ESSAYS ON FUNDING AND PATENTING IN THE INNOVATION PROCESS

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You have to dream before your dreams can come true.

- APJ Abdul Kalam

Dedicated to my parents

Mohinder Pal Singh and Paramjit Kaur Chhabra

and

wife Ajeet and daughter Aneet

for their unconditional love and support

throughout this journey.

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SUMMARY

The three essays in this dissertation focus on understanding inventors' operational decision-making in the context of new product development and innovation management. The main focus of this dissertation is to study the role of innovation platforms in product development and the effect of the inventor's decision on innovation success. Specifically, this dissertation: *(i)* employs empirical and analytical methods, and *(ii)* encompasses the following three areas: *innovation platforms*, *reward-based crowdfunding*, and *patenting*.

Innovation Platforms: Entrepreneurs often translate their ideas into commercially viable new products through a sequential process called innovation value chain. The innovation value chain supports a holistic view of the new product development activities. In this research, I revisit the innovation value chain, study various innovation platforms, such as crowdsourcing, crowdfunding, and hackathons, and highlight the role of these platforms that create value by decoupling the different stages of the innovation value chain. Finally, I highlight the entrepreneur's challenges of utilizing these platforms and discuss future research opportunities.

Reward-Based Crowdfunding: Reward-based crowdfunding acts as a pre-selling mechanism for innovative products offered as rewards, which serves two purposes for entrepreneurs: First, it provides funding to the resource-crunched entrepreneurs; second, it signals the idea's quality in terms of the future demand for the product. I study the impact of entrepreneurs' operational decisions on the reward structure design, i.e., the number of rewards and their pricing, on their innovative ideas' funding success. Through empirical analyses, I evaluate the effect of providing more rewards on the funding success of a campaign. Further, I provide guidelines on how the impacts of providing more rewards change with reward price dispersion, campaign type, and creators' crowdfunding experience.

Patenting: Inventors seek patents for technical viability that undergo a patent examination for a long duration. I study inventors' decision-making process to position their creative efforts while creating intellectual property under the uncertainty of longer patent pendency. Specifically, I analyze the effect of longer patent pendency on the inventor's effort allocation to innovative and routine activities through a multi-period analytical model, where belief update about the

expected patent pendency happens in a Bayesian framework. The analytical model's results motivate the hypotheses, and I test it using patent data published by the *United States Patent and Trademark Office* (USPTO). The empirical tests show significant evidence that patent pendency negatively affects the future patenting activities of inventors. Overall, the findings highlight nuances for inventors' effort allocation decisions and provide guidelines for managers to incentivize their teams under innovation adversaries.

CHAPTER 1
INTRODUCTION

Being in the heart of the innovation process, inventors often encounter several sources of uncertainty in translating their ideas into commercially viable new products. To reduce the commercialization uncertainty, an inventor may seek advanced validation regarding future demand (through crowdfunding) and technical viability (through patenting) of their inventions. My dissertation investigates the role of innovation platforms in product development and the effects of the inefficiencies - *information asymmetry* and *uncertainty* - associated with these mechanisms. Specifically, I study (i) innovation platforms in product development, and the effect of operational decision-making in (ii) *reward-based crowdfunding*, and (iii) *patenting*.

The first essay, titled "*Product Development and Open Innovation Platforms*," (Chapter 2) discusses the role of innovation platforms in the process of converting ideas to commercialization of products and the challenges entrepreneurs face on these platforms. Entrepreneurs often translate their ideas into commercially viable new products through a sequential process called innovation value chain. Each activity in the innovation value chain is a link in the chain, where a firm may excel in one or more activities - the firm's strongest links. Conversely, the firm may struggle in one or more activities - the firm's weakest links. The innovation value chain supports a holistic view of the new product development activities. In this research, I revisit the innovation value chain, study various innovation platforms, such as crowdsourcing, crowdfunding, and hackathons, and attempt to understand how these platforms create value by decoupling various stages of the innovation value chain. In doing so, I investigate numerous innovation platforms that have emerged in the last decade, map them on the innovation value chain, and highlight the value created for entrepreneurs. Finally, I highlight various challenges entrepreneurs face in creating value on these platforms and discuss future research opportunities.

The second essay, titled "*Designing Reward Structure for Crowdfunding Campaigns*," (Chapter 3) focuses on a creator's critical decision out of the numerous aspects of reward-based

crowdfunding that affect the funding success: how to design the reward structure in terms of the number of rewards and its contribution levels to maximize its funding performance. Individual entrepreneurs and small firms, often resource-crunched, lack the knowledge and resources to design their campaigns effectively. A campaign's reward-structure design, on the one hand, is critical because rewards form the primary motivation for backers. On the other hand, campaign design poses challenges due to the information asymmetry associated with reward-based crowdfunding: the customers are uncertain about the reward quality and the entrepreneurs' intentions to deliver the promised rewards. Research shows that 75% of *Kickstarter* 's campaigns do not deliver their rewards on time, and 9% campaigns do not deliver their rewards at all. To study the reward structure design for crowdfunding campaigns, I use a large dataset of campaigns from *Kickstarter*, the US's pre-eminent reward-based crowdfunding platform. I find that a reward-based crowdfunding campaign's funding success improves with the number of rewards at a diminishing rate. I also evaluate the moderating effects of dispersion of reward prices, reward type – experiential or product, and the creator's experience.

The third essay, titled "*Patent Pendency and Future Innovative Activities*," (Chapter 4) investigates the impact of longer patent pendency on inventors' future innovative activities. Patenting signals the ideas' commercial viability and provides legal protection required to launch new products. Inventors apply for patents that undergo a detailed patent examination to seek technical validation and safeguard their innovations. The patent examination process that evaluates inventions against three fundamental criteria - *novelty*, *usefulness*, and *non-obviousness* often result in longer patent pendency before grant. Due to longer patent pendency, the reduced benefits from patenting can demotivate inventors and move them away from innovation. To predict the inventor's effort allocation to innovative and routine tasks on experiencing longer patent pendency, I formulate the inventor's effort allocation problem in a multi-period analytical model where belief about the expected patent pendency is updated in a Bayesian framework. The results from the analytical model motivate the hypotheses that the inventor's effort on her innovative activities (1) reduces on experiencing longer patent pendency, (2) increases with more prior patents, and (3) the negative relationship between patent pendency and future innovative effort is positively moderated by the number of prior patents.

I use patent data published by the *United States Patent and Trademark Office* (USPTO) from $1975 - 2020$ to test these hypotheses and employ coarsened exact matching and panel data empirical methodologies to address endogeneity. I find support for all the hypotheses, demonstrating a significant negative effect of longer patent pendency on the inventor's future patenting activities.

CHAPTER 2

PRODUCT DEVELOPMENT AND OPEN INNOVATION PLATFORMS

2.1 Introduction

The innovation value chain is the sequential representation of the innovation activities starting with the idea generation to successful commercialization and diffusion of the knowledge and products (Hansen and Birkinshaw 2007). It is analogous to Michael Porter's value chain, which comprises a series of activities such as operations, logistics, and marketing that firms execute to derive value from them. Each activity in the innovation value chain is a link in the chain, where a firm may excel in one or more activities - the firm's strongest links. Conversely, the firm may struggle in one or more activities - the firm's weakest links. The innovation value chain framework suggests managers take an end-to-end view of the innovation efforts and discourage them from adopting practices that may address a part of the chain, which may not prove to be the critical one needing attention. To improve the innovation performance, it prompts to target the weakest link.

Traditionally, product development activities occur within the boundaries of a firm, which help accomplish coordination efficiency and privacy, referred to as closed innovation. However, lately, firms have started to open up their doors to external knowledge, referred to as open innovation (Chesbrough 2003). In *closed innovation*, firms generate their ideas and support development, manufacturing, and commercialization. In addition, firms invest heavily in internal R&D and hire the brightest minds to stay ahead of their competitors. With these investments and intellectual property protection, firms used to bring products first in the market to reap the benefits. Later, with the increase in inventor mobility and the availability of venture capital funding, firms started looking outside their boundaries to fulfill their needs of sourcing innovative ideas and funding. Chesbrough (2003) defined this new model as *open innovation*, where "*firms commercialize external (as well as internal) ideas by deploying outside (as well as in-house) pathways to the market*." In other words, firms can commercialize their internal ideas

through external funding and vice versa to generate value for the organization.

The *Innovation Value Chain*, as introduced by Hansen and Birkinshaw (2007), supported having a holistic view of the new product development activities performed by a firm. Most firms have a formal system of managing innovative ideas but fail in the execution due to the risk-averse and bureaucratic processes created to manage a vast and diverse population of employees. The impetus in the innovation value chain framework was how a firm could utilize the innovation value chain to create new processes or mobilize its resources to fix the weak or broken link in the innovation value chain to successfully bring products to the market. For example, to fix the idea-poor company, the company can create internal cross-unit networks or leverage external networks to generate ideas from new connections. To fix a conversion-poor company, the company can create an internal multi-channel funding group that supports innovative ideas. Finally, to fix a diffusion-poor company, the company may employ evangelists who preach the good word about an emerging product or business in their deep high-touch personal networks (Hansen and Birkinshaw 2007).

With the wide acceptance and proliferation of the open innovation model, firms can open up their boundaries to leverage open innovation by decoupling each stage of the innovation value chain. Several small firms or startups can master one or more stages by decoupling the innovation value chain, similar to the concept of decoupling in the customer value chain introduced by Teixeira (2009, 2019). The *customer value chain* refers to a series of activities that customers perform to fulfill their needs and wants, including evaluating, choosing, purchasing, and consuming. *Decoupling*, as defined by Teixeira (2009, 2019), "*is the separation, by a digital player, of the links between customer activities that have traditionally been provided together*." The concept of decoupling has also been studied in the design of service organizations to improve operating efficiency under high and low customer contact (Chase and Tansik 1983).

The digital players that create decoupling in the innovation value chain are the innovative online intermediary platforms (Billington and Davidson 2013). An intermediary platform or a network is defined as "*a formal or informal collection of people or companies that facilitates a productive working relationship between two previously unconnected parties, usually on a one-time basis*" (Billington and Davidson 2013). Online intermediary platforms enable

economic and social interactions between two or more user groups using the internet as their infrastructure (Arnold and Hildebrandt 2017). These platforms specialize in one or more activities that decouple the innovation value chain. For example, *InnoCentive*, an intermediary platform, facilitates idea generation. Another platform *Hubs* provides product development and manufacturing services. Some intermediary platforms may also support more than one activity. For example, *Quirky* provides idea selection, product development and manufacturing, and commercialization support.

The online intermediary platforms match demand and supply sides and bring together producers and users in efficient exchanges of value by leveraging network effects (Van Alstyne et al. 2016). These platforms maximize the contribution variety from a crowd's dispersed knowledge base. The crowd, which may include the customers of these products, plays a critical role in generating the network effects facilitated by the internet and mobile technologies. The network effects in these intermediaries are driven by the demand-side economies of scale, whereas the traditional businesses such as *General Electric* leveraged the supply-side economies to launch products successfully (Van Alstyne and Parker 2017). Due to the power of the network effects, these platforms efficiently unlock the unused capacity by reducing information, search, and transaction costs (Arnold and Hildebrandt 2017). Moreover, the benefits provided by the crowd on these platforms - scale, diversity, and intrinsic motivation as compared to traditional incentives of salaries and bonuses in firms - are challenging to match and makes these platforms equally beneficial for firms and entrepreneurs (Boudreau and Lakhani 2013).

In this research, we revisit the innovation value chain and study the role of intermediary platforms in the innovation value chain. We attempt to understand how intermediary platforms create value by decoupling the various stages of the innovation value chain. In doing so, we investigate numerous intermediary platforms that have emerged in the last decade, map them on the innovation value chain, and highlight the value created for entrepreneurs. Finally, we highlight various challenges entrepreneurs face in creating value on these platforms and discuss future research opportunities.

In the remainder of this study, we first define various stages of the Innovation Value Chain

in the context of open innovation in Section 2.2 and discuss how it can be leveraged to fill the gap between innovation capabilities and existing resources, discussed in Section 2.3, to create innovative products. Next, in Section 2.4, we define various types of open innovation mechanisms such as crowdsourcing, crowdfunding, and hackathons. Further, section 2.5 discusses various intermediary platforms mapped on the innovation value chain. Next, we highlight the entrepreneurs' challenges in leveraging these intermediary platforms and discuss future research opportunities in Section 2.6. Finally, we end with a discussion of concluding thoughts in Section 2.7.

2.2 Innovation Value Chain and Open Innovation

Whenever there is a mismatch between innovation capability and the available resources to create products, there occurs an efficiency gap, which can be fulfilled by utilizing the Innovation Value Chain (see Figure 2.1). The Innovation Value Chain is a sequential process of generating and converting ideas to commercially viable new products. Innovation value chain's stages constitute *idea generation*, *idea selection and funding*, *product development*, and *commercialization and diffusion* of developed concepts and products (Hansen and Birkinshaw 2007, Gaimon and Bailey 2013) (see Figure 2.2). Entrepreneurs require various capabilities in different stages of the innovation value chain, which can be acquired through knowledge assets imbibed in three principal intellectual capital. First, human capital refers to tacit knowledge retained in individuals. Structural capital is the accumulated codified tacit knowledge in routines, processes, and information systems. Finally, the relationships formed by individuals to facilitate knowledge sharing outside firm boundaries is called relational capital (Gaimon and Bailey 2013). With the rise of innovative platforms, it has become easier for firms and entrepreneurs to look outside their boundaries and acquire knowledge assets from external sources (Chesbrough 2003, Gaimon and Ramachandran 2020).

The innovation value chain begins with the *idea generation* stage, in which the main focus is to generate ideas in large quantities and with high variability through brainstorming (Girotra et al. 2010). One way to begin the idea generation process is by identifying a problem first when there is a gap between the consumer needs and the available solutions, called "market pull."

However, the opposite way to start the idea generation is with the availability of a new solution in the market, and the task is to find a practical problem that the new technology could solve, called "technology push" (Stefano et al. 2012). To achieve these objectives, entrepreneurs require alertness and creativity in the idea generation stage, which can be readily acquired through human capital and relational capital (Gaimon and Bailey 2013). In either way, opening up the idea generation process to the lead users in the crowd could increase the number and variability of the ideas generated, statistically improving the quality of the best idea (von Hippel 1986, King and Lakhani 2013).

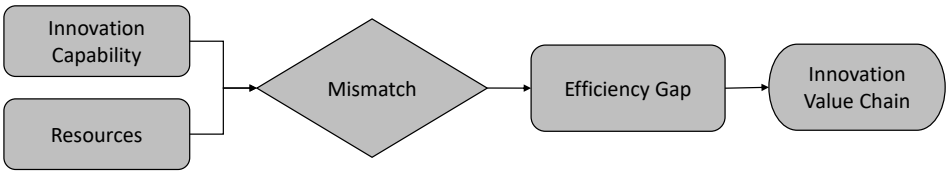


Figure 2.1: The Efficiency Gap and Innovation Value Chain

	Idea Generation	Selection/ Funding	Development	Commercialize/ Diffusion
Capabilities	Alertness, Creativity	Decision making under uncertainty	Exploration & exploitation, Knowledge dev. & transfer, Project mgt. under uncertainty	Value capture, Sharing networks
Resources	Human capital, Relational capital	Human capital, Relational capital, Funding	Human capital, Relational capital, Structural capital, Manufacturing	Human capital, Relational capital
Platforms Types	Crowdsourcing, Hackathon	Crowdsourcing, Hackathon, Crowdfunding	Crowdsourcing, Hackathons, 3D Printing marketplace	Crowdfunding, Crowdsourcing, IP Marketplace
Open Innovation Platforms	NineSigma, InnoCentive, IdeaConnection, Devpost, Kaggle, TopCoder	IdeaConnection, Quirky, Kickstarter, Indiegogo, Devpost, Catapooolt, TopCoder	Quirky, Devpost, Kaggle, TopCoder, Craftcloud, Hubs	IdeaConnection, Quirky, Etsy Kickstarter, Indiegogo, Shein Catapooolt, Innoget, Shapeways
Current Research	Idea quantity and variability, Solver pool size, Solver ability, Award schemes, Team structure, Crowd motivation	Idea quality, idea selection scheme, Reward scheme in crowdfunding, Geographical proximity, Campaign design, Information asymmetry, Trust, Signaling	Iterative coordination, Customer involvement, Norm-based IP systems	Legitimacy, Social capital, Norm-based IP systems
Future Research	(1)How to define a problem statement for innovation challenges? (2)How to motivate the crowd? (3)How to govern the interactions between seekers and solvers?	(1)How to improve idea selection? (2)How to build trust between the seeker and the crowd? (3)How to manage and influence crowd to provide funding?	(1)How to achieve coordination among various stakeholders? (2)How to deter competitive imitation? (3)How to ensure and improve the quality of the manufactured products?	(1)How to manage IP on these platforms?

Figure 2.2: The Innovation Value Chain

At the end of the idea generation stage, there is significant uncertainty about the actual success potential of the generated ideas. Therefore, the ideas are evaluated in the *idea selection* stage as the quality of the raw idea bears a direct impact on the success of the final product (Kornish and Ulrich 2014). New concepts could create bottlenecks in the value chain without efficient and robust screening processes instead of prospering. As a result, many companies lose novel ideas due to tight budgets, conventional thinking, and strict funding criteria. The opposite is also prevalent when managers do not adopt strict idea screening, resulting in too many ideas floating around without an alignment with the overall firm strategy (Hansen and Birkinshaw 2007). The screening process involves decision-making under uncertainty by complying with numerous judging criteria to evaluate ideas for strategic fit, financial potential, and operational fit against the existing capabilities to process it through the value chain to make the final product (Gaimon and Bailey 2013, Lee and Schmidt 2016). Entrepreneurs also evaluate the potential commercial value of the ideas against the projected risks and costs involved. In particular, the decision to abandon the concept or pursue it to the next stage is based on the environment, current requirements, and the projected rewards. The required knowledge may be acquired through data from predictions about the product or by testing it with customers in the market or on crowd platforms (Kornish and Hutchison-Krupat 2016).

The third stage in the innovation value chain is the *design and development* of the product, where an idea is converted to a viable prototype by exploration and exploitation of the new and existing resources. The exploration in a new space can lead to novel innovation outcomes, whereas the exploitation of the existing resources leads to marginal improvements in the product (March 1991). Managing the tension between maximization of innovation novelty and minimization of technological uncertainty is the key objective to balance the exploration and exploitation efforts (Gaimon and Bailey 2013). Moreover, the development stage involves numerous go/no-go decision reviews, where the product must pass several "gates" in the product development process. These reviews help solidify the product architecture and resolve projected manufacturing issues (Lee and Schmidt 2016). A key challenge in the development stage is to manage knowledge generation and transfer between the product design and the technology design teams. The development of products by the product design team and technology

by the technology design team entails complex environments in terms of the number of decision variables and interactions among the variables (Gaimon and Bailey 2013).

The last stage of the innovation value chain - *commercialization and diffusion* - involves making several decisions after producing and before launching the product. First, entrepreneurs have to decide when and where to launch the product. An optimal product entry is a crucial determinant of product success, where a critical trade-off in this stage is early market entry versus further developing the product (Krishnan and Ulrich 2001). Additionally, it is difficult to predict how customers and the market react to the new product. Customers may not like the product, and it may require a few changes in the product design before customers accept it, or the demand for the product may shoot up beyond entrepreneur's projections (Lee and Schmidt 2016). These scenarios are challenging to predict accurately and require diffusing the product knowledge among customers to receive their buy-in. The diffusion of product knowledge should not be among customers alone, but it should also be spread across the organization and in the community. The community disclosure along with product protection before launch may be achieved by patenting the product or the technology (Johnson and Popp 2003).

In the past, firms used to depend only on internal resources and internal intellectual capital to develop innovative products; a concept called closed innovation (Chesbrough 2003). Under this regime, firms invest heavily in internal R&D to generate ideas. Hiring the brightest and experienced individuals in senior management is indispensable and relied upon for idea selection to fund the promising ideas. A product development unit owns product development activities, and a marketing unit supports the commercialization and diffusion activities. By handling all the product development activities in-house, firms become asset-heavy and are challenging to manage. Building such large conglomerates was feasible only for large corporations like GE, IBM, and AT&T. These days, numerous startups compete with these large conglomerates and bring innovative products to market using open innovation. In this research, we extend the innovation value chain framework in the context of open innovation and discuss the role of open innovation platforms at different stages of the innovation value chain. Under open innovation, firms can leverage various open innovation platforms that provide specialized services in one or multiple stages of the innovation value chain. Next, we discuss resources and innovation

capabilities in Section 2.3 and various platform-based product development open innovation mechanisms in Section 2.4.

2.3 Resources and Innovation Capabilities

In recent years, knowledge and innovation management research has blurred the boundaries between these areas. Due to their intertwined boundaries, the creation and management of knowledge can be viewed as the central theme from the first stage of idea generation to the last stage of commercialization and diffusion in the innovation value chain. The capability to innovate and manage knowledge assets depends upon its intellectual capital - Human capital, Relational capital, and Structural capital (Gaimon and Bailey 2013, Subramaniam and Youndt 2005). Conceptualization of the different aspects of intellectual capital offers a means to synthesize the approaches to accumulate and use knowledge for creating innovations.

Human capital is defined as a combination of knowledge, skills, and abilities residing with and utilized by individuals to do productive work (Schultz 1961). Furthermore, human capital is characterized by the presence of *tacit knowledge*, which is sticky and resides in an individual's mind (von Hippel 1994). Human capital is transitory and can change depending on hiring, mobility, and turnover. Therefore, human capital requires investments in terms of hiring, training, and retaining of employees (Youndt et al. 2004).

Relational capital is defined as the embedded knowledge within individuals, available through and utilized by interactions of individuals with their interrelationship networks (Nahapiet and Ghoshal 1998). The knowledge associated with relational capital evolves through interactions among individuals or groups following predetermined rules and procedures delineated for accessing, sharing, or transacting knowledge (Subramaniam and Youndt 2005). The individuals in social networks can leave the group anytime, but individual mobility does not destroy the viability of the network as these networks stem from norms for collaboration, interaction, and sharing.

Structural capital is defined as the codified knowledge and experiences residing within and made available through databases, patents, manuals, and processes (Youndt et al. 2004). Creating, preserving, and enhancing the codified structural capital occurs through structured and

repetitive activities. Such codified databases, patents, and manuals are used by organizations to accumulate and retain knowledge, distinguishing such knowledge from the other two types of intellectual capital. It is also reflected in organizational structures, processes, and mandated procedures describing knowledge retrieval, sharing, and utilization rules. Structural knowledge stays with the organization, whereas human capital and relational capital are transitory and move with individual mobility (Subramaniam and Youndt 2005).

At the first stage of the innovation value chain, i.e., *idea generation*, successful retention of human capital provides capabilities of alertness and creativity required for generating multiple ideas with high variability (Gaimon and Bailey 2013, Girotra et al. 2010). *Alertness* is defined as abstract talent and unique knowledge that provides the ability to notice opportunities without search that have been previously overlooked (Kirzner 1963). Alertness, driven by cognitive abilities and a mental framework, leads to the discovery of new ideas by scanning through the environment, which impacts the quality and quantity of ideas generated (Bhave 1994). The mental framework assists individuals to be alert to opportunities and enables them to be objectively accurate and possess a more complex schema about their social environments (Baron 2004). Alert individuals can think outside the box because of their complex and adaptive mental framework.

Creativity, the most critical element of innovation, is defined as the development of ideas, products, services, or procedures that are novel and potentially useful (Amabile 1998). Creative individuals can generate inventions through a recombinant search by mentally merging previously unrelated ideas for better combinations of existing and new ideas (Fleming and Sorenson 2001). The value of the recombinant search process is determined by the number of novel outcomes generated. The probabilistic search for novel outcomes is impacted by the problem formulation and is highly dependent on the individual's stock of knowledge (Ward 2004). The likelihood of generating successful ideas in a large quantity can be improved by extending the knowledge boundaries to acquire relational capital through collaborations as customers are also a valuable source of knowledge and can provide a distinctive variety of ideas (von Hippel 1986, Yli-Renko et al. 2001).

At the second stage of the innovation value chain, i.e., *idea selection and funding*, the focus

of an entrepreneur shifts from quantity to quality of ideas. The main objective of this stage is to evaluate ideas and commit funding, which involves high uncertainty. This commitment involves predicting the success potential of ideas, and this prediction task is based on predetermined criteria, which is hard even if the criteria are known (Kornish and Hutchison-Krupat 2016). To resolve uncertainty, the entrepreneur can acquire the human capital of the crowd and utilize their relational capital to improve the efficacy of these probabilistic decisions (Boudreau and Lakhani 2013).

Cognitive factors play an essential role in decision-making under uncertainty as explained by prospect theory (Tversky and Kahneman 1974). Prospect theory centers around the subjective evaluation of gains and losses against a reference point. As per this theory, losses tend to "loom larger" than gains under uncertain decision-making. Moreover, every individual has a different reference point, and the efficacy of the ideas is uncertain. Since the performance of average beliefs improves with the size of the population, the idea selected by the crowd tends to be of higher quality than selected by any individual (Piezunka et al. 2021).

The third stage of the innovation value chain, i.e., *product development*, involves converting an idea to a prototype. In this stage, individuals often consider a trade-off of exploring new knowledge or exploiting the existing knowledge. Exploring new domains can lead to radically improved products, whereas exploiting the existing resources may lead to marginal improvements (March 1991). However, focusing on exploration can lead to novel ideas, but ideas executed with underdeveloped technologies and excessive focus on exploitation can result in a missed opportunity of developing novel products. Therefore, a managerial decision to balance the two by maximizing innovation novelty and minimizing technological uncertainty can lead to superior outcomes (Rothaermel and Deeds 2004, Gaimon and Bailey 2013).

The balanced exploration-exploitation approach of managing uncertainty in product development depends on individuals' human, relational, and structural capital. The human and relational capital facilitates exploration of the new tacit knowledge, whereas the structural capital drives exploitation of the existing codified knowledge in terms of processes and standards to develop products (Quinn et al. 2005). A key challenge in this stage is to develop skills to effectively transfer product knowledge to the process design team responsible for product

manufacturing (Özkan-Seely et al. 2015). Effective and efficient knowledge exchange can be optimized by investing in structural capital. The structural capital may be developed in-house or acquired through collaborations with external manufacturers (Rothaermel and Deeds 2004). However, considerable uncertainty remains in the sense that *ex-ante* it is challenging to know which external source will be the most rewarding.

In the fourth and the last stage of the innovation value chain, i.e., *commercialization and diffusion*, the likelihood of product survival in the market to capture value improves with effective management of human and relational capital (Yli-Renko et al. 2001). The relational capital facilitates the sharing networks between the entrepreneur and customers, and among customers that help diffuse the product knowledge to improve the chances of its success (Cornelius and Gokpinar 2020). Furthermore, investment in relational capital provides learning about product enhancement through collaborations (Candoğan et al. 2021). Moreover, the benefit of these interactions increases with investment in human capital that improves absorptive capacity for efficient absorption and implementation of the transacted knowledge (Cohen and Levinthal 1990).

2.4 Platform Based Open Innovation Mechanisms in Product Development

European Commission defined an *online platform* as "*an undertaking operating in two (or multi)-sided markets, which uses the internet to enable interactions between two or more distinct but interdependent groups of users so as to generate value for at least one of the groups*" (House of Lords 2016). On similar lines, the economics literature defines a *platform* as a two-sided or multi-sided market, where the platform facilitates interaction among two or more sides with cross-side network externalities (Eisenmann et al. 2006). For example, Airbnb matches providers and seekers of short-term accommodation and facilitates their transactions. However, the new product development or technology innovation literature defines a *platform* as a core module of a system, where the external members can easily connect and contribute to its development in order to expand the system (Zhu and Furr 2016). The platform not only performs the core functions of the ecosystem but also defines the interface rules (Wan et al. 2017). For example, *Keurig*'s "*K-cup*" coffee maker serves as an architecture that allows firms

to build related products or services. In addition to multi-sided intermediary platforms like *Airbnb* and architecture platforms like *Keurig*'s *K-cup*, platforms like video game consoles serve as both intermediary and architecture that facilitate online transactions among the users and enable developers to build games on the platform. We adopt the economics definition of the internet-based intermediary platforms in the context of the innovation value chain.

The objective of an intermediary platform is to maximize contributions from multiple agents with varying knowledge. A variety of agents participate in supporting the production and supply of products and services while maintaining independent goals and capacity, contributing to a collective goal through shared communication rules on these platforms (Consoli and Patrucco 2008). Platforms have attracted an increasing number of transactions in the modern economy through facilitating direct interactions among individuals and firms (Gawer 2014, Rochet and Tirole 2003). We discuss intermediary platforms that facilitate value generation through interactions among an extensive network of platform users (McIntyre et al. 2021). The assumption is that with a large customer base of users, third-party developers and sellers achieve more significant incentives through direct network effects by introducing their products and services on the platform (Katz and Shapiro 1985), thereby enhancing its value to the existing users (Cusumano and Gawer 2002). Apart from the direct effect, stakeholders on intermediary platforms also experience indirect network effects - the value that the users on one side draw from the increased presence on the other side of the platform (Cusumano and Gawer 2002, Rochet and Tirole 2003).

Such intermediary platforms are novel and valuable because of their lesser costs of developing and procuring innovative solutions than the conventional mechanisms. Moreover, these platforms can rapidly extend a firm's boundaries of innovation search by engaging millions of brains instantly and economically. In addition, these networks enable firms to access smaller companies, volunteers, retirees, or low-paid hobbyists to provide their expertise to resolve technical challenges, which were once believed to require internal specialized technical expertise. Finally, these platforms also demonstrate a stark contrast to traditional practices that only consider long-standing partners for innovation collaborations. Next, we define different intermediary platforms and then discuss a few platforms that map the innovation value chain. Mainly,

these intermediary platforms belong to different crowdsourcing, crowdfunding, and hackathon mechanisms.

2.4.1 Crowdsourcing

The term "*Crowdsourcing*" was first defined by Howe (2006) as "*an act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (a generally large) network of people in the form of an open call*." Estellés-Arolas and de Guevara (2012) combine 40 odd definitions and introduce a comprehensive definition of crowdsourcing: "*Crowdsourcing is a type of participative online activity in which an individual, an institution, a non-profit organization, or company proposes to a group of individuals of varying knowledge, heterogeneity, and number, via a flexible open call, the voluntary undertaking of a task. The undertaking of the task; of variable complexity and modularity, and; in which the crowd should participate, bringing their work, money, knowledge and/or experience, always entails mutual benefit. The user will receive the satisfaction of a given type of need, be it economic, social recognition, self-esteem, or the development of individual skills, while the crowdsourcer will obtain and utilize to their advantage that what the user has brought to the venture, whose form will depend on the type of activity undertaken*."

The proliferation of the internet, mobile technologies, and social media have made it possible to harness the power of the crowd in recent times. Earlier, engaging the crowd was limited to in-person settings. With the rise of innovation and social media platforms, today, organizations are equipped and in a much better position in engaging and utilizing crowds to solve their innovation-related problems (Lakhani and Panetta 2007). As a result, more and more researchers and industries are trying to understand its benefits and best practices to engage the crowd. It requires a basic understanding of different forms of crowdsourcing and the processes to facilitate contributions from the crowd in each of those categories (Prpić et al. 2015).

Crowdsourcing is a phenomenon of giving an open call to a crowd to solve a problem or generate ideas, and in turn, receive a predetermined economic and social benefit from the organizers of the contest (Babich et al. 2020, Bayus 2013). This phenomenon is not new and has its root in history. The historical evidence of crowdsourcing includes the *Longitude Prize*,

which was established in 1714, and the creation of the *Oxford English dictionary* in 1884. Later, there are also instances cited where kings and emperors used to offer prizes to anyone for suggesting the best solution to a particular problem in the form of an innovation contest (Allon and Babich 2020). Prpić et al. (2015) divide crowdsourcing into three major categories which are of particular interest to the OM community - *virtual labor markets*, *tournament crowdsourcing*, and *open collaboration*, and these forms are briefly discussed below.

Virtual Labor Markets

Virtual labor markets are spot labor markets mediated by technology such as *Amazon Mechanical Turk* and *FigureEight* and are used primarily for simple tasks. For example, *Amazon Mechanical Turk* enables businesses to crowdsource human intelligence to perform simple tasks that are not possible for computers. *FigureEight* is a technological platform that crowdsources human intelligence to transcribe text or annotate images to train machine learning computer algorithms. The more recent advancements in virtual labor markets are coding and software development marketplace such as *UpWork*, and driving platforms like *Ube*r and *Lyft*. These crowdsourcing platforms are more appropriate for well-defined tasks that do not require a significant level of subjective judgment.

Service platforms are another form of the virtual labor market. A platform connects the service-seeking customers and service-provider independent agents. The agents are independent because they decide when to work and whether the compensation is good enough to motivate them to complete the task. The compensation is either chosen by the agents or fixed by the platform depending upon the platform's business model. Prior research on virtual labor markets has studied ways to improve operational efficiency by engaging crowds on such platforms and their compensation dynamics. Allon et al. (2012) study a platform called *Upwork*, which connects the customer seeking professional services, such as software development, with skilled agents. *Upwork* allows individuals to choose their prices, and the platform act as facilitators for information gathering and sharing, routing requests, communication between the platform and agents, and managing competition among agents. Another similar example is product-sharing platforms like *Airbnb*, *Turu*. Customers book for the service in advance, and the agents set

prices and show heterogeneity in their offerings (Taylor 2018).

On the other hand, the on-demand platforms, such as *Uber*, *Lyft*, and *Doordash* are a part of the sharing economy platforms that dictate prices and coordinate customers and agents (Cachon et al. 2017, Taylor 2018). This model is different from a traditional employer-employee framework, wherein the employer determines when its employees work and how much salary to pay them. In these platforms, agents work at their preferred time, and the platform fixes the price. A significant challenge in these settings is incentivizing agents' capacity-related decisions. The platform's resource allocation policies and the agent's discretion over their work schedule affects the agent availability dynamics in the market (Cachon and Zhang 2007, Ibrahim 2017).

Tournament Crowdsourcing

As the name suggests, tournament crowdsourcing is a crowdsourcing contest in the form of a tournament or a competition. These contests are performed by the organizations on their platforms such as Dell's *Ideastorm* or Starbuck's *MyStarbucks*. These platforms allow individuals in the crowd to submit ideas to improve the brands. Starbucks's *MyStarbucks* was started in 2008 and generated more than $70,000$ ideas in the first year. This platform was eliminated in 2017 after generating $150,000$ ideas, out of which 300 have been implemented (Babich et al. 2020). In addition to brand-specific platforms, there are also third-party platforms, like Kaggle, owned by Google, which is more suitable for data science and machine learning contests. *Kaggle* allows users to host data sets and organize contests for an online community of data scientists. This type of crowdsourcing is more suitable for firms looking to leverage the crowd to generate more actionable solutions and ideas. However, it also threatens not reaching a predetermined goal due to misaligning incentives and a lack of accountability.

A specific type of crowdsourcing tournament studied in prior research is innovation contests. In an innovation contest organized by a firm, the firm seeks to source new ideas or solutions to an innovation-related problem. The agents (or solvers) well versed with the problem-solution space provide their ideas/solutions to the problem and collect a predetermined reward in the end. Prior research has studied the effect of the problem structure, several agents, and the reward scheme adopted to optimize the contest performance. Many solvers can lead to reduced

agent efforts, but at the time, it increases the solution diversity. However, offering a few rewards increases the quality of the best solution. In contrast, offering multiple rewards increases the contest's productivity. Additionally, the performance contingent reward structure performs better in motivating agents' efforts than the fixed rewards (Stouras et al. 2021, Terwiesch and Xu 2008).

Open Collaboration

Open Collaboration is a type of crowdsourcing where individuals contribute voluntarily to solve problems posed by organizations without gaining any monetary benefits. *Wikipedia* and communities created by a large organization like *Apple* and *Microsoft* are some successful examples of open collaboration. Another example is of *Google's Waze*, a free GPS navigation app, where *Waze* users provide live updates on traffic, accidents, road closures, and speed cameras, which helps other travelers either by alerting them or rerouting them. The success of open collaboration communities increases with its user base and with more collaborations. This type of crowdsourcing works well when problem-solving is facilitated by generating outside ideas and using the "wisdom of the crowd."

The social and economic impact of open collaborations has drawn scholarly interest to study the factors that affect performance in such settings (Baldwin and von Hippel 2011). The cooperative behavior of contributors to share their work with non-contributors drives performance in such settings. Though such behavior can be risky, cooperation is achieved by persistent interactions between the two parties due to their heterogeneous needs. At times, the non-contributors can motivate themselves to contribute in some way. For example, the users contribute to the open software by writing custom modules or doing software testing by using it. This motivation arises not because they want to contribute but from their own needs. They work on their private tasks, and while executing their tasks, they help others by providing resources. Performance in these settings is measured by the degree of collaborations (Levine and Prietula 2014).

2.4.2 Crowdfunding

The basic concept of crowdfunding originates from crowdsourcing, which uses the crowd to generate ideas and solutions to solve real-world problems. *Crowdfunding* is defined by Schwienbacher and Larralde (2012) as "*an open call, essentially through the Internet, for provision of the financial resources either in the form of donations or in exchange for some form of rewards and/or voting rights to support initiatives for specified purposes*." It enables seekers to take small amounts of funds from several individuals in the crowd and repay in terms of equity stakes in their company, interest income, by providing tangible or intangible goods, or blessings (Belleflamme et al. 2014).

Crowdfunding is of four types that vary depending on what backers obtain in return for their investments (Babich and Kouvelis 2018). The first is "*lending-based or debt crowdfunding*" (e.g., *Prosper* or *LendingClub*), where seekers repay the principal amount along with fixed interest on the principal. The second is ''*reward-based crowdfunding*" (e.g., *Kickstarter* or *Indiegogo*), where creators offer non-financial rewards to backers. The third is "*equity crowdfunding*" (e.g., *Sellaband*), where the investors receive equity rights for their investments. Finally "*donation-based crowdfunding*" (e.g., *GoFundMe* or *JustGiving*), where the donations are made for charitable purposes without expecting anything in return (Belleflamme et al. 2014). The online platforms host "*open call*" and facilitate interactions between the fund seekers and the crowd.

Despite being hosted online, there is some evidence that crowdfunding has geographical implications. Examining the geographic origin of individuals who invested in a music crowdfunding platform *SellaBand*, Agrawal et al. (2011) find that the artist-entrepreneurs are located $3,000$ miles away, on average, from the investors in the crowd. However, they receive early contributions from the local investors relatively earlier than the distant investors. They establish that there is less importance of spatial proximity overall. However, the spatial proximity can undoubtedly provide an initial push in the funding, which is generally necessary for the campaign to reach the requested funding goal target in the stipulated time (Kuppuswamy and Bayus 2017). Mollick (2014) study a crowdfunding platform called *Kickstarter* and find that the products originated from local geographical and cultural beliefs are more popular and have

a higher likelihood of achieving success in collecting the requested funding.

Social capital and herding have recently started gaining importance in crowdfunding (Colombo et al. 2015, Zheng et al. 2014). The investors engage not only in irrational herding, i.e., mimicking the behavior of the other investors but also in rational herding with observational learning that affects the venture's likelihood of success (Zhang and Liu 2012). Signaling has also been recognized to be an essential factor in crowdfunding success. Ahlers et al. (2015) study the importance of information sharing in equity crowdfunding by the entrepreneurs with the investors in the crowd using data from an Australian Small Scale Offerings Board (ASSOB). They present evidence that credible quality signals and sound information disclosures improve the venture's success. In reward-based crowdfunding, Kuppuswamy and Bayus (2018) examine data from *Kickstarter* and find that the funding decisions of other investors in a campaign play a crucial role in the success of the campaign.

Lending-Based or Debt Crowdfunding

Debt crowdfunding is a form of social lending enabled by online platforms. The organized social lending concept was transplanted with the Oxford Provident Building Association in Frankfort, PA, in 1831 from England to the United States. The association allowed its members to purchase up to five shares for five hundred per share. The association would loan five hundred dollars to any of its members whenever there is a collection of at least five hundred dollars. This approach is remarkably similar to today's debt crowdfunding platforms. One of the pioneering debt crowdfunding websites *Circle Lending* was founded in 2001, was later acquired by Virgin Money in 2007. After that, several debt crowdfunding portals have emerged worldwide. Today, the major platforms are *Prosper*, *Zopa*, *Kiva*, *Lending Club*, and *Virgin Money* (Zhang and Liu 2012).

In lending-based crowdfunding, the seekers ask for money for specific requirements, and the funders receive a specified amount of interest on their investments. *Prosper*, founded in 2006, is one of the largest debt crowdfunding platforms in the US. Typical campaigns hosted on Prosper include an entrepreneur asking for funds for a startup, individuals asking money to repay credit card loans, buying an expensive item, covering medical expenses, home improve-

ments, or for a wedding (Belleflamme et al. 2014). Such debt crowdfunding platforms do not have screening procedures like banks, but the investment risk is shifted onto the investors in the crowd.

Reward-Based Crowdfunding

Reward-based crowdfunding is a multi-faceted phenomenon that intrigues scholars' interest from different domains. In reward-based crowdfunding, capital is raised via an online platform (e.g., *Kickstarter*, *Indiegogo*) by the entrepreneur (creator) directly from several investors in the crowd (backers), and the entrepreneur provides the product to customers (backers) in return. It is an alternate form of raising capital in addition to the traditional sources such as borrowing from friends and family, bank loans, or venture capitalists (VCs), and it also provides a signal of the future demand of the product (Babich et al. 2020, Belleflamme et al. 2014).

Operations management scholars are especially interested in reward-based crowdfunding from the perspective of converting ideas into products. Therefore, various aspects like designing products and the campaigns, managing campaigns dynamically by reducing information asymmetry between backers and the creator of the campaign, managing interactions with backers, using backers' feedback to improve products, and managing the post-campaign reward production and delivery are some of the challenges in reward-based crowdfunding (Babich and Kouvelis 2018).

Marketing scholars study crowdfunding as a new advertisement and sales channel and ask questions like when a creator should advertise about her campaigns on social media like *Facebook* or *Instagram*. The timing and extent of information sharing on social media matters. There are also many opportunities to study investor psychology that could help improve product sales momentum and ultimately improve product success.

Recent research highlights the importance of signaling in dealing with the uncertainties associated with reward-based crowdfunding (Gerber and Hui 2013, Kuppuswamy and Bayus 2017, Chen et al. 2020). The two uncertainties that backers face due to information asymmetry are (1) fear of funds misappropriation, (2) receiving a low-quality reward (Belleflamme et al. 2014, Belavina et al. 2020, Chemla and Tinn 2020). Signaling helps to overcome such infor-

mation asymmetry challenges where the actions of both the parties involved in the transaction are not visible to each other (Akerlof 1970). Chakraborty and Swinney (2020) analytically demonstrate and Devaraj and Patel (2016) empirically verify that high target funding goal and high reward price signal superior product quality. Conversely, Frydrych et al. (2014) find that a lower target funding goal signals the legitimacy of a campaign. A creator's prior crowdfunding experience could also signal her trustworthiness (Gerber and Hui 2013). Further, Kunz et al. (2017) find that a detailed description of the campaign, lower campaign duration, more images and videos, and a higher number of rewards offered in a campaign also improve chances of success by signaling preparedness and trustworthiness of the creator.

Equity-Based Crowdfunding

Equity-based crowdfunding is another form of financing in which entrepreneurs make an open call on the internet to sell a specified amount of equity stakes or bond-like shares in a company to many small investors in the crowd (Ahlers et al. 2015). Equity crowdfunding platforms (e.g., *Crowdcube* and *Smart Angels*) facilitate financial transactions and provide the legal groundwork and charge a fee for providing this service (Ahlers et al. 2015). However, assessing the risks associated with investments rests with the crowd investors. Equity crowdfunding started gaining traction since the introduction of the Jumpstart Our Business Startups (JOBS) Act in the United States in November 2013 that allowed "nonaccredited" investors to invest funds in startups by exchanging equity shares through equity crowdfunding (Ahlers et al. 2015). However, most equity crowdfunding platforms follow the "All-or-nothing" type of funding model, where the fundraisers specify a target amount to be raised, and they receive funding only if the campaign collects sufficient funds from the crowd, which is more than the pre-specified target.

Donation-Based Crowdfunding

Donation-based crowdfunding is based on philanthropy and hosts humanitarian campaigns. A campaign in donation-based crowdfunding depends upon voluntary contributions from the crowd for charitable causes. This form of crowdfunding is similar to traditional charities and NGOs and does not offer monetary returns or any payments. Instead, funders gain blessings

and social recognition within a community. Donation-based platforms like *GoFundme* in the US hosts campaigns initiated by individuals asking for funds, or even their friends and family, and charge a 5% fee as administrative charges (Belleflamme et al. 2014).

2.4.3 Hackathons

A *hackathon* is a portmanteau word formed from "*hack*" (a slang introduced by computer programmers for exploratory software design) and "*marathon*" (a long-distance race), where several individuals, organized in small groups, participate in a problem-solving contest for a designated amount of time (Jones et al. 2015). Hackathons are accelerated new product development processes that bring together individuals at a predetermined location, forge temporary partnerships, and work intensively in teams to solve ambitious challenges and develop innovative products in a concise and constrained time frame (Lifshitz-Assaf et al. 2021). The typical duration of a hackathon event varies from a day to a few days depending upon its objective of conceptualizing and developing a new and innovative idea, product, or service. Technically, the first-ever hackathon was organized by OpenBSD in 1999 for a week in Calgary, Alberta, Canada, where a bunch of developers came together to integrate IPv6 and IPEC stacks into an operating system (OpenBSD 2021). Initially, these events were limited to computer hackers to develop software products, but its horizon is expanding to new business models, services, or consumer products (Jones et al. 2015, Lifshitz-Assaf et al. 2021).

Although hackathons originated among computer programmers, many entities such as corporations, universities, government agencies, and non-profit organizations sponsor hackathon events to develop innovative products. Before a hackathon event, organizers decide the challenge problem, the tools required, and ways to provide these tools to the hackathon participants. These events are promoted online by targeting the specific population of interest in social groups meant for hackathons (e.g., *Devpost*). Participants, primarily individuals, register online and disclose their skills and prior experiences.

Hackathons generally start with one or more presentations about the event, including the challenge, skill requirements, and prizes, if any. Then, the participants pitch their ideas among their peers and form teams based on their skills and interests. The participants further indulge

in exploration and exploitation of their ideas. Some teams typically follow organizational structures for new product development, whereas others depart from any predefined structures and invent new structures as required (Ghosh and Wu 2021, Lifshitz-Assaf et al. 2021). One of the differentiating factors of hackathons is that mentors provide feedback to each team in the hackathon several times during the event (Nolte 2019). Since hackathons typically last for 24-72 hours, eating and sleeping at these events is informal. Teams present their solutions to the judges - generally organizers and sponsors - at the end of the hackathon. Finally, the judges declare the winners of the hackathon and distribute prizes.

2.5 Open Innovation Platforms and the Innovation Value Chain

This section studies various platforms and maps them on the innovation value chain. Next, we organize platforms under various stages of the innovation value chain and position them under the primary field of service when the platforms provide support in multiple stages. Finally, we compile the list of the platforms discussed, the innovation value chain stages supported, and the value created for entrepreneurs in Table 2.1.

2.5.1 Stage 1 and 2: Idea Generation, Idea Selection, and Funding

NineSigma

NineSigma (www.ninesigma.com), launched in 2000, is a global privately-owned crowdsourcing company operating in the USA, Europe, and the Asia Pacific. *NineSigma* helps its clients in solving their problems through science and technology innovations by conducting innovation challenges, surveys, and technology scouting.

The challenges - directed or exploratory - posted by the clients are hosted on a digital innovation platform called *NineSights*, owned by *NineSigma*. *NineSigma*'s professional search team identifies solvers around the globe who are expected to be knowledgeable about the domain and more likely to have a solution to the problem. To participate in any directed challenge, the users (the solution providers) above 18 years of age and from any industry/domain need to register on the *NineSights* platform. Then, the solution providers can respond to any challenge with their proposed solutions. The platform also encourages solvers to provide additional doc-

umentation, such as their CV, white papers, product or company brochures, along with their responses to assess their expertise and capabilities by the clients. *NineSigma* reviews the solutions and compiles them to present to clients who choose their preferred solutions from the received proposals.

On the other hand, the exploratory challenges are solved through survey methods. With professional knowledge and experience in science and technology, the survey participants can register on another platform called Open Innovation Council (www.oicouncil.org). On "OI Council," the users are asked to advise the clients about their cutting-edge prototypes, business ideas, or challenges through a short questionnaire, and they receive a small reward in return.

InnoCentive

InnoCentive (www.innocentive.com), incepted in 2001 by Eli Lilly, connects research labs in large organizations to a diverse pool of external problem solvers through innovation contests (Lakhani 2008). It has emerged as a global crowdsourcing platform in London, USA, Bristol, and Copenhagen, enabling students, engineers, scientists, and professionals to engage and collaborate in problem-solving for R&D driven companies.

InnoCentive has captured $200K$ innovations by leveraging codified knowledge and has given away 60M USD in innovation awards, claiming a success rate of 80% (InnoCentive 2021a,b). The companies or individuals who pose challenging problems in a contest format are called "Seekers," and the companies and individuals who provide solutions are called "Solvers." Seekers are typically global businesses, governments, public sectors organizations, and non-profit organizations which pay a hefty amount to *InnoCentive* to access their pool of $500,000$ solvers (InnoCentive 2021a). What differentiates *InnoCentive* from other intermediaries is that *InnoCentive* verifies its solvers' skills with a minimum threshold on the problem-solving experience on each skill so that seekers can get assured that they are getting the right talent.

InnoCentive started with initial core coverage in life sciences and lately expanded its domain coverage to include other domains such as statistics, mathematics, engineering design, and entrepreneurship (Billington and Davidson 2013). Seekers clearly state the problem statement and explain the requirements and expectations in the online challenges hosted on the

platform. The solvers' responses can be captured and transmitted anonymously to the seeker to have an impartial judgment. In addition, seekers offer reward money in every challenge paid to the winning solvers at the end of the contest.

IdeaConnection

IdeaConnection (www.ideaconnection.com) is an open innovation platform founded in 2007 in Canada that provides access to $20,000+$ experts, thought leaders, scientists, and innovators across $180+$ countries. *IdeaConnection* helps small and large companies solve their challenging problems through collaborations with creative and innovative solvers, claiming a solve rate of 80% (IdeaConnection 2021a).

IdeaConnection serves in multiple fields ranging from nanotechnology, virtual reality, biochemistry, marketing, and sociology, and awards their experts on the pay-for-success basis to develop solutions to the technology challenges (Hossain 2012). The multitude of crowdsourcing services provided by *IdeaConnection* ranges from solution-seeking through confidential and public challenges, idea rally to brainstorming an idea or receiving feedback from experts, technology scouting, prior art citations search, marketing for the challenges, and crowdselling/licensing patents and inventions (IdeaConnection 2021b).

The clients' identity, information, challenges, and accepted solutions are kept confidential. Special teams of 3-4 chosen experts are made to handle client challenges, and once the clients accept the solutions from the submissions, *IdeaConnection* facilitates the transfer of ownership and the underlying intellectual property (Hossain 2012).

Idea rally is executed in a hackathon format where experts gather online for one week to discuss new ideas and contribute meaningfully. *IdeaConnection* provides directed participation through moderators who encourage and facilitate discussion and maintain participants' focus on the main problem. The participants are motivated through daily awards to the significant daily contributors and a separate major award to the winning team at the end of the rally. In addition, the participants used voting buttons to vote for the ideas throughout the rally. At the end of the rally, *IdeaConnection* provides a summary document to the client (IdeaConnection 2021c).

Quirky

Quirky (www.quirky.com), incepted in 2009 and headquartered in New York, USA, is a crowd-sourcing platform that helps inventors evaluate their ideas and refine concepts with the help of the crowd. After an inventor submits her idea on the platform, the community members vote for the idea if they like it, comment on the idea to suggest improvements, or express concerns. A few of the highest-voted ideas are selected every Thursday to discuss in the product evaluation meetings. The *Quirky* team organizes these meetings, and the audience participates through a live meeting to observe, comment, and vote for the ideas. *Quirky* facilitates idea generation and selection through crowd participation, but these collaborations often extend into the design. The best-voted product ideas are produced by *Quirky* and launched on the online store to be open for purchase (Lee and Schmidt 2016).

Kickstarter

Kickstarter (www.kickstarter.com) is one of the largest reward-based crowdfunding platforms in the USA, launched in 2009, has collected a total pledging of 5 billion USD from more than 17 million customers in almost $200K$ projects (Kickstarter 2020b). An entrepreneur (creator), with an innovative product idea and its prototype, creates an online campaign by providing product details, pictures and videos of the prototype, target funding required, duration of the campaign, team details, manufacturing plans, and other relevant details that can help customers (backers) make a pledging decision. Accumulating funds through small contributions also provides early demand signals to creators. In return, backers of successful campaigns receive pre-determined non-financial rewards in the form of innovative products (Belleflamme et al. 2014, Mollick 2014).

Once a campaign is launched, the backers can view the campaign and make an investment decision. The creator can engage with customers by providing updates on the campaign and status of product manufacturing and delivery. Backers can also indulge in two-way interactions with the campaign creator through the comment section. A comment section is where backers can ask questions and provide suggestions on the desired product features to help the creator improve the product. Since the product manufacturing starts on securing funding af-

ter the campaign is successful, it is possible and relatively more manageable for the creator to accommodate backers' requests for additional product features (Candoğan et al. 2021).

Kickstarter employs an all-or-nothing funding model, under which the entrepreneur receives money only if the campaign collects funding greater than the preset funding target in the stipulated campaign duration. *Kickstarter* deducts 5% of the total collected contributions as a fee, and the balance amount is transferred to the creator. If the campaign collects funding less than the target funding goal, the funds are routed back to the customers, and the campaign is deemed unsuccessful (Kickstarter 2020e). One key requirement to host a product campaign on *Kickstarter*, in addition to the product being novel, is that the entrepreneur should not have hosted a crowdfunding campaign for the product on any other platform.

Indiegogo

Indiegogo (www.indiegogo.com) is a reward-based crowdfunding platform, incepted in 2008 in USA. *Indiegogo* has 9 million customers and has completed $800K$ projects (Indiegogo 2021a) On the *Indiegogo* platform similar to Kickstarter, entrepreneurs launch their campaigns for innovative product ideas and provide details on the project along with pictures and videos of the prototype. *Indiegogo* provides a choice to entrepreneurs to choose between All-or-nothing (Fixed funding) and Keep-it-all type of funding models before launching the campaign. Under the All-or-nothing funding model, the entrepreneurs receive funds only if the collected funding is more than the preset target funding goal. Whereas, under the Keep-it-all funding model, the entrepreneurs can keep any funding raised by the campaign irrespective of the target amount requested (Indiegogo 2020b).

Another differentiating feature of *Indiegogo* is that entrepreneurs can launch their product campaigns on *Indiegogo* even if the same product campaign had been previously launched on another platform. *Indiegogo* calls it the *InDemand* program. Indiegogo also allows raising funds under the *InDemand* program even after reaching the funding target and ending the campaign while manufacturing the products (Indiegogo 2021c). *Indiegogo* deducts a 5% platform fee on all funds raised from the campaign, whereas the fee for the *InDemand* campaigns is 8%. In addition, *Indiegogo* does not charge any fee from a fixed funding campaign if it does not

meet its target funding goal (Indiegogo 2021d).

Devpost

Depost (www.devpost.com) is an online platform to host in-person and online hackathons, where hackers globally connect to create software and tech products. *Devpost* was initially launched in 2009 under the name *ChallengePost*, when it was a platform for online competitions. These competitions were based on various challenges such as videos, ideas, software, and recipes. Later the company narrowed down its focus to software and tech and rebranded the company as *Devpost* in 2015 (Shyam 2015).

The hackathon manager creates a hackathon page on *Devpost* and specifies the name of the hackathon, purpose and theme of the hackathon, contact details, hackathon rules, technologies required, dates, and prizes. Participants also create their accounts on *Devpost* that include details about them, their roles, their previous projects created, and their network of collaborations on the platform. The platform facilitates interactions among the participants, mentors, and organizers. The final submission includes links to their working project, the code, and a 3-5 minute video demonstration. The hackers can also vote on each others' projects, and the judges perform the final evaluation. Finally, the judges announce the winners as per the predetermined rules of the hackathon (Devpost 2021).

Kaggle

Kaggle (www.kaggle.com), a subsidiary of *Google LLC* and a platform for data science competitions launched in 2010 in the USA, is a strong community of six million data scientists and machine learners with a variety of skills and backgrounds from all over the world (Kaggle 2021). Firms can host challenges to solve data science problems by providing sample datasets. While setting up the challenge, firms also set rules of engagement, the evaluation metrics, which are generally the out-of-sample prediction accuracy, and the rewards offered. Then, the data scientists compete to build new algorithms to solve the problem with better accuracy than others in the competition. The team that provides the best-performing algorithm wins the competition and receives the prize money.

Kaggle performs various activities to increase its user base and encourage them to compete. First, *Kaggle* provides free online certificate courses to users who want to learn new concepts and techniques. Second, teams can submit their intermediate codes to receive interim feedback. Third, while providing feedback, *Kaggle* makes the relative position of the teams public on the leader board against others in the competition. Finally, with the relative position on the leader board, teams can modify their code or try altogether a different model to improve the prediction accuracy of their algorithm and resubmit their solutions (Mihm and Schlapp 2019).

Catapooolt

Catapooolt (www.catapooolt.com) is a reward-based crowdfunding platform, launched in 2013 in India. A creator with an innovative idea creates the online campaign and provides details about the project and the funding requirements. *Catapooolt* does not put any constraint on the campaign duration, but each campaign has a default duration of 30 days with a minimum mandate of 15 days. *Catapooolt* follows a flexible funding model, and the creator keeps any amount raised after deducting the transactional processing fee. While hosting a crowdfunding campaign on *Catapooolt* is free but the platform charges a fixed fee of 10% + taxes (Catapooolt 2021a).

Once a campaign is created and submitted for a review, *Catapooolt* reviewers perform a primary idea screening and turn the project into a crowdfunding campaign. The emphasis is on the uniqueness, interest level, and originality of the idea. In addition, the creator should show proof of progress and provide a video with a real story to connect. The reviewers also make suggestions on the rewards to be offered in the campaign (Catapooolt 2021b).

2.5.2 Stage 3: Product Development

TopCoder

Topcoder (www.topcoder.com), a USA-based company founded in 2001, is a two-sided platform for software development covering idea generation, idea selection, and product development stages in the innovation value chain. *Topcoder* has a strong global community of $1.6M$ designers, software developers, data scientists, and competitive programmers who have com-

pleted $79,000$ challenges and have won USD $126M$ in total prize money as of December 1, 2021 (TopCoder 2021).

Topcoder runs two business models - Talent as a Service and Enterprise Programs. Organizations can hire expert community members part-time or full-time in Talent as a Service and manage their work schedules. In Enterprise Program, organizations work with the *Topcoder* team and pose software development challenge competitions to the community. The *Topcoder* staff manages the competitions in collaborations with the seeking organizations. The team breaks the software development process into seven distinct but interrelated tasks; (1) Conceptualization, (2), Specification, (3) Architecture, (4) Component Production, (5) Application Assembly, (6) Certification, and (7) Deployment. Initially, *Topcoder* used to bill its clients for its staff's time to conceptualize and articulate their problems, set up modular design and development competitions, component assembly, and the final delivery of the finished solutions. However, later in 2009, the platform shifted to charging a fixed platform usage fee per month, which provided unlimited access to the reusable software components (Lakhani et al. 2010).

Topcoder also uses a community-based peer review system to assess the software development quality to determine the contest winners. The expert and experienced community members get paid to grade the competition submissions through a detailed scorecard and ultimately pick the contest winner. The winning competitors are awarded monetary prizes in each contest.

Craftcloud

Craftcloud (www.craftcloud3d.com), owned by *All3DP* and founded in 2014 in Germany, is a 3D printing marketplace. *Craftcloud* has printed $400,000$ products and served customers in 68 countries. *Craftcloud* connects customers seeking 3D printed products with an international network of 3D printing manufacturers. *Craftcloud* partners with 3D manufacturers worldwide such as *i.materialise* and *Sculpteo* in Europe, *Treatstock*, *Jawstec*, *Autotiv*, *Baysingers Additive Manufacturing*, and *hudson creative you* in the USA, and *Facefox*, *SuNPe*, and *Wenext* in China (Craftcloud 2021a).

Customers seeking 3D printing manufacturing for their products upload their 3D printing computer-aided design (CAD) files on the platform and receive real-time quotes for the chosen

printing techniques and materials. *Craftcloud* supports 3D printing using 16 technologies and 63 different materials (Craftcloud 2021b). After receiving a quote, customers can decide which manufacturer they want to order. *Craftcloud* manages everything from placing orders to payments and deliveries worldwide. Delivering products worldwide is economical for *Craftcloud* as they have 3D manufacturing partners located worldwide.

Hubs

Hubs (www.hubs.com) is an online manufacturing platform that provides access to on-demand manufacturing. The company was initially founded in 2013 in Amsterdam and was formerly known as *3D Hubs*. It was acquired by Protolabs, the USA in 2021 and got renamed as *Hubs* (Wired 2014, Hubs 2021a). *Hubs* empowers engineers to create new products by providing more accessible custom manufacturing options as against mass production. *Hubs* started as a peer-to-peer network of 3D printing marketplace, but later, after being acquired, expanded its capabilities with a wide range of manufacturing technologies, including CNC machining, injection molding, and sheet metal fabrication. As a result, *Hubs* has produced $6M+$ parts and prototypes using $42,000+$ machines with 240 manufacturing partners and helped $145,000$ customers and 35000 businesses globally (Hubs 2021b).

Hubs matches manufacturers in a global network with customers requiring manufacturing services to produce custom products using a wide variety of techniques and materials. It employs machine learning algorithms to provide instant quotes. In addition, their Design for Manufacturability (DfM) tool provides feedback on the manufacturability of parts and provides suggestions to reduce manufacturing costs. As a result, customers access custom manufacturing and get the manufacturing done at lower prices. The warehouses in Amsterdam and Chicago perform quality control checks on the manufactured products before delivery in Europe, UK, and United States.

2.5.3 Stage 4: Commercialization and Diffusion

Innoget

Innoget (www.innoget.com) is a global network for companies, scientists, experts, and startups, founded in Spain in 2006 to act as an intermediary in a two-sided market to connect companies, universities, and individuals. It facilitates a bidirectional search process - connecting solution-seeking companies with research universities and individuals seeking adopters for their technologies. *Innoget* hosts challenges and technologies in various disciplines like biosciences, chemistry, engineering, and IT, with guaranteed confidentiality and protection of intellectual property (Innoget 2021a). Organizations pose their problems in the form of challenges, and the solution providers can respond with their proposals, which organizations review themselves. Publishing a challenge on the *Innoget* website is free, but organizations pay a fee for each innovation lead they receive on their challenge. An innovation lead is a proposal that the organization decides to pursue further with the solution provider outside *Innoget* boundaries (Innoget 2021b). Research institutes can also offer their technologies for licensing on the *Innoget* website.

Shapeways

Shapeways (www.shapeways.com) is a New York based 3D printing marketplace founded in 2007. *Shapeways* has more than one million customers worldwide and has produced and delivered more than 20 million parts in 160 countries (Shapeways 2021a). *Shapeways* provides 3D printing on-demand service for designers who have sufficient knowledge of creating 3D printing files and want to get their products manufactured for personal use or selling to customers on *Shapeways* marketplace. *Shapeways* has also partnered with *ZVerse* to help designers who do not have the skills and resources to create 3D printing files (Shapeways 2021b).

Users create computer-aided design (CAD) models to be produced on 3D printers and upload them on *Shapeways* website. *Shapeways* prints the products using their 3D printing facilities in New York and the Netherlands. Customers can purchase the 3D printed products from *Shapeways* marketplace at a price set by *Shapeways*. Designers keep a markup in the prod-

uct price, and that is what they earn from their creations (Shapeways 2021c). *Shapeways* also provides easy integration with other marketplaces such as *Etsy* and *Shopify* to facilitate direct listing of the products on these platforms. Additionally, *Shapeways* provides a user community where designers and customers can interact with each other.

Shein

Shein (www.shein.com) is a Chinese fashion e-commerce company, which was initially founded in 2008 under the name *ZZKKO*, but later rebranded as *Shein* in 2012. The company sells women's wear, children's clothing, men's apparel, and other fashion items. The main target markets are Europe, America, Australia, the Middle East, and other regions, covering 150 countries. A team of in-house professional designers designs clothes, and outside vendors provide fabric and manufacture clothes. *Shein* clothes are professionally photographed, with models wearing them before selling the clothes online. To transport orders in different regions, *Shein* handles stacking, distribution, sorting, and packaging activities in a large warehouse and coordinates with transport companies to ship their products to customers in different countries (Shein 2021a).

Shein also operates a platform called *Shein X*, where indie fashion designers can showcase their designs on the platform, and *Shein* handles manufacturing, marketing, and selling. The designers share profits with *Shein* and keep ownership of their designs. In addition, the customers can filter clothes by designers, and the platform also features a designer spotlight to nudge customers to new designers (Shein 2021b).

Etsy

Etsy (www.etsy.com) is a marketplace where people around the world connect to buy and sell handmade craft goods. *Etsy*'s business model is based on selling handmade goods, where artists, designers, and collectors use the platform to sell their handmade and vintage goods to buyers worldwide. *Etsy* was founded in 2005 in the US with global offices in London, Dublin, Paris, Berlin, Canada, and Australia. *Etsy* is an intermediary that facilitates transactions but does not make any products, hold inventory, or ship any goods to customers (House of Lords

2016).

Joining and starting a shop on *Etsy* is free. The sellers have to create an online account. However, Etsy charges three selling fees: US$0.20 listing fee, 5% transaction fee, and 3-4% + CA$0.25 payment processing fee. The active duration of a listing is four months or until the item is sold. *Etsy* also provides an advertising service for a fee. The advertising fee is charged only if any sales are made outside the platform through the advertisements. Finally, *Etsy* provides a messaging service to interact with buyers, and buyers can also leave reviews about sellers.

Table 2.1: Innovation Platforms mapped on the Innovation Value Chain

Platform	Platform Type	IVC Stage	Value for Entrepreneurs
NineSigma	Crowdsourcing	Idea generation	Solver search, solver verification, solution verification, exploration and exploitation in the solution space
InnoCentive	Crowdsourcing	Idea generation	Large pool of solvers, skill verification
IdeaConnection	Crowdsourcing	Idea generation, Idea selection, Commercialize, Diffusion	Search for solvers and partners, expert advise on technical problems, prior art search for patents, crowdselling/license patents
Quirky	Crowdsourcing	Idea selection, Product development and manufacturing, Commercialize	Real-time idea selection, product design and manufacturing, selling marketplace
Kickstarter	Crowdfunding	Idea selection, Funding, Commercialize	Access to network of backers, funding, product testing, demand and product attraction estimation
Indiegogo	Crowdfunding	Idea selection, Funding, Commercialize	Access to network of backers, funding, concept testing, demand and product attraction estimation
Devpost	Hackathon	Idea generation, Idea selection, Product development	Collaborations, knowledge exchange, fast-paced learning, prototype development and concept testing
Kaggle	Crowdsourcing	Idea generation, Product development	Software product development, on-demand coding
Catapooolt	Crowdfunding	Idea selection, Funding, Commercialize	Access to network of backers, funding, concept testing, demand and product attraction estimation
TopCoder	Crowdsourcing	Idea generation, Idea selection, Product development	On-demand coding, access to part-time or full-time skilled labor, help in chunking the product development tasks, expert reviews
Craftcloud	Crowdsourcing	Product development	Access to a network of 3D printing manufacturers, global order management and payments
Hubs	Crowdsourcing	Product development	Access to peer-to-peer global network of 3D printers and manufacturers, instant quotes from multiple sites, design feedback
Innoget	Crowdsourcing	Commercialize, Diffusion	Bidirectional matching for innovative challenges and available technologies
Shapeways	Crowdsourcing	Commercialize	3D printing services, marketplace to sell products produced by the platform, design support, user community
Shein	Crowdsourcing	Commercialize	Access to a large customer base, low-price manufacturing with a reasonable quality of clothes, professional photography, supply chain management for worldwide shipping, payment gateway
Etsy	Crowdsourcing	Commercialize	Marketplace for handmade goods, user managed online shops, messaging service

2.6 Challenges of Using Open Innovation Platforms and Future Research Opportunities

Open innovation platforms organize and mediate an evolving and expanding share of economic and societal interactions in the digital age. These platforms attract many entrepreneurs and customers and support the entire innovation ecosystem. In doing so, these intermediaries pose enormous challenges for entrepreneurs in utilizing their full potential that lays out a path for future research. Foremost, entrepreneurs face two critical challenges in the *idea generation* stage - a problem statement and recruiting solvers to solve it. A problem can originate through a "mental invention," i.e., creativity, leading to a problem statement with a vast scope and few constraints. However, a problem can also start with a market pull or technology push, i.e., through alertness, which provides more constraints in the problem statement and reduce the scope of the inventions (Kornish and Hutchison-Krupat 2016). Problem framing with description and constraints provides the contextual depth and breadth of the problem. Additionally, constraints solve the problem of cognitive fixation as well as the choice overload in the solution space (Iyengar and Lepper 2000). Whereas, constraints may also impair innovation by not allowing enough room for creativity due to a narrowly defined problem statement (Kornish and Hutchison-Krupat 2016).

Solvers, the second challenge of the idea generation stage, may be recruited through internal and external networks. Due to the ever-changing technological space, it is difficult for employers to recruit new talent or motivate their internal workforce to update their skills constantly. The intermediary platforms that deal with specific domains, handle specific types of problems, and host domain-specific talented solvers provide access to external networks to recruit solvers for problem-solving (Boudreau and Lakhani 2013). The challenge of "who" should be recruited effectively reduces deciding which platform to host the open innovation challenge. However, simply giving the tasks to the crowd will not reap the benefits. These solvers have a vast diversity in their skills and performance levels that makes it challenging to manage their interactions (Grewal-Carr and Bates 2016).

Team structure also affects the performance in such contests (Lifshitz-Assaf et al. 2021). Seekers try to engage the crowd through personal feedback and by incentivizing them with

multiple prizes (Mihm and Schlapp 2019, Kornish and Hutchison-Krupat 2016). The award scheme design for contests helps attract talented solvers in large numbers that improve the quantity and quality of ideas generated (Girotra et al. 2010, Stouras et al. 2021, Terwiesch and Xu 2008). With this extant research on idea generation, there are some open questions: How should a problem statement be defined for an ideation or product development challenge? How to motivate the crowd? What is the best way to govern interactions among the crowd on these platforms?

Second, in the *idea selection and funding* stage, the main objective is to select an idea that can manage potential uncertainty to generate funding opportunities. The quality of raw ideas is a reliable input for predicting product success. However, it is complex and challenging to predict the success potential of ideas under uncertainty (Kornish and Ulrich 2014). Entrepreneurs can try different selection schemes to manage the uncertainty in the idea selection process. The performance of the idea selection process also improves with the size of the population (Piezunka et al. 2021). Research shows that a scoring scheme for idea selection performs better than a ranking scheme with averaging the results over a large population (Cui et al. 2018).

Bringing and implementing external ideas can create significant knowledge integration challenges. From an operational perspective, poor knowledge integration can impair the idea selection and implementation activities due to a lack of absorptive capacity. *Absorptive capacity* is defined as the ability of the recipient to recognize, assimilate, and exploit the knowledge created by an external agent (Cohen and Levinthal 1990). Building absorptive capacity might be easier for a firm when developing skills internally. However, it is difficult to manage when the absorptive capacity needs to be developed in external agents. For example, the crowd participates in idea selection on *Quirky* along with the *Quirky*'s staff. Only ideas that receive the highest votes are processed to manufacture products. Therefore, there is a risk of discarding novel ideas due to lack of sufficient knowledge or selecting ideas that are difficult to manufacture or have lower market potential (Kornish and Ulrich 2014). In either way, knowledge transfer is challenging in open innovation settings.

Knowledge is commonly characterized into two categories - tacit and explicit. Tacit knowledge is sticky, resides in an individual's mind, and is more personal and experiential (von

Hippel 1994). In contrast, explicit knowledge can be codified and easily transferred than tacit knowledge (Nonaka 1994). Another factor that could impair knowledge transfer is the trust between the knowledge partners. A high level of trust engenders a successful knowledge transfer, which is difficult to achieve in an open innovation setting, such as intermediary platforms, due to weak ties formed among the seeker and knowledge-generating agents (Inkpen and Tsang 2005). The online reputation systems through digital technologies make it easier to verify and certify the trustworthiness and reputation of any individual by facilitating easy tracking (Goldfarb and Tucker 2019). Despite these improvements, many platforms face challenges in building partnerships due to trust issues (Belavina et al. 2020).

Trust issues may also be observed in crowdfunding due to information asymmetry between the entrepreneur and the crowd. The entrepreneurs try several strategies to signal their trustworthiness (Belleflamme et al. 2014, Belavina et al. 2020, Chemla and Tinn 2020). Entrepreneurs often play with campaign design parameters to manage perceived risks and rewards for the campaign success (Chakraborty and Swinney 2020, Kunz et al. 2017, Du et al. 2017). Geographies also play a role in building trust. Spatial proximity is known to have a significant effect on the initial funding, which further drives the crowd towards the campaign and helps cross the funding target (Kuppuswamy and Bayus 2017, Mollick 2014). In addition to campaign design, scholars have also looked at the reward scheme design. Hu et al. (2015) study a reward scheme with two alternatives - single reward vs. two rewards - under buyer heterogeneity and finds that the campaign success improves with multiple rewards. Ultimately, legitimate ideas with good market potential have a higher likelihood of gaining funding success (Kuppuswamy and Bayus 2018). Future research may address these challenges associated with idea selection and funding. How can the idea selection process be improved? How to build trust between the seeker and the crowd? How to manage and influence the crowd to provide funding for the selected ideas?

Third, *product development* activities suffer from coordination issues among various stakeholders. Platforms typically subsidize one side of the users, who in large numbers are valued more by the money side of the users. The critical mass of the subsidy side users attracts more money side users and helps achieve coordination on these platforms (Eisenmann et al. 2006).

In software development, *DevOps* has emerged as a paradigm that helps deliver software products faster through automation. *DevOps* is a cultural shift for software product development combining software development, operations, and security into one framework driven by collaborations, automation, and transparency (Ebert et al. 2016). It forms a set of principles with a focus on delivery speed, continuous testing in an environment simulating the production environment, ready to be shipped anytime, continuous feedback, ability to react swiftly to changes, and teams working towards a shared goal instead of task orientation (Virmani 2015). Automation supports consistency, reliability, and efficiency across the organization. Open access to repositories allows providing continuous feedback. These activities facilitate continuous integration and delivery that combines every step of the software development into one integrated workflow. Teams, under *DevOps*, meet regularly to discuss the goals and timelines. These regular meetings help achieve coordination among various stakeholders. Team coordination structure has also been found to affect product performance significantly. Research recommends an iterative coordination structure, where various stakeholders frequently interact to improve the product design, performs better, and help prioritize value over novelty, both of which underlie innovation (Ghosh and Wu 2021). However, since such iterative coordination structures are more common on crowdsourcing and hackathon platforms, involving the crowd in product development through user communities leads to superior novel outcomes on crowdfunding platforms (Cornelius and Gokpinar 2020).

Crowd involvement in 3D printing marketplaces for product development creates intellectual property (IP) management challenges due to distributed manufacturing. For example, *MakerBot*, a company that created the first desktop 3D printer, introduced a platform called *Thingiverse* to facilitate sharing and selling of designs to be manufactured using their printers. As a result, *Thingiverse* users could trade their designs but could not capture value due to the inability to create proprietary designs, and the users had the freedom to sell/buy designs from outside (Zhu and Furr 2016). Nevertheless, involving the crowd in manufacturing on intermediary platforms like *Hubs*, primarily when distributed manufacturing is performed by the amateur crowd at home using non-industrial grade 3D printers (Rayna and Striukova 2016), entrepreneurs have no control over the product quality. How should product quality be ensured

and improved in such settings? How to deter competitive imitation in open innovation? How to achieve coordination among various stakeholders?

Finally, in *commercialization and diffusion* stage, entrepreneurs face challenges of managing and protecting their products and intellectual property (IP). The traditional IP protection provided by patent law favors closed innovation. However, any open exchanges of the IP outside the firm boundary are discouraged by the patent law (Lee et al. 2010). Nevertheless, patents are probabilistic, and the patent examination is often delayed, resulting in a longer patent pendency (Gans et al. 2008, Harhoff and Wagner 2009). A longer patent pendency might have severe consequences for a firm's human and relational capital.

Additionally, entrepreneurs face a trade-off of disclosing their inventions vs. IP protection (Johnson and Popp 2003). There is growing evidence of managing this trade-off with norm-based IP systems, which are self-organized and built on informal collective norms of the community (Bauer et al. 2016). Further research may evaluate the effectiveness of the existing and evolving protection regimes on these platforms and develop new strategies to protect innovation.

2.7 Discussion

Traditionally, firms have believed in self-reliance to fulfill their needs for resources to attain capabilities along the innovation value chain to bring innovative products to the market. However, with the rise of the internet and mobile technologies, open innovation platforms have made it feasible for firms to open themselves up to a wide range of external sources at a lower price (Chesbrough 2003). In addition, several innovation platforms with a narrow scope of specialization have decoupled the sequential stages of the innovation value chain to create value for the innovating firm, making it possible for firms and individual entrepreneurs to temporarily acquire resources to fill the gap between their innovation capability and the available resources along the innovation value chain. The core premise is that business problem solving has changed from solving problems to finding solutions, and it is cheaper to find a solution that already exists somewhere than developing it in-house (Billington and Davidson 2013). In this study, we revisit the innovation value chain and discuss the role of various open innova-

tion intermediary platforms in improving innovation success. We summarize the capabilities, resources, innovation platforms, current research, and future research opportunities along the innovation value chain in Figure 2.2.

The decoupling of the innovation value chain facilitates specialized knowledge creation and knowledge sharing on these platforms but at the same time creates new challenges for entrepreneurs. In addition to the operational challenges entrepreneurs face, highlighted in this study, several emerging issues remain. First, there are growing concerns regarding governance and intellectual property (IP) protection on these platforms (Chesbrough 2003). These lacking regulations affect not only the users but also the platform. The platforms generally specify guidelines of IP protection for efficient knowledge exchanges, but the onus lies on the community members, called norm-based IP systems (Bauer et al. 2016). Further research is required to assess its applicability and effectiveness in innovation platforms operating at different stages of the innovation value chain.

Second, what type of platform structure creates more value and attracts seekers and a large crowd of solvers than others. Some platforms serve only in one stage of the innovation value chain, providing specialization in their service. In contrast, others offer several services spanning multiple stages of the innovation value chain with a possibility of having specialization in fewer activities. How should entrepreneurs choose which platform can provide more benefits than others? Will extending the concept of decoupling and implementing on such platforms improve the value creation for entrepreneurs?

Third, new platforms might emerge with government support by further decoupling the technologies from products in the innovation value chain. For example, *Patents 4 Partnership* (https://developer.uspto.gov/ipmarketplace/search/patents) is an Intellectual Property (IP) marketplace platform, an initiative by the *United States Patent and Trademark Office* (USPTO) for Covid-19 related technologies. Though this platform is explicitly launched for Covid related technologies, there is a plan to open up this platform for other technologies (USPTO 2021a,b). This platform helps inventors who are open to licensing their patented technologies find organizations with the ability and resources to commercialize their inventions. This platform intends to reduce the search cost for both parties. It provides inventors a centralized place to

list technology patents granted by the USPTO, making it easier to find a licensee. It also offers a technology database to the potential licensees, making it easier to find their preferred technology.

Finally, how can large firms integrate the open innovation platforms into their closed innovation business models required to acquire intellectual property (Lee et al. 2010)? In which stages of the innovation value chain a large firm should utilize these intermediary platforms to bring products successfully and faster in the market? Crowd participation for innovation in product development is beneficial for firms, and not utilizing the crowd can mean losing an opportunity (Boudreau and Lakhani 2013). How can large firms bring synergies in their existing resources and the capabilities acquired through these platforms? In order to leverage open innovation, firms need to adjust their business and IP protection strategy and design tools to manage openness. Can formal governance means, i.e., contracts or informal means such as community norms and trust culture, coordinate the activities for efficient exchange between the seekers and the solvers? Unless such issues are sorted out, firms will not be able to utilize the full potential of the intermediary platforms.

CHAPTER 3

DESIGNING REWARD STRUCTURE FOR CROWDFUNDING CAMPAIGNS

3.1 Introduction

Reward-based crowdfunding has emerged as a valuable alternative to traditional approaches such as venture capital and debt to fund the creation of innovative products (Allon and Babich 2020, Babich et al. 2020, Fleming and Sorenson 2016).[1] Unlike venture capital, reward-based crowdfunding allows entrepreneurs (creators) to raise capital through crowdfunding campaigns, where potential consumers (backers) pledge small amounts of funds. Accumulating funds through small contributions also provides early demand signals to creators. In return, backers of successful campaigns receive pre-determined non-financial rewards in the form of innovative products (Belleflamme et al. 2014, Mollick 2014). Besides receiving innovative products, backers who support a campaign have the opportunity to obtain a novel product that may be unavailable elsewhere (Kickstarter 2020a). The mutual benefits to both parties have resulted in the growth of crowdfunding from USD $2.7\ bn$ in 2012 to USD $34\ bn$ in 2015; this is further expected to grow to USD $300\ bn$ by 2025 (Crowdsourcing.org, 2015).

Despite the growing popularity of reward-based crowdfunding, creators often struggle to convince a sufficient number of backers to provide funds for their projects; indeed, most reward-based crowdfunding campaigns result in not obtaining the requested funds (Burtch et al. 2020, Chemla and Tinn 2020, Mollick 2014). *Kickstarter*, the pre-eminent reward-based crowdfunding platform, reports a relatively low funding success rate (Kickstarter 2020b). Several factors contribute to this hurdle: First, backers have limited insights into the quality of the as-yet unavailable products (Chakraborty and Swinney 2020, Kuppuswamy and Bayus 2017); second, backers may be unable to assess a creator's ability and trustworthiness (Gerber and Hui

[1]The forms of crowdfunding vary depending on what backers obtain in return for their investments, and it ranges from the equity rights (e.g., *Sellaband*, where the investors receive equity rights for their investments), interest income (e.g., *Prosper* or *LendingClub*, where the seekers repay the principal amount along with fixed interest on the principal), non-financial rewards (e.g., *Kickstarter* or *Indiegogo*, where creators offer non-financial rewards to backers), to just blessings (e.g., *GoFundMe* or *JustGiving*, where the donations are made for charitable purposes without expecting anything in return (Belleflamme et al. 2014).

2013, Steigenberger 2017); these issues could be exacerbated by contemporaneous campaigns that divide the attention of backers (Lin et al. 2018). Finally, and perhaps most saliently in crowdfunding, backers in the crowd have heterogeneous valuations of the product itself (Hu et al. 2015, Kuppuswamy and Bayus 2017). Creators try to overcome this particular challenge by offering backers the opportunity to select from several rewards of varying denominations. The number of rewards and their contribution levels constitute the reward structure of a campaign. This paper's primary objective is to examine the relationship between the *reward structure* of a campaign and its funding success.

Creators face two key trade-offs in designing the reward structure of their campaigns. First, it is operationally easier to create and deliver a small number of rewards (Leone et al. 2018). Conversely, more rewards increase the likelihood that a backer will find a reward befitting their valuation of the product (Du et al. 2019, Hu et al. 2015). On the other hand, a proliferation of rewards could increase a backer's difficulty of making any reward selection; a phenomenon referred to as "choice overload" (Iyengar and Lepper 2000). This trade-off leads to the first question we investigate in this paper: *what is the association between the number of rewards and funding success of a reward-based crowdfunding campaign*? We conjecture that the increase in the number of rewards has a positive effect on the funding success of a campaign, but the marginal effect of each additional reward might decrease.

Second, by definition, crowdfunding campaigns must elicit pledges from a broad array of backers, who might have heterogeneous valuations of the artifact. The necessity to attract heterogeneous backers leads to an important decision for the creators: should the offered rewards be more or less similar? On the one hand, the low dispersion of reward prices, and thus high similarity between rewards, could make it difficult for a backer to weigh and compare different reward options. On the other hand, offering rewards in a wide range of contribution levels (with high dispersion of reward prices) might invite backers to contribute at a lower level. As a result, the dispersion of reward prices might enhance or diminish the benefit of offering more rewards. This trade-off leads to our second research question: *How does the dispersion of reward prices affect the association between the number of rewards and the funding success of the campaign?* We conjecture that campaigns that offer similar rewards with low dispersion of

reward prices will have higher funding success. Further, we hypothesize that a high dispersion of reward prices will have a stronger negative effect on the funding success of campaigns with many rewards.

A campaign's ability to attract contributions from backers could also depend on the *type* of rewards offered. Some campaigns promise *product* rewards (e.g., a new kind of movie camera), while others offer *experience* rewards (e.g., a preview show for a new movie). A question of interest is: *How does reward type affect the association between the number of rewards and funding success of the campaign?* Unlike experiences that are "consumed", products tend to be evaluated comparatively rather than individually (Carter and Gilovich 2010); this suggests that offering more choices is beneficial for campaigns that offer product rewards. Therefore, we conjecture that offering more rewards will be less fruitful for campaigns that offer experience rewards (relative to product rewards).

Backing a crowdfunding campaign is inherently risky because commitments are made well in advance before production starts. Research shows that 75% of the campaigns are unable to deliver their rewards on time (Leone et al. 2018, Mollick 2014), and 9% of the campaigns do not deliver their promised rewards at all (Mollick 2015). Creators may communicate their intent and the quality of their rewards to improve the likelihood of success of their campaigns (Belavina et al. 2020, Chakraborty and Swinney 2020), especially when they lack prior experience in crowdfunding (Gerber and Hui 2013). This raises the fourth and final research question that we seek to answer in this study, *How does a creator's prior crowdfunding experience affect the association between the number of rewards and the funding success of the campaign?* We conjecture that the benefit of providing more rewards is higher for less experienced creators.

We address these questions by collecting data from *Kickstarter*, the largest reward-based crowdfunding platform by volume of funding and number of successful projects. On this platform, we analyze $191,480$ successful and unsuccessful campaigns to study the effect of the number of rewards on funding success. We find that a reward-based crowdfunding campaign's funding success improves with more rewards, but the funding success has diminishing returns.[2] We also find that high dispersion of reward prices negatively impacts funding success, and

[2]The results are robust to the model specifications (Quadratic and Spline), as shown in Section 3.4.5.

funding success of a campaign increases with many rewards of low dispersion of their prices. Contrary to the hypothesized association, we find that the increase in funding success with more rewards is higher for campaigns in the experiential-reward categories as compared to campaigns in the product-reward categories. Finally, we find that more rewards have a positive effect on the campaigns created by creators with low crowdfunding experience than high crowdfunding experience. The number of rewards may be influenced by unobservable factors that hinge on the heterogeneous abilities of creators, making the number of rewards endogenous. To account for this source of endogeneity, we use a control function approach in a two-stage estimation. We discuss the control function approach in Section 3.4.3, and we find qualitatively similar results.

Our study makes three contributions. First, we extend the literature on reward-based crowdfunding by examining how the reward structure design can influence a crowdfunding campaign's funding success. Whereas prior studies have established various aspects of backer behavior - in terms of funding and knowledge-based contributions to the campaign - this is one of the few papers that empirically considers how the entrepreneur's campaign-level operational decisions influence the funding success of a campaign. We specifically focus on two critical components of reward structure design - the number of rewards, and the dispersion of reward prices. We find empirical evidence consistent with choice overload in the form of a non-linear relationship between the number of rewards and funding success. Additionally, we examine the moderating role of reward price dispersion on this relationship, which provides insights into the phenomenon of choice overload in a crowdfunding campaign.

Second, our study informs what factors can accentuate or attenuate the relationship between the number of rewards and funding success of a campaign. By examining the dispersion of reward prices and reward type as moderators at the campaign level, this study suggests that both these factors have a significant role and thus cannot be overlooked while designing reward structures.

Third, the identity of the creator is by itself a key asset for a crowdfunding campaign. By examining and confirming the moderating role of creator experience, we highlight how the reward structure for a campaign should account not just for campaign-specific factors, but also

incorporate factors specific to the creator. Overall, these findings not only enhance our theoretical understanding of how the reward structure impacts crowdfunding campaigns but also have the potential to be practically useful. Entrepreneurs can apply our framework to tune the number of rewards based on their past experience and the characteristics of their innovations.

The remainder of this paper is organized as follows. We review the crowdfunding literature and develop our research hypotheses in Section 3.2. The discussion on the data collection and the empirical methods is presented in Section 3.3. We present results, address endogeneity concerns, and demonstrate robustness in Section 3.4. In Section 3.5, we conclude this study by discussing the theoretical contributions and practical implications.

3.2 Literature Review and Hypotheses Development

3.2.1 Crowdfunding

Schwienbacher and Larralde (2012) define crowdfunding as "an open call, essentially through the Internet, for provision of the financial resources either in the form of donations or in exchange for some form of rewards and/or voting rights to support initiatives for specified purposes." Crowdfunding enables entrepreneurs to take small amounts of investments from several individuals and repay in terms of tangible or intangible products, interest income, equity, or blessings (Belleflamme et al. 2014). The *"open call*" takes place on an online platform such as *Kickstarter* or *Prosper*, which facilitates interactions between seekers and crowdfunders (Mollick 2014). We study reward-based crowdfunding where creators pre-sell their products as rewards to backers in the crowd (Chemla and Tinn 2020, Kuppuswamy and Bayus 2018).

The literature on reward-based crowdfunding is evolving from the perspectives of both creators and backers. From the standpoint of creators, the literature focuses on campaign design parameters (Zhang et al. 2017, Zhou et al. 2016), and the factors that improve the likelihood of funding success of a campaign (Agrawal et al. 2014, Frydrych et al. 2014). Creators design their online campaigns and provide details about their innovative products, select target funding goal, and campaign duration, and provide pictures and videos of the prototypes to increase the attractiveness of their campaigns (Cornelius and Gokpinar 2020, Kunz et al. 2017, Mollick 2014). Creators also share the risks and challenges that could affect the production

and delivery of the rewards (Leone et al. 2018). Most importantly, creators design the reward structure of their campaigns comprising the number of rewards and contribution levels (Du et al. 2019, Kunz et al. 2017). Backers consider the details provided by the creator and decide whether to back the campaign and at what contribution level (Burtch et al. 2013, Cordova et al. 2015). Backers face two dimensions of uncertainty in crowdfunding: (i) misappropriation of contributed funds, (ii) receiving a low-quality reward (Belavina et al. 2020, Belleflamme et al. 2014, Chemla and Tinn 2020). Therefore, backers' decisions of backing the campaign and choosing the contribution levels are influenced by information asymmetry between creator and backers (Belavina et al. 2020, Chakraborty and Swinney 2020). These concerns may nudge backers to wait until the later stages of a campaign in order to mimic other, potentially better-informed, backers (Alaei et al. 2016, Kuppuswamy and Bayus 2018).

3.2.2 Rewards in Crowdfunding

In this context, creators depend on rewards as the primary instrument to attract contributions from backers (Gerber and Hui 2013). Backers can select only one reward from the number of the rewards offered in a campaign (Kickstarter 2020c). Providing more rewards in a campaign attracts backers for two reasons. First, backers are heterogeneous in terms of their valuations of rewards (Gerber and Hui 2013, Hu et al. 2015). This heterogeneity among backers emanates from different preferences, and providing a larger set of alternatives can cater to the diversity of preferences (Diehl and Poynor 2010, Iyengar and Lepper 2000). More rewards, therefore, make a backer more likely to choose a reward; in turn, this improves the likelihood of the campaign's success.

Second, more alternatives in a campaign to select rewards provide backers a higher sense of personal control. For example, creators can increase the number of rewards by offering the same product in different materials, offer variants of the product, or bundle multiple products together. These mechanisms to increase the number of rewards can improve backers' intrinsic motivation to select a reward and pledge their contributions to the campaign, thus enhancing the likelihood of success (Cordova and Lepper 1996).

Extant research, however, also cautions about the inherent challenges of offering too many

alternatives (Iyengar and Kamenica 2010, Reutskaja and Hogarth 2009). These challenges include enhanced evaluation and integration of information that increases the cognitive processing cost, which induces choice overload (Iyengar and Lepper 2000). Thus, campaigns with a high number of rewards make the overall decision-making more complex for backers. This increased complexity, coupled with the *ex post* regret of not choosing their preferred reward from a large number of rewards, may lead backers to defer their decision, or not back a campaign altogether (Iyengar and Kamenica 2010).

Drawing upon these arguments, we hypothesize that the likelihood of success of a campaign improves with the number of rewards, but only to a certain level, after which an increase in the number of rewards may be detrimental.

***HYPOTHESIS* 1** (H1)**.** *A reward-based crowdfunding campaign's funding success improves with the number of rewards, but at a diminishing rate.*

3.2.3 Dispersion of Reward Prices

In addition to deciding the number of rewards, creators also choose their contribution levels (the different prices at which backers can contribute to a campaign). A key question for the creator is: how similar should the contribution levels be? In the extremes, a creator can offer either nearly identical rewards at tightly clustered contribution levels or offer highly differentiated rewards at a broad range of contribution levels. Thus, the dispersion of reward prices itself is an important decision.

Backers can evaluate the rewards separately when only a few rewards are offered; therefore, the level of price dispersion is unlikely to impact a campaign's outcome when backers are presented with only a few rewards. However, when many rewards are offered, creating a modicum of dispersion between contribution levels can be useful for the campaign. A distinctive aspect of crowdfunding is that a backer can signal the worthiness of a campaign to other members of the platform by making a large contribution (Hu et al. 2015).

Nevertheless, a high dispersion of reward prices could also reduce the overall contributions from backers for two reasons (Gourville and Soman 2005). First, the price dispersion in reward choices could create cannibalization within the product line, inducing backers who are willing

to contribute higher amounts to instead contribute at a lower reward level (Moorthy and Png 1992). Second, reward-based crowdfunding being an unregulated market, backers may perceive a risk of funds misappropriation by the creator (we elaborate on this part in Section 3.2.5). The perceived risk of forfeiture could increase in the presence of extremely high contribution levels (Agrawal et al. 2014, Belavina et al. 2020).

Drawing upon these arguments, we conjecture that the high dispersion of reward prices will reduce the benefit of offering more rewards. Therefore, we hypothesize that the dispersion of reward prices moderates the relationship between the number of rewards and funding success. In particular, this relationship will be weaker when the dispersion of reward prices is higher.

***HYPOTHESIS* 2** (H2)**.** *The dispersion of reward prices moderates the relationship between the number of rewards and funding success, such that the relationship will be weaker when the dispersion of reward prices is higher.*

3.2.4 Reward Type

Based on the type of rewards, crowdfunding campaigns can broadly be categorized into product-reward and experiential-reward categories. Campaigns in product-reward categories offer tangible rewards and constitute “search" goods. For search goods, it is possible to learn about the quality of rewards by searching through the available information (Nelson 1974). An example of a successful campaign in the product-reward categories is *“Pebble Time - Awesome Smartwatch"*[3] that was listed in the *Design* category on *Kickstarter*. Conversely, campaigns in the experiential-reward categories offer intangible rewards or constitute “experience" goods. For experience goods, the quality of rewards might only be determined by experiencing the rewards (Nelson 1974). An example of a successful campaign in the experiential-reward categories is *“The Veronica Mars Movie Project"*[4] that was listed in the *Film* category on *Kickstarter*. As with the notion of “search" and “experience" goods, experiences tend to be consumed and evaluated less comparatively than products, which suggests that making a selection among product rewards is relatively harder (Carter and Gilovich 2010). Thus, campaigns in experiential-

[3]https://www.kickstarter.com/projects/getpebble/pebble-time-awesome-smartwatch-no-compromises
[4]https://www.kickstarter.com/projects/559914737/the-veronica-mars-movie-project

reward categories might attract more funding than comparable campaigns in product-reward categories.

Studies comparing consumer decision-making in products and experiences show that a higher number of choices are warranted for products than for experiences (Carter and Gilovich 2010, Gilovich and Gallo 2020). A durable insight from this literature is that, unlike experiences, products are evaluated based on relative comparisons of tangible features and specifications between alternatives. In contrast, because experiences tend to be more personal, they are evaluated in a holistic way rather than on a feature-by-feature basis (Gilovich and Gallo 2020). In other words, backers can intuitively estimate their personal satisfaction from a particular experiential reward without assistance from other alternatives.

These differences lead us to conjecture that the type of rewards will moderate the relationship between the number of rewards and funding success. Therefore, we hypothesize:

***HYPOTHESIS* 3** (H3)**.** *Reward type moderates the relationship between the number of rewards and funding success such that the relationship will be weaker when the campaign is in experiential-reward categories rather than in product-reward categories.*

3.2.5 Creator's Experience

Contributing to reward-based crowdfunding campaigns presents an inherent risk for backers that can manifest in at least three forms. First, backers may misjudge the reward quality and may not receive the expected quality of the product (Belavina et al. 2020). Second, rewards may not be delivered on time. Indeed, rewards delivery for 75% of the campaigns are delayed due to post-campaign operational problems (Leone et al. 2018, Mollick 2014) and 9% of the campaigns do not deliver the promised rewards (Mollick 2015). Third, because most potential backers have no prior interaction with a creator in crowdfunding, backers may perceive a risk of fraud or misappropriation of funds by the creator (Belavina et al. 2020, Leone et al. 2018). Collectively, due to the lack of information about the intent and ability of a creator, backers may hesitate to commit funds to a campaign. By offering more rewards and sharing more details, a creator can communicate a deliberate product development plan and the ability to execute

it. Offering a greater number of rewards also mitigates a backer's risk of misjudging reward quality (Kunz et al. 2017).

The creator's prior crowdfunding experience can also mitigate the risks perceived by backers in an otherwise opaque setting. The creator's prior experience – which is readily accessible on crowdfunding platforms like *Kickstarter* – demonstrates the creator's ability and trustworthiness, and reduces the risk of fraudulent behavior (Gerber and Hui 2013, Zhou et al. 2016). Prior experience of a creator also provides implicit evidence that the creator is respectful of the crowdfunding platform's rules; e.g., *Kickstarter* does not allow running multiple campaigns simultaneously or launching a second campaign before fulfilling the first campaign if it was successful in attaining funds (Kickstarter 2020d). Thus, backers will contribute with less hesitation to a campaign whose creator has more crowdfunding experience than a creator who has less or no crowdfunding experience (Zhou et al. 2016). Furthermore, as noted by Belavina et al. (2020), the combined risk of operational opacity and misappropriation of funds is compounded by the uncertain legal framework, which does not provide meaningful recourse for backers who may be defrauded or aggrieved. Naturally, even *Kickstarter* recommends that creators should emphasize their prior experience in their current campaigns.[5]

Conversely, creators who have low or no prior experience in crowdfunding hence rely on the campaign's rewards as a key mechanism to elicit investment from potential backers. Drawing upon these arguments, we hypothesize that a creator's prior experience can moderate the relationship between the number of rewards and funding success. In particular, this relationship will be stronger (weaker) when the creator's prior experience is lower (higher).

***HYPOTHESIS* 4** (H4)**.** *The creator's prior experience moderates the relationship between the number of rewards and funding success such that the relationship will be weaker when the creator's prior experience is higher.*

We present the conceptual model for the hypotheses in Section 3.1.

[5]https://www.kickstarter.com/honest, last accessed on September 15, 2020.

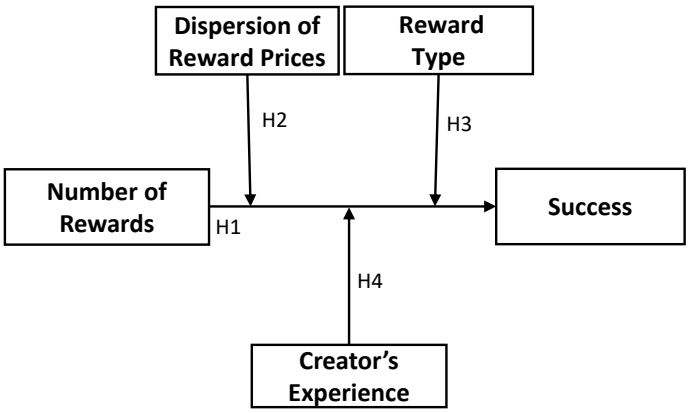


Figure 3.1: Conceptual Model

3.3 Data and Variables

3.3.1 Data

We test the hypotheses using data from *Kickstarter*,[6] the pre-eminent reward-based crowdfunding platform in the world. Since its inception in 2009, this platform has grown to be one of the largest online crowdfunding platforms with several million members and combined pledges running in billions of dollars to fund a large number of creative ideas (Kuppuswamy and Bayus 2017, Roma et al. 2018). Broadly, the steps involved in launching a campaign at *Kickstarter* are as follows: (1) The creator starts an online campaign and provides details about the target funding goal, campaign duration, the rewards to be offered, the number of rewards, and their denominations in addition to other details in the online campaign. An example of a reward-based crowdfunding campaign is provided in Appendix A. (2) If the platform approves the campaign, it becomes "live", and backers can pledge until the end of the campaign's duration. (3) Since *Kickstarter* follows "all-or-nothing" type funding model (Kickstarter 2020e), the funds are transferred to the creator only if the campaign collects funds more than or equal to the target funding goal at the end of the campaign duration, and the campaign is deemed successful. Otherwise, the money raised is refunded back to backers who had pledged for the campaign.

Creators can launch their campaigns in any of the fifteen categories on *Kickstarter*: *Art*, *Comics*, *Craft*, *Dance*, *Design*, *Fashion*, *Film*, *Food*, *Games*, *Journalism*, *Music*, *Photography*,

[6] Kickstarter is a benefit corporation and hosts publicly available data.

Publishing, *Technology*, and *Theater*. We categorize campaigns launched in these fifteen categories into product-reward or experiential-reward categories based on the nature of the rewards offered in the campaigns. The campaigns offering tangible rewards and "search" goods such as products, merchandise, or other physical objects are categorized in the product-reward categories. The campaigns offering intangible rewards or "experience" goods such as streaming a movie, membership access to professional activities, or concert tickets are categorized in the experiential-reward categories (Thurridl and Kamleitner 2016). The campaigns in *Art*, *Crafts*, *Design*, *Fashion*, *Publishing*, and *Technology* are grouped in the product-reward categories and the campaigns in *Comics*, *Dance*, *Film*, *Food*, *Games*, *Journalism*, *Music*, *Photography*, and *Theater* are grouped in the experiential-reward categories (more details are provided in Section 3.3.2).

We use data for a decade spanning from April 2009 to December 2018. We collect campaign and creator-level data for $196,651$ campaigns launched and completed in the studied duration. From this set, we remove $1,424$ campaigns that offer one reward, as they do not offer any choice to backers. The variable, target funding goal, explained in more detail in Section 4.6.2, is not only employed to create both the dependent variables but is also used as a control variable. Moreover, the target funding goal is also a consideration for creating the instrumental variables in Section 3.4.3. To eliminate outliers in the target funding goal, in each of the fifteen categories, we remove campaigns with funding goals that fall outside the 1^{st} and 99^{th} percentiles (Kuppuswamy and Bayus 2017, Mollick 2014); this results in the removal of $3,746$ campaigns. After this exclusion and after removing one additional campaign with data inconsistency issues, the final dataset contains $191,480$ successful and unsuccessful campaigns. There are $146,873$ unique creators in the dataset that includes $25,082$ unique creators who have created multiple campaigns.[7]

3.3.2 Variables

This section introduces dependent, independent, and control variables. Table 3.1 presents the variables, their construction, and measures. The Pearson correlations among the variables of

[7]We collect data on all the campaigns created by these creators in the studied duration.

interest are shown in Table 3.2.

Table 3.1: Description of Key Variables and Descriptive Statistics

Variable	**Description**	Mean	Median	SD
Success	Binary variable, 1 if funding collected $\geq$ target funding goal (0 otherwise)	0.59	1	0.49
Num_Rewards	Count of the number of rewards	8.90	8	5.62
CoefOfVar_Prices	Ratio of standard deviation to mean of contribution levels	1.31	1.28	0.53
Experiential_Category	Binary variable for experiential-reward categories (0 for product-reward categories)	0.57	1	0.50
Creator_Experience	ln(Number of prior campaigns created by creator)[a]	0.26	0	0.55
Kickstarter_Recommendation	Binary variable, 1 if *Kickstarter* recommends the campaign (0 otherwise)	0.15	0	0.35
Duration_Change	Binary variable for duration change from 90 to 60 days (1 after June 17, 2011, 0 otherwise)	0.94	1	0.25
Funding_Goal	ln(Target funding goal amount in $)	8.48	8.52	1.51
Campaign_Duration	Active duration of a campaign in days	33.24	30	12.26
Min_Reward_Price	ln(Minimum price of the rewards in $)[a]	1.85	1.79	0.99
Max_Reward_Price	ln(Maximum price of the rewards in $)[a]	6.29	6.22	1.66
Num_Images_Videos	ln(Count of number of images and videos in a campaign)[a]	2.19	1.95	0.73
Competition	ln(Number of active campaigns during the focal campaign)	7.70	7.69	0.41
Prop_Limited_Rewards	Ratio of limited Num_Rewards to total Num_Rewards	0.29	0.22	0.31
Creator_from_US	Binary variable for creator from the US (0 if from any other country)	0.87	1	0.34
Year_Trend	Linear trend for the campaign start year	6.44	7	2.15

Notes: Descriptive statistics are presented for the final dataset of $191,480$ *campaigns from 2009-2018.*

[a] *We add 1 to the variables before taking natural logarithm.*

Table 3.2: Pairwise Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Success	1															
(2) Num_Rewards	0.246	1														
(3) CoefOfVar_Prices	0.063	0.404	1													
(4) Experiential_Category	0.098	0.069	0.147	1												
(5) Creator_Experience	0.142	0.068	-0.148	0.025	1											
(6) Kickstarter_Recom.	0.248	0.216	0.132	0.015	0.028	1										
(7) Duration_Change	-0.075	0.050	-0.043	-0.103	0.083	-0.009	1									
(8) Funding_Goal	-0.191	0.250	0.306	0.011	-0.143	0.164	0.077	1								
(9) Campaign_Duration	-0.109	0.016	0.075	0.018	-0.140	-0.013	-0.239	0.186	1							
(10) Min_Reward_Price	-0.089	-0.265	-0.302	-0.038	0.019	-0.045	0.030	0.109	-0.001	1						
(11) Max_Reward_Price	0.072	0.463	0.780	0.137	-0.150	0.166	-0.045	0.529	0.111	-0.002	1					
(12) Num_Imgs_Videos	0.303	0.411	0.079	-0.139	0.206	0.238	0.202	0.236	-0.074	-0.101	0.144	1				
(13) Competition	-0.171	-0.011	-0.017	-0.082	-0.042	-0.013	0.544	0.095	-0.156	0.031	-0.029	0.076	1			
(14) Prop_Limited Rewards	0.052	0.223	0.053	-0.091	0.022	0.082	0.112	0.085	-0.039	0.024	0.112	0.207	0.076	1		
(15) Creator_from_US	0.066	0.030	0.043	0.072	0.046	-0.001	-0.044	-0.047	-0.034	-0.020	0.038	-0.118	-0.029	-0.033	1	
(16) Year_Trend	-0.124	-0.011	-0.164	-0.136	0.213	-0.030	0.491	0.065	-0.164	0.125	-0.152	0.306	0.322	0.103	-0.184	1

Notes: Correlations are presented for $191,480$ *campaigns.*

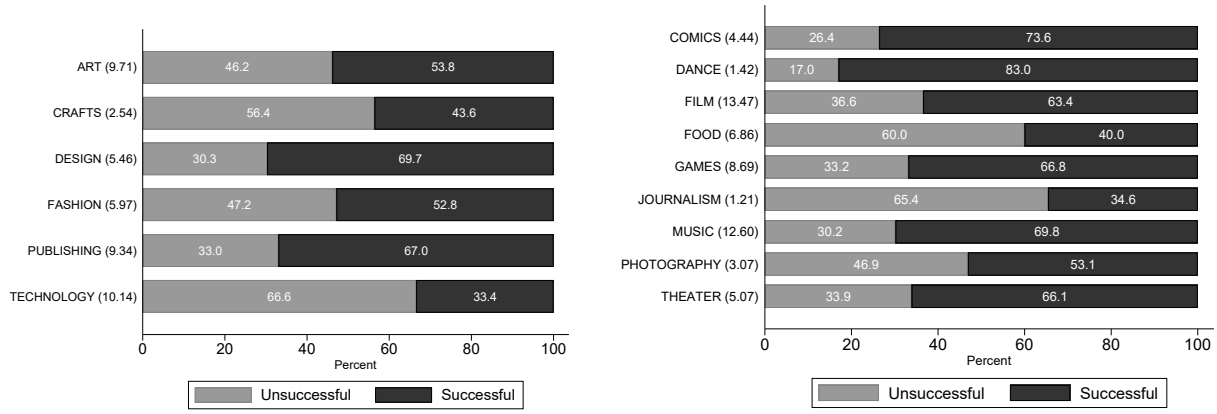
The continuous variables are natural log transformed due to their skewed distributions, refer Table 3.1 for details.

Correlations are significant at 5% level except for the ones having absolute value less than 0.009.

Dependent Variable

Funding Success: We measure *Funding Success* (*Success*) as a binary variable that indicates whether a campaign has total funding collected greater than or equal to the target funding goal (Cornelius and Gokpinar 2020, Oo et al. 2019). This measure aligns with *Kickstarter*'s "all-or-nothing" type of funding model. In the "all-or-nothing" type of funding model, a creator

receives contributions only if the collected amount equals or exceeds the target funding goal (Kickstarter 2020e). Otherwise, the campaign is considered unsuccessful, and the creator does not receive any money. This funding model has two significant advantages - it ensures a sense of urgency for backers to contribute, and at the same time, it safeguards backers' interests. Aligning with *Kickstarter*'s business model, we set *Success* to 1 if the campaign's collected funding is equal to or greater than its target funding goal; otherwise, *Success* is zero. In our dataset, about 59% campaigns are successful in obtaining funding. The percentage of successful and unsuccessful campaigns across different campaign categories are provided in Figure 3.2.



(a) Product-Reward Categories

(b) Experiential-Reward Categories

Figure 3.2: Percentage of Successful/Unsuccessful Campaigns in Each Category [N= 191,480]. The percentage of campaigns in each category is shown in parentheses

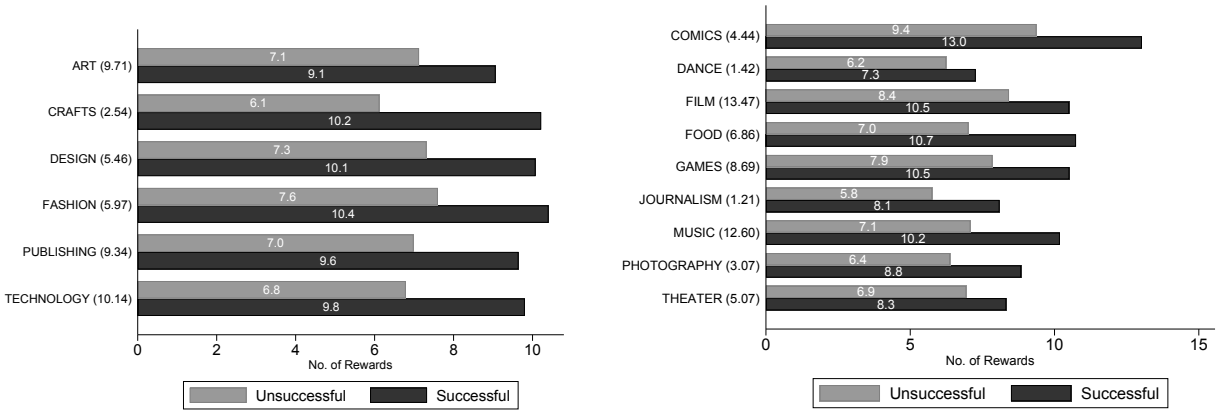
Besides using *Funding Success* as the dependent variable for our main analysis, we also employ *Funding Ratio* as an alternate dependent variable (Burtch et al. 2020). This variable aligns with the "keep-it-all" funding model adopted by *Indiegogo*, another reward-based crowdfunding platform that hosts campaigns under the "keep-it-all" and "all-or-nothing" funding models. *Indiegogo* provides an option for creators to choose the funding model before launching their campaigns (Indiegogo 2020b, Younkin and Kashkooli 2016). In the "keep-it-all" funding model, creators receive the funding collected irrespective of achieving or falling short of the target funding goal. We measure *Funding Ratio* as a ratio of the total funding collected to the target funding goal (See Section 3.4.4 for more details).

Independent and Moderating Variables

Number of Rewards: We operationalize *Number of Rewards* ($Num\_Rewards$) as the number of alternatives offered in a campaign from which backers can select a pledge to contribute in the campaign (Kunz et al. 2017). The mean of $Num\_Rewards$ is 8.90 rewards, and the median is 8 rewards. $Num\_Rewards$ is positively correlated (0.246) with the dependent variable $Success$.

Dispersion of Reward Prices: We operationalize *Dispersion of Reward Prices* as the coefficient of variation of reward prices (contribution levels), denoted by $CoefofVar\_Prices$ (Zhang et al. 2017). The coefficient of variation is defined as a ratio of the standard deviation to the mean of the reward prices. $CoefofVar\_Prices$ is positively correlated (0.063) with $Success$.

Reward Type: We operationalize *Reward Type* with a binary variable $Experiential\_Category$, which is zero for the campaigns in the product-reward categories and 1 for the campaigns in the experiential-reward categories. About 57% of the campaigns offer experiential rewards. Figure 3.2a and Figure 3.2b show the percentage of successful campaigns in campaign categories that offer product and experiential rewards, respectively. The mean number of rewards for successful and unsuccessful campaigns in the product- and the experiential-reward categories are given in Figure 3.3a and Figure 3.3b, respectively.



(a) Product-Reward Categories

(b) Experiential-Reward Categories

Figure 3.3: Mean Number of Rewards for Successful/Unsuccessful Campaigns in Each Category [N= 191,480]

Creator's Experience: We operationalize *Creator's Experience* ($Creator\_Experience$) as

the natural logarithm[8] of the number of campaigns created by the creator prior to the focal campaign (Cornelius and Gokpinar 2020, Steigenberger 2017). The mean of $Creator\_Experience$ is 0.26. The first time creators have a mean success rate of 55.3%, and it increases to 69.7% for the experienced creators on crowdfunding. The mean success rate with creator's experience is plotted in Figure 3.4.

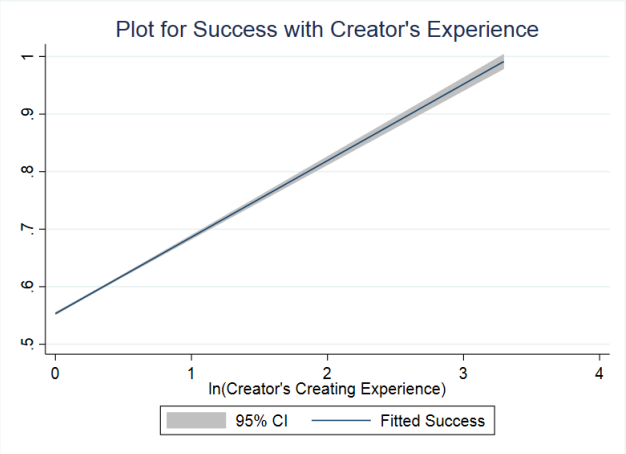


Figure 3.4: Plot for Success with Creator's Experience

Control Variables

We employ the following controls in the regression analysis. *Target Funding Goal*: To control for the size and complexity of a campaign, we operationalize *Target Funding Goal* (*Funding_Goal*) as the natural logarithm of the funds (USD) sought by the creator in the campaign. The funds sought by the creator is a measure of the minimum feasible budget to deliver the promised rewards (Chakraborty and Swinney 2020, Cornelius and Gokpinar 2020). The mean of *Funding_Goal* is 8.48, and the median is 8.52.

Campaign Duration: We include the total number of days a campaign is active, (*Campaign_Duration*), as a control. The active duration of a campaign measures the complexity of a campaign, and a longer duration reduces the likelihood of achieving success (Cornelius and Gokpinar 2020, Zhang et al. 2017). The mean of *Campaign_Duration* is 33.24 days with a median of 30 days.

Reward Prices: A higher minimum reward price and a higher maximum reward price would help to attain the target funding goal with fewer backers (Zhang et al. 2017). To control for the

[8]We add 1 to the variable before taking a natural logarithm.

contribution levels in the reward structure, we include natural logarithms[8] of the minimum reward price (*Min_Reward_Price*) and the maximum reward price (*Max_Reward_Price*).

Visuals: We include natural logarithm[8] of the *number of images and videos* provided in the campaign as a control (*Num_Images_Videos*). The perceived credibility of a campaign may be improved by providing more visuals in the campaign (Cornelius and Gokpinar 2020, Kunz et al. 2017, Mollick 2014). Creators on crowdfunding platforms provide visuals to build backers' confidence about the quality of rewards, which can increase the funding success (Chakraborty and Swinney 2020).

Competition: The focal campaign would attract reduced attention and, hence, lower backings when there are more active campaigns at the same time (Lin et al. 2018). To account for the *competition* (*Competition*) from the contemporary campaigns competing for the interest of backers, we include the natural logarithm of the number of campaigns active at the same time as the focal campaign.

Limited Rewards: Creators may also limit one or more number of rewards which are not available after a certain threshold set by the creator. The limited rewards are generally the early bird discounts given to the first few backers to gain initial momentum (Chakraborty and Swinney 2019). We include the proportion of the limited rewards (*Prop_Limited_Rewards*) in the reward structure of a campaign as a control. Providing limited rewards might improve funding success.

Platform Specific Controls: *Kickstarter* recommends certain campaigns by assigning a *"Project We Love"* badge (Dai and Zhang 2019). We capture the effect of this recommendation on funding success by incorporating a binary variable *Kickstarter_Recommendation*. *Kickstarter* also changed the maximum limit on the campaign duration from 90 to 60 days on June 17, 2011 (Kickstarter 2011), citing that a longer duration (90 days) does not create urgency and backers tend to procrastinate. We control for this change with a binary variable *Duration_Change*, which is 1 after June 17, 2011 and zero otherwise. We include a binary variable *Creator_From_US* to control for the nation-wide cultural diversity and the demography of creators, which is 1 if the creator is based in the United States, and zero if the creator is from another country. To account for any seasonality and trends, we include binary variables for

months and continuous trend for the campaign start year (Taeuscher et al. 2020). We code the trend variable (*Year_Trend*) with discrete values ranging from 1-10 for the years 2009-2018 in the dataset.

3.4 Empirical Analysis

3.4.1 Baseline Specification

The baseline econometric specification is presented in Equation (Equation 3.1). The dependent variable is a binary measure of funding success of the campaign 'i.' The main independent variable is the number of rewards ($Num\_Rewards_i$) offered in the campaign 'i.' To test the proposed non-linear relationship (H1), we also include the square of the number of rewards ($Num\_Rewards_i^2$) in the specification. Moderating variables are included in the vector mod_i, and $\beta_{3,j},\ j = 1, 2, 3$ represent the regression coefficients for the direct effects of the moderating variables. We include the interactions of the coefficient of variation of the reward prices ($CoefOfVar\_Prices_i$) with the number of rewards and its squared term to test the moderation of dispersion of reward prices (H2). To study the moderating effects of reward type (H3), we include interactions of the experiential category ($Experiential\_Category_i$) with the number of rewards and its squared term. Finally, we include the interaction terms of the creator's experience ($Creator\_Experience_i$) with the number of rewards and its squared term to test its moderation with the number of rewards (H4). The regression coefficients $\beta_{4,j}$ and $\beta_{5,j},\ j = 1, 2, 3$ represent the interaction effects of the moderating variables with the number of rewards and its squared terms. Finally, we include the control variables ($Controls_i$), and we test this model using logit regression in Stata.

$$
\begin{aligned}
Success_i = \beta_0 + \beta_1\, Num\_Rewards_i + \beta_2\, Num\_Rewards_i^2 + \sum_{j=1}^{3} \beta_{3,j}\, mod_{i,j} \\
+ \sum_{j=1}^{3} \beta_{4,j}\, mod_{i,j} \times Num\_Rewards_i + \sum_{j=1}^{3} \beta_{5,j}\, mod_{i,j} \times Num\_Rewards_i^2 \\
+ \tau\, Controls_i + \epsilon_i \\
where, mod_i = \{CoefOfVar\_Prices_i, Experiential\_Category_i, Creator\_Experience_i\}
\end{aligned}
\tag{3.1}
$$

3.4.2 Results

In the baseline analyses, as presented in Table 3.3, we perform logistic regression and add control variables, mean-centered independent variables, and mean-centered moderating variables sequentially in Models (1-6). We specify our regression models with heteroskedastic-robust standard errors clustered around creators. Model (1) presents the effects of control variables on *Success*. The results show that *Kickstarter*'s recommendation improves ($\beta = 1.7380, p < 0.01$) the likelihood of success. The policy change on reducing maximum campaign duration from 90 to 60 days has a positive effect on funding success ($\beta = 0.4210, p < 0.01$). A high target funding goal ($\beta = -0.7050, p < 0.01$) or a long campaign duration ($\beta = -0.0154, p < 0.01$) has a negative effect on funding success. The likelihood of success improves with a high minimum price ($\beta = 0.0806, p < 0.01$) or a high maximum price ($\beta = 0.2800, p < 0.01$) of the rewards because the funding collected increases in both of these scenarios. The likelihood of success improves with more visuals ($\beta = 1.4760, p < 0.01$), which signals the campaign's higher credibility to backers. The campaigns compete for the available fixed resources from backers as the likelihood of success of a campaign reduces under more competition from other contemporaneous campaigns ($\beta = -1.0260, p < 0.01$). The likelihood of success also reduces for a higher number of limited rewards in a campaign ($\beta = -0.0471, p < 0.05$).

Model (2) in Table 3.3 presents results for the number of rewards and its squared term, and Model (6) shows the complete specification. We draw inferences for the independent variables and the interactions from the complete specification presented in Model (6). A positive coefficient of β_1 (in Equation 3.1) would show that the likelihood of success improves with a higher number of rewards. A positive coefficient of β_1 and a negative coefficient of β_2 would demonstrate a concave relationship between the number of rewards and funding success. The number of rewards has a positive association ($\beta = 0.1020, p < 0.01$) and the square of the number of rewards has a negative association ($\beta = -0.0031, p < 0.01$) with funding success. Together these results demonstrate evidence of a concave relationship (H1) between the number of rewards and funding success. These results are also plotted in Figure 3.5 with 95% confidence interval. As the number of rewards increase, funding success increases and reaches a maximum value beyond which funding success reduces with an increase in the number of rewards.

Table 3.3: Baseline Analysis using Logit Regression (Dependent Variable: $Success$)

	(1)	(2)	(3)	(4)	(5)	(6)
Control Variables:						
Kickstarter_Recommendation	1.7380***	1.6670***	1.6700***	1.6660***	1.6670***	1.6700***
	(0.0223)	(0.0225)	(0.0225)	(0.0225)	(0.0225)	(0.0225)
Duration_Change	0.4210***	0.3950***	0.3990***	0.3910***	0.3960***	0.3950***
	(0.0365)	(0.0416)	(0.0416)	(0.0415)	(0.0417)	(0.0416)
Funding_Goal	-0.7050***	-0.7140***	-0.7120***	-0.7140***	-0.7140***	-0.7110***
	(0.0064)	(0.0065)	(0.0066)	(0.0065)	(0.0065)	(0.0065)
Campaign_Duration	-0.0154***	-0.0147***	-0.0148***	-0.0147***	-0.0147***	-0.0147***
	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Min_Reward_Price	0.0806***	0.1740***	0.1910***	0.1740***	0.1750***	0.1970***
	(0.0066)	(0.0081)	(0.0083)	(0.0080)	(0.0081)	(0.0084)
Max_Reward_Price	0.2800***	0.2020***	0.1850***	0.2010***	0.2000***	0.1770***
	(0.0050)	(0.0086)	(0.0090)	(0.0086)	(0.0087)	(0.0091)
Num_Images_Videos	1.4760***	1.3560***	1.3540***	1.3610***	1.3550***	1.3580***
	(0.0121)	(0.0130)	(0.0130)	(0.0131)	(0.0130)	(0.0132)
Competition	-1.0260***	-0.9250***	-0.9220***	-0.9230***	-0.9240***	-0.9180***
	(0.0227)	(0.0242)	(0.0242)	(0.0241)	(0.0242)	(0.0242)
Prop_Limited_Rewards	-0.0471**	-0.1190***	-0.1160***	-0.1210***	-0.1190***	-0.1180***
	(0.0208)	(0.0209)	(0.0210)	(0.0209)	(0.0209)	(0.0210)
Independent Variables:						
Num_Rewards		0.1110***	0.1130***	0.1020***	0.1110***	0.1020***
		(0.0023)	(0.0023)	(0.0029)	(0.0023)	(0.0029)
Num_Rewards^2		-0.0030***	-0.0032***	-0.0029***	-0.0031***	-0.0031***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
CoefOfVar_Prices		-0.3240***	-0.3050***	-0.3240***	-0.3210***	-0.2980***
		(0.0227)	(0.0236)	(0.0227)	(0.0226)	(0.0236)
Experiential_Category		0.5680***	0.5700***	0.5810***	0.5690***	0.5920***
		(0.0137)	(0.0137)	(0.0149)	(0.0136)	(0.0151)
Creator_Experience		0.1920***	0.1910***	0.1900***	0.1620***	0.1480***
		(0.0323)	(0.0323)	(0.0323)	(0.0314)	(0.0313)
CoefOfVar_Prices $\times$ Num_Rewards			-0.0259***			-0.0301***
			(0.0030)			(0.0030)
CoefOfVar_Prices $\times$ Num_Rewards^2			0.0011***			0.0013***
			(0.0002)			(0.0002)
Experiential_Category $\times$ Num_Rewards				0.0159***		0.0211***
				(0.0032)		(0.0033)
Experiential_Category $\times$ Num_Rewards^2				-0.0001		-0.0004**
				(0.0002)		(0.0002)
Creator_Experience $\times$ Num_Rewards					-0.0075*	-0.0122***
					(0.0042)	(0.0042)
Creator_Experience $\times$ Num_Rewards^2					0.0009***	0.0011***
					(0.0002)	(0.0002)
Intercept	9.9550***	9.7800***	9.8430***	9.7640***	9.7830***	9.8320***
	(0.1680)	(0.1730)	(0.1730)	(0.1730)	(0.1730)	(0.1730)
Month Indicators & Year_Trend	Yes	Yes	Yes	Yes	Yes	Yes
Creator_from_US Indicator	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-96,414	-93,059	-92,999	-93,039	-93,039	-92,940
Chi-squared	31,504	33,825	33,830	33,786	34,164	34,265
Observations	191,480	191,480	191,480	191,480	191,480	191,480

Notes: The dependent variable is Success. The continuous variables with skewed distribution are natural log transformed, refer Table 3.1 for details. Interaction variables are mean centered in the analyses. Heteroskedastic robust standard errors clustered around creators in parentheses.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

A higher number of rewards facilitate a better match for backers having independent product valuations (Hu et al. 2015, Kuppuswamy and Bayus 2017), but the marginal effect reduces with each additional reward. These results show evidence to support hypothesis 1. We perform additional analyses to test the diminishing returns results and find it robust to the model specifications (Quadratic and Spline), as shown in Section 3.4.5.

Further, the results on the dispersion of reward prices ($CoefOfVar\_Prices$) depict that a high dispersion of reward prices reduces the likelihood of success of a campaign ($\beta = -0.2980, p < 0.01$). The interaction of dispersion of reward prices with the number of rewards has a negative coefficient ($\beta = -0.0301, p < 0.01$), and with the square of the number of rewards has a positive coefficient ($\beta = 0.0013, p < 0.01$). These results for the low and high dispersion of reward prices ($\mu \pm 2\sigma$) are also plotted in Figure 3.6. As the number of rewards increases from a small value, the improvement in funding success is more significant for the low dispersion of reward prices compared to the high dispersion of reward prices. However, the peak of funding success for high dispersion of reward prices occurs later than the low dispersion of reward prices. Funding success is also higher for the high dispersion of reward prices compared to the low dispersion of reward prices at a very high number of rewards. These results show evidence to support hypothesis 2 and demonstrate that a higher number of rewards of low price dispersion improve funding success, but has diminishing returns.

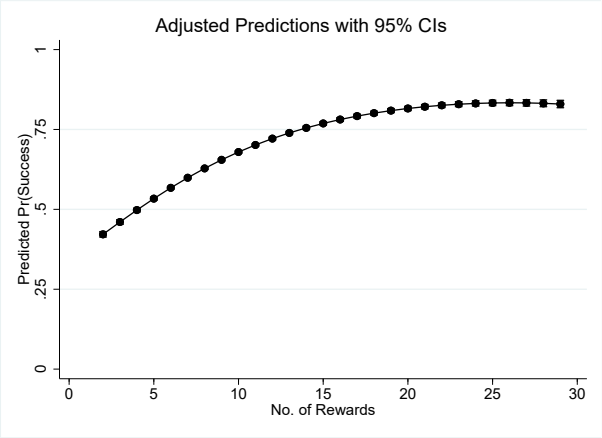


Figure 3.5: Association of Number of Rewards with Funding Success (H1)

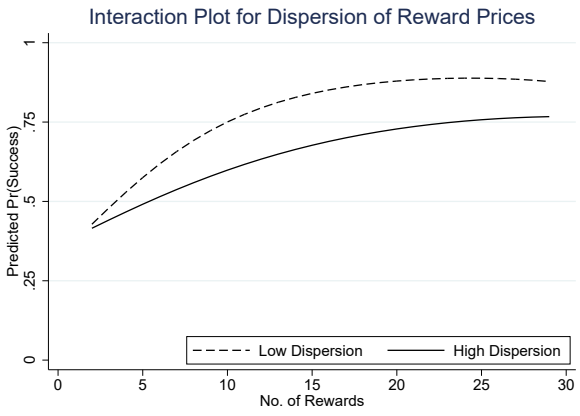


Figure 3.6: Interaction Effects of Number of Rewards with Dispersion of Reward Prices at $\mu \pm 2\sigma$ on Funding Success (H2)

Hypothesis 3 states that the association between the number of rewards and funding success

is weaker for campaigns in the experiential-reward categories. The results show that campaigns in the experiential-reward categories have a higher likelihood of success ($\beta = 0.5920, p < 0.01$) as compared to campaigns in the product-reward categories. The coefficient of the interaction of $Experiential\_Category$ is positive with the number of rewards ($\beta = 0.0211, p < 0.01$) and negative with the square of the number of rewards ($\beta = -0.0004, p < 0.05$). These results are also plotted in Figure 3.7. A campaign in the experiential-reward categories achieves higher funding success than a campaign in the product-reward categories. The increase in funding success with the increase in the number of rewards is also higher in the experiential-reward categories, but the rate of change is lower in the experiential-reward categories. Thus, the relationship between the number of rewards and funding success is stronger in the experiential-reward categories, and these results are opposite to what we conjectured in hypothesis 3.

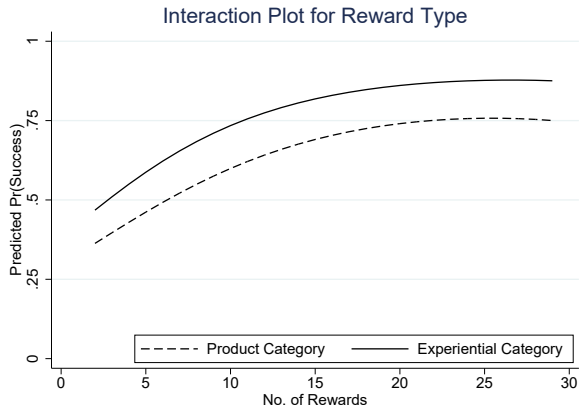


Figure 3.7: Interaction Effects of Number of Rewards with Reward Type on Funding Success (H3)

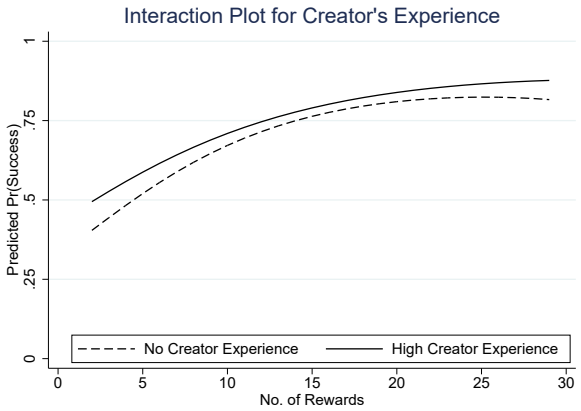


Figure 3.8: Interaction Effects of Number of Rewards with Creator's Experience on Funding Success (H4)

Hypothesis 4 states that the creator's experience moderates the relationship between the number of rewards and funding success. Funding success of a campaign increases with the high creator's experience ($\beta = 0.1480, p < 0.01$). The coefficient of the interaction of $Creator\_Experience$ is negative with the number of rewards ($\beta = -0.0122, p < 0.01$) and positive with the square of the number of rewards ($\beta = 0.0011, p < 0.01$). For a campaign with a higher number of rewards, *cetris paribus*, the increase in funding success is higher if created by a creator with a low crowdfunding experience as compared to a creator with a high crowdfunding experience. In other words, the marginal effect of providing an additional reward is

higher for a creator with a low crowdfunding experience than a creator with a high crowdfunding experience. In Figure 3.8, we illustrate this interaction effect by comparing campaigns of creators with high experience ($\mu + 2\sigma$) and campaigns of creators with no experience. We observe that, for any given number of rewards, the likelihood of success for a campaign is higher when the creator is more experienced. When the number of rewards is lower, we also observe that funding success increases with the number of rewards. This increase is less pronounced for creators with high experience. These results provide evidence to support hypothesis 4.

3.4.3 Instrumental Variable Model

We need to account for the extent to which the coefficients may be biased in the previous section examining the association between the number of rewards and funding success. If the number of rewards is endogenous and is influenced by factors that hinge on the heterogeneous abilities of creators, then the coefficients presented in the baseline results in the previous section may be biased. To account for this source of endogeneity, we use a control function approach in a two-stage estimation. In the first stage, we use ordinary least squares (OLS) and regress the endogenous variable, the number of rewards on two exogenous instruments. Then we use the predicted residuals from the first stage as an additional control variable in the second-stage logit regression.

The two exogenous instruments used in the first stage are: (1) the average number of rewards of campaigns in the same category that ended within the previous 30 days before the launch of the focal campaign and also have a funding goal within the range of $\pm 10\%$ (inclusive) of the focal campaign's funding goal, and (2) the average number of rewards of active campaigns in other categories with a funding goal within the range of $\pm 10\%$ (inclusive) of the focal campaign's funding goal.

Both these variables are appropriate to employ as exogenous instruments meeting the relevance and exclusion criteria (Greene 2003). The campaigns used to construct these instrumental variables share a similar funding goal as the campaign with the endogenous variable, the number of rewards. Moreover, these instrumental variables are uncorrelated with the error term. Specifically, for the first instrumental variable, considering closed campaigns in the

same category excludes the possibility of imposing any competing effect on the funding of the focal campaign by the active campaigns in the same category. Also, for the second instrumental variable, considering active campaigns in other categories is less likely to affect the focal campaign.

While running the two-stage estimation, to ensure the validity of standard errors, we adopt the recommended practice and report non-parametric bootstrap standard errors clustered around creators in the second stage (Cornelius and Gokpinar 2020, Wooldridge 2010). The results of the first stage and the second stage are presented in Table 3.4. The coefficients of the residuals predicted from Model (1), and included in the second stage Models (2-6) are significant, showing that the number of rewards is endogenous, and the instruments are valid. The second stage results are qualitatively similar to the baseline results and support the hypotheses, except for hypothesis 3.

3.4.4 Reward Structure Design and Funding Ratio

The effect of reward structure design could differ for “all-or-nothing" (e.g., *Kickstarter*) and “keep-it-all" (e.g., *Indiegogo*) type funding models prevailing in the reward-based crowdfunding. Besides using *Funding Success* as a dependent variable simulating the “all-or-nothing" type funding model, we also employ *Funding Ratio* as an alternate continuous dependent measure to simulate “keep-it-all" funding model (Burtch et al. 2020, Indiegogo 2020b, Younkin and Kashkooli 2016). In the “keep-it-all" funding model, creators receive the funding collected irrespective of achieving or falling short of the target funding goal. Unlike a binary dependent measure, a continuous dependent variable incorporates the differential effects of the instantaneous funding collected with respect to the target funding goal. The differential effects of the instantaneous funding collected, as in the goal gradient effect demonstrated by (Kuppuswamy and Bayus 2017), could help attract more backers to contribute as the campaign reaches near its target funding goal. Additionally, creators might intend to design their campaigns to collect the maximum possible funding beyond the target funding goal. To draw additional insights and to simulate the “keep-it-all" funding model as observed in other platforms (e.g., *Indiegogo*), we analyze the effect of reward structure design on the overall funding performance of a campaign.

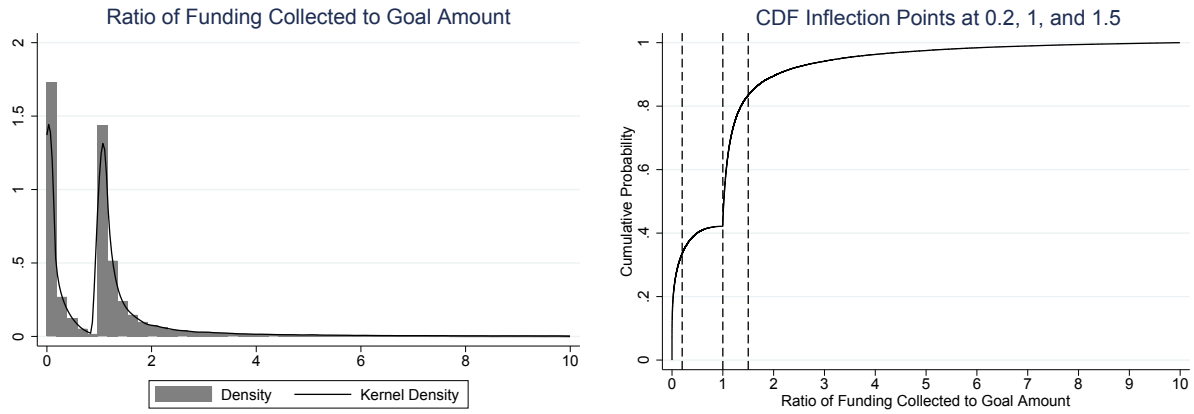
Table 3.4: Instrumental Variables Regression (Control Function Approach) (Dependent Variable: $Success$)

	OLS-First Stage	Logit-Second Stage				
	Num_Rewards	Success				
	(1)	(2)	(3)	(4)	(5)	(6)
Control Variables:						
Kickstarter_Recommendation	0.8840***	1.6360***	1.6370***	1.6430***	1.6360***	1.6460***
	(0.0299)	(0.0285)	(0.0286)	(0.0285)	(0.0286)	(0.0285)
Duration_Change	0.5030***	0.3460***	0.3480***	0.3480***	0.3460***	0.3510***
	(0.0603)	(0.0465)	(0.0464)	(0.0464)	(0.0467)	(0.0466)
Funding_Goal	-0.2470***	-0.7290***	-0.7260***	-0.7300***	-0.7290***	-0.7270***
	(0.0126)	(0.0070)	(0.0071)	(0.0070)	(0.0070)	(0.0070)
Campaign_Duration	0.0059***	-0.0147***	-0.0147***	-0.0147***	-0.0147***	-0.0146***
	(0.0009)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Min_Reward_Price	-1.3450***	0.2320***	0.2500***	0.2220***	0.2340***	0.2440***
	(0.0118)	(0.0239)	(0.0239)	(0.0237)	(0.0238)	(0.0238)
Max_Reward_Price	1.5010***	0.1380***	0.1190***	0.1480***	0.1350***	0.1250***
	(0.0121)	(0.0254)	(0.0255)	(0.0251)	(0.0253)	(0.0253)
Num_Images_Videos	2.1850***	1.2450***	1.2400***	1.2680***	1.2440***	1.2650***
	(0.0163)	(0.0382)	(0.0382)	(0.0382)	(0.0382)	(0.0382)
Competition	-0.2200***	-1.0500***	-1.0460***	-1.0520***	-1.0480***	-1.0460***
	(0.0348)	(0.0239)	(0.0240)	(0.0239)	(0.0239)	(0.0239)
Prop_Limited_Rewards	2.2400***	-0.2160***	-0.2160***	-0.1990***	-0.2160***	-0.1960***
	(0.0340)	(0.0428)	(0.0429)	(0.0427)	(0.0429)	(0.0428)
Independent Variables:						
Num_Rewards		0.1570***	0.1600***	0.1400***	0.1507***	0.1400***
		(0.0165)	(0.0165)	(0.0166)	(0.0164)	(0.0165)
Num_Rewards^2		-0.0030***	-0.0032***	-0.0030***	-0.0031***	-0.0031***
		(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
CoefOfVar_Prices	-0.5320***	-0.2980***	-0.2800***	-0.3020***	-0.2940***	-0.2770***
	(0.0355)	(0.0255)	(0.0263)	(0.0254)	(0.0255)	(0.0266)
Experiential_Category	0.4820***	0.5380***	0.5390***	0.5520***	0.5380***	0.5620***
	(0.0213)	(0.0170)	(0.0171)	(0.0180)	(0.0170)	(0.0180)
Creator_Experience	0.6480***	0.1670***	0.1650***	0.1710***	0.1350***	0.1270***
	(0.0198)	(0.0369)	(0.0369)	(0.0368)	(0.0370)	(0.0366)
CoefOfVar_Prices × Num_Rewards			-0.0244***			-0.0290***
			(0.0029)			(0.0031)
CoefOfVar_Prices × Num_Rewards^2			0.0011***			0.0013***
			(0.0002)			(0.0002)
Experiential_Category × Num_Rewards				0.0155***		0.0207***
				(0.0036)		(0.0036)
Experiential_Category × Num_Rewards^2				-0.0001		-0.0003
				(0.0002)		(0.0002)
Creator_Experience × Num_Rewards					-0.0094**	-0.0142***
					(0.0042)	(0.0043)
Creator_Experience × Num_Rewards^2					0.0009***	0.0012***
					(0.0002)	(0.0002)
Mean Num_Rewards in Category	0.1340***					
	(0.0035)					
Mean Num_Rewards in Other Categories	0.0230***					
	(0.0089)					
Residuals from 1st Stage		-0.0465***	-0.0481***	-0.0382**	-0.0467***	-0.0385**
		(0.0166)	(0.0166)	(0.0165)	(0.0166)	(0.0165)
Intercept	-11.2300***	11.5000***	11.5700***	11.4000***	11.5000***	11.4600***
	(0.2550)	(0.2250)	(0.2250)	(0.2260)	(0.2250)	(0.2270)
Month Indicators & Year_Trend	Yes	Yes	Yes	Yes	Yes	Yes
Creator_from_US Indicator	Yes	Yes	Yes	Yes	Yes	Yes
R^2/Adjusted R^2	0.4190					
rmse	4.2630					
Log likelihood	-514,846	-86,975	-86,924	-86,955	-86,955	-86,866
Chi-squared		35,606	36,305	35,871	36,052	36,877
Observations	179,465	179,465	179,465	179,465	179,465	179,465

Notes: The observations are reduced due to missing values of the instrumental variables. Interaction variables are mean centered in the analyses. The continuous variables with skewed distribution are natural log transformed, refer Table 3.1 for details. Standard errors (first stage Model (1)) and non-parametric bootstrap standard errors (200 replications; second stage models (2)-(6)) in parentheses.

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

In the same model as presented in Equation 3.1, we operationalize *Funding Ratio* ($Funding\_Ratio$) as the natural logarithm[8] of the ratio of cumulative funding collected by a campaign to its target funding goal (Zheng et al. 2014). This continuous measure takes the form of two consecutive power distributions, as shown in Figure 3.9a and Figure 3.9b. The mean of $Funding\_Ratio$ is 0.62, and the median is 0.70. The raw data shows that, on average, a campaign achieves 50% more funding than the target funding goal.



(a) PDF (b) CDF

Figure 3.9: Distribution of the Continuous Measure $Funding\_Ratio$

The regression results are presented in Table 3.5. We verify the assumptions for the regression analysis and rule out the issues of multicollinearity. To assess multicollinearity, we obtain variance inflation factors (VIFs) associated with each variable in the full model. VIF values for $Num\_Rewards$ and $Num\_Rewards^2$ are approximately six, and VIF values for the rest of the variables are below three, keeping VIFs within the prescribed limit of 10 (Belsley et al. 1980). The interaction variables are mean-centered and we report heteroskedastic-robust standard errors clustered around creators in Table 3.5.

Model (1) in Table 3.5 shows the results of the regression of the independent and control variables on *Funding_Ratio*. The interaction terms are added sequentially in the subsequent models, and we interpret results from Model (5), showing the complete specification. The coefficient of the number of rewards is positive ($\beta = 0.0208, p < 0.01$) and the square of the number of rewards is negative ($\beta = -0.0005, p < 0.01$). Together these results provide evidence to support hypothesis 1 on the increasing positive effect of the number of rewards with diminishing returns. These results, as plotted in Figure 3.10, demonstrate that *Funding_Ratio*

increases with the increase in the number of rewards, and its marginal effect decreases with each additional reward.

Table 3.5: Additional Analysis (Dependent Variable: $Funding\_Ratio$)

	OLS					OLS-First Stage	IV-Sec. Stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Funding_Ratio					Num_Rewards	Funding_Ratio
Control Variables:							
Kickstarter_Recommendation	0.2840***	0.2850***	0.2850***	0.2840***	0.2850***	0.8840***	0.2930***
	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0299)	(0.0057)
Duration_Change	0.0564***	0.0580***	0.0589***	0.0558***	0.0594***	0.5030***	0.0652***
	(0.0084)	(0.0084)	(0.0084)	(0.0087)	(0.0087)	(0.0603)	(0.0091)
Funding_Goal	-0.1390***	-0.1380***	-0.1380***	-0.1380***	-0.1370***	-0.2470***	-0.1330***
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0126)	(0.0017)
Campaign_Duration	-0.0013***	-0.0013***	-0.0013***	-0.0013***	-0.0013***	0.0059***	-0.0012***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0009)	(0.0001)
Min_Reward_Price	0.0252***	0.0298***	0.0250***	0.0260***	0.0305***	-1.3450***	0.0194***
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0022)	(0.0118)	(0.0043)
Max_Reward_Price	0.0358***	0.0306***	0.0360***	0.0346***	0.0294***	1.5010***	0.0416***
	(0.0020)	(0.0021)	(0.0020)	(0.0019)	(0.0020)	(0.0121)	(0.0048)
Num_Images_Videos	0.3440***	0.3440***	0.3420***	0.3420***	0.3400***	2.1850***	0.3580***
	(0.0036)	(0.0036)	(0.0036)	(0.0035)	(0.0036)	(0.0163)	(0.0075)
Competition	-0.1330***	-0.1330***	-0.1340***	-0.1330***	-0.1320***	-0.2200***	-0.1630***
	(0.0045)	(0.0045)	(0.0045)	(0.0046)	(0.0046)	(0.0348)	(0.0049)
Prop_Limited_Rewards	0.0163***	0.0170***	0.0170***	0.0164***	0.0177***	2.2400***	0.0379***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0340)	(0.0084)
Independent Variables:							
Num_Rewards	0.0165***	0.0168***	0.0207***	0.0170***	0.0208***		0.0122***
	(0.0006)	(0.0006)	(0.0008)	(0.0005)	(0.0007)		(0.0030)
Num_Rewards^2	-0.0004***	-0.0004***	-0.0005***	-0.0004***	-0.0005***		-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)
CoefOfVar_Prices	-0.1310***	-0.1180***	-0.1300***	-0.1300***	-0.1170***	-0.5320***	-0.1210***
	(0.0056)	(0.0058)	(0.0056)	(0.0055)	(0.0057)	(0.0355)	(0.0064)
Experiential_Category	0.0304***	0.0310***	0.0251***	0.0303***	0.0268***	0.4820***	0.0333***
	(0.0034)	(0.0034)	(0.0037)	(0.0034)	(0.0037)	(0.0213)	(0.0044)
Creator_Experience	0.1530***	0.1520***	0.1540***	0.1500***	0.1490***	0.6480***	0.1550***
	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0198)	(0.0100)
CoefOfVar_Prices × Num_Rewards		-0.0062***			-0.0062***		-0.0063***
		(0.0007)			(0.0007)		(0.0007)
CoefOfVar_Prices × Num_Rewards^2		0.0002***			0.0002***		0.0002***
		(0.0000)			(0.0000)		(0.0000)
Experiential_Category × Num_Rewards			-0.0073***		-0.0061***		-0.0061***
			(0.0007)		(0.0007)		(0.0008)
Experiential_Category × Num_Rewards^2			0.0001***		0.0001**		0.0001**
			(0.0000)		(0.0000)		(0.0000)
Creator_Experience × Num_Rewards				-0.0054***	-0.0061***		-0.0062***
				(0.0013)	(0.0013)		(0.0013)
Creator_Experience × Num_Rewards^2				0.0002***	0.0002***		0.0002***
				(0.0000)	(0.0000)		(0.0000)
Mean Num_Rewards in Category (Instrument)						0.1340***	
						(0.0035)	
Mean Num_Rewards in Other Categories (Instrument)						0.0230***	
						(0.0089)	
Residuals from First Stage							-0.0088***
							(0.0029)
Constant	1.8770***	1.8960***	1.8830***	1.8790***	1.9020***	-11.2300***	1.9760***
	(0.0311)	(0.0313)	(0.0311)	(0.0310)	(0.0310)	(0.2550)	(0.0466)
Month Indicators & Year_Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Creator_from_US Indicator	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2/Adjusted R^2	0.3640	0.3650	0.3650	0.3650	0.3660	0.4190	0.3730
rmse	0.4860	0.4860	0.4850	0.4860	0.4850	4.2630	0.4740
Log likelihood	-133,427	-133,345	-133,322	-133,357	-133,177	-514,846	-120,657
Observations	191,480	191,480	191,480	191,480	191,480	179,465	179,465

Note: Interaction variables are mean centered in the analyses. The continuous variables with skewed distribution are natural log transformed, refer Table 3.1 for details. Standard errors in parentheses - Het. robust clustered around creators in Models (1-5), and non-parametric bootstrap (200 replications) clustered around creators in Model (7).

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

The results from the complete specification, as presented in Model (5), demonstrate that the coefficient of dispersion of reward prices is negative ($\beta = -0.1170, p < 0.01$). The coefficient of the interaction of dispersion of reward prices with the number of rewards is negative ($\beta = -0.0062, p < 0.01$), and with the square of the number of the rewards is positive ($\beta = 0.0002, p < 0.01$). The results of this interaction, as plotted in Figure 3.11, for the high and low dispersion of reward prices ($\mu \pm 2\sigma$) show that the predicted *Funding_Ratio* is higher for the low dispersion of reward prices. The increase in *Funding_Ratio* with an increase in the number of rewards is also higher for low dispersion of reward prices, showing evidence to support hypothesis 2.

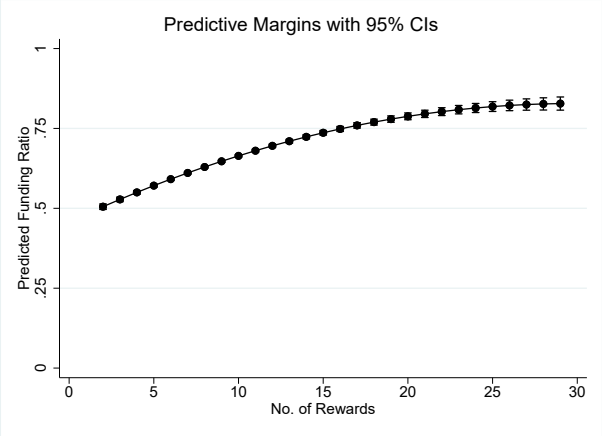


Figure 3.10: Association of Number of Rewards with Funding Ratio (H1)

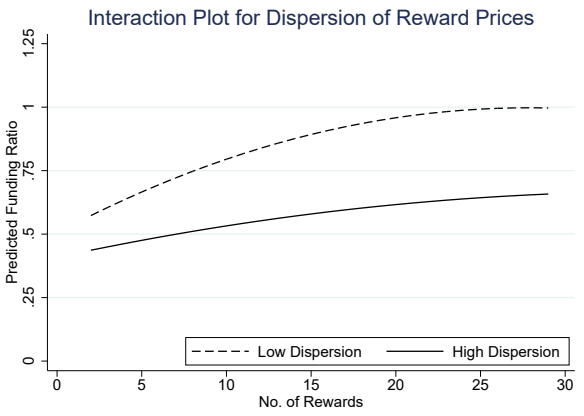


Figure 3.11: Interaction Effects of Number of Rewards with Dispersion of Reward Prices at $\mu \pm 2\sigma$ on Funding Ratio (H2)

Campaigns in the experiential-reward categories achieve higher performance ($\beta = 0.0268, p < 0.01$) as compared to the campaigns in the product-reward categories. The coefficient of the interaction of the $Experiential\_Category$ with the number of rewards is negative ($\beta = -0.0061, p < 0.01$) and with the squared number of rewards is positive ($\beta = 0.0001, p < 0.05$). The results for this interaction are also plotted in Figure 3.12. With the increase in the number of rewards from a low value, each additional reward's marginal effect is smaller for campaigns in the experiential-reward categories than in the product-reward categories. The binary dependent measure does not support hypothesis 3, but these results show evidence to support hypothesis 3 for the continuous measure *Funding_Ratio*.

The creator's prior crowdfunding experience has a positive effect on the *Funding_Ratio*

($\beta = 0.1490, p < 0.01$). The coefficient of the interaction of the creator's experience with the number of rewards is negative ($\beta = -0.0061, p < 0.01$), and with the squared number of rewards is positive ($\beta = 0.0002, p < 0.01$). Figure 3.13 plots this interaction at no and high creator's experience ($\mu + 2\sigma$). The *Funding_Ratio* at any given number of rewards is greater for high creator experience than for no creator experience. However, the slope for the relationship between the number of rewards and funding ratio appears more pronounced under no creator experience than under high creator experience, which shows evidence to support hypothesis 4.

We further test the results for the endogenous number of rewards in an instrumental variables model. We use the control function approach, as explained in Section 3.4.3, and employ the same instrumental variables. Model (6) in Table 3.5 presents the first stage results of the OLS regression of the number of rewards, and Model (7) shows the second stage with the control function method. The results are qualitatively similar to the baseline results and show evidence to support hypotheses 1-4 for the continuous measure *Funding_Ratio*.

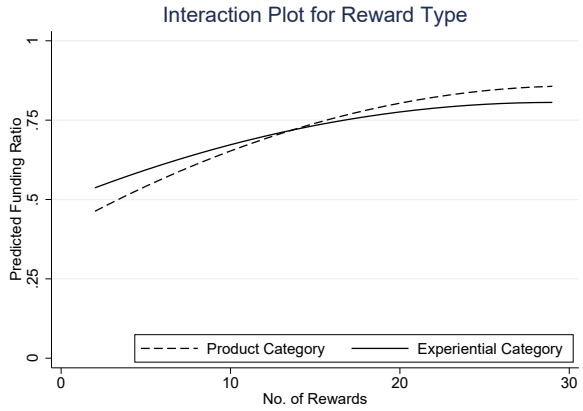


Figure 3.12: Interaction Effects of Number of Rewards with Reward Type on Funding Ratio (H3)

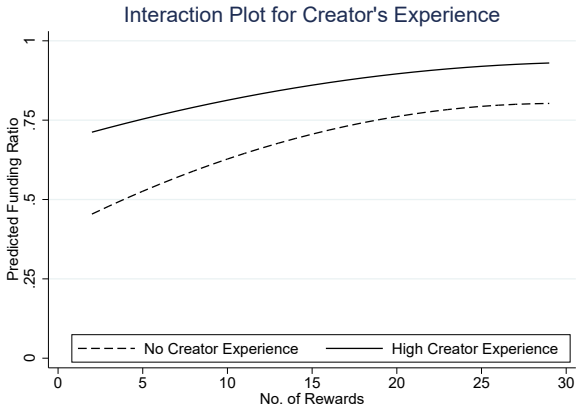
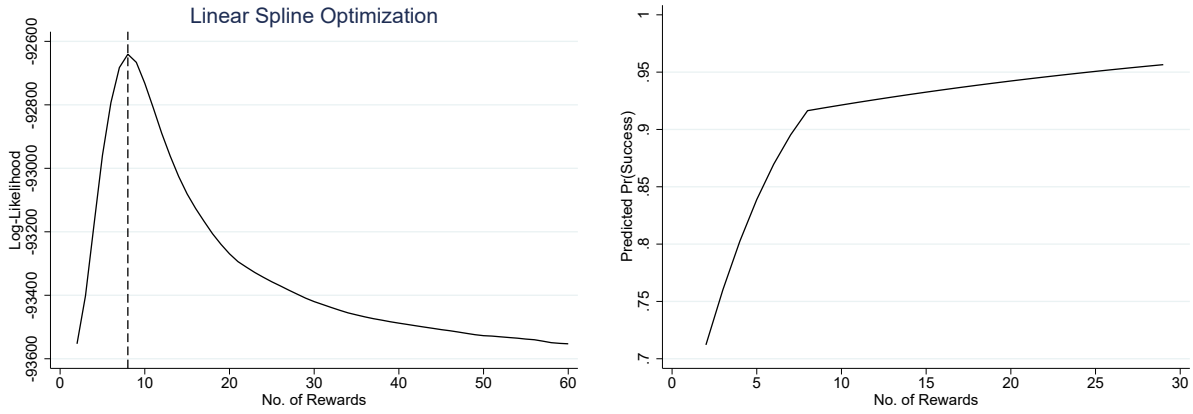


Figure 3.13: Interaction Effects of Number of Rewards with Creator's Experience on Funding Ratio (H4)

3.4.5 Robustness Checks

We present results with a quadratic fit for the number of rewards in Sections 3.4.2, 3.4.3, and 3.4.4. To provide additional support for the diminishing returns results for the number of rewards, as hypothesized in H1, and to assure that the assumption of a quadratic fit does not drive these results, we fit a piece-wise linear spline model with logit estimation for the binary

dependent variable $Success$. In the piece-wise linear spline logit regression model, we fix the starting knot and the ending knot positions at the minimum and maximum rewards (2 and 60, respectively). We identify the optimal location of the middle knot as the number of rewards that maximizes the log-likelihood function in the logit estimation. As shown in Figure 3.14a, the log-likelihood value is highest when the middle knot is located at 8 rewards. In Figure 3.14b, we present the corresponding linear two-segment spline, which maximizes the log-likelihood function. The slopes of both the splines are positive, as shown in Figure 3.14b, which demonstrates that funding success increases with the number of rewards. Additionally, the slope of the spline for less than 8 rewards is higher than the spline slope for more than 8 rewards. The positive slopes of the splines, coupled with the decline of the slope for a greater number of rewards, provide further evidence to support hypothesis 1 and show that the funding success improves with a higher number of rewards, but has diminishing returns to the number of rewards.



(a) Maximum Likelihood Optimization

(b) Optimized Linear Spline Fit

Figure 3.14: Piece-Wise Linear Spline Fit

Further, we perform additional robustness checks. We run a probit estimation on the binary dependent variable *Success*. The probit model assumes the normality of the residuals, which is relaxed in the logit model. We also run the instrumental variable estimation using the control function approach for the probit model. The results presented in Models (1-3) of Table 3.6 are qualitatively similar to the baseline results, providing support for hypotheses 1, 2, and 4.

Finally, as an additional robustness check, we utilize a multinomial logistic regression model of funding success by using a categorical dependent variable, $Categorical\_Success$ (Cornelius and Gokpinar 2020). Noting the significant variation in the fundraising perfor-

mance of crowdfunding campaigns, (Soublière and Gehman 2020) have proposed classifying campaigns into four distinct categories: (1) *Broken path failures* (which raised less than 20% of their goals), (2) *Path breaking failures* (which raised 20% or higher but less than 100% of their goals), (3) *Unsung successes* (which raised 100% or higher but less than 150% of their goals), and (4) *Blockbusters* (which raised 150% of their goals or higher). This classification provides a refinement to our main model by acknowledging that not all failures (and not all successes) are alike. We utilize the same thresholds to define our $Categorical\_Success$ variable; as such, the 20%, 100%, and 150% thresholds reflect the three inflection points in the distribution of the $Funding\_Ratio$ (Soublière and Gehman 2020), as shown in Figure 3.9b. The multinomial logistic regression results are presented in Model (4) of Table 3.6, where the base category is "*Broken path failures*," which collected less than 20% of their target funding goals. The first column of Model (4) in Table 3.6 shows results for the "*Path breaking failures*," the second column shows results for the "*Unsung successes*," and the last column shows results for the "*Blockbusters*." The coefficient of the number of rewards in the first column of Model (4) is positive and demonstrates that the likelihood of success increases with the number of rewards for the *Path breaking failures* compared to the *Broken path failures*. Further, the coefficients of the number of rewards in the second and third columns of Model (4) are also positive and demonstrate that the likelihood of success for these categories also increases compared to the *Broken path failures*. These results collectively demonstrate that several rewards in a campaign significantly increase the likelihood of attaining higher funding than the base category. The effect is significantly stronger for the *Blockbusters*, where the funding collected is $\geq 150\%$ of their target funding goals.

3.5 Discussion

Crowdfunding differs from conventional methods of financing for entrepreneurial ventures (Belleflamme et al. 2014). Since crowdfunding provides funding without debt or equity burdens in addition to early demand signals, platforms like *Kickstarter* are particularly attractive to independent creators (Gerber and Hui 2013). However, despite the motivation and efforts of creators, most campaigns remain unsuccessful in achieving the requested target funding goal

Table 3.6: Robustness Checks with Alternate Dependent Variables and Regression Models

	Probit	OLS First Stage	Probit Sec. Stage	mLogit		
	Success	Num_Rewards	Success	Cat. Success		
	(1)	(2)	(3)	(4)	(5)	(6)
Control Variables:						
Kickstarter_Recommendation	0.9490***	0.8840***	0.9380***	1.4680***	2.1370***	2.7680***
	(0.0124)	(0.0299)	(0.0158)	(0.0388)	(0.0316)	(0.0351)
Duration_Change	0.2160***	0.5030***	0.1990***	0.3680***	0.4940***	0.6600***
	(0.0258)	(0.0603)	(0.0286)	(0.0590)	(0.0452)	(0.0787)
Funding_Goal	-0.4110***	-0.2470***	-0.4210***	-0.5120***	-0.7780***	-1.1480***
	(0.0038)	(0.0126)	(0.0040)	(0.0091)	(0.0074)	(0.0115)
Campaign_Duration	-0.0087***	0.0059***	-0.0087***	-0.0065***	-0.0167***	-0.0161***
	(0.0003)	(0.0009)	(0.0003)	(0.0008)	(0.0006)	(0.0009)
Min_Reward_Price	0.1110***	-1.3450***	0.1310***	0.0804***	0.2390***	0.2180***
	(0.0049)	(0.0118)	(0.0137)	(0.0128)	(0.0096)	(0.0134)
Max_Reward_Price	0.1040***	1.5010***	0.0813***	0.0330**	0.1690***	0.1590***
	(0.0053)	(0.0121)	(0.0145)	(0.0137)	(0.0103)	(0.0145)
Num_Images_Videos	0.7810***	2.1850***	0.7380***	1.0120***	1.4190***	2.4610***
	(0.0076)	(0.0163)	(0.0220)	(0.0192)	(0.0153)	(0.0211)
Competition	-0.5160***	-0.2200***	-0.6030***	-0.6110***	-1.0490***	-1.2450***
	(0.0145)	(0.0348)	(0.0142)	(0.0348)	(0.0277)	(0.0346)
Prop_Limited_Rewards	-0.0632***	2.2400***	-0.0969***	0.0841***	-0.1910***	0.2370***
	(0.0123)	(0.0340)	(0.0247)	(0.0317)	(0.0241)	(0.0324)
Independent Variables:						
Num_Rewards	0.0592***		0.0763***	0.1180***	0.1380***	0.1650***
	(0.0017)		(0.0095)	(0.0045)	(0.0036)	(0.0045)
Num_Rewards^2	-0.0018***		-0.0018***	-0.0038***	-0.0041***	-0.0049***
	(0.0001)		(0.0001)	(0.0003)	(0.0002)	(0.0002)
CoefOfVar_Prices	-0.1750***	-0.5320***	-0.1660***	-0.1820***	-0.2010***	-0.7010***
	(0.0137)	(0.0355)	(0.0154)	(0.0369)	(0.0267)	(0.0386)
Experiential_Category	0.3430***	0.4820***	0.3280***	0.0928***	0.7100***	0.3420***
	(0.0087)	(0.0213)	(0.0104)	(0.0232)	(0.0174)	(0.0236)
Creator_Experience	0.0815***	0.6480***	0.0722***	0.3890***	0.1100**	0.7020***
	(0.0181)	(0.0198)	(0.0210)	(0.0397)	(0.0437)	(0.0537)
CoefOfVar_Prices × Num_Rewards	-0.0172***		-0.0165***	-0.0134***	-0.0364***	-0.0240***
	(0.0017)		(0.0018)	(0.0049)	(0.0035)	(0.0047)
CoefOfVar_Prices × Num_Rewards^2	0.0008***		0.0007***	0.0007**	0.0015***	0.0014***
	(0.0001)		(0.0001)	(0.0003)	(0.0002)	(0.0002)
Experiential_Category × Num_Rewards	0.0109***		0.0110***	0.0457***	0.0364***	0.0158***
	(0.0019)		(0.0021)	(0.0050)	(0.0038)	(0.0050)
Experiential_Category × Num_Rewards^2	-0.0002*		-0.0002	-0.0008**	-0.0006**	0.0004
	(0.0001)		(0.0001)	(0.0004)	(0.0002)	(0.0003)
Creator_Experience × Num_Rewards	-0.0100***		-0.0110***	-0.0119**	0.0124**	-0.0071
	(0.0024)		(0.0025)	(0.0054)	(0.0056)	(0.0064)
Creator_Experience × Num_Rewards^2	0.0007***		0.0007***	0.0009***	0.0008***	0.0009***
	(0.0001)		(0.0001)	(0.0003)	(0.0002)	(0.0003)
Mean Num_Rewards in Category (Instrument)		0.1340***				
		(0.0035)				
Mean Num_Rewards in Other Categories (Instrument)		0.0230***				
		(0.0089)				
Residuals from 1st Stage			-0.0174*			
			(0.0095)			
Intercept	5.6030***	-11.2300***	6.5800***	5.5210***	11.2900***	12.4300***
	(0.1010)	(0.2550)	(0.1320)	(0.2610)	(0.2010)	(0.2420)
Month Indicators & Year_Trend	Yes	Yes	Yes	Yes	Yes	Yes
Creator_from_US Indicator	Yes	Yes	Yes	Yes	Yes	Yes
R^2/Adjusted R^2		0.4190				
rmse		4.2630				
Log likelihood	-93,282	-514,846	-87,167	-183,511	-183,511	-183,511
Chi-squared	37,737		41,426	46,347	46,347	46,347
Observations	191,480	179,465	179,465	191,480	191,480	191,480

Note: Interaction variables are mean centered in the analyses. Standard errors in parentheses - Het. robust clustered around creators in Model (1) and Model (4), and non-parametric bootstrap (200 replications) clustered around creators in Model (3). $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

[a] *Base category in Multinomial Logit Regression is* $Funding\_Ratio$ *(FR) less than* 20%. *These categories are mutually exclusive.*

(Kuppuswamy and Bayus 2017, Mollick 2014). Our study provides insights into several factors at the campaign and the creator level that can help improve the likelihood of funding success.

Building on extant research in reward-based crowdfunding (Cordova et al. 2015, Kuppuswamy and Bayus 2017), this study examines the relationship between the reward structure of a campaign and its funding success. We find that the performance of a campaign improves with a higher number of rewards but with diminishing returns. Moreover, as hypothesized, the relationship between the number of rewards and funding success is stronger for campaigns, with a higher number of rewards under conditions of low dispersion of reward prices as compared to high dispersion of reward prices, and by creators with less crowdfunding experience as compared to more crowdfunding experience. However, we find that the relationship between the number of rewards and funding success is not stronger for campaigns with a higher number of rewards in the product-reward categories than in the experiential-reward categories. In fact, contrary to the hypothesis, the results are opposite and significant.

Our study contributes to the literature by highlighting the key factors in designing rewards under which creators can attain a high likelihood of funding success. The results for H1 show that the likelihood of funding success diminishes with the number of rewards. This finding aligns with the extant research that draws from the well-established concept of choice overload. Backers get motivated by rewards but face increased cognitive processing costs as the number of rewards increases (Carter and Gilovich 2010, Gourville and Soman 2005, Iyengar and Lepper 2000, Iyengar and Kamenica 2010). The findings for H2 suggest that dispersion of reward prices, that is, a high dispersion in contribution levels, influences the association between the number of rewards and the likelihood of funding success. More rewards with high dispersion of reward prices in a campaign increase the difficulty for backers to make a reward selection.

The support for H4 highlights that a creator should not overlook his or her prior experience when making campaign-level operational decisions in designing a campaign. Backers face information asymmetry issues of adverse selection and moral hazard that can be mitigated by increased creator experience. As backers consider the crowdfunding experience as a signal of trustworthiness, for achieving high finding success, there might be a lesser need to offer a higher number of rewards for a more experienced creator, as compared to a less experienced

one. These learnings may be translated to other innovation platforms, where prior experience might substitute for trust on these platforms. For example, solution seekers may doubt problem solvers' technical capabilities on crowdsourcing and hackathon platforms, and problem-solvers may doubt the solution seekers' honesty. The prior experience of problem solvers and solution seekers or their prior interactions may help build trust on such online social community platforms (Shi and Chow 2015).

An interesting area of future research is to delve further into the creator's prior crowdfunding experience. The findings from H4 suggest that creator experience can help overcome information asymmetry in reward-based crowdfunding campaigns. However, our study does not distinguish between prior successes from failures within the prior crowdfunding campaigns. Future research could incorporate learning models and distinguish between successful prior experiences from the unsuccessful ones while designing the reward structures. Moreover, since our focus was on reward-based crowdfunding campaigns, it will be insightful to know from the future if the findings are generalizable to other types of crowdfunding campaigns.

For H3, we consider either a campaign offers product rewards or experiential rewards. There is a possibility that a campaign offers mixed types of rewards. For example, a campaign providing a smartwatch as the primary reward also offers a chance to have dinner with the designers as a separate reward. With this limitation, our analysis reveals a nuanced role of type of rewards in the relationship between reward structure and performance. Campaigns with experiential rewards have a higher probability of achieving their goal when they offer more rewards; however, campaigns with product rewards raise more funding. These mixed results provide two interesting opportunities to explore for future research. First, research can investigate if the funding goal of campaigns needs calibration, depending upon whether the primary intent is to obtain funding success or a higher funding ratio. Second, research can also explore behavioral and perceptual differences between backers of experiential- and product-reward categories.

CHAPTER 4

PATENT PENDENCY AND FUTURE INNOVATIVE ACTIVITIES

4.1 Introduction

Schumpeterian growth models link a firms' economic growth and productivity to a series of successful innovations and their commercialization (Kogan et al. 2017). The commercialization of innovation involves producing the actual product, or technology trade and knowledge transfer between the original inventor and a firm capable of developing the product for the technology market (Teece 1986). However, the frictions in the technology market may significantly reduce the gains from commercialization. For example, inventors may find it threatening to disclose their inventions for the risk of imitation and expropriation (Arrow 1962). Furthermore, patents, by securing the inventor's intellectual property rights, protect against misappropriation, but the gains from the commercialization of innovation may be limited due to the uncertainties associated with the patenting process (Chao et al. 2009, Hall 2011, Popp et al. 2004). Moreover, the actual timing of the patent grant affects the costly search process to find and collaborate with a potential trade partner (Hellmann 2007, Gans et al. 2008). These numerous difficulties faced by inventors in commercializing their inventions may affect their incentives to innovate.

This paper evaluates the effect of frictions in the path of commercialization, such as a longer patent pendency, on the inventors' future innovative activities. Patent pendency is the time that patent examiners take to evaluate and grant patent applications after their filing with the patent office (Hegde and Luo 2018). The perception of a quick or long patent pendency may depend upon the inventors' belief about the patent examination duration (Tversky and Kahneman 1974). A patent accepted by the examiner in less time than expected would make a quick patent grant, whereas a patent granted in a longer time than expected would make the patent pendency longer, which may adversely affect the inventors' incentives to patent (Artz et al. 2010, Cohen et al. 2002, Hegde et al. 2020).

Patents serve several strategic and financial motives for inventors, whereas the patent ex-

amination's long pendency may reduce the perceived benefits from patenting. First, mere the ownership of a patent empowers individuals to demonstrate evidence that they meet the societal definition of "inventors" (Mazzoleni and Nelson 1998). Additionally, patents may serve as credentials on inventors' resumes, enabling inventors to receive additional benefits in terms of better position or salary (Rantanen and Jack 2019). Thus, the longer it takes for a patent to get granted, the longer inventors may have to wait for the recognition and gratification of their hard work.

Second, the reduction in the patents' perceived value due to longer patent pendency may lead to severe consequences for inventors, negatively affecting their growth and innovation (Farre-Mensa et al. 2016). Patents safeguard new products from imitation and prevent the competition from sharing returns from these products (Griliches 1998). Also, a patent grant has a significant effect on technology licensing (Gans et al. 2008). Moreover, patents not only serve as a protection mechanism for new products but also motivate new inventions by disclosing the knowledge developed (Mazzoleni and Nelson 1998). However, the realization of these benefits from patents relies on timely grants of patents (Cohen et al. 2002, Gans et al. 2008). These adverse effects resulting from a longer patent pendency on the inventors' incentives to patent leads to our research question: *how does a longer patent pendency affect the inventor's future innovative activities?*

To study the inventor's response to longer patent pendency, we develop a stylized model of a profit-maximizing inventor's decision of allocating her effort to the innovative and routine tasks in multiple periods. In settings where inventors can choose to invest their effort in innovative and routine tasks, a longer patent pendency can result in a relocation of the inventor's efforts between routine and innovative activities. Routine tasks have pre-determined wages and costs. However, outcomes of innovative activities are uncertain, and innovative activities are costly for the inventor.

We formulate the inventor's resource allocation problem in a multi-period setting where the belief about the patent pendency is updated in a Bayesian framework. In our model, an inventor allocates effort to innovative tasks and routine tasks in each period. In any given period, effort exerted in routine activities yields direct operational benefits that translate to predictable profits

in proportion to the effort. Increasing the effort in innovative activities improves the probability of making a patentable discovery. However, the rewards from innovation are obtained after the patent is granted. The duration of the examination time for a patent application is uncertain, and the patent loses value if the verdict is sufficiently delayed. Therefore, the optimal effort allocation depends on the inventor's belief about the probability of a longer patent pendency. The inventors update their belief about the probability of patent pendency based on their experience with the patent examination in each period. The inventor's objective is to maximize her profit from each period's innovative and routine tasks. The results from our analytical model show that (1) inventors reduce their effort in innovative activities on experiencing longer patent pendency in the past. We also find that (2) more successful inventors exert more effort on innovative activities, and (3) the adverse effects of longer patent pendency on innovative activities are more significant for inventors with fewer prior granted patents than inventors with more prior granted patents.

We hypothesize the analytical model's findings and test it using a matched sample constructed with inventor-patent data from the United States Patent and Trademark Office (USPTO) from $1975 - 2020$. This dataset contains about 4 million inventors and 7.2 million granted patents. To evaluate the effect of patent pendency on an inventor's future innovative activities, we construct a treated sample consisting of inventor-year observations where an inventor's prior patent takes longer in the patent examination before patent grant than the median patent pendency across the same industry. Then, we match these treated inventor-year observations using coarsened exact matching (CEM) with the inventor-year observations from the control sample. We also observe inventors' patenting lifespans and explore within variance using an inventor fixed-effects Poisson model in a panel setting.

The results from the empirical models provide evidence to support our hypotheses, confirming an adverse effect of longer patent pendency on the inventor's future innovative activities. We find evidence that a longer patent pendency negatively affects the future patenting activities of an inventor. We also find that inventors with more prior granted patents apply for more patent applications in a year. Furthermore, the adverse effects of patent pendency on innovative activities are more significant for inventors with fewer prior granted patents than inventors with

more prior granted patents. Finally, in an extension, we also find that inventors associated with small firms, than large firms, see a more significant reduction in their patenting due to longer patent pendency.

Our results have several implications and contribute to the discussions on resource allocation and incentive design (Aghion and Tirole 1994, Chao et al. 2009, Hellmann 2007). First, we study the inventor's resource allocation problem with an analytical model and provide empirical support for our findings, demonstrating the robustness of our results. Second, the innovation process involves several uncertainties, and often a times after completing a long journey, inventors fail to achieve the desired outcomes. For example, launching new products should have a positive impact on a firm, but a delay in the product launch negatively affects a firm's value (Hendricks and Singhal 1997). This paper evaluates the inventors' responses to such uncertainties in the innovation process and their effect on future innovative activities. Finally, less-successful inventors are more likely to reduce innovative activities on experiencing adverse outcomes. For example, when patent grants are sufficiently delayed, this may increase inventor churn. As a result, innovation becomes less lucrative for less successful inventors, and managers should adopt appropriate incentivizing strategies for the less successful inventors when patents cannot serve as devices to retain the inventive talent (Melero et al. 2020). Retaining inventive talent is essential for a firm because inventors' human capital is more critical than firms' capabilities for inventors' innovation output (Bhaskarabhatla et al. 2021). Overall, our study highlights potential negative consequences of innovation uncertainties and provides managerial insights to build and manage an innovative task force.

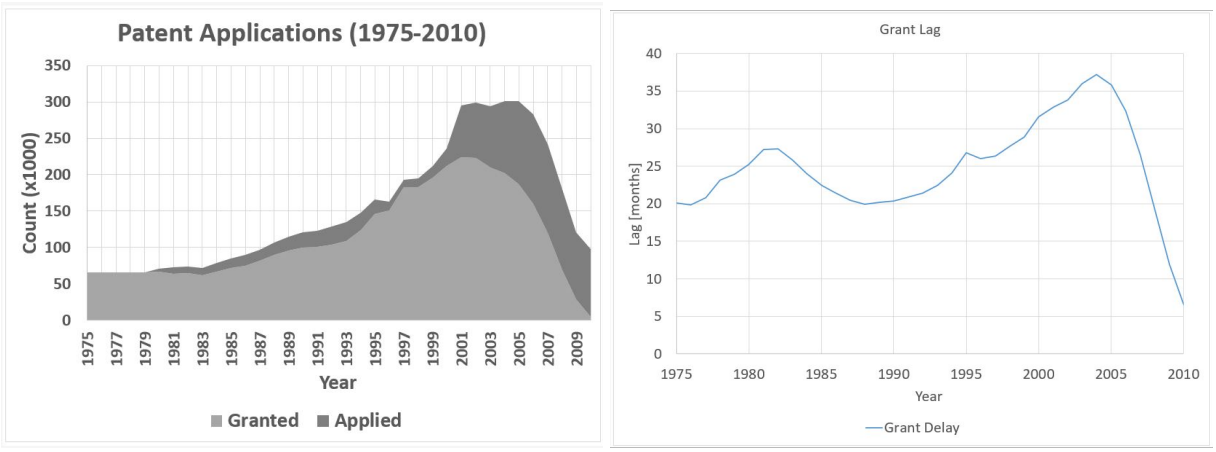
The organization of this paper is as follows. First, section 4.2 discusses the relevant literature, and section 4.3 introduces the analytical model and develops hypotheses. Next, we introduce data and variables and discuss CEM methodology in section 4.4 and present empirical methods and results in section 4.5. Then, section 4.6 discusses the panel data analysis and presents results. Finally, we conclude with a discussion of results in section 4.7.

4.2 Literature Review

Patenting inventions have been recognized in the Innovation literature as fulfilling several motives for inventors (Mazzoleni and Nelson 1998). First, patents incentivize innovation by serving the fundamental purpose of intellectual property protection that prevents competitors from imitating and producing products without seeking legal authority from inventors. This legal binding imposed by the patent system safeguards innovators and promotes innovation, but at the cost of granting a monopoly to inventors for the patent's active duration. Second, the patent system enables inventors to commercialize their inventions and appropriate value through licensing their patents. Third, inventors gain satisfaction and a sense of supremacy by legally disclosing their inventions to the world. The disclosure of inventions also avoids duplication of the existing inventions, thereby saving future losses. Finally, the patent system enables the patent holder through patent licensing to control the future inventions in their respective fields.

Additionally, patenting has direct benefits in promoting innovation and monetizing returns. Early market entry, enabled by patents' legal protection, has been seen as a critical milestone in reserving additional revenues, enabling firms to capture the majority of the demand and charge premium prices (Gaimon and Morton 2009, Kerin et al. 1992). First-mover advantage has also been recognized as a significant driver for the pace of innovation in short product life-cycle industries (Gaimon and Morton 2009). Research also provides empirical evidence to support this line of thought. Artz et al. (2010) analyze a dataset of 272 firms from 1986-2004 and find a positive relationship between a firm's number of patents and its development of new products. Cho and Pucik (2005) empirically analyze survey data of fortune 1000 firms and support a positive relationship between the firm's innovativeness, growth, and profitability.

The positive association between patents, innovation, and financial growth may motivate inventors to file more patent applications. Probably due to this positive association, the patent offices across the globe have observed tremendous growth in patenting activities in the last few decades (Harhoff and Wagner 2009, Popp et al. 2004). Figure 4.1a depicts the number of patent applications applied for and granted by the USPTO from 1975-2010. The number of applications filed increased faster than the available examiner resources, which has resulted



(a) Patents Applications (b) Patent Grant Lag

Figure 4.1: Patent Applications and Patent Grant Lag Distribution at the USPTO from 1975-2010

in a longer patent pendency as shown in Figure 4.1b. To address the issue of longer patent pendency, the USPTO has regularly recruited an increasing number of examiners. Figure 4.2 denotes the number of examiners and staff at the USPTO from 1993-2010. Due to a disproportionate increase in the examiners' workforce and patent applications over time, the examiners' workload has increased, which has reduced the examination quality, further fueling the growth in filing patent applications at the USPTO. This vicious circle has resulted in higher lags in the patent examination, irrespective of their quality (Régibeau and Rockett 2010).

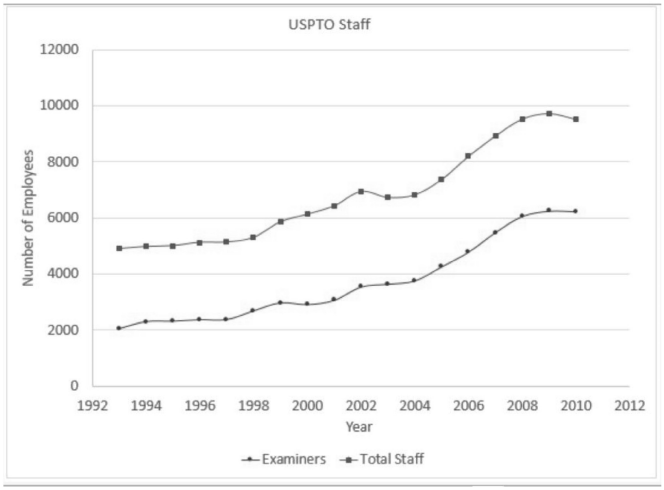


Figure 4.2: USPTO Staff from 1975-2010

In addition to the uncertain macroeconomic conditions in the innovation process, the patent

examination has several uncertainties that could negatively impact innovation monetization. The uncertainties associated with patent examination arise from different stages of the examination process. First, it is uncertain how many claims (scope) the USPTO confers in the grant of patents[1]. The USPTO examines each claim in the patent application against three fundamental criteria - *novelty*, *usefulness*, and *non-obviousness*, and fallback on any criteria could result in denial of the claim. Second, the outcome of the examination process is unknown until the USPTO mails the final notice to inventors with a decision to grant or reject the patent application. Finally, the commercialization of the invention depends on the outcome of the patent examination. More than the patent's grant or rejection, the final notice's timing also plays a significant role in realizing a licensing contract. Any delay in granting a patent could result in a lost opportunity for financial gains through licensing the inventions (Gans et al. 2008, Hegde and Luo 2018).

4.3 Model

4.3.1 Preliminaries

Our model applies to an inventor who makes an effort allocation decision between innovative and routine activities. Our model is similar to Hellmann (2007), who models a similar situation of an employee's choice to explore a new idea for intellectual property creation or focus on her assigned routine task. We consider an inventor who works on a new invention in each period and continues to invent in multiple equally spaced periods. It is possible to apply for one or more patent applications out of each invention if it is *novel*, *useful*, and *non-obvious* to someone practiced in the art (Conti et al. 2013).

The inventor invests her efforts in innovative activities to create intellectual property. Intellectual property not only helps to improve the current revenues but also generates new opportunities in future revenue streams from new products and patent licensing (Gans et al. 2008, Hall 2011). Thus investing efforts in innovative activities becomes more lucrative for inventors. On the other hand, routine activities are the core activities that help run the current business suc-

[1]A design patent application has only one claim, whereas a utility (technology) patent application can have more than one claim.

cessfully. e.g., performing activities related to manufacturing the existing products, technical consultation to teammates, official and managerial tasks. Therefore, we distinguish between innovative and routine activities as innovative activities can generate an intellectual property in terms of patents, whereas routine activities do not have such scope.

Let the effort spent on innovative activities at time t is e_t. Higher efforts improve the revenues generated out of innovative activities. Correspondingly, the effort spent on routine activities is $1 - e_t$. The total effort spent on innovative and routine activities in any period t is normalized to one. By normalizing the total efforts to one, e_t captures the notion that the inventor can improve the probability of obtaining a patentable invention in any period; further, it captures the (indirect) opportunity cost of innovation activities, which is the lost benefit from the routine activities.

4.3.2 Cost of Efforts

The inventor's resource allocation decisions on innovative and routine activities translate into costs of exerting these efforts - $C_1(e_t)$ for innovative activities and $C_2(1 - e_t)$ for routine activities. Innovative activities are riskier, unpredictable, labor-intensive, and idiosyncratic than routine activities (Holmstrom 1989). Let $C_i(0) = 0$ and C_i is increasing with efforts. We assume a convex cost function for innovative activities denoted by $\frac{1}{2}ce_t^2$, where c is the cost per unit effort spent on the innovative activities. Our assumption of a convex cost function showing diseconomies of scale for innovative activities is realistic over a considerable range of situations as innovative activities require considerable creativity and search in the unknown space (Chao et al. 2009). We assume a linear cost function for routine activities denoted by $d(1 - e_t)$, where d is the cost per unit effort spent on the routine (or "daily") activities.

4.3.3 Payoffs

The effort spent on innovative and routine activities generates two separate revenue streams for the inventor. The value generated from the innovative activities is uncertain and realized after the grant of the patent. The two factors that determine the value of a granted patent are its scope (which denotes the breadth of claims) and the timeliness of the patent examination

(Hegde et al. 2020) (which we discuss below in Section 4.3.4). The invention has a high value V_H if the patent is granted with a high scope with probability θ, and has a low value V_L if granted with a low scope with probability $(1-\theta)$. The expected returns from the innovative efforts in any period is given by $(\theta V_H + (1-\theta)V_L)e_t$. However, routine activities generate certain and immediate returns. Let the pay-off generated from routine activities is $w(1-e_t)$, where w is wage per unit of efforts with $w < V_H$ and $w \geq V_L$.

4.3.4 Probabilistic Patent Pendency

Commercialization of new inventions is affected by the technical, market, and patenting uncertainty (Chao et al. 2009, Hall 2011). Patent examination is prone to delays, which could reduce a patent's perceived value for inventors (Cohen et al. 2002, Mazzoleni and Nelson 1998). Even when the patent is granted with a high scope, a substantially longer patent examination process can result in loss of the patent's commercial value (Gans et al. 2008). In our model, the inventor losses (a portion of) the invention's commercial value if the patent is not granted within a duration of T_0; this parameter T_0 may be interpreted as a proxy for industry clock speed (Kessler and Chakrabarti 1996). The time T_0 may depend upon product launch, product or technology obsolescence, patent licensing, or any other personal or professional deadlines (Gans et al. 2008, Hall 2011, Rantanen and Jack 2019). Though the patent examination process is uncertain, the inventor forms a belief about patent examination duration by observing the examinations of their prior patents. The CDF of the distribution of patent pendency at time t is denoted by $P(T \leq T_0) = P_t$, where T_0 is the highest patent pendency duration for the patent to be useful for the inventor. If the patent takes lesser than T_0 to get granted, the patent realizes effort-dependent expected returns with probability P_t. Otherwise, the patent realizes a value of V_L with probability $(1-P_t)$.

We consider an exponential distribution for the patent pendency random variable T, the pending duration between the filing of patent i and its grant date. The assumption of an exponential distribution for the waiting time of the patent grant is reasonable due to the memorylessness property of the exponential distribution, which allows the patent pendency times of different patents to be independent of each other. Additionally, the assumption of an expo-

nential distribution is also in line with the literature where an exponential distribution has been used to model customers' waiting times in queues or patience time of customers waiting in queues (Lu et al. 2013, Wu et al. 2019). Let the realization of the random variable T for patent i at time t is s_{it} that captures the elapsed time from the patent filing date. Let the actual patent pendency duration for patent i from its filing date to its grant be denoted by t_i. i.e. $s_{it} \leq t_i$ as per the pending or granted status of patent i at time. The rate of the exponential distribution λ is apriori unknown to inventors. The PDF (CDF) of the exponential distribution of patent pendency duration, $T \sim Exp(\lambda)$, denoted by $f(s_{it})$ ($F(s_{it})$) and the mean of the random variable T are given by:

$$\begin{aligned} f(s_{it}) &= \lambda e^{-\lambda s_{it}} \\ F(s_{it}) &= 1 - e^{-\lambda s_{it}} \\ E[T] &= \frac{1}{\lambda} \end{aligned} \tag{4.1}$$

We assume that inventors, who do not have prior patenting experience, believe that the exponential distribution rate λ is Gamma distributed with shape parameter "a" and scale parameter "b," denoted by $\Gamma(a, b)$. The parameters of Gamma distribution change by the inventor's experience with the patent examination. We choose Gamma distribution for the prior of λ to accommodate the conjugate prior property of Gamma distribution for the exponential distribution, which ensures analytical tractability as suggested in the literature (Emadi and Swaminathan 2018). Due to the conjugate prior property, the posterior distribution of the conjugate prior λ is another Gamma distribution with the updated shape and scale parameters. The PDF of the Gamma distribution $\Gamma(a, b)$ of λ denoted by g(λ), its mean and variance are given by:

$$\begin{aligned} g(\lambda) &= \frac{b^a \lambda^{a-1} e^{-b\lambda}}{\Gamma(a)} \\ where,\ \Gamma(u) &= \int_0^\infty z^{u-1} e^{-z} dz = (u-1)\Gamma(u-1) \\ E[\lambda] &= \frac{a}{b} \\ Var(\lambda) &= \frac{a}{b^2} \end{aligned} \tag{4.2}$$

The belief update for the Gamma distribution happens as per the likelihood function for each inventor. For example, suppose the inventor has applied for n patents by time t. At the

time t, the inventor's belief update about the patent pendency happens based on her experience with these n patents. Thus, the likelihood function for grant times is given by:

$$\begin{aligned} L = f(S/\lambda) &= \prod_{i=1}^{n} \lambda e^{\lambda s_{it}} \\ &= \lambda^n e^{-\lambda S}, \quad S = \sum_{i=1}^{n} s_{it} \end{aligned} \tag{4.3}$$

where, s_{it} is the patent pending duration for patent i, which is equal to t_i if the patent i is granted by time t.

For a general case, let an inventor has filed n patent applications by time t, out of which a few of the patents are granted, and the rest are pending at time t. Let I_{it} is an indicator variable for patent i granted by time t.

$$I_{it} = \begin{cases} 0, & \text{if patent } i \text{ is pending at time } t \\ 1, & \text{if patent } i \text{ is granted at time } t \end{cases} \tag{4.4}$$

Proposition 1 characterizes inventors' belief updating process for n patents applied out of which some or all of the patents are pending or granted.

***PROPOSITION* 1.** *The parameters update of the Gamma distribution happens as per the following rule:*

$$\begin{aligned} \textit{Posterior Shape function, } A_t &= a + \sum_{i=1}^{n} I_{it} \\ \textit{Posterior Scale function, } B_t &= b + \sum_{i=1}^{n} s_{it} \end{aligned} \tag{4.5}$$

where, $s_{it} = t_i$ if $I_{it} = 1$, and s_{it} = Actual waiting time if $I_{it} = 0$. The CDF of the posterior distribution of patent pendency, denoted by $F^{Po}(T_0)$, is given by:

$$F^{Po}(T_0) = Pr(T \leq T_0) = 1 - \left(\frac{B_t}{B_t + T_0}\right)^{A_t} \tag{4.6}$$

Proposition 1 shows that the inventor's prior interactions with the USPTO affect their belief about patent pendency. The posterior shape parameter of the Gamma distribution represents the

number of patents granted, and the posterior scale parameter represents the cumulative patent examination duration of all the prior patent applications filed by inventor i irrespective of the prior patents' status as pending or granted. The shape parameter changes only if the patent is granted. In contrast, the scale parameter increases every period, even if the patent is pending with the USPTO. Thus, the parameter update of the Gamma distribution affects the posterior probability of patent pendency duration. The probability of a longer patent pendency is high if the prior patents took longer to get granted (refer Appendix B for proofs).

4.3.5 Inventor's Optimization Problem

The inventor's objective is to maximize her net payoff from innovative and routine activities in each period. The returns from innovative activities are uncertain and are realized after the patent grant. On the other hand, the returns from the routine activities are immediate. Therefore, the inventor's profit function at any time t is given by:

$$\begin{aligned} \pi_t &= P_t\left(\theta V_H + (1-\theta)V_L\right)e_t + (1-P_t)V_L e_t - \frac{1}{2}ce_t^2 + w(1-e_t) - d(1-e_t) \\ \text{or } \pi_t &= \left[P_t\left(\theta V_H + (1-\theta)V_L\right) + (1-P_t)V_L\right]e_t + w(1-e_t) - \frac{1}{2}ce_t^2 - d(1-e_t) \end{aligned} \tag{4.7}$$

Since the available quantum of efforts in any period is normalized to one, e_t may also be seen as the probability of obtaining a patentable invention. The inventor's payoff can be negative if no invention is discovered despite the inventor's high allocation of efforts to innovative activities. In contrast, the inventor should earn a positive payoff if she allocates all her efforts to routine activities. We assume that $w \geq d$ to focus on the non-trivial case where routine activities yield a positive payoff.

At the beginning of each period, the inventor updates her belief about patent pendency and chooses effort allocated to the innovative and routine activities that maximize her overall profits. Thus, our profit maximization model for efficient resource allocation is consistent with similar models found in the literature (Chao et al. 2009).

Proposition 2 characterizes the inventor's effort on innovative activities and the change in effort due to change in the model parameters.

***PROPOSITION* 2.** *Effort on the innovative activities, the rate of change of innovative effort w.r.t. patent pendency (B_t), and the rate of change of this partial derivative w.r.t. prior successful experience (A_t) are given as follows:*

(i) The effort on innovative activities are given by:

$$e_t = \frac{1}{c}\left[\left(1 - \left(\frac{B_t}{B_t + T_0}\right)^{A_t}\right)\theta(V_H - V_L) + V_L - w + d\right] \tag{4.8}$$

(ii) e_t *decreases in* B_t*, i.e.,* $\frac{\partial e_t}{\partial B_t} \leq 0$.

(iii) e_t *increases in* A_t*, i.e.,* $\frac{\partial e_t}{\partial A_t} \geq 0$.

(iv) $\frac{\partial e_t}{\partial B_t}$ *increases in* A_t*, i.e.* $\frac{\partial^2 e_t}{\partial B_t \partial A_t} \geq 0$.

Part (i) of Proposition 2 presents the optimal innovative effort of the inventor in any period as a function of her belief about patent examination duration and the expected revenues from innovative and routine tasks. On the other hand, part (ii) of Proposition 2 shows that inventors reduce their innovative effort after experiencing longer patent pendency.

Inventors form their belief about patent pendency and update it in every period as per the experience with their prior patent examinations. If a prior patent took longer than expected to get granted, it negatively affects their belief and vice versa. The negative belief update due to the long pendency of their prior patents reduces the probability of patent grants in the maximum advantageous duration T_0. As a result, the expected revenue generated from the innovative tasks also reduces. Since the total effort is fixed, and the routine tasks generate a higher revenue than the innovative tasks for the same amount of effort, the inventor reduces her effort on innovative tasks and spends more effort on routine tasks.

These arguments, with the results presented in Proposition 2(ii), lead to our first empirically testable hypothesis.

***HYPOTHESIS* 1** (H1)**.** *The inventor's effort on her innovative activities reduces on experiencing longer patent pendency (high B_t).*

Part (iii) of Proposition 2 shows that the inventor's innovative effort increases with more prior successful patenting experience. The probability of a patent grant in the expected duration

as per their belief depends upon the cumulative patent pendency experienced by the inventor and the number of prior granted patents. If an inventor has more prior granted patents for the same cumulative patent pendency, the average patent pendency reduces, increasing the inventor's belief about the probability of patent grant in a shorter duration within T_0. Due to the increased probability of shorter patent pendency, the revenues from the innovative tasks are expected to be higher than those from the routine tasks for the same amount of effort. Therefore, to maximize her overall profit, the inventor spends more effort on innovative tasks.

These arguments and results from part (iii) of Proposition 2 lead us to develop the following empirically testable hypothesis.

***HYPOTHESIS* 2** (H2)**.** *The inventor's effort on her innovative activities increases with more prior granted patents (high A_t).*

Part (iv) of Proposition 2 demonstrates that the reduction in innovative effort with longer patent pendency is lower for inventors with more prior successful patents than inventors with fewer prior granted patents. A longer patent pendency of prior patents reduces the inventor's belief about patent grants within time T_0, whereas more prior granted patents reduce average patent pendency, improving the probability of receiving a patent within the expected duration. Therefore, inventors with more prior granted patents are more optimistic with their belief about patent pendency than those with a few prior granted patents. As stated in hypothesis 1, inventors reduce their effort on the innovative tasks on experiencing longer patent pendency. However, due to the positive effect of more prior granted patents, the reduction in innovative effort is higher for inventors with fewer prior granted patents than inventors with more prior granted patents.

This intuition is in line with Farre-Mensa et al. (2016), who conducted an empirical study on startups and demonstrated that the patent approval for startups generates more jobs, improves growth prospects, and enables startups to innovate more and produce more patents. Patents also help inventors generate more business from their inventions by demonstrating technical superiority and patent licensing (Gans et al. 2008, Hegde and Luo 2018). These benefits are realized only by having successful patents, encouraging inventors to apply for more patents. Additionally, the dependence of rent appropriation from a single patent application reduces

as the inventor's patent portfolio increases with several successful patents (Chao et al. 2009). Therefore, the negative outcome of a single patent in terms of longer patent pendency is less likely to have a significant adverse effect on the inventor's choice of spending more effort on innovative tasks.

Prior successes also raise the inventor's self-efficacy; Repeated failures can have an opposite effect. *Self-efficacy* refers to one's belief about accomplishing a task, and it can also influence the choice of activities (Schunk 1995). The strength of the perception of self-efficacy dictates how much effort people will put in and how long they will sustain efforts in stressful and adverse situations (Bandura 1977). In the context of patents, inventors may consider the patent grants as positive feedback from an expert (patent examiner), and the repetitive successes reinforce the inventor's positive belief. This positive feedback from successful patent grants improves inventors' perception of their self-efficacy and may motivate inventors to exert more effort in innovative activities in adverse conditions.

These arguments and the results from part (iv) of Proposition 2 lead us to develop the following empirically testable hypothesis.

***HYPOTHESIS* 3** (H3)**.** *The prior granted patents moderate the relationship between the inventor's innovative effort and patent pendency such that the relationship will be weaker when the inventor has more prior granted patents (high A_t).*

We present the conceptual model for the hypotheses in Figure 4.3.

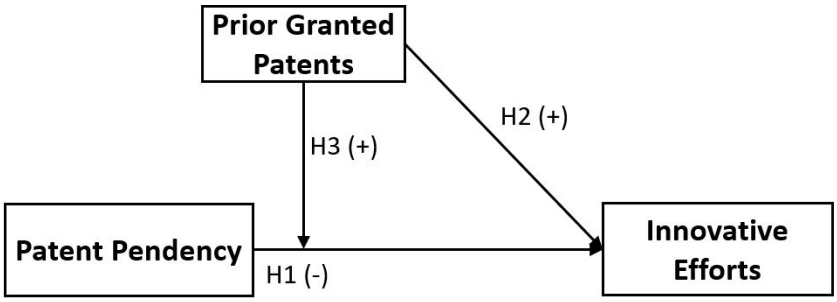


Figure 4.3: Conceptual Model

4.4 Methodology

4.4.1 Data Source

We use patent data from the United States Patent & Trademark Office (USPTO) between 1975 to 2020 in design and technology (utility) innovations. This dataset is compiled from several resources. We start with the inventor level patent data provided by Li et al. (2014), where disambiguation of inventor names has been performed to account for different names of the same inventor. This dataset has also been used by Melero et al. (2020) that includes granted patents from $1975 - 2010$. Next, we extend this data with the *USPTO* Patent Examination Research Dataset (Public Pair), compiled by Graham et al. (2018) that includes the abandoned applications from 1910 to 2014, which is further substantiated with the *PatentsView* (*https://patentsview.org*) raw data hosted by the USPTO to include all the applications until 2020. The abandoned and granted patent applications together proxy for the inventor's total effort on innovative activities.

There are several reasons why a patent application is denied a grant and abandoned. An abandonment could happen due to non-fulfillment of the examination requirements of proving radical difference from the existing prior art. Inventors may also fail to respond to the examiner's requests with the required details in the stipulated time, withdraw the patent application, or be unsuccessful in paying the patent application fees. We extract only the number of applications abandoned by each inventor in a year and add it to the number of patents granted to measure the total number of applications applied by an inventor in a year.

Additionally, we use industry to patent technology class matching data provided by North American Industry Classification System (NAICS). We categorize patent applications into six industry classifications - *Aerospace*, *Automotive*, *Chemical and Biotechnology*, *Computers and Electronics*, *Medical Equipment*, and *Others* (Hall et al. 2001).

4.4.2 USPTO Patent Process

The patent examination process at the United States Patent and Trademark Office (USPTO) constitutes four stages: the drafting and filing stages, the examination stage, and the appro-

priation stage. The invention's value is identified in the drafting stage, and the patent application package is prepared collectively by the technical staff, business decision-makers, and an intellectual property attorney. Figure 4.4 shows a timeline for different stages of the patent examination process at the USPTO for utility or process patents. For example, a utility patent has a life of twenty years from the date of its application, and the patent requires renewal by the inventor at 3.5 years, 7.5 years, and 11.5 years after its grant. On the other hand, though design patents have a similar process, a design patent has a life of fifteen years from the date of its application with no requirement to pay the additional fees for its renewal.

The *USPTO* has a provision of filing for different types of patent applications depending upon the invention stage at the time of filing. A provisional application may be filed to start the application process and reserve the priority date, even if the inventor is not ready to file a patent application for the invention. A non-provisional application must be filed to retain the priority date. The priority date determines the date before which the prior art will be considered to evaluate the patent application. The patent examination is started only after a non-provisional application is received by the *USPTO*, which has to be filed within one year from the filing date of the provisional application. A non-provisional application may also be filed directly if an invention is ready to be examined. Unlike patent offices of other countries, the *USPTO* automatically starts the examination process after a non-provisional patent application is filed. The *USPTO* grants patents on utility, design, and plant inventions. We study the utility and design patents granted for process and design inventions, respectively.

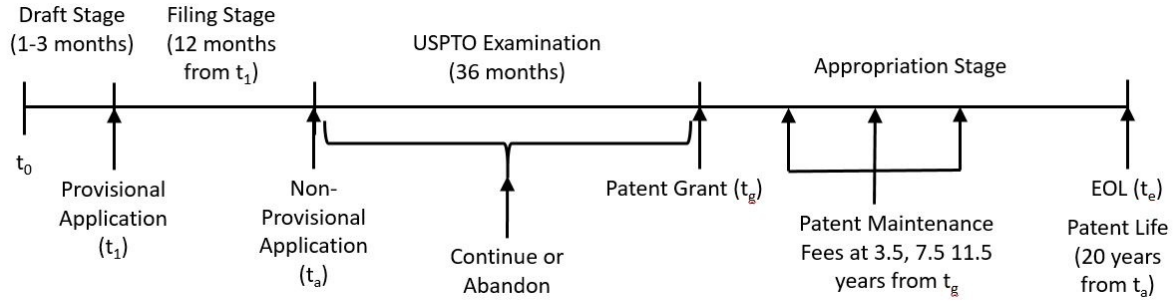


Figure 4.4: Patent examination process timeline for utility patents

Once a non-provisional patent application is filed, it is randomly assigned to an examiner in the respective art unit related to the patent's technology class (Farre-Mensa et al. 2019). The

examiner examines a patent application for *novelty*, *usefulness*, and *non-obviousness*. Once the examiner completes the preliminary examination, the "first action decision" with the required details is communicated to the inventor. The inventor has six months to respond to the examiner's concerns. On receiving a response from the inventor, the examiner has to submit his response in two months. Finally, if the examiner decides to grant the patent, the examiner communicates the patent application's acceptance to the inventors via *"Patent Allowance Notice."* After an administrative processing lag of 1-19 months post-patent allowance notice (Gans et al. 2008), the patent is granted to the inventor. We calculate patent grant lag from the time a non-provisional application is filed to when the examiner grants the patent. The USPTO allows modifying the patent application with the help of "continuing patent applications," facilitating a patent grant rate, maybe as high as 90% (Gans et al. 2008). Since most patent applications are finally granted, we consider the abandoned patent applications only in the calculation of an inventor's innovative efforts. Once a patent is granted, the inventor or assignee can appropriate its value by getting exclusive legal rights to manufacture and sell product/technology or earn revenues from the patent licensing (Mansfield 1986).

4.4.3 Empirical Strategy

We want to study the effect of patent pendency on inventors' future innovative activities, and the estimates from this model could be biased due to selection bias. The patent examination process requires several communications between the examiner and the inventor. Inventors have up to six months to respond to the examiner's queries in each round. Some inventors may have a strategic advantage in taking more time to respond to the examiner's queries to delay the patent examination. The extended examination period may be beneficial for the strategic inventors as it provides partial protection, postpones financial obligations of maintaining patents, and creates uncertainty for rivals for extended periods (Harhoff and Wagner 2009). A matching algorithm would randomly match such inventors with other inventors with similar characteristics who might have experienced different patent examination duration.

In order to address the selection bias in patent pendency, we employ Coarsened Exact Matching (CEM) procedure (Iacus et al. 2011, 2012) as our primary empirical strategy. We con-

struct a control sample equivalent to the treatment sample using CEM by balancing inventor-level pre-treatment covariates. Since the patent grant lag is a continuous variable and an inventor may experience patent pendency several times during her patenting tenure, we calculate a binary treatment variable for matching and capturing multiple treatments for an inventor. We provide more details on the treatment and matching in Sections 4.4.4 and 4.4.5 respectively.

4.4.4 Measures and Descriptive Statistics

This section describes our measures for the dependent variable, treatment, and inventor's characteristics to match treatment with controls using CEM. The variables and their descriptive statistics are presented in Table 4.1.

Innovative Effort

We measure our dependent variable as *Innovative Effort*, operationalized as the total number of patent applications filed by an inventor in a year (*NumApp*) (Farre-Mensa et al. 2019, Harhoff and Wagner 2009). This measure includes all patent applications filed by an inventor in a year, which might be granted or abandoned in the future. On average, an inventor files for 1.50 patent applications in a year with a median of 1. We consider a natural logarithmic transformation of this variable (*LogNumApp*) in the linear regression analyses due to its skewed distribution (Aggarwal and Hsu 2014, Hegde and Luo 2018). The mean and standard deviation of *LogNumApp* are 0.68 and 0.63, respectively.

Treatment

We calculate a binary treatment variable for matching based on the patent grant lag. We calculate patent grant lag (Lag) in months[2] as the difference between the patent grant date and the patent application's filing date (Singh and Agrawal 2011).

Next, we calculate the treatment variable by comparing the patent grant lag against a reference. An inventor experiences a treatment if the patent grant lag for any of her prior patent

[2]A month of 30 days assumed for calculation purposes.

Table 4.1: Description of Variables for CEM Sample (Before Matching)

Variable	**Description**	Observations	Mean	Median	SD
NumAPP	Yearly #Patent applications filed by an inventor	9,913,582	1.50	1.00	2.54
LogNumAPP	ln(NumApp)	9,913,582	0.68	0.69	0.63
Treated	1-Patent Grant Lag $>$ Median Patent Grant Lag for the class; 0-Otherwise	9,913,582	0.55	1.00	0.50
NormTreatedLag	Continous variable for the binary Treated variable and normalized lag for the last patent	9,913,582	-0.47	-0.19	0.74
CumNormLag	Cumulative Normalized Lag for prior patents	9,913,582	-3.68	-1.57	10.07
NormPriorLag	Normalized Lag for the last and prior pending patents	9,913,582	-2.73	-1.30	6.78
LogPriorPatents	ln(#Prior patents granted)	9,913,582	1.14	0.69	1.12
SmallFirm	1-Small Entity status or Individual; 0-otherwise	9,913,582	0.19	0.00	0.39
Category	1-Aerspace; 2-Automotive; 3-Chemical & Biotechnology; 4-Computers & Electronics; 5-Medical Equipment; 6-Others	9,913,582	4.53	4.00	1.28
US	1-US; 0-Others	9,913,582	0.49	0.00	0.50
Japan	1-Japan; 0-Others	9,913,582	0.18	0.00	0.39
Europe	1-Europe; 0-Others	9,913,582	0.15	0.00	0.36
RestOfTheWorld	1-Rest of the World; 0-US, Japan, and Europe	9,913,582	0.18	0.00	0.38
Application Year	Patent Application Filing Year	9,913,582	2005.12	2007.00	10.70

Notes: Descriptive statistics are presented for the initial dataset of $9,913,582$ *inventor-year observations from 1975-2020.* $NumApp$ *is winsorized at 0.05%.*

applications exceeds the median patent grant lag in the same technological class[3]. The median patent grant lag is calculated for all the patent applications in the previous year in the focal patent's technology class. An illustration is presented in Table 4.2. The patent number 0515296 applied in 1991 has a patent grant lag of 16 months, greater than the class-level median patent grant lag of 10 months. Therefore this patent is delayed and provides treatment to the inventor. However, this treatment is realized in the year 1992, ten months (median patent grant lag in class 410) after the application date of patent number 0515296. Had this inventor applied for a patent in 1992, the $Treated$ variable would be one for that year. Since this inventor does not have a patent applied in 1992, we create a row for 1992 and assign treatment to the inventor.

Similarly, the patent number 0515845, applied in 1996, is also delayed, and the inventor experiences treatment in 1999, 30 months (median patent grant lag in class 382) after the application date of patent number 0515845. Since this inventor does not have a patent applied in 1999, we create a row for 1999 and assign the treatment for this inventor. We use this dataset,

[3]Patents are assigned to specific technological fields, distributed in classes (Hall et al. 2001). A technological class relates a patent to a broad area of the invention's specific industry.

Table 4.2: Illustration of Treatment

Patent	Appl. Date	Appl. Year	Grant Date	Class	Lag	Class Med.	Delayed	Treated
0515296	05-10-1991	1991	09-10-1992	410	16	10	1	0
-	-	1992[a]	-	410	16	10	0	1
0515488	05-15-1993	1993	05-15-1995	386	24	28	0	0
0515845	05-10-1996	1996	01-10-1999	382	32	30	1	0
0516900	05-10-1998	1998	-	383	24	32	0	0
-	-	1999[b]	-	382	-	30	0	1

Notes: a. Patent number 0515296 is delayed and its effect is realized 10 months after the application date, ie. in year 1992.
b. Patent number 0516900 is delayed and its effect is realized 30 months after the application date, ie. in year 1999.

created with the additional rows, as explained above, for the CEM analysis.

Cumulative Normalized Patent Grant Lag

In order to align our empirical estimation with the analytical model, we define a continuous independent variable called *Cumulative Normalized Patent Grant Lag* and fit a regression model on the matched sample. We calculate patent grant lag for each of the prior patents of an inventor as per the pending or granted status of the prior patent applications before the focal patent's filing date. For any patent granted before the focal patent's application date, the patent grant lag is calculated as the difference in months between the patent grant date and its filing date. Suppose the prior patent application is pending by the focal patent's filing date. In that case, the grant lag is the difference in months between the focal patent's filing date and the filing date of the prior patent application[4]. As the patent grant lag distributions vary across different technological classes, we calculate the technological class level mean and standard deviation of the patent grant lags for all the patents applied a year before the focal patent's application year (Harhoff and Wagner 2009). We calculate *Cumulative Normalized Patent Grant Lag* as the sum of patent grant lags for the inventor's prior patents, normalized[5] w.r.t. the patent's technological class, and operationalize it as *CumNormLag*.

Table 4.3 presents an illustration of the calculations of *CumNormLag*. Suppose an inventor has three prior patent applications in 1991, 1993, and 1996, and is applying for her fourth patent

[4]Since inventors are informed about the patent grant decision at least one month or more before the actual patent grant (Gans et al. 2008), we consider the prior patent to be granted for calculation purposes if the prior patent is granted within a month after the filing date of the focal patent.

[5]$z = \frac{(x-\mu)}{\sigma}$

Table 4.3: Illustration of CumNormLag Calculations [All lags in months]

Patent	Appl. Date	Grant Date	Class	Lag	CumLAG	LogCumLAG
0515296	05-10-1991	09-10-1992	410	16	-	-
0515488	05-15-1993	05-15-1995	386	24	16	2.77
0515845	05-20-1996	-[a]	382	-	40	3.69
0516900	05-10-1998	-	383	-	$\left[40 + 24^{b}\right] = 64$	4.16

Notes: a. Patent not granted by the focal application date of May 1998.

b. Expected lag = (05-10-1998) - (05-10-1996) = 24 months

application in 1998. The Lag is calculated as of the fourth patent application's filing date in 1998. The patent applications filed in 1991 and 1993 are granted before 1998 with the patent grant lags of 16 and 24 months, respectively. Since the patent number 0515845 is pending as of *May 10, 1998*, its grant lag is calculated by subtracting the current date *(May 10, 1998)* and the application date of the patent number 0515845, i.e., *May 10, 1996*, which gives a patent grant lag of approximately 24 months. *CumNormLag* for the fourth patent is calculated by summing up the normalized patent grant lags for all the prior patents.

Additionally, we employ another independent variable, *NormPriorLag*, which is the normalized patent grant lag for the last patent and any prior pending patent. This variable is also in line with the treatment variable and captures its effect with a continuous variable.

Further, we define a variable $NormTreatedLag$, representing the continuous form of the $Treated$ variable. The calculations for $NormTreatedLag$ are similar to $CumNormLag$ and $NormPriorLag$. $NormTreatedLag$ is calculated for the $Treated = 1$ rows as the normalized lag of the patent that provides treatment, and for $Treated = 0$ rows, it is calculated as the average normalized lag of the previous year's patents.

Inventor Characteristics

To account for inventor heterogeneity, we include the inventors' observed portfolio size, associated firm size, demography, and industry. To test hypotheses 2 and 3, we measure *Prior Granted Patents* (*LogPriorPatents*) as a proxy for the inventor's portfolio size and measure it as the natural logarithm of the cumulative number of patents granted to the inventor before

the focal patent's application date (Chan et al. 2020, Harhoff and Reitzig 2004, Harhoff et al. 2016). A more extensive portfolio size would reduce the inventor's dependence on a single patent application for profits.

We define a measure *Small Firm* (*SmallFirm*) and operationalize this measure as a dummy variable with a value of one if the inventor claims "Small Entity Status" while filing the patent application with *USPTO* or the patent is assigned to an individual inventor instead of a firm (Cerqueiro et al. 2017, Graham and Hegde 2015). We assign a value of zero to *SmallFirm* by assuming[6] the rest of the inventors to be associated with large firms (not assigned a "Small-Entity Status" in the patent application). Patent applications filed by individual inventors, non-profits, and for-profit corporations with fewer than 500 employees are granted "Small-Entity Status" by the *USPTO* (Hall 2011, Graham and Hegde 2015, Graham et al. 2018). These applicants receive a discount of $50\% - 75\%$ on USPTO patent filing and examination fees[7]. There is likely a lesser chance of falsely reporting a small-entity status by large corporations' applicants for two reasons. First, falsely reporting a small entity status would make a ground for canceling the patent. Second, the *USPTO* fees are much smaller than the attorney fees, so the benefit of making a false claim on the patent application would be much smaller than the risks associated with this act (Graham et al. 2018).

We also include dummy variables for an inventor's country of origin to control its demographic effects. We distinguish inventors from the United States (*US*) (49% of applications in the sample), Japan (*Japan*) (18% of applications in the sample), Europe (*Europe*) (15% of applications in the sample), and the rest of the world (*RestOfTheWorld*) (18% of applications in the sample), where *US* is used as the reference group (Harhoff et al. 2016). To control for industry-level variations, we also operationalize a categorical variable ($Category$) and include six industry category dummies for the six categories - *Aerospace* (0.62% of applications in the sample), *Automotive* (4.20% of applications in the sample), *Chemical and Biotechnology* (15.27% of applications in the sample), *Computers and Electronics* (38.96% of applications in the sample), *Medical Equipment* (3.61% of applications in the sample), and *Others* (37.34% of applications in the sample), where *Others* is the base category.

[6]We also confirmed the assumptions behind this measure with an Ex. Chief Economist of the USPTO.

[7]For additional information, see the USPTO website at http://www.uspto.gov/web/offices/pac/mpep/s509.html

We use lagged values of these variables in matching before the treatment year. We also include lagged number of applications applied ($LogNumApp$) to match inventors on their effort levels before the treatment. Finally, we include filing year in matching, enabling us to find a control observation for the treated observation in the treatment year. This matching routine also allows a treated individual *i* to act as a control observation for another treated individual *j* in a year when inventor *i* does not receive treatment.

4.4.5 Coarsened Exact Matching (CEM)

The main goal of any matching algorithm is to ensure a distributional balance between the treated and control groups. Coarsened Exact Matching (Iacus et al. 2011, 2012) is a process that entails coarsening a set of observed pre-treatment covariates and performing matching on the strata created with the coarsened data. CEM method reduces monotonic imbalance among the covariates, which means that the balance between the treated and control groups is chosen ex-ante rather than discovered after matching. Additionally, adjusting imbalance on one variable does not affect the imbalance of any other variable in CEM (Blackwell et al. 2009). In CEM, each observation in the dataset is assigned to the strata, and the extra observations are pruned so that each stratum has at least one treated and one control observation. We perform one-to-one CEM matching, where each treated observation is matched to only one control observation. However, after matching, each stratum can have more than one treated and the corresponding control observations. Though matching is performed on the coarsened strata, regression estimations are performed on the original uncoarsened variables for the pruned matched data (Blackwell et al. 2009).

Table 4.4 presents the lagged matching variables for the treated and control observations. The table reveals a good balance among $3,200,292$ treated and $3,200,292$ control inventor observations. It also shows the difference between the means of treated and control observations and the t-statistics for their difference. All the differences are statistically insignificant, demonstrating a perfectly matched sample. Table 4.5 presents descriptive statistics of the treated, control, and total observations for the matched sample, and Table 4.6 shows their pairwise correlations.

Table 4.4: Balance between Treated and Control Groups after Matching

	Treated [N=3,200,292]		Control [N=3,200,292]			
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	t-stat (p-value)
LogNumApp_lagged	0.87	0.48	0.87	0.48	0.00	0.87 (0.38)
LogPriorPatents_lagged	1.00	1.06	1.00	1.06	0.00	0.64 (0.52)
Category_lagged	4.55	1.27	4.55	1.27	0.00	0.00 (1.00)
US_lagged	0.50	0.50	0.50	0.50	0.00	0.00 (1.00)
Europe_lagged	0.14	0.35	0.14	0.35	0.00	0.00 (1.00)
Japan_lagged	0.20	0.40	0.20	0.40	0.00	0.00 (1.00)
RestOfTheWorld_lagged	0.16	0.37	0.16	0.37	0.00	0.00 (1.00)
SmallFirm_lagged	0.17	0.38	0.17	0.38	0.00	0.00 (1.00)
Application Year	2004.56	10.31	2004.56	10.31	0.00	0.00 (1.00)

Notes: There are 3200292 treated and 3200292 control observations, with a total of 6400584 observations in the matched sample. "_lagged" signifies lagged values of the variables before the treatment year.

Table 4.5: Summary Statistics of the Treated and Control Groups after Matching

	Treated [N=3,200,292]		Control [N=3,200,292]		Total [N=6,400,584]	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
NumApp	1.99	2.00	1.12	2.13	1.56	2.11
LogNumApp	0.98	0.42	0.49	0.64	0.74	0.59
NormTreatedLag	-0.12	0.26	-1.01	0.86	-0.56	0.77
CumNormLag	-3.82	6.83	-3.42	6.66	-3.62	6.75
NormPriorLag	-2.65	4.77	-2.72	4.56	-2.68	4.67
LogPriorPatents	1.33	1.00	1.13	1.08	1.23	1.05
SmallFirm	0.18	0.38	0.17	0.38	0.17	0.38
Category	4.51	1.26	4.53	1.27	4.52	1.27
US	0.50	0.50	0.50	0.50	0.50	0.50
Europe	0.14	0.35	0.14	0.35	0.14	0.35
Japan	0.20	0.40	0.20	0.40	0.20	0.40
RestOfTheWorld	0.16	0.37	0.16	0.37	0.16	0.37
Application Year	2004.56	10.31	2004.56	10.31	2004.56	10.31

Notes: Descriptive are presented for the matched sample for $3,200,292$ *treated and* $3,200,292$ *control observations, with a total of* $6,400,584$ *observations.* $NumApp$ *is winsorized at 0.05%.*

Table 4.6: Pairwise Correlation for the Matched Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) LogNumApp	1										
(2) Treated	-0.405	1									
(3) NormTreatedLag	-0.244	0.548	1								
(4) CumNormLag	-0.425	-0.030	0.093	1							
(5) NormPriorLag	-0.447	-0.044	0.125	0.828	1						
(6) LogPriorPatents	0.434	-0.059	0.027	-0.290	-0.240	1					
(7) SmallFirm	-0.092	0.014	0.033	0.065	0.071	-0.081	1				
(8) US	-0.015	-0.009	-0.001	0.009	0.012	-0.029	0.159	1			
(9) Japan	0.105	-0.041	-0.018	-0.047	-0.041	0.196	-0.191	-0.468	1		
(10) Europe	-0.062	0.023	0.022	0.047	0.044	-0.066	-0.079	-0.414	-0.200	1	
(11) RestOfTheWorld	-0.023	0.032	-0.001	-0.012	-0.018	-0.094	0.063	-0.439	-0.218	-0.191	1

Notes: All pair-wise correlations are significant at 5% *level.*

4.5 Results

Equation 4.9 shows the empirical model. The dependent variable is the log number of patent applications ($LogNumApp$) filed by an inventor in a year. We employ four independent variables - a binary variable $Treated$ that captures the effect of the longer patent pendency, a continuous variable $NormTreatedLag$ that captures the effect of the treatment with a continuous variable, $CumNormLag$ that encapsulates the effect of patent pendency for all the prior patents of an inventor, and $NormPriorLag$, capturing the effect of the last patent and any prior pending patent (H1). In addition, we include $LogPriorPatents$ in the specification that demonstrates the effect of successful prior patents of an inventor (H2). The interaction of $LogPriorPatents$ with the independent variables demonstrates the effect of patent pendency on inventors as per their number of prior granted patents (H3). We fit these models with ordinary least squares (OLS) for the logged dependent variable and the Negative Binomial Model for the unlogged dependent variable.

$$\begin{aligned} LogNumApp_{i,t} &= \beta_0 + \beta_1 X_{i,t,j} + \beta_2\, LogPriorPatents_{i,t} \\ &\quad + \beta_3\, LogPriorPatents_{i,t} \times X_{i,t,j} + \alpha Controls_{i,t} + \epsilon_{i,t}, \;\; j = \{1,2,3,4\} \\ where, \;\; X_{i,t} &= \{Treated_{i,t},\; NormTreatedLag_{i,t},\; CumNormLag_{i,t},\; NormPriorLag_{i,t}\} \end{aligned} \tag{4.9}$$

Table 4.7 presents regression estimates for the matched sample. Models (1)-(2) in Table 4.7 present OLS estimates for the dependent variable $LogNumApp$ and the treatment variable $Treated$. As shown in Model (1), inventors reduce their effort on innovative activities after experiencing longer patent pendency ($\beta = -0.492, p < 0.01$). We add independent and control variables in Model (2) to account for any remaining imbalance in matching[8] (Aggarwal and Hsu 2014). The coefficient of $Treated$ remains significant and negative ($\beta = -0.459, p < 0.01$). i.e., inventors reduce their innovative effort by 37% ($exp(-0.459) - 1$) on experiencing longer patent pendency than inventors who experience shorter patent pendency. These results show evidence to support Hypothesis 1.

Hypothesis 2 states that inventors' innovative activities increase with more prior granted patents in the inventor's portfolio. The coefficient of $LogPriorPatents$ in Model (2) is significant and positive ($\beta = 0.071, p < 0.01$), which provides evidence to support Hypothesis 2.

Hypothesis 3 states that the negative effects of patent pendency on an inventor's innovative activities are lesser for inventors with more prior granted patents than inventors with fewer patents. The coefficient of the interaction of $Treated$ and $LogPriorPatents$ is positive and significant ($\beta = 0.188, p < 0.01$). These results demonstrate evidence to support Hypothesis 3.

Further, we repeat the same OLS analyses for the matched sample in Models (3), (4), and (5) with the same dependent variable $LogNumApp$ and the continuous independent variables $NormTreatedLag$, $CumNormLag$ and $NormPriorLag$ respectively. The coefficients of $NormTreatedLag$ in Model (3) ($\beta = -0.187, p < 0.01$), $CumNormLag$ in Model (4) ($\beta = -0.050, p < 0.01$), and $NormPriorLag$ in Model (5) ($\beta = -0.057, p < 0.01$) are negative and significant, showing a negative effect of patent pendency on innovative efforts and supporting Hypothesis 1. The significant and positive coefficients of $LogPriorPatents$ in Model (3) ($\beta = 0.197, p < 0.01$), Model (4) ($\beta = 0.143, p < 0.01$), and Model (5) ($\beta = 0.163, p < 0.01$) demonstrate a positive effect of prior granted patents on innovative efforts, which shows evidence to support Hypothesis 2. The coefficients of the inter-

[8]We used lagged values of these variables in CEM matching.

action of $NormTreatedLag$ and $LogPriorPatents$ in Model (3) ($\beta = 0.092, p < 0.01$), $CumNormLag$ and $LogPriorPatents$ in Model (4) ($\beta = 0.012, p < 0.01$), and $NormPriorLag$ and $LogPriorPatents$ in Model (5) ($\beta = 0.006, p < 0.01$) are also significant and positive, showing evidence to support Hypothesis 3.

Table 4.7: Regression Results for the Matched Sample

Model	OLS									Neg. Binomial			
Dependent Variable	LogNumApp					LogNumApp_tp1				NumApp			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Treated	-0.492***	-0.459***				-0.063***				-0.715***			
	(0.001)	(0.000)				(0.000)				(0.001)			
LogPriorPatents		0.071***	0.197***	0.143***	0.163***	0.092***	0.135***	0.092***	0.105***	0.130***	0.363***	0.247***	0.271***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Treated ×		0.188***				0.073***				0.448***			
LogPriorPatents		(0.000)				(0.001)				(0.001)			
SmallFirm		-0.073***	-0.060***	-0.019***	-0.023***	-0.081***	-0.079***	-0.046***	-0.047***	-0.195***	-0.170***	-0.048***	-0.053***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
NormTreatedLag			-0.187***				-0.062***				-0.293***		
			(0.003)				(0.001)				(0.001)		
NormTreatedLag ×			0.092***				0.032***				0.201***		
LogPriorPatents			(0.003)				(0.001)				(0.001)		
CumNormLag				-0.050***				-0.036***				-0.084***	
				(0.000)				(0.000)				(0.000)	
CumNormLag ×				0.012***				0.006***				0.022***	
LogPriorPatents				(0.000)				(0.000)				(0.000)	
NormPriorLag					-0.057***				-0.045***				-0.103***
					(0.000)				(0.000)				(0.000)
NormPriorLag ×					0.006***				0.000				0.019***
LogPriorPatents					(0.000)				(0.000)				(0.000)
Intercept	0.985***	1.078***	0.823***	0.868***	0.847***	0.521***	0.474***	0.473***	0.456***	0.814***	0.428***	0.392***	0.361***
	(0.000)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.013)	(0.012)	(0.008)	(0.008)
Category FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Appl. Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6400584	6400584	6400584	6400584	6400584	6400584	6400584	6400584	6400584	6400584	6400584	6400584	6400584
R^2	0.171	0.298	0.200	0.311	0.291	0.080	0.082	0.171	0.180				
Adjusted R^2	0.171	0.298	0.200	0.311	0.291	0.080	0.082	0.171	0.180				
Log likelihood	-5154875	-4623197	-5040908	-4561984	-4655634	-5777872	-5772750	-5444277	-5410428	-10052107	-10271752	-9533415	-9639355
Chi-squared										646061	486678	768874	939813

Notes: The dependent variable is $LogNumApp$ in OLS models (1)-(5). The dependent variable is $LogNumApp$ for time period t+1 in OLS models (6)-(9) to test persistence of the treatment in the subsequent year, and the dependent variable is $NumApp$ in Negative Binomial models (10)-(13). Continuous interaction variables are mean centered in the analyses.

Heteroskedastic robust standard errors clustered around inventors in parentheses.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Next, we perform robustness checks and test the persistence of the negative effects of patent pendency on innovative efforts in the subsequent year after the treatment. We run OLS specification in Models (6)-(9) for the dependent variable $LogNumApp$ one year after the treatment. We find that the coefficients of $Treated$ ($\beta = -0.063, p < 0.01$), $NormTreatedLag$ ($\beta = -0.062, p < 0.01$), $CumNormLag$ ($\beta = -0.036, p < 0.01$), and $NormPriorLag$ ($\beta = -0.045, p < 0.01$) reduce in absolute magnitude but retain the same signs and remain significant. We also find that the effects of $LogPriorPatents$ and its interaction with $Treated$,

$NormTreatedLag$, and $CumNormLag$ remain similar and significant, supporting Hypotheses 1-3, except for $NormPriorLag$, where the effect is insignificant.

Finally, we estimate the same specification for the unlogged $NumApp$ variable and the binary and continuous independent variables $Treated$, $NormTreatedLag$, $CumNormLag$, and $NormPriorLag$ in Models (10)-(13) using Negative Binomial specification. As conjectured in Hypothesis 1, the coefficient of $Treated$ in Model (10) is negative and significant ($\beta = -0.715, p < 0.01$). Inventors who experience longer patent pendency are likely to have 0.715 lesser applications in the subsequent year post-treatment than the untreated inventors. The coefficient of $LogPriorPatents$ is significant and positive ($\beta = 0.130, p < 0.01$), and the coefficient of the interaction of $Treated$ and $LogPriorPatents$ is also positive and significant ($\beta = 0.448, p < 0.01$). Similarly, Model (11) with $NormTreatedLag$, Model (12) with $CumNormLag$, and Model (13) with $NormPriorLag$ demonstrate similar results and provide additional evidence to support Hypotheses 1-3.

4.6 Panel Data Analysis and Model Extension

We present the three main hypotheses and adopt a matching methodology to support the hypotheses empirically in the previous sections. The cross-sectional analysis on the matched sample explores across-inventor heterogeneity and demonstrates the adverse effects of patent pendency on the inventor's innovative effort. In addition, the matching method addresses the concern of inventors' selection bias in the patent examination. This section employs a fixed-effects model and explores within-inventor heterogeneity to address the endogeneity concerns for patent pendency and test the core hypothesis. We also extend our analytical model and study the interaction of the control variable *Small Firm*, and employ additional measures and controls to corroborate the results.

The results presented in Proposition 2 may be further extended by taking partial differential w.r.t patent value differential ($V_H - V_L$).

***PROPOSITION* 3.** *Effort on the innovative activities, the rate of change of innovative effort w.r.t. patent pendency (B_t), and the rate of change of this partial derivative w.r.t. value differential ($V_H - V_L$) are given as follows:*

(i) The effort on innovative activities are given by (as presented in Proposition 2):

$$e_t = \frac{1}{c}\left[\left(1 - \left(\frac{B_t}{B_t + T_0}\right)^{A_t}\right)\theta(V_H - V_L) + V_L - w + d\right] \tag{4.10}$$

(ii) e_t *decreases in* B_t*, i.e.,* $\frac{\partial e_t}{\partial B_t} \leq 0$.

(iii) $\frac{\partial e_t}{\partial B_t}$ *decreases in* $(V_H - V_L)$*, i.e.* $\frac{\partial^2 e_t}{\partial B_t \partial (V_H - V_L)} \leq 0$.

4.6.1 Effect of Patent Value Differential

Part (iii) of Proposition 3 shows that the reduction in innovative effort with patent pendency is higher for inventors with considerable $(V_H - V_L)$ than inventors with small $(V_H - V_L)$. The difference in the realized values V_H and V_L depends upon the patent grant scope, which may have different implications for small and large firms (Gans et al. 2008, Hegde and Luo 2018). A patent granted with all the requested claims (high scope), ceteris paribus, can realize the same value V_H for small and large firms. However, a significant difference in $(V_H - V_L)$ can come from realizations of different V_L values for small and large firms when the patent is granted a reduced scope than requested by the inventor.

Firms have different usage and valuations of their intellectual properties. The main motive to patenting for small firms is to secure financing, whereas large firms quote patent blocking, using patents in negotiations, and preventing suits to be more important than financing or increasing revenues through patent licensing (Cohen et al. 2002, Graham et al. 2009). A small firm or an individual with no patent portfolio or a few patents intends to enter into an industry with a high-scope valuable patent. In contrast, a large firm intends to strengthen its position by building an extensive patent portfolio to maximize the combined portfolio value to ensnare its infringers. Moreover, the value of a patent is judged by the patent claim scope, which is not necessarily the number of claims but the scope and wording of the patent claims. Because the USPTO does not grant many claims in a single patent application, large firms seek to create patent portfolios to increase the claim scope in their portfolio. Thus, even a patent granted with a low grant scope could help strengthen the existing patent portfolio of a large firm. However, a small firm's patent granted with a low scope might not generate valuable outcomes. Small firms

realize the patent value through venture capital speculations about the innovation value of the patent, which is usually ephemeral and drops to almost zero with time for most patents. However, a minority of small firms evidence a significant increase in value by possessing high-value litigated patents (Hall and Ziedonis 2001, Coughlin 2007).

Although patent litigation signals a high value to venture capitals, patent litigation is increasingly becoming difficult to avoid and turning out to be a costly affair due to increased patent enforcement costs, making it difficult for small firms to protect their intellectual property. Large firms are advantaged over small firms in protecting their inventions because of two possible mechanisms. First, large firms are more likely to have large patent portfolios than small firms. An extensive portfolio reduces the likelihood of litigating any single patent in the portfolio. Second, large firms have more connections and avenues for repeated interactions with other firms over the same technology, a different product or markets, or patent licensing. Due to its reputation and possession of large patent portfolios, a large firm is more likely to have superior negotiating power than a small firm in repeated interactions with its rivals. Due to these inadequacies of small firms over large firms, small firms are less likely to succeed in protecting their inventions than large firms (Arundel 2001, Lanjouw and Schankerman 2004). The tendency of small firms to protect their inventions even reduces for a patent granted with a small scope, making the practical value of a low-scope patent almost equivalent to zero.

These arguments and the results from part (iii) of Proposition 3 lead us to conjecture that an inventor's affiliation with a small or large firm can moderate the relationship between patent pendency and inventor's future innovative effort, and we develop the following fourth empirically testable hypothesis.

***HYPOTHESIS* 4** (H4)**.** *The inventor's association with a large or small firm moderate the relationship between the inventor's innovative effort and patent pendency such that the relationship will be stronger for an inventor working for a small firm (high* $(V_H - V_L)$*).*

4.6.2 Measures and Controls

We employ the same measures and controls for the panel data analysis that we defined in Section 4.4.4. We use the baseline panel dataset in this section without the additional rows

for treatment as explained in Section 4.4.4. Table 4.8 presents variables, their construction, measures, and descriptive statistics. The Pearson correlations among the variables of interest are shown in Table 4.9.

Table 4.8: Description of Variables

Variable	Description	Observations	Mean	Median	SD
NumApp	Yearly #Patent applications filed by an inventor	6,460,972	2.30	1.00	2.84
CumNormLag	Cumulative Normalized Lag for prior patents	6,460,972	-4.70	-2.22	11.88
NormPriorLag	Normalized Lag for the last and all prior pending patents	6,460,972	-3.42	-1.72	8.11
LogPriorPatents	ln(1+#Prior patents granted)	6,460,972	1.42	1.10	1.11
SmallFirm	1-Small Entity status or Individual; 0-otherwise	6,460,972	0.17	0.00	0
Category	1-Aerospace; 2-Automotive; 3-Chemical and Biotechnology; 4-Computers and Electronics; 5-Medical Equipment; 6-Others	6,460,972	4.50	4.00	1.26
US	1-US; 0-Others	6,460,972	0.49	0.00	0.50
Japan	1-Japan; 0-Others	6,460,972	0.21	0.00	0.41
Europe	1-Europe; 0-Others	6,460,972	0.14	0.00	0.34
RestOfTheWorld	1-Rest of the World; 0-US, Japan, and Europe	6,460,972	0.16	0.00	0.37
Application Year	Filing year of the patent application	6,460,972	2004.46	2007.00	10.24

Notes: Descriptive statistics are presented for the final dataset of $6,460,972$ *inventor-year observations from 1975-2020 after discarding observations for the first year for each inventor to initiate CumNormLag variable.* $NumApp$ *is winsorized at 0.05%.*

Dependent Variable

We use the same dependent variable, as explained in Section 4.4.4, *Innovative Effort* as the total number of patent applications filed by an inventor in a year, operationalized as *NumApp* (Farre-Mensa et al. 2019, Harhoff and Wagner 2009). On average, an inventor files for 2.30 patent applications with a median of 1 and a standard deviation of 2.84.

Independent, Moderating, and Control Variables

The primary independent variable to test hypothesis 1 is *Cumulative Normalized Patent Grant Lag*, which is the sum of patent grant lags for the inventor's prior patents, normalized w.r.t. the patent's technological class, and operationalized as *CumNormLag*. We explain this measure in Section 4.4.4. The mean of *CumNormLag* is -4.70 with a standard deviation of 11.88.

Additionally, we employ another independent variable *NormPriorLag*, which is the normalized patent grant lag for the last patent and any prior pending patent. Unlike *CumNormLag*, which captures the cumulative lag for all of the inventor's prior patents, this variable captures the differential shocks in terms of patent grant lags and is more in line with the panel data structure. The mean of *NormPriorLag* is -3.42 with a standard deviation of 8.11.

Table 4.9: Pairwise Correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) NumApp	1								
(2) CumNormLag	-0.625	1							
(3) NormPriorLag	-0.671	0.838	1						
(4) LogPriorPatents	0.311	-0.287	-0.241	1					
(5) SmallFirm	-0.065	0.066	0.074	-0.057	1				
(6) US	-0.019	0.010	0.013	-0.042	0.167	1			
(7) Japan	0.027	-0.031	-0.027	0.176	-0.196	-0.512	1		
(8) Europe	-0.041	0.046	0.044	-0.053	-0.076	-0.391	-0.207	1	
(9) RestOfTheWorld	0.038	-0.025	-0.032	-0.085	0.066	-0.412	-0.226	-0.171	1

Notes: All non-zero pair-wise correlations are significant at 1% *level.*

The first moderating variable to test hypotheses 2 and 3, as explained in Section 4.4.4, is *Prior Granted Patents* (*LogPriorPatents*), measured as the natural logarithm of the cumulative number of patents granted to the inventor before the focal patent's application date (Chan et al. 2020, Harhoff and Reitzig 2004, Harhoff et al. 2016). The mean of *LogPriorPatents* in the dataset is 1.42 and a standard deviation of 1.11.

The second moderating variable, as explained in Section 4.4.4, to test hypothesis 4 is *Small Firm* (*SmallFirm*). There are 17% firms with a small firm status in the dataset, and 83% firms are considered large firms.

Finally, we also include dummy variables for an inventor's country of origin to control for its demographic effects. We distinguish inventors from the United States (*US*) (49% of applications in the sample), Japan (*Japan*) (21% of applications in the sample), Europe (*Europe*) (14% of applications in the sample), and the rest of the world (*RestOfTheWorld*) (16% of applications in the sample), where *US* is used as the reference group (Harhoff et al. 2016). To control for

industry level variations, we define a categorical variable $Category$ and include industry dummies for the six categories - *Aerospace* (0.54% patents), *Automotive* (4.05% patents), *Chemical and Biotechnology* (15.82% patents), *Computers and Electronics* (40.14% patents), *Medical Equipment* (3.69% patents), and *Others* (35.76% patents), where *Others* is the base category. Additionally, we also control for the fixed effects of inventors and the patent application year.

4.6.3 Estimation

The main estimation equation relates the innovation effort to the patent pendency experienced by an inventor and is presented in Equation 4.11 to test hypotheses 1-4. The dependent variable is *NumApp*, which is the number of patent applications applied by an inventor 'i' in year 't.' The main independent variable is the normalized cumulative lag experienced by the inventor (*CumNormLag*), which tests the effect of patent pendency on inventor's future activities (H1). We also test this model with the alternate independent variable *NormPriorLag*. The moderating variables are *LogPriorPatents* (H2 and H3) and *SmallFirm* (H4). Finally, we include controls and the fixed effects of inventors (λ_i) and patent application year (γ_t). The inventor fixed effects λ_i control for any time-invariant characteristics that determine an inventor's effort decisions based on patent grant delays. The filing year fixed-effects γ_t control for any macroeconomic changes at the USPTO. The regression coefficient β_1 is the main coefficient of interest that captures the effect of patent pendency on the inventor's innovative effort (H1). β_2 gives the direct effect of prior granted patents on the inventor's innovative effort (H2), and β_3 gives its interactions with patent pendency (H3). β_5 shows the moderating effect of an inventor's association with a small firm and patent pendency (H4).

$NumApp$ in Equation 4.11 is a discrete and non-negative count variable of inventor's innovation output. Following the literature, we test this model using the conditional fixed-effects Poisson model with quasi-maximum-likelihood (QML) standard errors clustered at the inventor level (Abadie et al. 2017, Sohn 2021). The QML (robust) standard errors are robust to the issues of serial correlation (Wooldridge 1999). Additionally, we use the same controls that we

employ to test Equation 4.9.

$$
\begin{aligned}
NumApp_{i,t} = \beta_0 + \beta_1\, X_{i,t,j} + \beta_2\, LogPriorPatents_{i,t} \\
+ \beta_3\, LogPriorPatents_{i,t} \times X_{i,t,j} + \beta_4\, SmallFirm_{i,t} \\
+ \beta_5\, SmallFirm_{i,t} \times X_{i,t,j} + \alpha\, Controls_{i,t} + \lambda_i + \gamma_t + \epsilon_{i,t}, \;\; j = \{1, 2\} \\
where, \;\; X_{i,t} = \{CumNormLag_{i,t},\; NormPriorLag_{i,t}\}
\end{aligned}
\tag{4.11}
$$

4.6.4 Results

Table 4.10 provides regression results for the fixed-effects Poisson model. Our hierarchical regression model includes regression variables step-by-step in Models (1-4) for *CumNormLag* and in Models (5-8) for *NormPriorLag*. Model (1) includes the primary independent variable and control variables. Models (2) and (3) show the interactions of the independent and the moderating variables. Finally, Model (4) presents the complete model, and we interpret our results from Model (4). Similarly, Model (8) demonstrates the corresponding results for the alternate independent variable *NormPriorLag*. These models include fixed effects of inventors and patent application filing year and specify heteroskedastic-robust standard errors clustered around inventors.

As shown in Model (4), inventors from Japan ($\beta = -0.030, p < 0.01$) and Europe ($\beta = -0.012, p < 0.10$) file a lesser number of patent applications per year than inventors from the US. There is no significant difference among inventors from the US and the rest of the world ($\beta = 0.004, p > 0.10$). Inventors in *Aerospace* ($\beta = -0.110, p < 0.01$), *Automotive* ($\beta = -0.048, p < 0.01$), *Chemical and Biotechnology* ($\beta = -0.060, p < 0.01$), and *Medical Equipment* ($\beta = -0.014, p < 0.01$) file a lesser number of patent applications as compared to inventors applying in *Others* category. Inventors patenting in *Computers and Electronics* ($\beta = 0.000, p > 0.10$) industry category are not different from those patenting in *Others* category.

Further, we evaluate the effects of independent and moderating variables. We conjectured a negative relationship between patent pendency and the inventor's innovative effort (H1). As

Table 4.10: Fixed-Effects Poisson Regression (Dependent Variable: $NumApp$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Country: Japan	-0.025*	-0.025**	-0.030**	-0.030***	-0.032***	-0.032***	-0.038***	-0.0379***
	(0.013)	(0.011)	(0.013)	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)
Country: Europe	-0.027***	-0.007	-0.032***	-0.012*	-0.025***	-0.0097	-0.031***	-0.015**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Country: RestOfTheWorld	-0.013***	0.003	-0.011**	0.004	-0.007	0.00576	-0.005	0.007
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
Category: Aerospace	-0.109***	-0.108***	-0.112***	-0.110***	-0.110***	-0.109***	-0.113***	-0.112***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Category: Automotive	-0.043***	-0.046***	-0.046***	-0.048***	-0.042***	-0.043***	-0.045***	-0.046***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Category: Chemical and Biotechnology	-0.064***	-0.060***	-0.064***	-0.060***	-0.065***	-0.063***	-0.065***	-0.064***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Category: Computers and Electronics	0.005***	0.003*	0.002	0.000	0.007***	0.006***	0.004*	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Category: Medical Equipment	-0.017***	-0.016***	-0.015***	-0.014***	-0.018***	-0.018***	-0.016***	-0.016***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
CumNormLag	-0.014***	-0.028***	-0.014***	-0.028***				
	(0.001)	(0.001)	(0.001)	(0.001)				
LogPriorPatents		0.038***		0.038***		0.025***		0.024***
		(0.002)		(0.002)		(0.005)		(0.005)
LogPriorPatents × CumNormLag		0.005***		0.005***				
		(0.000)		(0.000)				
SmallFirm			-0.084***	-0.077***			-0.096***	-0.090***
			(0.004)	(0.003)			(0.004)	(0.004)
SmallFirm × CumNormLag			-0.002**	-0.003***				
			(0.000)	(0.000)				
NormPriorLag					-0.015***	-0.026***	-0.015***	-0.063***
					(0.001)	(0.001)	(0.001)	(0.001)
LogPriorPatents × NormPriorLag						0.004***		0.004***
						(0.000)		(0.000)
SmallFirm × NormPriorLag							-0.010***	-0.008***
							(0.002)	(0.002)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Application Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5735129	5735129	5735129	5735129	5735129	5735129	5735129	5735129
Log likelihood	-7163820	-7004720	-7161321	-7002245	-7205082	-7132234	-7197817	-7126449
Chi-squared	16496	21352	18760	23816	18333	21630	20365	23677

*Notes: The dependent variable is $NumApp$, winsorized at 0.05%. Continuous interaction variables are mean centered in the analyses. All the models include inventor and year fixed effects. Industry category dummies are included, where "*Others*" is the base category. Country dummies are included, where "*US*" is the base category.*

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

shown in Model (4), inventors reduce their innovative effort on experiencing higher cumulative normalized patent grant lag (*CumNormLag*) ($\beta = -0.028, p < 0.01$). Similarly, evaluating the effect of patent pendency with *NormPriorLag* in Model (8), we find that inventors also reduce their effort on innovative activities on experiencing higher patent grant lags ($\beta = -0.063, p < 0.01$). These results demonstrate evidence to support hypothesis 1.

Next, we hypothesized a positive effect of prior granted patents on the inventor's innovative effort in hypothesis 2. Inventors having more prior granted patents, as shown in Model (4) ($\beta = 0.038, p < 0.01$) and Model (8) ($\beta = 0.024, p < 0.01$), apply for more patent applications than those with lesser prior granted patents. Evaluating the moderation of prior granted patents as conjectured in hypothesis 3, the reduction in the innovative effort due to patent pendency is smaller for inventors with more prior granted patents in Model (4) ($\beta = 0.005, p < 0.01$) and Model (8) ($\beta = 0.004, p < 0.01$). These results show evidence to support hypotheses 2 and 3.

Finally, hypothesis 4 negatively moderates the relationship between the patent pendency for inventors associated with small firms. Inventors working with small firms or individual inventors apply for a lesser number of patent applications than inventors working with large firms in Model (4) ($\beta = -0.077, p < 0.01$) and Model (8) ($\beta = -0.090, p < 0.01$). We also find that the reduction in innovative effort in Model (4) ($\beta = -0.003, p < 0.01$) and Model (8) ($\beta = -0.008, p < 0.01$) is higher for inventors working with small firms and experiencing longer patent grant lags than inventors working with large firms. These results present evidence to support hypothesis 4.

4.7 Discussion and Conclusions

Patenting is essential for innovating firms, and patenting activities are strongly related to a firm's innovation growth (Artz et al. 2010, Cho and Pucik 2005). The dependence of innovation growth on patenting makes it imperative for firms to continually grow their innovation portfolios to maintain a trail of growing revenues. In addition to fulfilling economic motives, patents are also seen as credentials for inventors (Rantanen and Jack 2019). However, despite the importance of patents, patent examination generally takes longer for various reasons, reducing inventors' incentives to patent. This paper studies the effects of longer patent pendency

on the inventors' resource allocation choices between allocating their efforts to innovative and routine activities.

Our stylized model of the inventor's decision of effort allocation to innovative and routine activities employs a belief update about the probability of patent pendency, which gets updated as per the inventor's prior experience with the patent examination. The results show a robust negative effect of a longer patent pendency on the inventor's future effort allocation to innovative tasks. The first conclusion from this study is that inventors reduce their patenting activities and orient their effort to routine activities on experiencing a longer patent pendency. The adverse effects of patent pendency on the inventors' incentives to patent make patenting less attractive due to delayed launch of NPIs, reduced licensing revenues, or delayed gratification (Gaimon and Morton 2009, Gans et al. 2008, Rantanen and Jack 2019).

We also find that inventors with fewer prior granted patents experience a more significant negative effect on their innovative activities than those with more prior granted patents. This result demonstrates less successful inventors' impatient behavior on experiencing innovation hurdles. As a result, less successful inventors are more susceptible to move away from innovative activities on experiencing a longer patent pendency, and managers should pay particular attention to such inventors to sustain innovation (Melero et al. 2020, Rahmani et al. 2018).

Finally, our study highlights the critical and immediate need for innovation success for small firms than large firms. Inventors associated with large firms are less affected by patent pendency as they have alternate ways to fund their efforts and are less dependent upon the revenues from patents. In contrast, individual inventors or inventors associated with small firms depend heavily on the revenues generated from their patents. Due to the pressing need to attain immediate funding to sustain, these inventors exhibit a substantial adverse effect of patent pendency (Conti et al. 2013).

Overall, our study highlights the effect of process delays associated with patenting and provides managerial insights for innovation teams. However, our study has various limitations. First, our study assumes that patent pendency is the result of only institutional delays and not because of any strategic motives of inventors (Noel and Schankerman 2013). Our results might be more significant if it is possible to segregate strategic patenting from the rest. For example,

strategic inventors would deliberately delay responding to the examiner's queries and file more patent applications, biasing the results towards a positive outcome of longer patent pendency.

Second, our results show that inventors in large organizations are less affected by patent pendency than inventors in small organizations. Large and small firms differ in terms of funds availability and invention orientation. There is a huge difference in how large and small firms invest in tangible and intangible assets such as R&D, brands, technology, and human resources. On average, in 2017, a large company spent $330 million on R&D, whereas an average small company spent about $6 million on R&D in 2017 (Govindarajan et al. 2019). The focus of large firms may also be more on higher market value innovations due to high investment power than small firms (Acs and Audretsch 1988). However, large firms perform fewer innovations per employee than small firms and startups (Acs and Audretsch 2005). Moreover, low-value patents, either granted with reduced scope or granted after the product demand period, may still have residual utility in a large firms' patent portfolio (Hall and Ziedonis 2001, Lanjouw and Schankerman 2004). Future research could extend this inquiry and explore inventors' and firms' interventions on experiencing longer patent pendency.

Third, our binary classification for small and large organizations might not capture heterogeneity due to firm size. For example, project teams in large organizations might perform as individual small organizations from the project execution point of view. Moreover, filing for patents may not be the only outcome of innovative activities, and inventors may access alternate channels to secure their intellectual property. For example, inventors may choose to protect their inventions through trade secrets or develop capabilities for design and manufacturing to profit from their inventions (Cohen et al. 2000, Farre-Mensa et al. 2019). Nevertheless, our dataset does not identify if inventors shift their attention to trade secrets or some other form of protection on experiencing patent examination adversaries. Future research may extend this conceptualization under innovation adversaries to capture nuances of availability of funding, infrastructural capabilities, and people resources in large organizations (Conti et al. 2013, Hegde and Luo 2018, Pennetier et al. 2019).

Appendices

APPENDIX A

EXAMPLE OF A CROWDFUNDING CAMPAIGN FOR CHAPTER 3

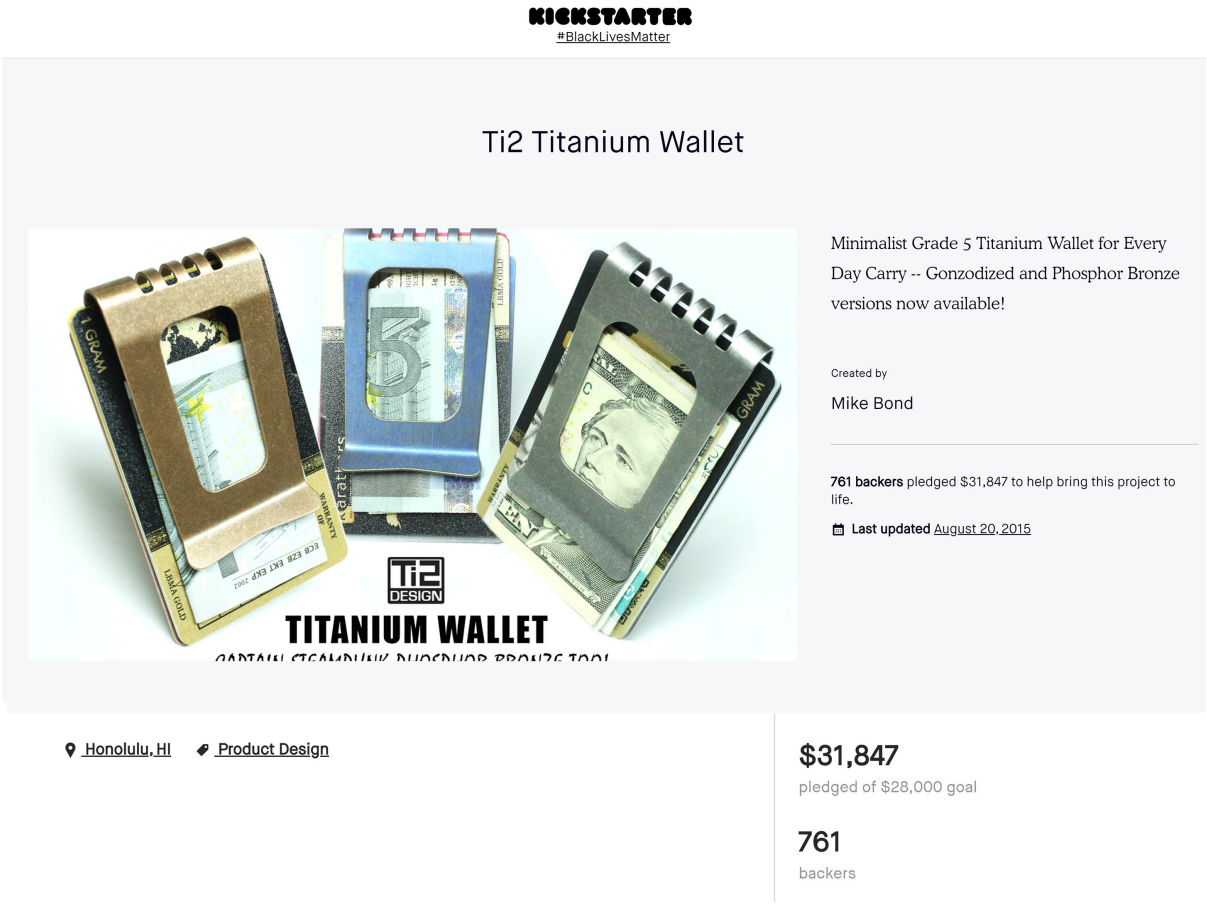


Figure A.1: *Kickstarter* Campaign - Ti2 Titanium Wallet

We present an example of a reward-based crowdfunding campaign from *Kickstarter*. The name of the campaign is “Ti2 Titanium Wallet"[1], created by Mike Bond from Honolulu, HI (A.1). The target funding goal for this campaign is $\$28,000$ and it has achieved a total funding of $\$31,847$ from 761 backers in the stipulated duration from Sep 9, 2014 to Oct 12, 2014 (A.1 and A.6). Therefore, this campaign is deemed successful. This campaign is in the *Product Design* sub-category under the *Design* category on *Kickstarter* and this campaign has not achieved “Project We Love" badge. The creator has provided details on the product, its features, and its

[1] https://www.kickstarter.com/projects/mikebond/28-titanium-wallet

usage, as shown briefly in A.2 and A.3. A.4 and A.5 show details on the variants of the product and the risks associated with this campaign. Figure A.6 depicts the reward structure of this campaign, which has ten rewards ranging from $28 to $134. There are few limited rewards, which will no longer be available once these rewards are claimed by the pre-determined number of backers. A.1 summarizes data for this campaign.

Figure A.2: Ti2 Titanium Wallet Specifics

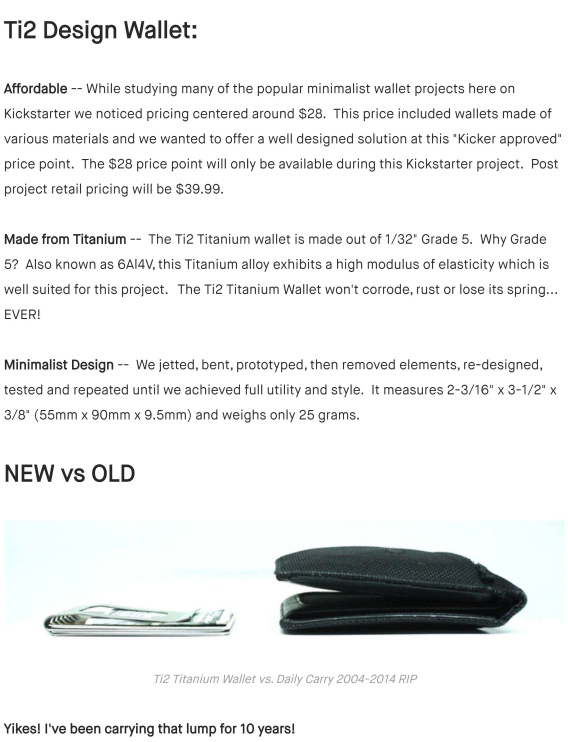


Figure A.3: Ti2 Titanium Wallet Details

Monogram Versions

With each Kickstarter project funded over our project goal, we've re-invested to diversify our capabilities. After our Para-Biner project we invested in a laser marking machine to help brand our products.

For this project we are offering up to 3 letter Monogramming for an additional $20. In standard monogram format, the middle letter of the 3 letter monogram is taller and the entire monogram measures 1.5" x 1.5" square. *** *Laser Finish may vary slightly.*

Color Monogramming options

SS-10

Figure A.4: Ti2 Titanium Wallet Variants

Risks and challenges

I have a background in design, machining and experience managing production jobs. I know the kinds of problems that arise in the shop and how to deal with them quickly and efficiently.

If this project funds and in order to fulfill we will need to:
1. Source Material -- Titanium -- Multiple vendors and quotes are lined up.
2. Machine the parts -- Lowest risk of the process, our machines are optimized for parts like this insuring quick production and high quality parts.
3. Finishing -- We have multiple finishing tumblers that can accommodate the tumbling needs.
4. Fulfillment -- We do our fulfillment in house to offer direct communication with our backers. Our experience on our last projects have helped us develop accurate fulfillment protocol.

The success of this project depends heavily on getting the word out. Every blog or social networking post counts, so please share. Thanks for your support.

Learn about accountability on Kickstarter

Figure A.5: Ti2 Titanium Wallet Risks

Table A.1: Descriptive Statistics for Ti2 Titanium Wallet Campaign

Variables	**Value**
Success	1
Num_Rewards	10
CoefOfVar_Prices	0.56
Experiential_Category	0
Creator_Experience	1.96
Kickstarter_Recommendation	0
Duration_Change	1
Funding_Goal	8.26
Campaign_Duration	32
Min_Reward_Price	3.37
Max_Reward_Price	4.91
Num_Images_Videos	3.22
Competition	8.22
Prop_Limited_Rewards	0.30
Creator_from_US	1
Year_Trend	6

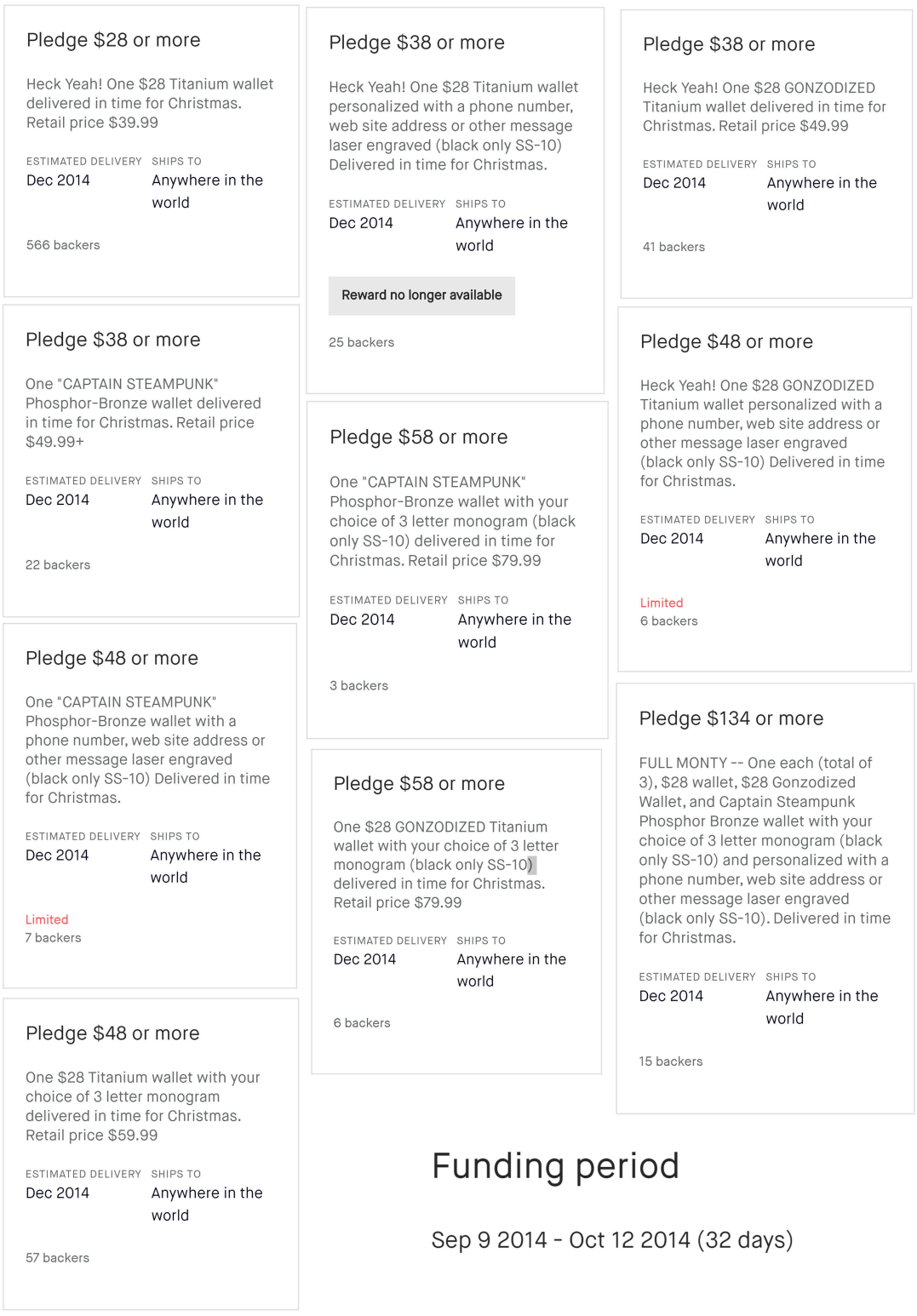


Figure A.6: Rewards for Ti2 Titanium Wallet

APPENDIX B

PROOFS OF PROPOSITIONS IN CHAPTER 4

B.0.1 Proof of Proposition 1

Posterior PDF:

The posterior PDF of the distribution of patent pendency for one patent applied and granted by time t is given by:

$$\text{Posterior PDF} = \frac{\text{Likelihood} \times (\text{prior PDF})}{\int_0^\infty \text{Likelihood} \times (\text{prior PDF}) d\lambda} \tag{B.1}$$

$$f^{Po}(\lambda/s_{it}) = \frac{f(s_{it}/\lambda)f(\lambda)}{\int_0^\infty f(s_{it}/\lambda)f(\lambda)d\lambda} \tag{B.2}$$

$$= \lambda e^{-\lambda s_{it}} \times \frac{b^a \lambda^{a-1} e^{-b\lambda}}{\Gamma(a)} \times \left[\int_0^\infty \lambda e^{-\lambda s_{it}} \times \frac{b^a \lambda^{a-1} e^{-b\lambda}}{\Gamma(a)} d\lambda\right]^{-1} \tag{B.3}$$

$$= \frac{b^a \lambda^a e^{-(b+s_{it})\lambda}}{\Gamma(a)} \times \left[\int_0^\infty \frac{b^a \lambda^a e^{-(b+s_{it})\lambda}}{\Gamma(a)} d\lambda\right]^{-1} \times \frac{a(b+s_{it})^{a+1}}{a(b+s_{it})^{a+1}} \tag{B.4}$$

$$= \frac{(b+s_{it})^{a+1} \lambda^a e^{-(b+s_{it})\lambda}}{\Gamma(a+1)} \times \left[\int_0^\infty \frac{(b+s_{it})^{a+1} \lambda^a e^{-(b+s_{it})\lambda}}{\Gamma(a+1)} d\lambda\right]^{-1} \tag{B.5}$$

$$[\Gamma(a+1) = a\Gamma(a)] \tag{B.6}$$

$$f^{Po}(\lambda/s_{it}) = \Gamma(a+1, b+s_{it}) \tag{B.7}$$

The numerator is the PDF of $\Gamma(a+1, b+s_{it})$ and the denominator is its integral, which is equal to 1.

The posterior PDF for n patents applied and granted by time t is given by:

$$f^{Po}(\lambda/s_{it}) = \frac{f(s_{it}/\lambda)f(\lambda)}{\int_0^\infty f(s_{it}/\lambda)f(\lambda)d\lambda} \tag{B.8}$$

$$= \lambda^n e^{-\lambda S} \times \frac{b^a \lambda^{a-1} e^{-b\lambda}}{\Gamma(a)} \times \left[\int_0^\infty \lambda^n e^{-\lambda S} \times \frac{b^a \lambda^{a-1} e^{-b\lambda}}{\Gamma(a)} d\lambda\right]^{-1} \tag{B.9}$$

$$= \frac{b^a \lambda^{a+n-1} e^{-(b+S)\lambda}}{\Gamma(a)} \times \left[\int_0^\infty \frac{b^a \lambda^{a+n-1} e^{-(b+S)\lambda}}{\Gamma(a)} d\lambda\right]^{-1} \tag{B.10}$$

$$\times \frac{(a+n-1).(a+n-2)...a.(b+S)^{a+n}}{(a+n-1).(a+n-2)...a.(b+S)^{a+n}} \tag{B.11}$$

$$= \frac{(b+S)^{a+n}\lambda^{a+n-1}e^{-(b+S)\lambda}}{\Gamma(a+n)} \times \left[\int_0^\infty \frac{(b+S)^{a+n}\lambda^{a+n-1}e^{-(b+S)\lambda}}{\Gamma(a+n)}d\lambda\right]^{-1} \quad \text{(B.12)}$$

$$f^{Po}(\lambda/s_{it}) = \Gamma(a+n, b+S) \qquad [\Gamma(a+n) = (a+n-1)\Gamma(a+n-1), \text{ and so on.}] \quad \text{(B.13)}$$

The numerator is the PDF of $\Gamma(a+n, b+S)$ and the denominator is its integral.

The posterior PDF for one patent applied and pending at time t is given by:

$$\begin{aligned} f^{Po}(\lambda/s_{it}) &= \frac{[1-F(t/\lambda)]\, f(\lambda)}{\int_0^\infty [1-F(t/\lambda)]\, f(\lambda)d\lambda} \\ &= e^{-\lambda s_{it}} \times \frac{b^a\lambda^{a-1}e^{-b\lambda}}{\Gamma(a)} \times \left[\int_0^\infty e^{-\lambda s_{it}} \times \frac{b^a\lambda^{a-1}e^{-b\lambda}}{\Gamma(a)}d\lambda\right]^{-1} \\ &= \frac{b^a\lambda^{a-1}e^{-(b+s_{it})\lambda}}{\Gamma(a)} \times \left[\int_0^\infty \frac{b^a\lambda^{a-1}e^{-(b+s_{it})\lambda}}{\Gamma(a)}d\lambda\right]^{-1} \times \frac{(b+s_{it})^a}{(b+s_{it})^a} \\ &= \frac{(b+s_{it})^a\lambda^{a-1}e^{-(b+s_{it})\lambda}}{\Gamma(a)} \times \left[\int_0^\infty \frac{(b+s_{it})^a\lambda^{a-1}e^{-(b+s_{it})\lambda}}{\Gamma(a)}d\lambda\right]^{-1} \end{aligned} \quad \text{(B.14)}$$

$$f^{Po}(\lambda/s_{it}) = \Gamma(a, b+s_{it})$$

Hence the equations for updating A_t and B_t can be written as stated.

CDF of Posterior Distribution:

The CDF of the posterior distribution of patent pendency is given as follows:

$$\begin{aligned} F^{Po}(T_0) = Pr(T \le T_0) &= \int_0^\infty (\text{CDF of Exponential})\,(\text{PDF of Posterior Gamma})\, d\lambda \\ &= \int_0^\infty \left(1-e^{-\lambda T_0}\right)\left(\frac{B_t^{A_t}\lambda^{A_t-1}e^{-B_t\lambda}}{\Gamma(A_t)}\right)d\lambda \\ &= \int_0^\infty \frac{B_t^{A_t}\lambda^{A_t-1}e^{-B_t\lambda}}{\Gamma(A_t)}d\lambda - \int_0^\infty \frac{B_t^{A_t}\lambda^{A_t-1}e^{-(B_t+T_0)\lambda}}{\Gamma(A_t)}d\lambda \\ &= 1 - \left(\frac{B_t}{B_t+T_0}\right)^{A_t}\int_0^\infty \frac{(B_t+T_0)^{A_t}\lambda^{A_t-1}e^{-(B_t+T_0)\lambda}}{\Gamma(A_t)}d\lambda \end{aligned}$$

$$F^{Po}(T_0) = 1 - \left(\frac{B_t}{B_t+T_0}\right)^{A_t} \quad \text{(B.15)}$$

where, the terms inside the first and the second integrals are the PDFs of $\Gamma(A_t, B_t)$ and $\Gamma(A_t, B_t+T_0)$ respectively.

B.0.2 Proof of Proposition 2

Taking first order derivative of Equation 4.7 w.r.t. e_t, the efforts on the innovative activities are given by:

$$e_t = \frac{P_t\left[\theta V_H + (1-\theta)V_L\right] + (1-P_t)V_L - w + d}{c} \tag{B.16}$$

The posterior probability of patent grant in time less than T_0 at time t is given by $P_t = \left[1 - \left(\frac{B_t}{B_t+T_0}\right)^{A_t}\right]$. The updated efforts on the innovative activities are given as follows:

$$\begin{aligned} e_t &= \frac{P_t\left(\theta V_H + (1-\theta)V_L\right) + (1-P_t)V_L - w + d}{c} \\ &= \frac{1}{c}\left[P_t\left(\theta V_H + V_L - \theta V_L - V_L\right) + V_L - w + d\right] \\ &= \frac{1}{c}\left[P_t\theta(V_H - V_L) + V_L - w + d\right] \\ i.e\ \ e_t &= \frac{1}{c}\left[\left(1 - \left(\frac{B_t}{B_t+T_0}\right)^{A_t}\right)\theta(V_H - V_L) + V_L - w + d\right] \end{aligned} \tag{B.17}$$

where, B_t represents the patent pendency duration and A_t represents the successful patenting experience. Differentiating Equation B.17 w.r.t. the pendency B_t gives the following:

$$\begin{aligned} \frac{\partial e_t}{\partial B_t} &= \frac{\partial}{\partial B_t}\left\{\frac{1}{c}\left[\left(1 - \left(\frac{B_t}{B_t+T_0}\right)^{A_t}\right)\theta(V_H - V_L) + V_L - w + d\right]\right\} \\ &= -\frac{1}{c}\theta(V_H - V_L)A_t\left(\frac{B_t}{B_t+T_0}\right)^{A_t-1}\left[\frac{(B_t+T_0) - B_t}{(B_t+T_0)^2}\right] \\ &= -\frac{1}{c}\theta(V_H - V_L)A_t\left(\frac{B_t}{B_t+T_0}\right)^{A_t-1}\left[\frac{T_0}{(B_t+T_0)^2}\right] \\ \frac{\partial e_t}{\partial B_t} &= -\frac{1}{c}\theta(V_H - V_L)A_t B_t^{A_t-1}\frac{T_0}{(B_t+T_0)^{A_t+1}} \leq 0 \end{aligned} \tag{B.18}$$

i.e. Efforts on the innovative activities decrease with longer patent pendency.

Differentiating Equation B.17 w.r.t. A_t gives:

$$\frac{\partial e_t}{\partial A_t} = \frac{\partial}{\partial A_t}\left\{\frac{1}{c}\left[\left(1 - \left(\frac{B_t}{B_t+T_0}\right)^{A_t}\right)\theta(V_H - V_L) + V_L - w + d\right]\right\} \tag{B.19}$$

$$= -\frac{1}{c}\theta(V_H - V_L)\frac{\partial}{\partial A_t}\left(\frac{B_t}{B_t + T_0}\right)^{A_t} \tag{B.20}$$

$$= -\frac{1}{c}\theta(V_H - V_L)ln\left(\frac{B_t}{B_t + T_0}\right)\left(\frac{B_t}{B_t + T_0}\right)^{A_t} \tag{B.21}$$

$$\frac{\partial e_t}{\partial A_t} = \frac{1}{c}\theta(V_H - V_L)ln\left(\frac{B_t + T_0}{B_t}\right)\left(\frac{B_t}{B_t + T_0}\right)^{A_t} \geq 0 \qquad \left[ln\left(\frac{B_t}{B_t + T_0}\right) \leq 0\right] \tag{B.22}$$

i.e. Efforts on the innovative activities decrease with more prior granted patents.

Differentiating Equation B.18 further w.r.t. A_t gives:

$$\begin{aligned}
\frac{\partial^2 e_t}{\partial B_t \partial A_t} &= \frac{\partial}{\partial A_t}\left\{-\frac{1}{c}\theta(V_H - V_L)A_t B_t^{A_t - 1}\frac{T_0}{(B_t + T_0)^{A_t+1}}\right\} \\
&= -\frac{1}{c}\theta T_0(V_H - V_L)\frac{\partial}{\partial A_t}\left\{A_t B_t^{A_t-1}(B_t + T_0)^{-A_t-1}\right\} \\
&= -\frac{1}{c}\theta T_0(V_H - V_L)\left\{B_t^{A_t-1}(B_t + T_0)^{-A_t-1} + A_t ln(B_t)B_t^{A_t-1}(B_t + T_0)^{-A_t-1}\right. \\
&\qquad\qquad \left. - A_t B_t^{A_t-1} ln(B_t + T_0)(B_t + T_0)^{-A_t-1}\right\} \\
&= -\frac{1}{c}\theta T_0(V_H - V_L)\frac{B_t^{A_t-1}}{(B_t + T_0)^{A_t+1}}\left\{1 + A_t ln(B_t) - A_t ln(B_t + T_0)\right\} \\
&= -\frac{1}{c}\theta T_0(V_H - V_L)\frac{B_t^{A_t-1}}{(B_t + T_0)^{A_t+1}}\left\{1 - A_t ln\left(\frac{B_t + T_0}{B_t}\right)\right\} \\
&= \frac{1}{c}\theta T_0(V_H - V_L)\frac{B_t^{A_t-1}}{(B_t + T_0)^{A_t+1}}\left\{A_t ln\left(\frac{B_t + T_0}{B_t}\right) - 1\right\} \\
&\geq 0 \text{ for high } A_t, \ < 0 \text{ for low } A_t.
\end{aligned} \tag{B.23}$$

i.e. the negative effects of patent pendency on inventor's efforts on the innovative activities increases with inventor's successful patenting experience.

Differentiating Equation B.18 w.r.t. $(V_H - V_L)$ gives:

$$\begin{aligned}
\frac{\partial^2 e_t}{\partial B_t \partial (V_H - V_L)} &= \frac{\partial}{\partial (V_H - V_L)}\left\{-\frac{1}{c}\theta(V_H - V_L)A_t B_t^{A_t - 1}\frac{T_0}{(B_t + T_0)^{A_t+1}}\right\} \\
&= -\frac{1}{c}\theta A_t B_t^{A_t-1}\frac{T_0}{(B_t + T_0)^{A_t+1}} \leq 0
\end{aligned} \tag{B.24}$$

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