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UNIVERSITY OF CALIFORNIA, SAN DIEGO

The Institutional Design for University Knowledge Transfer and Firm Creation

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy

in

Management

by

Kanetaka M. Maki

Committee in charge:

Professor Vish Krishnan, Chair
Professor Sanjiv Erat
Professor Josh Graff-Zivin
Professor Karsten Hansen
Professor Ulrike Schaede
Professor Robert S. Sullivan
Professor Lynne G. Zucker

2015

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The Dissertation of Kanetaka M. Maki is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Chair

University of California, San Diego

2015

DEDICATION

I dedicate my dissertation work to my grandmother, Fusako Maki. She passed away right before I started my Ph.D. program at University of California, San Diego. My grandmother raised me, and the time spent with her made me the entrepreneurial person I am today. Her influence is a large part of what enabled me to complete my dissertation. We spent a lot of precious time together, and she always supported me.

TABLE OF CONTENTS

Signature Page..... iii
Dedication..... iv
Table of Contents..... v
List of Figures..... vii
List of Tables..... viii
Acknowledgments..... x
Vita..... xiv
Abstract of the Dissertation..... xv
Chapter 1. Introduction..... 1
1.1. Background..... 1
1.2. The Reformation of the University System..... 3
1.3. Literature Review..... 7
1.4. University-Industry Collaborative Research Publications..... 9
1.5. University-driven Enterprise Formation: The Role of University-Professional Involvement..... 10
1.6. University-Led Process Innovations..... 12
1.7. Conclusion..... 13
References..... 15
Chapter 2. Gatekeeper and Gateway Effects of Technology Transfer Offices on Collaborative Open Science: Theory and Testing with a Natural Experiment in Japan..... 18
Abstract..... 18
2.1. Introduction..... 20
2.2. Literature Review..... 23
2.3. Theoretical Modeling..... 26
2.4. Empirical Data..... 38
2.4.1. Background: University-Industry Collaboration in Japan..... 39
2.4.2. Data..... 41
2.5. Empirical Methodology..... 43
2.6. Results..... 44
2.7. Robustness Checks..... 47
2.8. Conclusion and Future Work..... 48
Acknowledgments..... 49
References..... 61
Chapter 3. Inventor Involvement in the Success of University-Based Startups..... 65
Abstract..... 65

3.1. Introduction..... 67
3.2. Literature Review..... 69
3.3. Research Hypotheses..... 75
3.4. Datasets and Empirical Methodology..... 78
3.5. Results..... 81
3.6. Disentangling the Underlying Mechanism..... 88
3.7. Discussion, Future Work, and Conclusion..... 91
Acknowledgements..... 94
References..... 106
Chapter 4. Service Design for Improved Satisfaction: Decoding the Mechanism for Impact of Patient Call Back in Emergency Healthcare..... 111
Abstract..... 111
4.1. Introduction: Service Science and Healthcare..... 113
4.2.1. Performance Improvement and Re-Design of Emergency Department..... 115
4.2.2. Theoretical Framework..... 118
4.2.3. Service Design of Call Back in the Emergency Department..... 122
4.3.1. Research Design..... 124
4.3.2. Data Set..... 124
4.3.3. Setting..... 125
4.3.4. Empirical Methodology..... 127
4.4. Results..... 128
4.5. Discussion and Conclusions..... 130
Acknowledgements..... 133
References..... 145

LIST OF FIGURES

Figure 1.1: Multiple Pathways of University-Industry Technology Transfer…… 14
Figure 2.1: Overall Model with Mediation and Moderation Effects..... 50
Figure 2.2: Total Number of Articles..... 50
Figure 2.3: Total Number of Patents..... 51
Figure 2.4a: Mediated Moderation (Overall Effect)..... 51
Figure 2.4b: Mediated Moderation (Direct and Indirect Effect)..... 52
Figure 2.5a: Mediated Moderation (Overall Effect) for Senior Researchers..... 52
Figure 2.5b: Mediated Moderation (Direct and Indirect Effect) for Senior Researchers 53
Figure 2.6a: Mediated Moderation (Overall Effect) for Junior Researchers..... 53
Figure 2.6b: Mediated Moderation (Direct and Indirect Effect) for Junior Researchers..... 54
Figure 3.1: Causal Model of Inventor Involvement and Survival..... 95
Figure 3.2: Causal Model of Inventor Involvement and Exit..... 95
Figure 4.1: Emergency Department Service Process (Without Call Back) 134
Figure 4.2: Emergency Department Service Process (With Call Back) 134
Figure 4.3: Population of the Study..... 135
Figure 4.4: Treatment and Control..... 135

LIST OF TABLES

Table 2.1: Innovation Policy in Japan..... 55
Table 2.2: Launch of Technology Transfer Offices in Top 100 Universities in Japan.. 55
Table 2.3: Summary Statistics..... 56
Table 2.4: The Effect for Existing and New Links..... 56
Table 2.5: The Effect of Mediated Moderation..... 57
Table 2.6: The Effect of Mediated Moderation for Senior / Junior Researchers..... 58
Table 2.7: Robustness Check for Selection Bias (1) – Top 100 Universities (Research / CoAuthoring)..... 59
Table 2.8: Table 2.8: Robustness Check for Selection Bias (2) – All Universities / All Universities & All Years..... 60
Table 3.1: Summary Statistics..... 96
Table 3.2a: Cross Table for the SBIR Grant and Venture Funding..... 97
Table 3.2b: Binomial Test for the Order of SBIR Grant and Venture Funding..... 97
Table 3.3a: Cross Table for the SBIR Grant and First Sales..... 97
Table 3.3b: Binomial Test for the Order of SBIR Grant and First Sales..... 97
Table 3.4a: Cross Table for the Venture Funding and First Sales..... 97
Table 3.4b: Binomial Test for the Order of Venture Funding and First Sales..... 98
Table 3.5: Probit Analysis on Survival..... 98
Table 3.6: Probit Analysis on SBIR Funding, Venture Funding, and First Sales..... 99
Table 3.7: Tobit Analysis..... 99
Table 3.8: Exit – Inventor Involvement..... 100
Table 3.9: SBIR Funding – Inventor Involvement..... 101
Table 3.10: Venture Funding – Inventor Involvement..... 102
Table 3.11: Product Launch – Inventor Involvement..... 103
Table 3.12a: Mediation Test (IT)..... 103
Table 3.12b: Mediation Test (BM) 104
Table 3.13: Mediation Test: Existence of Inventor Involvement..... 104
Table 3.14: Mediation Test: Excluding Silicon Valley Effect..... 105
Table 3.15: Controlling Quality of Patents..... 105
Table 4.1: Patient Demographics for Self-Identified..... 136
Table 4.2a: Patient Demographics for Call Back Yes/No..... 136
Table 4.2b: Chi-Squared Test for Waiting Time and Contact to Patients..... 137
Table 4.3a: Patient Demographics for Two Hospitals..... 137
Table 4.3b: Patient Demographics for Call Back Yes/No Wait Time by Hospital..... 137
Table 4.4a: Ordered Logistic Regression for Overall Satisfaction (n=792 for Both

Hospitals) 138
Table 4.4b: Ordered Logistic Regression for Overall Satisfaction (Hospital "A" ; n=406) - Robustness Check with Hospital "A" with no significant difference in wait times between Callback and No Callback patients..... 139
Table 4.5a: Ordered Logit Regression for Overall Satisfaction (n=792) Moderation Effect of Callback on Waiting Times Impact of Likelihood to Recommend..... 140
Table 4.5b: Hospital "A" Moderation Effect of Callback on Waiting Times Impact of Likelihood to Recommend Robustness Check with Hospital "A" with no significant difference in wait times between Callback and No Callback patients..... 141
Table 4.6a: Ordered Logit Regression for Overall Satisfaction (n=792) Considering Effect of Age, Insurance, Gender..... 142
Table 4.6b: Ordered Logit Regression for Overall Satisfaction (n=792) - Interaction Effect..... 143
Table 4.7a: Ordered Logit Regression for Difference by Insurance Type..... 144
Table 4.7b: Ordered Logit Regression for Difference by Gender..... 144

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ABSTRACT OF THE DISSERTATION

The Institutional Design for University Knowledge Transfer and Firm Creation

by

Kanetaka M. Maki

Doctor of Philosophy in Management

University of California, San Diego, 2015

Professor Vish Krishnan, Chair

Universities are critical sources of innovation. In many countries, governments are working to introduce innovation policy packages to stimulate university-industry technology transfer (UITT). The Bayh-Dole Act of 1980 in the U.S. encouraged research universities to create Technology Transfer Offices (TTO). Since the Bayh-Dole Act was enacted, the dominant pathway of UITT has been through licensing. However, the challenge is that sometimes new scientific discoveries are not patentable, and licensing arrangements cannot capture the full value of a newly developed technology. In this dissertation, I analyze three other pathways in addition to licensing that enhance the

overall impact of innovation.

Chapter 2 examines the role of co-authoring academic publications between university and firm researchers. The TTO acts as a gateway to a university, by lowering search costs and enabling newer connections between the university and industry. The TTO also acts as a gatekeeper, asserting the university's intellectual property and seeking to ensure new discoveries are patented before they are published openly. The analytical model is conducted. The model is examined using panel data based on a natural experiment in Japan.

Chapter 3 studies the impact of inventor involvement to university-based start-ups. The research is based upon the University of California Start-up Dataset. The effect of inventor involvement on university-based start-ups on their success (survival and exit) is analayzed. The results show that receipt of SBIR funding and first sales by product launch mediate the impact of proportion of inventor involvement on survival rate of start-ups. Having a greater proportion of the inventors' involvement as a founder of a start-up firm increases the likelihood of receiving SBIR funding, and launching a product, which in turn increases the likelihood of survival.

Chapter 4 explores the university-led service innovation. Based on quasi-experiment setting at an emergency room university hospitals, the impact of a phone call to a patient for feedback after being discharged and their subsequent satisfaction rating is evaluated.

The body of work helps understand the underlying mechanism of UITT. The results offer policy implications to enhance the institutional design of UITT, and ultimately impacts the reformation of University system.

Chapter 1.

Introduction

1.1. Background

Universities are increasingly expected to do more than the traditional mission of teaching students. In the 20th century, they took on the job of *inventing* knowledge through organized research. In the 21st century, they are increasingly expected to innovate, which involves translating this new knowledge into economically and social beneficial offerings.

The 20th century leading University was mainly focused on two missions: research (producing new knowledge) and education (disseminating knowledge). As new technologies transform education and research with the rise of MOOCs (Massive Open Online Courses) and research think-tanks, Universities must do more to continue to thrive: they must translate and commercialize academic research contributing to the regional economic growth and job creation through entrepreneurial company formation by University professionals and technology licensing. We can refer to such Innovation and Entrepreneurship as a University's "third mission"(Etzkowitz and Leydesdorff 2000). Today, Universities are increasingly viewed as major sources of innovation (Jaffe 1989, Mansfield 1991).

Changes in the innovation policy as well as the rise of venture capital pushed the shift from a "closed innovation system" to an "open innovation system" (Chesbrough

2006). The proof of "Open Innovation" is widely recognized, but designing the appropriate collaboration model among the different entities is still a challenge. In the open innovation concept, each entity focuses on its core competence. This means, a space (gap), which no entity is responsible for, occurs. The characteristics of vertical integration and horizontal integration are the key (Baldwin and Clark 2000). In comparison with the vertical integration model, it is extremely difficult to bridge the gap in the horizontal integration model. The concepts of "national innovation system" (Nelson 1993) and "clusters" (Porter 1990, Saxenian 1996) explain the regional advantage to fill the gap. The concept of "Triple Helix" explains the importance of universities as the source of innovation and linkages among universities, industry, and government (Etzkowitz 2010). The previous research stream implies that an appropriate mechanism to fill the gap is critical.

Furthermore, technological breakthroughs in various fields, such as computing, biotechnology, and nanotechnology, stimulated the reformation of a national innovation system (Nelson 1993). The main research field of innovation is changing. Previously, information and communication technology were keys for innovation, but in the 21st century, science-related research is becoming more essential to creating competitive advantages for all countries, regions, and enterprises. Scientific research is becoming the key element for technological innovation (Fleming and Sorenson 2000).

According to Pisano (2006), the innovation process of the commercialization of science is not effectively working, based on his studies on biotech start-up industries. However, this failure is not because of the potentiality of the commercialization of science, but more because of the lack of the appropriate mechanism. The science industry

has several specific characteristics: high risk, difficulty of integration, the degree of information asymmetry, the need for investments in specialized assets, the tacitness of the know-how, and the degree to which the relevant intellectual property can be protected legally. These problems are caused by the lack of a translational mechanism that fills the gap between scientific research and commercialization.

As Chandler Jr (1993) proved organizational innovation occurred because of the invention of the railway and the telegraph, we have to seek an appropriate institutional mechanism that accelerates the commercialization of science. The transformation of the University system takes a critical role in this mechanism.

The focus of this doctoral dissertation is on University-driven Innovation and Entrepreneurship outputs, specifically (a) collaborative publications with the industry, (b) company formation by University professionals, and (c) process innovations led by Universities to transform existing industries. My objective is to help Universities enhance their innovative contributions in this century. In this chapter, I begin by reviewing recent policy changes around the world, followed by literature reviews, and a preview of the major modules of the dissertation.

1.2. The Reformation of the University System

The reformation of the University system, specifically focusing on the University's third mission, is increasingly becoming a prominent topic. The University is expected not only to pursue inventions but also to commit to the process of innovation. Invention is the creation of a product or service; on the other hand, innovation is the process of improving and making a significant contribution based on inventions.

Innovation is becoming one of the most important elements for both the economic prosperity of countries and improvement in the quality of life for people. The center pillar of the reformation is the implementation of the university-industry technology transfer (UITT) mechanism.

To increase the impact of innovation from University, the appropriate UITT mechanism is necessary. There are numerous benefits for stakeholders of UITT to be involved in this process. The collaboration with academia helps industry sectors acquire new knowledge for the sake of commercialization (Cohen et al. 2002). For University researchers, industry offers new research topics for publications that help the professional advancement of researchers (Thursby et al. 2007). For the University itself, collaboration offers the opportunity to earn revenues through licensing, or to receive research grants. By promoting incentives for UITT, policymakers anticipate job creation as well as national and regional economic growth (Phan and Siegel 2006).

In many countries, governments have been introducing innovation policy packages to stimulate UITT. For example, the U.S. Bayh-Dole Act of 1980 aimed to encourage universities to translate their discoveries into commercial solutions. In turn, Universities have promoted UITT via establishing an intermediary organization, the Technology Transfer Office (hereafter, TTO) on their campuses.

The transformation of University's role is not a unique phenomenon in the U.S. The increase in academic entrepreneurship activities is apparent in Europe as well. Universities in Europe, especially in the United Kingdom, Germany, Italy, and Sweden, have transformed their technologies to commercialized products. However, due to the lack of legal systems to assist UITT, these Universities are still lagging behind compared

to those of the U.S. (Chiesa and Piccaluga 2000).

In Japan, the UITT has emerged steadily since the late 1990s. Previously, the traditional Japanese UITT was considered underdeveloped compared to that of the U.S. The Japanese government started to develop a new system for UITT in the mid-1990s. Among the innovation stimulation packages in Japan, the TTO Act was enacted in 1998, which promoted Universities to set up TTOs. Among the top 100 universities in Japan, 65 universities launched TTO within three years (Maki and Krishnan 2013). In addition to the TTO Act, the "Hiranuma Plan" was announced in 2002. The plan aimed to launch 1,000 university-based start-ups within three years.

Since the Bayh-Dole Act, the predominant pathway of UITT in the U.S. was licensing (Siegel et al. 2003). However, the effectiveness of TTO continues to be in doubt (Mowery and Ziedonis 2002, Jensen et al. 2003, Kenney and Patton 2009, Grimaldi et al. 2011, Kenney and Patton 2011). There are two downsides to the licensing approach. First, new science discoveries are, by nature, not patentable (Zucker et al. 1998). Secondly, a licensing arrangement cannot capture the full value of technology (Franklin et al. 2001). UITT can take many forms, whereas protection of intellectual properties via patents is just one form of output that emerges from the collaboration. As Litan et al. (2008) points out, multiple pathways of UITT are possible. These pathways include, but are not limited to, licensing through TTO, research publications, joint research, co-authoring academic articles, start-ups, consulting, education, and providing direct service (i.e. university-affiliated hospitals) (Figure 1.1). "Open science" (i.e. published co-authored papers and reports, conferences and meetings, informal exchanges, and consulting), as opposed to the proprietary information and intellectual property, is the key channel for UITT (Cohen

et al. 2002). Based on the survey in MIT, Agrawal and Henderson (2002) estimates that among the whole range of activities of University faculty regarding UITT, the patent-related activities accounts for only 10% or less. University-based start-ups (i.e. spin-out companies from the University) represent another prominent way of UITT. However, despite the increasingly large sums invested in university research, only a very small fraction gets translated into successful start-ups (Ensley and Hmieleski 2005).

Ultimately, technology transfer is the movement of knowledge from one setting or organization to another. It has long been understood that knowledge can exist in various forms – explicit and tacit (Polanyi 1967, Nonaka and Takeuchi 1995). Explicit knowledge has been codified and can be transferred through modes of communication such as publications or patents. Yet, much knowledge is not completely explicit, but rather in the form of capabilities and skills, which are not codifiable. This is termed "tacit knowledge." Its mode of transfer is passed down through individuals, often operating in in-person methodology; Roberts (2000), and termed as "show-how". For cutting-edge inventions, the knowledge is embodied in the inventors themselves (Lowe 2006). Agrawal (2006) points out that some of type of knowledge is latent knowledge; it may be codified later on, but inventors do not have an incentive to codify it. In the context of UITT, the transfer of both codified and un-codified knowledge (i.e. both tacit and latent) can come into play. Novel discoveries are, by nature, tacit knowledge (Zucker et al. 1998).

1.3. Literature Review

Academic entrepreneurship (i.e. research field on University activities regarding patenting, licensing, creating new firms, facilitating technology transfer through incubators and science parks, and facilitating regional economic development) is actively studied in multi-disciplinary settings: management, economics, sociology, and public policy. As the study of academic entrepreneurship has been gaining traction, many pieces of literature have been published from the U.S. and Europe. These publications spread over multiple streams of research rather than forming a single unified body. Rothaermel et al. (2007) describes four research streams: (1) entrepreneurial research university, (2) productivity of technology transfer offices, (3) new firm creation, and (4) environmental context including networks of innovation.

The first research stream on the entrepreneurial research University focuses on entrepreneurial activities and the appropriate organizational design of the University to promote technology commercialization. Research questions in this research stream include the following: First, why are some universities more success than others in terms of entrepreneurial activities? Second, what are the obstacles for entrepreneurial universities? Third, what is an efficient way to be more successful in entrepreneurial activities? Last, how do universities relate to external institutions?

The second research stream on the productivity of TTOs investigates academic entrepreneurship as the function of the TTO. In order to determine the performance of a TTO, publications in this stream analyze system, structure, staffing, and mechanism of TTOs, as well as the stages of technology, faculty, University systems, and relationship with external institutions.

The third research stream on new firm creation focuses on university-based start-ups as the outcome of academic entrepreneurship activities. The researchers analyze University policy, faculty, TTO, underlying technology, investors, founding teams, networks, and external resources around the university.

The environmental context, which is the fourth research stream, represents a relationship between the academic entrepreneurship and external institutes and the outcome from relationship. Specifically, many researchers focus on networks of innovation. Networks of innovation represent the relationship among researchers, entrepreneurs, and external entities. There are two major questions in this stream: First, how do industry firms create links to universities and other institutions? Second, how do the characteristics of the network (network density, network centrality, etc.) influence the outcome of academic entrepreneurship?

Although a considerable number of works have conducted regarding academic entrepreneurship, the research on the institutional design facilitating un-codified knowledge transfer has received relatively less attention. This dissertation consists of the following three chapters: Chapter 2 examines the role of co-authoring academic publications between University and industry firm researchers. It evaluates the impact of the TTO using a theoretical model, and validates the model by empirical analysis based on a natural experiment in Japan. This is the intersection of research streams on entrepreneurial research Universities and productivity of TTOs. Chapter 3 studies the impact of inventors' involvement to university-based start-ups. This is the intersection of research streams on entrepreneurial research university and new firm creation. Chapter 4 focuses on a design of service provided by the University, which expands a traditional

perspective of the academic entrepreneurship research stream. In this chapter, the process design of the University-based hospitals is investigated.

1.4. University-Industry Collaborative Research Publications

Scientific discoveries are, by nature, tacit knowledge, and the co-authoring of academic articles between University and firm researchers is a prominent pathway of knowledge transfer. There are two contradicting views on the role of knowledge transfer. On one hand, the TTO promotes university-industry collaborative research publications because it acts as an intermediary between universities and industrial firms. On the other hand, TTOs are perceived to pursue a University's intellectual properties too aggressively, which leads firms to avoid working with University researchers. The aim of this work is to reconcile these two views by showing gateway and gatekeeper effect of TTOs. Reconsidering the role of TTOs for other pathways of UITT is critical in the reformation of the University system.

Based on the theoretical model, the effect of gateway and gatekeeper effects is shown. The gateway effect promotes co-authoring between University and firm researchers by lowering search costs of finding new partners. The gatekeeper effect promotes patent activities, and patent activities mediate the impact on co-authored publications. Furthermore, the effects of TTO can have a different impact on University researchers based on their seniority when it comes to collaboration with the industry sector.

Model predictions are validated by using data collected from Japan. Japanese universities were "forced" to launch a TTO by the government. The exogenous shock of

launching TTOs in Japanese universities provides an opportunity to analyze the effect of TTO as a natural experiment. The introduction of TTOs positively moderates the direct effect of co-authoring academic publications. In other words, the TTO increases joint publications, especially with new firms. At the same time, the TTO positively moderates the patent activities and indirectly increases the co-authoring publications. The impacts of the TTO are greater for junior researchers in comparison with senior researchers.

The two functions of the TTO, gateway and gatekeeper effects, explain the mechanism of TTOs. The role of a TTO is the center pillar of the transformation of the University system to increase the overall impact of innovation, and the results open up a new research strand.

1.5. University-driven Enterprise Formation: The Role of University-Professional Involvement

The role of university-based start-ups is particularly prominent because the commercialization of new scientific discoveries entails high-risk, which discourages existing firms from pursuing it. An analysis of the role of inventor involvement on start-up success demands further exploration. There is a long-lasting debate on the role of inventor involvement on university-based start-ups. The proponents of inventor involvement claim that inventor involvement is critical to transfer the tacit knowledge to start-ups. The opponents claim that due to the lack of business experience of the inventors, their participation detracts from the success of start-ups. By analyzing the underlying mechanism of inventor involvement, the aim is to reconcile these opposing point of views.

To a great extent, research streams regarding the impact of inventor involvement are often considered a success as a single outcome out of a single event. However, new firms perhaps evolve through some milestone events that may occur prior to a successful exit. Three key financially-related milestones in the growth of firms are used in this research: reception of Small Business Innovation Research (hereafter, SBIR) funding, venture capital funding, and first sales by product launch. Each of these events impacts a firm's growth trajectory.

Using the University of California Start-up Dataset, which includes the entire population of start-ups based upon on University of California licensed technology after the year 2000, the effect of inventor involvement on the survival of university-based start-up is explored. The results show that receipt of SBIR funding and first sales by product launch mediate the impact of the proportion of inventor's involvement on the survival rate of start-ups. In other words, having a greater proportion of inventor involvement as active founders of a start-up firm increases the likelihood of receiving SBIR funding and launching a product, which in turn increases the likelihood of survival.

The results in this chapter show when and how inventor involvement is necessary. To gain the best benefit of inventor involvement, University rules must be optimized. For example, the reconsideration of any conflict of interest rules, and the re-examination of the personnel system of researchers may be necessary. This research opens up a new research strand on inventor involvement to university-based start-ups, which guides the direction of the transformation of the University system.

1.6. University-Led Process Innovations

In order to transform university-owned knowledge into practice, having the university itself provide the model of best practices is the most effective means The following will focus on the design of process innovation in university hospitals.

The quality of healthcare service is becoming a major issue around the world. The service provided in one typical Emergency Room (ER) visit is one that is carefully scrutinized, and one of the most challenging areas to obtain a patients' satisfaction. There are three reasons why the service design of an ER is extremely difficult: The first reason is due to the unpredictability of a patient's arrival to the ER. Secondly, due to the variation of a patients' need in an ER, the appropriate response and job scope is quite wide. Finally, in some cases, immediate treatment is necessary to save patients lives. These characteristics of an ER service design leads to long waiting times for patients. Subsequently, the long waiting time drastically decreases a patients' satisfaction. Increasing the patients' satisfaction by reforming the service design is critical, because new compensation systems for hospitals based on patients' satisfaction levels are currently under consideration.

To investigate how this works, an analysis of the impact of a new innovative process implemented in hospitals at the University of California, San Diego is performed. As opposed to previous procedures, a healthcare provider now makes a follow-up call to patients after being discharged from the ER. The impact of the callback on patients' satisfaction in this quasi-experimental setting is evaluated. The findings indicate that the follow-up call back increases a patients' satisfaction; however, the magnitude differs by the patient characteristics.

The results provide a model of best practices of service design based on university-based knowledge. Furthermore, it proves that university-led service innovation is another prominent pathway of UITT. This opens up a new strand of research; further research on how the University itself provides the best practices to transform university knowledge into practice must be investigated.

1.7. Conclusion

These three preceding chapters share a single research focus on how to transfer un-codified knowledge from University to Industry. Instead of having a narrow focus of UITT solely being the thoroughfare for patent licensing activities, the aim of this thesis research is to explain the mechanism of knowledge transfer with other prominent pathways.

Taken as a whole, this dissertation gives insight to the development of an appropriate institutional design to increase the overall impact of innovation via UITT activities. The results will offer policy implications to enhance the institutional design of UITT. More generally, the three chapters above help frame a new way of studying academic entrepreneurship, and helps us understand the underlying mechanism of UITT, which supports the transformation of University system in the 21st century.

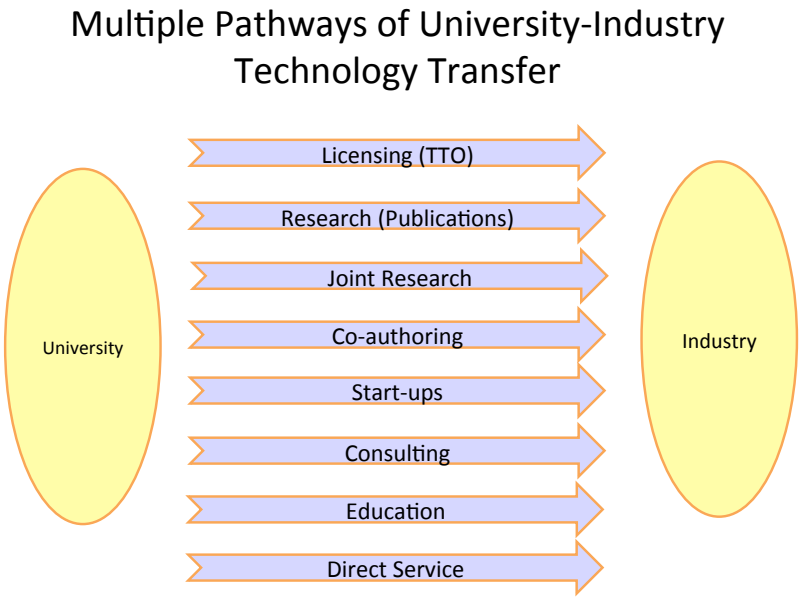


Figure 1.1: Multiple Pathways of University-Industry Technology Transfer

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Chapter 2.

Gatekeeper and Gateway Effects of Technology Transfer Offices on Collaborative Open Science: Theory and Testing with a Natural Experiment in Japan

ABSTRACT

The growing complexity of industrial research and development has created the need for collaboration between industry researchers and university faculty resulting in increased number of joint-authored publications. Drivers of such collaborative open science publications have received relatively little research attention, specifically the impact of an intermediary - the University's Technology Transfer Office (TTO). In this paper, we develop and empirically test a theoretical model of TTO and its impact on joint-authored publications. The TTO on the one hand acts as a gateway to the University, by lowering search costs and enabling newer connections between university and academic researchers. The TTO also acts as a gatekeeper asserting the University's intellectual property, and seeking to ensure new discoveries are patented (resulting in "proprietary science") before they are published openly. We formalize the gateway and gatekeeper effects of the TTO using a formal analytical model, showing that the TTO positively moderates the impact of budget on collaborative open-science publications and the effect is observed (mediated) through the increase in patents. Our modeling and analysis shows that TTO can have a differential impact on collaboration between junior

and senior university researchers. Specifically, the TTO's gateway and gatekeeper impact are larger for junior university researchers in comparison with senior university researchers. The model assumptions and predictions are examined using data collected based on a natural experiment in Japan. Japanese public universities were "urged" to introduce a TTO by their national government in the years 1998-2002. We consider this exogenous policy shock and examine the impact on University-Industry Collaboration. Using panel data, the results of our analysis weigh in on the model findings: first, we find that the introduction of a TTO is associated with the creation of more new industry-academic links and positively moderating the joint-authored publication output, pointing to the gateway effect. We also find that TTO's positively and significantly impact the University's patenting activity, and the joint-authored publication impact of TTO is largely felt through the patent-driven publications route, indicating a gatekeeper effect. As predicted by the model, the TTO tends to positively affect the patent production and indirectly stimulate collaborative open science. The data indicates TTO has a differential effect on junior versus senior university researchers. Our theoretical model and empirical evidence offers one of the first models of Collaborative Open Science validated with a novel empirical dataset and suggests that intermediaries such as TTO may be better understood and managed in terms of their gatekeeper and gatekeeper effects. Implications and next steps are discussed.

Keywords: collaborative open-science, technology transfer, natural experiment, co-authorship, patents

2.1. Introduction

The growing complexity of industrial research and development, especially in science and technology, has created the need for collaboration between industry researchers and university faculty. Universities are increasingly viewed as major sources of innovation (Jaffe 1989, Mansfield 1991). By working with academia, industry aims to fill the gaps in their technology portfolio and acquire new knowledge for commercialization (Cohen et al. 2002). In turn, Universities seek to capture some of the value of engaging in industry collaboration. For university researchers, industry offers a compelling context and the opportunity to create "open science" publications that help the professional advancement of researchers (Thursby et al. 2007). For the University, collaboration offers the opportunity to earn revenues through licensing of intellectual property (IP), which can help sponsor research and funding of students and post-doctoral fellows. By creating incentives for collaboration between University and Industry, policymakers aim to promote national and regional economic growth (Phan and Siegel 2006).

In many countries, governments are working to introduce innovation policy packages to stimulate University-Industry Collaboration (hereafter, UIC). As an example, the U.S. Bayh-Dole Act (passed in 1980) aimed to encourage Universities to translate their discoveries into commercial solutions. In turn, Universities have invested resources in stimulating such collaboration, specifically by establishing an intermediary organization, the Technology Transfer Office (hereafter, TTO) on their campuses. The TTO aims to promote collaboration between University and Industry *potentially* playing several roles: introducing university faculty to industry researchers, investigating

potential research that can be commercialized, applying for patents on newly created innovations, licensing patents to industry, and earning profits for the University and individual researchers. Almost all major research universities in the US have established the TTO. However, the effectiveness of TTO continues to be in doubt (Mowery and Ziedonis 2002, Jensen et al. 2003, Kenney and Patton 2009, Grimaldi et al. 2011, Kenney and Patton 2011).

Much existing research has focused on the licensing of patents as a key measure of UIC and the degree to which they are affected by the TTO. However, collaboration can take many forms, and protected intellectual properties such as patents are just one form of output that emerges from collaboration. As Litan et al. (2008) point out, multiple pathways of UIC are possible. Faculty members estimate that patent activity is less than 10% of the whole range of activities within UIC (Agrawal and Henderson 2002). "Open science" (i.e. published co-authored papers and reports in contrast with proprietary intellectual property) is a key channel for UIC (Cohen et al. 2002). Joint research by co-authoring academic articles with the industry is a major pathway for knowledge transfer (Zucker et al. 1998). Drivers of collaborative joint research between universities and firms resulting in co-authored publications, Collaborative Open Science (hereafter, COS), have received relatively less formal research attention (Lach and Schankerman 2008).

Investigating the impact on joint research, specifically co-authored academic articles between researchers from universities and firms and how it is affected by a TTO, forms the focus of this paper. Novel discoveries are by nature, tacit knowledge not patentable in all cases. New discoveries have characteristics of natural-excludability, and are transferable only through bench-science level collaboration. Therefore, measuring co-

authorship of academic articles between universities and firms would be a good indicator of UIC, because co-authoring forms the process of transferring tacit knowledge (Zucker et al. 1998).

We seek to develop an improved understanding of joint research between researchers in universities and firms and the impact of a University's TTO on such joint research. We adopt the approach of using an empirically-grounded analytical model to derive theory (testable hypotheses), which is then validated with empirical data from a natural experiment. Our modeling and analysis suggests that collaboration between university and industry researchers occurs at a particular level which could be enhanced or degraded by the addition of TTO. The TTO could have a positive impact on the amount of joint research by the lowering of search costs and fostering new university-industry connections (which we call the gateway effect wherein the TTO positively influences the formation of new university-industry links and stimulates new collaborations). However, the TTO's main objective is also to ensure the University earns intellectual property-based revenues, and it acts as a sort of gatekeeper in UIC. This gatekeeper effect can be seen in the mediating effect of patents in the UIC. Our model and analysis shows that the TTO impact (both gateway and gatekeeper effects) is larger for junior university researchers in comparison with senior university researchers. Since junior researchers have fewer networks with industry researchers, they gain more from TTO's service (gateway effect). At the same time, junior researchers tend to change their behavior to adopt new university rules, which leads to more gatekeeper effect.

The analytical model assumptions and predictions are examined using data collected based on a natural experiment in Japan. Japanese universities experienced an

exogenous shock by being "urged" by the government to establish TTO during the years of 1998-2002. We assemble a unique dataset using a variety of sources including the Nanobank, and several other datasets describing publication and patenting activities. Based on the aggregation, we assemble panel data to analyze university-industry joint publication activities in Japan during 1994-2004 (11 years) in the nanotechnology field. Using panel data, the results of our empirical analysis weighs in on our model assumptions. First, we find that the introduction of a TTO is associated with an increase in the number of new industry-academic links and positively moderates the joint authoring output, pointing to the gateway effect. We also find that the TTO's positively and significantly impacts the University's patenting activity, and the joint-authoring impact of TTO is largely felt through the patent-driven publications route, indicating what we refer to as a gatekeeper effect. As predicted by the model, the TTO has a differential effect on junior versus senior university researchers.

The rest of the paper unveils as follows. Section 2 reviews related literature. Section 3 presents a simple model of collaboration between university and industry researchers. Section 4 discusses data collection. Section 5 proposes an empirical analysis strategy, followed by the reporting of results in Section 6. Section 7 illustrates robustness checks. Finally, Section 8 concludes the paper.

2.2. Literature Review

The literature related to this paper can be organized into two major streams: research on collaborative innovation, and another stream on technology transfer from University to Industry.

A significant amount of recent research on innovation and product development has focused on approaches that go beyond the institutional boundaries. Specifically, open innovation in general and the contest approach to sourcing innovative ideas from the outside in particular have attracted growing interest among researchers as well as the industry (Huston and Sakkab 2006, Kornish and Ulrich 2009, Terwiesch and Ulrich 2009, Girotra et al. 2010, Kornish and Ulrich 2011, Erat and Krishnan 2012, Kornish and Ulrich 2012, Wooten and Ulrich 2013). A number of authors have studied the contractual joint development of new products between two or more firms (Crama et al. 2008, Savva and Taneri 2013). Global product development, where skilled engineers are dispersed globally, is also becoming a common trend in product development (Eppringer and Chitkara 2006, Savva and Scholtes 2013). While these authors focus on extended enterprise product development, collaborative joint research between universities and firms, has to the best of our knowledge received relatively little research attention. As the opportunity for collaboration increases due to the emergence of new networking technologies, it becomes useful to understand the factors that promote co-authored publications.

A significant and vast body of work exists on technology transfer from University to Industry, including the following work: Jensen and Thursby (2001), Mowery et al. (2001), Thursby and Thursby (2002), Di Gregorio and Shane (2003), Jensen et al. (2003), Siegel et al. (2003), Phan and Siegel (2006), Lach and Schankerman (2008), Walsh et al. (2008), Kenney and Patton (2009), Grimaldi et al. (2011), and Kenney and Patton (2011). There is also recent work in the Operations Management literature examining the nature of the contract between a University and its spinoffs (Savva and Taneri 2013).

One stream of research in this field evaluates the impact of Bayh-Dole Act. One question that has been asked is whether after Bayh-Dole the behavior of researchers has changed toward applied research rather than basic research. Based on patent analysis of three major universities in the US, the evidence illustrates that content of academic research did not change because of the presence of TTO (Mowery et al. 2001). Based on a survey of 64 US universities, the evidence suggests that the increase of university-industry technology transfer is caused not by the change of faculty members' research interests, but by the increased interest of industry (Thursby and Thursby 2002). Kenney and Patton (2009) argues effectiveness of university invention ownership model. Authors conclude that university invention ownership model does not accelerate technology transfer, and propose two alternatives: inventor ownership model and public domain strategy. Kenney and Patton (2011) investigates effectiveness of university invention ownership model by comparing with inventor ownership model. Using census data, authors claim that inventor ownership model is more efficient for technology transfer.

Much of this work focuses on patents, instead of joint research and co-authored publication between University and Industry (which is the focus of this work). Additionally, most of the previous empirical research is based on survey data, which suffers internal and construct validity issues. A notable exception is the work of Zucker and co-authors (Zucker et al. 1998), who have a long-standing program of research that focuses on identifying highly influential "star" academic scientists that contribute to technology of firms and local economic development. Our work focuses on the determinants of UIC, focusing specifically on the impact of TTO on COS between Universities and firm researchers.

2.3. Theoretical Modeling

We first seek to develop a testable analytical model of collaborative joint research between University and Industry researchers without and with a TTO. Our model considers the incentive compatibility and individual rationality of University researchers to engage in open science or proprietary science (patenting). In addition, when they choose to pursue open science, they may or may not engage in collaboration with industry researchers. The impact of the TTO is then considered.

University researchers decide whether to first publish their research output or patent it based on their relative costs and benefits. It is also possible that they could produce academic publications after receiving a patent, although the reverse (publishing the paper before patenting) is unlikely due to the patent examination process which requires that ideas not be disclosed prior to the patent process. When they decide to engage in open science, each researcher can choose to conduct their research on their own ("sole research"), or may choose to collaborate to produce co-authored publications ("joint research"). We propose that individuals make their choices based on the differential utilities realized through incentive compatibility constraints.

We propose that University researchers engage in collaboration if the net gain from joint research exceeds that of sole research. To be consistent with prior research, we use elements of modeling similar to prior research that has examined the matching between university researchers and firm researchers (Banal-Estañol et al. 2013) although this stream has not focused on studying co-authorship and has been driven by affinity-based characteristics for matching researchers.

In our modeling framework, the focus is on patents and research articles / publications produced by exerting effort. When university researchers produce a publication or a patent, the outcomes depend on their ability (δ_U), time/effort investment (I_U), and their differential utilities. We use the parameter δ_U to capture the *ability* of university researchers to produce publications / patent measured in amount of output per unit of effort. For parsimony, we assume that each researcher's ability is not different for publications and patents, although our model can easily incorporate differential ability to produce open and proprietary science. This ability could be intrinsic combined with skill gained from experience. To capture the heterogeneous abilities of researchers, we assume δ_U parameter to be uniformly distributed between 0 and 1 (our model generalizes to any distribution but for simplicity, we use the uniform distribution). The amount of output (publications or patent) resulting from this effort is $\delta_U I_U$.

We model that $v_o \mathrm{v_U}$ represents the valuation (benefit) for the university researcher from producing a open-science publication, and $v_p \mathrm{v_U}$ represents the valuation (benefit) for the researcher from producing a patent; Without loss of generality and for parsimony, we assume academic researchers derive greater valuation from producing a open-science publication than a proprietary output ($v_o > v_p$) – our analysis and results easily extend to the reverse case. Once again researchers are distributed in the benefit derived with some valuing the patent more and others (typically, but not always, junior faculty) caring more for open-science publications. We assume parameters v_o and v_p to be uniformly distributed between 0 and 1 (our model once again generalizes to any distribution but for simplicity, we use the uniform distribution).

The expected benefit of exerting effort to producing a publication and a patent, respectively, is given by $v_o\delta_U I_U$ and $v_p\delta_U I_U$. The cost of effort for each researcher is modeled as $C_p(I_U)$ and $C_o(I_U)$ for the proprietary and open science, respectively. For parsimony, we assume the costs are independent of the researcher, although the model can be generalized without difficulty.

When university researcher δ_U exerts effort I_U to engage in open science, their net utility is:

$$\pi_o(I_U) = v_o\delta_U I_U - C_o(I_U). \quad (1a)$$

$$\pi_o(I_U) > 0 \; for \; \delta_U > \delta^{o}_{U} = \frac{C_o(I_U)}{I_U v_o} \; and \; v_o > v_o^t = \frac{C_o(I_U)}{I_U\delta_U} \quad (1b)$$

It is clear that those with $\delta_U < \delta^{o}_{U} = \frac{C_o(I_U)}{I_U v_o}$ and $v_o < v_o^t = \frac{C_o(I_U)}{I_U\delta_U}$ do not satisfy the participation constraint (1b) and would not engage in open science. Those with $\delta_U > \delta^{o}_{U}$ *and* and $v_o > v_o^t$ are said to satisfy the open science participation cutoff and are candidates for engaging in open science. However, whether or not they engage in open science depends also on the utilities they drive from proprietary science.

When university researcher δ_U exerts effort I_U to engage in proprietary science, their net utility is:

$$\pi_p(I_U) = v_p\delta_U I_U - C_p(I_U) \quad (2a)$$

$$\pi_p(I_U) > 0 \; for \; \delta_U > \delta^{p}_{U} = \frac{C_p(I_U)}{I_U v_p} \; and \text{ and } v_p > v_p^t = \frac{C_p(I_U)}{I_U\delta_U} \quad (2b)$$

Those with $\delta_U < \delta^{p}_{U} = \frac{C_p(I_U)}{I_U v_p}$ and $v_p < v_p^t = \frac{C_p(I_U)}{I_U\delta_U}$ do not satisfy the participation constraint (2b); Those with $\delta_U > \delta^{p}_{U}$ and $v_p > v_p^t$ satisfy the proprietary science participation cutoffs and could potentially engage in proprietary science.

A comparison of the net utilities derived from open and proprietary science reveals which way researchers are headed (with their incentive compatibilities); these expressions offer a marginal researcher (v_{po}^{t}, δ_{U}^{po}) above whom individuals derive more utility from open science. We can simply show that:

$$v_{po}^{t} = v_p + \frac{C_o(I_U) - C_p(I_U)}{I_U \delta_U} \quad (3a)$$

$$\delta_U^{po} = \frac{C_o(I_U) - C_p(I_U)}{I_U(v_o - v_p)} \quad \text{when} \quad \frac{C_p(I_U)}{C_o(I_U)} < 1 \quad (3b)$$

$$= \quad 0 \text{ otherwise}$$

We call (v_{po}^{t}, δ_{U}^{po}) the *open science priority threshold* for university researchers. It is clear that when academic researchers derive greater valuation from producing a open-science publication than a proprietary output ($v_o > v_p$), no one will engage in proprietary science, unless the cost of patenting is less than the cost of producing a open science output, $\frac{C_p(I_U)}{C_o(I_U)} < 1$. When this condition is satisfied (i.e. cost of patenting is less than the cost of producing a open science output), the exact nature of engagement in open versus proprietary science, depends on the ratio of cost of patenting to cost of open science, $\frac{C_p(I_U)}{C_o(I_U)}$.

Case A: When this $\frac{C_p(I_U)}{C_o(I_U)}$ ratio is below 1 but not too small (specifically when $\frac{v_p}{v_o} < \frac{C_p(I_U)}{C_o(I_U)} < 1$), then $\delta_U^{po} < \delta_{U}^{o} < \delta_{U}^{p}$ all researchers who satisfy the participation cutoffs also satisfy the open science priority threshold. In this case, all researchers with δ_U in the range $\delta_{U}^{o} < \delta_U$ engage in publishing only, and no one engages in patenting first because everyone receives greater utility from publishing. This case corresponds to that of a

typical publish or perish junior university researcher who has high valuation for open-science publication (due to promotion and tenure demands leading to a low value of $\frac{v_p}{v_o}$) and no one in this category engages in patenting. If, for simplicity, we assume a uniform distribution of researchers in the δ_U dimension, then (1- δ_U^o) researchers engage in open science, and the remainder are inactive.

Case B: When this $\frac{C_p(I_U)}{C_o(I_U)}$ ratio is very small (i.e. $\frac{C_p(I_U)}{C_o(I_U)} < \frac{v_p}{v_o}$), then $\delta_U^p < \delta_U^o < \delta_U^{po}$ those researchers with δ_U in the range $\delta_U^o < \delta_U < \delta_U^{po}$ engage in patenting first before they publish their work. Researchers at the low-end $\delta_U^p < \delta_U < \delta_U^o$ engage only in proprietary science (patenting) as they do not satisfy the open science participation cutoff. High-end researchers with $\delta_U^{po} < \delta_U$ engage only in open science. All researchers with $\delta_U^o < \delta_U$ engage in open science like in Case A, but some intermediate ones ($\delta_U^p < \delta_U < \delta_U^o$) patent first before they openly publish their work. The condition $\frac{C_p(I_U)}{C_o(I_U)} < \frac{v_p}{v_o}$ is more likely to be the case for senior academic researchers (relative to junior researchers), as they may have relatively lower valuation for open-science publication than junior researchers. This case has a segment that engages only in proprietary science (patenting) without any open science publications that we do not see in the previous junior researcher case where everyone with $\delta_U^o < \delta_U$ publishes and no one engages in patenting.

Now, let us consider who among the publishing researchers engages in collaboration. Researchers who choose to engage in open science have a further choice to make: whether to engage in UIC or not. For collaborative open science publications, net gain depends on the ability of both university and firm participants: δ_U and δ_F (ability of

the firm researcher) and the investment of both participants, I_U and I_F. Collaboration has additional costs. Joint research involves search cost C_s to identify the partner. In addition, each researcher may receive only partial weight for co-authored publications. This is captured by a parameter, $\lambda_U, \lambda_F \in [0,1]$, which indicates the discount factor of the collaboration, to account for any partial weight in University / Industry evaluations. Consistent with prior research (Banal-Estañol et al. 2013), we assume that ability and investment in collaboration are complementary, and the positive side of collaboration is modeled as $(\delta_U + \delta_F)(I_U + I_F)$. For university researchers, we model the gains from collaboration as:

$$\pi_o(I_U, I_F) = v_o \lambda_U (\delta_U + \delta_F)(I_U + I_F) - C_o(I_U) - C_s \quad (4)$$

Similar term can be written for the net gain for firm researchers, although that is not our main focus. Researchers from the University pursue joint research (co-authoring) with the other side when:

$$\pi_o(I_U, I_F) > \pi_o(I_U) \quad (5)$$

These expressions (1a) (4) and (5) offer a marginal university researcher δ_U^C above whom collaboration happens and below whom (or whose ability level of δ_U^C) it does not. We call δ_U^C the collaboration cutoff for university researchers. We can simply show that:

$$\delta_U^C = \frac{C_s - v_o(\lambda_U \delta_F (I_U + I_F))}{v_o(\lambda_U (I_U + I_F) - I_U)} \quad (6)$$

In other words, all researchers with $\delta_U > \delta_U^C$ receive greater gain from collaboration than from sole authoring. When we model the δ_U parameter to be uniformly distributed between 0 and 1, then the number of researchers who receive greater gain

from collaboration than from sole authoring or *Collaboration Count*, N_U^C, is:

$$N_U^C = 1 - \delta_U^C = \frac{v_o(\lambda_U(I_U+I_F)(1+\delta_F) - I_U) - C_s)}{v_o(\lambda_U(I_U+I_F) - I_U)} \quad (7)$$

The introduction of a TTO could offer a number of changes to the model. First, TTO influences (and potentially reduces) the cost of searching for collaboration partners. The TTO offices at many universities provide web site/resources that help industry researchers to find appropriate university research partners. We model that the search cost with TTO is given by $\gamma_s\ C_s$. When the TTO results in the decrease of searching cost, $\gamma_s \in [0,1]$, it has the potential of helping to form new links between University and Industry partners. This is verified later in the paper using the data we have collected on the formation of new links.

The TTO's have a primary goal of maximizing the value captured from university research (Jensen et al. 2003). Most of them are measured and compensated based on the patent licensing and royalty revenues they generate for the University. The TTO staff and leadership, rewarded for patent-related outputs, respond by lowering/even eliminating the researcher's private cost of filing for a patent, $C_p(I_U)$, to $\gamma_c\ C_p$ where $\gamma_c \in [0,1]$. They may also increase/amplify the university researcher's valuation for intellectual property/proprietary science, v_p, to v_p^{TTO}.

Let us consider the impact of the TTO on the open and proprietary science participation cutoffs, δ_U^o, δ_U^p, and the proprietary science priority threshold, δ_U^{po}. If the TTO lowers the cost of filing for a patent, C_p, to $\gamma_c\ C_p$, then it directly lowers the proprietary science participation cutoff to δ_{UT}^p. The lowering of C_p raises the open science priority threshold δ_U^{po} *to* δ_{UT}^{po}.

Lemma 1: When a *TTO is added to a University and it lowers the university researcher's cost* C_p *of filing for patents, it (a) lowers the* proprietary science participation cutoff, , $\delta^{p}_{UT} < \delta^{p}_{U}$, (b) raises the open science priority *threshold* $\delta^{po}_{UT} > \delta^{po}_{U}$, *but (c) does not impact the open* science participation *cutoff* δ^{o}_{U} (or the total number of researchers who publish their work).

The proof of this can be seen quite simply from the expressions for the expressions in 2(b) and 3 (b). $Specifically, \delta_U^{po} = \frac{C_o(I_U) - C_p(I_U)}{I_U(v_o - v_p)}$ is raised when the cost of patenting C_p is lowered; therefore, the total amount of researchers who satisfy the rationality constraint (2) for filing patent and those who derive more utility from filing patent before publishing papers increases. The lowering of the proprietary science cutoff and raising the open science threshold increases the utility derived by the researchers from proprietary science and makes it more attractive for them to patent their discoveries. Thus a TTO has an effect of stimulating (positively moderating) the number of patents received from the application of a university researcher's effort. However, lowering the university researcher's cost of filing for patents and does not impact the cost of publishing papers or the valuations. *The open science* participation *cutoff,* $\delta^{o}_{U} = \frac{C_o(I_U)}{I_U v_o}$, is unaffected by the lowering of patent filing costs due to a TTO.

While the TTO may not significantly impact the open science output, it does have an influence on the nature of the open science output, specifically whether it is collaborative output or now. The collaboration cutoff with TTO, δ^{C}_{UT}, is:

$$\delta_{UT}^{C} = \frac{\gamma C_s - v_U(\lambda_U \delta_F (I_U + I_F))}{v_U(\lambda_U(I_U + I_F) - I_U)}. \quad (8a)$$

$$N_{UT}^{C} = 1\text{-}\delta_{UT}^{C} = \frac{v_o(\lambda_U(I_U+I_F)(1+\delta_F)- I_U)-\gamma C_S)}{v_o(\lambda_U(I_U+I_F)- I_U)} \quad (8b)$$

Lemma 2: *TTO, when it lowers the search cost of finding industrial partners, moves the collaboration cutoff for joint research to* δ_{UT}^{C}*, where* $\delta_{UT}^{C} < \delta_{U}^{C}$.

Thus, the total participation in collaborative open science output, N_{UT}^{C} *(=* $1\text{-}\delta_{UT}^{C}$*), is positively impacted by the TTO, i.e.* $N_{UT}^{C} > N_{U}^{C}$*. More importantly, while the impact of investment parameter* I_U *on collaboration cutoff is not unconditionally positive, the TTO unconditionally and positively moderates the impact of investment parameter on collaboration cutoff.*

Result 1 (Gateway Effect): *The TTO unconditionally and positively moderates the impact of investment parameter on collaborative collaboration cutoff,* N_{U}^{C}*, i.e.* $\frac{\partial^2 N_U^C}{\partial C_S \, \partial I_U} > 0$.

We refer to this unconditional positive moderation of the relationship between investment parameter and the collaboration cutoff (or number of co-authored publications) N_U^C as the Gateway Effect of TTO.

Proof of this result can be seen very simply from the expression (7), where the collaboration cutoff is lowered when the search cost is decreased. Thus, in the presence of TTO, collaborative open science output is positively impacted, which we refer to as the ***Gateway effect***. TTO can make introductions to industry researchers, paving the way for UIC. It is interesting that while the TTO may not impact the total amount of research, it can actually positively moderate the amount of collaborative open science publications.

It is noteworthy that once the TTO's were formed, all the patents (collaborative or not) are filed in the name of the University (there are no collaborative patents). Now

consider the increase in collaborative open science publications from TTO as in Lemma 2: $N_{UT}^{C} > N_{U}^{C}$.

Result 2 (Gatekeeper effect): The increase in the number of collaborative open science publications due to TTO (N_{UT}^{C} - N_{U}^{C}) is in part due to the researchers who publish after patenting their work.

The increase in the number of collaborative open science publications due to TTO (N_{UT}^{C} - N_{U}^{C}) can be attributed to two groups: Group 1 researchers who publish without patenting and (2) Group 2 researchers who publish after patenting. The *TTO by lowering the patenting cost, does not impact the open* science participation *cutoff* δ_{U}^{o} and therefore does not affect the total number of researchers who ultimately publish their work. As seen in Lemma 1, the TTO's lowering of patenting cost lowers δ_{U}^{p} and raises δ_{U}^{po} – increasing the number of Group 2 researchers who patent before they publish (and decreasing the number of Group 1 researchers who only publish without patenting. Since the increase in collaborative output due to reduction in search costs equally affects both Group 1 and Group 2, and the size of Group 2 increases more than Group 1, the increase in the number of collaborative open science publications due to TTO is at least in part due to the Group 2 researchers who publish after patenting their work. Thus, patents form the intermediate step in the TTO's positive moderation of co-authored publications.

The above result indicates that the positive impact on the collaborative open science should be felt through an increase in the patent activity. We refer to this patent-driven impact of the TTO on collaborative publications as the **Gatekeeper effect of the TTO**. In other words, the patent inclination of TTO is indicative of its commercial

orientation making it act like a gatekeeper to protect the University's intellectual property assets.

Now we consider the different types of university researchers, specifically junior and senior researchers, and how they are impacted by the addition of a TTO. First, let us consider the participation and priority cutoffs. We expect that senior researchers have lower search costs as the experience of university researchers varies. Anecdotal evidence suggests that senior university researchers collaborate more with firm researchers based on their existing network with industry, while junior university researchers may find it harder to find appropriate industry partners (due to lack of experience and exposure). The search costs for senior and junior university researchers are defined as c_{ss} and c_{sj}, respectively, where we model that $C_{ss} < C_{sj}$ to account for the differing experience levels. The collaboration cutoff for senior university researcher is

$$\delta_{US}^{C} = \frac{C_{ss} - v_o(\lambda_U \delta_F (I_U + I_F))}{v_o(\lambda_U (I_U + I_F) - I_U)}, \quad (9)$$

and the collaboration cutoff for junior university researcher is

$$\delta_{UJ}^{C} = \frac{C_{sj} - v_o(\lambda_U \delta_F (I_U + I_F))}{v_o(\lambda_U (I_U + I_F) - I_U)}. \quad (10)$$

Similarly, the collaboration cutoff for senior university researcher with TTO is

$$\delta_{UST}^{C} = \frac{\gamma C_{ss} - v_o(\lambda_U \delta_F (I_U + I_F))}{v_o(\lambda_U (I_U + I_F) - I_U)}, \quad (11)$$

and the collaboration cutoff for junior university researcher is

$$\delta_{UJT}^{C} = \frac{\gamma C_{cj} - v_o(\lambda_U \delta_F (I_U + I_F))}{v_o(\lambda_U (I_U + I_F) - I_U)}. \quad (12)$$

Note that the collaboration cutoff for senior university researcher δ_{US}^{C} is lower than that of junior university researchers δ_{UJ}^{C}.

Result 3 *When TTO is introduced, the change in the collaboration cutoff for junior university researchers,*$(\delta_{UJ}^{C} - \delta_{UJT}^{C})$ *is larger than the change in the collaboration cutoff for senior researchers,* $(\delta_{US}^{C} - \delta_{UST}^{C})$. *Thus, when TTO is introduced, the increase in joint research for junior university researchers is larger than the increase in joint research for senior university researchers.*

Proof: Since $C_{ss} < C_{sj}$, hence $C_{ss} - \gamma C_{ss} < C_{sj} - \gamma C_{sj}$. Therefore, $\delta_{US}^{C} - \delta_{UST}^{C} < \delta_{UJ}^{C} - \delta_{UJT}^{C}$.

Thus, the impact or the Gateway effect of TTO is larger for junior university researchers than for senior university researchers. What can we say about the Gatekeeper effect? As discussed before, junior researchers generally fall under Case A and senior researchers under Case B. Prior to the TTO, there is very little patenting activity in Case A (junior researchers) and some patenting activity in Case B. However, the significant lowering of search cost can move junior researchers into Case B (by lowering the ratio) and increase their patenting activity from zero to a moderate amount. Senior researchers might also a gradual lowering of their proprietary science participation cutoff and the increase in the open science priority threshold which leads to a gradual increase in the patenting activity (Gatekeeper effect).

Based on the above analytical results, we propose the following three testable hypotheses.

Hypothesis 1*: The launch of TTO positively moderates co-authored (open science) publication between universities and firms (gateway effect corresponds to positive moderation by TTO).*

Hypothesis 2*: The launch of TTO increases patent activity by university researchers. The increase in patenting mediates the moderating impact of TTO on co-authored publication between universities and firms. (gatekeeper effect is equivalent to mediated moderation with patents mediating the positive moderation effect of TTO on co-authored publications).*

Hypothesis 3*: The positive moderation (gateway) effect of launching TTO on University-Industry co-authored publications is expected be larger for junior university researchers than for senior researchers. The strength of the patent-based mediation (gatekeeper) effect due to TTO on University-Industry co-authored publications for junior university researchers versus senior researchers depends on the parameter settings.*

We now test our hypotheses using data collected based on a unique dataset from a natural experiment in Japan. We begin by discussing the data collection context and procedure.

2.4. Empirical Data

Universities in Japan were "urged" to create a TTO by government policy, representing an exogenous shock from new policy implementation – this offers us an opportunity of a natural experiment (Harrison and List 2004). A full dataset of UIC for 11 years including 1998 (year of policy change) in nanotechnology field is available. We use co-authorship of articles between researchers at universities and firms as an indicator of joint research and build panel data.

2.4.1. Background: University-Industry Collaboration in Japan

Japan's expenditure on science and technology is the second largest in the world[1]. Japanese policymakers became concerned that university research was not being successfully translated to commercialization. To address these shortcomings, the Japanese government put in place the Act on the Promotion of Technology Transfer from Universities to Private Business Operators, or more simply the TTO Act, in 1998 in order to accelerate UIC and transfer of technology from Universities to Industry.

Historically, Japan had a unique UIC system compared to the US (Zucker and Darby 2001, Walsh et al. 2008). National university professors (the majority of top universities in Japan are national universities) were officially not permitted to receive any kind of compensation from private firms. Professors were not provided any additional incentives / compensation to engage in UIC. However, in practice, university facilities were open for UIC and it was easy for industry to conduct joint research with professors using university facilities and equipment, even without explicit contracts. There was no systemic approach for the University to own intellectual property, so firms owned most of intellectual property rights to inventions from joint research between universities and firms. Firms provided donations to professors' research as "compensation" for their effort. Thus, a "market exchange" existed for traditional UIC in Japan (Zucker and Darby 2001, Walsh et al. 2008).

The UIC system in Japan has changed since the end of 1990s (Motohashi 2005, Schaede 2008, Walsh et al. 2008, Saito and Sumikura 2010). Because the traditional Japanese UIC model was considered underdeveloped in comparison with that of the US,

[1] OECD Factbook 2013: Economic, Environmental and Social Statistics

the Japanese government started working on a new system for UIC in the mid-1990s (Table 2.1). Among the innovation stimulation packages in Japan, the TTO Act was passed in 1998. The TTO Act created guidelines and processes for universities to set up TTO. According to the new law, launching a TTO involved the following steps: each individual university decides to create a TTO; each university proposes a plan to the Ministry of Economy, Trading, and Industry (METI) for approval; METI grants permission based on the validity of the plan; with approval, the university launches the office. Among top 100 universities, 65 universities launched TTO within 3 years (Table 2.2).

The new policy changed the Japanese UIC model drastically. With the TTO Act, Japanese government encouraged the formation of university-operated TTO to own all the intellectual property rights coming out of the academic research. The TTO manages university-generated intellectual property and files patents on behalf of faculty making it free for faculty to filing patents. If a firm has a need to use the patent, university will license the patent with firms paying license fees and royalty. In other words, universities in Japan moved totally to a university invention ownership model by lowering/eliminating the cost of filing patents and asserting the University's rights to intellectual property. This new system is similar to that of the US university tech transfer system.

Reaction to the new TTO act has been mixed. First, not surprisingly, University-owned patents seem to have increased steadily since 1998. However, critics argue that TTO's have caused universities to become overly aggressive in pursuing patent

ownership making UIC more difficult. We examine the data to see any of these opinions are indeed supported.

2.4.2. Data

We assemble our data using several databases. To capture the co-authoring between universities and firms, we use Nanobank (Zucker and Darby 2007) - a collection of data from scientific articles, patents and government grants in the domain of nanotechnology. As per the National Nanotechnology Initiative[2], nanotechnology is defined as "science, engineering, and technology conducted at the nanoscale - about 1-100 nanometers". The sources are the Science Citation Index, Arts & Humanities Citation Index, and Social Science Citation Index of the Institute for Scientific Information Inc. (ISI®). Altogether, all these indexes contain more than 24,250,000 entries from over 8,700 peer reviewed scientific journals. The article data consists of title, journal volume and issue numbers, publication years, author names, and the names and addresses of organizations affiliated with authors. Geographical information of address consists of county, city, state, and country. The dataset includes a unique identifier for the organization. To customize the Nanobank dataset for this research, we select the articles co-authored between universities and industry in Japan during the years 1994-2004.

To build the TTO characteristics dataset, we gathered the following data: month and year of TTO establishment, and number of patents granted to each TTO. The data for the establishment of TTO is gathered from press releases on Japanese ministry METI's website. During the period of 1998-2004, 149 out of all 684 universities established a TTO. Table 2.2 shows the creation of TTO in major universities, where the time

[2] http://www.nano.gov/

difference in startup is useful to conduct analysis. We capture the patent activity of TTO, by counting the aggregate number of patents for each TTO based on a white paper issued by the Japan Patent Office (Japan-Patent-Office 2013).

To aggregate the trend of nanotechnology research at each university, we use the "Database of Grants-in-Aid for Scientific Research <KAKENHI>" (National-Institute-of-Informatics 2005-2013). Grants-in Aid is a National Science Foundation (NSF)-like grant in Japan, which awards creative and pioneering research across a wide range of fields (Japan-Society-for-the-Promotion-of-Science 2010). The database includes the following information for granted projects: Title, ID, Year, Principal Investigator, Co-investigators, Keywords, Field, Category, Institution, and Total Budget Amount. We choose nanotechnology related projects (projects that include "nano" for keyword) for the time period 1994-2004. The constructed dataset includes the number of projects (equivalent to number of principal investigators) and the total budget per institution per year.

By aggregating Nanobank data, TTO data, and nanotechnology research trend data, we assemble a balanced panel dataset for the analysis. We choose the 85 Japanese national universities during the 11-year period of 1994-2004 as the sample. National universities are the appropriate sample for two reasons. First, a high proportion of the research universities in Japan are national universities. Private universities are, with some minor exceptions, non-research universities. Secondly, national universities were "nudged" by the government to create their TTO to a greater extent. Among them, five universities did not have any nanotechnology-related articles published. They are therefore excluded. The summary statistics are shown in Table 2.3.

2.5. Empirical Methodology

Figure 2.1 describes the overall model. "Budget" is the total amount of budget (input), which is an indicator of the volume of research conducted in universities. "CoAuthoring" is the total number of co-authored publication (output). "Patent" is total number of patents filed. Input "Budget" may directly affect "CoAuthoring" (1), as well as indirect effect through "Patent"(2 and 3). Following the work of Muller et al. (2005), a three-step empirical model is defined. The unit is individual university by the year.

$$\begin{aligned}\mathrm{CoAuthoring}_{it} = {} & \beta_{10} + \beta_{11}\log(\mathrm{Budget}_{it-2}) + \beta_{12}\mathrm{TTO}_{it} \\ & + \beta_{13}\mathrm{TTO} \times \log(\mathrm{Budget}_{it-2}) + \delta_t + \alpha_i + U_{it} \qquad (1)\end{aligned}$$

$$\begin{aligned}\mathrm{Patent}_{it+1} = {} & \beta_{20} + \beta_{21}\log(\mathrm{Budget}_{it-2}) + \beta_{22}\mathrm{TTO}_{it} \\ & + \beta_{23}\mathrm{TTO} \times \log(\mathrm{Budget}_{it-2}) + \delta_t + \alpha_i + U_{it} \qquad (2)\end{aligned}$$

$$\begin{aligned}\mathrm{CoAuthoring}_{it} = {} & \beta_{30} + \beta_{31}\log(\mathrm{Budget}_{it-2}) + \beta_{32}\mathrm{TTO}_{it} \\ & + \beta_{33}\mathrm{TTO} \times \log(\mathrm{Budget}_{it-2}) + \beta_{34}\mathrm{Patent}_{it+1} \\ & + \beta_{35}\mathrm{TTO} \times \mathrm{Patent}_{it+1} + \delta_t + \alpha_i + U_{it} \qquad (3)\end{aligned}$$

The dependent variable of model (1) and (3) is the number of co-authored papers ($\mathrm{CoAuthoring}_{it}$) between universities and firms. The dependent variable of model (2) is the number of patent granted.

Explanatory variable for models (1), (2), and (3) is the total budget for granted projects by individual university per year (Budget_{it}). Since Budget_{it} is skewed toward several universities and include zero values, we use monotonic transformation and then take the logarithm. Prior evidence suggests that it usually takes at least two years after a

research project starts to produce an outcome. Therefore, we use a two years lag for $BUDGET_{it}$.

Moderating variable is TTO_{it}, the existence of TTO (dummy variable) for individual university per year. $Patent_{it}$ is used as mediating variable in model (3). Prior evidence suggests that it usually takes at least a year for patents to be granted since the application. Therefore, we use one-year lag for $Patent_{it}$.

The time variable δ_t is dummied out for the control. The variable α_i captures unobservable individual characteristics of universities: size, willingness for the UIC, research quality, reputation, location etc. To deal with potential endogeneity of explanatory variables, we employ difference-in-difference estimation using OLS. To deal with potential heteroskedasticity, we use clustered standard errors.

2.6. Results

The trend of the total number of articles published is illustrated in Figure 2.2. Academic articles published by universities increased sharply. Academic articles published by firms and academic articles published jointly by universities and firms slightly increased. Figure 2.3 illustrates the increase of patents after the launch of TTO.

Next, we investigate the causal effect of our model. Table 2.4 describes the overall effect on existing links and new links. Among all co-authorship, new link and existing link may have different effect from launch of TTO. If co-authoring between university A and firm B existed prior years, we define that as an existing link. If co-authoring between university A and firm B never existed in prior year, we define that as a new link. Columns (1) and (2) are subsamples for existing links and new links,

respectively. The coefficients for the interaction effect of existence of TTO and total budget are both statistically significant for existing links and new links. Not only the increase of existing links but also increase of new links clearly explains decrease of search cost.

Table 2.5 illustrates mediated moderation effect of the model. Column (1) is the direct effect from "Budget" to "CoAuthoring". Column (2) is the direct effect from "Budget" to "CoAuthoring". Column (3) is the indirect effect from "Budget" to "CoAuthoring". The coefficients of β_{13} and β_{33} are both statistically significant. The size of β_{13} is larger than that of β_{33}. Both β_{23} and β_{33} are statistically significant. It indicates mediation effect of PATENT variable exists. In summary, the condition satisfies all the requirements of mediated moderation.

The evidence that coefficients of β_{13} and β_{33} are both statistically significant indicates the existence of TTO moderates co-authorship of university and firm researchers (Hypothesis 1 confirmed).

In Table 2.5, the coefficient β_{23} is positively statistically significant, which indicates that existence of TTO positively moderates co-authorship between university and firm researchers. At the same time, the size of β_{13} is larger than that of β_{33}. Both β_{13} and β_{33} are statistically significant. It indicates mediation effect of PATENT variable exists (Hypothesis 2 confirmed).

Figure 2.4a explains the overall effect of mediated moderation. As shown in the figure, coefficient before TTO is -0.302 while after TTO is 1. TTO seems to promote co-authoring academic articles between university and firms. It indicates that presence of TTO creates "gateway effect". Figure 2.4b demonstrates direct and indirect effect of

mediated moderation. As shown in the figure, direct effect before TTO is -0.170 and after TTO is 0.465. Clearly, the sizes of coefficients are smaller than that of overall effects. It indicates mediation effect by Patent exists. The coefficients for the impact of Budget to Patent are -0.019 before TTO and 0.549 after TTO, respectively. It demonstrates that the launch of TTO has positive effect for patenting. However, coefficients between Patent and CoAuthoring are both 0.656 for before and after TTO. TTO does not facilitate co-authoring academic article after patenting. This is a clear evidence of "gateway effect."

Next, we investigate the effect of TTO for senior and junior researchers. All researchers are categorized by the length of experience. A researcher with more than 10 years from his or her first publication is categorized as senior researcher, while those with less than 10 years from his or her first publication are categorized as junior researchers. Table 2.6 demonstrates the result of mediated moderation for senior and junior researchers.

For both the results for senior researchers and junior researchers, the following condition satisfies the requirement of mediated moderation: (1) The coefficients of β_{13} and β_{33} are both statistically significant. (2) The size of β_{13} is larger than that of β_{33}. (3) Both β_{23} and β_{33} are statistically significant.

Figures 2.5a, 2.5b, 2.6a, and 2.6b explain the overall, direct, and indirect effects of mediated moderation for senior and junior researchers, respectively. Overall effect for senior researchers is -0.343 before TTO and 0.995 after TTO. Overall effect for junior researchers is -0.965 before TTO and 3.78 after TTO. Net effects are 1.338 for senior researchers and 4.475, respectively. The net effect is significantly larger for junior researchers, which indicates that "gateway effect" is larger for junior researchers. The

coefficients of β_{33} are larger for junior researchers. It indicates that gatekeeper effect is also larger for junior researchers. Thus, we confirm hypothesis 3.

2.7. Robustness Checks

For this study, we selected national universities as the sample pool. A selection bias potentially exists. Now, we conduct robustness check for the selection bias. Table 2.7 and 2.8 describe mediated moderation with different sample selections. Columns (1), (2), and (3) in Table 2.7 illustrate mediated moderation with the sample of top 100 universities by the volume of research. Columns (4), (5), and (6) demonstrate mediated moderation with the sample of top 100 universities by the volume of co-authoring academic articles. Columns (1), (2), and (3) in Table 2.8 describe mediated moderation with sample of all universities. Columns (4), (5), and (6) explain mediated moderation with the sample including both all universities and all years. All four analyses satisfy the requirement of mediated moderation. Therefore, we conclude that our empirical analysis is robust for the selection bias.

Though national universities were "nudged" to establish their TTO, the treatment was not randomized in this natural experiment. It is possible that the willingness for UIC is positively correlated with all the dependent variables and explanatory variables, such that the current coefficients of TTO_{it} and $PATENT_{it}$ are positively biased. Since we are using fixed effects, we controlled the non-changing characteristics of universities including the willingness to collaborate. However, we cannot control the changing willingness of UIC, because getting data on the willingness of UIC is difficult without conducting extensive surveys. As the robustness check, we have checked the changes of

university ranking order, and we find no evidence significant change. Therefore, we conclude that non-changing characteristics of universities less likely to affect our results.

2.8. Conclusion and Future Work

In this research, we formalized the gateway and gatekeeper effects of the TTO using an analytical model. The model predicts that TTO positively moderates the impact of budget on COS, and the effect is mediated thorough patents as well. Additionally TTO has larger impacts for junior researchers than senior researchers. The model predictions were examined based on a natural experiment in Japan. The results were consistent with our predictions. The gateway and gatekeeper effects reconcile two contradicting views of TTOs.

There are three types of trust: process-based (trust tied to past or expected exchange), characteristics-based (trust tied to person), and institutional-based (truest tied to formal societal structures) (Zucker 1986). The traditional Japanese model for UIC was based on process-based trust. Researchers in universities and firms repeatedly collaborate to create long-term relationships. The creation of TTO aims to create institutional trust. TTO works as an intermediary to create trust between universities and firms for UIC activities. Senior researchers may rely on process-based trust, while junior researchers lack experience and process-based trust, and may benefit from the TTO as intermediary to promote UIC. Our result of mediation effect of patents urges the appropriate design of TTO as intermediary. As Siegel et al. (2003) point out if the TTO is protecting intellectual property too aggressively, firms may avoid working with universities. Also,

the TTO may behave like a monopolistic intermediary (Litan et al. 2008), maximizing licensing revenue and lacking an incentive to promote publishable research.

This ground-breaking study of UIC, with theory and empirical validation components, does suffer from several limitations. We used Nanobank, which only captures research in the nanotechnology field. Other fields and different countries (other than Japan) may have different characteristics.

ACKNOWLEDGMENTS

Data included herein is derived from Nanobank (Zucker and Darby 2007), Science Citation Index Expanded, Social Sciences Citation Index, and Arts & Humanities Citation Index of the Institute for Scientific Information (ISI).

Chapter 2, in part, is currently being prepared for submission for publication of the material. Maki, Kanetaka M.; Krishnan, Vish. The dissertation author was the primary investing and author of this paper.

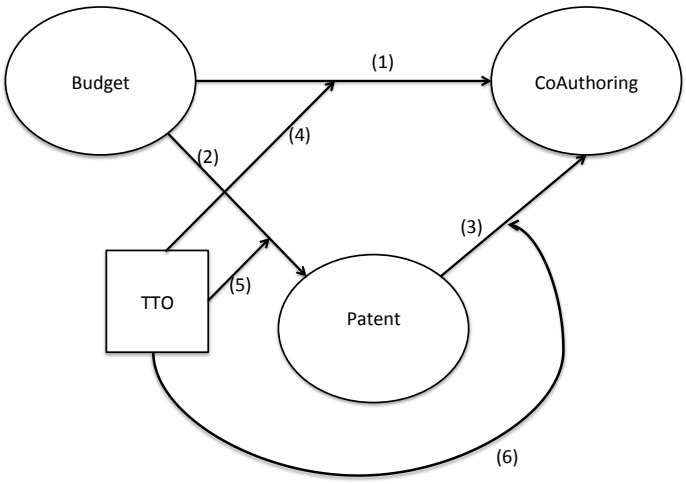


Figure 2.1: Overall Model with Mediation and Moderation Effects

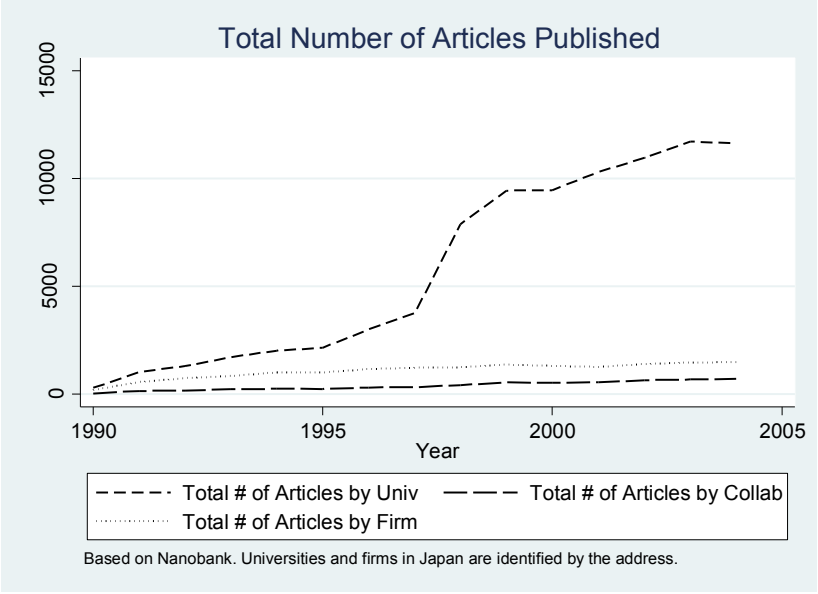


Figure 2.2: Total Number of Articles

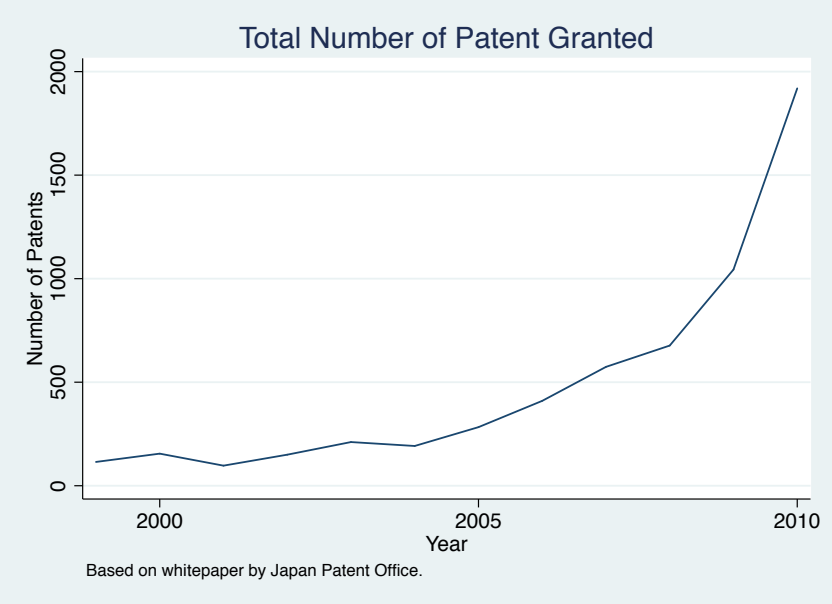


Figure 2.3: Total Number of Patents

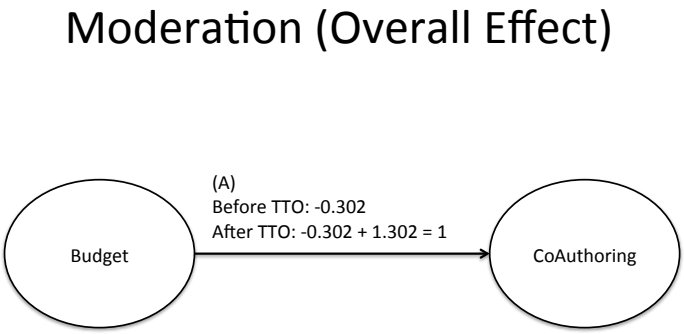


Figure 2.4a: Mediated Moderation (Overall Effect)

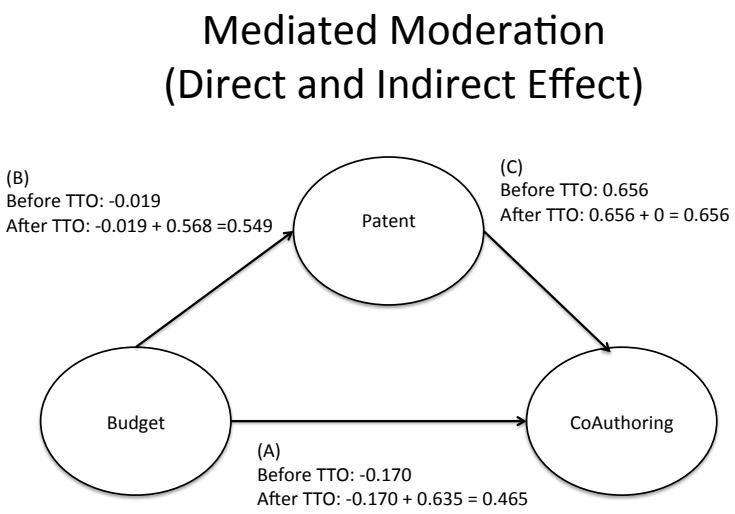


Figure 2.4b: Mediated Moderation (Direct and Indirect Effect)

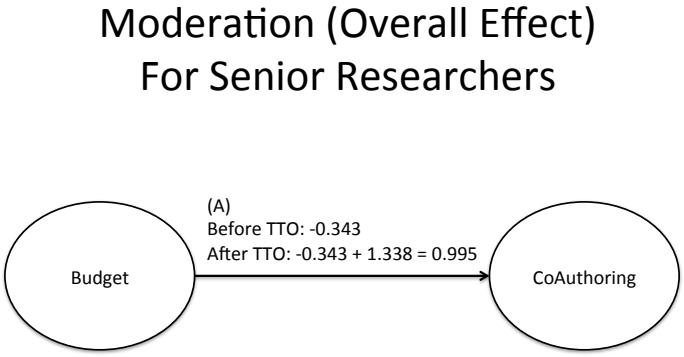


Figure 2.5a: Mediated Moderation (Overall Effect) for Senior Researchers

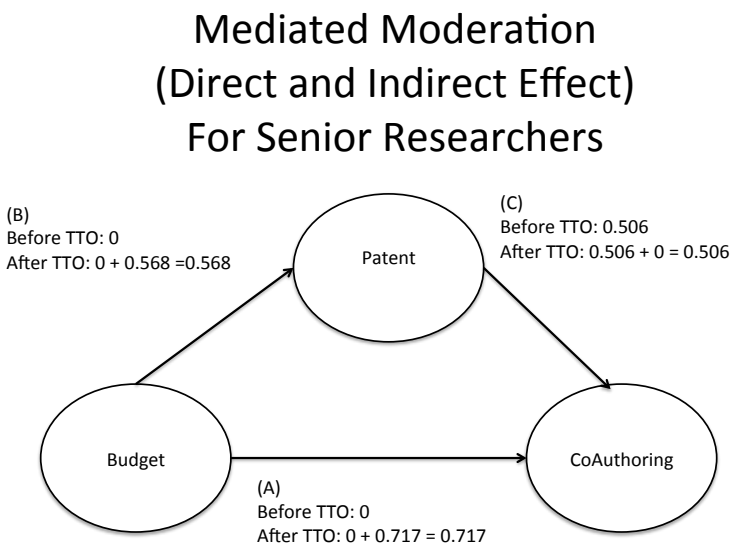


Figure 2.5b: Mediated Moderation (Direct and Indirect Effect) for Senior Researchers

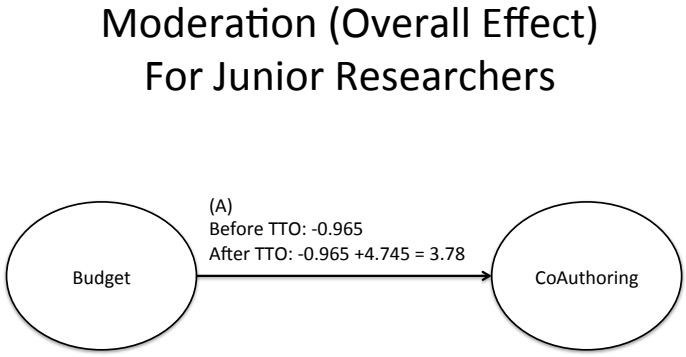


Figure 2.6a: Mediated Moderation (Overall Effect) for Junior Researchers

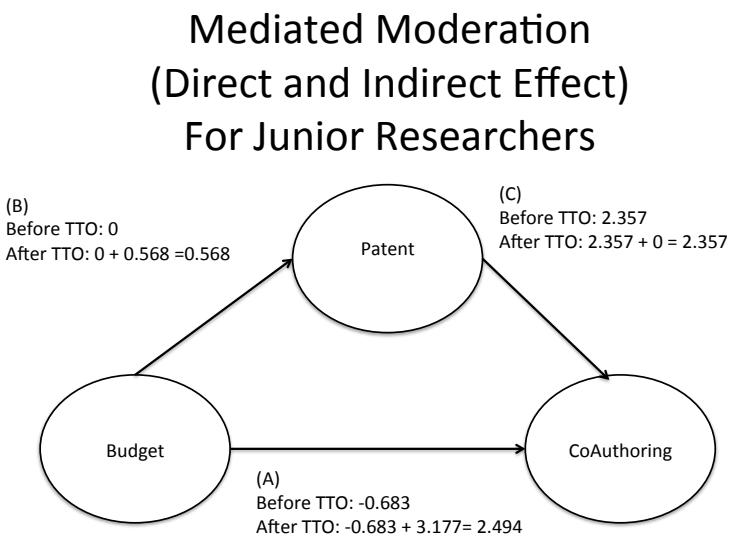


Figure 2.6b: Mediated Moderation (Direct and Indirect Effect) for Junior Researchers

Table 2.1: Innovation Policy in Japan

1998	Formulation of the Act on the Promotion of Technology Transfer from Universities to Private Industry (the TLO Act)
	Amendment of the Law for Facilitating Governmental Research Exchange
1999	Creation of the Small Business Innovation Research Program ("Japanese SBIR") Formulation of the Act on Special Measures for Industrial Revitalization (Japanese version of the Bayh–Dole Act) Establishment of the Japan Accreditation Board for Engineering Education (JABEE)
2000	Formulation of the Industrial Technology Enhancement Act
2001	"Hiranuma Plan" announced "Plan for 1,000 university-originated ventures in three years"
2002	Revision of the Ministry of Finance Property Administration Bureau Notification No. 1 Revision of the TLO Law Notification
2003	Formulation of the Intellectual Property Basic Act

Revised based on http://www.rieti.go.jp/jp/publications/nts/11e008.html

Table 2.2: Launch of Technology Transfer Offices in Top 100 Universities in Japan

Date	Organization
December, 1998	Univ Tokyo, Tohoku Univ, Kyoto Univ, Kyoto Inst Technol, Nihon Univ, Yamagata Univ, Nara Inst Sci & Technol, Ritsumeikan Univ, Iwate Univ, Doshisha Univ, Hirosaki Univ, Akita Univ, Ryukoku Univ
April, 1999	Univ Tsukuba, Waseda Univ
August, 1999	Tokyo Inst Technol, Keio Univ
December, 1999	Hokkaido Univ, Yamaguchi Univ, Muroran Inst Technol
April, 2000	Nagoya Univ, Kyushu Univ, Kobe Univ, Nagoya Inst Technol, Toyohashi Univ Technol, Toyama Univ, Gifu Univ, Kwansei Gakuin Univ, Toyama Prefectural Univ
June, 2000	Tokyo Denki Univ
September, 2000	Yamanashi Univ
December, 2000	Tokyo Metropolitan Univ, Univ Electrocommun, Hosei Univ, Toyo Univ, Kogakuin Univ
April, 2001	Yokohama Natl Univ, Univ Tokushima, Ehime Univ, Yokohama City Univ, Meiji Univ
August, 2001	Osaka Univ, Univ Osaka Prefecture, Osaka City Univ, Kumamoto Univ, Kansai Univ, Kinki Univ
December, 2001	Tokyo Univ Agr & Technol, Niigata Univ, Nagaoka Univ Technol
January, 2002	Univ Shizuoka, Shizuka Univ
April, 2002	Kyushu Inst Technol, Mie Univ, Fukuoka Univ
December, 2002	Kanazawa Univ
February, 2003	Kagoshima Univ
April, 2003	Shinshu Univ
May, 2003	Miyazaki Univ
September, 2003	Sci Univ Tokyo
October, 2003	Hiroshima Univ
December, 2003	Shimane Univ
April, 2004	Okayama Univ, Okayama Univ Sci, Konan Univ

Table 2.3: Summary Statistics

	count	mean	sd	min	max
Total # of Collaboration	880	4.49	10.17	0.0	73
Existence of TTO	880	0.24	0.43	0.0	1
# of Patents by TTO	880	0.72	2.24	0.0	22
Total # of Article	880	74.29	177.17	0.0	1246
# of PI	880	3.06	7.82	0.0	84
Total Budget	880	500.60	1906.83	0.0	26776
Articles with Senior Researcher	880	1.88	7.34	0.0	71
Articles with Junior Researcher	880	14.37	31.87	0.0	262
Observations	880				

Summary statistics for national universities for years of 1994-2004.
Sample was attained from Nanobank, COMET and KAKENHI database.

Table 2.4: The Effect for Existing and New Links

	(1)	(2)
VARIABLES	Existing Links	New Links
Total Budget (logarithm, 2 years lagged)	-0.314***	-0.0160
	(0.0968)	(0.0377)
Existence of TTO	-1.794**	0.185
	(0.695)	(0.240)
Interaction Effect: (Existence of TTO) x (Total Budget)	1.166***	0.206**
	(0.236)	(0.0816)
Constant	1.799***	1.001***
	(0.372)	(0.130)
Observations	880	880
R-squared	0.274	0.167
Number of CODE	80	80
Time Dummy Variables	Yes	Yes
Fixed Effect	Yes	Yes

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: The Effect of Mediated Moderation

	(1)	(2)	(3)
VARIABLES	COL	PATENT_lag1	COL
Total Budget (logarithm, 2 years lagged)	-0.302***	-0.0186	-0.170*
	(0.112)	(0.0549)	(0.0931)
Existence of TTO	-1.417*	-0.725**	-0.308
	(0.810)	(0.327)	(0.578)
Interaction Effect: (Existence of TTO) x (Total Budget)	1.302***	0.568***	0.635***
	(0.268)	(0.148)	(0.213)
Number of Patents Granted			0.656***
			(0.223)
Interaction Effect: (Existence of TTO) x (Number of Patents Granted)			0.194
			(0.347)
Constant	2.738***	0.0162	2.623***
	(0.436)	(0.134)	(0.394)
Observations	880	800	800
R-squared	0.305	0.322	0.399
Number of CODE	80	80	80
Time Dummy Variables	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.6: The Effect of Mediated Moderation for Senior / Junior Researchers

	(1)	(2)	(3)	(4)	(5)	(6)
	Senior Researchers			Junior Researchers		
VARIABLES	SENIOR	PATENT_lag1	SENIOR	JUNIOR	PATENT_lag1	JUNIOR
Total Budget (log, 2 years lagged)	-0.343**	-0.0186	-0.163	-0.965**	-0.0186	-0.683*
	(0.132)	(0.0549)	(0.101)	(0.459)	(0.0549)	(0.364)
Existence of TTO	-2.940**	-0.725**	-1.885**	-5.156*	-0.725**	-1.536
	(1.217)	(0.327)	(0.857)	(3.063)	(0.327)	(2.296)
IE: (TTO) x (Total Budget)	1.388***	0.568***	0.717*	4.745***	0.568***	3.177***
	(0.417)	(0.148)	(0.396)	(1.073)	(0.148)	(0.708)
Number of Patents Granted			0.506***			2.357***
			(0.168)			(0.876)
IE: (TTO) x (# of Patents Granted)			0.244			-0.183
			(0.445)			(1.378)
Constant	1.486***	0.0162	1.330***	8.704***	0.0162	8.458***
	(0.484)	(0.134)	(0.474)	(1.965)	(0.134)	(1.895)
Observations	880	800	800	880	800	800
R-squared	0.177	0.322	0.207	0.299	0.322	0.348
Number of CODE	80	80	80	80	80	80
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.7: Robustness Check for Selection Bias (1) –

Top 100 Universities (Research / CoAuthoring)

	(1)	(2)	(3)	(4)	(5)	(6)
	Top 100 Universities (Research)			Top 100 Universities (CoAuthoring)		
VARIABLES	COL	PATENT_lag1	COL	COL	PATENT_lag1	COL
Total Budget (log, 2 years lagged)	0.349***	-0.0716	0.305***	0.328***	-0.0582	0.291***
	(0.110)	(0.0537)	(0.0909)	(0.108)	(0.0535)	(0.0887)
Existence of TTO	-1.253*	-0.787**	-0.879	-0.987	-0.677**	-0.652
	(0.699)	(0.322)	(0.586)	(0.610)	(0.283)	(0.510)
IE: (TTO) x (Total Budget)	1.140***	0.566***	0.841***	1.116***	0.554***	0.820***
	(0.240)	(0.135)	(0.175)	(0.232)	(0.132)	(0.166)
Number of Patents Granted			0.446***			0.474***
			(0.165)			(0.165)
IE: (TTO) x (# of Patents Granted)			0.0636			0.0468
			(0.194)			(0.194)
Constant	5.613***	1.762***	4.751***	4.884***	1.479***	4.135***
	(0.596)	(0.306)	(0.560)	(0.519)	(0.266)	(0.489)
Observations	1,100	1,100	1,100	1,221	1,221	1,221
R-squared	0.292	0.266	0.348	0.284	0.258	0.343
Number of CODE	100	100	100	111	111	111
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.8: Robustness Check for Selection Bias (2) –

All Universities / All Universities & All Years

	(1)	(2)	(3)	(4)	(5)	(6)
	All Universities			All Universities & All Years		
VARIABLES	COL	PATENT_lag1	COL	COL	PATENT_lag1	COL
Total Budget (log, 2 years lagged)	-0.132	0.0221	-0.135*	0.621***	0.158***	0.752***
	(0.0818)	(0.0462)	(0.0693)	(0.148)	(0.0360)	(0.174)
Existence of TTO	0.215	-0.0375	0.234	-0.00861	-0.132	-0.0475
	(0.263)	(0.112)	(0.233)	(0.385)	(0.144)	(0.378)
IE: (TTO) x (Total Budget)	1.042***	0.518***	0.746***	1.048***	0.619***	0.577***
	(0.206)	(0.119)	(0.144)	(0.249)	(0.128)	(0.215)
Number of Patents Granted			0.497***			0.449**
			(0.136)			(0.191)
IE: (TTO) x (# of Patents Granted)			0.0545			0.236
			(0.178)			(0.342)
Constant	0.307***	-0.00204	0.308***	-0	0.199***	-0.594***
	(0.0480)	(0.0202)	(0.0449)	(0.0351)	(0.0414)	(0.176)
Observations	8,800	8,800	8,800	24,800	24,000	24,000
R-squared	0.240	0.211	0.311	0.294	0.337	0.389
Number of CODE	800	800	800	800	800	800
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Chapter 3.

Inventor Involvement in the Success of University-Based Startups

ABSTRACT

Inventor involvement in the success of university-based startups has been a longstanding debate concerning its effectiveness. Proponents argue that inventor involvement increases the knowledge transfer to exploit new-to-the-world technologies. On the other hand, opponents point out that inventors' lack of business experience distracts the success of the startups. Conventionally, research streams focusing on the impact of inventor involvement have only evaluated success as a single outcome. However, new firms evolve through some milestone events that may occur prior to the success. We identify three key financially related milestones in the growth of any firm: reception of Small Business Innovation Research (SBIR) funding, venture capital funding and first sales by product launch. Each of these events impacts a firm's growth trajectory. We aim to reconcile two contradicting views of inventor involvement using a growth view of startups. The present study is based on the University of California Startup Dataset, which includes the entire population of startups based upon on University of California licensed technology after the year 2000. The impact of inventor involvement on the success of university-based startup (firm survival and exit) is explored. The results show that receipt of SBIR funding and first sales by product launch mediate the impact of

inventor involvement on the survival rate of startups. In other words, having a greater proportion of the inventor involvement as founders of a startup firm increases the likelihood of receiving SBIR funding and launching a product, which in turn increases the likelihood of survival. However, this effect is only observed for biomedical startups. No mediation effect was found for firm exit; however, the results provide weak evidence that SBIR funding is the important intermediate step for explaining the impact of inventor involvement on the exit of startups.

Keywords: university-based startups, inventor involvement, success

3.1. Introduction

For university-based startups, one of the most controversial questions has been the importance of having inventors involved in the firm's founding team. Some have argued that academic inventors are not sophisticated business persons and thus are likely to frustrate the young firm's success (Franklin et al. 2001, Lockett et al. 2003, Wright et al. 2004), while others emphasize the importance of the inventors in assisting in the transfer process and thus find that their involvement is critical (Samsom and Gurdon 1993, Zucker et al. 1998, Jensen and Thursby 2001). The role of inventor involvement is particularly interesting for university-based startups, because they are nearly always based on new-to-the-world technology that may be far from commercialization (Jensen and Thursby 2001).

A young firm's growth can also be seen as a series of steps or milestones toward a successful exit event (Ndonzuau et al. 2002, Clarysse and Moray 2004, Druilhe and Garnsey 2004, Vohora et al. 2004). We examine three such variables – receipt of a Small Business Innovation Research (SBIR) grant, receipt of venture capital funding, and first sales by product launch. SBIR grant is an early non-dilutive fund for startups. Most university-based startups are still immature with implementing technologies; therefore, it is difficult for them to obtain external financing due to a high degree of uncertainty. SBIR grants increase the success rate of startups by filling the financial gap (Lerner 1996, Toole and Czarnitzki 2007, Howell 2014). Venture funding has been always recognized as the indicator of success for the startups (Amit et al. 1998, Shane and Stuart 2002, Hsu 2006, Puri and Zarutskie 2012). A launching a product as well as receiving a revenue out of the event is another indicator of financial success (Knockaert et al. 2011). These

indicators provide important new insights into the impact of inventor involvement in the formation and growth of new technology-based university startups.

There have been a great number of books and review articles on university-based startups (O'Shea et al. 2004, Shane 2004, Rothaermel et al. 2007, Djokovic and Souitaris 2008). However, because of the difficulty in assembling comprehensive datasets, results from this research stream were oftentimes hampered by inadequate data, small sample sizes, and "success" bias (Ruef et al. 2003, Shane 2004, Rothaermel et al. 2007). One of the larger studies was Shane and Stuart (2002), which examines the effect of founders' networks on success rate, using a dataset of 134 MIT startups.

This study is based on the University of California Startup Dataset, which includes the entire population of startups based upon on University of California licensed technology after 2000. Using binomial test, probit analysis and survival analysis, the effect of inventor involvement as founders upon startup success (survival or exit) rate is explored. It is considered the trajectory of key milestones in the growth of a new firm are characterized by the following three events: reception of SBIR funding, reception of venture funding, and the first sales by launch of the product. The analysis shows that receipt of SBIR funding and first sales by product launch mediate the impact of inventor involvement on the survival rate of startups. In other words, having a greater proportion of inventors involved as founders of a startup firm increases the likelihood of receiving SBIR funding, and first sales by launching a product, which in turn increases the likelihood of a firm's survival exit. However, this effect is only observed for biomedical startups. No mediation effect was found for firm exit; however, the results provide weak

evidence that SBIR funding is the important intermediate step to explain the impact of inventor involvement on the exit of startups.

This chapter is structured as follows: Section 2 reviews the existing literature. Section 3 develops the hypotheses. Section 4 describes the dataset and the empirical methodology. The results and further analyses are presented in Section 5 and 6. Finally, section 7 discusses the findings and concludes with some final thoughts.

3.2. Literature Review

New firms draw upon the stock of knowledge, contacts and resources that its founders possess (Jensen and Thursby 2001, Shane and Stuart 2002, Grandi and Grimaldi 2003, Rothaermel and Thursby 2005a). Startups using technology licensed from universities are particularly interesting because the license is almost always to novel technology that has been patented by the university. Therefore, team formation is particularly critical to the success of startups. Our research is built upon research streams of team formation and firm growth.

Team Formation

The output of the organization is based on several different characteristics of the founding team (Hambrick and Mason 1984). A significant amount of research has been conducted to find the relationship between the startup success rate and the characteristics of the entrepreneurial teams (Sexton and Smilor 1997, Colombo and Grilli 2005). Yet, the mechanism of founding teams upon the success of startups is still unclear.

Team formation for university-based startups is unique. University-based startups are comprised of the more homogeneous top management team, in comparison with

equivalent match startups (Ensley and Hmieleski 2005). Based on the composition of founding team, university-based startups can be classified according to three categories: inventor-led spinoffs, shopper-led spinoffs, and investor-led spinoffs (Shane 2004). Three types of startups occur with approximately the same frequency (Roberts and Malonet 1996). Three types of university technology-based startups have different characteristics related to the timing of launching firm, location, and inventor's involvement, which potentially impact the ultimate success of the startups (Roberts 1991, Franklin et al. 2001, Shane 2002, Golub 2003, Shane 2004).

Most technologies licensed from universities are in "embryonic state," and further involvement of inventors is necessary (Jensen and Thursby 2001). Therefore, inventors' involvement to university-based startups is critical. University faculty members are active in invention activities, especially on more applied projects outside of the university (Thursby et al. 2009). Inventors can still play an effective role in a part-time basis while holding their positions at the university (Samsom and Gurdon 1993).

Ultimately, technology transfer is the movement of knowledge from one setting or organization to another. It has long been understood that knowledge can exist in various forms – explicit and tacit (Polanyi 1967, Nonaka and Takeuchi 1995). Explicit knowledge has been codified and can be transferred through modes of communication such as publications or patents. Yet, some forms of knowledge are not completely explicit, but rather those in the forms of capabilities and skills are not codifiable. This is termed "tacit knowledge." In a university-industry technology transfer context, the transfer of both explicit and tacit knowledge can come into play. For cutting-edge inventions, much of the knowledge is embodied by the inventors themselves (Roberts

2000, Agrawal 2006, Lowe 2006). Novel discoveries are, by nature, tacit knowledge (Zucker et al. 1998). At the same time, even codified knowledge, such as patents or scientific articles describing a technique, to be useful or accessible, require absorptive capacity (Cohen and Levinthal 1990, Rothaermel and Thursby 2005b, Zahra et al. 2007). Therefore, the involvement of inventors in university-based startups is the critical factor.

Inventor involvement as founders has some additional advantages. First, inventors provide network ties to the startups (Nicolaou and Birley 2003b, Nicolaou and Birley 2003a). Second, they create affiliation with a university. The tie to a university helps to create the credentials for the startups (Grandi and Grimaldi 2003). The stronger the link to a university, the lesser the probability that the startup will fail (Rothaermel and Thursby 2005a). Support from university departments to which inventors belong has a large impact on firm's growth (Rasmussen et al. 2014).

In a university-based startup setting, founding teams often suffer from the lack of commercial experience. In order to avoid the lack of experience, founders often try to team-up with external members with business experience. The use of surrogate entrepreneurs (including the combination of inventors and surrogate entrepreneurs as a team) is one of the success factors of university-based startups (Franklin et al. 2001, Lockett et al. 2003, Wright et al. 2004).

Despite the fact that a strong link between universities and startups is beneficial in terms of the success of the startup, these two parties often clash as the academic and business culture are profoundly different (Samsom and Gurdon 1993). Strong ties to the university may lead startups to focus on basic research rather than the development of a product (Johansson et al. 2005). Stronger university links decrease the probability of

startups to graduate from the incubator (Rothaermel and Thursby 2005a). This may indicate that linking with a university increases survival rate, but does not increase the probability of growth. Clarysse and Moray (2004) explains the tension between inventors and an external CEO. In the early phase of startups, the CEO requires (a) a deep understanding of the technology and (b) the ability to develop the business by himself. In many cases, external CEOs do not have the ability to satisfy these requirements. On the other side of the equation, inventors do not accept external CEOs. The team that promotes the balance of scientific and commercial orientation increases the performance of the firm (Visintin and Pittino 2014).

Firm Growth and Evolution

As startups evolve, their business activities change (Druilhe and Garnsey 2004). Ndonzuau et al. (2002) proposes a four-stage model of firm growth, and each stage has different major issues to solve. For example, in the early stage, acquiring resources and relationships with the university are the key issues. In contrast, in the later stage, the change of growth trajectories is the key issue. Vohora et al. (2004) demonstrates a non-linear, four-stage model of development for university-based startups and explains "critical junctures" of the resource and capabilities to progress to next stage. Clarysse and Moray (2004) describe two different phases (idea phase and post-startup phase), and explain the higher rate of management turnover for the university-based startups. In the early phase, the main activity is further development of the technology, while the later phase requires business development. Rosenbloom (2007) proposes a causal model to explain the impact of university science and engineering capacity and patenting on SBIR grants, venture capital investment, and initial public offerings. The authors claim that

SBIR grants, venture capital investments, and initial public offering are not in the linear model, but rather interconnected. In summary, activities of startups can be categorized into multiple stages, and each stage has different goals that require different roles of inventors.

The percentage of founders of startups who are also in top management team has an inverted U-shaped relationship with patent invention performance. Furthermore, invention performance and tenure of top management team member are negatively associated (Liu et al. 2012). A founder's exit, as well as the entrance to the new top management team, increases the likelihood of a firm to achieve an IPO, which indicates that diversity in prior experiences among the team members is a key factor (Beckman et al. 2007).

It is necessary to adopt appropriate indicator variables in order to evaluate the success of startups, as the selection of indicators depends on a type analyses as well as the aims of the research. For example, it may be appropriate to use a number of employees or the survival rate to evaluate the policies of startups. On the other hand, success rate (IPO or M&A) is appropriate to disentangle the underlying mechanism of startup formation and growth. Storey (1982) uses a firm's survival as the indicator of ultimate success. Shane and Stuart (2002) uses receiving experiencing the IPO and experiencing the failure (i.e. survival rate) as the ultimate outcome of startups. When we take the staging model into account, indicator variables become even more complex. Shane and Stuart (2002) uses receiving venture capital financing as an intermediate variable. Knockaert et al. (2011) uses the likelihood of launching a product as the intermediate variable. Toole and Czarnitzki (2007) uses multiple intermediate indicators,

such as the likelihood of follow-on venture capital investment, the probability of patenting, and completing SBIR program. Howell (2014) uses the following indicators: likelihood to receive subsequent venture capital, to receive patents, and to achieve revenue.

The following three variables are particularly critical as intermediate variables because they support startups financially: receipt of an SBIR grant, receipt of venture capital funding, and first product shipment.

SBIR is an early non-dilutive fund for startups. Most university-based startups are still immature in terms of their technologies; external financing is difficult to obtain due to a high degree of uncertainty. SBIR grants increase the success rate of startups by filling the financial gap (Lerner 1996, Toole and Czarnitzki 2007, Howell 2014).

Based on case studies, Audretsch et al. (2002) explains that SBIR program has positive effects, because recipients alter their career choice, specifically to choose to become entrepreneurs. There is an empirical evidence of the impact of SBIR grants on the success of startups. However, validation of the underlying mechanism may vary. Lerner (1996) examines the effect of SBIR programs (both Phase I and II) and concludes that the receiving the award has a "certification effect" on the quality of a startup. In other words, the quantity of the grant does not matter, but the receiving the grant leads to receiving venture funding. Toole and Czarnitzki (2007) studied the effect of SBIR program focusing on biomedical academic startups. The authors conclude that the completion of the SBIR Program Phase I increases the probability of receiving the venture funding, rather than the Phase II award. In contrast, the work done by Howell

(2014), using a regression discontinuity design, illustrates that the grant money itself is valuable, rather than a "certification effect."

Venture funding has been always recognized as the indicator of success for the startups (Amit et al. 1998, Shane and Stuart 2002, Hsu 2006, Puri and Zarutskie 2012). There is a long lasting debate whether the decisions of venture capitalists should be based on the management team or the business idea (Kaplan et al. 2009). Launching a product and receiving revenue are other indicators in terms of financial success (Knockaert et al. 2011).

In summary, much progress has been made in predicting and understanding the team formation, specifically in terms of inventor involvement on startup success. However, two contradicting views of inventor involvement – whether inventor involvement assists or distract university technology-based startup success – remains an open question. We reconcile these two contradicting views by combining with a multi-stage model of startups growth.

3.3. Research Hypotheses

This paper explores the relationship between inventor involvement and the ultimate success of startups. In order to study the effects of intermediate variables as explained above, a sequencing type model is adapted. Survival rate and firm exit (IPO or M&A) are used as the indicators of ultimate success. Taking a multi-stage model into account, the intermediate variables include: receipt of an SBIR grant, receipt of venture capital funding, and first sales by product launch.

The natural question is whether or not these milestone events occur chronologically. The SBIR grant aims to fill the financial gap when receiving the venture funding is difficult for startups. The goal of an SBIR grant is to create a prototype. Venture capitalists often invest when startups have prototypes. Venture funding often helps startups to sell the product. The ultimate goal of a startup is to exit. Therefore, one may assume that events happen in the following order: an SBIR grant, product launch, and venture funding. Consequently, the following hypothesis was set forth:

(Hypothesis 1) The events of university-based startups occur in the following chronological order: an SBIR grant, venture funding, and first sales by product launch.

Securing financial resources has been found to be vital to startup success. One important source of early non-dilutive funds is SBIR grants (Lerner 1996, Toole and Czarnitzki 2007, Howell 2014). An SBIR program requires academic entrepreneurs to be involved in the startups. There is a question to be answered in regards to the hypothesis: how does inventor involvement affect the likelihood of receiving SBIR grants? The greater proportion of inventor involvement may increase the likelihood of receiving SBIR grant in two ways. First, the greater inventor involvement would result in a greater probability of applying the grant, as inventors must be part of the team to apply. Second, the greater proportion of inventor involvement may increase the quality of an SBIR grant proposal because more uncodified knowledge is transferred. Furthermore, an SBIR grant is not dilutive funds and should contribute to ultimate success. Therefore, the following hypotheses would examine the effect of SBIR grant on startups success:

(Hypothesis 2a) The receiving of an SBIR grant mediates the impact of inventor involvement as a startup founder increases the likelihood of a firm's survival rate.

(Hypothesis 2b) The receiving of an SBIR grant mediates the impact of inventor involvement as a startup founder increases the likelihood of a firm's exit.

For many firms, securing venture capital is another milestone in regards to growth (Lockett et al. 2002, Lockett and Wright 2005). Patents owned by startups act as the signaling of the quality of the firm, and therefore, the likelihood of receiving venture funding increases (Hsu and Ziedonis 2008). In a similar vein, greater involvement from inventors may be the signaling of the higher quality of startups. Therefore, greater involvement of inventors may lead to the greater probability of receiving venture capital financing. At the same time, venture funding has been always recognized as the indicator of success for startups (Amit et al. 1998, Shane and Stuart 2002, Hsu 2006, Puri and Zarutskie 2012). Therefore, the following hypotheses examine the effects of venture funding on startups:

(Hypothesis 3a) The receiving of venture funding mediates the impact of inventor involvement as a startup founder increases the likelihood of a firm's survival rate.

(Hypothesis 3b) The receiving of venture funding mediates the impact of inventor involvement as a startup founder increases the likelihood of a firm's exit.

Licensing a patent is not adequate to completely transfer tacit knowledge. As Knockaert et al. (2011) describes, the high proportion of inventor's involvement as a startup founder increases tacit knowledge transfer. The transfer of tacit knowledge is a critical factor for launching a product. Therefore, if the inventor becomes a founder of the startup, the probability of launching a product would increase. Consequently, the forth hypotheses were set as following.

(Hypothesis 4a) The product launch mediates the impact of inventor involvement as a startup founder increases the likelihood of a firm's survival rate.

(Hypothesis 4b) The product launch mediates the impact of inventor involvement as a startup founder increases the likelihood of a firm's exit.

3.4. Datasets and Empirical Methodology

Dataset

The present study analyzes the entire population of startups based on technology licensed from the University of California System (UC system) from 2000 to 2013. The UC system is comprised of ten campuses, five medical centers, three national laboratories, 150 academic disciplines, and 600 graduate degree programs. Six of the campuses are listed among top 50 universities in the world.[1]

The dataset (UCSUDB) is composed of 541 startups. Each startup was identified and verified by UC Office of President. The definition of UC startups is that the firm must be a legally organized/incorporated company whose formation depended upon a disclosed UC technology. It has to acquire the rights during its first year of operation and be formed independently from any pre-existing company. It should be noted that UCSUDB is based on startups with patent licensed from UC. Firms without patents (which are common in the IT sector) are not included. All ten campuses within the UC system share the same institutional setting.

The dataset includes the entire population of startups established after 2000 with a licensing agreement with the UC. It contains a name of the firm, names of the firm

[1] Academic Ranking of World Universities: http://www.shanghairanking.com/

founders, names of all the inventors, affiliations of the founders (university or non-university), calendar year of incorporation, exit year, reasons for exit (IPO, M&A,), firm's fate (survival or bankruptcy), existence of a product on the market, SBIR grants received for commercialization of the particular invention, venture capital funding dates, and receipt of royalties.

Empirical Methodology

For empirical analysis, due to the nature of the dataset, three analytical tests were combined: binomial test, probit analysis, and survival analysis. To test hypothesis 1, the binomial test is used to test the chronological order of events. To test hypotheses 2a, 3a, 4a (survival rate as the indicator of success), probit analysis is used. Probit test is particularly suited to examine firm's fate (survival or bankruptcy) since the dataset does not include the date of bankruptcy. To test hypotheses 2b, 3b, 4b (firm exit as the indicator of success), following the work of Shane and Stuart (2002), survival analysis is used.

The chronological order of three event – receiving SBIR grant, receiving venture capital funding, and achieving first sales – are analyzed by comparing the dates of events. Order comparison dummy variables are created for this purpose. For example, SBIR_VC is 1 when SBIR grant occurs prior to venture funding. On the contrary, SBIR_VC is 0 when SBIR grant occurs after the venture funding. Binomial tests are conducted for three combinations of three events. The null hypothesis is that event occurs randomly; in other words, the expected value of the order comparison dummy variable would be 0.5. Pearson's chi-squared tests are conducted to check the independence of events.

The outcome variable for probit analysis is survival (dummy variable). The events used for survival analysis are receipt of an SBIR grant, receipt of venture capital funding, product launch, and exit (IPO or M&A).

The explanatory variable is the proportion of the inventors that are reported as the firm's founders as well. In comparison with dummy variable of whether at least one inventor was one of the founders, the proportion of their participation as founders also captures the magnitude of involvement. The proportion of the inventors involved as founders is calculated as follows. Using the UC Patent Tracking System, names of inventors listed on patents licensed to startups are examined. The number of inventors' names matched to the founders' name of startups was divided by a total number of inventors. It should be noted that a startup may have several licensed patents.

Control variables includes the following: industry sector dummy variables (IT sector, biomedical sector, and other sectors), campus dummy variables (UCB, UCI, UCLA, UCM, UCR, UCSB, UCSC, UCSD, and UCSF), SBIR funding (dummy), venture funding (dummy), year dummy variables of firm formation, and year dummy variables for events. For survival analysis, firm age variables at the time of exit are included. Following Shane and Stuart (2002) work, firm age variables are dummy variables with two thresholds. Thresholds for a product launch, SBIR funding, and venture funding are two and three years, while thresholds for exit are four and seven years.

To test the impact of intermediate variables (SBIR funding, venture funding and the first sales by product launch) on a firm's success, the mediation test are conducted (Baron and Kenny 1986).

3.5. Results

Descriptive Analysis

Table 3.1 describes the summary statistics of the dataset. There were 541 startups formed since 2000. By excluding the samples with missing data, our total sample includes 533 firms. As of June 2013, 48 of these firms either made a public offering or were acquired. The campuses with the top three largest number of startups were UCSD, UCLA, and UCB. This is roughly consistent with their research expenditures.

Table 3.2a describes the cross table of receiving SBIR grant and receiving venture funding. There are 56 startups that received both SBIR grant and venture capital funding. Pearson's chi-squared test result rejects the null hypothesis that two variables (SBIR grant and venture funding) are independent (p-value = 0.038). Table 3.2b illustrates the binomial test of whether SBIR grant receiving occurs prior to the venture funding. The alternative hypothesis, where the probability of SBIR_VC is greater than 0.5, is statistically significant (p-value=0.0081). That being said, an event of receiving SBIR grants occurs prior to venture funding.

Table 3.3a describes the cross table of receiving SBIR grant and receiving first sales. There are 28 startups that received both SBIR grant and first sales. Pearson's chi-squared test result rejects the null hypothesis that two variables (SBIR grant and first sales) are independent (p-value=0.042). Table 3.3b illustrates the binomial test of whether or not SBIR grant receiving occurs prior to the first sales. We could not reject the null hypothesis. There is no evidence that receiving SBIR grant occurs prior to the first sales. However, it is possible that this may be due to the small sample size.

Table 3.4a describes the cross table of receiving venture funding and receiving first sales. There are 48 startups that received both venture funding and first sales. Pearson's chi-squared test result rejects the null hypothesis that two variables (venture funding and fist sales) are independent (p-value=0.002). Table 3.4b illustrates the binomial test of whether venture funding occurs prior to the first sales. The alternative hypothesis, in which the probability of FS_VC is greater than 0.5, is statistically significant (p-value=0.042). The first sales event occurs prior to venture funding.

As shown above, SBIR funding occurs prior to venture funding, and the first sales event occurs prior to venture funding. However, there was no evidence that SBIR funding occurs prior to first sales. Therefore, hypothesis H1 is rejected. The simultaneous feedback effect between SBIR funding and the first sales event may be occurring.

Analysis of Survival

Table 3.5 describes probit analysis on the probability of survival. Column (1) includes the explanatory variables (the proportion of inventors became founder). Column (2) includes industry dummy variables. Column (3) includes campus dummy variables. Column (4) includes time dummy variables of the incorporated year. Column (5), (6), and (7) include dummy variables of SBIR funding, venture funding, and first sales, respectively.

The explanatory variable is significant throughout all columns (p-values < 0.01 for columns 3, 4, and 6; p-value < 0.05 for column 1, 2, 5 and 7). This indicates that the greater proportion of inventor involvement increases the likelihood of survival. All coefficients of industry sectors are not statistically significant, which indicates that there is no difference by among industry sectors. The dummy variables for SBIR funding,

venture funding, and first sales are all positively statistically significant (p-value < 0.01). This indicates that all of three intermediate variables have a positive impact on the likelihood to survive.

Table 3.6 describes probit analysis on SBIR funding, venture funding, and first sales. Dependent variables are SBIR funding for column (1)-(3), venture funding for columns (4)-(6), and first sales for columns (7)-(9), respectively. Columns (2), (5), and (8) include industry sector dummy variables. Columns (3), (6), and (9) include campus dummy variable and year dummy variable for incorporation.

The explanatory variable is positively statistically significant throughout the SBIR funding columns and first sales columns (p-value < 0.01), but not for the venture funding columns. This indicates that the great proportion of inventor involvement increased the receiving of SBIR funding and first sales, but not venture funding. The dummy variable of biomedical sector is negatively statistically significant for columns (8) and (9) (p-value < 0.01), indicating that biomedical sector is less likely to receive the first sales in comparison with the IT sector.

Mediation tests are conducted for SBIR funding, venture funding and first sales as the mediator for survival. The coefficient of the explanatory variable in columns (4) of Table 3.5 is positively statistically significant (p-value < 0.01), which indicates the overall effect of inventor involvement on firm's survival rate exists. The coefficients of explanatory variable in columns (3) and (9) of Table 3.6 are positively statistically significant (p-value < 0.01), which indicates that the direct impact from inventor involvement to SBIR funding and first sales exist, respectively. The coefficient of explanatory variable in column (6) of Table 3.6 is not statistically significant, which

indicates there is no direct impact of inventor involvement on venture funding. The coefficients of SBIR funding and first sales in columns (5) and (7) of Table 3.5, respectively, are positively statistically significant (p-value < 0.01). The coefficients of inventor involvement in column (5) and (7) of Table 3.5 are 0.598 (p-value < 0.05) and 0.658 (p-value < 0.05), respectively. The magnitudes of these coefficients are smaller than the coefficient of explanatory variable in column (4) of Table 3.5, which is 0.773 (p-value < 0.01). These results indicate that SBIR funding and first sales mediate the impact of inventor involvement on the survival rate. On the other hand, venture funding does not mediate the relationship. Hypotheses 2a and 4a are confirmed, and hypothesis 3a is rejected.

The probit analysis incurs censoring issues. Individual firms are incorporated between years 2000 through 2014. The dummy variable of the survival rate is captured in the year 2014. It is the case that newer firms are more likely to survive. We have controlled year dummy variables of the year of incorporation. However, left censoring issue remains. To validate the censoring issue, we employ tobit analysis. Table 3.7 explains the mediation effects using tobit analysis. Columns (1), (2), (3) and (4) are tobit analysis on survival rate, receiving SBIR funding, receiving venture funding, and achieving first sales, respectively. Columns (5), (6) and (7) are tobit analysis on survival rate with controlling SBIR funding, venture funding, first sales, respectively. The mediation effects of SBIR grant and first sales sustain.

Analysis of Exit

In Tables 3.8, 3.9, 3.10, and 3.11, survival analyses are conducted to examine the effect of inventor involvement in the founding team on the probability of exit (IPO or

M&A), SBIR funding, venture funding, and first sales, respectively. For each table, column (1) includes an explanatory variable (the proportion of inventors who became founders). Column (2) controls firm age. Column (3) includes industry sector variables. Column (4) includes campus dummy variables and time dummy variables of the year incorporated. Column (5) includes other control variables such as first sales (dummy), SBIR funding (dummy), and venture funding (dummy). Column (6) includes interaction effects.

Table 3.8 illustrates the survival analysis of a firm's exit (IPO or M&A). The explanatory variable – the proportion of inventors who became the founder – is not statistically significant throughout all columns. This indicates that the magnitude of inventor involvement does not affect the exit. The firm age variable of between 4 and 7 years are negatively statistically significant for columns (2) through (6) (p-value < 0.01 for columns 4, 5 and 6; p-value <0.05 for columns 2 and 3). The firm age variable of more than 7 years is negatively statistically significant for columns (2) through (6) (p-value < 0.01). In column (2), the coefficient of firm age between 4-7 years is -0.773, and the coefficient of firm age with more than seven years is -1.787. This indicates that younger firms are more likely to exit. The older the firm, the lesser the probability of an exit. For the industry sector dummy variables, the biomedical sector is negatively statistically significant in column (3) (p-value < 0.01). In column (3), the coefficient of the biomedical sector is -0.796, which indicates that startups in the biomedical sector are less likely to exit. In column (5), the variable of SBIR funding and venture funding are (p-value < 0.05 for SBIR funding; p-value < 0.01 for venture funding). These results

indicate that there is an association between SBIR funding and exit, and venture funding and exit, respectively. In column (6), none of the interaction effects is found significant.

Table 3.9 demonstrates the survival analysis of the effect of inventor involvement on the probability of the SBIR funding. The explanatory variable (the proportion of inventors as founders) is positively statistically significant for all columns (p-value < 0.01). This indicates that the proportion of inventors who became founder impacts on receiving SBIR funding. The firm age variables are negatively statistically significant (p-value < 0.01) in all columns, except age of 2-3 years in column (4) (p-value <0.1). In column (2), the coefficient of firm age between 2-3 years is -1.681, and the coefficient of firm age with more than three years is -2.578. This explains why younger firms are more likely to receive SBIR funding. The longer the firm exists, the less probability of receiving SBIR funding. For the industry dummy variables, none is statistically significant. This indicates that there were no differences by industry in regards to receiving an SBIR grant. The control variable for first sales is positively statistically significant (p-value < 0.01). This indicates an association between the first sales and SBIR funding. In column (5), the event of first sales is positively statistically significant (p-value < 0.05), which indicates the association between SBIR funding and first sales exists. In column (6), the interaction effect between inventor involvement and venture funding are negatively marginally significant (p-value < 0.05). Interestingly, the interaction term is negative, which indicates that venture funding negatively moderates the effect of the proportion of inventor involvement with the probability of SBIR funding. In other words, with the condition of receiving venture funding, the proportion of

inventors who became founder negatively associated with the probability of receiving SBIR funding.

Table 3.10 demonstrates the effect of inventor involvement on the probability of venture funding. The explanatory variable (the proportion of inventors as founders) is not statistically significant for all columns, which indicates that the explanatory variable does not impact the probability of venture funding. The firm age variables are statistically significant (p-value < 0.01) for all columns. In column (2), the coefficient of firm age between 2-3 years is -1.056, and the coefficient of firm age with more than three years is -2.471. This means that younger firms are more likely to receive venture funding. The longer the firm exists, the lower the probability of receiving venture funding. The first sales dummy variable is positively statistically significant in columns (5) and (6), which indicates that the first sales event is associated with venture funding.

Table 3.11 demonstrates the result of survival analysis of the effect of inventor's involvement on the probability of product launch. The explanatory variable, the proportion of inventors as founders, is statistically significant for all columns (p-value < 0.01 for columns 1, 2, 3 and 6; p-value < 0.05 for columns 4 and 5). This indicates that when the proportion of the inventor involvement as founders increased, so did the probability of launching a product. The firm age variables are statistically significant for all columns (p-value < 0.01). In column (2), the coefficient of firm age between 2-3 years is -1.273, and the coefficient of firms older than three years is -3.259. This finds that younger firms are more likely to launch a product. The older the firm becomes, it is the less likely to launch a product. For the industry sector dummy variables, the biomedical sector was negatively statistically significant (p-value < 0.01) in column (3). The

coefficient of the biomedical sector is -0.684, indicating that biomedical startups were less likely to launch a product than IT. Furthermore, venture funding is positively significant (p-value < 0.5) in columns (5) and (6), which indicates that venture funding is potentially positively associated with launching a product.

Since there is no direct effect of the explanatory variable on the probability of exit (IPO or M&A), mediation effect is not found. Therefore, hypotheses 2b, 3b, and 4b are rejected. However, the explanatory variable has an impact on SBIR funding and the first sales event. Furthermore, SBIR funding and venture funding impact on the probability of exit. We find weak evidence that SBIR funding may explain the relationship between the proportion of inventor involvement and the exit.

3.6. Disentangling the Underlying Mechanism

The industry sector (i.e., IT or biomedical) may affect the importance of inventor involvement, team formation, and securing financial resources (Fontes 2005). The large sample size allows us to divide the population into industry sectors, thereby providing insight into whether types of industry sector might affect the characteristics and success rates of university startups. A full population of startups is divided into IT (144 firms) and biomedical (332 firms).

Table 3.12a and 3.12b are the results of mediation test for subsample by industry of IT and biomedical, respectively. Columns (1), (2), (3) and (4) are the results of probit analysis with dependent variables of firm survival, SBIR grant, venture funding, and receiving first sale, respectively. Columns (5), (6), and (7) are the results of probit

analysis with the dependent variable of survival. Columns (5), (6), and (7) includes control variables of SBIR funding, venture funding, and first sales, respectively.

Table 3.12a tests the mediation effect in the IT sector. The explanatory variable of Column (1) is not statistically significant. This indicates that there is no direct impact of inventor involvement on a firm's survival in the IT sector. Table 3.12b tests mediation effect in the biomedical sector. The coefficient of explanatory variable in columns (1), (2) and (3) is positively statistically significant (p-value < 0.01 for column 1 and 4; p-value < 0.05 for column 2). These results indicate that greater proportion of inventor involvement positively affects on survival rate, SBIR funding and first sales. The coefficients of SBIR funding and first sales in column (5) and (7), respectively, are positively statistically significant (p-value < 0.01 for column 5; p-value < 0.05 for column 7). The coefficient of explanatory variable in column (5) is smaller than that of the column (1). On the other hand, the coefficient of explanatory variable in column (7) is not smaller than that of the column (1). These results indicate that in biomedical sector, SBIR mediates the effect of inventor involvement on survival mediation effect, while first sales does not. The mediation test is partially confirmed for the biomedical sector but not for the IT sector.

Previously, we have confirmed the effect of inventor involvement. However, does the magnitude of inventor involvement matter? It may be possible that the involvement of one inventor is as important as the proportion of the inventors. Table 3.13 illustrates the result of mediation test to validate the existence of inventor involvement. Instead of using a proportion of inventors became the founder, a dummy variable of inventor became founder is used. The dummy variable becomes one when one of the inventors became the founder. The variable, inventor became founder, is statistically significant throughout the

columns (p-value < 0.01 for columns 1, 2, 3, 5, 6 and 7; p-value < 0.05 for column 4). This indicates that the existence of inventor involvement impacts on survival, SBIR funding, venture funding, and first sales. The mediation tests pass for all of three intermediate variables. Interestingly, for venture funding, the existence of inventor involvement matters, but not the magnitude of the involvement. Receipt of venture capital mediates the existence of inventor involvement on firm's survival. There may be two reasons for this mediation effect. First, inventor involvement may act as a signaling of the quality of startups to venture capitalists. Secondly, consistent with Kaplan et al. (2009)'s work, venture capitalists may decide the funding based on a business idea rather than team formation of inventors.

One may suspect that Silicon Valley's regional effect dominates overall results. Table 3.14 shows the subsample of firms excluding the startups from UCB and UCSF. The results are consistent with our previous results.

The quality of patents may affect the result. We use the number of claims and number of citations as the proxy variables of quality of patents by combining the patent dataset from COMETS (Zucker et al. 2011, Zucker and Darby 2014). Since the number of citations is affected by the timespan since the grant of patents, we only include startups with patents granted prior to the year 2005. The COMETS dataset includes patent data until the year 2005. For the citation count, we use the timeframe of five years since the grant of a patent for counting a number of citations. Table 3.15 shows the results including the quality of patents. Dependent variables are the probability of survival for columns (1) and (2), SBIR funding for columns (3) and (4), venture funding for columns (5) and (6), and first sales for columns (7) and (8), respectively. Control variables are

patent (number of claims) for columns (1), (3), (5) and (7), and patent (number of citations) for columns (2), (4), (6), and (8), respectively.

The explanatory variable – proportion of the inventors involvement – is positively statistically significant for columns (3), (4) and (8) (p-value < 0.01 for columns 3 and 4; p-value < 0.05 for column 8), and marginally significant for columns (2) and (7). Though the explanatory variable in column (1) is not significant, the p-value is relatively close to 0.1. This may due to the small sample size. The proxy variables of patent quality are only statistically significant for the first sales (p-value <0.05 for a number of claims; p-value < 0.01 for a number of citations). This indicates that the quality of patents impacts the first sales, but not survival rate, SBIR funding, and venture funding. We find weak evidence that our mediation results sustain. However, further investigation is necessary.

3.7. Discussion, Future Work, and Conclusion

The present research is built on previous work of team formation and firm growth. We aimed to reconcile two contradicting views of inventor involvement on university-based startups. The mediation effects of SBIR funding, venture funding, and first sales for the inventor involvement on ultimate success are analyzed.

Figure 3.1 and 3.2 summarize our findings. As Druilhe and Garnsey (2004) describes, as the business evolves, the business activity would change. Binomial tests result in that contrary to the original hypothesis, three major events (SBIR funding, venture funding, and first sales) do not happen in chronological order. However, the sequential order is found between SBIR funding and venture funding, and the first sales and venture funding. Figure 3.1 explains the mechanism of inventor involvement on

survival. SBIR funding and the first sales mediate the impact of inventor involvement on survival. The SBIR funding and the first sales have a positive impact on the probability of venture funding. The SBIR funding and the first sales are associated; however, we could not find the chronological order. Figure 3.2 explains the mechanism of inventor involvement on the exit. No mediation effect was found for all three intermediate variables. However, we found weak evidence that SBIR funding links the relationship between inventor involvement and exit. The negative moderation effect of venture funding on inventor involvement and SBIR funding is puzzling. The plausible explanation might be that university-based startups would be categorized into two types: low-growth startups and high-growth startups. Low-growth startups aim to launch a product, and the ultimate success is to survive. On the other hand, high-growth startups aims to receive venture funding, and the ultimate success is to exit. Our results show that greater proportion of inventor involvement is effective for firm's survival, but not for a firm's exit, which reconciles two contradicting views of inventor involvement.

The natural question comes to our mind is that whether our findings describes a causal relationship or association. Inventor involvement as a founder is always decided at the time of firm formation. It always occurs prior to any intermediate or ultimate events. However, we cannot completely rule out the possibility of reverse causality.

There are a number of policy implications. First, an inventor's involvement increases the probability of product launch and receiving SBIR funding. Inventor involvement is indeed a critical factor for startup, at least for the initial phase. How universities promote the inventor's involvement is the key. University rules regarding taking a leave of absence, as well as the conflict of interest, must be well-tuned to support

the startup's growth. Second, distinguishing between low-growth startups and high-growth startups is the key. For example, the selection process of SBIR grants must be reconsidered in this aspect: it is possible that smaller magnitude of inventor involvement may lead to firm's exit. Third, the present study shows various impacts, depending on the industry sector. This evidence indicates that one-size policies may not fit all startups (Druilhe and Garnsey 2004, Kenney and Mowery 2014).

There will be a number of opportunities for the future research. First, disentangling the characteristics of the founding team has to be investigated further. For example, does student inventor's involvement differs from faculty inventor's involvement? Does the gender or ethnicity of inventors influence whether or not they become founders? Second, is it possible to characterize university-based startups to high-growth and low-growth firms? If possible, what are the indicators to predict the firm's fate? Third, how do regional city-level characteristics impact an inventor's involvement? Since ten campuses share the same university rules with different clusters, it may be possible to analyze the effect of clusters on startups performance. Fourth, analyzing the impact of the federal research grant is another interesting topic to pursue. Is there any difference between the Department of Defense (DoD), National Science Foundation (NSF), and National Institutes of Health (NIH) grants on firm's success? Fifth, the current study was limited to investigating patent-based startups. How does the inventor involvement differ for non-patent based university technology-based startups? Finally, this study was limited to UC-based startups. Do other university-based startups react differently? Do public and private university differences impact inventor involvement? Startups located in California would be the exceptional case. Can we generalize our

results? Each university in the U.S. has its institutional policy. Thus, our findings may not be applicable to other institutions. The current research will open up several new strands of research streams.

ACKNOWLEDGMENTS

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Certain data included herein are derived from the COMETS database release 2.0. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the Ewing Marion Kauffman Foundation, the National Science Foundation, or other funders of COMETS.

Chapter 3, in part, is currently being prepared for submission for publication of the material. Maki, Kanetaka M.; Krishnan, Vish; Kenney, Martin. The dissertation author was the primary investing and author of this paper.

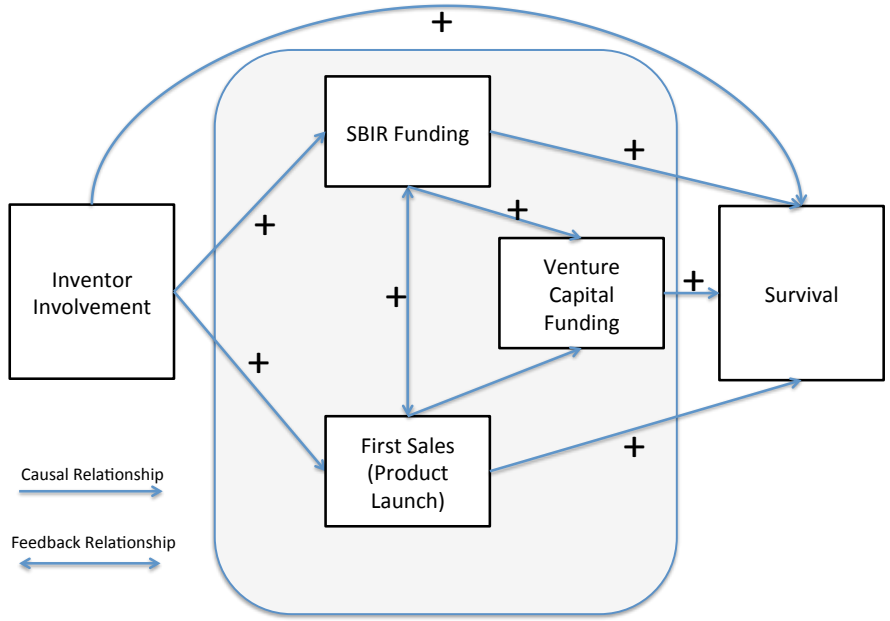


Figure 3.1: Causal Model of Inventor Involvement and Survival

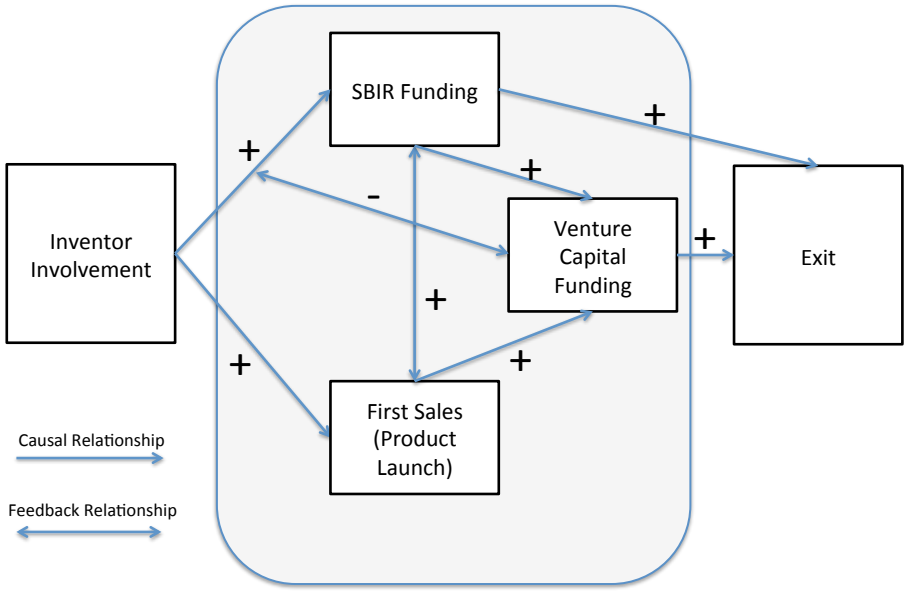


Figure 3.2: Causal Model of Inventor Involvement and Exit

Table 3.1: Summary Statistics

	count	mean	sd	min	max
Calendar Year Incorporated	533	2007.20	3.63	2000.0	2013
IPO	534	0.01	0.10	0.0	1
MA	534	0.08	0.27	0.0	1
Bankruptcy	534	0.02	0.14	0.0	1
Electronics and Software	534	0.26	0.44	0.0	1
Biomedical	534	0.62	0.49	0.0	1
Environment, Energy and New Technology	534	0.12	0.33	0.0	1
UCB	534	0.16	0.36	0.0	1
UCD	534	0.07	0.26	0.0	1
UCI	534	0.11	0.31	0.0	1
UCLA	534	0.22	0.42	0.0	1
UCM	534	0.01	0.07	0.0	1
UCR	534	0.03	0.17	0.0	1
UCSB	534	0.07	0.25	0.0	1
UCSC	534	0.02	0.14	0.0	1
UCSD	534	0.23	0.42	0.0	1
UCSF	534	0.09	0.29	0.0	1
Age of Firm for First Sales (< 2years)	534	0.13	0.34	0.0	1
Age of Firm for First Sales (= 2-3years)	534	0.13	0.33	0.0	1
Age of Firm for First Sales (> 3years)	534	0.74	0.44	0.0	1
Age of Firm for SBIR (< 2years)	534	0.13	0.34	0.0	1
Age of Firm for SBIR (= 2-3years)	534	0.18	0.38	0.0	1
Age of Firm for SBIR (> 3years)	534	0.74	0.44	0.0	1
Age of Firm for Venture Funding (< 2years)	534	0.16	0.36	0.0	1
Age of Firm for Venture Funding (= 2-3years)	534	0.14	0.35	0.0	1
Age of Firm for Venture Funding (> 3years)	534	0.70	0.46	0.0	1
Age of Firm for IPO/M&A (< 4 years)	534	0.31	0.46	0.0	1
Age of Firm for IPO/M&A (= 4-7 years)	534	0.31	0.46	0.0	1
Age of Firm for IPO/M&A (< 7 years)	534	0.37	0.48	0.0	1
Proportion of Inventors Became Founder	534	0.27	0.30	0.0	1
Inventor Became Founder (dummy)	534	0.60	0.49	0.0	1
First Sales (dummy)	534	0.17	0.38	0.0	1
Duration Period for First Sales (Days)	533	2180.72	1346.25	0.0	5293
SBIR Funding (dummy)	534	0.23	0.42	0.0	1
Duration Period for SBIR Funding (Days)	532	2127.19	1311.03	24.0	5290
Venture Funding (dummy)	534	0.38	0.49	0.0	1
Duration Period for Venture Funding (Days)	533	1982.56	1279.29	52.0	5290
Exit (IPO or M&A) (dummy)	534	0.09	0.29	0.0	1
Duration Period for Exit (Days)	533	2283.93	1263.09	0.0	5290
Observations	534				

Summary Statistics for the Variables

Table 3.2a: Cross Table for the SBIR Grant and Venture Funding

		Venture Funding		Total
		No	Yes	
SBIR Grant	No	265	148	413
	Yes	65	56	121
Total		330	204	534

Pearson chi2(1) = 4.3252 Pr = 0.038

Table 3.2b: Binomial Test for the Order of SBIR Grant and Venture Funding

Variable	Mean	Std. Err.	[95% Conf. Interval]	
SBIR_VC	.6607143	.0632697	.536708	.7847206

p = proportion(SBIR_VC)		z = 2.4054
Ho: p = 0.5		
Ha: p < 0.5	Ha: p != 0.5	Ha: p > 0.5
Pr(Z < z) = 0.9919	Pr(|Z| > |z|) = 0.0162	Pr(Z > z) = 0.0081

One-sample test of proportion SBIR_VC: Number of observation = 56

Table 3.3a: Cross Table for the SBIR Grant and First Sales

		First Sales		Total
		No	Yes	
SBIR Grant	No	350	63	413
	Yes	93	28	121
Total		443	91	534

Pearson chi2(1) = 4.1169 Pr = 0.042

Table 3.3b: Binomial Test for the Order of SBIR Grant and First Sales

Variable	Mean	Std. Err.	[95% Conf. Interval]	
SBIR_FS	.4285714	.093522	.2452718	.6118711

p = proportion(SBIR_FS)		z = -0.7559
Ho: p = 0.5		
Ha: p < 0.5	Ha: p != 0.5	Ha: p > 0.5
Pr(Z < z) = 0.2248	Pr(|Z| > |z|) = 0.4497	Pr(Z > z) = 0.7752

One-sample test of proportion SBIR_FS: Number of observation = 28

Table 3.4a: Cross Table for the Venture Funding and First Sales

		First Sales		Total
		No	Yes	
Venture Funding	No	287	156	443
	Yes	43	48	91
Total		330	204	534

Pearson chi2(1) = 9.8298 Pr = 0.002

Table 3.4b: Binomial Test for the Order of Venture Funding and First Sales

Variable	Mean	Std. Err.	[95% Conf. Interval]	
FS_VC	.625	.0698771	.4880434	.7619566

p = proportion(FS_VC)		z = 1.7321
Ho: p = 0.5		
Ha: p < 0.5	Ha: p != 0.5	Ha: p > 0.5
Pr(Z < z) = 0.9584	Pr(|Z| > |z|) = 0.0833	Pr(Z > z) = 0.0416

One-sample test of proportion FS_VC: Number of obs = 48

Table 3.5: Probit Analysis on Survival

VARIABLES	(1) survival	(2) survival	(3) survival	(4) survival	(5) survival	(6) survival	(7) survival
Inventor Involvement (proportion)	0.639**	0.662**	0.722***	0.773***	0.598**	0.797***	0.685**
	(0.253)	(0.258)	(0.260)	(0.282)	(0.287)	(0.288)	(0.285)
Biomedical Sector		-0.00957	-0.000947	0.0791	0.0436	0.0507	0.258
		(0.149)	(0.156)	(0.179)	(0.189)	(0.191)	(0.191)
Other Sectors		0.226	0.223	0.0712	0.0182	-0.158	0.205
		(0.233)	(0.246)	(0.283)	(0.293)	(0.297)	(0.289)
SBIR Funding (dummy)					0.872***		
					(0.201)		
Venture Funding (dummy)						1.002***	
						(0.179)	
First Sales (dummy)							0.978***
							(0.238)
Constant	0.714***	0.688***	0.593***	0.246	-0.0426	-0.180	-0.0713
	(0.0836)	(0.144)	(0.202)	(0.320)	(0.328)	(0.337)	(0.335)
Observations	534	534	509	408	408	408	408
Campus Dummy	No	No	Yes	Yes	Yes	Yes	Yes
Year Dummy	No	No	No	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The results are by probit analysis. All UC Startups since 2000 are included. The dependent variable is survival rate. Column (1) includes the explanatory variables (the proportion of inventor involvement). Column (2) includes industry sector dummy variables. Column (3) includes campus dummy variables. Column (4) includes time dummy variables of the incorporated year. Column (5), (6), and (7) include dummy variables of SBIR funding, venture funding and first sales, respectively.

Table 3.6: Probit Analysis on SBIR Funding, Venture Funding, and First Sales

VARIABLES	(1)	(2) SBIR Funding	(3)	(4)	(5) Venture Funding	(6)	(7)	(8) First Sales	(9)
Inventor Involvement (proportion)	0.585***	0.593***	0.682***	-0.0899	-0.0361	-0.0277	0.906***	0.815***	0.866***
	(0.187)	(0.190)	(0.197)	(0.179)	(0.182)	(0.192)	(0.197)	(0.204)	(0.221)
Biomedical Sector		-0.0212	-0.0140		0.167	0.181		-0.674***	-0.661***
		(0.141)	(0.153)		(0.132)	(0.142)		(0.146)	(0.158)
Other Sectors		0.0735	0.142		0.302	0.461**		-0.394*	-0.411
		(0.212)	(0.231)		(0.194)	(0.207)		(0.224)	(0.253)
Constant	-0.917***	-0.915***	-0.265	-0.276***	-0.432***	-0.0511	-1.228***	-0.780***	-0.402
	(0.0807)	(0.135)	(0.291)	(0.0727)	(0.127)	(0.292)	(0.0898)	(0.134)	(0.311)
Observations	534	534	530	534	534	533	534	534	517
Campus Dummy	No	No	Yes	No	No	Yes	No	No	Yes
Year Dummy	No	No	Yes	No	No	Yes	No	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results are by probit analysis. All UC Startups since 2000 are included. Dependent variables are SBIR funding for column (1)-(3), venture funding for columns (4)-(6), and first sales for columns (7)-(9), respectively. Column (2), (5), and (8) include industry sector dummy variables. Column (3), (6), and (9) include campus dummy variable and year dummy variable for incorporation.

Table 3.7: Tobit Analysis

VARIABLES	(1) survival	(2) SBIR	(3) VC	(4) FS	(5) survival	(6) survival	(7) survival
Inventor Involvement (proportion)	0.195***	0.785***	-0.0398	1.076***	0.151**	0.198***	0.147**
	(0.0656)	(0.220)	(0.176)	(0.257)	(0.0642)	(0.0650)	(0.0656)
Biomedical Sector	0.00892	-0.0325	0.168	-0.798***	0.00886	-0.00670	0.0478
	(0.0464)	(0.179)	(0.130)	(0.181)	(0.0459)	(0.0454)	(0.0465)
Other Sectors	0.0410	0.162	0.391**	-0.477	0.0301	-0.000268	0.0688
	(0.0655)	(0.271)	(0.176)	(0.305)	(0.0643)	(0.0626)	(0.0636)
SBIR Funding (dummy)					0.218***		
					(0.0426)		
Venture Funding (dummy)						0.251***	
						(0.0415)	
First Sales (dummy)							0.224***
							(0.0482)
Constant	0.540***	-0.295	0.0365	-0.512	0.455***	0.415***	0.462***
	(0.132)	(0.345)	(0.246)	(0.393)	(0.132)	(0.128)	(0.131)
Sigma	0.433***	1.276***	1.011***	1.324***	0.424***	0.417***	0.425***
	(0.0213)	(0.0519)	(0.0383)	(0.0646)	(0.0205)	(0.0202)	(0.0206)
Observations	533	533	533	533	533	533	533
Campus Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results are by tobit analysis. All UC Startups since 2000 are included. Columns (1), (2), (3) and (4) are the results with the dependent variable of firm survival, SBIR grant, venture funding, and receiving first sale, respectively. Columns (5), (6), and (7) are the results of with dependent variable of survival. Columns (5), (6), and (7) includes control variables of SBIR funding, venture funding, and first sales, respectively.

Table 3.8: Exit – Inventor Involvement

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Inventor Involvement (proportion)	-0.0697	-0.0773	-0.258	-0.226	-0.452	-0.860
	(0.457)	(0.456)	(0.451)	(0.443)	(0.561)	(0.938)
Age of Firm for IPO/M&A (= 4-7 years)		-0.733**	-0.719**	-1.793***	-2.267***	-2.262***
		(0.329)	(0.325)	(0.474)	(0.481)	(0.492)
Age of Firm for IPO/M&A (< 7 years)		-1.787***	-1.751***	-4.220***	-4.476***	-4.481***
		(0.359)	(0.360)	(0.439)	(0.427)	(0.423)
Biomedical Sector			-0.796***	-0.801**	-0.716*	-0.715*
			(0.295)	(0.378)	(0.416)	(0.433)
Other Sectors			-0.650	-0.168	-0.280	-0.268
			(0.491)	(0.434)	(0.456)	(0.456)
SBIR Funding (dummy)					0.690**	0.483
					(0.351)	(0.519)
Venture Funding (dummy)					0.800***	0.712
					(0.299)	(0.472)
First Sales (dummy)					0.469	0.630
					(0.358)	(0.536)
IE of Inventor's Commitment and SBIR Funding						0.743
						(1.074)
IE of Inventor's Commitment and Venture Funding						0.469
						(1.368)
IE of Inventor's Commitment and First Sales						-0.557
						(1.321)
Constant	-10.14***	-9.124***	-8.584***	-6.091***	-6.832***	-6.785***
	(0.187)	(0.269)	(0.320)	(0.498)	(0.665)	(0.684)
Observations	532	532	532	532	532	532
Campus Dummy	No	No	No	Yes	Yes	Yes
Year Dummy	No	No	No	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The result is by survival analysis. The dependent variable is the probability of Exit (dummy & duration). All UC Startups since 2000 are included. (1) The explanatory variable is included. (2) Age of firms is included. (3) Industry sector variables are included. (4) Campus dummy and year dummy variables are included. (5) Other control variables are included. (6) Interaction variables are included.

Table 3.9: SBIR Funding – Inventor Involvement

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Inventor Involvement (proportion)	0.924***	0.672***	0.662***	0.603***	0.610***	0.851***
	(0.255)	(0.212)	(0.218)	(0.232)	(0.232)	(0.311)
Age of Firm for SBIR (= 2-3years)		-1.681***	-1.685***	-0.998*	-1.299***	-1.262***
		(0.360)	(0.358)	(0.521)	(0.450)	(0.442)
Age of Firm for SBIR (> 3years)		-2.578***	-2.568***	-3.075***	-3.081***	-3.041***
		(0.174)	(0.174)	(0.168)	(0.168)	(0.173)
Biomedical Sector			-0.157	-0.000590	0.0653	0.0366
			(0.181)	(0.217)	(0.217)	(0.218)
Other Sectors			0.0732	0.144	0.220	0.190
			(0.273)	(0.306)	(0.314)	(0.310)
Venture Funding (dummy)					0.00245	0.354
					(0.189)	(0.260)
First Sales (dummy)					0.592***	0.396
					(0.208)	(0.314)
IE of Inventor Involvement and Venture Funding						-1.134**
						(0.566)
IE of Inventor Involvement and First Sales						0.484
						(0.584)
Constant	-9.418***	-7.191***	-7.103***	-6.638***	-6.861***	-6.976***
	(0.126)	(0.148)	(0.210)	(0.358)	(0.380)	(0.393)
Observations	532	532	532	532	532	532
Campus Dummy	No	No	No	Yes	Yes	Yes
Year Dummy	No	No	No	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The result is by survival analysis. The dependent variable is the probability of Exit (dummy & duration). All UC Startups since 2000 are included. (1) The explanatory variable is included. (2) Age of firms is included. (3) Industry sector variables are included. (4) Campus dummy and year dummy variables are included. (5) Other control variables are included. (6) Interaction variables are included.

Table 3.10: Venture Funding – Inventor Involvement

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Inventor Involvement (proportion)	0.000747	-0.109	-0.0578	-0.0667	-0.130	0.193
	(0.222)	(0.195)	(0.196)	(0.181)	(0.182)	(0.239)
Age of Firm for Venture Funding (= 2-3years)		-1.056***	-1.043***	-1.056***	-1.052***	-1.015***
		(0.163)	(0.164)	(0.150)	(0.153)	(0.153)
Age of Firm for Venture Funding (> 3years)		-2.471***	-2.457***	-3.012***	-2.989***	-2.899***
		(0.137)	(0.136)	(0.121)	(0.122)	(0.128)
Biomedical Sector			0.162	0.106	0.179	0.166
			(0.152)	(0.149)	(0.152)	(0.153)
Other Sectors			0.383*	0.350*	0.415**	0.373*
			(0.199)	(0.189)	(0.192)	(0.193)
SBIR Funding (dummy)					0.0460	0.300
					(0.128)	(0.183)
First Sales (dummy)					0.347***	0.448***
					(0.133)	(0.168)
IE of Inventor Involvement and SBIR Funding						-0.966*
						(0.529)
IE of Inventor Involvement and First Sales						-0.356
						(0.421)
Constant	-8.553***	-6.519***	-6.692***	-6.325***	-6.490***	-6.546***
	(0.0865)	(0.119)	(0.172)	(0.265)	(0.276)	(0.278)
Observations	533	533	533	533	533	533
Campus Dummy	No	No	No	Yes	Yes	Yes
Year Dummy	No	No	No	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The result is by survival analysis. The dependent variable is the probability of Exit (dummy & duration). All UC Startups since 2000 are included. (1) The explanatory variable is included. (2) Age of firms is included. (3) Industry sector variables are included. (4) Campus dummy and year dummy variables are included. (5) Other control variables are included. (6) Interaction variables are included.

Table 3.11: Product Launch – Inventor Involvement

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Inventor Involvement (proportion)	1.418***	0.969***	0.861***	0.783**	0.777**	1.260***
	(0.294)	(0.260)	(0.271)	(0.327)	(0.337)	(0.483)
Age of Firm for First Sales (= 2-3years)		-1.273***	-1.181***	-1.282***	-1.329***	-1.394***
		(0.244)	(0.240)	(0.209)	(0.220)	(0.218)
Age of Firm for First Sales (> 3years)		-3.259***	-3.102***	-4.006***	-3.959***	-3.988***
		(0.211)	(0.221)	(0.241)	(0.238)	(0.241)
Biomedical Sector			-0.684***	-0.174	-0.258	-0.230
			(0.213)	(0.244)	(0.254)	(0.257)
Other Sectors			-0.254	-0.0582	-0.228	-0.222
			(0.312)	(0.356)	(0.375)	(0.376)
SBIR Funding (dummy)					0.140	0.257
					(0.181)	(0.386)
Venture Funding (dummy)					0.454**	0.814**
					(0.220)	(0.324)
IE of Inventor Involvement and SBIR Funding						-0.401
						(0.765)
IE of Inventor Involvement and Venture Funding						-1.018
						(0.674)
Constant	-9.915***	-7.282***	-6.963***	-5.811***	-6.087***	-6.226***
	(0.155)	(0.184)	(0.211)	(0.387)	(0.399)	(0.427)
Observations	532	532	532	532	532	532
Campus Dummy	No	No	No	Yes	Yes	Yes
Year Dummy	No	No	No	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The result is by survival analysis. The dependent variable is the probability of Exit (dummy & duration). All UC Startups since 2000 are included. (1) The explanatory variable is included. (2) Age of firms is included. (3) Industry sector variables are included. (4) Campus dummy and year dummy variables are included. (5) Other control variables are included. (6) Interaction variables are included.

Table 3.12a: Mediation Test (IT)

VARIABLES	(1) survival	(2) SBIR	(3) VC	(4) FS	(5) survival	(6) survival	(7) survival
Inventor Involvement (proportion)	0.562	0.901**	-0.0993	0.972**	0.452	0.725	0.211
	(0.449)	(0.376)	(0.364)	(0.380)	(0.453)	(0.465)	(0.473)
SBIR Funding (dummy)					0.463		
					(0.392)		
Venture Funding (dummy)						0.955***	
						(0.361)	
First Sales (dummy)							1.175***
							(0.415)
Constant	0.00564	-6.107***	-0.606	-0.629	0.0148	-0.279	-0.288
	(0.559)	(0.432)	(0.520)	(0.490)	(0.562)	(0.569)	(0.561)
Observations	87	133	135	119	87	87	87
Campus Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results are by probit analysis. A subsample of IT startups is included. Columns (1), (2), (3) and (4) are the results with the dependent variable of firm survival, SBIR grant, venture funding, and receiving first sale, respectively. Columns (5), (6), and (7) are the results of with dependent variable of survival. Columns (5), (6), and (7) includes control variables of SBIR funding, venture funding, and first sales, respectively.

Table 3.12b: Mediation Test (BM)

VARIABLES	(1) survival	(2) SBIR	(3) VC	(4) FS	(5) survival	(6) survival	(7) survival
Inventor Involvement (proportion)	1.023***	0.623**	-0.0955	0.875***	0.797**	1.109***	1.060***
	(0.380)	(0.264)	(0.249)	(0.308)	(0.385)	(0.397)	(0.383)
SBIR Funding (dummy)					1.184***		
					(0.260)		
Venture Funding (dummy)						1.074***	
						(0.244)	
First Sales (dummy)							0.907**
							(0.403)
Constant	0.611	0.394	0.425	-0.510	-0.0359	0.0170	0.373
	(0.414)	(0.360)	(0.365)	(0.371)	(0.463)	(0.426)	(0.440)
Observations	262	325	329	314	262	262	262
Campus Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results are by probit analysis. A subsample of biomedical startups is included. Columns (1), (2), (3) and (4) are the results with the dependent variable of firm survival, SBIR grant, venture funding, and receiving first sale, respectively. Columns (5), (6), and (7) are the results of with dependent variable of survival. Columns (5), (6), and (7) includes control variables of SBIR funding, venture funding, and first sales, respectively.

Table 3.13: Mediation Test: Existence of Inventor Involvement

VARIABLES	(1) survival	(2) SBIR	(3) VC	(4) FS	(5) survival	(6) survival	(7) survival
Inventor Involvement (dummy)	0.686***	0.719***	0.346***	0.370**	0.552***	0.616***	0.659***
	(0.151)	(0.143)	(0.123)	(0.147)	(0.155)	(0.156)	(0.153)
Biomedical Sector	0.0786	-0.0191	0.208	-0.694***	0.0427	0.0415	0.268
	(0.180)	(0.153)	(0.141)	(0.157)	(0.190)	(0.190)	(0.194)
Other Sectors	0.0747	0.147	0.524**	-0.507**	0.0208	-0.145	0.228
	(0.290)	(0.237)	(0.204)	(0.249)	(0.295)	(0.299)	(0.296)
SBIR Funding (dummy)					0.786***		
					(0.204)		
Venture Funding (dummy)						0.932***	
						(0.179)	
First Sales (dummy)							0.974***
							(0.248)
Constant	0.0611	-0.493*	-0.266	-0.340	-0.163	-0.291	-0.293
	(0.317)	(0.289)	(0.300)	(0.322)	(0.328)	(0.326)	(0.329)
Observations	408	530	533	517	408	408	408
Campus Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results are by probit analysis. All UC Startups since 2000 are included. Columns (1), (2), (3) and (4) are the results with the dependent variable of firm survival, SBIR grant, venture funding, and receiving first sale, respectively. Columns (5), (6), and (7) are the results of with dependent variable of survival. Columns (5), (6), and (7) includes control variables of SBIR funding, venture funding, and first sales, respectively.

Table 3.14: Mediation Test: Excluding Silicon Valley Effect

VARIABLES	(1) survival	(2) SBIR Funding	(3) Venture Funding	(4) FS	(5) survival	(6) survival	(7) survival
Inventor Involvement (proportion)	0.851**	0.544**	0.00779	0.923***	0.751**	0.831**	0.785**
	(0.348)	(0.243)	(0.227)	(0.270)	(0.357)	(0.347)	(0.349)
Biomedical Sector	0.00386	-0.241	0.0787	-0.822***	0.0250	0.0248	0.187
	(0.214)	(0.176)	(0.163)	(0.183)	(0.225)	(0.223)	(0.226)
Other Sectors	0.304	0.0522	0.374	-0.365	0.254	0.140	0.421
	(0.343)	(0.258)	(0.235)	(0.286)	(0.359)	(0.358)	(0.344)
SBIR Funding (dummy)					0.829***		
					(0.239)		
Venture Funding (dummy)						0.796***	
						(0.201)	
First Sales (dummy)							0.873***
							(0.283)
Constant	-0.0728	-1.070***	0.193	-0.920**	-0.165	-0.504	-0.274
	(0.348)	(0.365)	(0.335)	(0.373)	(0.348)	(0.364)	(0.357)
Observations	301	397	400	374	301	301	301
Campus Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results are by probit analysis. A subsample of firms excluding from UCB and UCSF is included. Columns (1), (2), (3) and (4) are the results with the dependent variable of firm survival, SBIR grant, venture funding, and receiving first sale, respectively. Columns (5), (6), and (7) are the results of with dependent variable of survival. Columns (5), (6), and (7) includes control variables of SBIR funding, venture funding, and first sales, respectively.

Table 3.15: Controlling Quality of Patents

VARIABLES	(1) survival	(2) survival	(3) SBIR Funding	(4) SBIR Funding	(5) Venture Funding	(6) Venture Funding	(7) FS	(8) FS
Inventor Involvement (proportion)	0.689	0.709*	1.115***	1.050***	-0.0963	-0.0139	0.798*	0.918**
	(0.430)	(0.431)	(0.383)	(0.384)	(0.371)	(0.374)	(0.416)	(0.417)
Patent – Number of Claims	0.000199		0.000332		0.00132		0.00225**	
	(0.000641)		(0.000571)		(0.00101)		(0.00101)	
Patent – Number of Citations		0.00106		-0.00403		0.00657		0.00967***
		(0.00208)		(0.00258)		(0.00439)		(0.00358)
Biomedical	0.222	0.240	-0.0544	-0.0664	-0.00135	0.0699	-0.500*	-0.339
	(0.269)	(0.269)	(0.251)	(0.255)	(0.232)	(0.235)	(0.272)	(0.277)
Other Sectors	0.490	0.507	0.685*	0.681*	0.779**	0.848**	-0.300	-0.172
	(0.383)	(0.382)	(0.356)	(0.363)	(0.346)	(0.347)	(0.377)	(0.388)
Constant	-0.0330	-0.0738	-0.480	-0.222	-0.108	-0.237	-0.644	-0.813*
	(0.410)	(0.416)	(0.411)	(0.435)	(0.402)	(0.420)	(0.402)	(0.418)
Observations	165	165	196	196	191	191	192	192
Campus Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results are by probit analysis. A subsample of firms with patents granted prior to the year 2005. Dependent variables are probability of survival for columns (1) and (2), SBIR funding for columns (3) and (4), venture funding for columns (5) and (6), and first sales for columns (7) and (8), respectively. Control variables are patent (number of claims) for columns (1), (3), (5) and (7), and patent (number of citations) for columns (2), (4), (6), and (8), respectively.

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Chapter 4.

Service Design for Improved Satisfaction: Decoding the Mechanism for Impact of Patient Call Back in Emergency Healthcare

ABSTRACT

Healthcare delivery is becoming a significant proportion of the service economy around the world. Within healthcare, the Emergency Department (ED) constitutes one of the most challenging areas of service delivery. Patient (customer) arrival is highly unpredictable, job scope is variable and uncertain, and timely service response is essential to save lives. In addition, emergency physicians and hospitals may soon be monitored and compensated based on patient satisfaction measured after service delivery. In this paper, we seek to understand how a process design piloted at two academic EDs – involving the addition of a new process step that uses health provider follow-up patient calls after discharge from the emergency department - influences patient assessment of the service. We examine the overall impact of this process redesign on patient satisfaction as measured by the "likelihood to recommend" question on patient surveys and develop an identification strategy to uncover the mechanism by which callbacks influence patient satisfaction. Our findings indicate that the follow-up call back design improves patient appraisals across the board, and not just as a service recovery tool where it moderates the assessment of select patient groups. Callbacks also do not have a clear main effect of

improving patient appraisals. These findings can help hospitals implement a redesign of the ED service process for call back in an effective manner. Underlying fundamental implications and future work possibilities are discussed.

Keywords: Emergency Medical Service, Process Innovation, Call Back

4.1. Introduction: Service Science and Healthcare

As the economy transitions from a product to a service-heavy economy, it becomes important to understand and improve service performance (Karmarkar 2004), a body of knowledge that is being referred to as service science (Spohrer et al. 2007, Maglio and Spohrer 2008). Within the service sector, healthcare represents a challenging area for performance improvement, as it becomes a significant portion of the budget expenditure in many countries. According to the National Coalition on Healthcare (NCHC), US health spending is presently estimated at 2.7 trillion dollars annually or 17% of GDP and is expected to reach more than 20% of GDP by 2018[1]. While many factors underlie this cost escalation, organizations including private sector companies and the US government are searching for innovative approaches to improve performance of healthcare services.

Within healthcare, the Emergency Department (hereafter, ED) constitutes one of the most difficult areas of service delivery due to a combination of factors including process complexity and demand uncertainty. By its very nature, patient arrival is highly unpredictable in emergency medicine. In addition, the service delivery process is significantly variable, due to the differing diagnostic complexity and variable response of patients to treatments. Some patients present themselves with life-threatening emergencies, while others come in with complex and enigmatic conditions/symptoms that may be difficult to diagnose. Timely service response is essential to both save lives and reduce discomfort to patients who arrive in the ED.

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[1] http://www.nchc.org/facts/cost.shtml

As part of new health care initiatives around the world, such as the Affordable Care Act (ACA) in the USA, EDs are being monitored and compensated with a new set of "pay for performance" metrics including patient assessments captured after service delivery (Newell 2015). While customer satisfaction is a commonly used and tracked metric in the service sector, it is particularly challenging to improve in the ED due to demand variability and service process complexity discussed above as well as the fact that most patients are walk-in customers and the service provider-customer *relationship* is not well-established. Also, some patients who end up waiting for substantial amounts of time due to the capacity-demand mismatch in the ED or due to lack of severity-driven priority might appraise the service more negatively than others. The leaders of ED's are hard at work to find new ways to improve patient outcomes and experience, potentially leading to improved service appraisals by patients.

A significant body of literature exists in the service science literature on service process optimization to improve performance, some of which pertain to healthcare as well. We can classify this literature into two broad streams of research. The first stream takes a "designing the service" approach (Cottam and Leadbeater 2004). Researchers in this stream aggregate case studies to investigate the requirements of the services and to propose recommendations (Mogre et al. 2009, Saviano et al. 2010). The second stream involves researchers from the operations research domain approaching services in general and healthcare in particular as an analytical/optimization problem to manage waiting times and decide service capacity (Guinet and Chaabane 2003, Kuo et al. 2003, Green et al. 2006, Al-Najjar and Ali 2011, Pines et al. 2011).

A more recent stream of work focuses on how customers evaluate services (Rolland et al. 2013), finding that the evaluation differs depending on whether the overall service experience/impression is negative or positive. Specifically, based on an examination of outpatient healthcare customer satisfaction surveys, this research finds that the underlying service attributes are mapped into an overall satisfaction evaluation in a compensatory manner when the evaluation is negative and the evaluation function is conjunctive when the evaluation is positive. Our work complements this and is focused on re-designing the service process to improve satisfaction. In this paper, we take a data-driven approach to examine and deeply understand the redesign of an ED process and its impact on patient satisfaction. By focusing on acute care services, we are able to study performance in an important class of service systems with high levels of variability, uncertainty, and process complexity, lessons learned from which can then be applied to other service settings with equally high levels of complexity.

4.2.1. Performance Improvement and Re-Design of Emergency Department

Achieving higher patient assessment is becoming increasingly critical due to the growing pay for performance trends in health care. In the USA, one of the largest payer organizations, Center for Medicare and Medicaid Services (CMS), is planning on linking hospital payments to the degree to which certain performance metrics are met. Increasing emphasis on patient appraisals in health care may have led to the common use of patient surveys in ED settings and the growth of commercial vendors that provide surveying services to health care organizations. The growing visibility of patient appraisals is also

evidenced by the reporting of assessment on the Hospital Compare[2] website. Patients have easier access to this data based on which facility choice decisions may be made, intensifying competition among service providers.

Achieving higher levels of satisfaction is particularly challenging in the ED service setting for various reasons. As mentioned before, patient arrivals and case complexity are highly variable. ED practitioners are responsible for providing quick, medically appropriate and cost effective care to all patients, *irrespective of their insurance status and economic affluence*. This is particularly challenging for hospitals located in close proximity to economically disadvantaged neighborhoods (as with one of our study sites). Additional factors contributing to this challenge include the highly variable census and patient acuity both on a day-to-day as well as hourly basis. This along with a myriad of process related issues such as laboratory and imaging turnaround, medical consultant response times, inpatient census and lack of inpatient hospital beds can result in excessive periods of waiting and prolonged ED stays.

Prior studies have demonstrated that patient satisfaction is correlated with many factors including age, waiting time, perception of waiting time, total duration of ED stay, patient provider communication, and severity of illness (Trout et al. 2000, Boudreaux et al. 2004, Walrath et al. 2004, Toma et al. 2009, Soleimanpour et al. 2011, Soremekun et al. 2011). Some of these factors (such as patient age and severity of illness) cannot be influenced by the management/leadership of the ED. Others such as waiting time and total duration of ED stay can be influenced through the re-allocation or addition of

[2] For example, http://www.medicare.gov/hospitalcompare/search.html

capacity, and has been studied extensively in the Operations Management literature as exemplified by Green et al. (2006).

In the services management literature, the Servqual framework and a multi-item scale have been developed for customer assessment of service quality (Parasuraman, Berry, & Zeithaml, 1991). This framework proposes that customer satisfaction judgments are the result of the gap between customer's perceptions of service customer's and their prior expectations entering a service. The gap model, as this is often referred to, suggests that expectations are shaped by word of mouth from prior customers and perceptions are shaped to the degree to which the service designed and delivered matches customer needs. The gap model seems to largely focus on established services (with well-formed expectations) than new service innovations. While the literature on the gap model does get into customer appraisal of services based on provider competence and empathy, it does not delve deeply into the processes that lead to appraisal formation. One of the contributions of this paper is to build and test the underlying psychological foundations for appraisal formation, based on the deeper emotions induced by the service delivery process.

An alternative approach to improving patient satisfaction involves service process redesign to better utilize capacity. In this paper, we consider a specific design involving the addition of post discharge follow-up calls to ED patients by care providers. As part of this approach, follow-up telephone calls are to be made to the patients by attending physicians, ED residents or nurses involved in the patient's care. During the call, the care provider asks the patients about the patient's current condition, clarify any questions, and reminds them of discharge instructions including prescriptions. The follow-up callback

approach tackles a number of issues faced by the ED. Due to patient arrival variability, ED's can experience acute care provider shortage during certain periods of time leading to higher patient waiting and a somewhat hurried examination of cases, which are not life-threatening. When the capacity shortage is relieved, care providers can follow-up with patients who were already discharged and check with them ensuring a more precise diagnosis. The service delivery process is to a degree extended beyond discharge – doctors/care providers, for example, can ensure that patients filled their prescription and continue to comply with discharge instructions. There may be a psychological benefit as well, with the patient feeling that the specialist cares for them through such follow-up, which leads them to assess the encounter positively. The call back approach is not altogether new (Shesser et al. 1986), although it is not widespread and not well understood. Specifically, the management of the emergency services is faced with the question of whether callback should be used on a contingency basis with patients who have had a particularly bad experience (due to long wait times etc.) or a systematic but randomized approach to the maximal extent possible given the capacity constraints of the facility. This quest to understand the fundamental role of call-backs in the process design forms the central focus of this paper. Through theory development and analysis, we try to unearth if patient callbacks are a service recovery mechanism or an across the board patient/customer appraisal improvement approach.

4.2.2. Theoretical Framework

We draw on the Appraisal Tendency Framework (ATF) from Psychology (Lerner and Keltner 2000) to understand patient/customer assessment/appraisal of the service

process. A key question for the leaders of the ED department is when and how the assessment might be impacted with the post-discharge call back step added to the service process design.

According to the ATF, two types of emotions - "integral and incidental emotions" - carry over from encounters to influence customer's appraisals/judgments. *Integral emotion* refers to the influence of core experiences relevant to appraisals – in the emergency/acute healthcare service setting, it could include patient-experienced anxiety, fear and frustration during the wait and the process of care delivery which influence how the patient appraises the service and even decisions about continuing to wait/balk, or whether to return to the service facility in the future. *Incidental emotions*, on the other hand, are due to extraneous peripheral items (such as the entertainment offered in the waiting room or the food offered in the hospital cafeteria) that should normatively not influence appraisals but end up influencing them anyway often even to the surprise of care providing organizations. The ATF considers the differing magnitude of these specific emotions and the manner in which they impact appraisals/judgment.

While integral emotions like experienced fear and anticipated regret are central to the service experience and appraisal, the ATF has paid particular attention to the incidental emotions because (a) they encompass the puzzling influence of subjective emotional experiences that should be normatively irrelevant to present judgments and choices and (b) they can be experimentally manipulated independently and more easily. From a normative perspective, incidental emotions could be somewhat surprising – in fact, customers are often not consciously aware of the influence of incidental emotions arising from such peripheral factors as the ambient weather, music, reception room

friendliness etc. (Lerner, Small, & Loewenstein, 2004). For these and other reasons, ATF emphasizes incidental emotions to help subjects become aware of and attenuate (unwanted) incidental emotions.

Service process customer engagement through post-discharge patient call back can influence both the integral and incidental emotions experienced by patients that influence their appraisals. Specifically, patients are able to have additional questions answered/concerns addressed and waits explained during the call back, which could lower their anxiety and positively impact their integral emotion. Patients may generally appreciate recall a call back from a medical service provider (especially a doctor), which could boost both their incidental emotions. Any negative emotions *carried over* from the ED visit can be muted with a callback, thereby resulting in improved patient assessment of the experience as stated in Hypothesis 1.

Hypothesis 1: Healthcare Provider Call-back-based Service Design is expected to have a positive main effect on patient likelihood to recommend.

Our major focus in this paper, is however, on the way (mechanism by which) patient callbacks influence likelihood to recommend. In our context, if integral emotions dominate the appraisal, then those patients who experience significantly longer waiting times and associated integral emotions should experience the biggest jump in satisfaction due to callbacks. Frustrated by their extraordinary waiting experience, such patients may provide severely negative assessment of the services. In these cases, call-backs could serve as a service recovery tool and moderate the negative appraisal of such patients with long wait times. However, if incidental emotions have a dominant sway (warranting the emphasis from ATF), then callbacks should influence/improve the appraisal of all

patients (significant direct effect), but not selectively affect the appraisal of select segments. In other words, callbacks should not have a significant moderating influence for specific groups (such as those with long wait times), although we may see a directional effect of callback on patient satisfaction.

Hypothesis 2: Patient call-backs do not significantly moderate the negative influence of waiting times on service appraisals; A significant interaction effect with wait time on patient likelihood to recommend is not predicted, due to incidental emotions dominating patient/customer appraisals.

We thus hypothesize that callbacks are not as much a service recovery mechanism (that help assuage the sentiments of patients who had a bad service experience) but an appraisal improvement mechanism that improves the appraisal of all patients across the board due to the broader impact of incidental emotions. We examine this hypothesis using data collected from this study in a health system with two emergency departments.

Preliminary retrospective studies, discussed in earlier work, found a positive association between ad hoc post discharge calls to ED patients and their subsequent satisfaction as measured by the response to a "Likelihood to Recommend" question (Guss et al. 2012, Guss et al. 2013). The findings from these studies and the reported experience of the Studer Group coupled with years of failure to improve satisfaction through other levers (such as capacity addition) led to the design of the service process with the addition of a follow-up health care provider telephone calls to discharged ED patients. The prior papers did not dwell into the underlying mechanism by which callbacks influence patient appraisal, and this paper offers a more rigorous theoretical foundation and testing for callbacks.

The objective of this paper is to discern the underlying mechanism associated with the impact of post-discharge telephone calls to patients. We examine if specific patient segments are associated with impact of calls on "likelihood to recommend" in the satisfaction survey (administered by the company Press Ganey) while controlling for the potentially confounding variables of wait time, total throughput (service) time and patient triage classification (into various seriousness categories). We also ask the central question of whether callbacks are a service recovery tool or appraisal improvement vehicle.

The rest of the paper is organized as follows. In section 2.3, the service design of the call back in ED is described. Research design and the data set are described in section 3. Section 4 illustrates the result of analysis, followed by conclusions in Section 5.

4.2.3. Service Design of Call Back in the Emergency Department

Two EDs in separate hospitals in the University of California San Diego (UCSD) Health System implemented the post-discharge call back step in their service design process. In this section, we describe the ED service process with and without the call back.

Figure 4.1 describes the regular process of emergency care. Upon arrival, patients are triaged based on the time criticality/severity of their situation. The triage codes are defined as immediate, urgent, and delayed. Once their turn arrives, patients are ushered into the exam room. After receiving treatment by Medical Doctor (MD), patients can be transferred, admitted, or discharged. The waiting time is defined as the time period from triage to placement in an exam room. The length of stay is defined as time period from triage to left the ED..

After the visit, a survey is mailed to a random sample of 50% of discharged patients (for logistical reasons, only non-incarcerated and non-admitted patients with a valid mailing address in the registration system are included). Survey questions include "likelihood to recommend" the ED to evaluate satisfaction. Response for all questions on the survey includes following: 1- very poor, 2- poor, 3- fair, 4- good, and 5- very good.

Figure 4.2 illustrates the process of emergency care, after the introduction of call back procedure. The program of call back by MD or a Registered Nurse (RN) started in the second half of 2010. The operation of call back is placed in after care area. Call backs were made 1-3 days after patients' visit to the ED. MDs and RN were expected to make at least one patient call back per shift worked. In addition, a single RN full-time resource capacity was secured exclusively for the call back program. Even after these steps the system faced resource constraints, and only approximately 50% of eligible patients received a call back. If the patient did not answer the call a message was left but only in cases where there was a voicemail greeting identifying the patient. The only fixed cost is the single RN FTE that was approximately $90,000/year. All other resources placed callbacks when spare capacity was available.

To access the impact of call back, a custom question was added to the Press Ganey (PG) survey. This question regarding the call back was: "after discharge, did you receive a phone call from an ED staff member to check on your condition? (Yes / No)". The PG survey is anonymous, but the respondent has the option to identify themselves. The ED employed a comprehensive electronic health record "WEBCHARTS" that was developed in house. It contains patient demographics, event time stamps, health provider

notes, orders and treatments, but access to confidential medical records data is highly restricted due to the privacy of health information.

4.3.1. Research Design

Our study is a framed field-experiment in the ED in the UCSD Health System. Two EDs were included. The UCSD Human Research Protection Program Institutional Review Board (IRB) approved our study. By aggregating data sets from Press Ganey survey and medical records, we assembled a data set that we use to conduct statistical analysis to evaluate the impact of call back on patients' satisfaction.

4.3.2. Data Set

Our data set comprised of response for the survey and the medical records. All surveys returned between 9/22/2010 and 12/7/2010 were reviewed and those in which the patient self-identified were selected for inclusion. Self-identified charts were selected to allow for identification of the associated electronic health record and query for selected variables. These variables were: waiting time (triage to placement in an exam room), triage code (1- immediate, 2- urgent, 3- delayed), gender, age, type of insurance, and the call back characteristics (verbal contact by MD, verbal contact by RN, message left by MD, and message left by RN).

Figure 4.3 describes the population of our study. In the 7 month study period, approximately 36,000 patients were discharged from the two hospitals. Roughly 18,000 discharged patients (50%) were randomly selected and surveys mailed. A total of 1852 surveys were returned for a typical response rate of about 10%. Approximately 50% of

36,000 discharged patients had received a call back attempt. Among those responding to PG survey 813 patients self-identified (45%), who were included in this analysis. Figure 4.4 illustrates the population of self-identified patients. Among 813 self-identified patients, 407 patients answered "Yes" to the call back question, while 301 patients answered "No".

Table 4.1 explains characteristic differences between patients who self-identified and those who did not self-identify (Student's T-test). Characteristics of age, receiving phone call, hospital, and satisfaction are significantly different for patients who self-identified or not. Table 4.2 below illustrates differences between patients who received or not received of call back. (Student's T-test). The mean age for treatment group was 51.66 (95% CI 49.82-53.49) and control group was 58.46 (95% CI 56.43-60.49). Gender and triage code were similar for two groups, but insurance type was quite different in two groups. Different characteristics in two groups, due to the non-randomness of treatment, will be discussed in later section. Specifically, there is a sizable difference in waiting time (and length of stay) between Call Back No and Call Back Yes. This is in part because more calls seem to have been placed in Hospital "B" which has much lower wait times as discussed in the next subsection. We discuss how to correct for this bias later in the paper.

4.3.3. Setting

Both our study sites - hospitals - are in urban settings, but they have different patient demographics. Table 4.3a describes Student's T-test of the two study settings. Mean age for Hospital "A" is 5 years older than that of Hospital "B" (p-value < 0.01). The proportion of triage code for "urgent" is 7% higher in Hospital "A" (p-value < 0.05),

while the proportion of triage code for "Delayed" is 6% higher in Hospital “B” (p-value < 0.07). The proportion of insurance for "Self Pay" is 8% higher in Hospital “A” (p-value < 0.00), the proportion of insurance for "MediCal " is 5% higher in Hospital “A” (p-value < 0.04), and the proportion of insurance for "Private Insurance" is 9% higher in Hospital “B” (p-value < 0.02). Hospital “A” is skewed towards an underinsured /economically disadvantaged population with a census of 38,000. Hospital “B” serves a mostly Medicare and commercially/privately insured population with a census of 23,000. Furthermore, staff compositions in two hospitals are somewhat different. Staff in Hospital “A” include Emergency Medicine faculty, emergency medicine residents and, students & residents (rotating from other specialties). Staff in Hospital “B” includes Emergency Medicine faculty and emergency medicine residents (working for 10 hours per day). Admission rate for two hospitals is roughly the same (20%.).

The difference in waiting time for Call Back No and Yes patients can be attributed due to the difference between Hospitals A and B. Much higher percentage of patients seem to have been called back in Hospital “B” than Hospital “A” (73% for Hospital “B” versus 42% for Hospital “A”). Also note that Hospital “B” has much lower wait times than Hospital “A”. As seen in Tables 4.3b, there is no significant difference in wait time between Callback Yes and Callback No patients for Hospital “A”. At Hospital “B”, Wait Time for Callback No patients is 14.93 minutes versus 7.48 minutes for Callback Yes patients, a significant difference. This is perhaps due to the discretion offered to doctors in call back. In summary, Hospital differences primarily account for the difference in wait time for “Callback No” and “Callback Yes” patients. We are able to use the difference across the hospitals to good use. Specifically, because Hospital “A”

does not have a significant difference in wait times between "Callback No" and "Callback Yes" patients, we repeat our overall analysis for Hospital "A" to verify the results are valid.

4.3.4. Empirical Methodology

The empirical model is presented as equation (1).

$$\text{LikelihoodToRecommend}_i = \beta_0 + \beta_1\text{ContactMD}_i + \beta_2\text{ContactRN}_i + \beta_3\text{Urgent}_i + \beta_4\text{Delayed}_i + \beta_5\text{WaitingTime}_i + \beta_6\text{LengthOfStay}_i \quad (1)$$

The dependent variable is the patient's "likelihood to recommend" ($\text{LikelihoodToRecommend}_i$) obtained as a response from the survey. We believe this variable is a reasonable estimate of (proxy for) the overall patient satisfaction.

Explanatory variables are contact by MD (ContactMD_i) and contact by RN (ContactRN_i) which refers to the callback by MD or the nurse. Control variables in the equation include the following: triage code for immediate, urgent and delayed (Urgent_i, Delayed_i), waiting time (WaitingTime_i), and length of stay (LengthOfStay_i).

To test Hypothesis 2, we run the following model:

$$\text{LikelihoodToRecommend}_i = \beta_0 + \beta_1\text{Contact}_i + \beta_2\text{Urgent}_i + \beta_3\text{Delayed}_i + \beta_4\text{WaitingTime}_i + \beta_5\text{LengthOfStay}_i + \beta_6\, Contact_i \times \text{WaitingTime}_i \quad (2)$$

The addition of the interaction variable ($\beta_6\, Contact_i \times \text{WaitingTime}_i$) helps test for the moderation effect of Callback on the negative appraisal by patients with high waiting times. If the coefficient of interaction term is (not) significant, then the moderation effect is (not) strong suggesting service recovery effect and (proving) disproving Hypothesis 2. We test similar interaction effects with other patient variables (such as age, gender,

insurance type) as discussed below. We employ ordered logistic regression to calculate the coefficient for likelihood to recommend, while controlling for triage code, waiting time and length of stay.

4.4. Results

Table 4.4a provides results for the ordered logistic regression model. The ordered logistic model generates a coefficient and standard errors for overall satisfaction. The coefficient for contact by MD is 0.764, while the coefficient for contact by RN is 0.336, after controlling waiting time and triage code. Both contact by MD and RN are statistically significant (p-value< 0.01 and p-value <0.05, respectively) supporting Hypothesis 1. This indicates that although contact by MD has larger impact for the patients' satisfaction, contact by RN is also effective to a moderately significant level. RN's cost less, offering a more cost-effective approach to improving patient appraisals. Cutoff points are included in the table, which all of them are statistically significant.

Because of the significant difference in wait times between "Callback Yes" and "Callback No" patients in the overall data (combining both the hospitals), we repeat the above analysis for Hospital "A". Recall from the previous section that Hospital "A" did not have a significant difference in wait times between "Callback Yes" and "Callback No" patients. Table 4.4b shows the results for the ordered logistic regression model, where the coefficient for contact by MD is 0.858, while the coefficient for contact by RN is 0.29, after controlling for waiting time and triage code. Again, the coefficient for contact (callback) by MD is strongly significant, supporting Hypothesis 1. Interestingly, for this

subsample (Hospital "A"), the coefficient for contact (callback) by nurse (RN) is not significant!

We now consider Hypothesis 2 by running the interaction model in Equation (2). Table 4.5a provides results for the ordered logistic regression model. The coefficients for the newly added interaction terms, contact_md_wt and contact_rn_wt are not significant, supporting Hypothesis 2. This indicates that contact by MD and contact by RN are not differentially more effective for patients with longer waiting times. In Table 4.5b, we repeat these results for Hospital "A" for which there is no significant difference in waiting between "Callback Yes" and "Callback No" patients. Even for Hospital "A", these coefficients are not significant suggesting that the result about the lack of a moderating influence of callbacks is relatively robust.

We next look into decomposing the characteristics of patients to understand the underlying patterns. All patients are categorized by age, type of insurance, and gender. Table 4.6a shows the overall results and the influence of age, insurance, and gender. Age variable was categorized for under 40, between 40 and 65, and over 65. Type of insurance carried by the patient was categorized under Self Pay, MediCal and Private Insurance (since Medicare is highly correlated with age over 65, it was not included as a separate category). Among 813 self-identified patients, 169 patients were under 40, 361 patients were between 40 and 65, 262 patients were over 65. As seen in Table 4.6b, the only statistically significant explanatory variable is the patient age with older patients more likely to recommend, independent of callbacks.

Table 4.6b considers the interaction effects between contact (callback) by medical professionals and these variables of age, insurance, and gender. Along the lines of the

previous results regarding wait times, none of the interaction terms are significant. This finding suggests that the hospital administration should implement callback in a randomized manner rather than target specific patient segments clustered by age, gender or insurance. Tables 4.7a and 4.7b report ordered logit regression results for Difference by Insurance Type and gender for subsamples segregated by insurance types and gender. These tables (analysis of subsamples) show that patients under some insurance types (Medicare, MediCAL) and gender experience a stronger impact of callbacks. It is interesting to note that men respond strongly to callback by nurses, and women to callback by MD's. However, these are directional effects that are found in the subsample analysis but not in the full sample.

4.5. Discussion and Conclusions

Improving the performance in health care services in general and emergency medicine in particular is quite challenging. Patients enter the service system with anxiety and discomfort (or in an unconscious/life-threatening situation), and their emotional state can be further aggravated by the waiting time they must endure. They could leave in a bad emotional condition, and based on research in Psychology (specifically the Appraisal Tendency Framework), this emotional state could carry over in patients' appraisal of the service delivered. Although lower waiting time can help reduce their angst, it can be costly to lower wait times by adding capacity in the ED.. Also, past experience at this ED found that lower wait times are not enough to significantly impact patient appraisals.

The service re-design involving post-discharge patient call back by the care provider (during periods of excess capacity) helps achieve improved patient appraisal notwithstanding the waiting time. A key question for the leaders of the ED department is

when and how the assessment might be impacted with the post-discharge call back step added to the service process design. It is not surprising that call back by an MD results in a significant improvement in appraisal than the call back by a nurse, as measured by the statistically significant improvement in likelihood to recommend. This improved appraisal may be due to the impact on both integral and incidental emotions as predicted by the Appraisal Tendency Framework. We develop an Identification strategy in our analysis by arguing that *Integral emotions* are likely to dominate for those who experience higher waiting times, so if integral emotions were to dominate, callbacks should have a significant moderating effect on wait times influence on patient appraisals. However, if ATF's emphasis on incidental emotions is to be followed, call-back based contact by medical professionals should *not* have a significant interaction effect with other contextual variables (such as wait times). While, incidental emotions seem to be anomalous, they do seem to play a stronger role in our setting as well where there is no significant interaction effect of patient callbacks suggesting that incidental emotions dominate integral emotions in the patient appraisal.

The findings in this study offer some pointers for improving service appraisal at the host institution. While we do find a slight "directional effect" of callback in older patients than younger patients and also some patterns where patients of certain insurance type respond more strongly to callbacks in subsample analysis, the interaction effect of callback with age, gender, and insurance type is not statistically significant in the overall model. These findings suggest that the health system leadership should largely implement callbacks in a randomized manner just like other rigorous approaches in health sciences (including patient surveys). On the whole, the call back design better aligns

service capacity and customer demand: patients can be called back when excess capacity is available. This approach may even be considered beyond the emergency departments to other parts of the health system, starting with urgent care, a growing area. The ED process, after discarding admissions, is somewhat similar to an "outpatient" urgent care , although the emergency patients are often more complex.

There are several limitations of this study. Clearly this was an exploratory field study and we could only illustrate an association between call back and patients' satisfaction. We controlled for several important variables that affect the relationship, but omitted variable bias still remains. Analyzing individual patient-level data tends to be challenging due to the privacy issues associated with the medical records data. There could be potential selection bias- for example, patients reporting call back had much lower wait times in the over sample. We are able to compensate for this by repeating our analysis for Hospital “A” where there was no significant difference in wait times. Overall, we are using the data for self-identified patients, who may be more likely to be satisfied. One way to address this issue is to require all patients to rate the satisfaction and self-identify themselves, but this is operationally unrealistic in an ED setting. Also, this research was conducted with two EDs in a single healthcare system, so more research is needed to see how this would generalize to other settings. Nearly identical impact for the two different ED sites with different patient socio-economic characteristics offers some endorsement of the broader validity.

We view this paper as the starting point of investigating the mechanism of using service process design to improve customer satisfaction in highly complex services. The impact on patient satisfaction in this case due to the service innovation was impressive in

comparison with prior approaches - including reducing waiting time, communication scripting and facility enhancements encouraging the organization to adopt the new design broadly across the organization. In conclusion, despite some limitations, the call back service redesign seems to better align capacity and demand of health specialists. In doing so, the service design helps improve patients appraisals which is one of the key metrics for the leadership and management of the hospital system - as it is in other type of service setting – potentially leading to improved operational, financial, and market performance. Our analysis allows to get under-the-hood of emergency medicine survey data and unearth possible routes by which callbacks influence patient likelihood to recommend. Based on the current data in a setting with minimal expectations of callback, we find callbacks to be less of a service recovery tool and more of an across the board appraisal improvement mechanism that the leaders of emergency medicine can use to extend care beyond the confines of the ED service setting.

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Chapter 4, in full, is currently being prepared for submission for publication of the material. Krishnan, Vish; Maki, Kanetaka M.; Castillo, Edward M.; Guss, David A. The dissertation author was the primary investing and author of this paper.

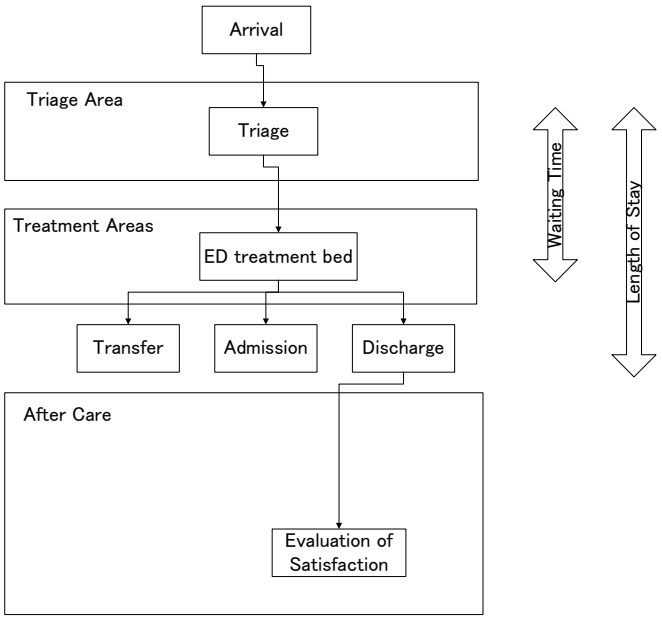


Figure 4.1: Emergency Department Service Process (Without Call Back)

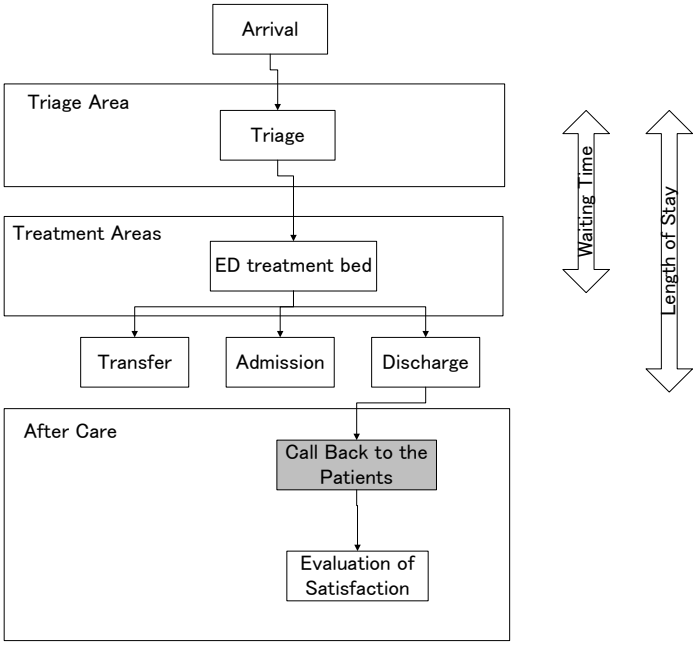


Figure 4.2: Emergency Department Service Process (With Call Back)

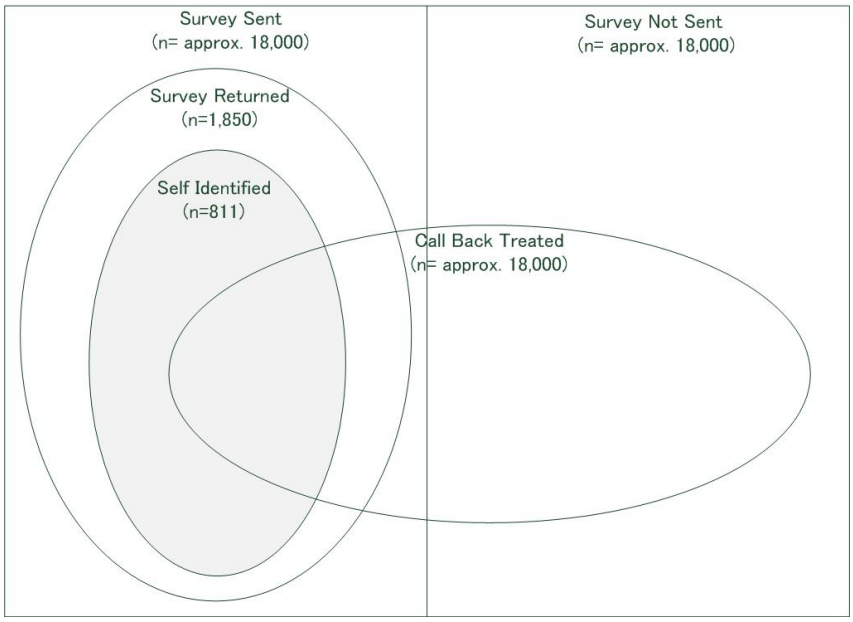


Figure 4.3: Population of the Study

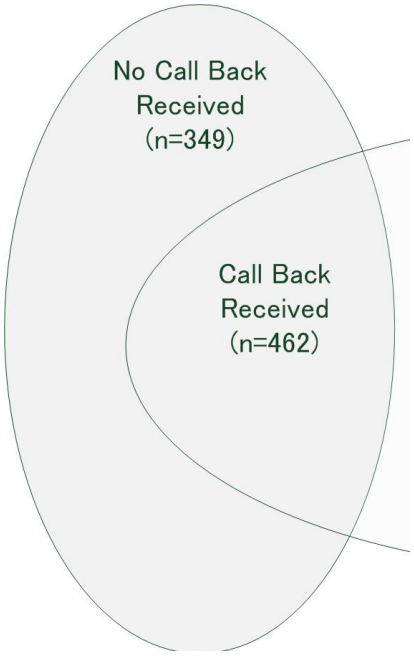


Figure 4.4: Treatment and Control

Table 4.1: Patient Demographics for Self-Identified

	Not Self Identified (n=1039)	Self Identified (n=811)	Difference	P-value
Age (Survey) – mean	51.06	55.20	-4.14	0.00
Male Patients (Survey) - %	0.38	0.43	-0.04	0.07
Length of Stay (Survey) – minutes	275.23	298.21	-22.98	0.11
Received Phone Call After Discharge (Survey) - %	0.54	0.60	-0.06	0.02
Hospital "B" - %	0.58	0.48	0.09	0.00
Overall Satisfaction – 5 ranked mean	4.30	4.51	-0.20	0.00

Student's t-test

Table 4.2a: Patient Demographics for Call Back Yes/No

	Call Back No (n=349)	Call Back Yes (n=462)	Difference	p-value
Age – mean	52.45	56.83	-4.38	0.00
Male Patient - %	0.11	0.42	-0.30	0.00
Female Patient - %	0.14	0.58	-0.44	0.00
Triage code – Immediate - %	0.01	0.03	-0.02	0.00
Triage code – Urgent - %	0.16	0.61	-0.45	0.00
Triage code – Delayed - %	0.08	0.36	-0.28	0.00
Insurance – medicare - %	0.06	0.32	-0.26	0.00
Insurance - self pay - %	0.03	0.08	-0.04	0.00
Insurance – MediCal - %	0.04	0.10	-0.06	0.00
Insurance - Private Insurance - %	0.12	0.50	-0.39	0.00
Wait Time - minutes	29.79	20.10	9.69	0.02
Length of Stay - minutes	267.93	240.83	27.11	0.02
Hospital "B" - %	0.51	0.62	-0.11	0.00
Overall satisfaction - 5 ranked mean	4.32	4.61	-0.29	0.00

Student's t-test

Table 4.2b: Chi-Squared Test for Waiting Time and Contact to Patients

Waiting Time	Contact to Patients		Total
	No	Yes	
Short (<24 min)	251	379	630
Long (>= 24 min)	97	82	179
Total	348	461	809

Pearson chi2(1) = 11.7081 Pr = 0.001

Table 4.3a: Patient Demographics for Two Hospitals

	Hospital "A"	Hospital "B"	Difference	p-value
Age – mean	51.65	58.46	-6.81	0.00
Female Patient - %	0.55	0.60	-0.05	0.19
Triage code – Immediate - %	0.05	0.02	0.03	0.04
Triage code – Urgent - %	0.60	0.64	-0.03	0.37
Triage code – Delayed - %	0.35	0.34	0.00	0.92
Insurance – medicare - %	0.23	0.34	-0.12	0.00
Insurance - self pay - %	0.16	0.03	0.13	0.00
Insurance – MediCal - %	0.18	0.06	0.13	0.00
Insurance - Private Insurance - %	0.42	0.56	-0.14	0.00
Wait Time - minutes	37.29	9.51	27.78	0.00
Length of Stay - minutes	274.19	225.29	48.90	0.00
Call Back (Yes) - %	0.42	0.73	-0.30	0.00
Overall satisfaction – 5 ranked mean	4.36	4.66	-0.30	0.00

Student's t-test

Table 4.3b: Patient Demographics for Call Back Yes/No Wait Time by Hospital

	Call Back No	Call Back Yes	Difference	p-value
Wait Time Hospital "A" – minutes	36.43	38.47	-2.03	0.77
Wait Time Hospital "B" – minutes	14.93	7.48	7.46	0.02

Table 4.4a: Ordered Logistic Regression for Overall Satisfaction

(n=792 for Both Hospitals)

VARIABLES	(1) overall
Contact by MD	0.764***
	(0.233)
Contact by RN	0.336**
	(0.171)
Triage code - Urgent	-0.212
	(0.445)
Triage code - Delayed	-0.410
	(0.464)
Wait Time (minutes)	-0.00364***
	(0.00140)
Length of Stay (minutes)	-0.000516
	(0.000574)
Constant cut1	-3.664***
	(0.511)
Constant cut2	-3.157***
	(0.497)
Constant cut3	-2.328***
	(0.483)
Constant cut4	-1.118**
	(0.476)
Observations	792

Table 4.4b: Ordered Logistic Regression for Overall Satisfaction (Hospital "A" ; n=406)

Robustness Check with Hospital "A" with no significant difference in wait times between Callback and No Callback patients

VARIABLES	(1) overall
Contact by MD	0.858***
	(0.296)
Contact by RN	0.297
	(0.245)
Triage code - Urgent	-1.144*
	(0.642)
Triage code - Delayed	-1.659**
	(0.664)
Wait Time (minutes)	-0.00102
	(0.00157)
Length of Stay (minutes)	-0.000521
	(0.000705)
Constant cut1	-4.369***
	(0.708)
Constant cut2	-3.935***
	(0.694)
Constant cut3	-3.008***
	(0.679)
Constant cut4	-1.741***
	(0.668)
Observations	406

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.5a: Ordered Logit Regression for Overall Satisfaction (n=792)

Moderation Effect of Callback on Waiting Times Impact of Likelihood to Recommend

VARIABLES	(1) overall
Contact by MD	0.741***
	(0.256)
Contact by RN	0.329*
	(0.188)
Interaction Effect Between Contact by MD and Wait Time	0.000786
	(0.00370)
Interaction Effect Between Contact by RN and Wait Time	0.000242
	(0.00298)
Triage code - Urgent	-0.210
	(0.445)
Triage code - Delayed	-0.407
	(0.464)
Wait Time (minutes)	-0.00386**
	(0.00191)
Length of Stay (minutes)	-0.000511
	(0.000575)
Constant cut1	-3.668***
	(0.512)
Constant cut2	-3.161***
	(0.498)
Constant cut3	-2.331***
	(0.484)
Constant cut4	-1.122**
	(0.476)
Observations	792

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.5b: Hospital "A" Moderation Effect of Callback on Waiting Times Impact of Likelihood to Recommend Robustness Check with Hospital "A" with no significant difference in wait times between Callback and No Callback patients

VARIABLES	(1) overall
Contact by MD	0.927***
	(0.338)
Contact by RN	0.225
	(0.283)
Interaction Effect Between Contact by MD and Wait Time	-0.00173
	(0.00398)
Interaction Effect Between Contact by RN and Wait Time	0.00169
	(0.00348)
Triage code - Urgent	-1.141*
	(0.642)
Triage code - Delayed	-1.667**
	(0.664)
Wait Time (minutes)	-0.00116
	(0.00204)
Length of Stay (minutes)	-0.000543
	(0.000707)
Constant cut1	-4.383***
	(0.709)
Constant cut2	-3.949***
	(0.695)
Constant cut3	-3.020***
	(0.679)
Constant cut4	-1.753***
	(0.669)
Observations	406

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6a: Ordered Logit Regression for Overall Satisfaction (n=792)

Considering Effect of Age, Insurance, Gender

VARIABLES	(1) overall	(2) overall	(3) overall	(4) overall
Contact by MD	0.764***	0.785***	0.735***	0.754***
	(0.233)	(0.236)	(0.235)	(0.234)
Contact by RN	0.336**	0.308*	0.283	0.345**
	(0.171)	(0.174)	(0.173)	(0.171)
Triage code - Urgent	-0.212	-0.173	-0.177	-0.203
	(0.445)	(0.447)	(0.447)	(0.445)
Triage code - Delayed	-0.410	-0.341	-0.367	-0.387
	(0.464)	(0.468)	(0.466)	(0.464)
Wait Time (minutes)	-0.00364***	-0.00335**	-0.00333**	-0.00364***
	(0.00140)	(0.00140)	(0.00142)	(0.00139)
Length of Stay (minutes)	-0.000516	-0.000647	-0.000420	-0.000546
	(0.000574)	(0.000579)	(0.000575)	(0.000575)
40 < age < 65		0.634***		
		(0.197)		
age >= 65		0.547**		
		(0.214)		
Insurance - self pay			-0.362	
			(0.277)	
Insurance - MediCal			-0.348	
			(0.251)	
Insurance - Private Insurance			0.115	
			(0.188)	
Gender				-0.237
				(0.160)
Constant cut1	-3.664***	-3.214***	-3.661***	-3.801***
	(0.511)	(0.531)	(0.531)	(0.520)
Constant cut2	-3.157***	-2.702***	-3.154***	-3.293***
	(0.497)	(0.518)	(0.517)	(0.506)
Constant cut3	-2.328***	-1.864***	-2.326***	-2.463***
	(0.483)	(0.506)	(0.504)	(0.493)
Constant cut4	-1.118**	-0.642	-1.108**	-1.250***
	(0.476)	(0.500)	(0.497)	(0.484)
Observations	792	792	792	792

Table 4.6b: Ordered Logit Regression for Overall Satisfaction (n=792) – Interaction Effect

VARIABLES	(1) overall	(2) overall	(3) overall
Contact to patients	0.296	0.637**	0.469*
	(0.310)	(0.295)	(0.247)
Triage code - Urgent	-0.160	-0.165	-0.193
	(0.448)	(0.448)	(0.445)
Triage code - Delayed	-0.318	-0.349	-0.365
	(0.468)	(0.467)	(0.465)
Wait Time (minutes)	-0.00338**	-0.00344**	-0.00365***
	(0.00139)	(0.00142)	(0.00139)
Length of Stay (minutes)	-0.000544	-0.000338	-0.000475
	(0.000575)	(0.000574)	(0.000572)
Insurance - self pay		-0.306	
		(0.372)	
Insurance - MediCal		-0.242	
		(0.343)	
Insurance - Private Insurance		0.382	
		(0.287)	
Interaction effect of contact and self pay		0.0477	
		(0.559)	
Interaction effect of contact and medical		-0.112	
		(0.506)	
Interaction effect of contact and private insurance		-0.443	
		(0.378)	
40 < age < 65	0.548**		
	(0.275)		
age >= 65	0.316		
	(0.316)		
Interaction effect of contact and age (40 < age 65)	0.123		
	(0.390)		
Interaction effect of contact and age (age>=65)	0.356		
	(0.422)		
Gender			-0.252
			(0.229)
Interaction effect of contact and gender			0.00216
			(0.318)
Constant cut1	-3.264***	-3.487***	-3.773***
	(0.552)	(0.546)	(0.525)
Constant cut2	-2.753***	-2.980***	-3.266***
	(0.539)	(0.533)	(0.511)
Constant cut3	-1.918***	-2.153***	-2.437***
	(0.528)	(0.520)	(0.498)
Constant cut4	-0.699	-0.936*	-1.226**
	(0.522)	(0.513)	(0.489)
Observations	792	792	792

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.7a: Ordered Logit Regression for Difference by Insurance Type

Characteristics	Medicare (n=228)		Self Pay (n =76)		MediCal (n = 98)		Private Insurance (n =387)	
Call Back								
Contact by MD	1.295***	(0.499)	0.984	(0.682)	1.890**	(0.800)	0.211	(0.331)
Contact by RN	0.370	(0.315)	0.702	(0.597)	0.0311	(0.481)	0.0974	(0.265)
Triage Category								
Immediate								
Urgent	-0.151	(0.860)	0.0924	(1.345)	2.105*	(1.258)	-0.793	(0.768)
Delayed	-0.427	(0.908)	-0.268	(1.363)	1.880	(1.307)	-0.923	(0.791)
Wait Time	0.00532	(0.00383)	-0.00401	(0.00412)	0.00293	(0.00328)	-0.00874***	(0.00216)
Length of Stay	-0.00144	(0.00112)	0.000962	(0.00145)	-0.000847	(0.00148)	-6.24e-05	(0.000947)
/Cut1	-3.640***	(0.986)	-2.955**	(1.477)	-1.262	(1.377)	-4.605***	(0.866)
/Cut2	-3.265***	(0.963)	-2.202	(1.427)	0.120	(1.380)	-3.904***	(0.839)
/Cut3	-2.572***	(0.935)	-1.381	(1.403)	1.704	(1.396)	-3.060***	(0.822)
/Cut4	-1.073	(0.913)	-0.0727	(1.383)			-2.034**	(0.812)
Observations	228		76		98		387	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.7b: Ordered Logit Regression for Difference by Gender

Characteristics	Male (n=340)		Female (n=452)	
Call Back				
Contact by MD	0.428	(0.330)	1.068***	(0.339)
Contact by RN	0.564**	(0.283)	0.227	(0.218)
Triage Category				
Immediate				
Urgent	-0.813	(0.783)	0.171	(0.557)
Delayed	-1.096	(0.808)	0.0916	(0.585)
Wait Time	-0.00157	(0.00207)	-0.00601***	(0.00196)
Length of Stay	-6.69e-05	(0.000877)	-0.000875	(0.000776)
/Cut1	-3.990***	(0.857)	-3.513***	(0.665)
/Cut2	-3.563***	(0.841)	-2.939***	(0.641)
/Cut3	-2.903***	(0.826)	-1.987***	(0.620)
/Cut4	-1.675**	(0.812)	-0.761	(0.612)
Observations	340		452	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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