependence across decisions (not just transactions across industries). This latter, more comprehensive view of complexity, affects firm performance in ways not currently studied by the industrial policy literature.

The third key factor in the literature on boundedly rational search, *environmental instability*, refers to how frequently the payoff from firms' choices changes as a result of external shocks. The search literature suggests that some instability can be beneficial: although environmental instability makes it more difficult for firms to adapt (March 1991, Siggelkow and Rivkin 2005, Posen and Levinthal 2012), it also creates opportunities for the firm to dislodge itself from suboptimal local peaks. Policy instability can certainly be viewed as a type of environmental instability; after all, a changed government policy alters the payoffs from firms' choices and thus alters the landscape on which firms search. Thus, the search literature suggests that policy instability may not always hurt firm performance.

In sum, this section suggests it is worth exploring whether and under what conditions the results from the industrial policy literature change when one accounts for boundedly-rational search considerations. In particular, the literature on search suggests that: (i) complexity plays a role in the effectiveness of industrial policy; (ii) firms may benefit from intervention by a government with limited ability; and (iii) policy instability need not reduce firm performance. The model we describe next will be used to examine whether (and when) these three conjectures hold.

III.3 Model

Our model extends the conventional NK model, enabling it to examine the influence of industrial policy on firm behavior and performance while taking into account firms' bounded rationality and the environment's complexity. We begin by describing the conventional NK model, which we then extend to accommodate industrial policy considerations.

III.3.1 Conventional NK model

Following the conception of firms as systems of interdependent decisions (Levinthal 1997), each firm is assumed to make N binary decisions. Hence a vector $\mathbf{d} = (d_1, d_2, \ldots, d_N)$, where the d_i's are each either 0 or 1, represents a firm's configuration of decisions. The fitness—or performance—of a configuration depends on the contribution of all decisions, each of which typically interacts with some other decisions. In other words: each decision d_i contributes a value c_i to the overall fitness, and c_i depends not only on the focal decision d_i but also on K other interacting decisions. Formally,

$$c_i = f_i(d_i; K \text{ other } d_j\text{'s}). \tag{8}$$

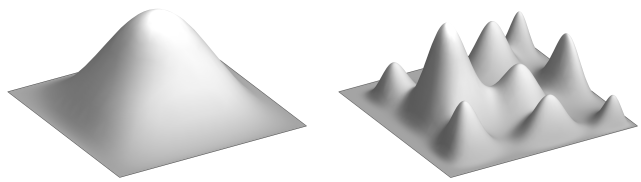
Here K captures the *complexity* of the environment—how interdependent decisions are in generating the payoff. The overall fitness of a configuration $\mathbf{d}$ is the average of its N contributions; that is, fitness$(\mathbf{d}) = \frac{1}{N}\sum_{i=1}^{N} c_i(\cdot)$. Standard practice is for the K decisions that interact with the focal decision to be randomly chosen and for the values taken by $c_i(\cdot)$ to be randomly drawn from a 0–1 uniform distribution. (Since $c_i(\cdot)$ depends on $K+1$ binary decisions, $c_i(\cdot)$ can take 2^{K+1} values.)

This way of mapping firm decisions to fitness is often metaphorically described as a fitness *landscape*. A position on the landscape represents a vector of decisions that a firm could make (i.e., $\mathbf{d}$), and the "height" of that position represents the firm's fitness. Each firm's goal is to find a high position on the landscape—a specific set of decisions that generates high overall fitness.

Since firms are only boundedly rational, they identify high positions through local search; this is usually modeled as firms being able to "see" only neighboring positions on the landscape. More specifically: in each period, a firm evaluates choice configurations that vary from the current configuration by only one decision and then pick the configuration with the highest fitness. Complexity K has a strong influence on the success of local search. The reason is that, as K increases, the landscape becomes more rugged and multi-peaked (see Figure III.1); therefore, an increase in K makes it more likely that firms settle on a local peak than on the global maximum.

Figure III.1: Landscapes of low and high complexity

(a) Low complexity (b) High complexity



III.3.2 Modeling industrial policy

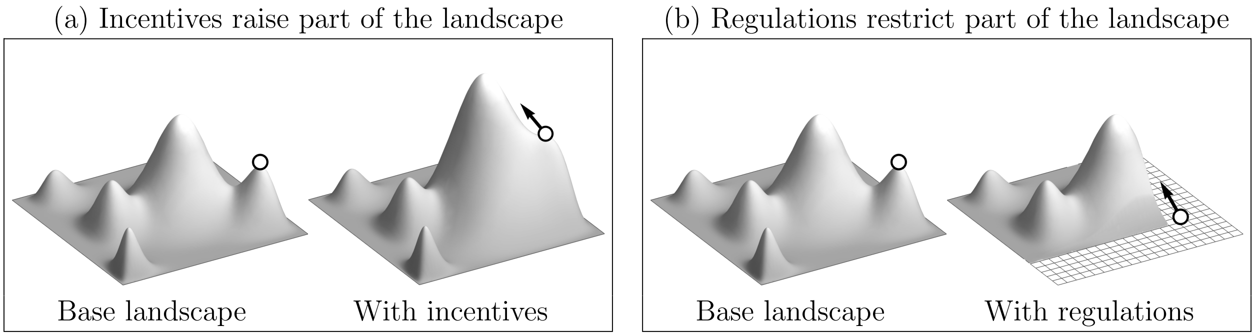
We extend the conventional NK model by conceptualizing industrial policy as modifying the landscape on which firms search. Simply put, we model incentives as raising part of the landscape (as in Figure III.2a) and model regulations as restricting firms' search to a sub-area of the landscape (Figure III.2b). We model incentives as raising part of the landscape because when certain decisions are incentivized by the government, firms adopting these decisions receive higher payoffs. We model regulations as restricting search to a sub-area of the landscape because government, when it regulates, reduces the potential search area by forbidding certain decisions.

The panels in Figure III.2 illustrate the gist of our approach. In both panels, the firm (represented by the white dot) is initially stuck at a local peak (see the "base landscape" on the left side of each panel). In panel (a), incentives alter the payoffs of neighboring positions and so a local peak becomes a stepping stone to the global peak. In panel (b), regulations ban the area where a local peak resides, forcing firms to move elsewhere.[13] Below we provide a formal description of how industrial policy is modeled.

In our model, an industrial policy is described by two components: its content and its type. Policy *content* specifies which part of the landscape is modified by the government, whereas policy *type* specifies how the landscape is modified (i.e., through incentives or regulations).

[13]Two examples mentioned in the Introduction help illustrate Figure III.2's panels. Panel (a) could correspond to Denmark's subsidies on wind energy, which incentivized firms to move away from the local peak of fossil fuel technologies. Panel (b) could correspond to Massachusetts' regulations on toxic chemical disposal, which forced firms to change their production processes.

Figure III.2: Illustration of how we model incentives and regulations



We model policy content as a vector that expresses the government's preference with regard to each firm decision.[14] We denote that government preference as an N-length vector $\mathbf{g}$, where each element g_i can take the value 0, 1, or #. Values 0 and 1 mean that the government intervenes in decision i and favors 0 or 1 respectively; whereas value # means that the government does *not* intervene in that decision and so is indifferent concerning that decision being 0 or 1. Suppose, for instance, that automobile firms must make these three decisions: a car's power source (gas-powered or electric), plant location (domestic or overseas), and size (compact or full-size). In this case the government might issue a policy $\mathbf{g} = (\textit{electric}, \textit{domestic}, \#)$, thereby indicating its preference for electric cars and domestic plants as well as its indifference to the size of cars.

We call the number of decisions for which the government has expressed a preference (i.e., the number of non-# elements in $\mathbf{g}$) the *span* (S) of government intervention. Span S captures how broadly the government intervenes in firm decisions (in the preceding car example, $S = 2$). As we shall illustrate, a larger S indicates that a larger area on the landscape is modified by industrial policy. Because we are interested in understanding the overall effect of S, the particular elements that are chosen to be non-# are randomly determined.

Recall that policy type can be either incentives or regulations and that we model the former as raising part of the landscape. Specifically, incentives raise the landscape by giving firms a premium for each decision they make that aligns with governmental preferences. More

[14]This approach accords with the literature's view of industrial policy's defining feature: its specificity regarding the particular choices firms make (Johnson 1982:19).

formally, under incentives, instead of using c_i as the contribution function of decision i, we use c_i', which is defined as

$$c_i' = \begin{cases} c_i + P & \text{if } d_i = g_i; \\ c_i & \text{otherwise.} \end{cases} \tag{9}$$

Here P is the *government premium*, or the firm's additional payoff for each of its government-favored decisions. The government's policy in our car example was $\mathbf{g} = (\textit{electric}, \textit{domestic}, \#)$; hence firm $\mathbf{d} = (\textit{gas-powered}, \textit{overseas}, \textit{compact})$ would receive no government premium whereas firm $\mathbf{d} = (\textit{electric}, \textit{domestic}, \textit{compact})$ would receive two "units" of premium (i.e., $2P$).

Regulations are modeled as restricting firms' search to a sub-area of the landscape. Toward that end, we require firms to adopt government-favored decisions and allow firms to make their own decisions only where the government declines to intervene (i.e., in those decisions where the government's policy contains #'s). Returning again to our car example, if $\mathbf{g} = (\textit{electric}, \textit{domestic}, \#)$ is the government's policy, using regulations means that all firms must produce electric cars and must do so domestically; they have no freedom of choice except as regards their decision about car size.

III.3.3 Modeling industrial policy contingencies

We incorporate the contingencies highlighted by the industrial policy literature—government ability and policy instability—as follows.

We model a government's ability as its capacity to predict where the global peak is; so for each decision in which the government intervenes, its preferred decision will correspond to the global peak with probability A. More formally, let $\mathbf{d}^*$ denote the configuration of the global peak, where d_i^* represents the optimal decision on each dimension. The government sets $g_i = d_i^*$ with probability A and sets $g_i = 1 - d_i^*$ with probability $1 - A$. Continuing with our car example, suppose the global peak was $\mathbf{d}^* = (\textit{electric}, \textit{overseas}, \textit{compact})$. If the government has an ability of (say) 0.8, then in this case there is an 80% probability that it chooses to favor electric cars and the same probability that it will favor overseas production.[15]

In essence, the probability A expresses the likelihood that the landscape area raised (under incentives) or "fenced in" (under regulations) by government intervention actually contains the global peak. Consistent with literature on government capability, we use A as an encompassing measure that reflects multiple aspects of a government. First, it can indicate the cognitive competence of a government to solve a problem. Note that this competence may depend on not only the skills and knowledge of policymakers but also the difficulty of the problem they face; for example, identifying the global peak is arguably much harder in the nascent robot industry than in the traditional oil industry. In this sense, A can be understood as a measure of the government's bounded rationality. One may say that the government's bounded rationality could alternatively be modeled by having the government search on a "policy landscape"; we do not follow that approach, because our study focuses on the consequences (rather than the process) of government's search, and that approach would render the model more difficult to understand yet without a commensurate increase in insight toward our end. Second, the parameter A can also reflect the benevolence of a government. Therefore, we allow for the possibility that corruption or lobbying by private sectors causes the government to prefer a non-global-peak area.[16]

Several examples may help illustrate the government ability parameter. A government with high A can be exemplified by the South Korean government in the 1960s and 1970s, which recruited well-educated bureaucrats and was growth-oriented (Kohli 2004). In contrast, a government with lower A can be exemplified by the Nigerian government in the 1950s staffed with incompetent bureaucrats (Nicolson 1969) and the Philippine government from

[15] Note that A is a "per-decision" measure. This implies that the government's likelihood of a totally accurate prediction (about the global peak's position) is smaller—and possibly much smaller—than the value of A. For example, if ability $A = 0.8$ and span $S = 9$, then the government has only a 13% ($= 0.8^9$) chance of getting everything correct.

[16] In some settings, government ability and environmental complexity could be correlated. For example, in a highly complex environment such as a high-technology industry, government's predictive accuracy could be hampered. We model complexity and government ability as two separate parameters because complexity affects, but does not determine, government ability. In fact, research has shown wide variation in the ability of different governments to deal with the same industry (see, e.g., Kremer 2002, Redmond 2004).

the 1940s to the 1970s, which allowed large family conglomerates to control its policy making through bribery and cronyism (Kang 2002).

We use the *policy instability* parameter I to capture how frequently the government changes its policy. In each time period, the government changes its policy with probability I. Therefore, $I = 0$ signifies that government policy remains stable and $I = 1$ that government policy is respecified every period; intermediate values of I interpolate between these two extremes. When the government policy is respecified, the following happens: (a) the government selects a random set of S dimensions to intervene in (i.e., it decides which elements in $\mathbf{g}$ should be non-#'s) and (b) it decides which decisions to prefer for the selected dimensions (i.e., whether it prefers 0 or 1 for each non-# decision).

III.3.4 Performance measure

Following previous research, we measure performance in terms of the firm's "height" at each period. To ensure comparability across simulations, we scale the fitness of the underlying landscape (before incentives or regulations are applied) such that the search landscape's global peak has a fitness of 1 and its lowest position has a fitness of 0.

We measure *performance* as follows. In the case of regulations, performance is identical to fitness. In the case of incentives, we measure fitness "net of incentives"—that is, fitness minus any incentives received. We do this, as incentives are simply cash or resources transferred from the government. One can think of this performance measure as capturing firms' value creation (Brandenburger and Stuart 1996).

One benefit of using value creation as our performance measure is that value creation is relevant both to the government and the firms. For the government, increasing value creation by firms is consistent with the welfare goal of industrial policy. This is because increasing value creation means increasing willingness-to-pay (i.e., quality) or decreasing cost, which generally increases social welfare.[17] For firms, value creation is also important because

[17]Social welfare (i.e., the sum of consumers' and producers' surpluses; Tirole 1988:9) increases as the wedge between willingness-to-pay and cost increases, as long as any potential inefficiency (e.g., due to monopoly

increasing willingness-to-pay or decreasing cost is a necessary condition for sustainable profits. Moreover, unlike increased profits due to cash transfers from the government, increased value creation is likely to persist even after the government incentive is removed. Another benefit of using value creation as the performance measure (i.e., not including government transfers in the performance measure) is that it makes the performance of incentives and regulations comparable.

In summary, the model allows us to study how performance is contingent on five parameters. Four of these (the span S of intervention, government premium P, government ability A, and policy instability I) characterize industrial policy, and the fifth (complexity K) characterizes the environment.[18] Table III.1 summarizes the notation used to describe the model. We use this model to explore how the effect of incentives and regulations on performance depends on the values of these parameters.

III.4 Results

We report our results in graphical plots that offer an intuitive and precise display of the model's behavior as the contingent parameters are varied. Each graph plots firm performance (under incentives and regulations) as a function of span S under particular values of complexity K, premium P, government ability A, and policy instability I. The particular values used to generate these plots were chosen after exhaustively exploring the model and verifying that the selected plots are representative of the full behavior of the model.

We fix the total number of decisions that each firm makes at $N = 10$, since changing this value has no qualitative effect on the results (provided K is scaled proportionally to N). We test three values (low, medium, and high) for complexity ($K = 3, 5, 7$) and also for instability ($I = 0, 0.4, 0.8$); government ability (i.e., the accuracy of its global peak predictions) takes

power) does not outweigh the increased value creation. This assumption is representative of settings where there is sufficient competition or reasonable regulations limiting inefficiency.

[18] Of course, the effect of industrial policy on firm performance may also depend on other characteristics. We focus on the effect of five parameters that are particularly relevant in the literature (as mentioned in Section III.2) and that can be well-studied using a model. In Section III.5.3 we discuss several ways in which further work—both theoretical and empirical—could extend our research.

Table III.1: Summary of the notation

Symbol	Description	Landscape metaphor	Plotted values
$\mathbf{d}$	Vector denoting a firm's configuration of decisions, with d_i being 0 or 1	A position on the landscape	
$\mathbf{d}^*$	Vector denoting the configuration of decisions that yields the maximum fitness	The global peak of the landscape	
$\mathbf{g}$	Vector denoting the government's preference toward each firm decision, with g_i being 0, 1, or # (# means indifference)	The area on the landscape that is modified by the government	
N	Number of decisions each firm makes (i.e., number of elements in $\mathbf{d}$)	Dimensionality of the landscape	10
K (Complexity)	Degree of interdependence among firm decisions in determining fitness	Ruggedness of the landscape	$3, 5, 7$
S (Span)	Number of decisions the government intervenes in (i.e., number of non-# elements in $\mathbf{g}$)	How large is the area that is modified by the government	$0, \ldots, 10$
P (Premium)	Additional payoff a firm receives for each government-favored decision (a parameter only for incentives but not regulations)	How high is the area raised by government incentives	0.9
A (Government ability)	Probability that a government-favored decision corresponds to the global peak (i.e., probability that $g_i = d_i^*$)	How likely is that the area raised (under incentives) or "fenced in" (under regulations) contains the global peak	$0.5, 0.8, 0.95, 1$
I (Policy instability)	Probability in each period that the government respecifies its policy	How frequently the government changes which area to modify	$0, 0.4, 0.8$

low, medium, high, and perfect values ($A = 0.5, 0.8, 0.95, 1$). Because the premium P has a straightforward monotonic effect, we fix its value at $P = 0.9$. This value means that the total fitness of a configuration of decisions can be increased at most by 0.09 if $S = 1$ and at most by 0.9 if $S = 10$ (depending on how many government-favored decisions the configuration contains).

On each graph's x-axis, the span S ranges from 0 (no intervention) to 10 (maximal intervention). On the y-axis of each graph we report average performance after firms have searched for 20 periods—because firm performance reaches a steady state by that time. Performance is averaged across 40,000 runs of simulations to ensure results are not sample dependent.

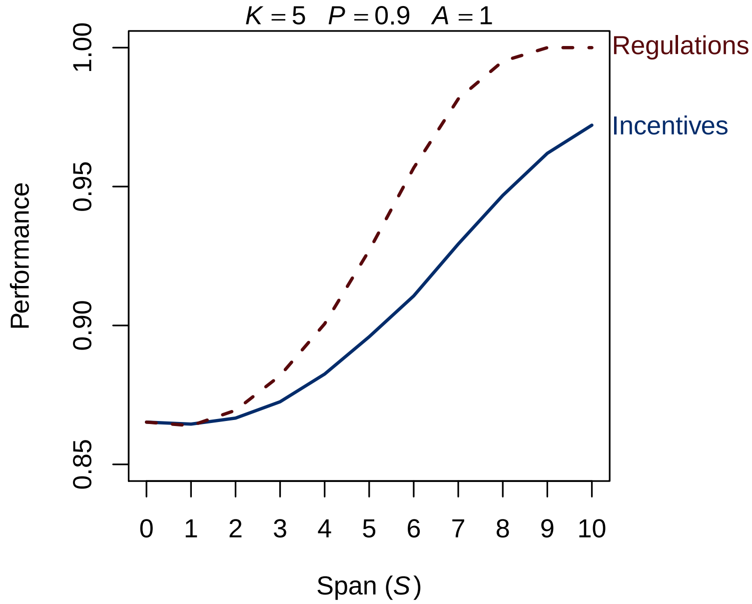
To develop an understanding of the model's behavior, we start by analyzing the simplest case of a government with perfect ability with respect to global peak predictions ($A = 1$). Thereafter we explore, in turn, the effects of varying premium P, ability A, complexity K, and instability I.

III.4.1 Baseline: Government with perfect ability

Figure III.3 illustrates the effects of incentives and regulations on average firm performance under perfect ability ($A = 1$)—that is, when the government correctly guides firms to search in an area that includes the global peak—while keeping fixed both the premium P and complexity K and allowing for no policy instability (i.e., $I = 0$). Although perfect ability is not realistic in most situations, we discuss this case in order to establish a baseline understanding about the way incentives and regulations operate.

A first observation from Figure III.3 is that performance increases with span S for both incentives and regulations. This is a straightforward consequence of the perfect ability assumption, which implies that a larger S allows the government to more effectively influence firms to move in the right direction, thereby increasing the likelihood of firms reaching the global peak. In terms of the firm's search landscape, increasing S under *incentives* is

Figure III.3: Firm performance under a government with perfect ability



equivalent to modifying a *larger* area of the landscape so as to render more salient the government's favored decisions—which coincide (when $A = 1$) with those of the global peak. Under *regulations*, increasing S corresponds to the government setting up more restrictions and thus leaving a *smaller* area for firms to search; the result is that firms are forced to search the area in which the government knows (again provided $A = 1$) the global peak is located.

Second, this figure reveals that regulations are better than incentives at improving firm performance, especially when S is large. This difference stems from the different mechanisms underlying incentives and regulations: while incentives work through motivating firms, regulations work through restricting them. In other words: while under regulations firms can only move within the restricted area, when it comes to incentives, it is not guaranteed that the intervention will successfully induce changes in firm decisions.

Another way to understand how incentives and regulations operate is in terms of how they affect the complexity of the landscape on which firms search. Incentives reduce complexity by "smoothing" the landscape—in effect, laying a smooth landscape over the base landscape.[19]

[19]The overlaid incentives correspond to a $K = 0$ landscape, since each decision can either provide or not provide a premium.

Regulations reduce complexity by cutting out part of the rugged landscape, "erasing" the complexity of the forbidden area. Whereas eliminating some of the landscape can reliably reduce complexity, overlaying a smooth landscape has a less certain effect. Overall, then, if the government is infallible then regulations are more effective than incentives at improving firm performance. That is, if $A = 1$ then regulations urge firms more *forcefully* toward the government's favored search area. As we shall see, this advantage of regulations over incentives changes with decreasing government ability.

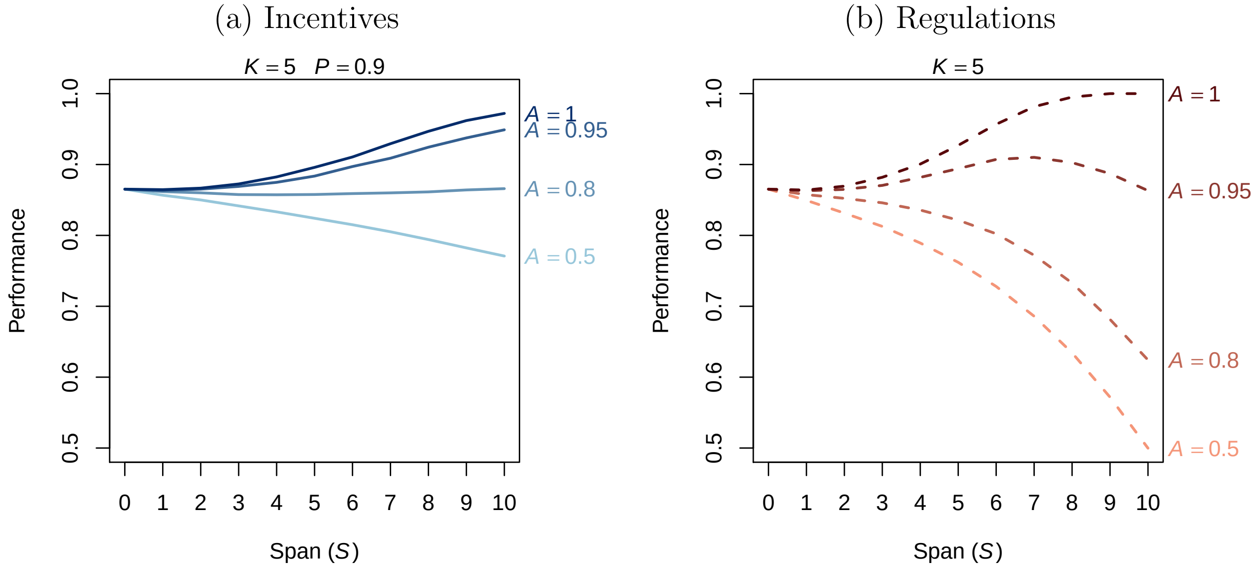
We now briefly address the role of premium P because its effect is straightforward and discussing it here will simplify later discussions. As the government premium P rises, performance under incentives increases and approaches the performance under regulations. This dynamic follows because higher premiums make the incentives more forceful—to the extent that incentives increasingly produce an effect similar to that of regulations. In the limit, incentives can be just as effective as regulations; however, they would be much less ideal owing to the payment incurred by the government. Likewise, the effect of incentives declines as the premium falls. In the limit, when $P = 0$, incentives become irrelevant and this is equivalent to the case of no intervention. In the remaining analyses, we keep P fixed at 0.9 (as in Figure III.3) because the effect of changing it is entirely predictable.

III.4.2 Effects of less-than-perfect government ability

Figure III.4 shows how performance changes with span S under four different levels of government ability A. To help distinguish trends, we plot incentives and regulations separately in panels (a) and (b). Observe first of all that performance declines with decreasing A. The reason for this result is straightforward: decreased ability means that the government is less able to guide firms in the right direction.

A second observation from Figure III.4 is that the effect of S varies with A: while increasing S improves performance when A is high, it impairs performance when A is low (the darker lines have positive slopes while the lighter lines have negative slopes). This relation

Figure III.4: Effects of the government ability (A)



can be explained as follows. A large span allows the government to more effectively guide firms to a specific position. Therefore, increasing the span of a competent government's interventions helps ensure that firms arrive at the global peak; if the government is inept, however, then a higher S serves mainly to lock firms more securely into what is likely a bad position. This result is consistent with the industrial policy literature's "government failure" argument, which concludes that inept governments should refrain from market interventions.

An instructive comparison is that between incentives and regulations under high span (see the right halves of panels (a) and (b) in Figure III.4): unlike incentives, high-span regulations are rarely beneficial (except under extremely high government ability) and hurt performance much more severely than incentives when government ability is low. This difference arises because regulations with a large span restrict firms to a small area, leaving firms with almost no leeway to search. Therefore, unless the government is extremely accurate in predicting the global peak, firms are very likely to remain stuck in some wrong place (i.e., at a suboptimal position) with no other choice. An implication is that unless the government has extremely high ability, it should avoid using high-span regulations. This finding matches Killick's (1978) description of the Ghanaian government instructing factories to be set up at unreasonable locations and demanding production that was a poor fit with local geographical features and market demands. Our results here suggest that, had the Ghanaian government used incentives rather than regulations, its intervention would have done less harm to the economy.

We can summarize the results so far in this way. Comparing incentives and regulations reveals that, although regulations are more powerful when government ability is high, they could lead to severely negative outcomes when government predictions are inaccurate and span is large. In short: regulations are a high-risk, high-return proposition.

III.4.3 Effect of complexity

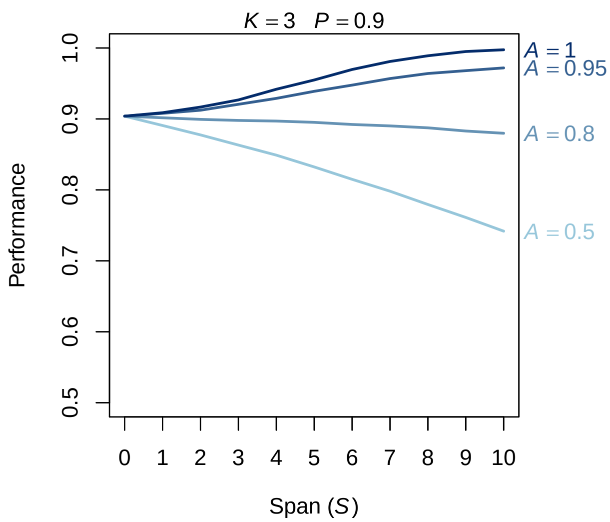
So far we have explored the effects of span, premium, and government ability while keeping complexity K fixed; we now look at the effects of varying K. Figure III.5 presents the cases of low K ($K = 3$) in the upper row and those of high K ($K = 7$) in the lower row (note that Figure III.4 would fit as a middle row here).

The key observation from Figure III.5 is that complexity strongly moderates the effect of industrial policy in that higher complexity delays the "fanning out" of the performance curves. More specifically: whereas the performance curves under low K (figures III.5a and III.5b) start fanning out at $S = 1$, the curves under high K (figures III.5c and III.5d) do not really start to fan out until $S = 3$. The contrast would become even sharper were K to take more extreme values.

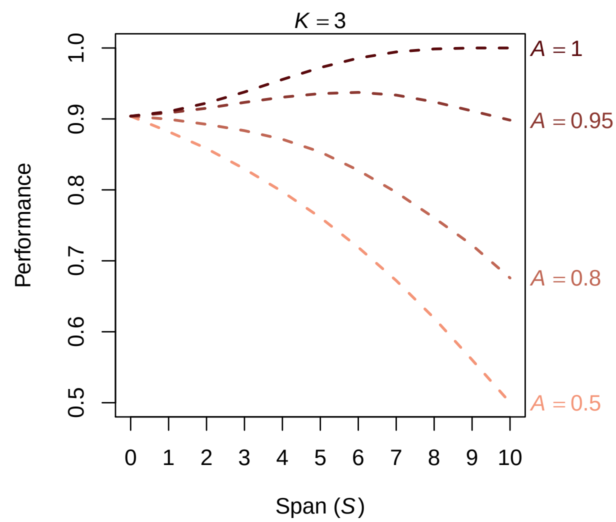
This delaying effect of high complexity suggests that, the higher the complexity, the higher the minimal level of intensity needed for government intervention to be effective (i.e., to produce a noticeable effect). The reason for such a pattern is as follows. When K is high, a policy with low span is unlikely to change search outcomes: under regulations, it "fences out" only a small part of the landscape and still leaves a large area for firms to search in, resulting in firms easily getting stuck at a new local peak; under incentives, overlaying a small area of smooth slope on top of a highly rugged landscape can hardly smoothen the landscape, resulting in firms remaining stuck at the local peak rather than being moved.

Figure III.5: Effects of environmental complexity (K)

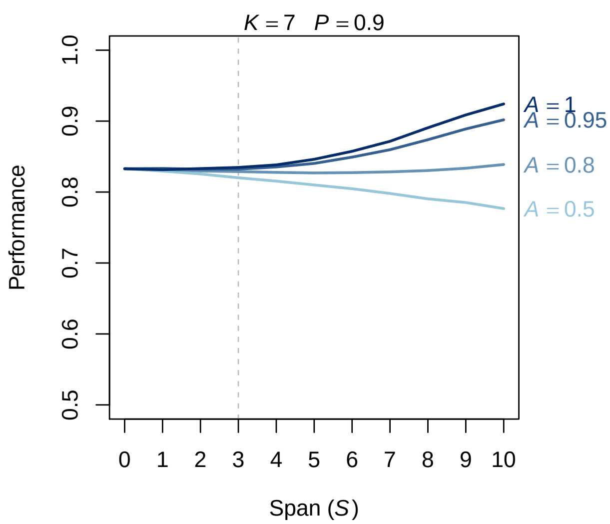
(a) Incentives, low complexity



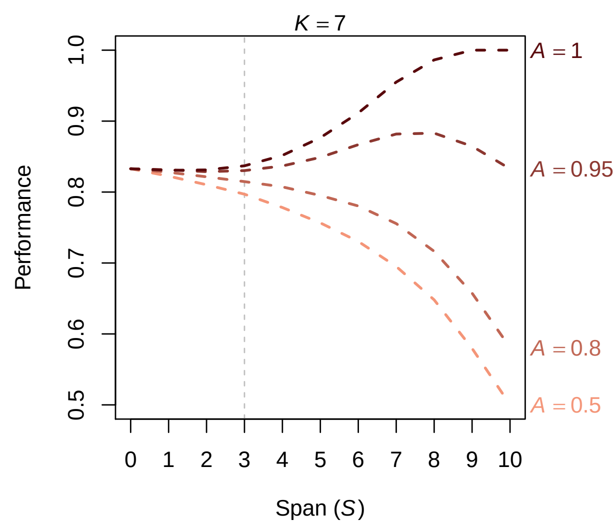
(b) Regulations, low complexity



(c) Incentives, high complexity



(d) Regulations, high complexity



Therefore, when K is high, the effect of government intervention becomes noticeable only if the span is sufficiently large and when a fair number of local peaks have been excluded or smoothed out.[20]

One implication of K's delaying effect is that, when complexity is high, a successful intervention depends on the government ensuring that the *scale* of the intervention is large enough—for example, by intervening in multiple firm decisions simultaneously or (if incentives are used) by assigning incentives of sufficient size. Yet the converse implication also applies; that is, low complexity makes it easier for an inept government to impair firm performance. Thus, in Figure III.5, the lowest lines begin to drop at about $S = 1$ under low complexity (upper row) but not until about $S = 3$ under high complexity (lower row). We therefore conclude that, under low complexity, even a small-scale policy may be detrimental if it is devised by a low-ability government.

III.4.4 Effect of policy instability

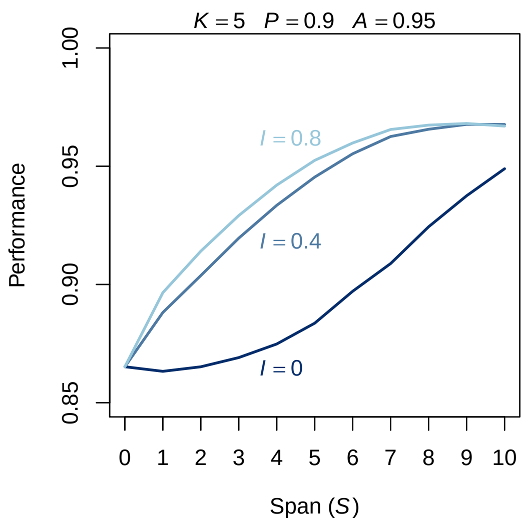
Our analyses have so far focused on stable government interventions. In this section we explore the effect of policy instability I, our measure of how frequently the government changes policy. In Figure III.6, the lighter the line, the more frequently the policy changes. We present results for both high (upper row of the figure) and medium (lower row) values for A. We omit the case of low A because it simply amounts to a further performance decrease from our results for medium A.

A striking observation from Figure III.6 is that there are conditions under which increasing policy instability actually improves firm performance (in figures III.6a, III.6c and part of III.6b, the lighter a line is, the higher its performance). This result goes against the conventional view in the industrial policy literature, so it is paramount that we understand the mechanisms that underlie it. In what follows, we discuss the cases of high and medium ability separately

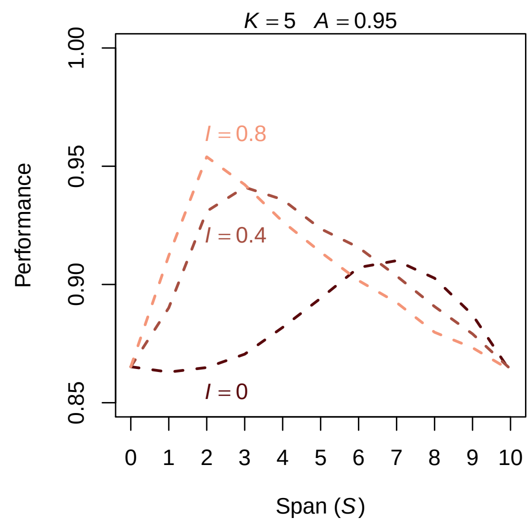
[20]Since premium P is another measure of intervention intensity, the result that complexity increases the intensity needed for government intervention to be effective also applies to increasing premium (results available from the authors upon request).

Figure III.6: Effects of policy instability (I)

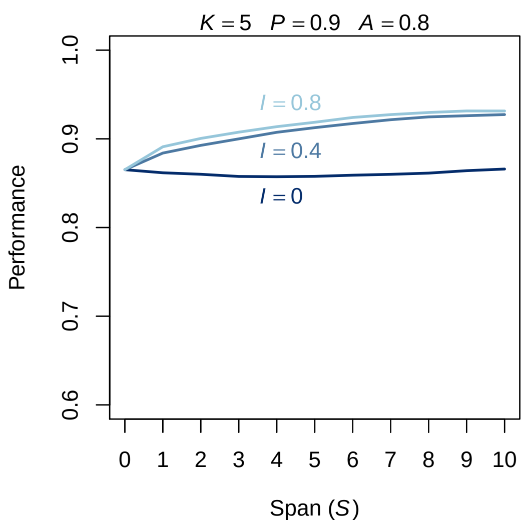
(a) Incentives, high ability



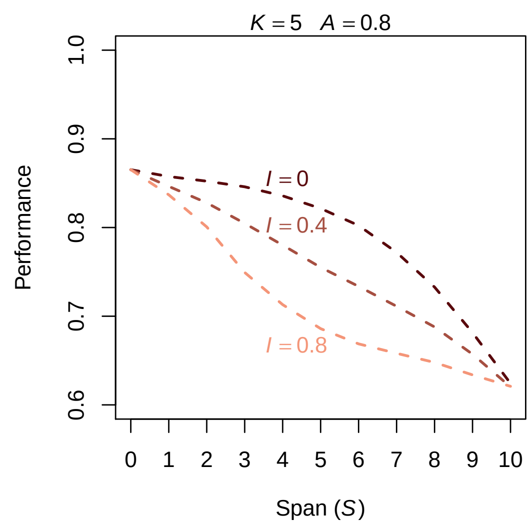
(b) Regulations, high ability



(c) Incentives, medium ability



(d) Regulations, medium ability



because their respective underlying mechanisms differ.

High government ability. When government ability is high (see the upper panels in Figure III.6), the government has valuable knowledge about firms' optimal decisions. So by re-determining which policies to intervene in, the government has additional opportunities for transferring knowledge to firms. We label this phenomenon the "training effect" in analogy to how management trainee programs increase participants' knowledge by rotating them across different functions.

The training effect works under incentives regardless of the span of government intervention (i.e., performance increases with I throughout panel (a)). In contrast, under regulations, the training effect only works under low spans of intervention (performance increases with I only in the left half of panel (b)). This happens because, as discussed in the context of Figure III.4, high-span regulations under less-than-perfect accuracy can lock firms in a wrong place. Hence, for the "training effect" to work under regulations, it requires a lower span than under incentives.

Because small-span policies tend to be cheaper and more manageable than large-span policies, one implication of the training effect is that the government can implement a small-span policy and then boost its effect by periodically reshuffling what is targeted by the policy; in Figure III.6(a), for example, the same performance is achieved by an $I = 0$ policy and large S as by an $I = 0.4$ policy and a medium S. This implication is consistent with the South Korean government's practice, from 1962 to 1991, of implementing consecutive five-year plans—each prioritizing a different set of industries (Chang 1994). Changing the target industries in this way enabled the South Korean government to intervene widely in the economy while keeping the scale of intervention manageable. By highlighting the knowledge transfer from government to firms, the training effect echoes the motto of Chilean president Pedro Aguirre Cerda during the 1930s: "To govern is to educate."

Medium government ability. Next we turn to explaining how increasing policy instability can be beneficial also when incentives are offered by a government of medium ability; see

Figure III.6(c). (Recall that A is a per-decision measure; hence, $A = 0.8$ is substantially lower than $A = 0.95$, particularly as S increases.) In this case, despite the government's inaccurate predictions, the government occasionally changing what is incentivized allows firms to dislodge themselves from local peaks and thereby increase their odds of finding the global maximum; we label this phenomenon the "dislodging effect." This effect applies only in the case of incentives, not regulations, because dislodging requires that firms be able to search broadly—a process that is restricted by regulations.[21]

A crucial implication of the dislodging effect is that the industrial policy advanced by a government of medium ability may also improve performance, creating better outcomes than would no intervention at all. That is, intervention by a government that is neither particularly capable nor stable can still increase firm value. One could argue that many democratic governments exemplify this case. Elections among multiple parties create semi-random changes in policy, which allow for the dislodging of firms and the creation of beneficial outcomes without requiring much ability from either party. Perhaps an upside of democratic government is precisely that firms need to periodically adapt to changing policies due to changes in government.

To sum up, our results here suggest that policy instability can improve firm performance through two different mechanisms. When government ability is high, periodically changing its policy gives the government additional chances to transfer knowledge to firms; this is our training effect. When government ability is lower, periodically changing the policy facilitates the dislodging of firms from their current local peaks—the dislodging effect—and thus makes search efforts more likely to succeed.[22]

[21]The finding that the dislodging effect happens for incentives but not regulations corroborates Porter and van der Linde's (1995) view that government's environmental policies, when accompanied by sufficient freedom for firms to search, stimulate innovation.

[22]The observation that policy instability can improve performance concurs, although via different mechanisms, with Nickerson and Zenger's (2002) positive view on organizational vacillation. Their mechanism is the alternation between discrete states so as to approximate an optimal configuration; our mechanisms are the training and dislodging effects.

III.5 Discussion

In this chapter we have developed a model for studying effects on firm performance of the two main types of industrial policy—incentives and regulations—while accounting for key considerations from the literatures on industrial policy and boundedly rational search. Next we discuss (i) implications regarding how industrial policy affects firms, (ii) broader implications for the strategic management literature, and (iii) avenues for further research.

III.5.1 Implications for how industrial policy affects firms

Here we summarize our main results and discuss their implications for how industrial policy affects firms. A first finding is that, unlike the common wisdom presented in the industrial policy literature, policy instability does not always harm the firm's performance; we find that, instead, policy instability can be beneficial through mechanisms we term the training effect and the dislodging effect. The training effect captures the notion that policy instability gives the government additional opportunities to transfer knowledge to firms; the dislodging effect captures that policy instability increases firms' exploration. These effects, in turn, yield two implications regarding how the government influences firms: (a) the government may be able to intervene more effectively by using a small-scale policy and reshuffling it periodically and (b) if policy instability is unavoidable, then the government should use incentives rather than regulations.

A second finding is that industrial policy by a government that does not have high ability can indeed improve firm performance. Our results show in particular that, when the government uses incentives and periodically reshuffles its policy, intervention with even a modicum of predictive accuracy achieves better performance than no intervention at all. This result implies that, if the government's ability is limited—owing to an insufficiency of competence or benevolence—then using incentives and not regulations, while periodically adjusting policy, can create more favorable outcomes than a hands-off approach.

Third, we find that complexity moderates the effect of industrial policy in important ways:

it raises the minimum level of intervention intensity required for the policy to be effective, and it limits the detrimental effects of a government's lack of ability. In practical terms, this finding suggests that the government should care about different elements depending on the level of complexity. On the one hand, for high-complexity industries the government must ensure that its policy's scale is large enough (e.g., by intervening in multiple firm decisions simultaneously and/or increasing subsidy amounts) to produce a noticeable effect. On the other hand, for low-complexity industries the government must ensure that its landscape predictions are accurate—because in this case even a small-scale policy can be detrimental if not well formulated.

III.5.2 Illuminating the strategy literature

Our research also provides four more general contributions to the strategy literature. A first contribution is the development of an understudied aspect of how the government affects firm performance. The strategy literature has studied government influence from the perspectives of nonmarket strategy, state ownership, and the institutional environment, but it has devoted little attention to industrial policy. Yet as industrial policy becomes increasingly more pervasive, a thorough understanding of its effects helps firms to prepare for, cope with, and benefit from its effects and thereby to create a competitive advantage. More specifically, our results on the effects of government incentives can inform decisions about whether or not to ignore those incentives. For instance, it is advisable for firms to take advantage of incentives offered by a government with medium or high ability and that adjusts its policy periodically. However, firms are better-off *ignoring* incentives when the government has low ability (see Figure III.4). Although such incentives may improve firm profits in the short run, they are likely to derail search in the long run. Our results also inform decisions about entering foreign markets. For instance, entering a market where the government is of high ability and periodically adjusts incentives can increase firms' exploration and performance; in contrast, performance can be jeopardized by entering a market where the government is of low-ability and relies mainly on regulations to affect its industrial policy.

Second, this study offers a novel way to think about how the government affects firm behavior. In particular, we connect government intervention with firms' search; in this we view incentives as deforming and regulations as restricting firms' search landscape. This way of thinking enables a better understanding of how government intervention affects firms' performance by influencing their search process. For example, our analyses show how stable regulations by an inept government severely harms the performance of firms by trapping them in areas far from the global peak. We also explain how the periodic changing of incentives by a government with moderate ability can improve firms' performance because it allows for dislodging from local peaks. This way of thinking also allows us to identify environmental complexity as an important moderator of the success of government intervention.

Third, our work advances research that recognizes the government's role as a booster of exploration. Lazzarini (2015:100) discusses how industrial policy can encourage "resource churning"—increasing firms' exploration by inducing them to make different decisions and to re-allocate resources. Along the same lines, Porter (1991) proposes that environmental policies, despite their high compliance costs, can enhance firms' competitiveness by spurring innovation (for a review, see Ambec et al. 2013). Our research furthers this line of thought by fleshing out contingencies that determine how effectively the government can influence exploration. For example, we show that industrial policy can enhance firms' exploration and performance if the government is at least of medium ability, uses incentives (but not regulations), and periodically reshuffles what the policy incentivizes. We also show that greater environmental complexity requires government to increase the scale of its policy in order to influence exploration effectively.

Finally, this study deepens our understanding of how search landscapes can be "designed" or "shaped" to improve firm performance. Among studies that model firms as searching on a fitness landscape, most assume the landscape to be exogenously given; yet there is a stream of research that considers how the landscape can be purposefully altered. For instance, Levinthal and Warglien (1999) discuss how managers can manipulate the search landscape's ruggedness, and Gavetti et al. (2017) explore how firms can alter its payoff structure by "reshaping" their business contexts (e.g., by developing new technology or changing consumers' perceptions). By viewing government as a landscape designer, our study considers industrial policy as another means of shaping the search landscape. Moreover, we identify and assess how such shaping depends on "tunable" levers such as policy type, intervention intensity, and frequency of change.[23]

From this perspective of landscape design, our model can be used to generate insights in contexts other than industrial policy. In a within-organization context, this model can shed light on the governance of R&D activities. Consider, for example, whether Microsoft's R&D lab should guide its staff's R&D activities by way of incentives (e.g., extra funding for research in certain areas) or through regulation-like rules (e.g, allowing research to proceed only in certain areas). Our study offers guidance on how the lab should choose among these governance means. In particular, our results suggest that, when the lab faces a new technology area and so its managers' understanding of the landscape is only moderate, periodically adjusting incentives can help increase exploration and improve R&D results. Our model can be applied also to cross-organizational contexts, such as managed ecosystems (Gulati et al. 2012:580). For instance, our results suggest that Google should periodically adjust incentives for external app developers; our study (as discussed in the context of Figure III.5) also suggests that Google should tailor its policy depending on the complexity of app development (e.g., increase the size of the perks offered in its Developer Community Program for app development of higher complexity).

[23]Our view that government can act as a landscape designer also furthers Amsden's (1989) perspective on how government can facilitate economic development. She points out that government may deliberately distort the market in order to incentivize firms; such distortion is reflected in our model as the government altering the landscape. Our model helps identify the most effective way to distort the market under different contingencies.

III.5.3 A research agenda for behavioral industrial policy

By modeling the government as shaping the landscape where firms search, this chapter provides an approach to study how firms and governments interact while taking into account the behavioral nuances of firms and governments. This behavioral approach to industrial policy opens up a number of research opportunities. Below we organize ideas for future research in terms of those that (i) validate our model empirically and (ii) extend our model to investigate additional processes.[24]

In terms of empirical work, future work could test our model's predictions. For convenience, Table III.2 states our major predictions as testable propositions. Take Proposition 5 as an example. Future research could use a measure of interdependence (e.g., like the one used by Lenox et al. 2010) to study whether the impact of incentives decreases as industry interdependence increases. Future research could also incorporate contingencies that are not part of our model but are likely to be relevant. For instance, it could examine the extent to which firm differences—such as firm size, organizational structure, and board composition—affect the predictions of our model.

China offers a promising "fruit fly" type of setting to carry out the abovementioned analyses. China's decentralized political system (Xu 2011, Chang and Wu 2014) and frequent use of policy experimentation (Heilmann 2008) provide much variation in government interventions within and across its 34 regions (in fact, Chan et al. 2010 show that regional differences are much larger in China than in the US).

In terms of investigating additional processes, future work could add several mechanisms to our model. Below we propose five possible ways of doing this.

Competition. Future work could combine our model with an economic model of firm competition. Doing so could allow for measuring not just value creation but value capture and, hence, examining more directly how profits and social welfare are affected by industrial

[24]The authors thank the Senior Editor and two anonymous reviewers for several research ideas discussed below.

Table III.2: Some testable propositions that follow from our model

Testable propositions	Source
1. When government ability is high, the more intensively the government intervenes, the higher the performance of firms.	Figure III.3
2. When government ability is high, using regulations yields better firm performance than using incentives.	Figure III.3
3. The lower the government ability, the lower the performance of firms.	Figure III.4
4. When a low-ability government intervenes intensively, using regulations yields lower firm performance than using incentives.	Figure III.4
5. The impact of government intervention decreases as complexity increases.	Figure III.5
6. Under incentives, the higher the policy instability, the higher the performance of firms.	Figures III.6a and III.6c
7. A medium-ability government that uses subsidies and periodically reshuffles what is incentivized yields better firm performance than a medium-ability government that does not intervene.	Figure III.6d

Note. All propositions here pertain to average firm performance and assume other factors are held constant.

policy. For ways of incorporating competition, see Lenox et al. (2006) and Adner et al. (2014), who respectively add Cournot and Lancasterian competition to NK models.

Regulatory compliance. While our model assumes perfect enforcement of government policy, future research could explore cases where there is selective or lax enforcement (Stigler 1975b) and where firms are able to choose strategically whether or not to comply with regulations (Short and Toffel 2008). For instance, one could examine how firm compliance depends on the likelihood of being detected and the size of the penalty (Becker 1968) and how these contingencies affect firms' search and value creation.

The role of firms in shaping the environment. An assumption of our model is that the external environment is exogenous to firms. Future research could relax this assumption and study how firms may actively shape the environment; that is, change the payoff structure of the environment (for one way of modeling this, see Gavetti et al. 2017). Our modeling approach suggests that there are two fundamentally different shaping activities: those that shape the "base landscape" versus those that shape the government-modified landscape (i.e., modifying the actual technological landscape *vis-à-vis* modifying just what the firms perceive; or in terms of Figure III.2, changing the left- versus the right-hand side of each panel). An example of shaping the base landscape is the creation of a standard (e.g., the 5G standard created a new peak in the telecommunications industry landscape by reducing costs and increasing demand; Xia 2017, Contreras 2014). An example of shaping the government-modified landscape is regulatory capture (e.g., how South Korean *chaebols* influenced policy making through bribery; Kang 2002). In this case, firms do not change the base landscape but influence which areas of the landscape are restricted or raised by the government.

Environmental change. While our study assumes a static technological environment, future work could study the effect of environmental turbulence (which occurs, e.g., when there is technological change and industry convergence; for one way of modeling turbulence, see Siggelkow and Rivkin 2005). Because governments vary in their ability to detect and act on environmental changes, one could further refine this line of research by analyzing the effect of sensing and acting lags.

Information-based policy. While our study focuses on incentives and regulations, another component of industrial policy that future research could study is information-based policy—government intervention that uses information to influence firm behaviors (Bowen and Panagiotopoulos 2018). Since information-based policy works through various mechanisms, we propose three possible ways to model it. One type of information-based policy allows firms to access new information (e.g., distributing booklets that introduce a new technology; Vedung 1998). This could be modeled as providing more accurate information about distant parts of the landscape. Another type of information-based policy creates transparency (e.g., the US Department of Agriculture establishment of an organic foods label, which alleviated information asymmetry and increased demand for organic foods; Lenox and Chatterji 2018:127). This could be modeled as raising the parts of the landscape that are made more transparent. A third type of information-based policy creates a platform for firms to learn from and collaborate with each other (e.g., R&D consortia; Doz et al. 2000). This could be modeled as facilitating imitation across firms in the landscape (akin to how Csaszar and Siggelkow 2010 model imitative jumps).

III.5.4 Concluding remarks

In this chapter we developed a formal model to study the effect of industrial policy on firm performance while recognizing key behavioral nuances of firms; in doing so, we brought together the fields of industrial policy and strategic management. Our results provide novel insights on how industrial policy affects firms—and how it allows firms to gain a competitive advantage by more effectively coping with and leveraging governmental influence.

An interesting pattern emerges when we look at the historical relationship between the fields of industrial policy and strategic management. The field of strategic management, which was originally known as "business policy," drew ideas from economic theories devised to answer industrial policy questions. In fact, some of the earliest answers to the question of how firms can sustain high profitability—along with notions such as strategic groups and mobility barriers—were based on the structure–conduct–performance paradigm developed to guide industrial policy (see Porter 1981). Subsequently, strategic management departed from industrial policy by representing firms with increased behavioral plausibility. Almost 40 years since that departure, strategic management may now be in a position to contribute back by helping advance a behavioral industrial policy—an approach to study industrial policy that takes into account the behavioral nuances of firms and the government. This study takes a step in that direction, and it thereby contributes not only to the industrial policy literature but also to a deeper understanding of how firms and the government interact.

CHAPTER IV

Firms vs. Hobbyists:

Participation in Production Communities and the Balance of Exploration and Exploitation

IV.1 Introduction

Production communities, such as open-source software development communities and Wikipedia, where participants voluntarily collaborate to create goods or services, have become an important way of organizing high-quality production and innovation (von Hippel and von Krogh 2003, O'Mahony and Ferraro 2007, O'Mahony and Lakhani 2011, West and Bogers 2014, Bogers et al. 2017). Recently, it is increasingly common for production communities to involve not just hobbyists but also firm participants, who pay their employees to spend work time contributing to these communities (von Hippel and von Krogh 2003, Nagle 2018, Jordan 2019). For example, on GitHub—a large online platform for open-source software development projects—Google employees were reported to contribute to over 40,000 projects (Tung 2020). One primary motive for firms to do this is to gain control over the quality of the community-developed products upon which the firms' business replies (von Hippel and von Krogh 2003, Nagle 2018). Several studies have looked into firm-affiliated participants in production communities, investigating their motivation, who they develop ties with, and how intensively they contribute to production communities (Dahlander and Wallin 2006, Nagle 2018, Zhang et al. 2019). However, despite the valuable insights generated by this growing literature, there is still much we do not know about firm participation in production communities.

In particular, although communities represent an increasingly important source of innovation nowadays (West and Bogers 2014), there is a lack of understanding of how exactly firms engage in the joint innovation process of communities. For example, we know little about *what* firms contribute during their participation: compared to hobbyists, do firm-affiliated participants make more incremental contributions that reflect a more exploitative search process, or do they make more novel contributions that reflect a more exploratory search process? Do firm-affiliated participants tend to focus on a limited set of problem areas or explore a broader set? A good understanding of questions like these will provide important insights on how firms' community participation—an increasingly prevalent business strategy—may influence community-based innovation, which plays an increasingly important role in today's economy.

This chapter aims to take one step toward filling this gap in the literature by examining the micro-level search behaviors of firms during their participation in production communities. More specifically, I explore how firm-affiliated participants differ from hobbyists in their search behavior by looking at what they contribute to the communities. Drawing upon research that distinguishes between exploration and exploitation (e.g., March 1991, Gupta et al. 2006) and research that distinguishes between problem search and solution search (e.g., Nickerson and Zenger 2004, Nickerson et al. 2012), I argue that firm participants and hobbyists exhibit different exploration tendencies during problem search and solution search, due to the different kinds of constraints they face. In particular, compared to hobbyists, firm participants are more goal constrained (i.e., required to focus on the specific needs of their firm from the community-developed product) but less resource constrained (i.e., having more time, financial resources, and access to their firm's knowledge repertoire). As a result, compared to hobbyists, firm participants may be less exploratory during problem search but more exploratory during solution search.

Empirically, this study uses the software development communities on GitHub as the context. Specifically, I track over one million contributions made by participants in 290 open source development projects on GitHub. Hobbyists and firm participants are distinguished based on whether the participants use personal or firm-affiliated emails to submit contributions (Zhang et al. 2019). Problem exploration and solution exploration are captured by analyzing the title and the source code of each contribution. A contribution involves exploration during problem search if its title indicates that it aims to solve a new problem rather than fixing an existing problem (Temizkan and Kumar 2015). A contribution involves exploration during solution search if the source code of the contribution changes a novel combination of source files (in a similar spirit to the science evaluation studies that measure the novelty of a paper by whether it cites a novel combination of journals; e.g., Uzzi et al. 2013, Wang et al. 2017). The results are generally consistent with the proposed theory but also highlight an important contingency—a firm's prior commitment to the community. The findings show that, as the firm's prior commitment to the community increases, firm participants increasingly engage in less problem exploration but more solution exploration than hobbyists.

Overall, this chapter aims to provide a better understanding of how firms engage in the innovation process of production communities. The chapter highlights the different levels of goal and resource constraints faced by firm participants and hobbyists, which, in turn, lead to their different search behaviors. Interestingly, the results suggest that, as firms become more involved in a community, there seems to be a "division of labor," with firm participants focusing on exploring novel solutions to existing problems whereas hobbyists focusing on applying existing solutions to novel problems. In this way, this study also speaks to the ambidexterity literature (e.g. He and Wong 2004, O'Reilly and Tushman 2008), by suggesting that community-based innovation may be able to achieve a balance of exploration and exploitation through the joint effort of firm-affiliated participants and hobbyists.

The chapter proceeds as follows. In Section IV.2, I bring together literatures on production communities and adaptive search and propose a theory of how firm-affiliated participants and hobbyists may exhibit different search behaviors during the joint innovation process. In Section IV.3, I describe the empirical setting and the methodology. Section IV.4 presents the main findings. In Section IV.5, I discuss the theoretical and managerial implications and the conclusion of this chapter.

IV.2 Theory and Hypotheses

In this section, I first summarize existing research on firms' participation in production communities. I then introduce the frameworks of adaptive search that I will draw upon to understand firms' innovation activities during their community participation. Finally, I propose hypotheses regarding how firm participants may differ from hobbyists in their search behavior during the innovation process.

IV.2.1 Firm participation in production communities

With the fast development of information and communication technologies, communities have become an increasingly common way of organizing high-quality production and innovation (von Hippel and von Krogh 2003, O'Mahony and Ferraro 2007, O'Mahony and Lakhani 2011, West and Bogers 2014, Bogers et al. 2017). While a large part of the literature investigates the production communities' governance and coordination mechanisms, a growing line of research looks at firms' engagement in these communities, as more and more firms have become not only users of community-developed products (Dahlander and Magnusson 2008) but also participants in these communities (Dahlander and Wallin 2006, Nagle 2018, Zhang et al. 2019). In particular, in order to gain control over the quality of the community-developed products that their businesses rely on (von Hippel and von Krogh 2003, Nagle 2018), it is increasingly common for firms to pay employees to spend work time contributing to these communities.

However, we are only beginning to understand the patterns and implications of firm participation in production communities. For example, investigating from a social network perspective, Dahlander and Wallin (2006) find that firm-affiliated participants tend to interact with more central individuals in the community than participants who are hobbyists. Zhang et al. (2019) track the quantities of firm contributions in an open-source software platform and find that firms made highly unbalanced contributions across different projects depending on their business type.

While existing research has provided valuable insights into the interaction pattern and the contribution distribution of firm participants, there is a lack of understanding of the type and content of the contributions made by firms. However, with communities becoming an increasingly important source of innovation (West and Bogers 2014), having a more fine-grained understanding of firms' contributions can be crucial, as it reveals the micro-level search behavior of firms during the joint innovation process. As a result, such an understanding can provide valuable insights into how exactly firms engage in community-based innovation and what their engagement implies for this increasingly prevalent form of innovation.

IV.2.2 Two common ways of characterizing search

The innovation process is often conceptualized as an adaptive search process in which actors seek to identify attractive new alternatives. Existing literature features two important ways to characterize search: (i) distinguishing between two stages of search—problem search vs. solution search—and (ii) distinguishing between two types of search efforts—exploration vs. exploitation. More specifically, the extant literature highlights that search is often a two-stage process. The first stage involves finding problems worth tackling based on newly emerged customer needs or symptoms exhibited in the firm (Lyles and Mitroff 1980, Nickerson and Zenger 2004, Baer et al. 2013), whereas the second stage involves solving the selected problems through identifying and evaluating alternative solutions (e.g., Levinthal 1997 and the major body of its subsequent research on NK landscape search). Moreover, the extant literature also highlights the crucial difference between exploration and exploitation. While the former focuses on tackling unknown areas, experimenting, and making long jumps, the latter focuses on refining existing knowledge, making incremental changes, and engaging in local search.

Figure IV.1: Two common ways of characterizing search

	Solution exploitation	Solution exploration
Problem exploitation	(1) Incremental adjustments	(2) Novel solutions to an existing problem
Problem exploration	(3) Old solutions to a novel problem	(4) Novel solutions to a novel problem

Based on these two ways of characterizing search, innovation activities can be described by how exploratory they are during the problem search and the solution search stage and be categorized into four types, as shown in Figure IV.1. Quadrant 1 represents exploitation during both problem search and solution search, which mainly involves incremental adjustments. An example of this type of innovation is Amazon's same-day delivery policy, which is a further improvement of Amazon's existing solution in its existing business area. Quadrant 2 represents exploitation during problem search but exploration during solution search, which manifests as identifying novel solutions to an existing problem. Amazon's use of drones for delivery is an example of this type. Quadrant 3 represents exploration during problem search but exploitation during solution search, which involves identifying an uncharted problem area but applying existing technology to solve it. An example here is Amazon Web Services, which results from Amazon's deployment of its existing cloud infrastructure for a whole new business area. Quadrant 4 represents perhaps the most challenging of innovation activities, exploration during both problem search and solution search, which entails identifying an uncharted problem area and solving it with a novel technology. Amazon's production of its original shows can be categorized into this type, which involves entering a new business area and using technologies distant from their existing expertise.

Based on the aforementioned framework, when it comes to the innovation activities in production communities, I argue that firm-affiliated participants and hobbyists exhibit different exploration–exploitation tendencies during problem search and solution search. That is, compared to hobbyists, firm participants are more likely to engage in some types of innovation efforts represented in Figure IV.1 but are less likely to do so for other types. As will be explained below, the primary reason for the difference is that firm participants tend to be more goal constrained during search whereas hobbyists tend to be more resource constrained.

IV.2.3 Goal constraints and problem exploration

Compared to solution search, a unique feature of problem search is the important role of goals. Since decisions about which problems to solve determine the direction in which an organization creates new value (Nickerson et al. 2012), the problem search process is heavily influenced by the searchers' interpretation of the organization's goals as well as their own objectives of being involved in that organization (Lyles and Mitroff 1980, Baer et al. 2013). When it comes to problem search in a production community, firm participants may exhibit different behaviors from hobbyists because the former is more goal constrained than the latter. More specifically, firms pay their employees to engage in production communities mainly to control the quality of the community-developed products that the firms' businesses reply on (von Hippel and von Krogh 2003, Nagle 2018). As a result, firm-affiliated participants tend to focus on the specific needs of the company and the existing functions of the community-developed products. In contrast, hobbyists are much less constrained in their objectives of engaging in community production. For example, in the context of open-source software development communities, the primary motives of hobbyists to participate include learning and deriving enjoyment from creating code (Roberts et al. 2006, Shah 2006). As a result, hobbyists tend to more freely explore new needs that can be addressed by their product. Therefore,

Hypothesis 1: *Firm participants are less likely to engage in problem exploration than hobbyists.*

An important moderator for the relationship specified in Hypothesis 1 is the firm's prior commitment to the production community, namely, the intensity of its prior participation in the community. Greater commitment signifies and reinforces the reliance of the firm's business on the community-developed product (Zhang et al. 2019), and further locks the participants' attention to the firm's specific needs from the product. As a result, with greater prior involvement in the community, firm participants become even less likely to search for new problems during the innovation process compared to their hobbyist counterparts. In other words,

Hypothesis 2: *The greater the prior commitment in the project, the greater the extent to which firm participants are less likely to engage in problem exploration than hobbyists.*

IV.2.4 Resource constraints and solution exploration

After a problem is picked, organizations engage in solution search to identify a satisfactory solution to the problem. Compared to local search, which focuses on exploiting existing solutions, a more explorative search process that yields more novel output usually requires more resources including time, access to diverse knowledge bases, and the flexibility to change mental representations (Leiponen and Helfat 2010, Csaszar and Levinthal 2016, Kneeland et al. 2020). As a result, in production communities, firm participants and hobbyists may engage in different levels of solution exploration due to the different amount of resources available to them. More specifically, since firm-affiliated participants get paid to engage in community production, they are able to spend more time on solution search. In contrast, hobbyists, only working in their spare time, tend to be more time constrained and sometimes even overwhelmed by the tasks from the production communities (Eghbal 2020). Moreover, firm participants also enjoy other types of support from their company, including legitimate help from their colleagues (sometimes even a dedicated office; Wilcox 2019) and access to the firm's knowledge repertoire. This allows them to leverage a more diverse knowledge base for solution search (Dahlander and Wallin 2006), which increases the likelihood of an effective solution exploration (Kneeland et al. 2020). In sum, given that hobbyists tend to be more resource constrained than firm participants, I propose that:

Hypothesis 3: *Firm participants are more likely to engage in solution exploration than hobbyists.*

Similarly, the relationship specified in Hypothesis 3 can also be enhanced by the firm's commitment to the production community. First, greater prior participation signifies and reinforces the importance of the community-developed product to the firm, making firm participants more motivated to search for better, more innovative solutions. Additionally, greater prior participation also familiarizes the firm with the technology of the community-developed product, allowing their participants to better leverage the firm's knowledge base to explore solutions. Therefore,

Hypothesis 4: *The greater the prior commitment in the project, the greater the extent to which firm participants are more likely to engage in solution exploration than hobbyists.*

IV.3 Method

IV.3.1 Empirical setting and the sample

The proposed hypotheses are examined in the context of GitHub (github.com), an online platform that allows developers to work collaboratively on open-source software development projects. In this chapter, I focus on the contributions made by participants who have access to directly change the source code of the software. GitHub records detailed information about every contribution, including the submission time, the submitter, the title that summarizes the main goal of the submitted changes, and the source code that implements the changes. The detailed information allowed me to determine whether a contribution was made by a hobbyist or a firm-affiliated participant and which type of search activity a contribution belongs to. The sampling of software development projects included in this study follows the same criteria as in Chapter II. The final sample includes 1,043,232 contributions in 290 open source development projects on GitHub.

IV.3.2 Measures

Dependent variables

The gist of my measurement approach is to decide whether each contribution involves problem exploration (rather than problem exploitation) and whether it involves solution exploration (rather than solution exploitation). Below, I describe how problem exploration and solution exploration are each measured.

Problem exploration. Whether or not a contribution involves problem exploration is determined based on the title of the contribution, which specifies the main goal of that contribution. A contribution involves problem exploration when the main goal is to solve a new problem rather than an existing one. In terms of operationalization, building upon Temizkan and Kumar (2015), problem exploration is measured by a dummy variable that equals 0 if the contribution's title contains keywords including "error", "bug", "fix", "issue", "mistake", "incorrect", "fault", "defect", and "flaw", and equals 1 otherwise. Inclusion of any of these keywords in the title means that a contribution aims to fix or refine an existing feature of the software, which represents the opposite of problem exploration.

Solution exploration. Whether or not a contribution involves solution exploration is determined by the novelty of the source code of the contribution—that is, given the goal of the contribution, to what extent the submitted source code alters the software in a novel way. To capture novelty, I borrow from studies in the field of science evaluation, which measure the novelty of a research paper based on the extent to which it cites a novel combination of journals (Uzzi et al. 2013, Lee et al. 2015, Wang et al. 2017). This approach of measuring novelty is also consistent with the line of strategy research that conceptualizes solution exploration as entailing distant recombination of knowledge areas (e.g., Kneeland et al. 2020). Following a similar spirit, I measure the novelty of a solution in a contribution based on the extent to which the contribution changes a novel combination of source files. In terms of implementation, the novelty of a solution is determined in two steps. First, a cosine distance is calculated for each pair between the source file set changed by the focal contribution and that changed by each of the previous contributions in the past 30 days. Second, following common practice, the 10% percentile of all the cosine distances is used as the final value of solution novelty. This value of solution novelty is used as the measure of solution exploration, with greater novelty meaning more exploratory solution search. Note that unlike problem exploration, which is measured dichotomously, solution exploration is measured continuously.

Independent variables

The key independent variable, whether a contribution is made by a firm participant or a hobbyist, and the proposed moderator, past commitment, are measured in the following way.

Firm participant. Following existing literature (e.g., Zhang et al. 2019), whether a contribution is made by a hobbyist or a firm participant is determined based on the domain of the email used to submit their contribution. More specifically, the contributor is identified as a firm participant if a firm-affiliated email is used to submit the contribution, and as a hobbyist if a personal email is used.

Prior commitment. Prior commitment is measured by the percentage of contributions made by the same email domain out of all the past contributions to the project.

Controls

At the software project level, I control for the project's age (*ProjectAge*), total number of contributions (*TotalContributions*), and number of contributions in the past 30 days (to capture activeness; *Contributions30d*). I also control for the number of different parties that actively contribute to the project and the concentration of the contributions across parties, using the number of unique email domains used to submit contributions in that quarter (*Parties_quarter*) and the Herfindahl index of the contributions across unique email domains (*PartConcentrt_quarter*). At the contribution level, the submission year (*Year*) and the number of lines of code changed (*nLinesChanged*) are controlled for. At the contributor level, I control for experience ($AuthorExp$), measured by the number of past contributions made by the contributor.

IV.3.3 Model specification

The analysis is conducted at the contribution level. Since problem exploration and solution exploration are measured using a dummy and a continuous variable, respectively, I use a linear probability model for problem exploration and an OLS for solution exploration. To account for unobservable heterogeneity of the software development projects and the macro-environment that could confound the results, the estimation includes project and year fixed effects:

$$\begin{aligned} \mathbb{P}\left[ProblemExplore = 1\right] = \alpha_0 &+ \alpha_1 FirmParticipant + \alpha_2 PriorCommitment \\ &+ \alpha_3 FirmParticipant \times PriorCommitment \\ &+ Controls + ProjectFE + YearFE; \end{aligned} \tag{10}$$

$$\begin{aligned} \mathbb{E}\left[SolutionExplore\right] = \beta_0 &+ \beta_1 FirmParticipant + \beta_2 PriorCommitment \\ &+ \beta_3 FirmParticipant \times PriorCommitment \\ &+ Controls + ProjectFE + YearFE. \end{aligned} \tag{11}$$

IV.4 Results

This section first provides a description of the summary statistics of the variables and then discusses the main regression results.

IV.4.1 Descriptive statistics

Table IV.1 reports the summary statistics of the variables. Overall, around 33% of the contributions are made by firm-affiliated participants. 83% of the contributions are categorized

Table IV.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
FirmParticipant	0.329	0.470	0.000	1.000
ProblemExplore	0.826	0.379	0.000	1.000
SolutionExplore	0.670	0.353	0.000	1.000
PriorCommitment	0.457	0.332	0.000	1.000
TotalContributions	4802.302	6145.616	1.000	38811.000
nLinesChanged	364.516	1493.623	0.000	12298.000
ProjectAge_days	994.030	935.817	0.000	7092.000
Parties_quarter	6.015	5.429	1.000	54.000
PartConcentrt_quarter	2.702	1.758	1.000	15.451
AuthorExp	943.081	1601.594	1.000	14901.000
Contributions30d	260.836	462.928	1.000	4237.000
Year	2015.056	2.903	2000.000	2019.000

as problem exploration, and the value of solution exploration shows sufficient variation. On average, the projects in the sample are 994 days old (approximately 33 months old) and have 6 different parties actively contributing each quarter.

Table IV.2 reports the correlations of the variables. Overall, the low correlations do not seem to pose multicollinearity problems. The average variance inflation factor (VIF) across the variables used in the regressions is 1.74, which is well below the common threshold of 10 for multicollinearity concerns (Hair et al. 2009:193).

IV.4.2 Main results

Table IV.3 reports the main results for problem exploration. Model 1 includes only the main effects of firm affiliation and prior commitment to the project. Model 2 includes the interaction between the two. Model 3 adds controls and the year fixed effects and Model 4 adds the project fixed effects.

In Hypotheses 1 and 2, I propose that firm participants are less likely to engage in problem exploration than hobbyists and that this difference will further increase as the firm's prior commitment to the project increases. The results in Table IV.3 do not show a significant main

Table IV.2: Variable correlations

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1. *FirmParticipant*												
2. *ProblemExplore*	−0.01***											
3. *SolutionExplore*	−0.02***	−0.02***										
4. *PriorCommitment*	0.16***	−0.00***	−0.06***									
5. *TotalContributions*	−0.00	−0.00	0.27***	−0.13***								
6. *nLinesChanged*	−0.02***	0.06***	0.04***	−0.01***	0.06***							
7. *ProjectAge_days*	0.07***	−0.07***	0.02***	−0.22***	0.35***	−0.03***						
8. *Parties_quarter*	−0.17***	−0.05***	0.18***	−0.29***	0.06***	−0.02***	0.12***					
9. *PartConcentrt_quarter*	−0.10***	−0.06***	0.12***	−0.05***	−0.02***	−0.02***	0.03***	0.73***				
10. *AuthorExp*	0.12***	−0.00	0.15***	0.05***	0.53***	0.01***	0.28***	−0.05***	−0.08***			
11. *Contributions30d*	−0.10***	0.03***	0.25***	−0.01***	0.54***	0.08***	−0.14***	0.09***	0.09***	0.12***		
12. *Year*	−0.01***	−0.01***	−0.07***	−0.07***	0.09***	0.02***	0.19***	0.13***	0.17***	−0.05***	0.01***	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

effect of firm affiliation but show a significant negative interaction between firm affiliation and prior commitment. In other words, firm participants and hobbyists do not exhibit much difference in their problem exploration tendency on average, but as the firm becomes more involved in the project, firm participants begin to show a smaller tendency to engage in problem exploration than hobbyists. More specifically, the coefficient of the interaction term in Model 4 means that one standard deviation increase in prior commitment makes firm participants 0.8% less likely than hobbyists to engage in problem exploration.

Table IV.4 reports the main results for solution exploration. This table follows the same structure as the previous one: Model 1 includes only the main effects of whether a contributor is firm-affiliated and the firm's prior commitment to the project. Model 2 includes the interaction between the two. Models 3 and 4 add the controls, the year fixed effects, and the project fixed effects in steps.

I propose in Hypotheses 3 and 4 that firm participants tend to engage in more solution exploration than hobbyists and that the difference will increase with the firm's prior commitment. Results in Table IV.4 do not show a clear-cut picture of the main effect of firm affiliation—its direction and significance vary across model specifications. However, the results consistently show a significantly positive interaction effect between firm affiliation and prior commitment. This means that firm participants become increasingly more explorative during solution search when the firm is more involved in the community. The coefficient of the interaction term in Model 4 shows that one standard deviation increase in prior commitment makes firm participants come up with solutions that are 0.07 standard deviation more novel than those by hobbyists.

In sum, the regression results show that, on average, firm participants do not exhibit much different search behaviors when compared to hobbyists. However, as firms become more involved in the communities, the difference in behaviors begins to increase: firm participants become increasingly less likely to engage in problem exploration but more likely to engage in solution exploration.

Table IV.3: Firm participation and problem exploration

	(1)	(2)	(3)	(4)
	ProblemExplore	*ProblemExplore*	*ProblemExplore*	*ProblemExplore*
FirmParticipant	-0.010	-0.007	-0.006	0.008
	(0.007)	(0.007)	(0.006)	(0.005)
PriorCommitment	-0.002	0.006^{+}	0.002	-0.000
	(0.003)	(0.003)	(0.003)	(0.002)
FirmParticipant×PriorCommitment		-0.022^{***}	-0.027^{***}	-0.008^{+}
		(0.006)	(0.006)	(0.004)
TotalContributions			-0.004	0.019^{***}
			(0.006)	(0.006)
nLinesChanged			0.021^{***}	0.021^{***}
			(0.001)	(0.001)
ProjectAge			-0.025^{**}	-0.021^{+}
			(0.008)	(0.013)
Parties_quarter			0.000	-0.009^{*}
			(0.004)	(0.004)
PartConcentrt_quarter			-0.023^{***}	-0.004
			(0.005)	(0.003)
AuthorExp			0.007^{*}	0.004
			(0.003)	(0.003)
Contributions30d			0.008	0.010^{**}
			(0.007)	(0.003)
Observations	1,035,535	1,035,535	974,658	974,655
R-squared	0.001	0.002	0.010	0.060
Year FE	Y	Y	Y	Y
Project FE	N	N	N	Y

Notes. Two-way cluster robust standard errors by project and year in parentheses. All non-dummy variables are standardized for ease of interpretation. The intercept is not reported to save space.

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

Table IV.4: Firm participation and solution exploration

	(1)	(2)	(3)	(4)
	SolutionExplore	*SolutionExplore*	*SolutionExplore*	*SolutionExplore*
FirmParticipant	-0.017	-0.023	0.053^{*}	0.009
	(0.044)	(0.042)	(0.025)	(0.014)
PriorCommitment	-0.057^{***}	-0.087^{***}	-0.028^{+}	-0.028^{***}
	(0.016)	(0.018)	(0.014)	(0.008)
FirmParticipant×PriorCommitment		0.087^{**}	0.078^{***}	0.070^{***}
		(0.034)	(0.024)	(0.015)
TotalContributions			0.193^{***}	0.143^{***}
			(0.026)	(0.036)
nLinesChanged			0.021^{***}	0.002
			(0.006)	(0.005)
ProjectAge			-0.041^{*}	-0.021
			(0.018)	(0.050)
Parties_quarter			0.155^{***}	0.110^{***}
			(0.024)	(0.024)
PartConcentrt_quarter			0.030	0.056^{***}
			(0.024)	(0.014)
AuthorExp			0.035^{*}	0.001
			(0.018)	(0.007)
Contributions30d			0.119^{*}	0.212^{**}
			(0.057)	(0.076)
Observations	981,774	981,774	974,658	974,655
R-squared	0.022	0.024	0.137	0.295
Year FE	Y	Y	Y	Y
Project FE	N	N	N	Y

Notes. Two-way cluster robust standard errors by project and year in parentheses. All non-dummy variables are standardized for ease of interpretation. The intercept is not reported to save space.

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

IV.5 Discussion

In this study, I investigated the different search behaviors of firm-affiliated participants and hobbyists during the joint innovation process in production communities. Analyses of data of over one million contributions in 290 software development projects on GitHub show that, as a firm's prior commitment to a project increases, firm participants become increasingly less exploratory during problem search but more exploratory during solution search than hobbyists. Below, I discuss the theoretical and practical contributions of this study and close with a conclusion.

IV.5.1 Contributions

First, this study contributes to research on production communities (e.g., Dahlander and Wallin 2006, O'Mahony and Ferraro 2007, Nagle 2018) by providing a better understanding of how firms engage in the innovation process in these communities. While existing research has provided insights into why firms participate, who they interact with, and how much they contribute, we know little about the type and content of firms' contributions. This study speaks to this gap, by analyzing the title and source code of each contribution and documenting firms' exploration tendencies during both problem search and solution search. In doing so, this study sheds light on the micro-level search behaviors of firms during their community participation.

This chapter also adds to research on innovation ambidexterity (e.g., He and Wong 2004, O'Reilly and Tushman 2008), by suggesting one potential way for production communities to balance exploration and exploitation. More specifically, results in this chapter show that, as firms become more involved in the community, a division of labor seems to emerge between firm participants and hobbyists, with the former focusing more on discovering novel solutions to existing problems (Quadrant 2 in Figure IV.1) and the latter on applying existing solutions to novel problems (Quadrant 3 in Figure IV.1). In other words, due to the different goal and resource constraints faced by firms and hobbyists, they end up focusing on exploration on different fronts. This implies that a community mixed with firm participants and hobbyists may achieve a better balance of exploration and exploitation than a community dominated by either one type.

In addition, the two-by-two matrix presented in Figure IV.1 provides a more fine-grained framework to study firms' innovation activities. While existing research tends to focus on either comparing exploitation vs. exploration or comparing problem search vs. solution search, this study shows that the crossover between the two pairs of comparisons is also worth examining. In particular, findings in this chapter highlight that it is likely for searchers to display exploration tendency in one stage of search but not the other, depending on their goals and available resources.

Finally, the findings of this study provide several managerial implications for firms. For example, the different exploration tendencies of firm participants and hobbyists show that, while it is important for firms to participate in production communities for quality control, it is not wise to crowd out hobbyist participants. Moreover, firm participants' tendency to focus on solution exploration suggests that firms may want to seek additional ways to incentivize their employees if they want them to engage more in problem exploration.

IV.5.2 Conclusion

In this chapter, I examined how firm-affiliated participants differ from hobbyists in their search behavior in production communities. The chapter highlights the different levels of goal constraints and resource constraints faced by firm participants and hobbyists, which lead to their different tendencies of problem exploration and solution exploration. In doing so, this chapter provides a better understanding of how firms engage in the innovation process of production communities. It also provides insights on the ambidexterity of community-based innovation.

CHAPTER V

Conclusion

Considerable research efforts have been put into understanding the adaptive search process of firms. However, due to the team-theoretical assumption often adopted in the search literature, there is only a limited understanding of how heterogeneous preferences and politics may influence search, even though politics have been recognized as a central theme in organizational life by a rich literature. This dissertation speaks to this gap in the search literature and consists of three studies that examine how different aspects of search may be influenced by internal and external politics.

Chapter II presents a study in which I examine internal politics in the context of proposal evaluation. Analyses of over 110,000 proposal evaluations collected from GitHub show that both informational and political challenges can arise during the evaluation of proposals that target central components in the organization's interdependence structure, which leads to lower evaluation effectiveness. A key insight from this chapter is that it is important to consider the political aspect of interdependence, when existing research on search mainly focuses on its technological and informational aspects. This study also proposes an organizational design lever that mitigates the negative impact of the political conflicts caused by interdependence: knowledge overlap across the evaluators.

Chapter III presents a study that examines how search can be influenced by external politics, more specifically, the government's imposition of its preferences for certain practices onto firms through industrial policy. We develop a computational model to study this question. The results show that the influence of industrial policy on search crucially depends on government ability, policy stability, and environmental complexity. One interesting insight from this chapter is that externally imposed preferences by a less able government may also improve firms' search—when a government with moderate ability reshuffles what it incentivizes, it can benefit firm performance by allowing firms to dislodge from local peaks.

Chapter IV presents a study that looks at firms' participation in production communities, which have become an increasingly important type of stakeholders and source of innovation for firms. In this study, I analyze over one million contributions in 290 open source software development projects on GitHub and show that, due to their different goals and resources, firm-affiliated participants and hobbyists exhibit different search behaviors. Specifically, as firms become more engaged in the communities, firm participants increasingly engage in less problem exploration but more solution exploration than hobbyists. An interesting implication of this study is that, due to their different goals and resources, firm-affiliated participants and hobbyists focus on different types of exploration and exploitation, which, when combined, may lead to an overall balance of exploration and exploitation.

Overall, this dissertation shows the prevalent role of divergent preferences and politics in innovation, at different levels and influencing different aspects of innovation. Moreover, the findings show that, while divergent preferences can lead to political struggles that harm decision effectiveness, there are also channels through which divergent preferences may benefit innovation. By studying politics and innovation, this dissertation seeks to contribute to one of the "forgotten pillars" of the Carnegie School (Gavetti et al. 2007) and to add to a more behaviorally realistic understanding of search, which takes into account both bounded rationality and the divergent preferences of relevant parties.

APPENDICES

Appendix A: Robustness checks for Chapter II

Table A.1: Adding controls and fixed effects in steps

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	GoodDec	*GoodDec*	*GoodDec*	*GoodDec*	*GoodDec*	*GoodDec*
ProposalCentrality (log)	-0.080^{***}	-0.087^{***}	-0.087^{***}	-0.088^{***}	-0.075^{***}	-0.071^{***}
	(0.010)	(0.009)	(0.008)	(0.008)	(0.006)	(0.006)
KnBreadth	0.023	0.027	0.013^{+}	0.013^{+}	0.010^{*}	0.012^{+}
	(0.008)	(0.008)	(0.007)	(0.007)	(0.004)	(0.006)
KnOverlap	0.019	0.018	0.012	0.012	0.014^{*}	0.003
	(0.011)	(0.010)	(0.008)	(0.008)	(0.006)	(0.005)
KnBreadth×ProposalCentrality (log)		0.027^{***}	0.023^{***}	0.023^{***}	0.011^{**}	0.012^{**}
		(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
KnOverlap×ProposalCentrality (log)		0.031^{**}	0.029^{***}	0.028^{***}	0.014^{**}	0.012^{**}
		(0.006)	(0.006)	(0.006)	(0.005)	(0.004)
KnProximity			0.023^{***}	0.022^{***}	0.018^{***}	0.016^{***}
			(0.006)	(0.006)	(0.004)	(0.004)
nReviewers			−0.029	−0.025	0.016	−0.005
			(0.024)	(0.021)	(0.027)	(0.018)
nDiscussants			-0.026^{**}	-0.025^{**}	-0.034^{***}	-0.031^{***}
			(0.009)	(0.009)	(0.005)	(0.004)
ByContributor			−0.013	−0.013	-0.014^{*}	−0.010
			(0.014)	(0.013)	(0.007)	(0.007)
nFilesChanged			-0.045^{***}	-0.045^{***}	-0.042^{***}	-0.042^{***}
			(0.005)	(0.005)	(0.005)	(0.004)
Acquaintance			0.013	0.014	0.015^{***}	0.009
			(0.016)	(0.014)	(0.004)	(0.008)
Workload (log)			0.006	0.006	0.003^{+}	0.007^{**}
			(0.004)	(0.004)	(0.002)	(0.002)
ProjectAge			0.005	0.003	0.011	−0.013
			(0.009)	(0.009)	(0.055)	(0.035)
nCoreDevelopers			−0.030	−0.033	0.004	0.001
			(0.021)	(0.021)	(0.015)	(0.013)
Year FE	N	N	N	Y	Y	Y
Project FE	N	N	N	N	Y	Y
Evaluator FE	N	N	N	N	N	Y
Observations	58,931	58,931	58,636	58,635	58,630	58,377
R-squared	0.040	0.046	0.075	0.077	0.182	0.228

Notes. Two-way cluster robust standard errors by project and year in parentheses. All non-dummy variables are standardized for ease of interpretation. The intercept is not reported to save space.

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

Table A.2: Using alternative robust standard errors, alternative estimation model, and alternative measurement

	Panel A	Panel B	Panel C		
	Alternative SE	Alternative model	Alternative measurement		
	Clustered by project	Logistic model	Project quality (cycliness)	Kn. overlap (cos similarity)	Proposal centrality (max centrality)
	GoodDec	*GoodDec*	*GoodDec*	*GoodDec*	*GoodDec*
ProposalCentrality (log)	-0.071^{***}	-0.514^{***}	-0.030^{***}	-0.071^{***}	-0.086^{***}
	(0.007)	(0.031)	(0.004)	(0.006)	(0.006)
KnBreadth	0.012^{+}	0.073^{+}	0.004	0.010^{+}	0.011^{+}
	(0.006)	(0.043)	(0.003)	(0.006)	(0.006)
KnOverlap	0.003	0.004	0.000	-0.002	0.004
	(0.006)	(0.043)	(0.005)	(0.005)	(0.005)
ProposalCentrality (log)×KnBreadth	0.012^{**}	0.049^{*}	0.009^{*}	0.007^{+}	0.011^{**}
	(0.004)	(0.024)	(0.004)	(0.004)	(0.004)
ProposalCentrality (log)×KnOverlap	0.012^{*}	0.054^{*}	0.007^{*}	0.009^{*}	0.011^{*}
	(0.006)	(0.026)	(0.003)	(0.004)	(0.005)
KnProximity	0.016^{***}	0.154^{***}	0.005	0.016^{***}	0.016^{***}
	(0.004)	(0.035)	(0.003)	(0.004)	(0.004)
nReviewers	-0.005	-0.041	0.020	-0.005	0.005
	(0.018)	(0.120)	(0.015)	(0.018)	(0.018)
nDiscussants	-0.031^{***}	-0.229^{***}	-0.030^{***}	-0.031^{***}	-0.028^{***}
	(0.004)	(0.004)	(0.004)	(0.005)	(0.032)
ByContributor	-0.010	-0.075	-0.025^{***}	-0.010	-0.012^{+}
	(0.008)	(0.054)	(0.007)	(0.007)	(0.007)
nFilesChanged	-0.042^{***}	-0.254^{***}	-0.039^{***}	-0.042^{***}	-0.031^{***}
	(0.004)	(0.022)	(0.004)	(0.004)	(0.004)
Acquaintance	0.007	0.069	0.012	0.007	0.008
	(0.008)	(0.091)	(0.011)	(0.008)	(0.008)
Workload (log)	0.007^{**}	0.065^{**}	0.004^{**}	0.007^{**}	0.007^{**}
	(0.002)	(0.021)	(0.001)	(0.002)	(0.002)
ProjectAge	-0.013	-0.093	-0.001	-0.014	-0.012
	(0.035)	(0.277)	(0.028)	(0.035)	(0.035)
nCoreDevelopers	0.001	-0.001	-0.009	0.000	0.000
	(0.010)	(0.089)	(0.007)	(0.013)	(0.013)
Observations	58,377	54,725	50,980	58,377	58,377
(Pseudo) R-squared	0.228	0.204	0.218	0.228	0.236

Notes. Two-way cluster robust standard errors by project and year in parentheses in Panels B and C. Year, project, and evaluator fixed effects are included in all models. All non-dummy variables are standardized for ease of interpretation. The intercept is not reported to save space.

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

Table A.3: Dealing with other omitted variable concerns

	Panel A			Panel B	Panel C
	Include submitter, submitter–evaluator pair, and project–year pair FEs			Control for total knowledge	Control for decision experience
	GoodDec	*GoodDec*	*GoodDec*	*GoodDec*	*GoodDec*
ProposalCentrality (log)	−0.070***	−0.069***	−0.070***	−0.071***	−0.071***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
KnBreadth	0.005	0.002	0.014*	0.012*	0.012+
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
KnOverlap	0.003	0.004	0.004	0.004	0.003
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
ProposalCentrality (log)×KnBreadth	0.014***	0.013**	0.013**	0.012**	0.012**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ProposalCentrality (log)×KnOverlap	0.013**	0.014**	0.012**	0.012**	0.012**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
TotalKnowledge				−0.028	
				(0.023)	
DecExperience					0.053+
					(0.032)
KnProximity	0.019***	0.018***	0.018***	0.017***	0.015***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
nReviewers	−0.007	−0.003	−0.014	−0.005	−0.009
	(0.017)	(0.017)	(0.019)	(0.018)	(0.014)
nDiscussants	−0.025***	−0.020***	−0.030***	−0.031***	−0.031***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ByContributor	−0.050	−0.078	−0.007	−0.010	−0.010
	(0.070)	(0.078)	(0.007)	(0.007)	(0.007)
nFilesChanged	−0.041***	−0.040***	−0.041***	−0.042***	−0.042***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Acquaintance	0.006+	−0.000	0.006	0.007	0.006
	(0.003)	(0.003)	(0.008)	(0.008)	(0.008)
Workload	0.005*	0.005*	0.004*	0.007**	0.007***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
ProjectAge	−0.010	−0.019	−0.000	0.006	−0.028
	(0.036)	(0.036)	(0.047)	(0.035)	(0.034)
nCoreDevelopers	0.006	0.005	0.013	0.002	−0.002
	(0.015)	(0.013)	(0.030)	(0.013)	(0.013)
Submitter FE	Y	N	N	N	N
Submitter–evaluator pair FE	N	Y	N	N	N
Project–year pair FE	N	N	Y	N	N
Observations	56,396	54,093	58,352	58,377	58,377
R-squared	0.311	0.329	0.247	0.228	0.228

Notes. Two-way cluster robust standard errors by project and year in parentheses. Year and project fixed effects are included in all models except the third model of Panel A (where the year–project pair fixed effects are included instead). Evaluator fixed effects are included in all models except the second model of Panel A (where the submitter–evaluator pair fixed effects are included instead). All non-dummy variables are standardized for ease of interpretation. The intercept is not reported to save space.

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

Table A.4: Dealing with decisions with multiple evaluators

	Panel A	Panel B	Panel C
	One-evaluator proposals only	Combine rows of multiple evaluators	Include a dummy of having multiple evaluators
	GoodDec	*GoodDec*	*GoodDec*
ProposalCentrality (log)	-0.070^{***}	-0.072^{***}	-0.070^{***}
	(0.006)	(0.006)	(0.006)
KnBreadth	0.006	0.010^{*}	0.011^{+}
	(0.005)	(0.005)	(0.006)
KnOverlap	0.010^{*}	0.010^{*}	0.003
	(0.005)	(0.005)	(0.005)
KnBreadth×ProposalCentrality (log)	0.011^{+}	0.012^{**}	0.012^{**}
	(0.005)	(0.005)	(0.004)
KnOverlap×ProposalCentrality (log)	0.011^{*}	0.012^{**}	0.012^{**}
	(0.004)	(0.004)	(0.004)
KnProximity	0.014^{***}	0.019^{***}	0.016^{***}
	(0.003)	(0.004)	(0.004)
nReviewers		-0.014	
		(0.021)	
MultipleReviewers			-0.031^{***}
			(0.008)
nDiscussants	-0.035^{***}	-0.035^{***}	-0.029^{***}
	(0.006)	(0.005)	(0.004)
ByContributor	-0.004	-0.010	-0.010
	(0.007)	(0.006)	(0.007)
nFilesChanged	-0.037^{***}	-0.038^{***}	-0.041^{***}
	(0.004)	(0.005)	(0.004)
Acquaintance	0.011^{**}	0.004	0.007
	(0.004)	(0.006)	(0.008)
Workload (log)	0.002	0.002	0.007^{***}
	(0.002)	(0.002)	(0.002)
ProjectAge	-0.041	0.010	-0.011
	(0.032)	(0.044)	(0.036)
nCoreDevelopers	0.002	0.004	0.004
	(0.012)	(0.011)	(0.013)
Observations	33,150	47,201	58,377
R-squared	0.170	0.176	0.229

Notes. Two-way cluster robust standard errors by project and year in parentheses. Year and project fixed effects are included in all models. Evaluator fixed effects are included in Panel C. All non-dummy variables are standardized for ease of interpretation. The intercept is not reported to save space.

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

Table A.5: Explicating the role of knowledge breadth and knowledge overlap by splitting the sample

	Low proposal centrality	High proposal centrality
	GoodDec	*GoodDec*
KnBreadth	0.002	0.014*
	(0.004)	(0.006)
KnOverlap	−0.001	0.024**
	(0.005)	(0.008)
KnProximity	0.007	0.016**
	(0.005)	(0.005)
nReviewers	−0.003	0.039
	(0.021)	(0.036)
nDiscussants	−0.038***	−0.030***
	(0.007)	(0.007)
ByContributor	−0.017*	−0.011
	(0.007)	(0.010)
nFilesChanged	−0.031***	−0.054***
	(0.007)	(0.005)
Acquaintance	0.010^{+}	0.018***
	(0.006)	(0.004)
Workload (log)	0.001	0.005*
	(0.002)	(0.003)
ProjectAge	0.057	0.004
	(0.045)	(0.075)
nCoreDevelopers	0.001	−0.004
	(0.010)	(0.022)
Observations	27,940	30,685
R-squared	0.137	0.179

Notes. Two-way cluster robust standard errors by project and year in parentheses. Year and project fixed effects are included. All non-dummy variables are standardized for ease of interpretation. The intercept is not reported to save space.

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

Appendix B: Ruling out alternative explanations for Chapter II

An alternative explanation for the negative relationship between proposal centrality and decision effectiveness is that central proposals might be more likely to increase the propagation cost of the software (e.g., modifying a key feature may make increasing propagation cost unavoidable). Since most proposals on GitHub were accepted, I end up observing many "bad" central proposals being accepted. To rule out this explanation, first note that the correlation between a proposal's impact on propagation cost (i.e., $\Delta PropagCost$) and its centrality is 0.01, suggesting that central proposals do not necessarily increase the propagation cost. To further test this alternative explanation, I rerun the analyses using two different dependent variables: the incidence of commission errors and omission errors (i.e., the cases of false positive and false negative in Figure II.3). If the alternative explanation is driving the results, proposal centrality should be associated with more commission errors but not more omission errors. However, the results, reported in Panel A of Table A.6, show that proposal centrality significantly increases both commission and omission errors, arguing against this alternative explanation.

An alternative explanation for the positive interactions between knowledge breadth and proposal centrality and between knowledge overlap and proposal centrality is that evaluators with higher knowledge breadth and overlap might be more conservative when evaluating proposals. Since central proposals may inevitably increase the propagation cost, I end up observing those evaluators making better decisions by rejecting more "bad" central proposals. First, as noted earlier, the correlation between a proposal's impact on propagation cost and its centrality is low, suggesting that central proposals do not necessarily increase the propagation cost. Second, if this alternative explanation is true, I would observe knowledge breadth and knowledge overlap significantly reduce an evaluator's likelihood of accepting a proposal. I rerun the analyses using the dummy variable of acceptance as the dependent variable. The results, reported in Panel B of Table A.6, do not support this alternative explanation: the likelihood of acceptance does not depend on the evaluators' knowledge breadth or overlap.

Regarding the positive interaction between knowledge overlap and proposal centrality, another alternative explanation is that knowledge overlap increases other people's ability to monitor evaluations. As a result, the evaluators may strive to make high-quality decisions and refrain from engaging in power seeking. I conduct two analyses to rule out this explanation. First, I use a new dependent variable: the duration of decision making. The alternative explanation suggests that evaluators with greater knowledge overlap may try to make good decisions by spending more time evaluating the proposals. However, the results, reported in Panel A of Table A.7, show that knowledge overlap does not significantly influence the amount of time it takes to evaluate a proposal. In the second analysis, I include a three-way interaction among knowledge overlap, proposal centrality, and the number of files changed in a proposal ($nFilesChanged$). Having more files changed in a proposal makes it more time-consuming and energy-consuming to determine the impact of a proposal, which increases the monitoring cost. If knowledge overlap is playing a role through improving monitoring, the number of files changed in a proposal would reduce the benefit of knowledge overlap (i.e., a negative coefficient for the three-way interaction term). However, the results, reported in Panel B of Table A.7, show that the number of files changed in a proposal does not significantly influence the benefit of knowledge overlap, providing no support for the alternative explanation.

Table A.6: Ruling out alternative explanations

	Panel A		Panel B	
	Predict commission errors	Predict omission errors	Predict acceptance	
	CommitDec	*OmitDec*	*Accept*	*Accept*
ProposalCentrality (log)	0.068***	0.001+	−0.008***	−0.008***
	(0.006)	(0.001)	(0.002)	(0.002)
KnBreadth	−0.009	−0.000	0.004	0.004
	(0.006)	(0.001)	(0.002)	(0.003)
KnOverlap	−0.003	−0.001	0.002	0.002
	(0.005)	(0.001)	(0.002)	(0.002)
ProposalCentrality (log)×KnBreadth	−0.011*	−0.001		0.003
	(0.005)	(0.001)		(0.002)
ProposalCentrality (log)×KnOverlap	−0.012**	0.000		0.001
	(0.005)	(0.001)		(0.001)
KnProximity	−0.018***	0.000	−0.001	−0.001
	(0.004)	(0.000)	(0.001)	(0.001)
nReviewers	0.017	−0.002	0.022***	0.022***
	(0.017)	(0.004)	(0.006)	(0.006)
nDiscussants	0.006	0.011***	−0.033***	−0.033***
	(0.004)	(0.002)	(0.003)	(0.003)
ByContributor	−0.015*	0.010***	−0.031***	−0.031***
	(0.007)	(0.002)	(0.005)	(0.005)
nFilesChanged	0.038***	0.006***	−0.008***	−0.008***
	(0.004)	(0.001)	(0.002)	(0.002)
Acquaintance	0.009*	−0.004*	0.019***	0.019***
	(0.004)	(0.002)	(0.005)	(0.005)
Workload	−0.006*	−0.000	0.001	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
ProjectAge	0.038	−0.009+	0.027*	0.027*
	(0.033)	(0.006)	(0.013)	(0.013)
nCoreDevelopers	0.000	0.001	−0.000	−0.000
	(0.012)	(0.001)	(0.006)	(0.006)
Observations	58,377	58,377	59,897	59,897
R-squared	0.241	0.224	0.229	0.229

Notes. Two-way cluster robust standard errors by project and year in parentheses. Year, project, and evaluator fixed effects are included in all models. All non-dummy variables are standardized for ease of interpretation. The intercept is not reported to save space.

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

Table A.7: Ruling out alternative explanations (cont'd)

	Panel A		Panel B	
	Predict duration of decision making		Test whether proposal size moderates the mitigating role of knowledge overlap	
	DecisionHrs(log)	*DecisionHrs(log)*	*GoodDec*	*PowerSeekingDec*
ProposalCentrality (log)	0.160^{***}	0.161^{***}	-0.072^{***}	0.021^{**}
	(0.015)	(0.016)	(0.006)	(0.007)
KnBreadth	-0.062^{+}	-0.063^{+}	0.011^{+}	0.096^{***}
	(0.032)	(0.032)	(0.006)	(0.022)
KnOverlap	0.009	0.008	0.004	0.003
	(0.033)	(0.033)	(0.005)	(0.017)
ProposalCentrality (log)×KnBreadth		−0.003	0.012^{**}	0.003
		(0.016)	(0.004)	(0.006)
ProposalCentrality (log)×KnOverlap		−0.003	0.012^{**}	-0.023^{**}
		(0.017)	(0.004)	(0.007)
KnProximity	-0.079^{***}	-0.079^{***}	0.016^{***}	0.007
	(0.016)	(0.016)	(0.004)	(0.009)
nReviewers	1.018^{***}	1.018^{***}	−0.004	0.064^{***}
	(0.164)	(0.163)	(0.018)	(0.018)
nDiscussants	0.840^{***}	0.840^{***}	-0.031^{***}	-0.021^{**}
	(0.026)	(0.026)	(0.004)	(0.007)
ByContributor	0.270^{***}	0.270^{***}	−0.010	-0.058^{**}
	(0.051)	(0.051)	(0.007)	(0.019)
nFilesChanged	0.220^{***}	0.220^{***}	-0.042^{***}	0.021^{***}
	(0.021)	(0.021)	(0.004)	(0.005)
KnOverlap×nFilesChanged			−0.005	0.009^{+}
			(0.003)	(0.005)
ProposalCentrality (log)×nFilesChanged			-0.016^{***}	0.003
			(0.004)	(0.006)
ProposalCentrality (log)×KnOverlap×nFilesChanged			0.002	0.008
			(0.004)	(0.005)
Acquaintance	-0.267^{***}	-0.267^{***}	0.006	0.014
	(0.048)	(0.048)	(0.008)	(0.018)
Workload	-0.033^{**}	-0.033^{**}	0.007^{**}	−0.003
	(0.011)	(0.011)	(0.002)	(0.010)
ProjectAge	0.631^{***}	0.630^{***}	−0.013	0.038
	(0.184)	(0.183)	(0.035)	(0.060)
nCoreDevelopers	0.124^{*}	0.124^{*}	0.001	0.007
	(0.054)	(0.054)	(0.013)	(0.025)
Observations	59,897	59,897	58,377	9,472
R-squared	0.429	0.429	0.229	0.477

Notes. Two-way cluster robust standard errors by project and year in parentheses. Year, project, and evaluator fixed effects are included in all models. All non-dummy variables are standardized for ease of interpretation. The intercept is not reported to save space.

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

Appendix C: Procedures used to calculate the main variables in Chapter II

To provide a better idea of how the variables are calculated and how the counterfactuals for rejected proposals are established, this section provides a brief description of the procedures. For every project and every proposal in the sample, the following steps are carried out:

Step 1: Restore the historical version of the software source code to the point in time when the proposal was submitted.

Step 2: Analyze the source code, generate the function call network, and calculate the propagation cost and the proposal centrality based on the function call network.

Step 3: Calculate the knowledge characteristics of the evaluators based on the code editing history up to the time when the proposal was submitted.

Step 4: Regardless of the actual decision on the proposal, accept the proposal in my local version of the source code.

Step 5: Re-analyze the source code, re-generate the function call network, and re-calculate the propagation cost.

Step 6: Calculate $\Delta PropagCost$ based on the propagation costs obtained in Steps 2 and 5. Decide the decision effectiveness by comparing $\Delta PropagCost$ with the actual decision made on the proposal.

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