INTERACTIONS AND INNOVATION

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To all those who have paved the way.

"Die Grenzen meiner Sprache bedeuten die Grenzen meiner Welt"

Translated from German: "The limits of my language mean the limits of my world"

(Wittgenstein, 1921)

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TABLE OF CONTENTS

Acknowledgments v

List of Tables xi

List of Figures xiv

Chapter 1: Introduction and Background 1

Chapter 2: Taking Interactions and Innovation to the Neighborhood: The Role of Street Infrastructure 6

2.1 Introduction 6

2.2 A Physical Environment that Connects 10

2.3 Estimation Strategy 12

2.3.1 The Unit of Analysis 12

2.3.2 Threats to Identification 12

2.3.3 Addressing Threats to Identification 13

2.4 Dataset Construction 18

2.4.1 Measuring Features of a Location 19

2.4.2 Measuring Innovation 22

2.5 Results 24

2.5.1 OLS Regression Results 24

2.5.2 IV Results . . . 26

2.5.3 Is There Any Knowledge Exchange? . . . 29

2.5.4 Interactions Between the Physical and Social Space . . . 31

2.5.5 Limitations . . . 32

2.6 Discussion and Conclusion . . . 33

Chapter 3: Taking Interactions and Innovation to Co-Working Spaces: The Impact of Proximity on Technology Adoption and Startup Performance Outcomes . . . 45

3.1 Introduction . . . 45

3.2 Conceptual Framework . . . 49

3.2.1 Physical Proximity . . . 49

3.2.2 The Interplay of Physical Proximity with Other Dimensions of Proximity . . . 50

3.3 Empirical Strategy and Data . . . 53

3.3.1 Estimation Strategy . . . 53

3.3.2 Data Sources and Construction . . . 54

3.3.3 Descriptive Statistics . . . 58

3.4 Results . . . 59

3.4.1 Baseline Results: Physical Proximity . . . 59

3.4.2 Interaction Results: Physical and Other Proximity Dimensions . . . 62

3.4.3 Could physical proximity be shaping interaction? . . . 64

3.4.4 Performance . . . 65

3.5 Discussion . . . 66

Chapter 4: Taking Interactions and Innovation to the Lab: Exposure to an Entrepreneurial Advisor . . . 90

4.1 Introduction . . . 90

4.2 Background . . . 96

4.2.1 Commercialization and Academia . . . 96

4.3 Data Construction . . . 100

4.4 Estimation Strategy and Results . . . 103

4.4.1 The Ideal Experiment . . . 103

4.4.2 Threats to Identification . . . 104

4.4.3 Addressing Threats to Identification and Results . . . 105

4.5 Potential Mechanisms . . . 117

4.5.1 Professor-Level Innovation Outcomes . . . 117

4.5.2 Training and Mentoring . . . 119

4.5.3 Organizational Changes . . . 119

4.6 Limitations . . . 121

4.7 Discussion and Conclusion . . . 122

Appendix A: Taking Interactions and Innovation to the Neighborhood . . . 141

A.0.1 Geographic Hierarchy and Boundaries . . . 141

A.0.2 A Different Approach to Grouping Observations . . . 143

A.0.3 Measuring Street Networks . . . 143

A.0.4 Heterogeneity in Firm Size Composition . . . 145

Appendix B: Taking Interactions and Innovation to Co-Working Spaces . . . 164

Appendix C: Taking Interactions and Innovation to the Lab 168

C.0.1 Inverse Probability of Treatment Approach 168

C.0.2 Student Career Outcomes - Multinomial Logit Approach 169

References 200

LIST OF TABLES

1.1 Summary Statistics on the Census Block Group Level 39

1.2 Patenting and Connectivity - OLS Regressions 40

1.3 The Likelihood of Having a Patent or Not 41

1.4 Instrumental Variable Estimation 42

1.5 Patent Citation Patterns 43

1.6 Interaction of Connectivity with Population, Employment, No.of Bars . . 44

2.1 Summary Statistics on the Firm and Dyad Level 76

2.2 Operationalization of Proximity Dimensions 77

2.3 Pairwise characteristics do not predict geographic proximity - OLS Regressions 78

2.4 Distance negatively affects peer technology adoption - OLS Regressions . 79

2.5 Distance negatively affects peer technology adoption - LPM Regressions . 80

2.6 Close proximity positively affects peer technology adoption - LPM Regressions 81

2.7 Common-area overlap increases technology adoption and substitutes for proximity - LPM Regressions 82

2.8 Centrally-located rooms substitute for proximity - LPM Regressions . . . 83

2.9 Female-firm dyads overcome the distance discount - LPM Regressions . . 84

2.10 Successful-dyads are more likely to adopt technologies from each other and success substitutes for proximity - LPM Regressions 85

2.11 Product-market proximity substitutes for geography - LPM Regressions . 86

2.12 Proximity increases joint attendance of community-wide events - OLS Regressions 87

2.13 Conditional on jointly attending event, room proximity increases event checkin-line proximity - OLS Regressions 88

2.14 Shared resources predict technology adoption - LPM Regressions 89

3.1 Summary Statistics - Students of Entrepreneurial Advisors 130

3.2 PhD Patenting and Publishing during the PhD Program 131

3.3 Interaction of Student Quality Indicators with Professors' Prior Founding Experience 132

3.4 IV Estimation Approach 133

3.5 PhD Patenting and Publishing during the PhD Program including Lab Size Interaction 134

3.6 Productivity 1-5 Years Post-PhD 135

3.7 Employment Type 136

3.8 First Position by Employment Type 137

3.9 Long Term Employment Outcomes 138

3.10 Mentorship Quality 139

A1.1 Variable Description 154

A1.2 Correlation of Distinct Density Measures with Connectivity 155

A1.3 Different Dependent Variable Construction 156

A1.4 Conditional Fixed-Effects Poisson Model 157

A1.5 OLS - Different Measures of Connectivity 158

A1.6 2SLS Using Different Housing Ages as Instruments 159

A1.7 Instrumental Variable Estimation - Including Pathways and Trails 160

A1.8 Control Function Approach Using FE Poisson in the Second Stage 161

A1.9 Interaction of Connectivity with Assignee Size 162

A1.10 Patent Citation Patterns - Including Pathways and Trails 163

A2.1 Variable Description 167

A3.1 Summary Statistics - By Advisor Type 179

A3.2 Summary Statistics - All Advisors 180

A3.3 Robustness: PhD Outcomes Including Student and Professor Controls . . 181

A3.4 Robustness: PhD Outcomes Using IHS Transformation 182

A3.5 Robustness: PhD Outcomes Using IHS Transformation - Including Individual Controls 183

A3.6 First-Authored Publications 184

A3.7 Robustness: PhD Student Outcomes - Excluding Students that were never and always exposed 185

A3.8 PhD Student Outcomes by Year of Graduation 186

A3.9 Robustness: Inverse Probability of Treatment 187

A3.10 What predicts PhD Student Outcomes? 188

A3.11 Average Student Productivity - Interaction with Age at Founding 189

A3.12 Average Student Productivity - Interaction With Federal Funding 190

LIST OF FIGURES

1.1 Example for Differences in *Connectivity*: New York County, New York . 36

1.2 Distribution of *Connectivity* (log) by Commuting Zone using within Commuting Zone Cutoffs 37

1.3 *Connectivity* (log) Coefficient by Decile 38

2.1 Conceptual Approach 69

2.2 Floor Plan of the Co-working Space 70

2.3 Physical Proximity Quartile Plots 71

2.4 Common Area Quartile Plots 72

2.5 Adoption by Technology Overlap Quintiles 73

2.6 Probability of Raising a Seed Round by Technology Overlap Quintile of Proximate Firms 74

2.7 Probability of Raising $1MM by Technology Overlap Quintile of Proximate Firms 75

3.1 Innovative Output of Professors Over Time 124

3.2 Number of Founders by Year 124

3.3 Innovative Output of Professors - By Founder or Not 125

3.4 Yearly Outcomes for Students by Time of Graduation from Founding . . . 126

3.5 Before and After Founding Year - Student Characteristics 127

3.6 Professor Outcomes as a Function of Founding a Company using Department-Year vs. Professor FE . . . 128

3.7 Phd Student Outcomes and Exposure by Field of Research Type . . . 129

A1.1 Depiction of Sample Selection using CZ 9100 (Atlanta, GA) as an Example 148

A1.2 Scatterplot of the Relationship between *Connectivity* and Patents . . . 149

A1.3 The Relationship between *Connectivity* and Controls . . . 150

A1.4 *Connectivity* by Percentage of Small Firms . . . 151

A1.5 Interaction of *Connectivity* (log) with Population, Employment, and No. Bars . . . 152

A1.6 Kernel Density Distribution of Assignee Size in the Sample and in Full Data Set . . . 153

A2.1 Heterogeneous Effects of Physical Proximity: Social Proximity . . . 165

A2.2 Heterogeneous Effects of Physical Proximity: Product-market Proximity 166

A3.1 Number of Startups per Professor-Founder . . . 171

A3.2 Duration of the PhD Program . . . 171

A3.3 Binscatter Plots - Student Outcomes and Exposure . . . 171

A3.4 Yearly Outcomes for Students by Time of Graduation from Founding - Stylized Approach . . . 172

A3.5 Yearly Outcomes for Students by Time of Graduation from Founding . . . 173

A3.6 First-Authored Publications . . . 173

A3.7 Interaction of Student Quality Indicators with Professors' Prior Founding Experience . . . 174

A3.8 Binscatters First Stage(s) IV . . . 175

A3.9 Cumulative Hazard of Founding a Company by Professor Age . . . 176

A3.10 Point Estimates of the Effect of Founding on Student Job Outcomes . . . 176

A3.11 Average Marginal Effects of Founding on Student Job Outcomes 177

A3.12 Number of Incoming Students from Time of Founding 177

A3.13 First-authored Publications and Exposure by Field of Research Type . . . 178

SUMMARY

Interaction between individuals is especially crucial for innovation as it enables the exchange and recombination of knowledge necessary to create new or improve existing technologies, processes, or products. In my dissertation, I examine the impact of interpersonal exchange on innovation in three different contexts: neighborhoods, co-working spaces, and university laboratories. On the neighborhood-level, I analyze how the physical layout of cities affects innovation by influencing the organization of knowledge exchange. Here, I exploit a novel data set covering all Census Block Groups in the contiguous United States with information on innovation outcomes, street infrastructure, as well as population and workforce characteristics. My results suggest that variation in street network density may explain regional innovation differentials beyond the traditional location externalities found in the literature. In the second chapter (co-authored), I examine the interplay between physical proximity and other proximity dimensions in predicting technology adoption decisions at one of the largest technology co-working spaces in the United States deriving important implications for firm performance. I discuss the role of balancing physical and other proximity dimensions in promoting the diffusion of ideas within a fast-changing entrepreneurial ecosystem through organizing personal interactions. Finally, in the third chapter, I analyze the impact of exposure to an entrepreneurial lab head on the innovative output of their PhD students. Using a unique matched sample of advisors and advisees in computer sciences and engineering at a top US research university, my findings indicate important hidden costs to academic entrepreneurship that fall largely on the shoulders of PhD students. Overall, this dissertation takes an important step towards understanding how the environments of knowledge producers impact innovation via the extent to which they enable or inhibit interpersonal exchange and influence the types of interactions that occur among individuals.

CHAPTER 1
INTRODUCTION AND BACKGROUND

In a very literal sense, this dissertation is taking innovation from being up "in the air" (Marshall, 1890) to concrete features of neighborhoods, co-working spaces, and university laboratories that facilitate (or impede) interaction between individuals and thereby impact innovative outcomes. I examine the role of street infrastructure, proximity dimensions and activities of direct supervisors on innovation using three unique datasets and contexts. In the three chapters of this dissertation, I provide evidence that these features predict innovative outcomes via their influence on the type and extent to which interpersonal exchange can take place.

In general, the diffusion of ideas has been found to be highly localized (Allen, 1977; Arzaghi and Henderson, 2008) and, in theory, the assumption pervades that knowledge (especially more tacit and complex know-how) transfers via face-to-face interaction between individuals (Gaspar and Glaeser, 1998; Jacobs, 1969; Moretti, 2004; Rosenthal and Strange, 2001). Such interaction between individuals is especially crucial for innovation as it enables the exchange and recombination of knowledge necessary to create new or improve existing technologies, processes, or products (Fleming and Sorenson, 2004; Gaspar and Glaeser, 1998; Hargadon, 1998; Simonton, 2003). Moreover, over the past decades, knowledge production has increasingly become a team process involving multiple individuals and requiring the frequent transfer of complex ideas (Wuchty et al., 2007). This makes it ever more important to understand what structures best support collaboration especially provided that the individuals involved in knowledge production operate in different physical and social environments that are organized in distinct ways. The specific features of these environments and the manner that they are organized may impede or facilitate interpersonal exchange.

In this regard, an established literature has demonstrated the importance of features like physical proximity in explaining information flows between individuals. Results indicate that these distances can be as little as a few hundred meters in certain circumstances (Catalini, 2017; Cowgill et al., 2009; Kerr and Kominers, 2015; Reagans et al., 2005). A further stream of work provides evidence for the importance of other features such as social proximity in governing exchange between actors (Granovetter, 1973; McPherson and Smith-Lovin, 1987; Singh, 2005; Reagans, 2011; Carrell et al, 2013; Ingram and Morris, 2007; Kato and Shu, 2016) and more recent studies push even further suggesting that prior ties may affect the extent to which individuals are receptive to peer effects in the first place (Hasan and Koning, 2019). Moreover, the observation that peers – in other words entities that interact with each other – influence performance outcomes (Chan et al., 2014b, a; Mas and Moretti, 2009; Hwang, Liberti and Sturgess, 2018; Sacerdote, 2001; Oettl, 2012; Catalini, 2017) renders this a fundamental topic for the field of strategy.

In this dissertation, I build on prior research by examining different features of environments that influence innovative outcomes and performance via their impact on the extent to which and what type of interpersonal exchange takes place. I do so using three unique data sets covering three novel settings that I compiled over the course of my PhD program. My findings suggest that a) the physical street structure of neighborhoods can explain innovation differentials, b) both social and product-market proximity may serve as substitutes for physical proximity, and some knowledge space proximity bolsters and too much reduces the impact of physical distance on technology adoption decisions, and that c) students experience a reduction in their scientific productivity when they are exposed to an entrepreneurial lab head.

In the first chapter, *Taking Interactions and Innovation to the Neighborhood: The Role of Physical Structures*, I analyze how the physical layout of cities affects innovation by influencing the organization of knowledge exchange. Here, I exploit a novel data set covering all Census Block Groups in the contiguous United States with information on innovation outcomes, street infrastructure, as well as population and workforce characteristics. The results suggest that variation in street network density may explain regional innovation differentials beyond the traditional location externalities found in the literature. As such, this chapter makes two main contributions to the empirical literature on geography and innovation. First, I use a unique dataset covering the entire contiguous USA on the smallest geographic entity for which information on street infrastructure is available. Previous research has not been able to apply such a micro-geographic lens to assess innovation outcomes. Second, I go beyond the traditional location externalities examined in the empirical literature and test how physical features of a neighborhood can affect innovation outcomes. This type of structural difference on this level of analysis has not been considered before in empirical work and has potentially far-reaching consequences for cities, organizations, and individuals.

In the second chapter (co-authored), *Taking Interactions and Innovation to Co-Working Spaces: The Interplay of Different Proximity Dimensions*, I focus on the interplay between physical and other proximity dimensions on technology adoption decisions at one of the largest technology co-working hubs in the United States. I further discuss implications for startup performance and the design of entrepreneurial ecosystems. Using floor plans to measure physical proximity, I find that close proximity greatly influences the likelihood of adopting an upstream (production) technology also used by a peer firm. This effect, however, quickly decays with distance where startup firms that are more than 20 meters away are no longer influenced by each other. The results suggest that both social and product-market proximity may serve as substitutes for physical proximity, some knowledge space proximity bolsters and too much reduces the impact of physical distance on technology adoption decisions. My findings further indicate that too much technology adoption may not necessarily improve startup performance. This goes in line with previous research suggesting limits to the amount and frequency of technology adoption (Swank and Visser, 2015; Hassan and Mertens, 2017) and indicating that observational learning is error prone (Bikhchandani et al., 1998). Overall, this chapter provides fundamental insights for the design of communities that support knowledge production, entrepreneurship, and innovation.

In my third chapter, *Taking Interactions and Innovation to the Lab: Exposure to an Entrepreneurial Advisor*, I examine the impact of exposure to an advisor engaged in entrepreneurship on the innovative output of their advisees. Using a unique sample of advisors and advisees in computer sciences and engineering at a top US research university from 2000 - 2013, I assess variation in PhD students' innovative and career outcomes before and after research faculty transitions into entrepreneurship. I do so by applying rich, restricted-access data on over 4,500 PhD students and over 800 professors. I address concerns associated with sorting using both student and professor fixed effects models and by examining factors determining an advisor-advisee match. To control for the potential endogeneity of entrepreneurial activity, I construct an instrument using the amount of venture capital investments by field-year capturing demand for commercial entrepreneurship. My results suggest that although starting a company only slightly impacts a lab head's own productivity, exposure to a lab head engaged in entrepreneurship has a substantial negative influence on PhD student publication during and after completion of the PhD program. Further, I find that exposed students are more likely to become entrepreneurs upon graduation, less likely to have their first position at a prestigious firm, and less likely to hold faculty positions. I provide evidence that these results are unlikely to be driven by selection on observable quality characteristics or reduced mentoring, but more likely a result of managerial changes. Overall, this chapter takes an important step towards understanding the consequences of entrepreneurship for scientific productivity and the development of human capital providing broader implications for the organization of science and management research.

Taken together, the findings of the chapters of this dissertation are relevant for our understanding of what urban structures best support local innovation, how other structural and social features interact with physical proximity in predicting technology adoption, as well as the consequences of exposure to an entrepreneurial lab head on lab member productivity. As such, they highlight both benefits to increasing the potential for individuals to interact, but also the possible costs of interaction (e.g., with an entrepreneurial lab head) in terms of performance outcomes. Much more work on understanding this balance is needed, and I must acknowledge that my dissertation sheds but a small light on features that can aid in organizing environments that support knowledge production, entrepreneurship, and innovation.

CHAPTER 2

TAKING INTERACTIONS AND INNOVATION TO THE NEIGHBORHOOD: THE ROLE OF STREET INFRASTRUCTURE

"Streets and their sidewalks, the main public places of a city, are its most vital organs" (Jacobs 1969: 29).

2.1 Introduction

The geographic concentration of innovation in metropolitan areas across space is well documented in the literature (Acs et al., 2002; Carlino and Kerr, 2014; Jaffe et al., 1993; Rosenthal and Strange, 2003) and a wide stream of research identifies the importance of geographic environments in organizing and supporting innovation (Porter, 1996; Saxenian, 1996; Scott and Storper, 2003). But not all geographic environments such as cities, and the neighborhoods within, are equally equipped to do so. Cities and their neighborhoods vary in size and scope, in their density of activities and amenities, as well as in the manner they facilitate or impede the movement of individuals.

In order to understand the roots of innovation differentials across cities, much work has focused on modeling the innovative output from cities as a function of agglomeration economies and, more specifically, urban size and density. The empirical evidence suggests that by facilitating exchange, urban density helps knowledge spread (Arzaghi and Henderson, 2008; Carlino et al., 2007; Kantor and Whalley, 2014; Lin, 2011; Rosenthal and Strange, 2008). However, it remains puzzling that regions with similar population and even inventor density differ so starkly in innovation output (Agrawal et al., 2014).

A further stream of research suggests that urban efficiencies are not only a function of agglomeration economies, but can also be attributed to non-agglomeration channels. Early research points out that these efficiencies may depend on the nature of urban exchange

(Chinitz, 1961; Jacobs, 1969) that is partially determined by social structures and industrial practices (Saxenian, 1996). More recent findings highlight the importance of physical structures for growth and innovation within a region. For instance, by supporting the circulation of local knowledge, regional transportation infrastructure has been found to increase patenting output (Agrawal et al., 2017).

In this paper I introduce an additional factor that has received little attention in the innovation literature thus far, but may have important implications for innovation: the physical layout of neighborhoods. I specifically examine the effect of neighborhoods' street infrastructure on innovation. My main notion is that a more physically connected infrastructure, as determined by its street network, positively affects the extent to which interpersonal exchange can take place and is organized. For one, within a strongly connected environment the number of potential contacts is high, thereby increasing the likelihood of more serendipitous knowledge exchange. For another, a strongly connected environment enables more efficient time allocation between travel and planned interpersonal knowledge exchange. For instance, shorter travel distance between economic partners, to formal knowledge centers, and to places where social activity is hosted both reduces the costs associated with interpersonal knowledge exchange and increases the available amount of time for interaction.

Providing more potential contacts and higher levels of interaction efficiency are important for innovation given that interpersonal exchange facilitates the recombination of existing knowledge and creation of new knowledge (Fleming and Sorenson, 2004; Hargadon, 1998; Simonton, 2003; Singh and Fleming, 2010). Moreover, knowledge production is increasingly a collaborative endeavor between multiple individuals (Wuchty et al., 2007). This is why I expect any physical infrastructure that more efficiently organizes the circulation of individuals to also positively affect innovation.

The data for the analyses come from various publicly available data sources that I have collected on the neighborhood level. My definition of a neighborhood encompasses the most micro-geographic unit of analysis available for street infrastructure: the Census Block Group (hereinafter BG). In this paper, I measure the physical connectivity of a BG using street network density and proxy innovation with the number of US patents applied for in a BG. I only retain those patents where assignees are located and inventors reside within the same larger metropolitan area. In doing so, I ensure that the location of each patent indeed reflects the place where the creation of the underlying idea most likely took place. To control for traditional location externalities, I include measures that capture both historic and contemporaneous employment and population density, as well as characteristics of the workforce employed in a BG.

The decision where to locate entails a long term commitment. As such, individuals and organizations pay particular attention to the features of a place when deciding where to settle down. Consequently, location choices are likely endogenous to economic outcomes making it difficult, from an empirical standpoint, to identify causal relationships (Hanson, 2001). To address endogeneity concerns, I apply a fixed effects and instrumental variable approach. One aggregate geographic boundary I use for the fixed effects estimation is the commuting zone. The commuting zone is a natural boundary definition determined by places of residence and work of employees. Access to amenities, fiscal policies, exposure to a certain culture or life style and other unobservable features will be similar within the commuting zone boundaries. By holding this type of general environment constant, I can exploit within commuting zone variation. To deal with concerns about simultaneity, I construct instruments based on historic city planning. The instruments I use are the percent of housing units built prior to 1940 and 1940-49, which (conditional on controls) should have little effect on innovation today other than through their effect on street layout. First stage results show that both instruments together strongly predict contemporary street infrastructure. The second stage results from the instrumental variable estimation reveal a positive causal relationship between physical connectivity and innovation.

In order to provide more insight into the mechanisms that might be driving my results, I first analyze citation patterns on the neighborhood level. Here, the results indicate that physical connectivity does, to some extent, influence local inter-organizational knowledge exchange within a neighborhood. Next, I interact physical connectivity with measures for social activity finding that the physical layout of neighborhoods bolsters the impact of social factors on innovation. Taken together, these results provide suggestive evidence that higher physical connectivity has a positive impact on innovation by increasing local knowledge circulation in a neighborhood.

My findings are relevant to our understanding of what urban structures best support local innovation offering useful insights for the (micro-)geography of innovation literature, organizations faced with the decision where to locate, and regional policy makers wishing to influence local conditions. The geography of innovation literature has shown mixed results with regard to proximity and innovation outcomes. For example, empirical studies find that large corporate plants are relatively isolated from knowledge externalities whereas small, single plant firms are those that seem to benefit most from proximity (Beardsell and Henderson, 1999). Based on the evidence I provide in this paper, this could possibly be explained by the fact that certain organizations select into places where local infrastructure is not as conducive to facilitating inter-organizational knowledge flows. My findings are also informative for organizations faced with location choice that should be aware of how their most immediate environment may influence knowledge flows (Moretti, 2004). Like industry structure, local infrastructure presents a factor that can either promote, or prevent knowledge from spilling over. Similarly, I highlight that street infrastructure may represent an important asset policy makers and regions can leverage as a source of competitive advantage.

The paper is structured as follows. In the next section, I develop the basic theoretical framework to guide empirical predictions and interpretations of the findings. The third section describes the empirical estimation strategy. Section four provides an overview of how the data were constructed, followed by the main results. I conclude this paper with a discussion of the results, including limitations, implications and opportunities for future research.

2.2 A Physical Environment that Connects

Agglomeration economies, and especially knowledge spillovers, until now have mainly been viewed as a function of urban size or density (Arzaghi and Henderson, 2008; Glaeser et al., 1992; Lin, 2011). The empirical evidence suggests that by facilitating exchange, urban density helps knowledge spread (Carlino et al., 2007). In light of these findings, it remains a puzzle that regions with similar population and even inventor density are found to differ in innovation output (Agrawal et al., 2014).

More recently, as an explanation for these disparities, the impact of transportation infrastructure on innovation has been receiving attention. The evidence provides valuable insights into the implications transportation infrastructure has for reducing costs associated with knowledge exchange. One example is Agrawal et al. (2017), who exploit interstate highway system plans, railroads, and exploration maps as instruments to study the impact of highways on patenting.[1]

In this paper, I combine previous findings on both the effects of urban density and inter-urban transportation infrastructure on innovation and highlight a novel dimension that goes in line with these findings. Moving from regional to neighborhood-level infrastructure, I analyze the impact of physical connectivity on innovation via its effect on increasing both the potential for and efficiency of interaction. Interaction between individuals is especially crucial for innovation as it enables the exchange and recombination of existing knowledge necessary to create new or improve existing technologies, processes, or products (Fleming and Sorenson, 2004; Gaspar and Glaeser, 1998; Hargadon, 1998; Simonton, 2003). Moreover, over the past decades, knowledge production has increasingly become a team process involving multiple individuals (Wuchty et al., 2007) making it ever more important

[1] Similarly, in most recent work, Davis and Dingel (2019), propose a system of cities model with costly knowledge exchange as the primary agglomeration force. The authors thereby stress the important role transportation infrastructure plays in determining at what frequency interactions can feasibly occur in the first place.

to understand what structures best support collaboration.

The individuals involved in knowledge production operate in different physical environments that are organized in distinct ways. Research has shown that the physical structure of the environment has strong implications for the frequency and likelihood of interaction (Allen, 1977; Estabrook and Sommer, 1972; Festinger et al., 1950). One aspect of the physical environment influencing the frequency and likelihood of interaction between actors is street network structure (Levinson, 2012). Street network structure thereby determines the physical connectivity within a given area. Most importantly, denser street networks have been found to be strongly correlated with lower car usage, increased non-auto travel, and more direct trips (Parthasarathi, 2014); factors that make trips both shorter and faster. Generally, we are more likely to find elevated levels of street density in metropolitan areas rather than rural areas. But even within metropolitan areas not all street networks are created equally, there being much heterogeneity between and within regions and agglomerations.

A more strongly physically connected environment creates greater potential for interpersonal encounters and enables a more efficient organization of interaction. This should positively affect the extent to which interpersonal knowledge exchange occurs since both the number of contacts and the amount of time spent with partners relative to the time spent traveling increase with higher physical connectivity. In other words, higher physical connectivity should reduce both execution costs (e.g., the cost of face-to-face meetings, coordination costs, monitoring costs, and costs incurred for the transfer of tacit knowledge) and search costs (e.g., finding collaborators, suitable technologies, and identifying facilities that provide certain instruments) associated with knowledge production (Agrawal et al., 2006; Catalini, 2018; Mors, 2010). This difference in organization could translate into important innovation differentials found between cities, neighborhoods within a city, and the organizations located there. From this, and capturing physical connectivity through street network density, I expect that *with increasing street network density, innovative output will rise*.

2.3 Estimation Strategy

2.3.1 The Unit of Analysis

The unit of analysis for this study is the neighborhood, which represents the natural boundary of most individuals' daily work activities and routines (excluding the commute to work). In this paper, I define a neighborhood as a Census Block Group (BG) and use it to probe deeper into the impact of the *immediate* environment on innovative outcomes. I base my definition on prior literature providing evidence that social interactions are notably local in nature. Studies in this body of research suggest that localization effects may, indeed, be strongest within 500 meters or less (Arzaghi and Henderson, 2008) and decay rapidly with distance (Rice et al., 2006; Rosenthal and Strange, 2003, 2008). Considering that a standard Block in Manhattan is 200x500 feet (roughly 61x152 meters), walking along the one or the other Block side, 500 meters is the equivalent of three to eight Blocks. This is slightly less than the amount of Blocks in the average Manhattan BG.[2]

2.3.2 Threats to Identification

What would be the best way to measure the effect of physical connectivity on innovation? In an Utopian world, a neighborhood would be randomly assigned to one of two groups with different conditions. The two possible conditions would be a) having high or b) having low street network density. Through randomization, neighborhoods would not chose different street infrastructure based on their characteristics, nor would simultaneously occurring events influence this decision allowing the researcher to cleanly estimate the effect of street network density on innovation. Although, a randomized trial solves this type of identification problem, it is, evidently, not possible and extremely impractical in the real world given an array of associated economic and social costs. Nonetheless, this thought-experiment

[2]Until recently, applying this level of analysis has not been possible without sacrificing geographic scope or depth. Please refer to the Appendix, Section A1, for a description of US geographic boundaries, and how their documentation has improved over time.

highlights two major threats to identification that I must be aware of and address as far as possible: omitted variable bias and selection.

With regard to omitted variable bias, urban growth, economic activity and infrastructure may be simultaneously determined and regions that were developed earlier may have attracted more people and created more employment than younger regions. In the case of innovation, many amenities such as laboratories or even a scientific culture take time to establish. As such, it is likely that amenities necessary for innovation are found in older neighborhoods and locations. These locations may then have also continuously attracted more people who need access to such amenities - inventors. Additionally, it is feasible that some areas may have historically been more suitable for development than others even within one commuting zone. These factors may still persist today and affect both street infrastructure and other infrastructure that supports innovation. For example, a reason why a place may have been or remains more suitable for development could be access to water (Duranton and Turner, 2012).

With regard to selection, firms may choose and/or be forced to locate in certain areas because of their characteristics. Especially large firms might find it difficult to acquire or rent enough space to house their operations within denser metropolitan areas given geographic boundaries or restrictions imposed by the built environment. It is also feasible that the most innovative firms move to areas with high levels of connectivity because they value connectivity more than less innovative firms who do not rely on knowledge exchange. Alternatively, the most innovative firms could locate in less densely connected areas to avoid outward knowledge spillovers (Alcácer and Chung, 2007). In either case, selection poses a threat to identifying the actual effect physical connectivity has on innovation.

2.3.3 Addressing Threats to Identification

To best address issues of omitted variable bias, I apply a fixed effects approach on the commuting zone level (c). Commuting zones are clusters of counties that are characterized by strong commuting ties within commuting zones, and weak commuting ties across commuting zones (Autor et al., 2013; Tolbert and Sizer, 1996).[3] Using commuting zone fixed effects I can keep unobservable features of a place, such as culture, or access to amenities constant since individuals located within the same work place and residential boundaries should be equally affected by these unobservable factors. The equation I estimate on the BG level is displayed below:

$$\begin{aligned} I_{c,b} =& \alpha Connectivity_{c,b,2010} \\ &+\eta(SocialActivityCONTROLS_{c,b}) \\ &+\theta(FormalKnowledgeCONTROLS_{c,b}) \\ &+\beta(HumanCapitalCONTROLS_{c,b}) \\ &+\delta(Socio-DemographicCONTROLS_{c,b}) \\ &+\gamma(PhysicalGeographyCONTROLS_{c,b}) + f_c + \epsilon_{c,b} \end{aligned} \tag{1.1}$$

In the equation, f_c represents the commuting zone fixed effects, $\epsilon_{c,b}$ is the error term and standard errors are clustered on the commuting zone level to account for intra-group correlation.

The measure for innovation ($I_{c,b}$) is the amount of granted patents the assignees located in a BG applied for from 2011 to 2013. By using patent application dates, I measure as much as possible the timing of innovation produced in a BG and by counting only patents that were granted from such applications, I condition on valuable technologies (Conti and Graham, Forthcoming).[4]

The main independent variable of interest is *Connectivity*, which I measure using street density in every BG (b) within a commuting zone (c). This variable includes those streets where pedestrians and automobiles are both permitted (as of 2010), and other modes of street transportation are possible. An important feature of these streets is that they are inclusive

[3]Please refer to the Appendix, Section A2, for a closer description of how commuting zones boundaries are determined.

[4]An exact description of how all variables were constructed and what restrictions apply will follow in the next section.

to distinct forms of movement and extend prior findings on the effect of automobiles and highways to other means of transportation and contact.

I control for components that may both influence the gains from higher physical connectivity and innovation. The *SocialActivityCONTROLS* include the number of bars, restaurants, and hotels in a BG. This is in line with the Saxenian argument that establishments where social interaction takes place, such as the much acclaimed Wagon Wheel bar in Silicon Valley, contribute to informal transfer of knowledge (Saxenian, 1996). Similarly, the exposure to relevant social events, and thus the locations they take place, has been found to reduce the costs of building social ties, which in turn affect collaboration and innovation (Agrawal, 2006). I include an indicator equal to one if the BG has a postsecondary education campus (*FormalKnowledgeCONTROLS*) given that a) campuses are usually designed to have dense street structures, and b) proximity to universities and other formal knowledge centers have been found to have a profound effect on the rate and direction of local research activity (Belenzon and Schankerman, 2013; Kantor and Whalley, 2014). The *HumanCaptialCONTROLS* consist of historic inventor counts from 2000, and 2005 as well as employment levels for 2005 and 2010, the amount of college degree holders in 2000 and 2010 (by work location), and the amount of working age population that is within a 45 minute commute from a focal BG (in 2010). By holding these factors constant in the main specification, I can determine if the effect of physical connectivity persists beyond traditional measures of human capital density (Arzaghi and Henderson, 2008; Glaeser et al., 1992; Lin, 2011; Rosenthal and Strange, 2008). Similarly, I include *Socio-DemographicCONTROLS* to account for an explanation that could be linked to a pure agglomeration of people regardless of infrastructure (Carlino et al., 2007). These controls are population counts for 2000 and 2010.[5] I further include *PhysicalGeographyCONTROLS* to ensure that the effect of physical connectivity on innovation is not based on natural geographic conditions (Duranton and

[5]Please note, that population refers to the place of an individual's residence and employment refers to an individual's place of work. Given that in most metropolitan areas across the USA workers live in different places than they work and either employment or residential areas can vary from purely employment/residential to mixed use, I control for both.

Turner, 2012; Hoxby, 2000). These are the area covered by water, the area of developable land, and total land area.

In addition to the standard OLS model with fixed effects described in equation (1), I apply an instrumental variable estimation approach (hereafter referred to as IV) to address endogeneity concerns (Angrist and Pischke, 2008). In this case, an appropriate instrument to detect the causal relationship between street layout and innovation would have to be strongly related to current street networks, but have little influence on today's innovative activity other than through its effect on street layout.[6]

The main instrumental variable I use for the IV estimation is the percentage of housing units in a given BG that were built before 1940 (I additionally use the the percentage of housing units built between 1940 and 1949 to test my model specification). A typical feature of neighborhoods built in the first half of the twentieth century is a grid-like street network structure that was constructed under the intention to grant city dwellers access to the main means of public transportation – the street car (Montgomery, 2013; Wells, 2013). Though built over 100 hundred years ago, street car lines still have a profound effect on the local circulation of people and information given the major impact street cars had on urban street network development (Kenneth, 1985). Historically, street car lines were built and run by private companies anticipating short and medium term profits. These lines initially led to recreational sites or largely undeveloped land (Young, 2016). So called "Street Car Neighborhoods" were developed around the lines; usually by the same companies that ran them. The goal was to make the street car accessible within a short walk from all points in the neighborhood leading to the construction of many side and connecting streets (Wells, 2013). A typical feature of districts built in the early twentieth century was, therefore, the high density of streets oriented towards transit and pedestrian traffic (Montgomery, 2013). After the World Wars and with the introduction of affordable privately owned fuel driven vehicles, automobiles, also came the demise of the street car in the USA and a drastic

[6] Similar instruments used in the urban economics literature that are related to transportation infrastructure are railway lines, rivers and highways (Agrawal et al., 2017; Duranton and Turner, 2012; Hoxby, 2000).

shift in street network design. By the mid-twentieth century most of the original street car companies had shut down their operations for good and streets built in the time after were no longer devised for pedestrian travel, nor street cars or other transit but primarily to accommodate cars (Wells, 2013).

Taking the percentage of housing units built before 1940 in a BG as an instrument, and including relevant controls, the IV estimation can be written as follows:

First stage:

$$
\begin{aligned}
Connectivity_{c,b,2010} =& \theta(HUpre1940_{c,b,2010}) \\
&+\eta(SocialActivityCONTROLS_{c,b}) \\
&+\theta(FormalKnowledgeCONTROLS_{c,b}) \\
&+\beta(HumanCapitalCONTROLS_{c,b}) \\
&+\delta(Socio-DemographicCONTROLS_{c,b}) \\
&+\gamma(PhysicalGeographyCONTROLS_{c,b}) \\
&+f_c+\omega_{c,b}
\end{aligned}
\tag{1.2}
$$

With $\epsilon_{c,b}$ from equation (1.1), only identified if:

$$\theta \neq 0 \tag{c.1}$$

and

$$Cov(HUpre1940, \epsilon_{c,b}) = 0 \tag{c.2}$$

In equation (1.2), f_c represents the commuting zone (c) fixed effects and $\epsilon_{c,b}$ is the error term. Condition (c.1) requires that, conditional on controls, the instrument predicts the endogenous dependent variable (relevance condition). Condition (c.2) denotes the exclusion restriction. In this case, the exclusion restriction entails that the percentage of housing units built prior to 1940 does not *directly* affect innovative output today.

The IV estimation approach is only credible if I can make a plausible argument that Condition (c.2) is not violated. One reason I believe the exclusion restriction is valid is based on the changes in and spatial movement of economic and innovative activity the USA has experienced over the past century (Agrawal et al., 2017; Carlino and Kerr, 2014). Especially, in the Post-WWII period many cities throughout the USA experienced major population shifts as well as technology booms and busts (Klepper, 2010). In the case of individual neighborhoods, these types of trends are arguably even more volatile. What was considered a great neighborhood to live, work or innovate in in the early twentieth century is unlikely to be so in the present day.

Another reason I the exclusion restriction should hold is that the percentage of housing units built prior to the 1940s is unlikely to have a *direct* effect on innovation other than through the *indirect* channels (social activity, formal knowledge, human capital, socio-demography, and physical geography) I control for. It is important to note that the exclusion restriction requires orthogonality of innovation and the percentage of housing units built before 1940 *conditional* on these control variables and not unconditional orthogonality (Duranton and Turner, 2012). In other words, *conditional* on controls (as laid out in the section on *Addressing Threats to Identification*) the instrument should only affect innovation today through its effect on the street network.[7]

2.4 Dataset Construction

The data I use in this paper come from various sources. They can be divided into two main components: Location and Innovation. For a description of all the variables used for estimation, and their original source, please refer to Appendix Table A1.1.

[7]For example, some areas may have historically been more suitable for development than others even within one commuting zone. This raises concerns that the percent of housing units pre-1940 and street network density both depend on an omitted variable. For example, areas with water access were often developed earlier than those without (Duranton and Turner, 2012). If this type of omitted variable is important to my estimation I would detect that including such observable physical characteristics strongly affect the results. The IV results remain qualitatively unchanged when I include or exclude water access.

2.4.1 Measuring Features of a Location

To construct the variables measuring location efficiency, I use the Smart Location Database (SLD) provided by the US Environmental Protection Agency (EPA).[8] This database was developed as a tool to consistently compare the attributes of locations across the USA. The SLD includes demographic, employment, and built environment measures for every BG in the United States for 2010. These variables were constructed using BG boundaries from the 2010 Census TIGER shapefiles (Topologically Integrated Geographic Encoding and Referencing), data from the US Census, the American Community Survey (ACS) and the US Census Longitudinal Employer-Household Dynamics (LEHD) Statistics.[9] The spatially derived variables, such as street network density, were built using the NAVTEQ (now part of the HERE Group) NAVSTREETS dataset. This US-wide street network includes information such as pedestrian restrictions and accessibility metrics. In order to determine the amount of land that is protected from development, information from the US Geological Survey (USGS) on the protection status of public lands was included in the SLD as well as additional NAVTEQ geographic information system (GIS) layers that include water features and land use layers (Ramsey and Bell, 2014).

Connectivity is constructed using the total miles of multimodal streets in a BG, in 2010, divided by total BG area (in sq.miles).[10] Following the SLD, multimodal streets are roads that can be accessed by at least two different modes of transportation (e.g., pedestrians and automobiles; hereinafter referred to as *Streets*). I use this category of streets since it most closely reflects the features I expect to support knowledge exchange on the micro-geographic level. These are a) being inclusive to pedestrian travel, and b) enabling auto travel that is sufficiently fast and unobstructed. The other mutually exclusive road categories are those intended primarily for pedestrian travel (hereinafter referred to as *Pathways and Trails*) and

[8] This dataset can be found under: *www.epa.gov/smartgrowth/smart-location-mapping*.

[9] Information for the 2005 employment variable used in this paper was similarly collected from the LEHD Statistics (US Census Bureau, 2017*b*). Some data coverage restrictions apply.

[10] Please refer to Table A1.2 in the Appendix for correlations of the *Connectivity* measure used in this paper with other network measures.

where only auto travel (hereinafter referred to as *Auto Only Roads*) is permitted.[11] In Figure 1.1, I provide a visual example of how *Connectivity* (=*Street Miles/Total Area*) is constructed using a snapshot from New York County, New York. I provide each BG's corresponding *Connectivity* value in the table placed under the map and shade the BG according to these values.

<Insert Figure 1.1 here>

An important pre-condition for the inclusion of commuting zone fixed effects is within commuting zone variation in *Connectivity*. Figure 1.2 depicts the 99th percentile, the 90th percentile, median, and 10th percentile for *Connectivity* within all commuting zones (rank ordered from the lowest to highest value of the 99th *Connectivity* percentile). As displayed, I can identify substantial variation within commuting zones in terms of street network density. The range of values by percentile are relatively uniformly distributed among most commuting zones, though there are strong differences between the lowest 50 and upper 40 commuting zones with regard to the values representing the local 90th and 99th percentiles.[12]

<Insert Figure 1.2 here>

I further use the variable *Accessibility* provided by the SLD that captures the amount of working age population that is within a 45 minute commute from the focal BG. To measure attributes of the physical geography of a BG, I use variables provided by the SLD that measure the area of developable land and the area covered by water. I exclude very large rural areas following the transportation literature that proposes to use a ceiling of one sq.mile (640 acres or 2.6 km^2), the size of a large superblock, when analyzing street networks, since

[11] To construct *Connectivity*, I use those streets classified as multimodal in the SLD. For all of these streets, automobile and pedestrian travel must be allowed. Amongst others, these streets are arterial or local streets where car travel is permitted in both directions and the speed limit is between 41 and 54 mph, arterial or local streets with a speed limit between 31 and 40 mph, as well as arterial or local streets with a speed limit between 21 and 30 mph and car travel is restricted to one way traffic. Please refer to Appendix, Section A3, for a further description of how street categories are determined and measured.

[12] The results remain robust when excluding the upper 40 commuting zones.

huge rural tracts are unrepresentative of the places most residents live and work and can distort averages (Ewing et al., 2003).

To construct the variable equal to one if the BG has a postsecondary education campus, *Campus*, I geolocate all campuses listed on the US Department of Education's database of accredited postsecondary institutions and programs in 2010 (U.S. Department of Education, 2018). In the first step I search for their geo-coordinates via the Google Maps Geocoding API and then join them with 2010 Census TIGER shapefiles in order to assign the corresponding BG.

I collect data from the US Census County Business Pattern series to construct a variable measuring the number of bars, restaurants, and hotels (NAICS 72) in a BG, and to create firm size measures (US Census Bureau, 2017*a*). The lowest level of geography provided is the ZIP Code level. Using crosswalks provided by the Missouri Census Data Center via the Geographic Correspondence Engine and the Census Bureau ZIP Code Tabulation Area (ZCTA) Relationship files (Missouri Census Data Center, 2012), I map ZIP Codes to the BG level and weight accordingly since ZIP Codes and BGs do not correspond perfectly. A BG boundary may encompass entire ZIP Codes, and in turn, a ZIP Code may cross multiple BGs. Due to inconsistencies in the ZIP Code boundaries, I am missing information for historic employment and number of bars, restaurants, and hotels for some BGs.

I further include data from the Integrated Public Use Microdata Series (IPUMS) Census Demographics on the age of housing structures in a given BG, the instrument in the IV estimation approach. From IPUMS, I also collect historic decennial population counts for every BG and the level of educational attainment for workers. At the time the data was collected and assembled, information on educational attainment was only publicly available on the census tract level (Manson et al., 2017) and is missing for some BGs.

2.4.2 Measuring Innovation

The measure for innovation is the amount of US granted patents located in a BG that were applied for 2011-2013. To construct this variable, I use the Morrison et al. (2017) disambiguated patent data set, a data set containing geo-coordinates of all patent assignees and inventors registered in the USPTO, WIPO, and EP patent databases, from 1975-2013. The information for this dataset are sourced from Harvard's Dataverse Project for USPTO patents and from both the RegPat and Citation databases of the OECD. By joining the geo-coordinates of both assignees and inventors with 2010 Census TIGER Shapefiles of USA Block Group Boundaries[13] in ArcGIS, I am able to obtain the corresponding BGs for every inventor's and assignee's location.

In the next step I identify, as far as possible, where the creation of an idea took place. Since inventors may use their residential address and assignees may use one central address handling all intellectual property, I do not know for certain from the data where the idea actually originated. I apply a conservative approach to determine the most likely set of patents that were created in a specific place. To do so, I take both the location of all inventors and all assignees of a patent and determine their corresponding commuting zone (Autor et al., 2013). If all inventors are in the same commuting zone as an assignee, I include that patent in the sample and link it to the matched assignees' location.[14]

The Morrison et al. (2017) disambiguated patent data set locates assignees and inventors using the Yahoo Geocoding API and is missing exact street level information for a number of assignees. To increase the sample of patents from inventors and assignees in the same commuting zone, I conduct a further search for the assignees which had not been successfully located on the exact street level in the original dataset. Using the Google Maps Geocoding

[13]This data can be found under: *https://www.census.gov/geo/maps-data/data/tiger.html*.

[14]I follow the same procedure using looser constraints. In the Appendix, Table A1.3, I report the main results using all patents where at least one inventor is in the same commuting zone as the assignee and locating them in the BG of the assignee. The point estimate and standard errors are slightly larger. In the subsequent analysis, I use the stricter approach described in the main text. In the case that there are multiple assignees, I keep the assignee which matches all inventors on the commuting zone. Please refer to the Appendix, Figure A1.1, for a stylized depiction of the approach just described.

API, I query the geo-coordinates of the assignees by specifically searching for the assignee name, conditional on being in the specific state and county code listed in the Morrison et al. (2017) disambiguated patent dataset. This search approach only returns coordinates if the name queried is found within the strict geographic boundary conditions provided. The end sample consists of 42,259 assignees located on the exact street address for 2011-2013.

From the Morrison et al. (2017) dataset, I further attain information on the number of inventors, and citations. From this information, I construct variables that capture the number of historic inventors in a BG for 2000, and 2005. These are determined using the exact geo-coordinates of all inventors and matching these to TIGER Census Boundaries in ArcGIS.

<Insert Table 1.1 here>

Table 1.1 displays summary statistics of all variables for the 122,899 BGs in the end sample. The number of aggregate patents in a BG is highly skewed with an average of 0.18 and a maximum value of 1,025. Of the BGs in the sample, 4,916 applied for at least one patent between 2011 and 2013. Similarly, the physical network structure of BGs across the USA also varies strongly, with an average of 2.83 miles of streets, to a maximum of 466.98 miles of streets divided by BG area (the next highest value is 144.72). The average percentage of housing units that were built before 1940 is 20. I also report key descriptives for all the control variables.[15]

[15]Please refer to Figure A1.2 in the Appendix for a visual depiction of the relationship between patenting and *Connectivity* where I label outliers across the USA. I further provide separate plots for California and Massachusetts to a) provide more evidence that the main results are not driven by one state/region alone and to b) support the choice of the BG level given extreme within-city variation (which is especially visible for Boston, MA and San Francisio/Bay Area, CA).

2.5 Results

2.5.1 OLS Regression Results

As laid out in an earlier section, threats to identification are a serious concern, a reason why the OLS results serve primarily as a description of the relationship between *Connectivity* and patenting output with no claims to causality. I first estimate equation (1) with commuting zone fixed effects (and with county fixed effects for robustness). The dependent variable is the amount of granted patents applied for by assignees located in a BG. In order to estimate the OLS fixed effects model, I log transform the dependent variable.

$<$Insert Table 1.2 here$>$

Table 1.2 presents the results of the regressions predicting the change in log patenting as a function of physical connectivity (*Connectivity*), social activity, formal knowledge, human capital, socio-demographic, and physical geography controls.[16] The reported standard errors are robust and clustered on the commuting zone (county) level. Column 1 reports the relationship of patenting with *Connectivity* only, Column 2 includes the number of bars, restaurants, and hotels in a BG. Column 3 presents the results with an indicator equal to one if the BG encompasses a postsecondary education campus. Column 4 presents regression results with employment in 2005 and 2010. Column 5 includes population controls as measured in 2010, and 2000. The results reported in Column 6 display the relationship between *Connectivity* and patent output including a measure for the number of workers who live within 45 minute driving distance from a focal BG (*Accessibility*).[17] Column 7 presents the relationship with historic inventor counts and the number of workers by work location with an undergraduate college degree or higher. The model in Column 8 consists of *Connectivity* and the physical geography control variables and Column 9 shows the full

[16] Note that the number of observations vary depending on the variables included in the regression model. This is due to missing data for the variable *Number Bars* (short form of the measure for number of bars, restaurants and hotels in a BG) and *College*, as described earlier. In addition, I run the models only using those commuting zone where there was at least one patent to insure comparability across models.

[17] Given that the accessibility coefficient is very small, I exclude this variable in the IV estimation models to increase degrees of freedom.

model with all controls. Column 10 reports the results of the full model using county fixed effects.[18] Overall, there is little change to any of the coefficients comparing the commuting zone and county fixed effects models. The coefficient on *Connectivity* in the full model suggests that a one percent increase in *Connectivity* is associated with a 0.004 percent increase in patenting.[19] The results indicate that all of the included types of controls explain some of the relationship of *Connectivity* and patent output.[20] Individually, the strongest control variable is contemporaneous employment. Including employment measures (2010, 2005) quarters the *Connectivity* coefficient.[21]

In a next step I analyze if the relationship between physical connectivity is linear or could possibly be driven by a few outliers. To do so, I run the full model using deciles of the connectivity measure as the main independent variable of interest. Figure 1.3 presents the results from this estimation displaying the coefficients of the connectivity measure by decile. The figure clearly illustrates a non-linear trend and highlights that most of the effect seems to be driven by the upper two deciles. The BGs in these deciles are not concentrated in one state, but in fact, dispersed amongst all states. The ten states with the highest number of BGs in the top decile are, in descending order, California, New York, Texas, Massachusetts, Pennsylvania, New Jersey, Illinois, Florida, Maryland, and Tennessee.

$<$ Insert Figure 1.3 here $>$

I further examine the relationship between *Connectivity* and patenting using an indicator

[18] Note that in the model with county fixed effects, additional singleton observations are dropped. As such, the sample is slightly different leading to distinct point estimates.

[19] I run the full model using different time spans of the dependent variable and patents from the USPTO only. The results remain robust. I further use a Fixed Effects Poisson Model (see Appendix Table A1.4) and count data to view if the directionality and statistical significance hold. Both models confirm the findings of the OLS estimation.

[20] In Figure A1.3 of the Appendix, I report the relationship between *Connectivity* and all continuous controls together as well as the individual relationship between *Connectivity* and the control variables used in the fully specified model. Note that here I can identify that the employment measures and *Connectivity* are the most strongly correlated of all controls.

[21] In the Appendix, Table A1.5, I provide the results from estimating Columns 1, 8 and 9 using alternative measures of *Connectivity*. These alternative measures are: a) *Pathway and Trail Density*, b) *Connectivity* including pathways and trails, c) *Intersection Density*, and d) *Transit Frequency*. With the exception of a), the full model holds using these alternative measures. A likely reason is that areas with many pathways and trails are parks/recreational areas with no or little economic activity.

equal to one if a BG had at least one patent and zero otherwise. The results reported in Table 1.3 show similar magnitudes of the coefficients as compared to Table 1.2 where I use the natural log amount of patenting as the dependent variable. Column 1 shows the reduced model without any controls, columns 2 and 3 present the fully saturated model with commuting zone and county fixed effects. Together, these results provide suggestive evidence that, albeit small in magnitude, there is a robust relationship between physical connectivity and innovation.

<Insert Table 1.3 here>

Theoretically, I may have expected the increase in patenting to be larger on the intensive margin than on the extensive margin. Although, a comparison of the results from Table 1.2 and 3 may suggest a larger effect on the extensive margin of patenting, it is still plausible that my theoretical argument holds. One possible scenario is that by increasing knowledge exchange, physical connectivity leads to more ideas or induces latent ideas to improve in quality, and this, in turn, makes it more likely that ideas cross the threshold of patentability.

2.5.2 IV Results

Next, I estimate equation (2). First stage results as presented in Table 1.4 indicate that the instrument, the percentage of housing units built pre-1940 (*HUpre1940*) taken alone, is strong with F-statistics of over 50 in the model including all controls. Table 1.4 further presents the second stage results obtained from estimating equation (1) instrumenting *Connectivity* with *HUpre1940*. I apply commuting zone fixed effects and report robust standard errors. Like in the OLS regressions, I log transform the dependent variable. Column 1 displays the IV estimation results without controls except *PhysicalGeographyCONTROLS*, Column 2 presents the results adding *SocialActivityCONTROLS*, and an indicator equal to one if the BG encompasses a postsecondary education campus, Column 3 adds *Socio-Demogr.CONTROLS* to the equation, and Column 4 excludes *Socio-Demogr.CONTROLS*, but adds *HumanCapitalCONTROLS* to the equation. Including all controls (Column 5) almost halves the magnitude of the *Connectivity* coefficient in comparison to the results in Column 1. These results suggest that the IV estimation is highly sensitive to the inclusion of distinct controls. In order to provide more support that my model is correctly specified, I include a further instrument in Column 6 - the percentage of housing units built between 1940 and 1949 (*HU1940-1949*). Using two instruments allows us to apply a Hansen J test evaluating overidentification assumptions. Although I cannot test the exclusion restriction directly, a non-statistically significant Hansen J-Statistic gives us more confidence in the validity of the model. It is, however, important to point out that this approach only tests overidentifying assumptions conditional on having one correctly identified instrument. The first stage F-statistics remain strong, albeit slightly weaker than in the model with one instrument. Taken together, the results of the full model (Column 6) can be interpreted such that, conditional on controls, a one percent increase in *Connectivity* causes a 0.04 percent increase in patenting output.[22, 23, 24]

<Insert Table 1.4 here>

At this point, a reconciliation of my results with those provided by previous research is useful. Note, however, that to date most studies examining the relationship between urban features and patenting have largely been on the MSA level. One example is Agarwal et al. (2017), who find that a 10 percent increase in highways leads to a 1.7 percent increase in patenting over 5 years on the MSA level. Similarly, Carlino et al. (2007) find that a 10 percent increase in employment density results in a 2 percent increase in patent intensity

[22]To confirm the choice of the age categories used in the IV estimation, I run the full IV model with all possible age categories. The results are presented in the Appendix, Table A1.6. Note, that more recent Housing Age Categories are a) far more likely to violate the exclusion restriction (closer in time), and b) to negatively affect street density given the rise of automobile transportation post-1950s.

[23]In the Appendix, Table A1.7, I report the IV results including pathways and trails in my measure of *Connectivity*. The results remain robust, with slightly smaller point estimates.

[24]I report the results from implementing a control function approach (CF), using a poisson model in the second stage in the Appendix, Table A1.8. The outcome I report is the number of patents in a BG and the coefficients represent incidence rate ratios. A special feature of the CF is that it enables us to study the nature of self-selection (Wooldridge, 2015). As reported, the residuals suggest that there is negative selection into places with high levels of *Connectivity*. Coefficients smaller than one indicate a lower incidence rate ratio (the equivalent of a negative sign in the OLS regressions).

(patents per capita) over a 10 year period.

In addition, over the past years, there has been much research effort put into applying a more micro-geographic lens on the foundations of agglomerations. For instance, Rosenthal and Strange (2008) determine their unit of analysis based on concentric rings, finding strong evidence of an urban wage premium. Their results suggest that the elasticity of wage to the number of workers within five miles is about 4.5 percent. Also using distance rings, Arzaghi and Henderson (2008) find that a one unit increase in the number of neighboring advertising agencies within 250 meters results in an increase of new establishment births by 2 percent.

In comparison to these studies, my estimates are smaller. This is not unexpected since the time period I examine is shorter, and the unit of analysis is at a very micro-level. Larger geographic areas tend to conflate direct responses and are, therefore, likely to overstate the size of local point estimates. I find that a 10 percent increase in *Connectivity* is associated with a 0.05 – 0.2 percent increase in patenting in the OLS model and results in a 0.4 – 0.96 percent increase in the IV model. Using IV estimates from the fully saturated model, an increase from the 25^{th} percentile of Connectivity (0.86) to the 95^{th} percentile (7.94), would roughly translate into a 35 percent increase in patenting.

The magnitude of the coefficient on *Connectivity* is larger in the IV than in the OLS model. Three possible reasons why this is the case are that a) the exclusion restriction is violated, b) there may be reverse causation, or that c) the results reflect a much larger local average treatment effect than an average treatment effect (e.g., through negative selection). I cannot, empirically, rule out that the exclusion restriction is violated and my estimation relies heavily on the assumption that the percentage of housing units built before 1940 (and 1940-1949) only affects innovation via its effect on the street network conditional on controls. However, the results from the Hansen J overidentification test, provide some support that my model is correctly specified. With regard to reverse causation, it may be that BGs which experienced negative shocks to innovation, conditional on controls, also experience positive shocks to the amount of streets. Since my data only include details on street infrastructure from 2010, I cannot test this hypothesis. Viewing the third explanation, it is possible that the IV is shifting the "behavior" of a subgroup of BGs for which the returns to *Connectivity* are larger than average, such as central business districts and those BGs in the upper quintile of *Connectivity*. If the local average treatment effect is larger than the average treatment effect, it is very plausible that IV estimates are larger than OLS estimates because of heterogeneity in the sample I am analyzing.

As discussed earlier, one manifestation of selection - in this case negative selection - could be that large firms are opting out of locating in areas with high levels of *Connectivity*. Compared to smaller firms, it is likely that large firms would benefit less from physical connectivity in the first place (which could explain differences between average and local average treatment effects). I base this on the assumption that larger firms already have access to an abundance of skills and knowledge sources in-house and may, therefore, not rely on external exchange as much.[25]

2.5.3 Is There Any Knowledge Exchange?

The main set of results provide evidence that physical connectivity increases innovation. The question remains if increased knowledge exchange is a possible channel through which denser street networks affect innovation. One way to test if *Connectivity* indeed affects innovation via its effect on knowledge exchange, is to examine knowledge flows of actors in a BG. A conservative approach to measuring such knowledge flows is using patent citations (Belenzon and Schankerman, 2013; Jaffe et al., 1993; Thompson, 2006). Naturally, not all citations represent knowledge flows, but studies comparing citation data with surveys of inventors have detected a strong correlation between patent citations and knowledge flows (Duguet and MacGarvie, 2005; Hall et al., 2005). In order to examine the relationship between physical connectivity and knowledge flows, I create a) a count of

[25]For further discussion of this potential explanation based on BG heterogeneity in firm size composition, please refer the Appendix Section *A4. Heterogeneity in firm size composition.* Results displayed in Figure A1.4 and Table A1.9 of the Appendix provide support for this explanation.

citation pairs in a BG, excluding self-citations, and b) a count of self-citation pairs within a BG. I construct citation pairs using patents that were applied for between 2010 - 2013, the patents these cite, and counting only those patent pairs whose assignees are in the same BG. *Connectivity* should have a positive effect on a) to support the notion that *Connectivity* increases knowledge exchange between inventors. In the case of self-citations, a positive effect of *Connectivity* on innovation could also be attributed to other factors. For example, more self-citations could imply that *Connectivity* increases competitive pressures pushing organizations to patent strategically (Singh, 2005) and/or create patent thickets (Shapiro, 2000).

<Insert Table 1.5 here>

Table 1.5 presents the results for the two citation outcomes I estimate using equation (1) and (2) instrumenting *Connectivity* with the percentage of housing units that were built before 1940 and 1940-1949, and including the number of patents applied for 2011-2013 in a given BG as a control. Column 1 presents the main effect of *Connectivity* on non-self citations within a BG (mean of 0.002) only including *PhysicalGeographyCONTROLS*. Column 2 reports the results for non-self citations using the full model, Column 3 presents the IV model with all controls and Column 4 includes the log number of patents as a further control. Columns 5-8 present the corresponding models using self citations (mean of 0.03) as the outcome variable. *Connectivity* positively predicts the number of non-self citations across all models, whereas in the IV model examining self citations the coefficient is negative and no longer statistically significant.[26]

Together, these findings suggest that strategic patenting is unlikely to be driving the relationship between physical connectivity and patenting I detect in the previous set of results, and that knowledge exchange is a feasible channel. The findings indicate that actors use relatively more local external knowledge sources in BGs with denser street networks. Besides the specific type of technical knowledge exchange, which occurs and

[26]The results for Table 1.5 including *Pathways and Trails* in my measure for physical connectivity can be found in the Appendix, Table A1.10.

is captured by patent citations, it is likely that at least some of the innovation productivity advantage found in the earlier set of results is also related to the exchange of other types of knowledge and/or increased interaction efficiency. Higher productivity could, for example, stem from knowledge on how to better organize a lab that individuals learn about via informal conversations (e.g., at bars), or shorter distances to exchange partners.

2.5.4 Interactions Between the Physical and Social Space

As mentioned earlier, previous research has provided evidence for the importance of social factors, such as population and employment density as well as local meeting points in explaining regional innovation differences. The main channel underlying the relationship between these social factors and inventive activity are similar to what I propose in this paper: density influences interpersonal exchange. As such, examining the interaction of social factors with physical connectivity, could provide more insight on the role of interpersonal exchange as a channel driving the main results.

To do so, I run OLS regressions including interaction terms of the physical and social space. The corresponding results are reported in Table 1.6. In Columns 1-2, I interact *Connectivity* with an indicator equal to one if population is over 1,650, and equal to zero otherwise. In Columns 3-4 I use an indicator equal to one if the number of bars, restaurants or hotels is over 5, and is zero otherwise interacting this with *Connectivity*. Columns 5 and 6 report the results from including the interaction between physical connectivity and an indicator equal to one if employment is over 950, and is zero otherwise. The even numbered columns present the estimates only including *PhysicalGeographyCONTROLS* and the uneven numbered columns display the results using the full model with all controls.

<Insert Table 1.6 here>

The main effect of *Connectivity* remains statistically significant and is positive across all models (meaning when population is equal or below 1,650, employment is equal or under 950, and there are 5 or fewer bars, there is still an effect of *Connectivity*). Overall, there seems to be a positive interaction relationship between high levels of population and *Connectivity*, although, the main effect of *High Population* is negative. The results further indicate a positive interaction relationship between high levels of employment and *Connectivity*. In the case of *High Employment*, the main effect is also positive and statistically significant meaning that with no *Connectivity*, having a high level of employment has a positive impact on innovative output. The interaction between *High No.Bars* and *Connectivity* is positive and statistically significant. However, the main effect of *High No.Bars* no longer holds when including the interaction term. This suggests that without *Connectivity* there may be no additional effect of elevated numbers of bars, restaurants and hotels in a BG on patenting.[27]

Taken together, these findings indicate that high levels of population, employment, as well as bars, restaurants, and hotels may be complementary to physical connectivity. This backs the idea that the physical layout of a place quite plausibly affects innovation by facilitating exchange among individuals.

2.5.5 Limitations

There are several limitations to this study. One is that patents are not the ideal measure of innovation given that not all types of innovation are patentable. In fact, in some industries, inventors rarely seek patent protection, but resort to other mechanisms such as secrecy or first-to-market advantages instead (Cohen et al., 2000). A reason why inventors do not seek patent protection are the high costs associated with patent filing (Graham et al., 2009). From this, it could be that I am measuring a specific type of innovation only, or it could be that I am possibly capturing a BG culture of patenting/propensity to patent. For example, it is plausible that the patenting behavior of one or more actors in close proximity make it necessary for all actors to patent.

In addition, I only include those patents where I locate inventors and assignees in the

[27]To add more transparency about the data and to show that outliers are not driving the results, I also present the interactions with high levels of population, employment and bars in visual form (please refer to the Appendix, Figure A1.5).

same commuting zone. It is possible that this sample selection approach introduces a bias that goes towards underestimating the patenting output of large corporations. Large corporations may tend to centrally organize the handling of their intellectual property at established headquarters. Consequently, it could be that the assignees in my sample are, on average, smaller than the general population of firms. Though possible, my robustness checks do not indicate a large systematic size bias.[28]

A further limitation to this study is that I can only proxy knowledge exchange and do not directly measure it. Capturing actual interaction between actors is a tedious and difficult endeavor. Not only does it require very micro-level data, but also close observation of the behavior of individuals. There have been advances in tracking the possible ways that interaction takes place within larger human agglomeration, such as in Williams and Currid-Halkett (2014). Over two weeks, the authors tracked 77 fashion designers working in the Garment District and the larger New York region. Using cellphone data and social-media tools they captured geographical movements and documented exact real-time data. A similar approach covering a larger geographic area may be possible in the future but does not seem feasible today.

Another limitation is that I base my analysis on cross-sectional data. To get closer to understanding actual selection processes, I would need a panel data set. Although most of the variables in this current data set are available for multiple years, I only have access to information on infrastructure for 2010.

2.6 Discussion and Conclusion

In a very literal sense, this paper is taking innovation from being up "in the air" (Marshall, 1890) to the streets and makes two main contributions to the empirical literature on geography and innovation. First, I use a unique dataset covering the entire contiguous USA on the smallest geographic entity for which information on street infrastructure is

[28] Please refer to Appendix, Figure A1.6, for the results from comparing kernel density distributions of assignee size (determined by the amount of patents) for the sample and full dataset.

available. Previous research has not been able to apply such a micro-geographic lens to assess innovation outcomes. Second, I go beyond the traditional location externalities examined in the empirical literature and test how physical features of a neighborhood can affect innovation outcomes. This type of structural difference on this level of analysis has not been considered before in empirical work and has potentially far-reaching consequences for cities, organizations, and individuals.

I identify a causal relationship between physical connectivity, as measured through local street network density, and innovation. I further examine the relationship between physical connectivity and citation flows identifying a non-negligible link. In addition, I provide evidence that physical connectivity may bolster the impact of population, social activity, and employment on innovation. Together, my findings are in line with the theoretical argument that physical connectivity is likely to affect innovation through a more local and more efficient organization of knowledge exchange. Moreover, my results can be viewed as support for the idea that the actual physical capacity to connect people and ideas may, in fact, be one reason why cities, and some neighborhoods are more conducive for innovation than others (Glaeser et al., 1992).

My findings have important policy implications for regional and city planners designing places that are aimed to foster innovation. The results of this paper highlight that a dense local infrastructure represents a crucial component for innovation. Especially in light of initiatives such as the "Smart City", the importance of spaces for social interaction and connectivity between people should be stressed. As such, street infrastructure can be viewed as an important input and source of competitive advantage for metropolitan areas and for firms located there.

This article opens several promising avenues for research. First, my study highlights that less obvious (and largely unintentional) aspects of urban infrastructure have the potential to explain regional variation in innovation beyond the traditional location externalities found in the literature. For example, including city layout may help understand why certain regions and/or firms can exploit diverse or specialized knowledge better than others. Second, it would be interesting to assess the effect of physical connectivity on other measures of innovation such as trademarks. Third, in order to make recommendations for firm location choice, it would also be relevant to better comprehend who benefits (and loses) from proximity and the capacity of a place for connecting people.

In 1922, Henry Ford stated that "[t]he modern city is probably the most unlovely and artificial site this planet affords. The ultimate solution is to abandon it (...). We shall solve the City Problem by leaving the city" (in Wells 2013: 63). About 100 years later, this statement stands corrected. Leaving the dense street network the city provides is hardly the solution – at least not for innovation.

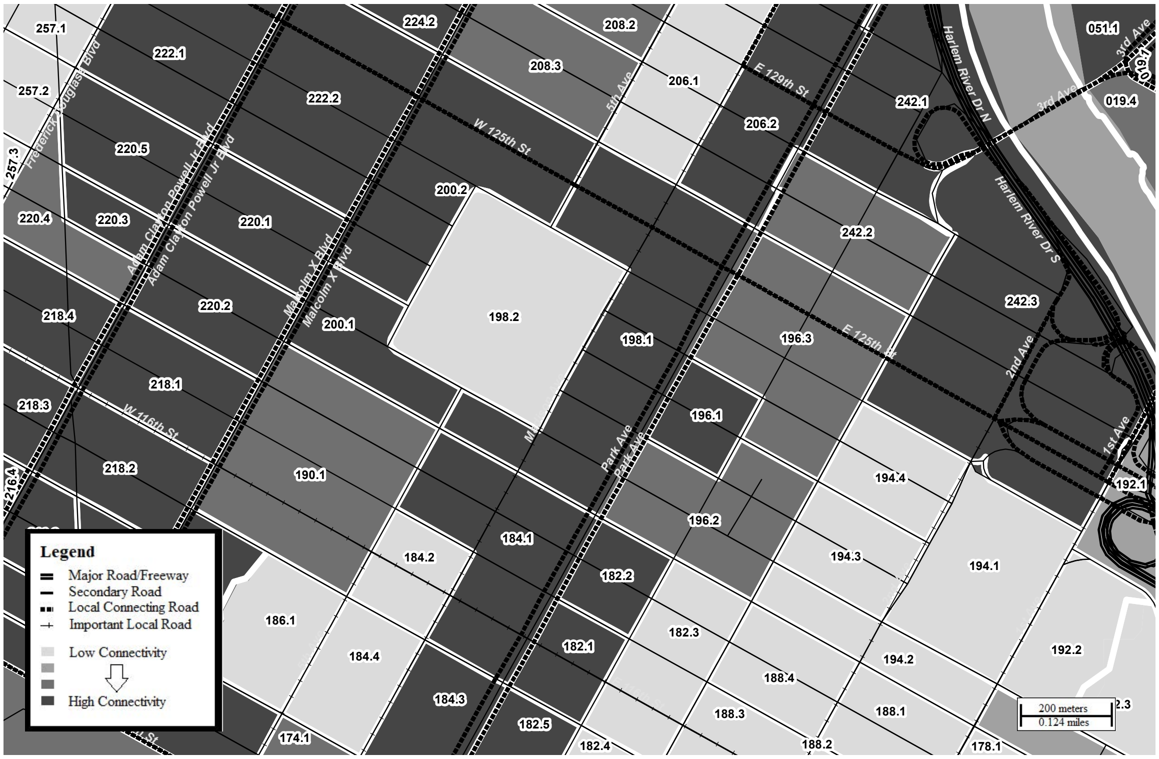


Figure 1.1: Example for Differences in *Connectivity*: New York County, New York

Notes: This figure is a snapshot of an area in Harlem, New York. The white, bold lines represent BG boundaries (with corresponding numbers in black surrounded by white). The thin black lines represent all roads and streets with no further special characteristics. Trails are not displayed. Major roads/freeways, secondary roads, connecting and important local roads are identified as shown in the legend (bottom left). The corresponding map scale can be found in the bottom right corner of the image. Each BG's *Connectivity* level for the census tracts that appear fully in the image are reported in the table below. *Connectivity* is calculated using the total amount of street miles in a BG that are oriented to both pedestrian and automobile use (*Street Miles*; other mutually exclusive facility categories are auto-only oriented roads and pedestrian-only oriented pathways and trails) divided by total block group area (in sq.miles). As a reference, the last column displays the total miles of all types of roads (*All Road Types*; including auto-only roads, streets, pathways and trails). The color shading of each BG reflects the *Connectivity* value of the corresponding BG (= *Street Miles/Total Area*). *Image source*: created by authors in ArcGIS using Census TIGER shapefiles and values from the EPA SLD.

Census Tract #, Block Group #	**Street Miles** (miles)	**Total Area** (sq.miles)	**Connectivity** (miles/sq.miles)	All Road Types (miles)
Census Tract 190, Block Group 1	0.20	0.040	5.00	1.00
Census Tract 194, Block Group 1	0.01	0.026	0.31	0.70
Census Tract 194, Block Group 2	0.00	0.014	0.00	0.46
Census Tract 194, Block Group 3	0.00	0.014	0.00	0.40
Census Tract 194, Block Group 4	0.00	0.014	0.00	0.50
Census Tract 196, Block Group 1	0.10	0.010	10.1	0.30
Census Tract 196, Block Group 2	0.10	0.024	4.10	0.86
Census Tract 196, Block Group 3	0.15	0.035	4.40	1.00
Census Tract 198, Block Group 1	0.35	0.050	7.00	1.80
Census Tract 198, Block Group 2	0.00	0.040	0.00	2.50
Census Tract 200, Block Group 1	0.10	0.015	6.70	0.35
Census Tract 200, Block Group 2	0.25	0.035	7.10	0.93

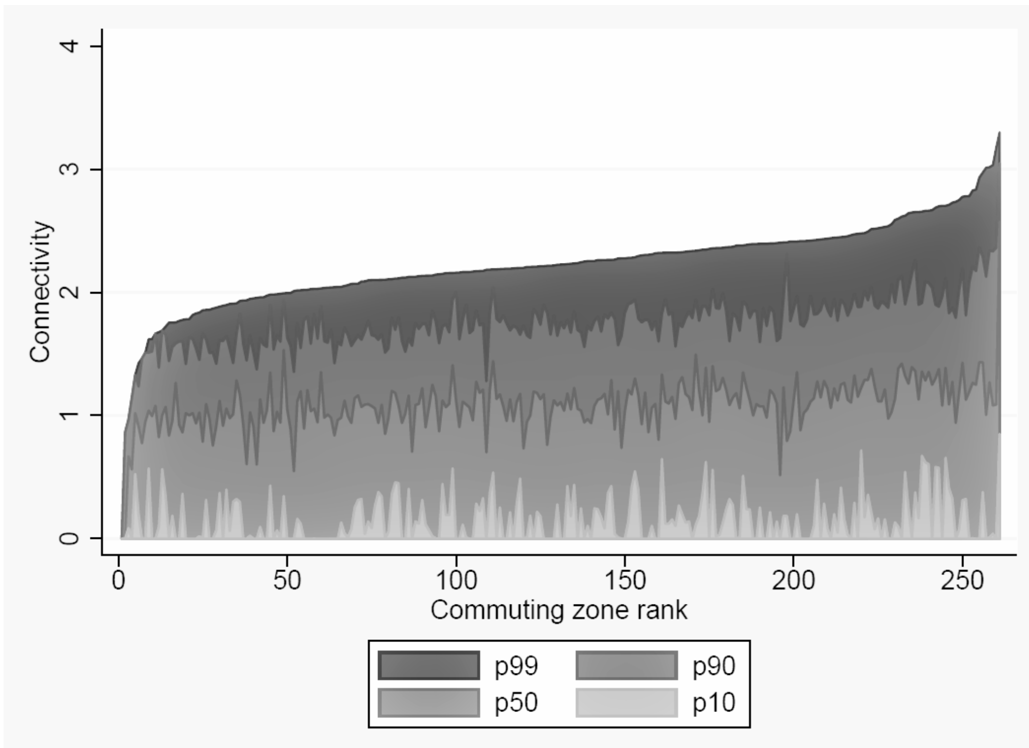


Figure 1.2: Distribution of *Connectivity* (log) by Commuting Zone using within Commuting Zone Cutoffs

Notes: This figure presents the distribution of *Connectivity* (log) by commuting zone. The commuting zones appear in rank order from lowest to highest value of the 99th *Connectivity* percentile. The figure displays variation within commuting zones in terms of *Connectivity* and across with regard to what constitutes a *Connectivity* value in the local 99th, 90th, 50th, and 10th percentile.

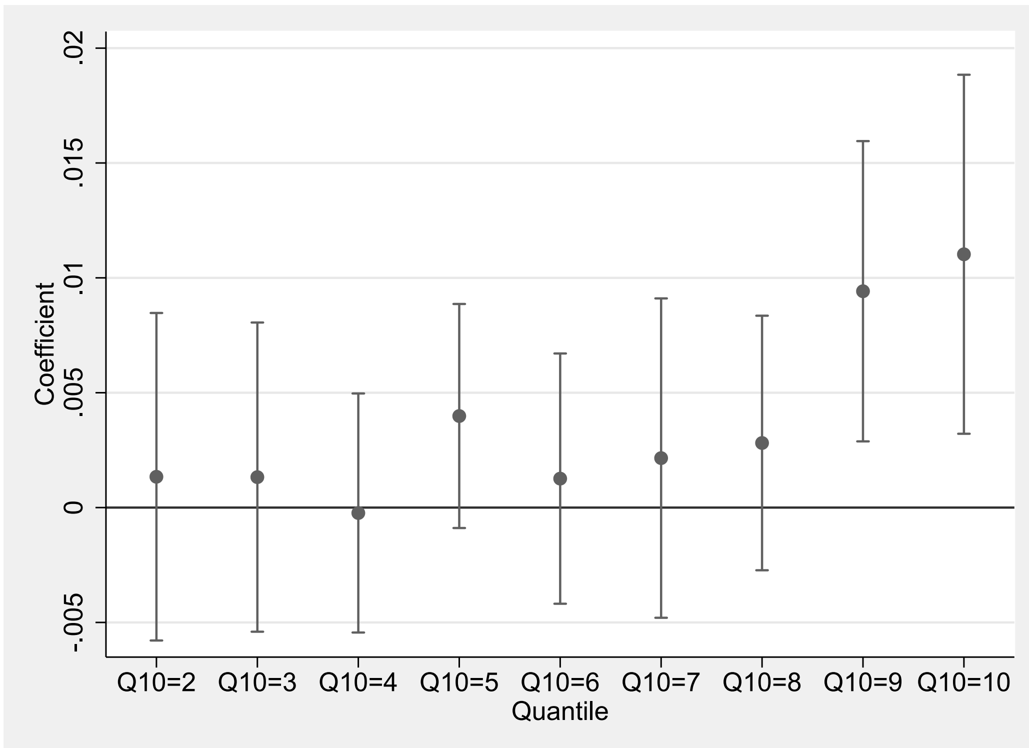


Figure 1.3: *Connectivity* (log) Coefficient by Decile

Notes: This figure displays the coefficients from estimating equation (1) by decile of the *Connectivity* measure. The horizontal line marks the value zero, the dots represent the point estimates by decile, and the vertical lines mark the 95 percent confidence intervals of the estimate.

Table 1.1: Summary Statistics on the Census Block Group Level

Census Block Group Level	min	p25	mean	p50	p95	max
Innovation:						
Number of Patents (2011-2013)	0.00	0.00	0.61	0.00	2.00	1025.00
Patent (= 0/1)	0.00	0.00	0.04	0.00	0.00	1.00
Knowledge Exchange:						
Total Same BG Citations	0.00	0.00	0.03	0.00	0.00	612.00
Self Same BG Citations	0.00	0.00	0.03	0.00	0.00	607.00
Non-self Same BG Citations	0.00	0.00	0.002	0.00	0.00	33.00
*Physical Network Structure (*in miles/sq.mile):*						
Connectivity*	0.00	0.86	2.83	2.20	7.94	144.72
HUpre1940	0.00	0.00	0.20	0.06	0.73	1.00
HU1940-1949	0.00	0.00	0.08	0.04	0.31	1.00
Social Activity:						
Number of Bars, Restaurants, and Hotels	0.00	1.00	2.54	2.00	6.00	143.00
Formal Knowledge:						
Campus	0.00	0.00	0.01	0.00	0.00	1.00
*Human Capital (*in thousands)*						
Accessibility*	0.00	97.74	292.91	194.05	1039.11	1598.20
Employment 2010*	0.00	0.05	0.55	0.16	2.03	232.46
Employment 2005*	0.00	0.00	0.42	0.07	1.70	167.37
Inventors 2005	0.00	0.00	0.02	0.00	0.00	18.00
Inventors 2000	0.00	0.00	0.02	0.00	0.00	10.00
Socio-Demographic (in thousands)						
Population 2010	0.00	0.88	1.32	1.19	2.48	19.51
Population 2000	0.00	0.88	1.28	1.17	2.33	12.78
Physical Geography (in hundred acres)						
Area Water	0.00	0.00	0.05	0.00	0.23	5.47
Area Developable Land	0.00	0.73	1.79	1.38	4.85	6.40
Area Land	0.004	0.77	1.86	1.45	5.02	6.40
Observations	122,899					

Table 1.2: Patenting and Connectivity - OLS Regressions

	OLS Models									
DV: Number of Patents (log)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Connectivity (log)	0.0164***	0.0149***	0.0158***	0.00426**	0.0174***	0.0154***	0.0151***	0.0203***	0.00452***	0.00425***
	(0.00289)	(0.00243)	(0.00281)	(0.00184)	(0.00305)	(0.00260)	(0.00257)	(0.00342)	(0.00129)	(0.00140)
No. Bars		0.0120***							0.00361***	0.00381***
		(0.00132)							(0.00107)	(0.00103)
Campus			0.224***						0.0982***	0.0996***
			(0.0394)						(0.0227)	(0.0227)
Employment 2005				0.00214					0.00417	0.00400
				(0.00707)					(0.00617)	(0.00517)
Employment 2010				0.0393***					0.0369***	0.0368***
				(0.00696)					(0.00551)	(0.00492)
Population 2000					-0.0277***				-0.0227***	-0.0235***
					(0.00688)				(0.00717)	(0.00697)
Population 2010					0.0389***				0.0133**	0.0121*
					(0.00695)				(0.00602)	(0.00618)
Accessibility						0.0000336*			0.0000346**	0.0000246
						(0.0000195)			(0.0000159)	(0.0000218)
Inventors 2000							-0.00224		-0.00498	-0.00437
							(0.00324)		(0.00327)	(0.00377)
Inventors 2005							-0.000939		-0.000153	0.00107
							(0.00344)		(0.00333)	(0.00344)
College Degree 2000							-0.0282***		-0.00384	-0.00716
							(0.00878)		(0.00657)	(0.00745)
College Degree 2010							0.0500***		0.0200***	0.0182***
							(0.00903)		(0.00662)	(0.00656)
Area Water								0.0191***	0.0139***	0.0163***
								(0.00386)	(0.00488)	(0.00414)
Area Developable Land								0.0132***	0.00632	0.00882**
								(0.00315)	(0.00384)	(0.00390)
Area Land								0.00415	0.00360	0.00282
								(0.00299)	(0.00316)	(0.00335)
Observations	121398	119159	121398	121398	121398	121398	96973	121398	95294	95207
R-squared	0.00183	0.0198	0.00715	0.0938	0.00485	0.00224	0.00840	0.00996	0.0996	0.0970
Fixed Effects	czone	czone	czone	czone	czone	czone	czone	czone	czone	county
Number of Groups	261	257	261	261	261	261	257	261	253	972

Notes: Employment and population measures are in thousands. Geographic area variables are in hundreds. Please refer to Table A1 in the Appendix for a definition of the variables included in the models. *No.of Bars* is the written short form in the above table for the *Number of Bars, Restaurants, and Hotels* in a BG. Standard errors (in parentheses) are clustered at the commuting zone (Column 1 - 9) and county (Column 10) level. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***} p < 0.01$.

Table 1.3: The Likelihood of Having a Patent or Not

	OLS Models		
DV: Patent (= 0/1)	(1)	(2)	(3)
Connectivity (log)	0.0108***	0.00492***	0.00466***
	(0.00179)	(0.00115)	(0.00104)
Social Activity Controls	No	Yes	Yes
Formal Knowledge Controls	No	Yes	Yes
Human Capital Controls	No	Yes	Yes
Socio-Demogr. Controls	No	Yes	Yes
Phys. Geography Controls	No	Yes	Yes
Observations	121398	95294	95207
R-Sq.	0.00148	0.0760	0.0756
Fixed Effects	czone	czone	county
Number of Groups	261	253	972
Std. Errors	Robust	Robust	Robust
Log Likelihood	30061.2	27711.2	28274.2

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

Notes: This table reports the results obtained from estimating the relationship between *Connectivity* and patenting. The outcome variable is an indicator equal to one if the BG has a patent and zero otherwise. Column 1 shows the reduced model without any controls. Columns 2 and 3 present the fully saturated model with commuting zone and county fixed effects. The *SocialActivityCONTROLS* include the number of bars, restaurants, and hotels in a BG. *FormalKnowledgeCONTROLS* is an indicator equal to one if the BG has a postsecondary education campus. The *HumanCaptialCONTROLS* consist of historic inventor counts from 2000, and 2005 as well as employment levels for 2005 and 2010, the amount of college degree holders in 2000 and 2010 (by work location), as well as the amount of working age population that is within a 45 minute commute from a focal BG. *Socio-DemographicCONTROLS* are population counts for 2000 and 2010. *PhysicalGeographyCONTROLS* are the area covered by water, the area of developable land, and total land area. Standard errors (in parentheses) are clustered at the commuting zone (column 1 and 2) and county (column 3) level.

Table 1.4: Instrumental Variable Estimation

	2SLS Models					
DV: Number of Patents (log)	(1)	(2)	(3)	(4)	(5)	(6)
	Second Stage					
Connectivity (log)	0.0965***	0.0915***	0.0799***	0.0517***	0.0504***	0.0426**
	(0.0183)	(0.0176)	(0.0163)	(0.0195)	(0.0192)	(0.0188)
Social Activity Controls	No	Yes	Yes	Yes	Yes	Yes
Formal Knowledge Controls	No	Yes	Yes	Yes	Yes	Yes
Human Capital Controls	No	No	No	Yes	Yes	Yes
Socio-Demogr. Controls	No	No	Yes	No	Yes	Yes
Phys. Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
	First Stage					
HUpre1940	0.2928***	0.2926***	0.2874***	0.2168***	0.2146***	0.2467***
	(0.0359)	(0.0367)	(0.0362)	(0.0393)	(0.0392)	(0.0331)
HU1940-1949						0.1872***
						(0.0486)
Social Activity Controls	No	Yes	Yes	Yes	Yes	Yes
Formal Knowledge Controls	No	Yes	Yes	Yes	Yes	Yes
Human Capital Controls	No	No	No	Yes	Yes	Yes
Socio-Demogr. Controls	No	No	Yes	No	Yes	Yes
Phys. Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120926	118838	118838	95097	95097	95097
First Stage F-stats	66.71	63.22	62.92	51.43	52.09	32.80
Hansen J Stat.P-value						0.212
Fixed Effects	czone	czone	czone	czone	czone	czone
Number of Groups	260	256	256	252	252	252

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Notes: This table reports the results obtained from instrumenting *Connectivity* with *HUpre1940* (column 1-6) and *HU1940-1949* (column 6). In the *Second Stage*, the outcome variable is the log amount of U.S. granted patents applied for between 2011-2013 in a BG. In the *First Stage*, the outcome variable is *Connectivity (log)*. *HUpre1940*, is the percentage of housing units built before 1940 and *HU1940-1949*, is the percentage of housing units built between 1940-1949. The *SocialActivityCONTROLS* include the number of bars, restaurants, and hotels in a BG. *FormalKnowledgeCONTROLS* is an indicator equal to one if the BG has a postsecondary education campus. The *HumanCaptialCONTROLS* consist of historic inventor counts from 2000, and 2005 as well as employment levels for 2005, and 2010, and the amount of college degree holders in 2000, and 2010 (by work location). *Socio-DemographicCONTROLS* are population counts for 2000, and 2010. *PhysicalGeographyCONTROLS* are the area covered by water, the area of developable land, and total land area. Variation in the number of observations depending on the included controls is due to missing values for the number of bars, restaurants, and hotels, as well as college education. We report *First Stage* F-statistics in all columns and the p-value obtained from the Hansen J Statistic, which tests the validity of the overidentifying restrictions in column 6. Standard errors (in parentheses) are clustered at the commuting zone level.

Table 1.5: Patent Citation Patterns

	Non-self				Self			
DV: Number Citations (log)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Connectivity (log)	0.000540*** (0.000152)	0.000213** (0.000103)	0.00421** (0.00210)	0.00377** (0.00187)	0.00316*** (0.000796)	0.000759* (0.000417)	-0.000241 (0.00961)	-0.00549 (0.00747)
Number of Patents (log)				0.0220*** (0.00484)				0.214*** (0.0203)
Social Activity Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Formal Knowledge Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Human Capital Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Socio-Demogr. Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Phys. Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model	OLS	OLS	IV	IV	OLS	OLS	IV	IV
			First Stage				First Stage	
HUpre1940			0.189*** (0.033)	0.189*** (0.033)			0.189*** (0.033)	0.189*** (0.033)
HU 1940-1949			0.200*** (0.044)	0.200*** (0.044)			0.200*** (0.044)	0.200*** (0.044)
Number of Patents (log)			No	Yes			No	Yes
Other Controls			Yes	Yes			Yes	Yes
First Stage F-stats			25.42	25.53			25.42	25.53
Hansen J Stat.*P*-value			0.901	0.624			0.658	0.743
Observations	121398	119142	95097	95097	121398	119142	95097	95097
R-Sq.	0.000470	0.00322	-0.00606	0.0350	0.00141	0.00815	0.00798	0.297
Fixed Effects	czone	czone	czone	czone	czone	czone	czone	czone
Number of Groups	261	257	252	252	261	257	252	252
Std. Errors	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust

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

Notes: This table reports the results obtained from estimating the relationship between *Connectivity* and citation patterns. The outcome variable in columns 1-4 is the log amount of same-BG citation pairs between distinct assignees (*Non-self Citations*). The outcome variable in columns 5-8 is the log amount of same-BG citation pairs between the same assignee (*Self Citations*). Columns 1, 2, 5, and 6 report the results estimating the OLS model. Columns 3, 4, 7, and 8 report the results using an instrumental variable approach where we use *HUpre1940* and *HU1940-1949* as instruments for *Connectivity*. For the IV models, we report *First Stage* F-statistics and the *p*-value obtained from the Hansen J Statistic, which tests the validity of the overidentifying restrictions. Columns 1 and 5, represent the overall effect without controls (but incl. geographic controls). The other columns present the fully saturated model. *SocialActivityCONTROLS* include the number of bars, restaurants, and hotels in a BG. *FormalKnowledgeCONTROLS* is an indicator equal to one if the BG has a postsecondary education campus. The *HumanCaptialCONTROLS* consist of historic inventor counts from 2000, and 2005 as well as the natural log of employment for 2010, and the amount of college degree holders in 2010 (by work location) in a focal BG. *Socio-DemographicCONTROLS* include the natural log of population for 2010. *PhysicalGeographyCONTROLS* are the area covered by water, the area of developable land, and total land area. Standard errors (in parentheses) are clustered at the commuting zone level.

Table 1.6: Interaction of Connectivity with Population, Employment, No.of Bars

DV: Number of Patents (log)	(1)	(2)	(3)	(4)	(5)	(6)
Connectivity (log)	0.0163***	0.00357**	0.00336***	0.00187*	0.0124***	0.00239*
	(0.00292)	(0.00146)	(0.000940)	(0.00106)	(0.00217)	(0.00123)
High Population=1	-0.0202***	-0.00525				
	(0.00548)	(0.00420)				
High Population =1 $\times$ Connectivity (log)	0.0209***	0.00881**				
	(0.00522)	(0.00411)				
High Employment =1			0.0911***	0.0611***		
			(0.0172)	(0.0172)		
High Employment =1 $\times$ Connectivity (log)			0.0590***	0.0274**		
			(0.0139)	(0.0129)		
High No.Bars =1					-0.00619	-0.00299
					(0.0174)	(0.00778)
High No.Bars =1 $\times$ Connectivity (log)					0.0813***	0.0360***
					(0.0150)	(0.00835)
Other Social Activity Controls	No	Yes	No	Yes	No	No
Formal Knowledge Controls	No	Yes	No	Yes	No	Yes
Other Human Capital Controls	No	Yes	No	Yes	No	Yes
Other Socio-Demogr. Controls	No	Yes	No	Yes	No	Yes
Phys. Geography	Yes	Yes	Yes	Yes	Yes	Yes
Observations	121398	95294	121398	95294	119159	95294
R-squared	0.0105	0.0991	0.0551	0.0855	0.0217	0.0999
Fixed Effects	czone	czone	czone	czone	czone	czone
Number of Groups	261	253	261	253	257	253

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

Notes: This table presents results from interacting *Connectivity* with a variable indicating *High Population* (population$>$1,650), *High Employment* (employment$>$950), and high numbers of bars, restaurants, and hotels in a BG (*High No.Bars*; bars$>$5) (all as measured in 2010). The outcome variable is the amount of U.S. granted patents applied for between 2011-2013 in a BG. The columns with uneven numbers represent the overall effect without controls (but incl. *PhysicalGeographyCONTROLS*). The columns with even numbers present the fully saturated model. The *SocialActivityCONTROLS* include the number of bars, restaurants, and hotels in a BG. *FormalKnowledgeCONTROLS* is an indicator equal to one if the BG has a postsecondary education campus. The *HumanCaptialCONTROLS* consist of historic inventor counts from 2000, and 2005 as well as employment levels for 2005, and 2010, and the amount of college degree holders in 2000, and 2010 (by work location). *SocioDemographicCONTROLS* are population counts for 2000, and 2010. *Other* denotes that the coefficients of the corresponding controls are not already displayed in the table. Standard errors (in parentheses) are clustered at the commuting zone level.

CHAPTER 3

TAKING INTERACTIONS AND INNOVATION TO CO-WORKING SPACES: THE IMPACT OF PROXIMITY ON TECHNOLOGY ADOPTION AND STARTUP PERFORMANCE OUTCOMES

(with Alexander Oettl and Christian Catalini)

3.1 Introduction

> *"Space is the 'body language' of the organization. (...) [S]pace design has its own grammar that can be tweaked to bolster desirable habits."*
>
> *(Doorley and Witthoft 2012:38)*

Over the past 30 years, the average startup size has decreased to about two founders for technology ventures (Ewens and Marx, 2017; Kaplan et al., 2009). Smaller firms imply greater external dependence both on resources and environments that provide support as well as on production inputs (e.g., computing/labor platforms, etc.). Perhaps in response to this greater external dependence, startups have been increasingly setting up shop in co-working spaces, often referred to as hubs, in metropolitan areas around the world (e.g., Social Impact Hub, WeWork). These co-working spaces aim to accommodate the needs of small firms and startups by creating a place that provides physically proximate access to support and production inputs, thereby serving as a potential way to expand the traditional boundaries of the firm (Argote et al., 2003).

The importance of place for innovation, entrepreneurship and firm performance has been the focus of a long-standing literature examining agglomeration spillovers and economic geography (e.g., Rosenthal and Strange 2004; Michelacci and Silva 2007; Samila and Sorenson 2011; Glaeser et al. 2015). Depending on the industry in question, and primarily focusing on state, city, or neighborhood variation, findings indicate that cluster effects decay rapidly with distance (Rice et al., 2006; Rosenthal and Strange, 2003, 2008) and may, indeed, be strongest within as little as 500 meters (Arzaghi and Henderson, 2008). In this paper, we propose that spatial distances at which these agglomeration externalities activate may be even shorter than has been detected thus far and that especially knowledge diffusion - a fundamental source of competitive advantage for firms (Argote and Ingram, 2000) - is influenced at very micro-geographic levels and in more immediate environments.

One such micro-geographic environment is the workplace, which has been found to play an important role in influencing entrepreneurial entry decisions (Dobrev and Barnett, 2005; Elfenbein et al., 2010; Parker, 2009; Sørenson, 2007). In addition, the workplace may also have an especially strong impact on entrepreneurial learning given that it is a) the location where working-aged individuals spend most of their time, and b) individuals only have limited discretion over who their interaction partners are. As such, the workplace represents a setting for unexpected influences, and for the serendipitous flow of information and ideas.

The literature has pointed out that proximity is a crucial source of influence on individual decision-making in the workplace (Allen, 1977; Cowgill et al., 2009; Blau, 1977). Proximity can thereby be classified along an array of characteristics, including along, a) physical (Allen, 1977; Cowgill et al., 2009; Agrawal et al., 2017; Roche, Forthcoming), b) social (Blau, 1977; McPherson and Smith-Lovin, 1987), c) knowledge-space (Cohen and Levinthal, 1990; Lee, 2019), and d) product-market dimensions (Wang and Zhao, 2018; Alcácer et al., 2015; Saxenian, 1996). However, our understanding about the strength of these different dimensions and how they interact with each other is still limited. Particularly in light of more recent work stressing the importance of taking such factors into account when engineering peer effects (Carrell et al., 2013; Hasan and Koning, 2019), we suggest that these dynamics have crucial implications for designing communities that support knowledge production, and as such entrepreneurship and innovation.

In this study, we first examine the influence of micro-geographic proximity on new (to the entrepreneur) technology adoption decisions at one of the largest technology co-working spaces in the United States. The building consists of five floors, covering 9,300 m^2 (100,000 sq.ft.). To deal with endogenous geographic clustering, we rely on the random assignment of office space to the hub's 251 startups. Using floor plans to measure geographic distance, we find that close physical proximity greatly influences the likelihood of adopting an upstream (production) technology also used by a neighboring firm. This effect, however, quickly decays with distance where startup firms that are more than 20 meters (66 feet) away are no longer influenced by each other. In addition, we find that when firms overlap with common areas at the hub (e.g., kitchens), the distance of influence increases, revealing the important role that these spatial features play in extending geographic reach and in promoting knowledge exchange.

We further exploit individual characteristics of the startups in the co-working space to examine the interplay between physical proximity and a) social proximity, b) knowledge-space proximity, and c) product-market proximity. This approach allows us to extend our understanding of the established importance of micro-geography for knowledge diffusion to include other non-geographic features of the workplace. We thereby detect important nuances in terms of how the interplay with other proximity dimensions impacts the relationship between physical proximity and technology adoption. Our results suggest that both social and product-market proximity may serve as a substitute for physical proximity, and that some knowledge-space proximity bolsters and too much reduces the impact of physical distance on technology adoption decisions.

The observation that peers affect performance has been demonstrated in a host of environments such as retail (Chan et al., 2014*b*,*a*; Mas and Moretti, 2009), finance (Hwang et al., 2019), education (Sacerdote, 2001), and science (Catalini, 2018; Oettl, 2012). Further, these peer effects have been found to manifest themselves through a variety of channels including knowledge sharing, helping (co-production), and effort exertion/setting expectations (e.g., Mas and Moretti 2009; Housman and Minor 2016; Herbst and Mas 2015). Building off this research, we examine to what extent interaction between peers is a viable mechanism driving entrepreneurial learning and how such peer learning, which we measure through firm-level technology adoption decisions, influences startup performance outcomes.

This paper contributes to previous research in three important ways. First, we provide insight into a fundamental decision early stage, high tech ventures face: technology adoption. Especially in our context (of predominately software startups), the adoption of upstream technologies may be considered very similar to supplier adoption in more traditional industries - a crucial decision, which tends to imply significant path dependency (Arthur, 1994; Murray and Tripsas, 2004). Second, where previous research has emphasized formal, structural features of the workplace such as firm size, age and prior social ties for the entrepreneurial process (Elfenbein et al., 2010; Hasan and Koning, 2019), our analyses show that we can better understand firm-level variation in rates of entrepreneurial technology adoption choices by attending to multiple distinct classifications of proximity as well as to competitive pressures and their interplay with each other. We highlight that understanding which firms and how they respond to their peer firms matters for designing effective environments for early stage startups. Unlike related work examining these dynamics, notably Hasan and Koning (2019), we focus on proximity to other firms and not individual team members or co-workers. Third, we speak to the literature examining accelerators, bootcamps, incubators and other interventions targeted at early stage entrepreneurs (e.g., Hassan and Mertens 2017; Cohen et al. 2019; Lyons and Zhang 2018) by introducing an additional type of entrepreneurial environment yet to be examined in more detail: the co-working hub.

In a more broader sense, our results are relevant to the literature on regional variation in entrepreneurship, which examines the role of distinct channels (e.g., entrepreneurial culture and knowledge spillovers) in establishing and reinforcing clusters of economic activity (Saxenian, 1996; Sorenson and Audia, 2000; Fallick et al., 2006; Giannetti and Simonov, 2009). Whereas this literature has generally relied on aggregate city- or state-level data with information on labor flows and entrepreneurship, we provide evidence from fine-grained micro-geographic data that highlight important nuances guiding our understanding of the role of physical proximity. Most importantly, our findings suggest that other structural, social, knowledge-based, and competition-related features can substitute for or reinforce the impact of physical proximity - even on the micro-geographic level/one floor - and thereby impact an organization's ability to leverage co-location to improve performance. These findings carry fundamental implications for the design of work spaces for innovation and entrepreneurial communities.

3.2 Conceptual Framework

3.2.1 Physical Proximity

The diffusion of ideas has been found to be highly localized (Allen, 1977; Arzaghi and Henderson, 2008). In theory, the assumption pervades that knowledge (especially more tacit know-how) transfers via face-to-face interaction between individuals (Gaspar and Glaeser, 1998; Jacobs, 1969; Moretti, 2004; Rosenthal and Strange, 2001). Empirical research supports this idea with results indicating that the extent to which physical proximity explains information flows between individuals can depend on as little as a few hundred meters in certain circumstances (Catalini, 2018; Cowgill et al., 2009; Kerr and Kominers, 2015; Reagans et al., 2005).

One important environment where many interactions occur and information exchange takes place on a daily basis is the workplace. As such, the workplace represents a setting for unexpected influences, and for the serendipitous flow of information and ideas. With regard to the physical layout of the workplace, early research dating back to Allen (1977), has established the fundamental role of proximity in determining and shaping workplace interactions. Studies have tested this in the context of, e.g., science (Boudreau et al., 2017; Catalini, 2018), options exchange (Baker, 1984), technology companies (Cowgill et al., 2009), and e-commerce (Lee, 2019) finding that physical proximity strongly influences collaboration patterns and the transmission of information.

The importance of (work)place for knowledge diffusion also has strong implications for entrepreneurs and, especially, for entrepreneurial learning. Generally, entrepreneurs learn from a variety of sources, though one particularly important channel is learning from fellow entrepreneurs (Nanda and Sørensen, 2010; Lerner and Malmendier, 2013). This is provided that entrepreneurs predominately operate in fast-paced and uncertain environments, making local search (Cyert et al., 1963) based on experimentation and frequent adjustments (Lippman and McCall, 1976; Gavetti and Levinthal, 2000; Gans et al., 2019) a crucial component in the early stages of a venture. Simply being close to other entrepreneurs facing similar problems may reduce the costs of accessing relevant information, for example, through direct observation of successful techniques and/or teaching (Chan et al., 2014*b*). Since individual decision-making depends on an individual's stock of knowledge and available information (Simon, 1955), *we expect that physical proximity influences a startup's decision to adopt new (to the focal startup) technologies already used by other startups.*

Another feature of the physical layout of office spaces are common areas many workers pass through on a regular basis. These spaces, such as kitchens, elevators or the "watercooler" provide opportunities for individuals to see and meet each other and facilitate informal, and unplanned interactions (Fayard and Weeks, 2007). We propose that common areas operate similarly to physical proximity by reducing frictions associated with information access. In addition, it is possible that such central meeting places connect firms that otherwise would be too distant to exert an influence on each other's technology adoption decisions. From this, *we expect that common areas serve as substitutes for geographic proximity and may, furthermore, extend the reach of physical proximity*.

3.2.2 The Interplay of Physical Proximity with Other Dimensions of Proximity

Besides physical proximity, other dimensions of proximity have been found to impact knowledge transfer. The three types which we will focus on in this paper are, as displayed in Figure 2.1, a) the social (Blau, 1977; McPherson and Smith-Lovin, 1987), b) the knowledge-space (Cohen and Levinthal, 1990), and c) the product-market dimensions (Wang and Zhao, 2018; Alcácer et al., 2015; Saxenian, 1996). Although most recent research has pushed on extending our knowledge as to the consequences of the interplay with prior social ties (Hasan and Koning, 2019), we have yet to understand how other features interact with physical proximity and whether these dynamics between peer firms promote startup performance. This becomes especially pressing as incomplete understanding may incur misleading recommendations (Carrell et al., 2013) as for the design of entrepreneurial workplaces. In what follows, we hone in on the interplay between these three dimensions and physical proximity thereby assessing the role of social-, information- and competition-based dynamics.

<Insert Figure 2.1 here>

Social proximity

A large literature has demonstrated the importance of social proximity in governing exchange between actors (Granovetter, 1973; McPherson and Smith-Lovin, 1987; Singh, 2005). For example, in the context of education (Reagans, 2011; Carrell et al., 2013), social mixers (Ingram and Morris, 2007), and manufacturing (Kato and Shu, 2016), social proximity has been found to impact network formation, interaction patterns, and reference groups. More recent studies push further and suggest that prior ties may impact the extent to which individuals are receptive to peer effects in the first place (Hasan and Koning, 2019; Aral and Nicolaides, 2017). Overall, social proximity, similar to physical proximity, seems to *govern* the flow of knowledge and with whom information is exchanged. We, therefore, *expect that physical proximity and social proximity are substitutes for predicting technology adoption decisions.*

Knowledge proximity

Beyond geographic proximity, knowledge-space proximity has been shown to influence idea exchange (Cohen and Levinthal, 1990). One early example for this line of research is Jaffe (1986) who finds that knowledge-space proximity of firms has spillover effects on patenting behavior. More recent work supports these findings and further suggests that knowledge-space proximity has important implications for both market value, and productivity of a firm (Bloom et al., 2013). However, the relationship between physical proximity and knowledge-space proximity is likely nuanced. As proposed by previous research, this relationship depends on both the ability of a peer to absorb (Cohen and Levinthal, 1990) and the amount of non-redundant and relevant information available between two peers (Azoulay et al., 2019; Burt, 2004; Oh et al., 2006). In other words, both peers with a low and high degree of knowledge overlap are unlikely to learn from each other. In turn, peers with a medium degree of knowledge overlap are those most capable of absorbing knowledge shared between physically proximate peers. As such, *we expect that the interaction between physical and knowledge-space proximity has a non-linear impact on new technology adoption decisions.*

Product-market proximity

In conjunction with physical proximity, proximity in product-market space may have implications for the amount and type of information shared amongst peers (Wang and Zhao, 2018). Two peers in the same or similar product-market space may not share information, and exercise heightened secrecy precisely because they are co-located competitors (barriers to knowledge exchange). As peers become more distant in product-market space the likelihood to share information with proximate neighbors may increase (Jacobs, 1969). If this is the case, then *the interaction between physical proximity and product-market space proximity should be negative with regard to technology adoption.*

Alternatively, two peers in the same or similar product-market space may only then share information if they are both close in product-market and physical space. Being closer may reduce barriers for knowledge spillovers to occur (Marshall, 1890; Stefano et al., 2017; Saxenian, 1996). As peers become more distant in product-market space the likelihood to share information with proximate neighbors may decrease given that the available information from one peer is too different to be useful for the other peer. If this is the case, then *the interaction between physical proximity and product-market space proximity should be positive with regard to technology adoption.*

3.3 Empirical Strategy and Data

3.3.1 Estimation Strategy

Estimating the role of physical proximity on a startup's decision to adopt a new technology not only requires data at a highly granular geographic level, but is also likely to yield biased estimates of the effect size. Specifically, as has been well documented in the context of peer learning by Manski (1993), these biases may be driven by issues of endogenous sorting, contextual effects, and other correlated effects. On the one hand, technology adoption could be a function of characteristics of the group (e.g., industry type) where firms that would use similar technologies like to locate close to each other. On the other hand, firms that are in physical proximity often experience similar social phenomena which could drive technology exposure. To deal with such endogenous geographic clustering, we rely on the random assignment of office space to the hub's 251 startups, while to deal with contextual contaminants we specifically examine firm i's adoption decisions of technologies that have already been adopted by firm j. Table 2.1 shows that pairwise characteristics do not correlate with physical proximity, serving as a robustness check of our random room assignment assumption (and confirmed by multiple senior staff at the co-working space).

<Insert Table 2.1 here>

Cognisant of the potential bias evoked by unobservable firm characteristics, we include firm fixed effects. This allows us to keep individual firm characteristics constant while examining the treatment effect of distance ($distance_{ij}$) on a) the count of technologies $firm_i$ adopts that $firm_j$ has already adopted, and b) the probability that $firm_i$ adopts a technology that $firm_j$ has already adopted. Applying the unique firm dyad as our unit of analysis, we estimate the following specification using OLS:

$$Y_{ij} = \beta ln(distance_{ij}) + X_{ij} + \theta_i + \phi_j + \eta \tag{2.1}$$

where Y_{ij} represents the count of adopted technologies/probability of adoption, X_{ij} is a vector of dyad-specific controls θ_i and ϕ_j are $Room_i \times Firm_i$ and $Room_j \times Firm_j$ fixed effects, respectively. Standard errors are two-way clustered at the $firm_i$ and $firm_j$ level. We extend our analysis by interacting variables with $distance_{ij}$. In these instances we de-mean $distance_{ij}$ so that its level can be interpreted as the effect size at its mean.

In alternate explanations we estimate the following specification:

$$Y_{ij} = \gamma Close_{ij} + X_{ij} + \theta_i + \phi_j + \eta \tag{2.2}$$

where $Close_{ij}$ is equal to 1 if firms i and j are in the first quartile of the $distance_{ij}$ distribution and 0 otherwise.

3.3.2 Data Sources and Construction

The data for our study were collected at one of the five largest technology co-working spaces in the United States (in 2016). Designated as a startup hub where new ventures work side by side, the building consists of five floors, 9,300 m^2 (100,000 sq.ft.) and 207 rooms. The data covers a period of 30 months from August 2014 – January 2017, during which 251 unique startups had rented a room in the co-working space. Approximately 35 percent of the startups ceased operations or left the co-working space each year. For our analyses, we only examine interactions between firms on the same floor resulting in 10,840 unique firm dyads.

According to senior administrators at the co-working space, typically the reason why startups leave is either because they fail, grow out of the space, or occasionally fall stagnant and do not want to pay for an office when they can work from home. The vacant office spaces are then assigned to startups based off a wait-list. Firms on the wait-list are prioritize as follows: tech startups over service providers, and local vs. non local startups. During the time we examine, only eight startups moved out because they outgrew their offices. At the co-working hub, these successful startups are considered to have "graduated" from the building.

The layout of the floors we examine (floors two - five), is depicted in Figure 2.2.[1] We measure the distance between rooms from available floor plans using space syntax software (Bafna, 2003).[2] One useful feature of space syntax software is that it calculates distances between rooms as people would walk rather than the shortest euclidian distance on a plane or "as the crow files." For each room dyad we calculate the shortest walking distance. The variable *Close* is an indicator equal to one if the shortest distance between $firm_i$ and $firm_j$ located on the same floor is within 20 meters; the 25$^{\text{th}}$ percentile of pair-wise distances between all rooms).[3] The variable *Distant* equals to one if $firm_i$ and $firm_j$ are located further than 44 meters (the 75$^{\text{th}}$ percentile of pair-wise distance between all rooms) from each other on the same floor. We further flag dyads for whom the shortest paths between rooms directly pass through a common area (*Common Area*). Common areas are the kitchens and zones in front of the elevator on each floor as well as the open sitting space on the second floor.

$<$Insert Figure 2.2 here$>$

Our main outcome variable of interest is new technology adoption. To construct this variable, we exploit a novel data set, covering over 25,000 Internet technologies (e.g., ana-

[1] We exclude the ground level since the work space on this floor is a) open space and b) the work stations are allocated to individuals and not complete firm entities (so called "hotdesks").

[2] Using this software, distance is measured by steps. One step is the equivalent of roughly 1.42m.

[3] For a summary and description of all variables, please refer to Table A2.1 of the Appendix.

lytics, advertising, hosting, and CMS) that tracks how technology usage of firms change on a weekly basis (*builtwith.com*). From this website we collect information on the technology input of the startups in our sample, including the exact date of implementation and abandonment. We construct two measures for technology adoption. The first is the number of technologies $firm_i$ adopts from $firm_j$ (*ln(*$AdoptCount_{ij}$ *+ 1)*). An adopted technology is a technology used by $firm_i$ in the focal period that $firm_i$ had not implemented in any previous period, but $firm_j$ had already put to use. The second measure is *1(*$AdoptTech_{ij}$*)*, which equals one if $firm_i$ adopts a technology from $firm_j$. The control variable ***Pre-period Technology Overlap*** corresponds to the percentage of technologies $firm_i$ has adopted from $firm_j$ before both of the two firms are active at the co-working hub.

For each of the startups, we conducted extensive web-searches to find detailed information regarding startups' characteristics, such as industry and business models. For industry classification, we follow the industry categories found on AngelList (*angellist.com*) and BuiltWith. The individual industries are Administration&Management, Data, Design&Development, Digital, Education, Energy&Construction, Entertainment, Finance&Legal, Healthcare, Marketing&PR, Real Estate, Retail, Science&Technology, Security, and Software&Hardware. For our analyses we use each venture's primary industry (the most prominent on their websites), since many operate in more than one. The variable ***Same Industry*** equals to one if $firm_i$ and $firm_j$ operate in the same primary industry. Similarly, the variables ***Both B2B Companies*** and ***Both B2C Companies*** indicate if $firm_i$'s and $firm_j$'s main customers are other businesses (B2B) or individual consumers (B2C).

We additionally identified the firm age at the co-working hub and gender composition of the startups using information provided by the co-working space. As derived from the entry date into the co-working space, $|age_i\text{-}age_j|$ reflects the absolute value of the age difference between $firm_i$ and $firm_j$. The variable ***Both Majority Female*** flags firm dyads where team members in both $firm_i$ and $firm_j$ are predominately female (over 50 percent female).

To capture differences in the quality of startups, we further identify those ventures that have received an award from the Technology Association of the local state. Judged by a panel of industry leaders on a yearly basis, these ventures are regarded as the top 40 most innovative technology startups in the state in a given year. In addition, we use two startup performance measures provided by the co-working space. One is raising financial capital in excess of $10 million (Seven Figure Club), and the other, identifies startups that have a minimum of $100,000 in trailing 12 month revenue or have received $100,000 in funding (Village Verified certificate). We also identify startups that have raised a seed round or have ever raised VC seed investment from information provided on AngelList. Taken together, we classify startups that have received a state award, have received the Village Verified certificate, are Seven Figure Club members, have raised a seed round or have ever raised a VC seed investment as *Successful*.

Each member of the co-working space enters and exits the building, rooms, elevators and amenities provided by the co-working space using a unique key-card. For a selected period of time (October 2015 - February 2016, and May 2016 - July 2016) and from the exact time stamps of entry into these spaces we identify those firms who make use of the roof patio, the mailroom and gym. The variables *Both Use Roof*, *Both Use Mail*, and *Both Use Gym* equal to one if at least one member on both startups has ever used the respective amenity and zero otherwise.

We further exploit a joint-event hosted at the co-working space on a weekly basis to analyze the impact of proximity on the propensity of the entrepreneurs in our sample to interact. This joint event is a lunch (open to the public) organized by the co-working space every Friday at noon. The average number of people who attend the lunch is approximately 250 every week. The price for non-members is $10. This shared meal is intended to give members the opportunity to "network with other startups" and to "meet, greet and chowdown." The co-working space keeps track of the exact order individuals (both members and non-members) enter to attend the lunch. For a period of time (January 2016 - December 2016), we identify the number of lunches hosted at the co-working space that at least one team member of $firm_i$ and $firm_j$ both attend (*# Event $Both_{ij}$ Attend*). We further exploit the order of entry to create an indicator equal to one if at least one team member of $firm_i$ and $firm_j$ appear within 1, 2, 5, 10, or 25 people in line for the lunch (*1(Ever within X people in line)*). Similarly *ln(min line $distance_{ij}$)* reflects the log distance of entry between members of $firm_i$ and $firm_j$.

3.3.3 Descriptive Statistics

On average, each firm is at risk of learning from 53 other firms. The average distance between room dyads is approximately 32m and the average room size is ca. 27 m^2 (288 sq.feet). Twenty-eight percent of the rooms (by floor) are located close to each other and 38 percent of the shortest paths between two rooms pass through a common area. Of the 251 startups, 12 percent are predominately female and 24 percent are considered to be successful startups. On average, the startups in our sample have been at the co-working space for approximately one year. The use of web technologies is highly skewed, ranging from a minimum of 0 to a maximum of 255. In Table 2.2, the variable *Min. Technology Usage* (*Max. Technology Usage*) displays the minimum (maximum) amount of technologies a startup ever hosted while at the co-working space. Over time, the startups in our sample adopt about 7.33 technologies on average, 53 percent adopt at least one new technology.

<Insert Table 2.2 here>

The main focus of our analyses is on startup dyads. A key component is thereby the characteristics both startups have in common. Of the startup-dyads in the co-working hub, 11 percent operate in the same industry, 48 and 11 percent both have a B2B and B2C business model respectively. The percentage of startup-dyads where the majority of team members are female is 1.3 percent (N = 138), 47 percent of the startup-dyads consist of firms that are both located in small rooms, and eight percent of the startup-dyads are considered successful. The average age difference between startups in a dyad is 7.30 months. We identify that 20 percent, 19 percent, and four percent of the startup-dyads both used the mail room, the gym and accessed the roof patio respectively.

3.4 Results

In this section we turn to the results following the estimation strategy we laid out in an earlier section. For the purpose of this study, we operationalize the distinct proximity dimensions as displayed in Table 2.3.[4] *Physical Proximity* is measured using the geographic distance (in meters) between rooms on one floor. *Social Proximity* captures when both firms possess a salient characteristic that only a minority of the firms in the co-working space have. We identify socially proximate firms as those where both startups are a) majority female, and b) successful. We measure *Knowledge-Space Proximity* using the mean pre-period technology overlap between focal $firm_i$ and all other close firms. We break this measure into quintiles. In this paper, *Product-Market Proximity* captures when the consumers of two firms' products are similar. We measure product-market proximity by using a combination of two firm characteristics: a) industry, and b) business model. Two firms are proximate in their product-market if they either operate in the same industry or have the same business model.

<Insert Table 2.3 here>

3.4.1 Baseline Results: Physical Proximity

Average effects of distance

Table 2.4 presents the results from estimating the effect of distance on peer technology adoption (*ln(*$AdoptCount_{ij}$ *+ 1)*) using a standard OLS model. In the full model using firm-x-room fixed effects and controlling for industry, business model, gender, age and pre-period technology overlap, we find that distance reduces the amount of peer technology

[4] We go into more detail on the rationale behind each measure in the following subsections.

adoption (= - 0.035, cluster-robust standard errors 0.014). The magnitude and statistical significance of the effect remains robust to including different covariates. As displayed in Table 2.5, the results from a linear probability model confirm the findings from the OLS model indicating that distance is negatively associated with the likelihood of peer technology adoption (= - 0.017, cluster-robust standard errors 0.006 in the full model, column 6). Here also, the magnitude and statistical significance of the effect remains robust to including different covariates.

<Insert Tables 2.4 and 2.5 here>

To get a better understanding of the precise spatial distances that predict technology adoption, we further distinguish between dyads located within 20 meters of each other (*Close*), between 20-44 meters and those located more than 45 meters apart (*Distant*). In Table 2.6, we display the results from estimating equation 1 using this more nuanced classification of distance. The results in columns 1-3 indicate that close proximity positively influences the likelihood of adopting an upstream (production) technology also used by a peer firm. Including all spatial distance categories (column 3) we find that being in close proximity is associated with a two percentage point higher probability of adopting a peer technology (= 0.019, cluster-robust standard errors 0.006). This finding remains robust to including different covariates. As displayed in columns 4-6, applying an OLS model and estimating the count of adopted peer technologies ($ln(AdoptCount_{ij} + 1)$) provides a similar result. In the full model (column 6), the point estimate on the coefficient for close proximity is 0.045 (cluster-robust standard errors 0.017). Switching to a room in close proximity would translate into a five percent increase in the number of peer technologies adopted from the mean.

<Insert Table 2.6 here>

The results from a quartile regression (Figure 2.3) provide further evidence that startup firms that are less than 20 meters away are most influenced by each other and that the proximity effect is non-linear. The effect of distance more than halves in the 2nd quartile compared to the 1st and goes toward zero in the 3rd quartile when comparing to the most distant rooms (omitted category).

<Insert Figure 2.3 here>

Another feature of the physical layout of the office space are common areas provided by the co-working space, such as the kitchens on each floor. In the regressions presented in Table 2.7 we include a variable equal to one that indicates if the shortest path between $firm_i$ and $firm_j$ is across a common area (*Common Area*). As shown in Table 2.7, column 1, common area overlap is associated with a higher likelihood of technology adoption (= 0.018, robust standard errors 0.010). Interacting common area overlap with an indicator equal to one if startups are located within 20 meters from each other (*Close*), we find that common area overlap may, in fact, substitute for being located in close proximity. In order to get a deeper understanding of the precise spatial distances this applies to, we break our distance measure into quartiles (recall that $Close$ corresponds to the first quartile) and interact these quartiles with the $CommonArea$ dummy (using $CommonArea\times$ 4th distance quartile as the omitted category). The results are displayed in Figure 2.4, which reveals two things. First, being close (first quartile of distance) to a firm increases technology adoption likelihood independent of whether or not the two firms pass through a common area. Second, and more interestingly, the likelihood of technology adoption for a peer in the second quartile (between 21 and 30 meters apart) also is greater but this effect only activates for firm dyads that pass through a common area. In other words, it appears that these common areas extend the co-location premium to firms that are more distant from one another.

<Insert Table 2.7 and Figure 2.4 here>

We next examine the extent to which physical proximity to other firms and offices may reduce the benefits of dyadic proximity. We do so by constructing a remoteness variable as follows: $remoteness_i = \frac{1}{N}\sum_{j=1}^{N} distance_{ij}$ for all pairwise distances between the room of firm i and firm j on the same floor. We next construct a dummy variable, $CentralLocation$ equal to 1 if $remoteness_i$ is in the first quartile (the most central office locations) and 0 otherwise. Because $CentralLocation$ does not vary within our $Firm_i \times Room$ Fixed Effects we are only able to estimate its interaction with $ln(distance_{ij})$ or $Close$. As shown across a number of specifications in Table 2.8, firms with more central office locations suffer from less of a distance penalty. Conversely, the proximity premium we have empirically demonstrated across various specifications matters much more for firms that are not centrally located. In line with the common area results shown in Table 2.7, firms that are more isolated are influenced to a greater degree by proximate firms.

<Insert Table 2.8 here>

3.4.2 Interaction Results: Physical and Other Proximity Dimensions

We now turn to the results on the interplay between physical proximity and a) social, b) knowledge-space, and c) product-market proximity.

Interplay with social proximity

Regarding social proximity, we first examine how the gender composition of the firm dyads may influence the effect of physical proximity on peer technology adoption. In the case of our setting, female startups represent a minority group. As suggested by Reagans (2011), demographic characteristics that define minority status are more likely to be salient. Salience is important because individuals are more likely to identify with a salient characteristic, and identification with a characteristic generates positive affect for in-group members (Hogg and Turner, 1985; Grieve and Hogg, 1999). As shown in Table 2.9, we find that dyads where both startups are predominately female overcome the distance discount suggesting that these startups rely on alternate mechanisms to overcome the negative effects of distance or, as a minority within the co-working space, may have different networking behavior (Kerr and Kerr, 2018).

<Insert Table 2.9 here>

Another salient characteristic of startups is success. Similar to demographic characteristics, success is a characteristic that is a) easily identifiable, and b) likely to generate a positive affect for in-group members. Table 2.10, displays the results from examining how quality differences impact the effect of physical proximity. In the full model (column 4), we find that both main effects on being close and both startups being successful are positively associated with technology adoption. In addition, the interaction between being close and both successful is negative suggesting that success and proximity may be substitutes.

<Insert Table 2.10 here>

Interplay with knowledge-space proximity

In Figure 2.5, we present the results including an interaction of physical proximity and our knowledge-space overlap measure. As predicted, the results indicate that the interaction between knowledge-space overlap and physical proximity have a non-linear relationship with predicting peer technology adoption. Our findings suggest that the strongest interaction is between being physically close and in the 2^{nd} quintile in terms on knowledge-space proximity. The size of the interaction coefficient almost halve from the 2^{nd} to 3^{rd}, more than halves from the 3^{rd} to 4^{th}, and is close to zero for the 1^{st} and 5^{th} quintiles. Put differently, firms do not learn from firms in close proximity that have very little or very much knowledge overlap.

<Insert Figure 2.5 here>

Interplay with product-market proximity

In Table 2.11, we present the results including an interaction of physical and product-market proximity. The interaction between product-market and physical proximity is negative, thereby indicating that product-market proximity may be a substitute for physical proximity. In addition, the main effect of physical proximity remains positive and statistically significant on a level of $p<0.01$ across all specifications, whereas in the fully specified model (column 4) the main effect of product-market proximity does not. This implies that physical and product-market proximity are possible substitutes. Being physically close and in the same product-market may thereby act as a barrier to knowledge exchange.

<Insert Table 2.11 here>

3.4.3 Could physical proximity be shaping interaction?

One plausible mechanism that could explain our previous set of results is that physical proximity shapes the interactions individuals engage in (Hasan and Bagde, 2015). To explore the extent to which this is the case in the startup hub context, we further exploit a joint event - a lunch - hosted at the co-working space on a weekly basis. Table 2.12, columns 1-3, present the results using the number of lunches hosted at the co-working space that at least one team member of $firm_i$ and $firm_j$ both attend (*# Event* $Both_{ij}$ *Attend*). As shown in column 3, startup dyads that are within 20 meters attend 0.26 more lunches together than those located 20-44 meters from each other (omitted category), whereas dyads that are located more than 45 meters apart do not differ from the omitted category. The results using an indicator equal to one if at least one team member of $firm_i$ and $firm_j$ both attend (*1(*$Both_{ij}$ *Attend)*) as the dependent variable (columns 4-6) confirm the results in columns 1-3.

<Insert Table 2.12 here>

We further exploit the order of entry to calculate the log distance of entry between members of $firm_i$ and $firm_j$ (*ln(min line* $distance_{ij}$*)*) and to create an indicator equal to one if at least one team member of $firm_i$ and $firm_j$ appear within 1, 2, 5, 10, or 25 people in line for the lunch (*1(Ever within X people in line)*). In Table 2.13, we present the results from estimating the effect of room proximity on check-in line proximity, conditional on jointly attending the event. The results indicate that close room proximity (within 20 meters) only increases check-in line proximity for the group of people within 1-5 individuals from each other at check-in and not for those individuals further away in line. Together, these results suggest that social groups - in other words, the set of individuals who have a high propensity to chat with each other - are also partially induced by geographic location where spatial distances as short as 20 meters seem to matter most.

<Insert Table 2.13 here>

Similarly to joint events, we would expect a positive relationship between joint amenity use and peer technology adoption if interaction between individuals were a viable mechanism explaining our prior results. The idea here is that in places such as roof-top patios and mailrooms, individuals have a heightened propensity to chat with other individuals using the space. In Table 2.14, we report the results from estimating the relationship between amenity use and the likelihood of technology adoption. As displayed, we find heterogeneous results in terms of joint amenity usage and the likelihood of technology adoption. When both startups have at least one member who uses the roof-top patio or mailroom, these dyads are more likely to adopt technologies from each other. This, however, is not the case for gym-use where neither gym-usage without proximity nor the interaction with close proximity is statistically significant. We interpret the results for gym usage as a placebo given that the roof-top patio and mailroom are places where individuals are more likely to interact, hence have a higher propensity to chat, than at the gym where individuals tend to focus on their workout activity.

<Insert Table 2.14 here>

3.4.4 Performance

Via their impact on technology adoption decisions, physical and other proximity dimensions may also shape startup performance outcomes. Spatial design - by means of "...its own grammar that can be tweaked to bolster desirable habits" (Doorley and Witthoft, 2012) - may thereby impact performance by determining the set of immediate peers (potential interaction partners) a startup has in the first place. The notion that peers drive performance has been demonstrated in a host of different environments such as retail (Mas and Moretti, 2009; Chan, Li and Pierce, 2014a,b), finance (Hwang, Liberti and Sturgess, 2018) and science (Oettl, 2012; Catalini, 2017). The idea being that by sharing knowledge, helping, and setting expectations (e.g., Mas and Moretti, 2009; Herbst and Mas, 2015; Housman and Minor, 2016), performance is enhanced.

To examine the potential performance implications of proximity and peer technology similarity at the firm-level, we estimate the probability of achieving two important startup performance milestones as a function of the technology characteristics of firms within 20 meters of the focal firm. These two startup outcomes, which have been used in prior literature as measures for new venture financial performance (e.g., Hochberg et al. 2007; Nanda and Rhodes-Kropf 2013), are raising either a seed round (Figure 2.6) or $1MM (Figure 2.7). We further control for firm characteristics such as industries, age and size. As Figures 2.6 and 2.7 display, falling into the third quintile of mean technology similarity to close firms positively predicts both outcomes. In line with previous research (Swank and Visser, 2015; Hassan and Mertens, 2017; Bikhchandani et al., 1998), our findings indicate that both too little, but also too much (or frequent) technology similarity does not aid startup performance. This suggests that there may be important limits to promoting interaction and resulting entrepreneurial peer learning for new venture performance.

<Insert Figures 2.6 and 2.7 here>

3.5 Discussion

We contribute to the discussion on workplace design for knowledge workers and entrepreneurs as well as the micro-geography of technology diffusion in four important ways. First, our findings indicate that distance matters for entrepreneurial learning, and more specifically, for technology adoption. We show that in one of the largest entrepreneurial co-working spaces in the US, startups are influenced by peer startups that are within a distance of 20 meters and no longer at greater distances.

Second, we contribute to the literature examining proximity and knowledge spillovers, by combining multiple dimensions of proximity and analyzing their interdependencies. We thereby provide evidence for heterogeneity in the effect of physical distance on technology adoption depending on other types of proximity. Here, our results provide suggestive evidence that socially proximate peers may be able to overcome the distance discount given stronger within-group ties (and presumably more planned interactions). However, precisely this way of sharing knowledge may be reinforcing divides between groups since new information may not be dispersed equally. Further, we find that some knowledge-space proximity bolsters and too much reduces the impact of physical proximity, providing suggestive evidence that the extent to which different startups respond to information is nuanced and relies both on social and informational processes. In addition, our results indicate that the interaction between product-market and physical proximity has a negative impact on technology adoption decisions. This implies that competitive pressures in the context of the co-working hub may be creating non-negligible barriers to knowledge exchange.

Third, the micro-geographic perspective we apply, presents a possible avenue to reconcile Marshall-Arrow-Romer specialization externalities (Romer, 1986) and Jacobs' type diversification externalities (Jacobs, 1969). It is plausible that both types of externalities may be operating at different geographic levels (Beaudry and Schiffauerova, 2009) or - given our results indicating that more isolated firms are influenced to a greater degree by proximate firms than centrally located ones - depend on how remote/central a firm's location is. Understanding this balance between concentration and diversity has important implications, especially, for promoting the diffusion of ideas within a fast-changing entrepreneurial ecosystem.

Fourth, we provide insight on the implications of technology adoption for startup performance. Our findings seem to indicate that a moderate amount of technology adoption contributes to achieving important startup performance milestones. This goes in line with previous research highlighting limits to technology adoption (Swank and Visser, 2015; Hassan and Mertens, 2017) and suggests that there are important trade-offs associated with the amount of and frequency at which new (to the firm) technologies are incorporated.

We acknowledge that our paper is not without limitations. For one, we restrict our analysis to only one co-working space. In this case we are trading-off a higher level of generalizability for richer data. Given the large sample of heterogeneous startups both in terms of technology sophistication and industries, the findings we present should nonetheless be fairly representative for the population of startups working in similar co-working spaces around the world. Furthermore, we restrict our focus to one type of decision entrepreneurs make: technology adoption. We use this measure since, on the one hand, choices regarding the technology of a firm are especially fundamental for startups (Murray and Tripsas, 2004), and on the other hand, because we can clearly identify the time these changes were implemented.

Taken together, our findings provide fundamental insights for the design of communities that support knowledge production, entrepreneurship, and innovation. We highlight important trade-offs and stress that understanding which firms and how they respond to their peers matters for creating effective environments for early stage ventures. Where physical structure may lay the groundwork for exchange to take place, other factors may determine how firms actually enact on presented opportunities.

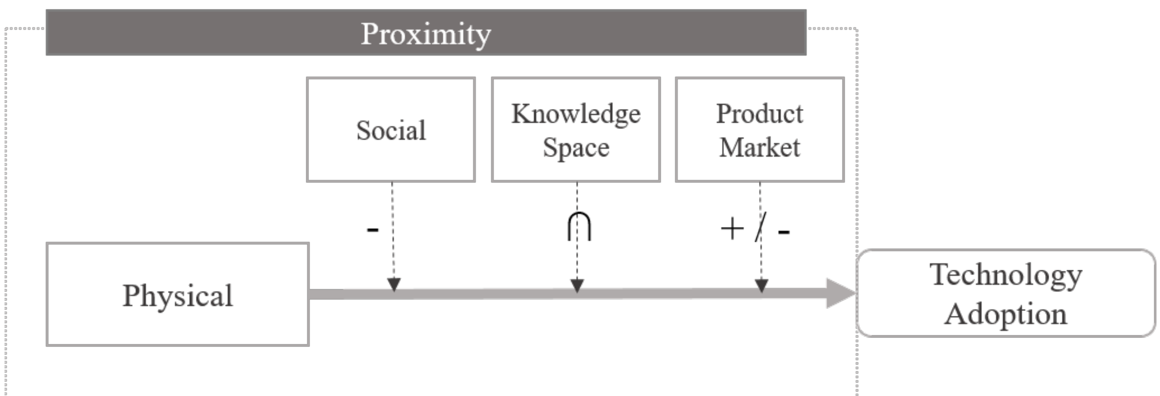


Figure 2.1: Conceptual Approach

Notes: This figure stylistically displays our conceptual approach. Each symbol represents our prediction as elaborated in the main text.

Figure 2.2: Floor Plan of the Co-working Space

Notes: This figure displays the floor-plans of the co-working hub we examine. The legend and scale can be found on the bottom right corner of the figure.

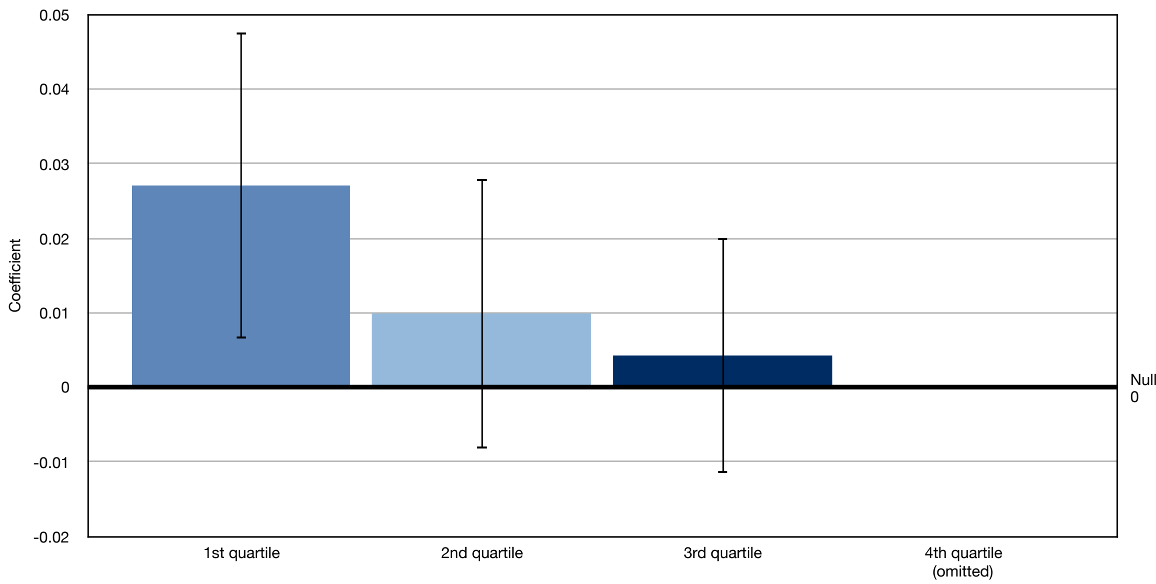


Figure 2.3: Physical Proximity Quartile Plots

Notes: This figure displays the results from estimating equation (1) using a quartile regression. We thereby split our distance measure into quartiles instead of using a continuous measure of distance. The omitted category is the 4^{th} quartile, representing the furthest distance.

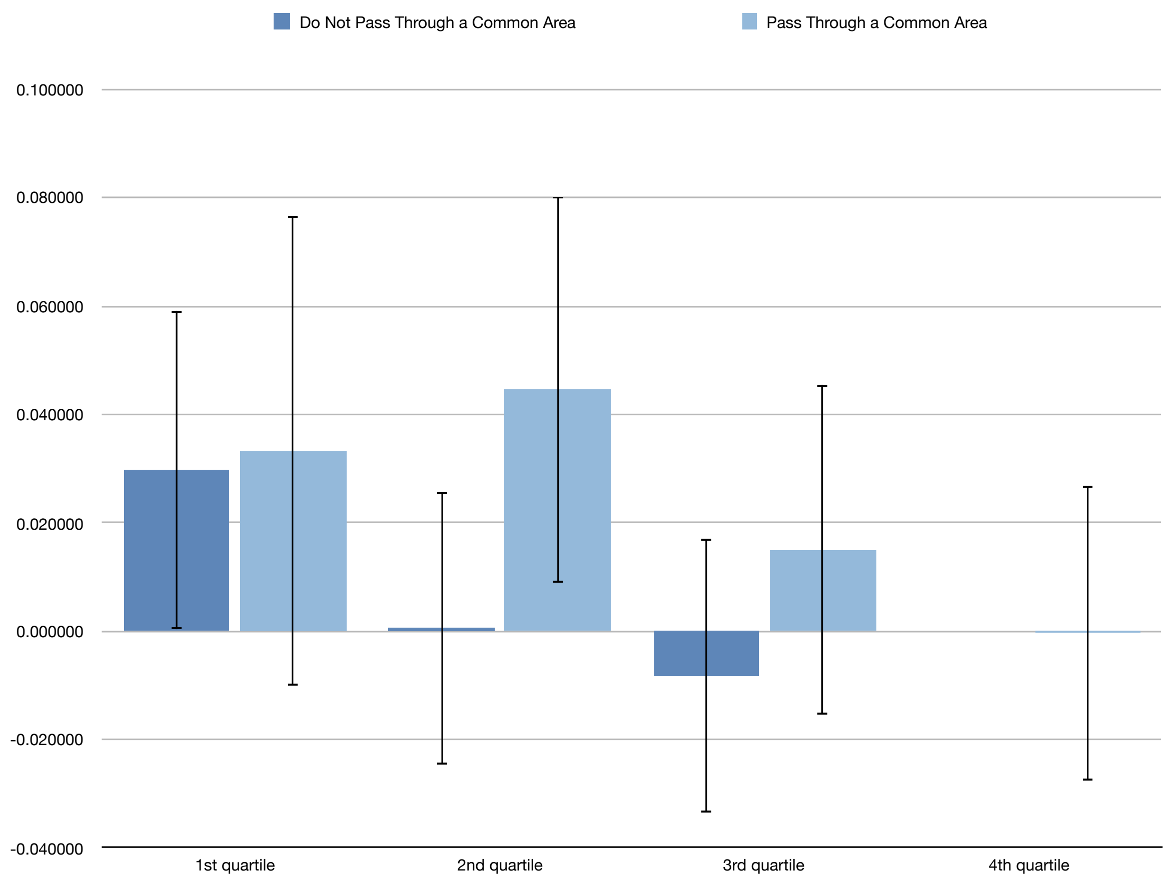


Figure 2.4: Common Area Quartile Plots

Notes: This figure displays the results from estimating equation (1) using a quartile regression and including an interaction with the $CommonArea$ dummy. We thereby use $CommonArea \times$ 4$^{\text{th}}$ distance quartile as the omitted category.

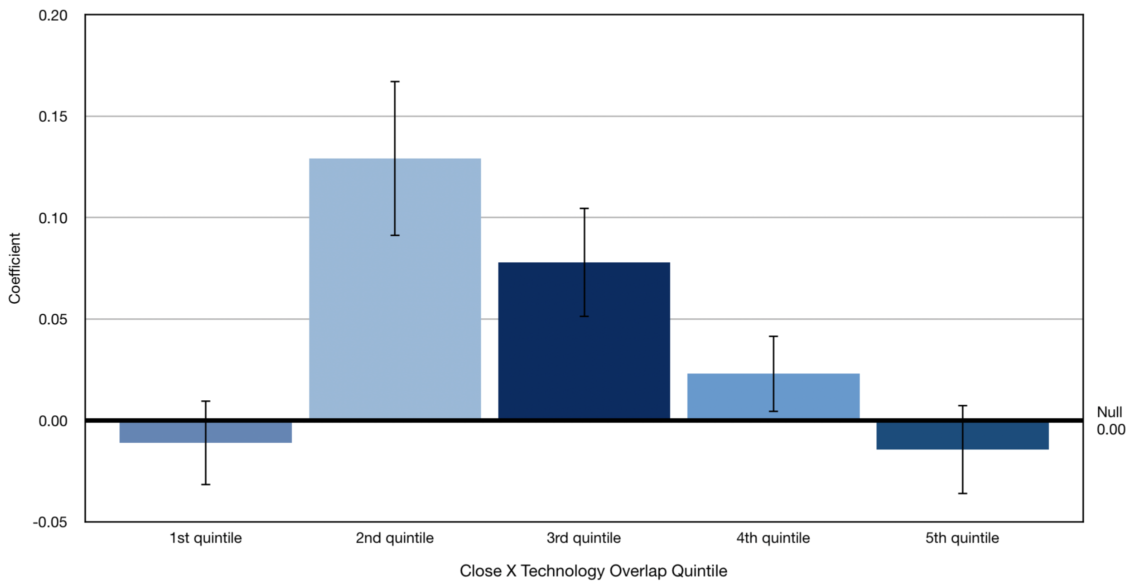


Figure 2.5: Adoption by Technology Overlap Quintiles

Notes: This figure presents the results from estimating equation (1) and including the interaction of physical proximity and knowledge-space overlap. We measure knowledge space proximity using the mean pre-period technology overlap between focal $firm_i$ and all other close firms and break this measure into quintiles (omitted category is *not close*).

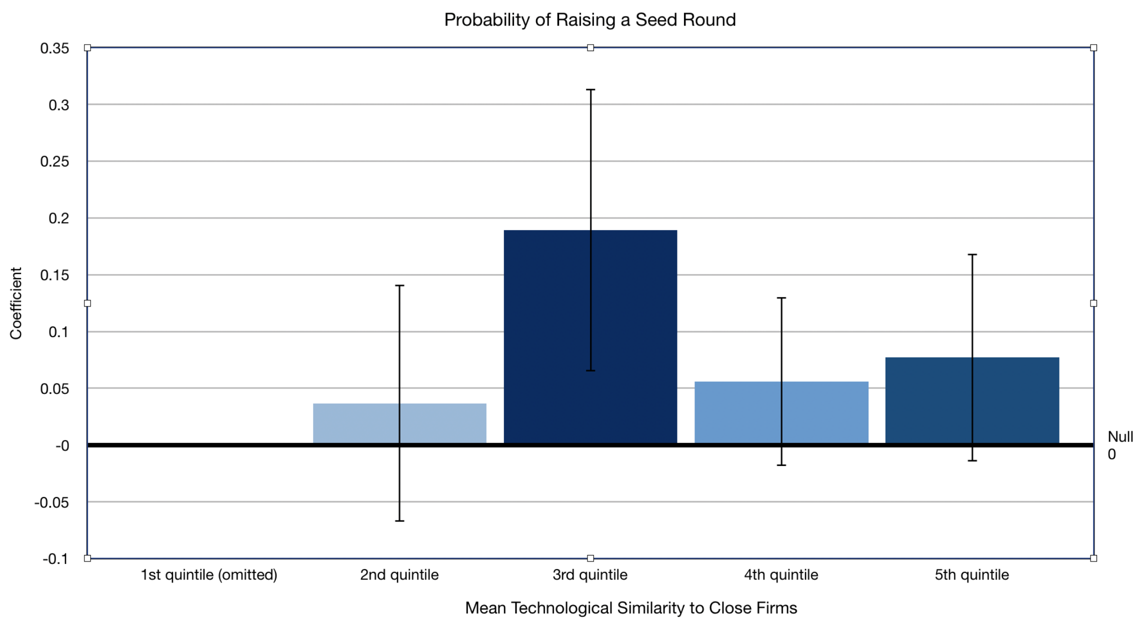


Figure 2.6: Probability of Raising a Seed Round by Technology Overlap Quintile of Proximate Firms

Notes: This figure displays the results from estimating the probability of raising a seed round as a function of the technology characteristics of firms within 20m of the focal firm. We thereby control for firm characteristics such as industries, age and size. *Mean Technological Similarity to Close Firms* is the average technology overlap of $firm_i$ technologies with other firms within 20m distance, which we break into quintiles is this figure. The 1st quintile is the omitted category and 95% confidence intervals are displayed.

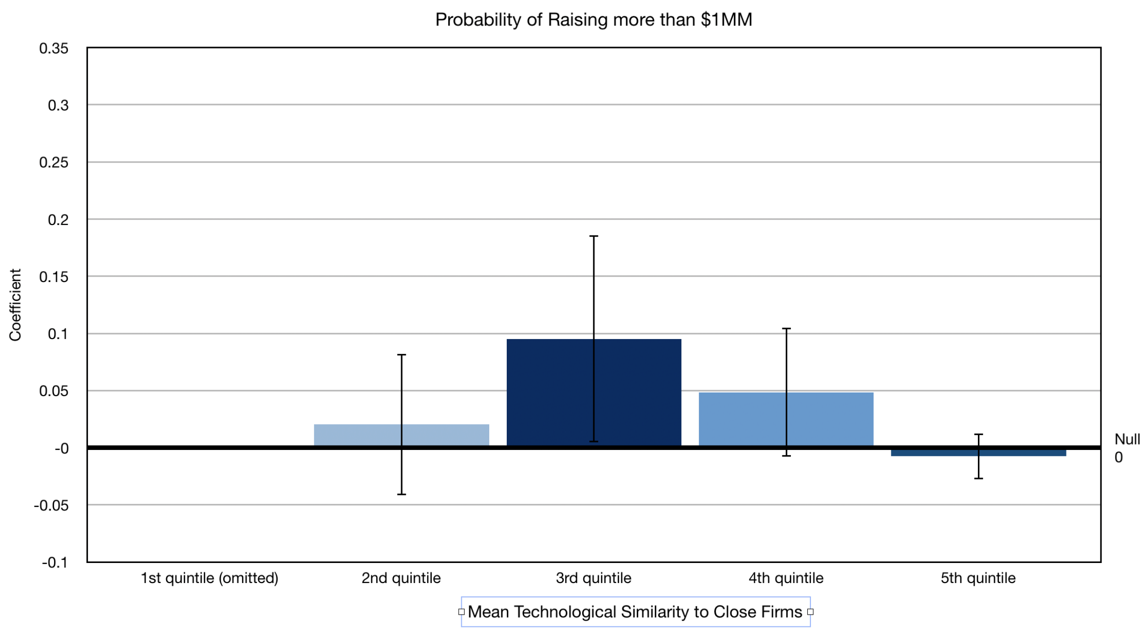


Figure 2.7: Probability of Raising $1MM by Technology Overlap Quintile of Proximate Firms

Notes: This figure displays the results from estimating the probability of raising $1MM as a function of the technology characteristics of firms within 20m of the focal firm. We thereby control for firm characteristics such as industries, age and size. *Mean Technological Similarity to Close Firms* is the average technology overlap of $firm_i$ technologies with other firms within 20m distance, which we break into quintiles is this figure. The 1st quintile is the omitted category and 95% confidence intervals are displayed.

Table 2.1: Summary Statistics on the Firm and Dyad Level

Firm level (N = 251)	mean	sd	min	p25	p50	p75	max
Age (in months)	12.24	9.59	0	3	11	20	29
Room size (in sq.feet)	288.28	327.69	50	134	143	255	1878
Room size (in m^2)	27.78	30.44	4.64	12.45	13.29	23.70	174.50
Female (= 0/1)	0.12	0.32	0	0	0	0	1
B2B (= 0/1)	0.74	0.44	0	0	1	1	1
B2C (= 0/1)	0.39	0.49	0	0	0	1	1
Successful (= 0/1)	0.24	0.43	0	0	0	0	1
Min. Technology Usage	33.15	33.15	0	0	28	54	168
Max. Technology Usage	51.06	49.70	0	0	43	79	255
Use Mail	0.37	0.48	0	0	0	1	1
Use Gym	0.37	0.48	0	0	0	1	1
Use Roof	0.17	0.38	0	0	0	0	1
Dyad level (N = 10840)	mean	sd	min	p25	p50	p75	max
Adopted a Technology (= 0/1)	0.53	0.50	0	0	1	1	1
Number of Adopted Technologies	7.33	10.49	0	0	2	12	76
Distance	32	15.20	4.30	20	30	44	77
Close (= 0/1)	0.28	0.45	0	0	0	1	1
Common Area (= 0/1)	0.38	0.48	0	0	0	1	1
Pre-period Technology Overlap (%)	0.14	0.18	0	0	0	0.27	0.85
Same Industry (= 0/1)	0.11	0.31	0	0	0	0	1
Both B2B (= 0/1)	0.48	0.50	0	0	0	1	1
Both B2C (= 0/1)	0.11	0.31	0	0	0	0	1
Both Majority Female(= 0/1)	0.013	0.11	0	0	0	0	1
Age Difference	7.30	7.28	0	1	5	12	29
Both Small Room (= 0/1)	0.47	0.50	0	0	0	1	1
Both Successful (= 0/1)	0.08	0.27	0	0	0	0	1
Both Use Mail (= 0/1)	0.20	0.40	0	0	0	0	1
Both Use Gym (= 0/1)	0.19	0.39	0	0	0	0	1
Both Use Roof (= 0/1)	0.04	0.19	0	0	0	0	1

Notes: This table displays summary statistics for the startups operating at the co-working space we examine. We report summary statistics both on the firm and dyad level.

Table 2.2: Operationalization of Proximity Dimensions

Dimension	**Operationalization**
Physical Proximity	Geographic distance (in meters) between rooms on one floor.
Social Proximity	Both firms possess a salient characteristic that only a minority of the firms in the co-working space have. We apply two measures to identify socially proximate firms: those where both startups are a) majority female, and b) successful.
Knowledge Space Proximity	We measure knowledge space proximity using the mean pre-period technology overlap between focal $firm_i$ and all other close firms. We break this measure into quintiles.
Product Market Proximity	The consumers of two firms' products are similar. We measure product market proximity by using a combination of two firm characteristics: a) industry, and b) business model. Two firms are proximate in their product market if they either operate in the same industry or have the same business model.

Notes: This table displays how we operationalize the various proximity dimensions used in this paper for the purpose of our empirical analyses.

Table 2.3: Pairwise characteristics do not predict geographic proximity - OLS Regressions

	(1)	(2)
Unit of Analysis	Firm$_i$-Firm$_j$ Dyad	
Dependent Variable	ln(distance$_{ij}$)	
Same Industry	0.000	0.001
	(0.019)	(0.019)
Both B2B Companies	0.029	0.030
	(0.040)	(0.040)
Both B2C Companies	0.031	0.030
	(0.021)	(0.020)
Both Majority Female	0.014	0.014
	(0.026)	(0.028)
$\lvert$age$_i$-age$_j\rvert$	0.001	0.001
	(0.001)	(0.001)
Pre-period Technology Overlap		-0.073
		(0.070)
Firm$_i$ X Room Fixed Effects	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓
Observations	10840	10840
R^2	0.12	0.12

Notes: Robust standard errors 2-way clustered at the firm$_i$ and firm$_j$ level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.4: Distance negatively affects peer technology adoption - OLS Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Unit of Analysis			Firm$_i$-Firm$_j$ Dyad			
Dependent Variable			$ln(AdoptCount_{ij}+1)$			
ln(distance$_{ij}$)	-0.073^{**}	-0.044	-0.056^{**}	-0.043^{**}	-0.043^{**}	-0.035^{**}
	(0.037)	(0.030)	(0.026)	(0.017)	(0.017)	(0.014)
Same Industry					0.056^{*}	0.021
					(0.033)	(0.024)
Both B2B Companies					0.004	-0.034
					(0.038)	(0.026)
Both B2C Companies					0.007	0.030
					(0.026)	(0.025)
Both Majority Female					-0.095	-0.102
					(0.098)	(0.080)
$\|age_i-age_j\|$					-0.004^{**}	-0.006^{***}
					(0.002)	(0.002)
Pre-period Technology Overlap						3.624^{***}
						(0.250)
Firm$_i$ Fixed Effects		✓				
Firm$_j$ Fixed Effects			✓			
Firm$_i$ X Room Fixed Effects				✓	✓	✓
Firm$_j$ X Room Fixed Effects				✓	✓	✓
Observations	10840	10840	10840	10840	10840	10840
R^2	0.00	0.35	0.44	0.80	0.80	0.86
F	3.90	2.13	4.79	6.29	2.11	37.57

Notes: Robust standard errors 2-way clustered at the firm$_i$ and firm$_j$ level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.5: Distance negatively affects peer technology adoption - LPM Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Unit of Analysis	Firm$_i$-Firm$_j$ Dyad					
Dependent Variable	$\mathbb{1}$(AdoptTech$_{ij}$)					
mean	0.531					
ln(distance$_{ij}$)	-0.030^{**}	-0.022^{*}	-0.024^{**}	-0.019^{***}	-0.019^{***}	-0.017^{***}
	(0.014)	(0.012)	(0.010)	(0.007)	(0.007)	(0.006)
Same Industry					0.015	0.005
					(0.012)	(0.010)
Both B2B Companies					0.004	-0.007
					(0.016)	(0.013)
Both B2C Companies					-0.002	0.005
					(0.011)	(0.011)
Both Majority Female					0.015	0.013
					(0.043)	(0.041)
$\|$age$_i$-age$_j\|$					-0.001	-0.001^{**}
					(0.001)	(0.001)
Pre-period Technology Overlap						1.007^{***}
						(0.095)
Firm$_i$ Fixed Effects		✓				
Firm$_j$ Fixed Effects			✓			
Firm$_i$ X Room Fixed Effects				✓	✓	✓
Firm$_j$ X Room Fixed Effects				✓	✓	✓
Observations	10840	10840	10840	10840	10840	10840
R^2	0.00	0.37	0.42	0.79	0.79	0.83
F	4.34	3.44	5.46	6.98	1.60	18.17

Notes: Robust standard errors 2-way clustered at the firm$_i$ and firm$_j$ level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.6: Close proximity positively affects peer technology adoption - LPM Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad					
Dependent Variable	$\mathbb{1}$(AdoptTech$_{ij}$)			$ln(AdoptCount_{ij})$		
mean	0.531					
	(1)	(2)	(3)	(4)	(5)	(6)
Close	0.025***	0.022***	0.019***	0.057***	0.048***	0.045***
	(0.008)	(0.007)	(0.006)	(0.020)	(0.016)	(0.017)
Distant			−0.011			−0.007
			(0.008)			(0.018)
Pre-period Technology Overlap		1.007***	1.007***		3.624***	3.624***
		(0.095)	(0.095)		(0.250)	(0.250)
Same Industry		0.005	0.005		0.021	0.021
		(0.010)	(0.010)		(0.024)	(0.024)
Both B2B Companies		−0.007	−0.007		−0.034	−0.034
		(0.013)	(0.013)		(0.026)	(0.026)
Both B2C Companies		0.004	0.004		0.029	0.029
		(0.011)	(0.011)		(0.025)	(0.025)
Both Majority Female		0.012	0.013		−0.103	−0.103
		(0.041)	(0.041)		(0.080)	(0.080)
$\|age_i - age_j\|$		−0.001**	−0.001**		−0.006***	−0.006***
		(0.001)	(0.001)		(0.002)	(0.002)
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	10840	10840	10840	10840	10840	10840
R^2	0.79	0.83	0.83	0.80	0.86	0.86
F	9.58	18.40	16.21	7.88	37.88	33.38

Notes: Robust standard errors 2-way clustered at the firm$_i$ and firm$_j$ level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.7: Common-area overlap increases technology adoption and substitutes for proximity - LPM Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad			
Dependent Variable	$\mathbb{1}$(AdoptTech$_{ij}$)			
mean	0.531			
	(1)	(2)	(3)	(4)
ln(distance$_{ij}$)	-0.027^{***}	-0.024^{***}		
	(0.009)	(0.009)		
Common Area$_{ij}$	0.018^{*}	0.034^{**}	0.010	0.011
	(0.010)	(0.013)	(0.008)	(0.009)
Common Area$_{ij}$ $\times$ ln(distance$_{ij}$)		-0.035		
		(0.023)		
Close			0.029^{***}	0.032^{***}
			(0.009)	(0.009)
Close $\times$ Common Area$_{ij}$				-0.036^{*}
				(0.019)
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓
Observations	10840	10840	10840	10840
R^2	0.79	0.79	0.79	0.79

Notes: The variable ln(distance$_{ij}$) is mean centered. Robust standard errors 2-way clustered at the firm$_i$ and firm$_j$ level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.8: Centrally-located rooms substitute for proximity - LPM Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad			
Dependent Variable	$\mathbb{1}$(AdoptTech$_{ij}$)			
mean	0.531			
	(1)	(2)	(3)	(4)
ln(distance$_{ij}$)	-0.025^{***}	-0.021^{***}		
	(0.009)	(0.007)		
ln(distance$_{ij}$) $\times$ Central Location	0.038^{**}	0.030^{**}		
	(0.015)	(0.014)		
Close			0.034^{***}	0.028^{***}
			(0.010)	(0.009)
Close $\times$ Central Location			-0.040^{**}	-0.026^{*}
			(0.016)	(0.014)
Pre-period Technology overlap		1.007^{***}		1.006^{***}
		(0.095)		(0.095)
Same Industry		-0.011		-0.011
		(0.008)		(0.008)
Both B2B companies		-0.005		-0.005
		(0.013)		(0.013)
Both B2C companies		0.004		0.004
		(0.011)		(0.011)
Both Female CEOs		0.016		0.016
		(0.041)		(0.041)
$\lvert$age_i-age_$j\rvert$		-0.001^{**}		-0.001^{**}
		(0.001)		(0.001)
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓
Observations	10840	10840	10840	10840
R^2	0.79	0.79	0.79	0.79

Notes: The variable ln(distance$_{ij}$) is mean centered. Robust standard errors 2-way clustered at the firm$_i$ and firm$_j$ level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.9: Female-firm dyads overcome the distance discount - LPM Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad			
Dependent Variable	$\mathbb{1}$(AdoptTech$_{ij}$)			
mean	0.531			
	(1)	(2)	(3)	(4)
Close	0.024^{***}		0.019^{***}	
	(0.007)		(0.007)	
Both Majority Female	0.018^{***}	-0.026^{*}	0.007	-0.009
	(0.006)	(0.014)	(0.005)	(0.011)
Close $\times$ Both Majority Female	-0.088^{***}		-0.078^{***}	
	(0.024)		(0.027)	
Pre-period Technology overlap	1.006^{***}	1.007^{***}	1.006^{***}	1.005^{***}
	(0.095)	(0.096)	(0.095)	(0.095)
Distant		-0.020^{**}	-0.011	
		(0.009)	(0.008)	
Distant $\times$ Both Majority Female		0.059^{***}	0.023	
		(0.021)	(0.021)	
ln(distance$_{ij}$)				-0.018^{***}
				(0.007)
ln(distance$_{ij}$)$\times$ Both Majority Female				0.053^{***}
				(0.018)
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓
Observations	10840	10840	10840	10840
R^2	0.83	0.83	0.83	0.83

Notes: The variable ln(distance$_{ij}$) is mean centered. Robust standard errors 2-way clustered at the firm$_i$ and firm$_j$ level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.10: Successful-dyads are more likely to adopt technologies from each other and success substitutes for proximity - LPM Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad			
Dependent Variable	$\mathbb{1}$(AdoptTech$_{ij}$)			
mean	0.531			
	(1)	(2)	(3)	(4)
Close	0.033^{***}	0.029^{***}	0.027^{***}	0.025^{***}
	(0.010)	(0.010)	(0.009)	(0.007)
Close $\times$ Successful$_i$	-0.030^{**}			
	(0.015)			
Close $\times$ Successful$_j$		-0.012		
		(0.014)		
Both Successful$_{ij}$			0.041^{***}	0.025^{**}
			(0.015)	(0.011)
Close $\times$ Both Successful$_{ij}$			-0.029^{*}	-0.036^{**}
			(0.017)	(0.015)
Pre-period Technology Overlap				1.006^{***}
				(0.095)
Same Industry				0.005
				(0.010)
Both B2B Companies				-0.007
				(0.013)
Both B2C Companies				0.004
				(0.011)
Both Majority Female				0.013
				(0.041)
$\lvert age_i - age_j \rvert$				-0.001^{**}
				(0.001)
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓
Observations	10840	10840	10840	10840
R^2	0.79	0.79	0.79	0.83

Notes: Robust standard errors 2-way clustered at the firm$_i$ and firm$_j$ level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.11: Product-market proximity substitutes for geography - LPM Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad			
Dependent Variable	$\mathbb{1}$(AdoptTech$_{ij}$)			
mean	0.531			
	(1)	(2)	(3)	(4)
Close	0.044^{***}	0.037^{***}	0.041^{***}	0.033^{***}
	(0.011)	(0.009)	(0.010)	(0.008)
Same Industry/Business Model$_{ij}$	0.020^{*}	0.013	0.018^{*}	0.014
	(0.011)	(0.009)	(0.010)	(0.009)
Close $\times$ Same Industry/Business Model$_{ij}$	-0.031^{***}	-0.023^{***}	-0.029^{***}	-0.024^{***}
	(0.009)	(0.009)	(0.010)	(0.009)
Distant			-0.008	-0.008
			(0.013)	(0.012)
Distant $\times$ Same Industry/Business Model$_{ij}$			0.003	-0.003
			(0.011)	(0.011)
Both Majority Female		0.013		0.014
		(0.041)		(0.041)
$\|age_i - age_j\|$		-0.001^{**}		-0.001^{**}
		(0.001)		(0.001)
Pre-period Technology overlap		1.005^{***}		1.006^{***}
		(0.095)		(0.095)
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓
Observations	10840	10840	10840	10840
R^2	0.79	0.83	0.79	0.83
F	6.03	21.58	3.96	16.31

Notes: Robust standard errors 2-way clustered at the firm$_i$ and firm$_j$ level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.12: Proximity increases joint attendance of community-wide events - OLS Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad					
Dependent Variable	# Events Both$_{ij}$ attend			$\mathbb{1}$(Both$_{ij}$ Attend Event)		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(distance$_{ij}$)	-0.156^{*}			-0.002		
	(0.091)			(0.005)		
Common Area$_{ij}$	0.156	0.147	0.110	0.002	0.006	0.002
	(0.122)	(0.105)	(0.111)	(0.008)	(0.006)	(0.007)
Close		0.240^{**}	0.255^{**}		0.012^{**}	0.014^{**}
		(0.094)	(0.104)		(0.006)	(0.006)
Distant			0.082			0.011
			(0.130)			(0.007)
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	10840	10840	10840	10840	10840	10840
R^2	0.47	0.47	0.47	0.54	0.54	0.54

Notes: Robust standard errors 2-way clustered at the firm$_i$ and firm$_j$ level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.13: Conditional on jointly attending event, room proximity increases event checkin-line proximity - OLS Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad					
		$\mathbb{1}$(Ever within X people in line)				
Dependent Variable	ln min line distance$_{ij}$	1 person	2 people	5 people	10 people	25 people
	(1)	(2)	(3)	(4)	(5)	(6)
Close	-0.135	0.064^{**}	0.091^{***}	0.093^{**}	0.010	-0.027
	(0.098)	(0.031)	(0.034)	(0.043)	(0.038)	(0.030)
Common Area$_{ij}$	-0.196^{*}	0.019	0.061^{*}	0.057	0.047	0.056^{**}
	(0.102)	(0.029)	(0.032)	(0.040)	(0.038)	(0.028)
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	1398	1398	1398	1398	1398	1398
R^2	0.61	0.42	0.45	0.47	0.51	0.47

Notes: Robust standard errors 2-way clustered at the firm$_i$ and firm$_j$ level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.14: Shared resources predict technology adoption - LPM Regressions

	(1)	(2)	(3)
Close	0.022***	0.019**	0.022***
	(0.007)	(0.008)	(0.008)
Both Use Roof	0.034*		
	(0.018)		
Close x Both Use Roof	0.010		
	(0.022)		
Pre-period Technology Overlap	1.293***	1.294***	1.293***
	(0.122)	(0.122)	(0.122)
Both Use Gym		0.015	
		(0.012)	
Close x Both Use Gym		0.016	
		(0.011)	
Both Use Mail			0.025*
			(0.014)
Close x Both Use Roof			0.003
			(0.011)
Firm_i X Room Fixed Effects	✓	✓	✓
Firm_j X Room Fixed Effects	✓	✓	✓
Observations	10840	10840	10840
R^2	0.84	0.84	0.84

Notes: The variable ln(distance$_{ij}$) is mean centered. Robust standard errors 2-way clustered at the firm$_i$ and firm$_j$ level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

CHAPTER 4

TAKING INTERACTIONS AND INNOVATION TO THE LAB: EXPOSURE TO AN ENTREPRENEURIAL ADVISOR

"The [PhD] students do the research, I'm (...) the director and they're like the actors, actresses."

(from interviews with Mechanical Engineering professors).

4.1 Introduction

Entrepreneurship is widely perceived as a fundamental engine for overall economic growth and welfare and, as such, has been increasingly receiving attention and (financial) support from the public and policy makers alike. However, particularly in the case of employee entrepreneurship, incentives for entrepreneurial engagement may also interfere with incentives for core employment tasks thereby potentially leading to underinvestment in innovation and/or the execution of main job responsibilities (Hellmann, 2007). This may become especially pronounced for supervisors whose tasks, which include responsibilities such as human resource management (e.g., recruitment, mentoring), work allocation, as well as monitoring (e.g., quality control), have crucial implications for their own and other employees' productivity (Bloom, 2013).

In this paper, I ask: Does a supervisor's engagement in entrepreneurship affect their subordinates' innovative productivity? I empirically test this research question in the context of academia and further highlight possible consequences for subordinates' career trajectories. Academia represents a suitable setting to examine this question given that conflicting demands and goals both exist and are detectable, multiple stakeholders are involved, fine-grained proxies for individuals' ability and information on innovative activity is available, and provided the important implications the findings may have for management and policy research (Fini et al., 2019).

Over the past few decades, the university has broadened its role of knowledge producer to include the commercialization of academic discoveries (Hsu et al., 2007). In response to opportunities, policy initiatives[1] and organizational changes, universities (and researchers) have become much more proactive in their efforts to commercialize scientific discoveries (Crespi et al., 2011; Mowery et al., 2004). In fact, since the late 1990s, over 80,000 US patents have been issued to academic institutions, and over 11,000 startups have been formed out of universities (AUTM, 2017). Yet, commercial involvement goes against the traditional norms that regulate the university, especially the norm that scientific findings are a common good (Arrow, 1971; Dasgupta and David, 1994; Merton, 1973). As such, the resulting conflicting demands of science and business could carry important consequences for the overall production of knowledge both within and outside of the university.

Thus far, the existing literature provides some evidence on the implications of academics' involvement in commercialization for knowledge production. However, in this line of research most efforts are focused on examining the impact of commercialization on professors' own publication output and provide mixed results. For example, although Thursby and Thursby (2011) find that commercial activities have no significant effect on the production of scientific publications, Murray and Stern (2007) document a drop in citation rates to scientific publications once they receive formal IP protection. Moreover, whereas findings by Agrawal and Henderson (2002) as well as Fabrizio and Di Minin (2008) indicate possible complementarities between patenting and publishing activity, Crespi et al. (2011) suggest that patenting, in fact, may crowd out publication efforts.

What has been left largely unexplored in this body of research is how professors' commercial activity, particularly their *active* engagement in entrepreneurship, impacts their subordinates, and more specifically, their PhD students. Not only do PhD students constitute a fundamental vehicle for the transfer of knowledge, but they also represent one of the major

[1]One example is the Innovation Corps (I-Corps) program introduced by the National Science Foundation (NSF) with the goal to train students for careers in entrepreneurship (Roach, 2017).

players involved in the production of knowledge within and, upon graduation, outside of the university. Therefore, in this study, I specifically examine how professors' engagement in entrepreneurship affects the innovative output and career trajectories of their advisees. To do so, I track professors and their PhD students at a top-ranked US research university from 2000-2013, assessing variation in student outcomes before and after research faculty transitions into entrepreneurship.

I focus my analyses on the fields of computer sciences and engineering. The data underlying this study come from a host of sources consisting of both restricted administrative and publicly available information. These data encompass, amongst others, information on professors' nationality, gender, ethnicity, age, yearly amount of federal funding, teaching evaluations, the number and quality of professors' publications, as well as information on their patenting output and the number of startups they establish. I complement these data by matching professors to their PhD students, based on information provided by the Office of Enrollment at the examined institution. For PhD students, I have access to detailed information on their nationality, gender, ethnicity, age, year of admission and graduation, major, GRE scores, GPAs, as well as their previous degree-granting institutions. I additionally collect data on students' careers before and after graduation, as well as on their publications, patents and respective citations.

My baseline findings provide suggestive evidence that exposure to an entrepreneurial advisor is associated with a decrease in the yearly total amount and number of highly-cited publications PhD students produce. Conversely, exposure does not seem to impact patenting output. These results, however, may be driven by a host of alternative explanations, which I address in this paper step-by-step using different estimation techniques.

For one, there is concern of potential omitted variable bias regarding professors. Consequently, rather than identifying a treatment effect of exposure to an entrepreneurial professor, the results I find could be driven by specific features of the advisors that the econometrician cannot observe. For example, those professors who transition into entrepreneurship may be different from other professors along certain dimensions such as ability, personal traits (e.g., related to taking initiative and exercising leadership (Feldman et al., 2019)) and social skills (that could give them a competitive edge in fundraising, or networking). To address this concern, I apply professor fixed effects to my estimation models.

A further challenge to identifying the impact of exposure to an advisor engaged in entrepreneurship on PhD students' innovative output lies in possible changes to the composition of incoming PhD cohorts. For example, entrepreneurial professors could deliberately pick students based on their suitability for commercial activity. These students may then already be relatively less oriented towards academia before starting their PhDs. This could explain any negative outcomes in relation to publishing activity or academic career paths I find. In turn, students with relatively "lower academic quality" or more commercial orientation could pick entrepreneurial professors over other more academically orientated professors thereby biasing the results with regard to commercially oriented output such as patents upward.

To address this, I examine what factors determine the match between PhDs and their specific advisors using all professors present at entry of a student in the advisor's department as the group of potential advisors. Here, I apply both student and professor fixed effects and interact a professor's entrepreneurial experience prior to a student's entry with a host of student characteristics. The findings suggest that a student's academic quality, nationality, and prior work experience does not determine the match with an entrepreneurial professor.

In addition to compositional changes, the timing of a professor's entrepreneurial activity may be confounding the main results. To control for the potential endogeneity of a professor's transition into entrepreneurship, I apply an instrumental variable approach (IV). The instrument I use is the cumulative likelihood that a professor becomes a founder, which I predict using the amount of venture capital (VC) investments by field-year. Following this approach, the instrument should only influence the publication output of professors' students through its effect on commercialization while addressing the empirical context of this study. The results I ontain from the IV estimation provide suggestive evidence for a causal relationship between exposure to an advisor engaged in entrepreneurship and student publication output.

My findings indicating a negative impact of exposure to an advisor engaged in entrepreneurship on students' traditional academic output also carry implications for PhDs' long-term productivity and careers. Notably, the negative relationship I find during the PhD program persists and becomes stronger after graduation. Similarly to the results for productivity during the PhD program, I do not find a consistent effect of exposure to an entrepreneurial advisor on the patenting output of students. In addition, PhD students exposed to an advisor engaged in entrepreneurship are less likely to work at a prestigious company and more likely to become founders themselves upon graduation. This effect does not hold in the long-run. In turn, in the short run, PhD students exposed to an advisor engaged in entrepreneurship are more likely to pursue a postdoc, but ultimately less likely to ever become professors.

In this paper, I further explore several possible mechanisms that could explain my main findings. One potential avenue could be that professors' own productivity goes down as a result of entrepreneurial engagement. A further possible explanation for the results I find could be that the type (or intensity) of training students receive once their advisors transition into entrepreneurship changes and shifts away from traditional output channels. It is also feasible that students exposed to entrepreneurial professors are less productive during the PhD program because of organizational changes made to the lab. Taken together, the results I present suggest that the latter is more likely the case. For one, examining professors' publication and patenting output I find only a slight decrease in the publication output of professors' several years after they start their companies and an increase in patenting in the years around the time of founding.[2] Second, publication output and long-run academic

[2] I can also confirm previous findings that professor-founders are among the more productive in their respective departments (Agrawal and Henderson, 2002; Zucker et al., 1998, 2002; Toole and Czarnitzki, 2010; Higgins et al., 2011).

career trajectories are most affected by exposure to an advisor engaged in entrepreneurship, whereas patenting output is not. Third, I do not detect changes in advisors' mentoring scores, but instead find some indication for managerial changes by exploring possible boundary conditions. I thereby contrast the main results from the fields of computer sciences and engineering with the context of more basic sciences. Students in the basic sciences tend to be more autonomous and rely less on the overall management of their corresponding labs for the production of output throughout the PhD process. Therefore, if managerial changes are indeed plausibly driving the results, I would expect an advisor's impact on student's productivity to be weaker. My findings support this explanation.

In sum, this paper takes an important step towards understanding how advisors engaged in commercial entrepreneurship affect their advisees innovative productivity and provides insights on implications for advisees' career outcomes. Given the empirical setting, I specifically highlight potential consequences of academic entrepreneurship affecting innovative output from universities and the productivity of future innovators. These findings may also be extended to similar situations outside of academia where employees are faced with a conflicting multi-task incentive regime (Hellmann, 2007). As such, this study speaks both to the literature at the intersection of academic science and commercial activity (Dasgupta and David, 1994; Owen-Smith and Powell, 2001; Stuart and Ding, 2006; Shane, 2004; Murray, 2010; Azoulay et al., 2017; Rothaermel et al., 2007; Zucker et al., 2002), as well as to the body of research examining human capital development and the subsequent implications for the rate and direction of inventive activity (Agrawal and Henderson, 2002; Lerner and Stern, 2014; Nelson, 2015).

This paper is structured as follows. In the next section, I provide a brief overview of the existing literature. Section three describes the data sources. The fourth section lays out the empirical estimation strategy and main results. I then discuss potential mechanisms and limitations concluding with a section where I deliberate implications and opportunities for future research.

4.2 Background

Besides the widely recognized positive aspects of entrepreneurship, important trade-offs with regard to entrepreneurial engagement exist that may carry negative consequences for overall productivity and innovation (Campbell et al., 2012). For example, incentives for entrepreneurship could be in conflict with employees' incentives to complete core job tasks (Hellmann, 2007). This situation could then possibly lead to underinvestment in innovation and/or the execution of employees' main responsibilities. In the case of supervisors, the execution of their core responsibilities has been found to have strong implications for their own and their subordinates' productivity (Bloom, 2013). These tasks include human resource management (e.g., recruitment, mentoring, training), work allocation, as well as monitoring (e.g., quality control), which could be impacted by a supervisor's engagement in entrepreneurship and may, therefore, potentially entail important changes to the output produced by both supervisors and subordinates.

One context that provides a suitable setting to examine if and how a supervisor's engagement in entrepreneurship may affect their subordinates innovative productivity is academia. This is provided that within academia conflicting demands and goals exist, multiple stakeholders are involved, and fine-grained proxies for individuals' ability as well as information on innovative activity is available (Fini et al., 2019). In what follows I focus on presenting more background on the relevant literature for the context of this study.

4.2.1 Commercialization and Academia

In the case of academia, a long standing stream of literature has provided evidence for the impact of the inventive output from academic research on productivity growth in the economy and its role for stimulating greater private sector R&D through knowledge spillovers (Jaffe, 1986; Lach and Schankerman, 2008; Audretsch et al., 2006; Shane, 2004). Predominately, inventive output from academia is transferred to the public domain via publications. However, over the past decades, the traditional scope of academia has expanded to include more commercially oriented channels, such as patents and new ventures, which have increased dramatically in number ever since (Acs and Audretsch, 1990; AUTM, 2017).

To date, most research examining faculty engagement in commercialization has focused on understanding why professors get involved in commercial activity, the characteristics of those professors who do and what the implications of commercialization are for professors' own innovative output. This body of literature points out that the participation of academic professors in commercial activity is partially a response to university organizational mechanisms and public policies that shape incentives (Mowery et al., 2004; Toole and Czarnitzki, 2010; Lach and Schankerman, 2004) as well as other individual-level motives (Cohen et al., 2018). Moreover, the empirical evidence suggests that the most productive academic life scientists are those involved in commercialization (Agrawal and Henderson, 2002). Specifically in the case of biotechnology, an influential stream of research points to the fundamental role "star" scientists play in transferring new academic knowledge to industry (Zucker et al., 1998, 2002; Toole and Czarnitzki, 2009; Higgins et al., 2011). In addition, prior findings indicate that both publication and patent counts are positively related to the precise timing of when life scientists start (or join) new ventures (Stuart and Ding, 2006).

Extant research has investigated the impact of the adoption of commercial attitudes and behaviors by academic life science researchers on a number of outcomes (Louis et al., 1989; Dasgupta and David, 1994; Powell and Owen-Smith, 1998; Etzkowitz, 2003; Stephan, 2012; Stuart and Ding, 2006). These include the amount, direction and quality of publications. Some express concerns about commercial engagement of academic scientists and its potentially detrimental impact on academic research. For one, involvement in commercial activities could cause a shift in the content of scientific research and induce academic scientists to exit to industry (Azoulay et al., 2009). For another, and since faculty participation is critical to successful commercialization, this incurs significant costs straining professors' available time, energy, and other resources (Zucker et al., 1998; Jensen and Thursby, 2001; Shane, 2004; Agrawal et al., 2006; Lach and Schankerman, 2004). Others are less concerned, finding that commercialization enhances traditional scholarship (Goldfarb et al., 2009) and does not seem to detract from university knowledge production (Thursby and Thursby, 2007).

Nonetheless, what we know so far only paints a partial picture of the possible ramifications of commercial activity in academia. At this point, we must acknowledge that within academia, professors are not the only producers of knowledge, but rely heavily on their lab members. This reliance on lab members is especially pronounced in more applied fields of research. Here, in most cases, professors head their own laboratories as principal investigators (PIs) with PhD students representing the majority of their lab members.[3] Given their role as lab heads, professors largely determine the everyday tasks of their students and, given their roles as educators, also largely determine what their students learn. Professors frequently interact and work together closely with their PhD students in day-to-day activities thereby strongly influencing the research trajectories of their advisees.[4]

Although substantial interest has been paid to professors' publication and patenting output, the literature on the impact of faculty engagement in entrepreneurship on their PhD students remains sparse. Intuitively, there are likely to be heterogeneous effects both positively and negatively impacting student outcomes. For example, as pointed out by Powell and Owen-Smith (1998), entrepreneurial engagement could weaken the traditional academic and education mission of professors thereby negatively impacting the academic training students receive. Exposure to an advisor engaged in entrepreneurship could also bolster students' outcomes, especially their future ability to commercialize knowledge

[3] Working as research assistants in labs is the predominant way PhDs fund their graduate studies in Computer Sciences and Engineering. In fact, taking numbers from the 2016 Survey of Earned Doctorates, roughly 80 percent of all doctoral recipients in engineering were funded by a research assistance or research grants (National Science Board, 2018). The remaining 20 percent were teaching assistants or relied on other sources of funding.

[4] In contrast to the relationship PIs have with their postdocs, the relationship with PhD students is far more developmental requiring larger investments from the advising professor.

and career prospects in industry. But, it is also possible that a professor's engagement in entrepreneurship does not affect students at all if the additional task of starting a company does not take away resources that would have been spent training students (Thursby and Thursby, 2007) or change a professor's direction or quality of research. From this, it is not clear *ex-ante* to what extent professors alter the inventive output and career prospects of their graduate students both in academia and industry by starting entrepreneurial ventures. As such, the main guiding question of this study can be stated as: *Does exposure to an advisor engaged in entrepreneurship affect advisees' innovative output and career trajectories?*

Besides getting a better understanding of if exposure to an advisor engaged in entrepreneurship affects students' innovative output, and more specifically what type of output it affects, it is crucial to shed light on the possible channels through which this could occur. For one, it could be that advisors change their own direction of research and amount of output as a function of entrepreneurial activity. As members of the lab and co-authors, students may then too experience a reduction in their output. Another potential way an advisor's engagement in entrepreneurial activity could affect their students, is via a change in the type (and intensity) of training students receive once their advisors transition into entrepreneurship. These differences in training could have long-term implications for students' innovative outcomes and career trajectories. Recent studies highlight that young scientists adopt their advisors' orientations toward commercial science (Azoulay et al., 2017) and that the commercial orientation of the institution an individual was trained at determines the likelihood of an individual's future adoption of technology transfer practices (Bercovitz and Feldman, 2007). If this explanation is driving the results, then we should perceive that exposure to an entrepreneurial professor increases patenting persistently, industry employment, and a student's likelihood of becoming a founder.

An additional channel through which an advisor's engagement in entrepreneurial activity could affect their students, is via adjustments to the organizational structure of a professor's lab resulting in changes to the quality and stock of innovative output students produce during the PhD program. Especially in engineering, students rely heavily on the distribution of work by their advisors and their output is, therefore, strongly linked to their advisors' lab management. Consequently, changes in, e.g., the size of the lab could explain differences in student productivity.

Either explanation could have a persistent impact on students' post-PhD productivity and lead to fundamental alterations in a student's starting conditions when entering the job market, such as the characteristics of the first position they can secure. These differences could then translate into important changes in long-term job characteristics and research productivity of recently minted PhDs. As suggested by research examining the starting conditions of students entering the job market, both the quality and type of an individual's first job have a causal effect on long-term job characteristics. For instance, using data on economics PhDs, Oyer (2006) finds that better initial placement increases long-term research productivity. Exploiting an extensive university-employer-employee dataset, Oreopoulos et al. (2012) provide evidence that the effects of negative starting conditions persist up to ten years. As such, any productivity differences detected during the PhD program should persist or even become stronger over time.

4.3 Data Construction

To address the research question, I compiled a unique data set using rich administrative information from various sources. The core information on the sample underlying this study is based off confidential data provided to us by the research university examined. The research design was approved by the university's Institutional Review Board. Consent of subjects was not required by the IRB and records of all subjects were anonymized prior to analysis.

For the purpose of this study, I focus on the colleges of computer sciences and engineering covering a total of eight distinct fields. Aerospace Engineering (AERO), Biomedical Engineering (BIOMED), Chemical & Biomolecular Engineering (CHEME), Civil Engineering (CIVIL), Electrical and Computer Engineering (ECE), Computer Sciences (CS), Mechanical Engineering (ME), and Materials Science and Engineering (MATERIALS). Three reasons why I select these areas are, a) to exploit across-field diversity, b) because these areas produce the majority of doctoral recipients (with the strongest upward growth trend (National Science Board, 2018)), and c) provided that most entrepreneurial activity that is based on scientific discoveries and is research intensive originate from these fields (Agrawal and Henderson, 2002; Goldfarb et al., 2009).

In what follows, I will describe the precise data sources accessed to construct the dataset and the extent of coverage I was able to attain. I base the sample of professors from information provided to us by the Office of Faculty Affairs. The initial sample consists of 1,053 professors who were faculty at the focal research university between 2001 and 2017. For all of these professors I have access to detailed demographic information including age, nationality, gender, ethnicity, as well as, department affiliations, and tenure milestones. In addition, I collect data on professors' publication output from Scopus (*scopus.com*), and retrieve information on patenting from the USPTO Patentsview Patent Database (*patentsview.org*). I further gather information on professors' amount of NSF and NIH funding from each foundation's/institution's respective website. Details on the entrepreneurial activity of professors' was provided by the university's business outreach organization. I was also granted access to professors' teaching evaluation scores from the institute.

The base sample of PhD students (5,722) was provided to us by the university's Office of Enrollment. For all of these students, I have access to detailed demographic information including age, nationality, gender, ethnicity, as well as, department affiliations, majors, year of admission, graduation, their prior degree granting institutions, level of degree attainment as well as standardized test scores and incoming GPAs. Of these students, 2,980 completed the PhD program. Based on the official advisor recorded at the Office of Enrollment, I match students to their advisors. As I proceeded with professors, I also collect information on each student's publication output from Scopus (*scopus.com*), and retrieve data pertaining to patents from the USPTO Patentsview Patent Database (*patentsview.org*).[5] I additionally classify students' previous degree granting institutions based on the World Academic Ranking of Universities (*shanghairanking.com*) where I denote a university as high quality if it is under the top 50 in a student's field of enrollment. I restrict the sample that I analyze to those students entering the PhD program between 2001- 2013 in order to track post-PhD career outcomes and to ensure comparability of the results across models. In order to address my research question, I further search for students' CVs on LinkedIn. For those who do not have a LinkedIn profile, I conduct extensive searches on the web using secondary sources such as university and company websites, publication and patent affiliations, CrunchBase and Bloomberg. Overall, I was able to attain career information for 82 percent of these students.

<Insert Table 3.1 here>

In Table 3.1 I report key descriptives for PhD students of entrepreneurial advisors only, encompassing a total of 615 students with 81 entrepreneurial advisors.[6] Of these students, 64 percent were exposed to an entrepreneurial advisor during their PhD program. The average length of exposure is 2.5 years and goes up to a maximum of 9 years. I further report the GPA and GRE scores at entry into the program. The variation in terms of GPAs is larger given that over 60 percent of the students are foreigners and GPAs outside of the US do not correspond directly to those in the US. With regard to the GRE scores, however, variation is more limited, the median quantitative score being close to the maximum attainable score. The range of students' publication and patenting output during the PhD program is wide, a reason why I log transform (log(X+1)) these variables in my subsequent analyses. I was able to find CV records for over 85 percent of entrepreneurial advisors' students.

[5] I define publications as highly-cited if the citation count of a publication (including articles and conference proceedings) is above the median of the type of publication published at the same department in the same year.

[6] Please refer to Appendix A1, for a comparison of students by type of advisor and to A2, for summary statistics of all professors and all professors with at least one patent or who are founders. Looking at the means, students of advisors who ever become founders have better performance on average.

Figure 3.1 displays the innovative output of professors at the research institute I examine (the square denotes the mean). Over time, although there has been variation in the range of publication and patenting output of individual professors, the university average has remained stable. Note that the university I examine has consistently ranked nationally among the top 5 most innovative public (top 20 overall) research universities.[7]

<Insert Figure 3.1 here>

Figure 3.2 depicts the number of faculty founders at the research university by year from 2001 - 2017. There is strong variation in the amount of startups created in each year. Overall, there are 100 unique founders who founded 128 startups.

<Insert Figure 3.2 here>

In Figure 3.3, I display the innovative output of professors at the research institute I examine, contrasting entrepreneurial and non-entrepreneurial professors. As shown, entrepreneurial professors tend to produce more patents, citation-weighted patents, publications, and highly-cited publications.[8]

<Insert Figure 3.3 here>

4.4 Estimation Strategy and Results

4.4.1 The Ideal Experiment

What would be the best way to examine the effect of exposure to an entrepreneurial professor on students' innovative outcomes? At this stage, a thought-experiment may be useful to highlight potential threats to identification. Ideally, in order to analyze the effect of advisors' entrepreneurial activity on their PhD students' innovative and career

[7] *https://www.reuters.com/article/us-amers-reuters-ranking-innovative-univ/reuters-top-100-the-worlds-most-innovative-universities-2017-idUSKCN1C209R*

[8] In the Appendix, Figure A3.1, I report the distribution of number of startups per founder.

outcomes I would run a randomized control trial (RCT). This would entail the random assignment of entrepreneurial activity to professors as well as the random assignment of students to professors. As such, professors would not select into entrepreneurship based on their characteristics, nor would simultaneously occurring events influence this decision. The random assignment of students further ensures that the composition of student characteristics within a lab following the transition to entrepreneurship does not change allowing the researcher to cleanly estimate the effect of exposure to entrepreneurship on student outcomes. Although, a RCT would solve this type of identification problem, it is infeasible to implement given this would strongly interfere with individuals' lives. Nonetheless, this thought-experiment highlights several major threats to identification: omitted variable bias, and selection.

4.4.2 Threats to Identification

In terms of the first threat, omitted variable bias, any results I find could be driven by specific features of the advisors (or students) that the econometrician cannot observe. For example, those professors who transition into entrepreneurship may be different from other professors along certain dimensions such as ability, personal traits (e.g., related to taking initiative and exercising leadership (Feldman et al., 2019)) and social skills (that could give them a competitive edge in fundraising, or networking). If these traits also induce latent entrepreneurial professors to be different advisors (e.g., in terms of training quality) than those professors who never transition into entrepreneurship, these traits may mask the true impact engagement in entrepreneurial activity has on students.

The second major challenge to identification relates to possible changes in the composition of PhD students professors advise once they transition into entrepreneurship. For example, entrepreneurial professors could deliberately pick students that fit the demands of their startup/commercial interests and may already be relatively less suited for academia before starting their PhDs.[9] In turn, students less interested in an academic career or who are more commercially orientated could pick entrepreneurial professors over other more academically orientated ones. If this is the case, then there may be a negative relationship between exposure to an advisor engaged in entrepreneurship and innovative output transmitted through traditional "academic" channels (publications) and careers as well as a positive effect on more commercially oriented output (patents) and careers (industry) given the initial advisor-advisee selection rather than treatment.

4.4.3 Addressing Threats to Identification and Results

Given that running the ideal experiment laid out earlier is not a feasible option, I take a step-by-step approach towards addressing the major threats to identification. In what follows, I first describe each step, then display and discuss the results.

Student-level Outcomes During the PhD Program

In this section, I turn my focus to the student-level and examine students' aggregate innovative and career outcomes produced during the PhD program. To deal with concerns of omitted variable bias, I implement a professor fixed effects approach (and include professor-year trends). Doing so, enables me to keep unobservable features of individual advisors, such as ability and social skills constant. Advisors' advisees should be equally affected by these unobservable factors. In order to focus the analyses on the relevant population of professors, I restrict the sample to those professors who are potentially at risk of becoming entrepreneurs. These are professors who have either ever applied for a patent, are founders, or both. The equation I estimate on the student level (s) is displayed below, where f_p represents advisor fixed effects, f_t represent start-year fixed effects, $f_{p,t}$ captures professor-year trends (the year used is a student's year of entry), f_m stands for a student's major, and $\epsilon_{s,p,t,m}$ is the error term. Standard errors are clustered on the advisor level to account for intra-group

[9] Anecdotal evidence from interviews suggests that these are not factors advisors consider when selecting students.

correlation.

$$I_{s,p,m,t} = \alpha EXPOSURE_{s,p} + f_p + f_t + f_{p,t} + f_m + \epsilon_{s,p,t,m} \tag{3.1}$$

In equation (3.1), $EXPOSURE_{s,p}$ is the main independent variable of interest which I measure in different ways: a) using an indicator equal to one denoting if a student was ever exposed, b) using the number of years exposed to an entrepreneurial professor, and c) using the number of years exposed to an entrepreneurial professor divided by the duration of the PhD program. The outcome variable $I_{s,p,m,t}$ refers to the innovative output of a student *s* during the PhD program.[10] These outcomes are the total amount of patents, citation-weighted patents, publications, and highly-cited publications.[11]

<Insert Table 3.2 here>

Table 3.2 displays the results from estimating equation (3.1). In *Panel A*, I report student outcomes using an indicator equal to one if a student was ever exposed to an entrepreneurial advisor during the PhD. In *Panel B*, I report student outcomes using a continuous measure of years exposed to an entrepreneurial advisor. *Panel C*, displays outcomes using relative exposure (continuous measure of exposure divided by PhD duration). Over all specifications, I find that exposure to an advisor engaged in entrepreneurship is associated with negative publication outcomes, and do not find a consistent impact on patenting outcomes.[12,13] Taking

[10] I measure PhD student outcomes using a five year time window from entering the PhD program, which represents the average and median PhD duration and accounts for publication time-lags. I provide a graph in the Appendix, Figure A3.2, displaying the average duration of a PhD.

[11] In the Appendix, Table A3.3, I report outcomes from estimating a model without professor-year trends, but including student and professor controls. These are a professor's publication stock in the five years prior to entry, the number of student in a lab at entry of student, rank and age (log) to control for time-varying characteristics of a professor ($ProfessorCONTROLS_{s,t}$). The $StudentCONTROLS_s$ I include are gender, ethnicity, nationality, GRE scores, and indicators for students' previous degree level. Table A3.4 reports the results from estimating equation (3.1) but log transforming the outcome variables using the inverse hyperbolic sine (IHS) transformation of each outcome ($\ln(I_{s,p,m,t} + ((I_{s,p,m,t}{}^2 + 1)^{0.5})))$). Similarly, Table A3.5 reports the results from Table A3.3, but with IHS transformation.

[12] In the Appendix, Table A3.6, I report the results for the amount of first-authored publications produced by students.

[13] In the Appendix Figure A3.3, I report the results from estimating the model including professor fixed effects and professor-year trends using binned scatterplots. To generate a binned scatterplot, the x-axis variable

the coefficients reported in *Panel A*, the results suggest that exposure is associated with a decrease from the median of slightly more than two publications and one highly-cited publication during the PhD program. For further robustness, I estimate the same equation, but excluding those students always or never exposed. The results, as displayed in the Appendix, Table A3.7, remain similar.

Next, I examine differences in PhD students by estimating their aggregate outcomes depending on students' precise graduation date. In Figure 3.4, I visually depict the relationship between exposure (the x-axis indicates how many years of exposure; negative values indicate how many years before founding a student graduated from the program) and students' inventive output (y-axis; all outcomes in log).[14] The omitted category is a graduation date 7 or more years prior to founding, the values -6 and 6 capture students who graduated 6 years before and 6 or more years after the founding date. The results are obtained using professor and year fixed effects, professor-year trends as well as controlling for a student's major and program duration.[15] I cluster standard errors on the advisor level. 95 percent confidence intervals are displayed.[16]

<Insert Figure 3.4 here>

The results support the previous findings that exposure to an entrepreneurial advisor has a negative impact on PhD students overall publication and highly-cited publication output, but does not seem to impact their patenting productivity as much until the cohort graduating 6 or more years post-founding year. With regard to publication output there is a perceivable

is first grouped into equal-sized bins. Next, the mean of the x- and y-axis variables within each bin is calculated. These data points are then displayed in a scatterplot, the so called binned scatterplot. I obtain the linear fit line using OLS and additionally include a control for the student's major.

[14]In the Appendix, Figure A3.4, I stylistically depict this approach for a student's *yearly* overall publication and highly-cited publication output. In Figure A3.5 of the Appendix, I report the corresponding outcomes of Figure A3.4 using indicators equal to one if a student had any patent, any citation-weighted patent, publication, or highly-cited publication in a given year and zero otherwise. The results remain unchanged and are similar to those using the aggregate measures over the PhD.

[15]In the Appendix Table A3.8, I present coefficients obtained from using this approach but using students' yearly outcomes. I report the outcomes for patenting using an indicator equal to one if a student had a) a patent, or b) a citation-weighted patent given that there is little difference to the total amount. Publication outcomes are reported in log.

[16]I report the equivalent graph for first-authored publications in the Appendix, Figure A3.6.

drop starting three years prior to the founding date. The results do not seem to differ from the omitted category - seven or more years prior to founding - six, five, and four years prior to founding.[17]

Professor-Student Matching

The previous set of results I report deal with certain issues pertaining to omitted variable bias on the side of professors. Nonetheless, the concern still remains that the type of students joining an advisor's lab could be changing as a function of professors' entrepreneurial activity. To address this type of sorting, I first collect information from the PhD program coordinators of Mechanical Engineering and Chemical & Biomolecular Engineering on how their schools organize the matching process. In the time-span I examine (there have been changes in more recent years), students centrally apply to the program and not to a specific advisor. PhD applicants are then accepted to the school based on faculty's assessment of an applicant's grades, test scores (GRE, GPAs, and TOEFL for foreign students), and overall application package. Once admitted to the program, PhD students rotate among labs with available funding for a student in order to identify the research projects and professors that they are most interested in working on and with. Typically, before the end of the first semester, PhDs and professors have established a match.

Based on this information, I further empirically examine if the characteristics of students change with an advisor's entrepreneurial engagement. I thereby use all professors present at entry of a student in the advisor's department as the group of potential advisors. I include all students entering a PhD program regardless if they finish or not leading to an overall sample of 4,902 graduate students and 829 professors. The characteristics of students' I examine are the quality of a student's previous degree granting institution, a student's incoming GPA, GRE scores (log), nationality (equal to one if the student is a US citizen), and previous work experience, which I interact with an indicator equal to one if a professor started a company

[17] In Appendix Section A1 and Table A3.9, I describe an inverse probability of treatment approach, which serves as robustness check to the main findings. The results are similar.

in the five years prior to a student's entry.[18] To control for the individual characteristics of both professors and students, I apply professor and student fixed effects. The results are displayed in Table 3.3.[19] As shown, the interaction of having founded a company in the five years prior to entry of a student with the different measures for student characteristics does not predict a match (on a statistically significant level of p-value$<$0.08).

<Insert Table 3.3 here>

Next, I visually examine if there are any changes in the academic quality, nationality, and prior work experience of students before and after a professor becomes an entrepreneur. To determine this, I again use GRE Scores, previous GPAs, the quality of a student's previous degree granting institution, US citizenship, and previous work experience as proxies for incoming students quality and characteristics. Here, I restrict the analyses to students of entrepreneurial advisors only. As depicted in Figure 3.5, there is no evidence that students differ in terms of their GRE scores, previous GPAs, quality of previous degree granting institution, US citizenship, or previous work experience before or after an advisor transitions into entrepreneurship. I obtain Figure 3.5 by including professor fixed effects, department fixed effects, year fixed effects and department-year trends, as well as controlling for a student's major. Standard errors are clustered on the advisor level to account for intra-group correlation.

<Insert Figure 3.5 here>

Instrumental Variable Approach

Given the previous analyses, I can reasonably rule out that sorting on available and observable quality characteristics is driving the main results. However, keeping in mind

[18] I further examine what characteristics of students most strongly predict their future publication and patenting output. The results are reported in the Appendix Table A3.10. There are differences with regard to which factors predict higher publishing and patenting productivity, the strongest being GRE scores and previous work experience.

[19] The corresponding figure can be found in the Appendix, Figure A3.7.

that the previous analyses suggest changes may already be taking place approximately three years prior to founding, the earlier results may be biased if latent characteristics of entrepreneurial advisors that induce them to start companies also make them less productive advisors as measured by their students' output. To address such potential endogeneity concerns, I apply an instrumental variable estimation approach (hereafter referred to as IV; Angrist and Pischke (2008)) on the professor-year level. In this case, an appropriate instrument to detect the causal relationship between founding and average student outcomes would have to be strongly related to founding, but have little impact on a professor's average student outcomes.

The instrument I identify for the purpose of the analyses is the number of VC investments ($VC_{d,t}$) into a professor's field by year (Goldfarb et al., 2009). The rationale is that year by year changes in VC flows should reflect changes in the perceived relative returns to starting a company. Albeit, individual scientists are unlikely to be aware of the precise amount of VC investment made in a year, the amount of VC investment is plausibly correlated with the information flows that influence beliefs about the potential returns to starting a company. Given that when new and promising areas appear, VC flows towards it (Gompers and Lerner, 2004), the amount of VC investment is likely to capture demand for commercial innovation. Other than through shaping individuals' beliefs about returns to entrepreneurial investment it should not affect the publication output of an advisor's students.[20]

The analyses, however, require a further step than traditional IV approaches given that, although transitioning into entrepreneurship is time-variant, the regime of entrepreneurial activity I have identified is a step function. In other words, I am contrasting outcomes before and after an advisor becomes entrepreneurial (step-function), but the identified instrument can only help us predict the timing of founding and not necessarily the impact in the years once turned entrepreneurial. To address this potential issue, I instead use the

[20]Since VC investment may impact patenting behavior similarly to entrepreneurial behavior, the exclusion restriction with regard to patenting output is likely violated, which is why I exclude patenting as an outcome from the analyses.

initial instrument - the amount of VC funding in the year prior - to predict the likelihood that an individual founded in time *t*. Following Goldfarb et al. (2009), I collect information on the total amount of VC funding by field and year using PWC's Moneytree report (*pwc.com/us/en/industries/technology/moneytree.html*) to construct this measure. I then estimate the likelihood of founding in a given time *t* applying professor, year and department fixed effects. Taking the rolling sum of these predicted values, I create a measure capturing the cumulative likelihood of founding a company in each year and use this value as the instrument in the first stage.[21] Following this approach, the constructed instrument (*Cuml.likelihood of founding*) should predict the post founding period (*found*), but should not be correlated with the error term in the second stage. From this, the first stage I estimate is as follows:

$$Found_{p,t} = \alpha \textit{ Cuml.likelihood of founding}_{d,t} + \mathrm{f}_p + f_t + \omega_{p,t} \tag{3.2}$$

Where $\omega_{p,t}$ is the error term, $Found_{p,t}$ is an indicator equal to one denoting the post-founding period, f_p are professor fixed effects, and f_t year fixed effects.[22] I cluster standard errors on the professor-level.[23]

I instrument the predicted value of $FOUND_{p,t}$ $(\widehat{Found_{p,t}})$ from the first stage in the following equation:

$$AvI_{p,t} = \alpha FOUND_{p,t} + f_p + f_t + \epsilon_{p,t} \tag{3.3}$$

where $\epsilon_{p,t}$ is the error term, and $FOUND_{p,t}$ is an indicator equal to one denoting the post-founding period. I further include year fixed effects (f_d) and cluster standard errors on the professor level. The results from the IV approach are estimated on the professor-year

[21] Similar to Sampat and Williams (2019), I use a different sample - restricting to founders and patenters only - in the IV estimation model.

[22] Department/field fixed effects are captured by professor fixed effects

[23] In the Appendix, Figure A3.8, I display the relationships exploited for the instrumental variable approach using binned scatterplots (20 bins, mean average): the likelihood of founding in a given year as a function of the amount of VC investment (log) in a professor's field one year prior, and the relationship between founding and the cumulative likelihood of founding.

level using each advisor's students' average innovative output produced within a 5 year time window from t ($AvI_{p,t,d}$) as the outcome variable. These outcomes are the average publications, and highly-cited publications their students have.

Each step taken in this estimation approach and the corresponding results are displayed in Table 3.4. Generally, the instrument passes the rule of thumb for a sufficiently strong instrument with *F-statistics* of over 18. Compared to the OLS results displayed in columns 1 and 2, the IV results in columns 3 and 4 are roughly four times the size.

<Insert Table 3.4 here>

Three possible reasons why the magnitude of the coefficient on $\mathbb{1}(Found_{p,t})$ is larger in the IV than in the OLS model are that a) the exclusion restriction is violated, b) there may be reverse causation, or that c) the results reflect a much larger local average treatment effect than an average treatment effect. I cannot, empirically, rule out that the exclusion restriction is violated and the estimation relies heavily on the assumption that the amount of VC funding only affects publishing output via its effect on founding. With regard to reverse causation, it may be that the findings are driven by changes in the behavior of students and not their advisors. This type of reverse causality would imply an effect of entrepreneurial students on their advisors' innovative outcome rather than an effect of professors on their students.[24] Viewing the third explanation, it is possible that the IV is shifting the "behavior" of a subgroup of students for which the negative impact of their advisor's engagement in entrepreneurship are larger than average. If the local average treatment effect is larger than the average treatment effect, it is plausible that IV estimates are larger than OLS estimates because of heterogeneity in the sample I am analyzing. One type of heterogeneity could be,

[24]In the Appendix, Table A3.11 and Figure A3.9 I provide robustness checks to address the concern that life-cycle effects could be driving the results. I first provide OLS results where I interact an indicator equal to one for post-founding period with an indicator equal to one if the professor was 50 years old or older at founding (the 43 is the mean age at founding). The results are displayed in Table A3.11. The main effect remains unchanged although the interaction coefficient seems to indicate that older professors can mitigate the negative main effect. Figure A3.9 in the Appendix, displays the results from estimating the hazard of becoming a founder by age using a Cox Proportional Hazard Model. From these results, it seems that there is no clear age that predicts founding a company.

for example, lab size. As shown in Table 3.5, when I interact lab size (proxied using the number of students in a given lab in a given year) with the post-founding period (*Found*), the magnitude of the main effect more than doubles (the main effect of lab size is negative). This may indicate heterogeneous effects of founding depending on the size of a lab.

<Insert Table 3.5 here>

Student-level Outcomes After Graduation

Starting conditions at entry into the labor force have been found to have long-term consequences for individuals' careers and scientific output (Oyer, 2006; Oreopolous et al., 2012). In this section, I examine if and to what extent being exposed to an entrepreneurial advisor has similar persistent effects on students' post-graduation productivity and their subsequent careers. The outcomes I examine are the amount of patents, publications, and highly-cited publications a student has within 1-5 years from graduation. I estimate equation (3.1), including indicators for the type of first job (academia and lab, industry is the omitted category) since this may have consequences for the type of output produced, and include professor, and start-year fixed effects as well as professor-year trends and control for the student's major.

<Insert Table 3.6 here>

Table 3.6, *Panel A*, displays the results for post-graduation outcomes. As shown in columns 2 and 3 exposure to an advisor engaged in entrepreneurship during the PhD is associated with a stronger negative effect on overall amount and quality of publication output after graduation than during the PhD. Conversely, as reported in column 1, there does not seem to be a persistent effect on patenting output. In *Panel B*, I estimate the same models and add the amount of publications and patents (both log) students produce during the PhD program to gauge how much of the post-PhD program effect could be driven by students' productivity during the PhD. Across all specifications, the magnitude of the exposure coefficients is smaller (maximum change is a 32 percent decrease) and the

R-squared is much larger in *Panel B* (maximum change is roughly 55 percent), suggesting that productivity during the PhD has a relevant impact on post-PhD productivity.

Next, I examine if and to what extent being exposed to an advisor engaged in entrepreneurship affects the type and characteristics of a student's first position. Before describing the estimation approach, a brief overview of the possible career paths available for PhD students in Computer Sciences (CS) and Engineering is warranted. Upon graduation PhDs have three broad choices of employment type: academia, industry, national labs/government. The positions they pursue include from working as a R&D scientist or as consultants in industry, or as faculty, research technicians or postdocs in academia. Typically the postdoc is viewed as a necessary step towards becoming faculty in Science & Engineering areas (although there are important field differences and starting as faculty is possible) and can be completed at a host of different research institutions including national labs. Taking numbers from the 2016 Survey of Earned Doctorates, roughly 14 percent of Engineering graduates (30 percent CS and Mathematics graduates) who had plans to stay in the US post-graduation reported definite non-postdoctoral academic employment commitments, whereas 35 percent (30 percent CS and Mathematics graduates) reported commitments to pursue a postdoc (National Science Board, 2018). The type of position a PhD obtains also has important implications for their salaries. Again using information from the 2016 Survey of Earned Doctorates, the median basic annual salary of a newly minted PhD graduate in Engineering (CS) was around US$100,000 (US$122,000) in industry, approximately US$80,000 (US$70,000) in academia, and in the vicinity of US$47,000 (US$59,000) as a postdoc (National Science Board, 2018).

To provide insight on the impact of engagement in entrepreneurship on students' career outcomes, I estimate an OLS model applying professor, major, and start-year fixed effects and relate these to the likelihood of finding a first position in Academia/Lab, Industry or as a Founder. The sample includes students of professors who ever were founders or patent-holders. As displayed in the uneven-numbered columns of Table 3.7, the results suggest a reduction in the likelihood to find a first position in industry (24 percent decrease from the mean) and an increase in the likelihood of becoming a founder (over 400 percent increase from the mean). Academic careers do not seem to be impacted by exposure to an entrepreneurial advisor indicating that preferences to pursue an academic career may not be changing. In the even-numbered columns I include measures capturing the amount of highly-cited publications and patents (both log) a student produced during the PhD program and also include their Quantiative GRE scores as well as start-year, major and professor fixed effects. Including these variables does not greatly change the magnitude of the coefficients. However, these results suggest that publication output during the PhD predicts finding first employment in Academia/Lab, and is negatively associated with finding first employment in Industry.[25]

<Insert Table 3.7 here>

Next, I examine if there are differences in the types of positions students obtain post-graduation using the same approach as in Table 3.7. The positions I distinguish are pursuing a postdoc (*Postdoc*), becoming a professor (*Professor*), other positions in Academia/Labs (*Other*), working at a prestigious company (*Prestigious*; as listed in LinkedIn's Top 50 Companies in 2018: *linkedin.com/pulse/linkedin-top-companies-2018-where-us-wants-work-now-daniel-roth/*) or other industry employment (*Other*). All models are obtained using OLS. The results reported in the even-numbered columns present the full model including the amount of highly-cited publications and patents (both log) students produced during their PhDs, as well as their Quantitative GRE scores. I include Quantitative GRE scores since they are a relevant factor in determining students' productivity (see Table A3.10 of the Appendix). The results are presented in Table 3.8. Here, I find that exposure to an advisor engaged in entrepreneurship is positively associated with pursuing a postdoc (columns 1 and 2) and negatively associated with working in at a prestigious company (columns 7 and 8).[26]

[25]In Section A2 of the Appendix, I present an alternative estimation approach using a multinomial logit model. Figures A10 and A11 of the Appendix display the results from this estimation.

[26]In order to detect further nuances in the quality characteristics of the positions students pursue upon

<Insert Table 3.8 here>

In addition, I examine the extent to which a student is exposed to an entrepreneurial advisor impacts the likelihood that a PhD student ever becomes a professor, ever works at a prestigious firm or ever becomes a founder controlling for the type of her first position. Table 3.9 displays the OLS models I estimate using the sample of students whose advisors ever were founders or patent-holders as well as including professor, start-year and major fixed effects. In the models reported in the even-numbered columns, I include the amount of highly-cited publications (log) and the amount of patents (log) a student produced during the PhD.

<Insert Table 3.9 here>

The results presented in Table 3.9 suggest that PhDs' likelihood of ever becoming a professor decreases by 11 percentage points for those exposed to an entrepreneurial advisor (73 percent from the mean). Conversely, exposure does not seem to have a statistically significant impact on ever working at a prestigious firm, or ever becoming a founder. Although including productivity controls does alter the magnitudes of each effect, the directionality remains the same and the statistical significance of the results are robust. Highly-cited publications, as expected, are correlated with academic career outcomes, whereas patenting output predicts long-term entrepreneurial career outcomes and Quantitative GRE scores predict working at prestigious firms.[27]

graduation, I estimate the likelihood that students find their first position post-PhD at a top university, or other university as a function of having been exposed to an entrepreneurial advisor. My results suggest that exposure to an advisor engaged in entrepreneurship does not impact the likelihood that students find their first position post-PhD at a top university.

[27] At this point it is difficult to evaluate if these changes in the distribution of students' careers is desirable or not from an overall welfare perspective. Based on previous research finding that startups founded by newly minted PhD students are also those most likely to fail (Conti and Roche, 2018; Roche et al., 2019 - WP), the overall impact could be negative given the associated loss of income/personal bankruptcies. However, experiencing failure and hands-on entrepreneurial experience could represent valuable knowledge for students' future careers. In addition, startups are considered important drivers of economic growth (Samila and Sorenson, 2011; Glaeser et al., 2015). As such, gauging the net effect requires a much more detailed analysis, which is beyond the scope of this paper.

4.5 Potential Mechanisms

In the previous set of results, I find that an advisor's engagement in entrepreneurial activity negatively affects their students' academic productivity during the PhD and seems to have persistent effects on post-PhD productivity as well as on job outcomes. What remains an open question is through which mechanisms this negative effect operates. In what follows, I explore several possible mechanisms.

4.5.1 Professor-Level Innovation Outcomes

One possible channel could be that advisors change their own direction of research and amount of output as a function of entrepreneurial activity. As members of the lab and co-authors, students may too experience a reduction in their output. To examine this potential explanation, I turn my attention to entrepreneurial professors and their respective research outcomes relative to non-entrepreneurial professors. The basic descriptives I provide in the data section, indicate that professor-founders are more productive than non-founder professors. From these graphs, however, I do not know how the time of founding relates to these outcomes. In order to shed light on this, I estimate the following:

$$I_{p,t,d} = \alpha FromFounding_{p,t} + f_{d,t} + \epsilon_{p,t,d} \tag{3.4}$$

In equation (3.4), $f_{d,t}$ represents the department-year (d,t) fixed effects and $\epsilon_{p,t,d}$ is the error term. Standard errors are clustered on the department level to account for intra-group correlation. $FromFounding_{p,t}$ denotes the time to or after founding a company. The outcome variable $I_{p,t,d}$ refers to the innovative output of professor *p* in a given year. In this paper, I use the total number of patents, the total number of citation-weighted patents, the total number of publications, and the total number of highly-cited publications a professor has in a given year as measures for innovative output. Each of these outcome variables is log transformed (ln($I_{p,t,d}$+1)).

<Insert Figure 3.6 here>

Figure 3.6 displays the results from estimating equation (3.4) in the top row, and additionally estimating equation (3.4) using professor fixed effects in addition to department-year fixed effects in the bottom row (standard errors are clustered on the professor-level). By including individual fixed effects, I can keep unobservable features of individual professors, such as ability and social skills constant. The x-axis denotes the time $FromFounding_{p,t}$, meaning that -2 indicates outcomes measured two years before, and 2 indicates outcomes two years after the founding date. The category 5 denotes all years five or more post-founding date. The omitted category is six or more years prior to start-up. A comparison of the coefficients from both models highlights that entrepreneurial professors tend to be more productive than non-entrepreneurial professors, and that their own relative publication productivity changes slightly as a function of transitioning into entrepreneurship. In the case of the total amount of publications, the drop becomes detectable four years after founding, for highly-cited publications this occurs three years after founding. This represents a roughly 20 percent decrease (approximately one publication and half a highly-cited publication), which is less than the impact on students' output. Professor's own patenting output, however, increases in the two years prior to founding until three years post-founding. Additionally, professors' citation-weighted patents increase three years prior to startup and experience a relative drop in the 4^{th} year post-founding. The differences in outcomes depending on the fixed effects applied, for one, suggest that using professor fixed effects is indeed more suitable for identifying the effect of exposure to an entrepreneurial professor. This is provided that a fixed effects approach allows us to compare within professor changes, keeping all other unobservable features of a professor constant. For another, the results in the department-year fixed effects model suggest that adverse selection with regard to founding and the timing of startup is unlikely given that, relative to other professors in their department, professor-founders' performance stays stable.

4.5.2 Training and Mentoring

Another potential channel is based on differences in the type of training students receive once their advisors transition into entrepreneurship. Given that I do not perceive changes in the patenting output of PhD students both during the PhD and in the long-run, it is unlikely that there is a shift in training at least in terms of this specific outcome.[28] However, it is plausible that there are changes towards more entrepreneurial training given the short-term career results I present. To provide more insight on possible changes in training and/or mentorship, I further examine the quality of professors' mentoring before and after they transition into entrepreneurship. To do so, I measure mentor quality using professors' graduate-level teaching evaluation scores applying both professor and year fixed effects. As displayed in Table A3.10, founding does not seem to impact mentor quality, not the number of students taught. There does, however, seems to be a negative impact on the number of graduate-level classes taught.

<Insert Table 3.10 here>

4.5.3 Organizational Changes

A further potential explanation could be that rather than receiving more commercially oriented training, the entrepreneurial engagement of a professor leads to organizational changes in the lab. These changes could then impact a professor's labs' and, therefore, each lab members' overall amount and quality of innovative output. To examine this explanation, I first analyze variation in the number of students professors advise as a function of transitioning into entrepreneurship since this could serve as one indicator for organizational change. As displayed earlier in Table 3.5, lab size does not seem to change as a function of exposure to an entrepreneurial advisor, but including this variable does

[28]In results left unreported, there do not seem to be any changes in the number of patents students apply for with their advisors suggesting that "strategic omission" of students from patents is unlikely to be driving my results.

increase the magnitude of the negative effect by over a factor of 2.[29]

Another way I may be able to infer other types of organizational changes, such as task assignment and monitoring is by exploring boundary conditions. To do so, I examine if and how the results from the fields of computer science and engineering differ in the context of more basic sciences. Qualitative interviews I conducted with PhD students in Mechanical Engineering revealed that most students are assigned their respective projects by their advisors and rarely pursue research projects independently. In contrast, students in the basic sciences tend to be more autonomous throughout the PhD process (Stephan, 2012). As such, I would expect an advisor's impact to be weaker if an advisor's reduced management of a lab are indeed driving the results.

To do so, I increase my initial sample of students and professors (additional 167 students and 24 professors) to include those advised by professors in the institute's biology or chemistry departments (basic sciences). In Figure 3.7, I report the results from binned scatterplots (15 bin, mean) distinguishing between students majoring in biology or chemistry (*Auton*=1) and those students in the main sample. Supporting my conjecture that organizational changes may constitute an important factor in explaining performance changes, the effect of exposure to an advisor engaged in entrepreneurship is weaker in the more autonomous fields (or even flips direction).[30]

<Insert Figure 3.7 here>

An additional aspect of how organizational changes can manifest themselves is in the funding structure of a lab. Given limited availability of information on funding from industry (and military), I examine federal funding (NIH and NSF) only. As displayed in Table A3.11 of the Appendix, I find that transitioning into entrepreneurship is associated with an increase in the amount of federal funding a lab receives. One possible explanation could be that once

[29] In the Appendix, Figure A3.12, I present the coefficients from estimating the number of incoming students as a function of time from founding. I obtain the graphs by including professor and year fixed effects. As displayed, there seems to be a slight drop (not statistically significant) in the number of incoming students starting in the third year prior to founding, which remains stable thereafter.

[30] In Figure A3.13, we report the corresponding results for PhD students' first-authored publications.

an entrepreneur, PIs reduce their funding ties to industry and, instead, apply for more federal funds given possible conflicts of interest or to avoid spillovers to competitors. Another explanation could be that federal funding is linked to the commercial activity of advisors. This is plausible given that one merit review criteria of the NSF, namely *Benefits to Society*, specifically evaluates the commercial potential of a proposed project. When awarding grants, it is possible that the successful commercialization of research in the form of patents or startups may thereby serve as an important signal to funding agencies increasing an advisor's likelihood of receiving federal grants.[31] Overall, federal funding (2001-2013 time-frame) does not seem to substantially change the magnitude of the negative effect of transitioning into entrepreneurship.

4.6 Limitations

The strongest limitation to this study is likely the generalizability of the findings I present since the data come from one research university only and are restricted to the university setting. There are, however, several reasons I believe this context, though unique in some ways, can apply to other similar research institutions.

For one, the sample I am studying is part of the relevant population. Over the period I examine, the focal university has consistently been ranked as one of the leading research universities and public colleges in the USA. Every year, the institute provides education to more than 25,000 undergraduate and graduate students in fields ranging from engineering, computing, and sciences, to business, design, and liberal arts. Given its high standing as an innovative top research institution, this school is a likely destination for students who want to be research active. Second, within the university itself there is a lot of variation in terms of department quality within the different colleges. Some of these are small, others among the largest in their field worldwide. Program rankings also vary strongly from number one to top 50 in the nation. Third, the school's business incubators are ranked within the top 20 in the

[31] The NSF i-Corps Program did not take off until the very end of the period I examine and as such only few professors had received this federal grant type by then.

USA, one of which is among the oldest in the country. This existing support system should, if anything make transitioning into entrepreneurship easier and reduce professors' resource constraints relative to other universities (rankings and numbers from university website). Fourth, the number of professor founders and startups emanating from the university are comparable to similarly ranked public universities (sources: Crunchbase and private VC information).

4.7 Discussion and Conclusion

This study highlights the trade-off between two different channels of knowledge transfer from universities to private firms. One is through the creation of university spinoffs, while the other is embodied by students. Incentives for faculty engagement in entrepreneurship may be shifting the attention of those professors who train the most successful future innovators away from the educational and academic mission of the university towards commercial activity. Whether this is desirable from the university's or society's perspective as a whole remains an open question.

In this paper, I focus on the effect of a professor's entrepreneurial engagement on their PhD students. Using rich administrative data, and applying multiple estimation techniques, I provide suggestive evidence that exposure to an advisor engaged in entrepreneurship may cause lower student productivity in traditional academic output channels. A likely reason for this finding is that entrepreneurial engagement of a professor is associated with managerial changes reducing lab member's overall amount and quality of innovative output. The lower productivity of students during their PhD programs seem to impact the type of jobs they can secure upon graduation and their subsequent innovative output. It may be that students are losing their competitive advantage traditionally based on a relatively more established academic track record prior to entering the workforce.

In addition to the academic setting, this paper carries implications for broader management research. As suggested by classical organizational theory, supervisors play an important role in coordinating, training, and monitoring their subordinates leading to important gains in overall productivity (Taylor, 1911). Applying these concepts to the context of science, I provide suggestive evidence that when supervisors are faced with conflicting demands and pursue multiple tasks those who seem to be affected most in terms of their productivity may be subordinates.

This article also opens several promising avenues for research. First, this study extends prior research on the potential side-effects of entrepreneurship/commercial activity by examining how this affects PhD students. To get a better understanding of if incentives to promote academic entrepreneurship are warranted, more research on examining these trade-offs is needed. Second, since entrepreneurial professors are generally those professors who perform best, this also opens up further questions with regard to the role of entrepreneurial ability in explaining a successful academic career. Third, related to this research, it is fundamental to understand if allowing and providing professors incentives to engage in entrepreneurship is necessary for personnel retention. It may well be that without this type of freedom, the most productive professors will leave academia altogether lured, for example, by higher pay or new challenges (Toole and Czarnitzki, 2010). Especially in "hot" fields where human capital is in high demand, university professors may become more susceptible to joining the private sector, which has been suggested to have an important negative impact on innovation (Gofman and Jin, 2019). One prominent example is the case of Uber and the National Robotics Engineering Centre at Carnegie Mellon University. In 2015, 40 of the center's 140 staff, left to join the taxi-hailing company (The Economist, 2016). Fourth, since I only examine one research university in this paper, future research which extends these findings to other institutions, settings, or countries may provide additional important insights.

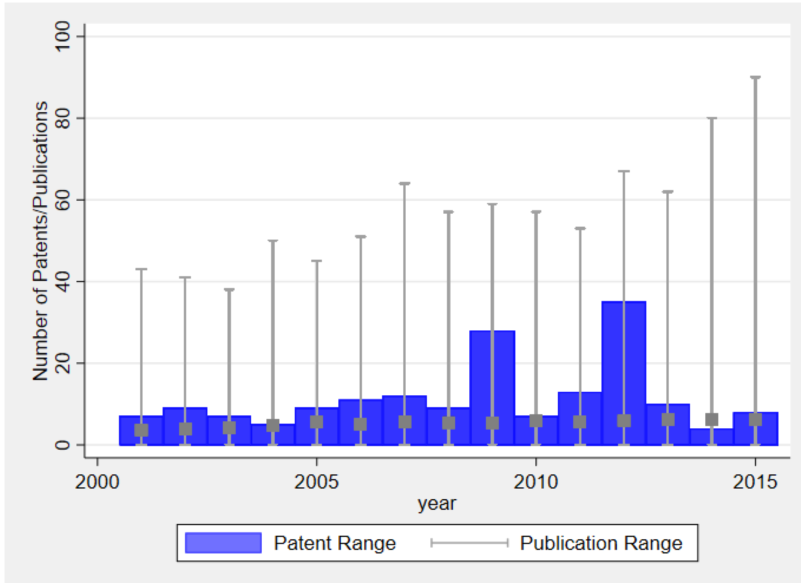


Figure 3.1: Innovative Output of Professors Over Time

Notes: This figure displays the range of patents (blue bar) and publications (gray line) produced by individual professors at the examined university by year. The gray box indicates the average for publications, the average for patents is below one in every year.

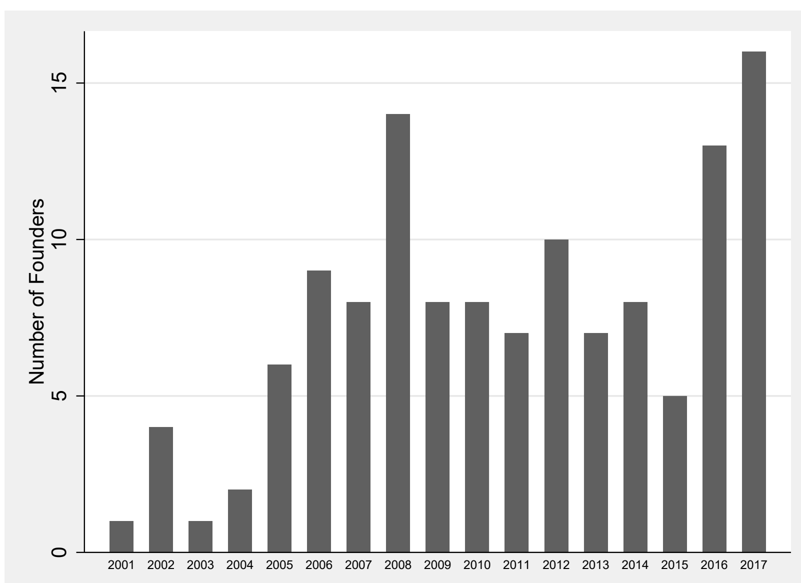


Figure 3.2: Number of Founders by Year

Notes: This figure depicts the amount of faculty founders (not unique founders) at the research university by year from 2001 - 2017.

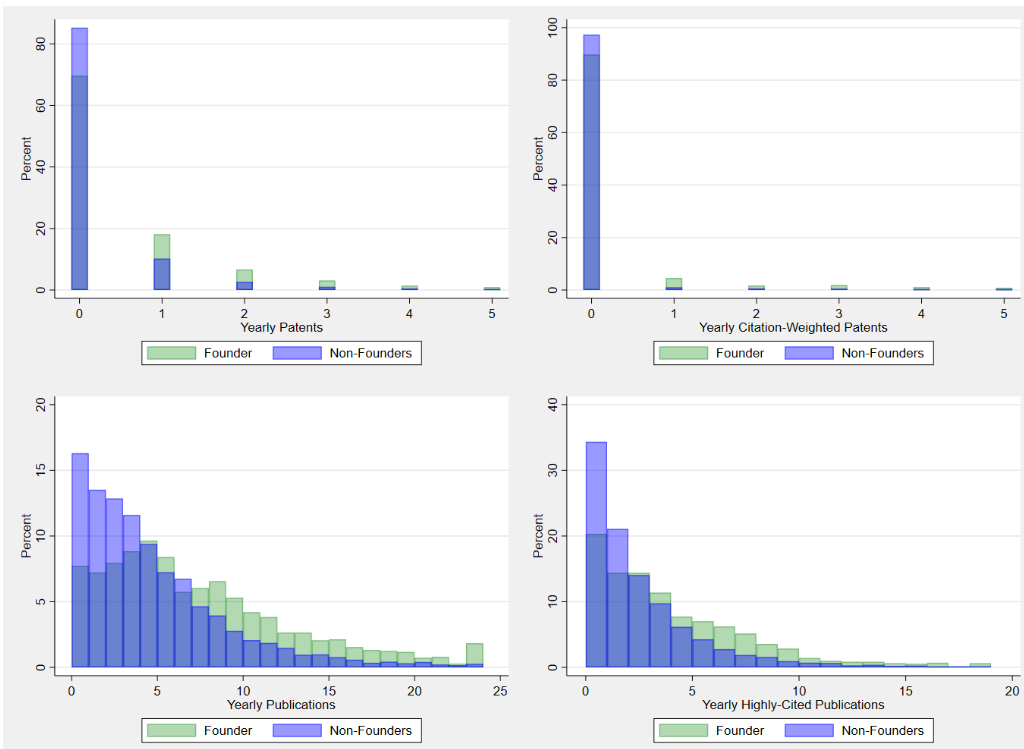


Figure 3.3: Innovative Output of Professors - By Founder or Not

Notes: This figure displays the distribution of yearly patents (top), and publications (lower) produce by all non-founder professors (blue) vs. professor-founders (green).

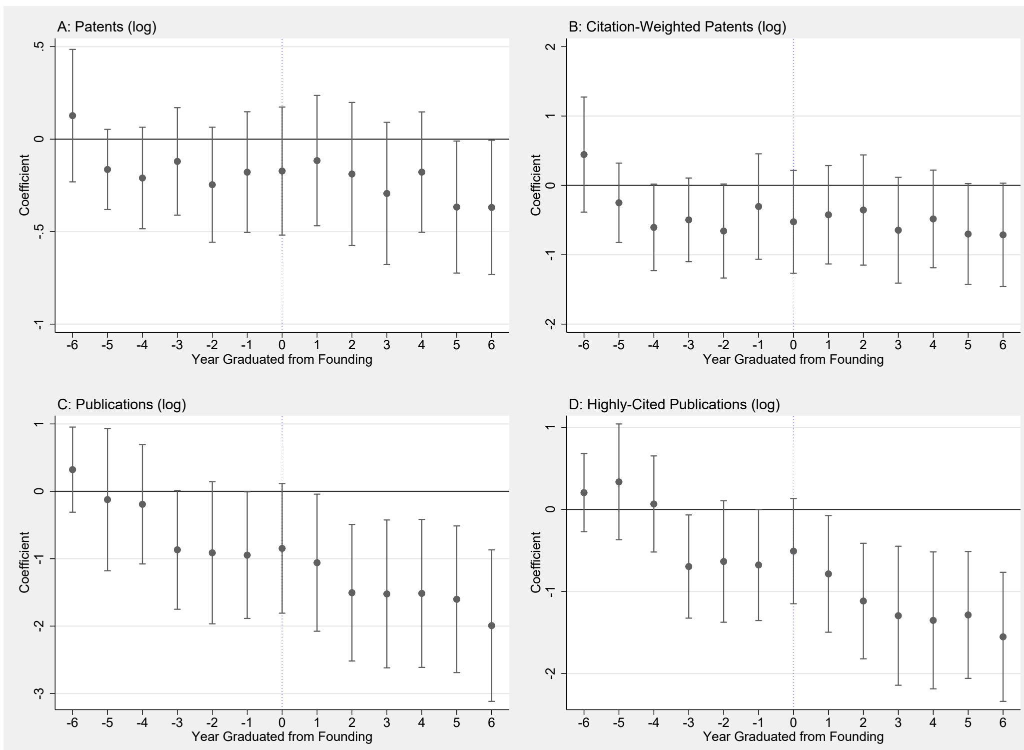


Figure 3.4: Yearly Outcomes for Students by Time of Graduation from Founding

Notes: In this figure, I visually depict the yearly outcomes of PhD students (the x-axis indicates the time a student graduated relative to the time of founding; negative values indicate how many years before founding a student graduated from the program) and students' inventive output (y-axis represent coefficients; all outcomes in log). The omitted category is 7 or more years prior to founding, the values -6 and 8 capture students who graduated 6 years before and 8 or more years after the founding date. The results are obtained using professor fixed effects, start-year fixed effects and professor-year trends as well as controlling for a student's major. The dashed vertical lines indicate the time of founding. I cluster standard errors on the advisor level. 95 percent confidence intervals are displayed.

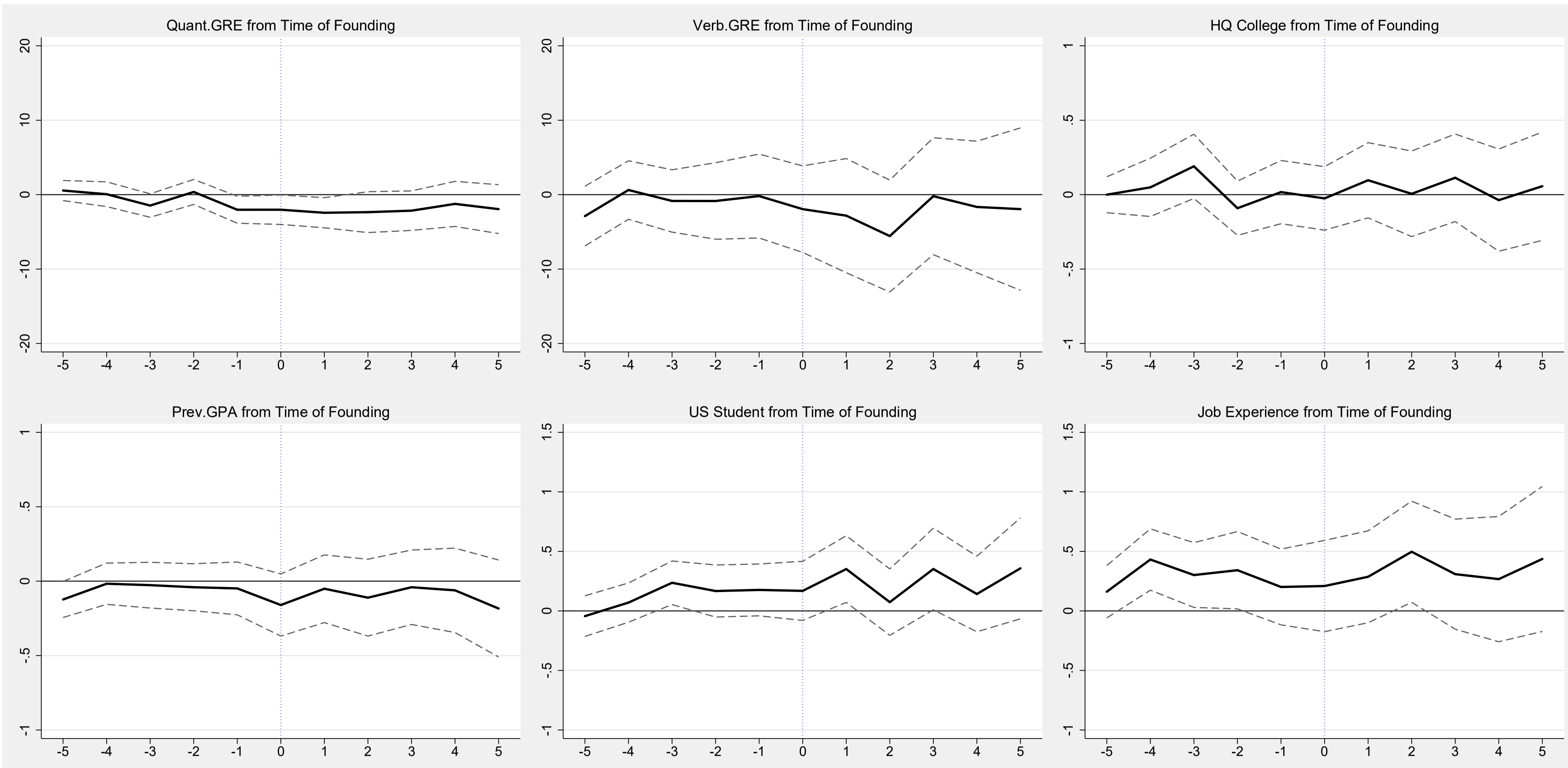
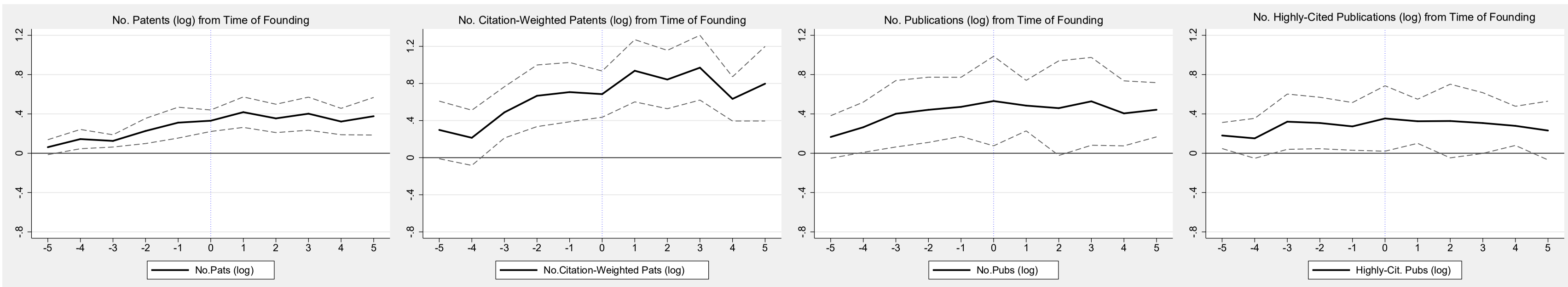


Figure 3.5: Before and After Founding Year - Student Characteristics

Notes: This figure displays the coefficients from estimating the relationship between incoming student characteristics and time from founding. The characteristics I examine are GRE Scores, the quality of a student's previous degree granting institution, previous GPAs, US citizenship, and previous work experience. I obtain the figures by including professor fixed effects, field fixed effects, year fixed effects, field-year trends, and controlling for a student's major. The dashed vertical lines indicate the time of founding. Standard errors are clustered on the advisor level to account for intra-group correlation. 95 percent confidence intervals are displayed.

Panel A: Department-Year FE



Panel B: Professor FE

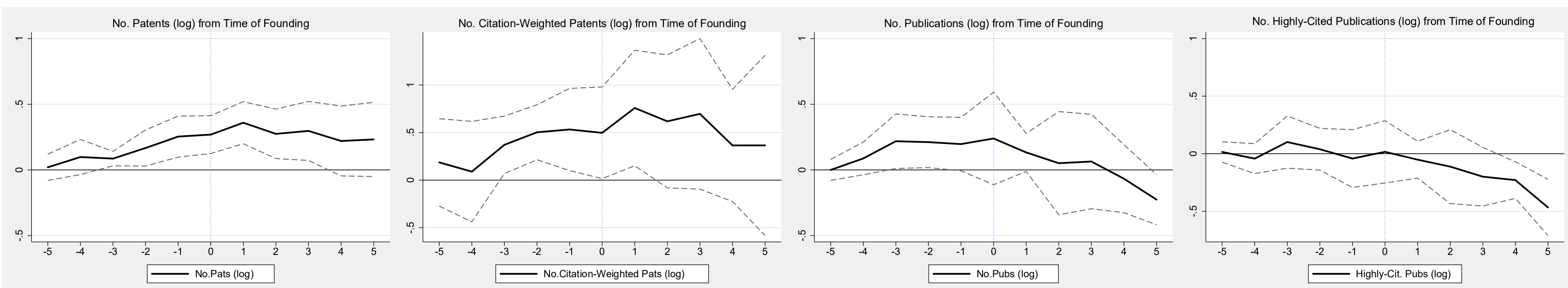


Figure 3.6: Professor Outcomes as a Function of Founding a Company using Department-Year vs. Professor FE

Notes: This figure displays the relationship between founding (x-axis indicates the time from startup year) and professors' inventive output (y-axis; all outcomes in log). The results are obtained estimating equation (3.1) using department-year fixed effects (top) and adding professor fixed effects (bottom). The category 5 denotes all years five or more post-founding date. The omitted category is six or more years prior to start-up. The dashed vertical line indicates time of founding and the confidence intervals displayed are at the 95 percent-level.

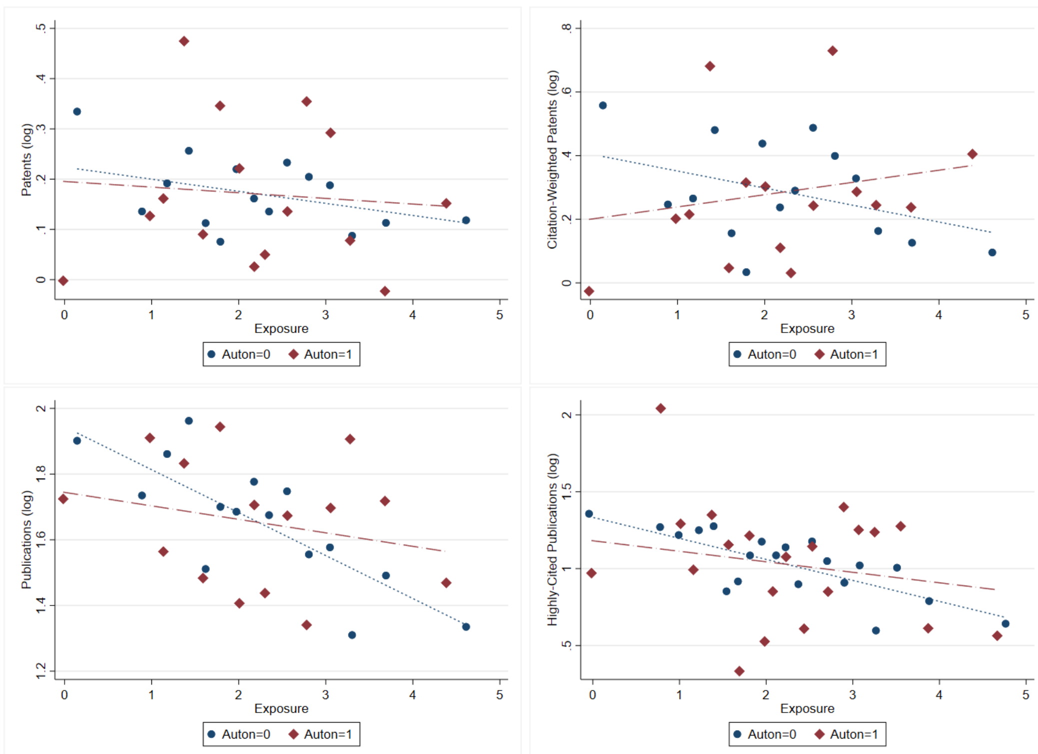


Figure 3.7: Phd Student Outcomes and Exposure by Field of Research Type

Notes: This graph reports the results from estimating the relationship between exposure (continuous) and student outcomes using binned scatter plots (15 bins, mean average) by type of major (autonomous=1 if students are enrolled in biology or chemistry) and including professor and year fixed effects. I obtain the linear fit line using OLS.

Table 3.1: Summary Statistics - Students of Entrepreneurial Advisors

	min	mean	p50	max
Students:				
Exposure (continuous)	0.00	2.46	2.00	9.00
Exposure (=0/1)	0.00	0.64	1.00	1.00
Duration of PhD	1.00	4.92	5.00	11.00
Gender:				
- Female	0.00	0.20	0.00	1.00
Departments:				
- AERO	0.00	0.03	0.00	1.00
- BIOMED	0.00	0.09	0.00	1.00
- CHEME	0.00	0.14	0.00	1.00
- CIVIL	0.00	0.02	0.00	1.00
- CS	0.00	0.09	0.00	1.00
- ECE	0.00	0.35	0.00	1.00
- MATERIALS	0.00	0.11	0.00	1.00
- ME	0.00	0.16	0.00	1.00
Ethnicity:				
- Asian	0.00	0.59	1.00	1.00
- Black	0.00	0.02	0.00	1.00
- Hispanic	0.00	0.03	0.00	1.00
- Two Or More	0.00	0.02	0.00	1.00
- White	0.00	0.34	0.00	1.00
Other Characteristics:				
- US citizen	0.00	0.37	0.00	1.00
- Previous GPA	2.31	3.62	3.66	4.00
- Verbal GRE	131.00	155.07	156.00	170.00
- Quant. GRE	144.00	163.01	164.00	170.00
- CV Record	0.00	0.85	1.00	1.00
Outcomes During PhD:				
- Patents	0.00	0.35	0.00	17.00
- Citation-Weighted Patents	0.00	2.02	0.00	95.00
- Publications	0.00	7.25	5.00	61.00
- Highly-Cited Publications	0.00	3.43	2.00	51.00
First Job:				
- Academia	0.00	0.37	0.00	1.00
- Industry	0.00	0.57	0.00	1.00
- Gov./Nat. Lab	0.00	0.04	0.00	1.00
- Founder	0.00	0.02	0.00	1.00
Advisor Characteristics at Entry of Student:				
Female	0.00	0.06	0.00	1.00
Age at time	25.00	44.31	42.00	72.00
Full Professor	0.00	0.54	1.00	1.00
Size of Cohort (by year)	1.00	2.47	2.00	8.00
Outcomes in 5-Years prior:				
- Publications	1.00	49.50	34.00	270.00
- Highly-Cited Publications	1.00	25.41	18.00	199.00
- Patents	0.00	3.89	2.00	32.00
- Amount Federal Funding (in $million)	0.00	0.74	0.10	10.74
Observations	615			

Notes: This table displays summary statistics for the students of professor-founders only and their respective advisors. The values displayed reflect the characteristics of the advisors at the time of entry of the student.

Table 3.2: PhD Patenting and Publishing during the PhD Program

	Patents		Publications	
during PhD (in log)	amount	cit.-weighted	amount	highly-cited
	(1)	(2)	(3)	(4)
Panel A				
Exposure (=0/1)	-0.0150	-0.0481	-0.483**	-0.472***
	(0.0794)	(0.143)	(0.192)	(0.166)
Major FE	Yes	Yes	Yes	Yes
Prof-X-Year Trends	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes
R-squared	0.165	0.227	0.181	0.198
Panel B				
Exposure (cont.)	-0.0349*	-0.0318	-0.167***	-0.144***
	(0.0179)	(0.0369)	(0.0373)	(0.0316)
Major FE	Yes	Yes	Yes	Yes
Prof-X-Year Trends	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes
R-squared	0.169	0.228	0.193	0.206
Panel C				
Exposure/PhD Dur.	-0.279	-0.367	-0.914***	-0.996***
	(0.178)	(0.371)	(0.294)	(0.260)
Major FE	Yes	Yes	Yes	Yes
Prof-X-Year Trends	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes
R-squared	0.169	0.229	0.182	0.201
Observations	1248	1248	1248	1248
Number of Professors	186	186	186	186

Notes: This table displays the results from estimating equation (2). *Panel A* reports student outcomes using an indicator equal to one if a student was ever exposed to an entrepreneurial advisor during the PhD. *Panel B* reports student outcomes using a continuous measure of years exposed to an entrepreneurial advisor. *Panel C*, displays outcomes using relative exposure (continuous measure of exposure divided by PhD duration). Standard errors are reported in parentheses and are clustered on the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.3: Interaction of Student Quality Indicators with Professors' Prior Founding Experience

	$\mathbb{1}(Match_{s,p,d})$
Founder x HQ College	0.00838 (0.00656)
Founder x Prev.GPA (log)	0.0152 (0.0168)
Founder x GRE Quant (log)	-0.00554 (0.0260)
Founder x GRE Verb (log)	0.00125 (0.0264)
Founder x St.US	-0.00642* (0.00354)
Founder x Prev. Job Exp.	0.00181 (0.00364)
Professor FE	Yes
Student FE	Yes
Observations	304565
R-squared	0.0326

Notes: This figure displays the interaction coefficients between a professor having founded in the 5 years prior to a student's entry and student quality indicators. The characteristics examined are the quality of a student's previous degree granting institution, previous GPAs, GRE Scores, US citizenship, and previous work experience as proxies for incoming students quality and characteristics. The model used includes both student and professor fixed effects. Standard errors are reported in parentheses and are clustered on the advisor-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.4: IV Estimation Approach

Step 1: Likelihood of Founding				
	$\mathbb{1}(Founded_{p,t})$			
Amount VC_{t-1}	0.0264**			
	(0.007)			
Professor FE	Yes			
Year FE	Yes			
Observations	1730			
R-squared	0.1029			
F-stat	13.98			
Step 2: First Stage				
	$\mathbb{1}(Found_{p,t})$			
Cum.likelihood of $\text{founding}_{p,t}$	0.612***			
$= \sum \mathbb{1}(\widehat{Founded_{p,t}})$	(0.141)			
Professor FE	Yes			
Year FE	Yes			
Observations	1081			
First Stage F-stat	18.06			
Step 3: Second Stage				
Advisor's Average	amount	highly-cited	amount	highly-cited
PhD Publ. (5y log)	(1)	(2)	(3)	(4)
$\mathbb{1}(Found_{p,t})$	-0.252***	-0.210***		
	(0.0737)	(0.0581)		
$\mathbb{1}(\widehat{Found_{p,t}})$			-0.972**	-0.858**
			(0.462)	(0.367)
Professor FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Model	OLS	OLS	IV	IV
incl. Instrument				
$\sum \mathbb{1}(\widehat{Founded_{p,t}})$			Yes	Yes
Observations	1081	1081	1081	1081
R-squared	0.442	0.487	-0.0583	-0.0762
First Stage F-stats			18.60	18.60

Notes: This table displays the results from estimating the Instrumental Variable Model described in equation (3). The table includes the results from estimating the likelihood of founding in a given time *t* applying professor, year and department fixed effects including all professors at risk of starting a company (Step 1). Taking the rolling sum of these predicted values, I create a measure capturing the cumulative likelihood of founding a company in each year and use this value as our instrument in the first stage (Step 2). Following Sampat and Williams (2019), I use a different sample - restricting to founders only - in the IV model. Columns 1 and 2 report the results obtained from the OLS model, columns 3 and 4 display the results using the cumulative likelihood of founding a company as the instrument. Standard errors are reported in parentheses and clustered on the professor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.5: PhD Patenting and Publishing during the PhD Program including Lab Size Interaction

	Lab Size	*Average PhD Output (5y log)*		
	(Mean = 3.91)	Patents	Publications	
		amount	amount	highly-cited
	(1)	(2)	(3)	(4)
$\mathbb{1}(Found_{p,t})$	0.334	-0.217***	-0.475**	-0.516***
	(0.336)	(0.0790)	(0.203)	(0.165)
Lab Size		-0.00878	-0.0257**	-0.0268**
		(0.00624)	(0.0126)	(0.0119)
$\mathbb{1}(Found_{p,t}) \times$ Lab Size		0.0249	0.0647	0.0752*
		(0.0188)	(0.0443)	(0.0398)
Professor FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1044	1044	1044	1044
R-squared	0.626	0.395	0.477	0.503

Notes: This table displays the results from estimating an advisor's average PhD publication (5 year window in log) including a continuous measure for lab size (*Lab Size*), which is proxied using the number of PhD students in a lab in a given year. Standard errors are reported in parentheses and clustered on the advisor-level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.6: Productivity 1-5 Years Post-PhD

	Patents		Publications	
1-5 years from graduation (in log)	amount	cit.-weighted	amount	highly-cited
	(1)	(2)	(3)	(4)
Panel A: Excluding Productivity During the PhD				
Exposure (=0/1)	0.00253	-0.0531	-0.619**	-0.614***
	(0.153)	(0.219)	(0.244)	(0.216)
Job Academia	-0.0897*	-0.118	0.841***	0.643***
	(0.0503)	(0.0867)	(0.103)	(0.0919)
Job Lab	-0.126	-0.0674	0.652***	0.579***
	(0.118)	(0.145)	(0.207)	(0.165)
Prof-X-Year Trends	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes
Start-Year FE	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes
R-squared	0.268	0.297	0.344	0.325
Panel B: Including Productivity During the PhD				
Exposure (=0/1)	0.0168	-0.0446	-0.423*	-0.470**
	(0.141)	(0.201)	(0.215)	(0.199)
Publications during PhD (log)	0.0537*	0.0377	0.620***	0.459***
	(0.0321)	(0.0450)	(0.0427)	(0.0362)
Patents during PhD (log)	0.443***	0.540***	0.157	0.195**
	(0.0814)	(0.122)	(0.0954)	(0.0876)
Prof-X-Year Trends	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes
Start-Year FE	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes
First Job Type FE	Yes	Yes	Yes	Yes
Observations	866	866	866	866
R-squared	0.352	0.360	0.535	0.472
Number of Professors	173	173	173	173

Notes: This table displays the results from estimating equation (2) predicting student patenting and publishing output within 1-5 years after completing their PhDs. *Panel B* includes the amount of patents and publications a student produced during the PhD program. The models include professor fixed effects, professor-year trends, start-year fixed effects, major fixed effects and indicators for the type of first job (academia and lab, industry is the omitted category; in *Panel B* these are included in *First Job Type FE*). Standard errors are reported in parentheses and are clustered on the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.7: Employment Type

	First Job					
	Academia or Lab		Industry		Founder	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure (=0/1)	0.0974	0.106	-0.146**	-0.154**	0.0488*	0.0477*
	(0.0748)	(0.0737)	(0.0738)	(0.0732)	(0.0251)	(0.0245)
Highly-Cited Publ. during PhD (log)		0.0527***		-0.0508***		-0.00187
		(0.0184)		(0.0187)		(0.00373)
Patents during PhD (log)		0.00374		-0.0227		0.0189
		(0.0449)		(0.0457)		(0.0117)
Quant. GRE		-0.00255		0.00279		-0.000236
		(0.00490)		(0.00489)		(0.000954)
Start-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.37	0.37	0.62	0.62	0.01	0.01
Observations	932	932	932	932	932	932
R.squared	0.0585	0.0671	0.0597	0.0683	0.0509	0.0561

Notes: This table displays the results from estimating the likelihood that students find their first position post-PhD in Academia/Government or a National Lab (columns 1 and 2), in Industry (columns 3 and 4), or as a founder (columns 5 and 6) as a function of having been exposed to an entrepreneurial advisor. The results displayed are obtained using OLS and the sample includes all students of professors who ever were founders or patent-holders. The even-numbered models report the full model including the amount of highly-cited publications and patents (both log) students produced during their PhDs, as well as their Quantitative GRE scores. Robust standard errors are clustered at the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.8: First Position by Employment Type

	First Job in Academia or Lab						First Job in Industry			
	Postdoc		Professor		Other		Prestigious		Other	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Exposure (=0/1)	0.131**	0.131**	-0.0411	-0.0376	-0.0152	-0.0108	-0.0822**	-0.0874**	-0.0640	-0.0667
	(0.0648)	(0.0649)	(0.0496)	(0.0494)	(0.0352)	(0.0357)	(0.0362)	(0.0377)	(0.0737)	(0.0728)
Highly-Cited Publ. during PhD (log)		0.00565		0.0198*		0.0249**		-0.0265*		-0.0243
		(0.0156)		(0.0115)		(0.0119)		(0.0138)		(0.0228)
Patents during PhD (log)		0.0215		-0.000274		0.00512		0.00438		-0.0270
		(0.0295)		(0.0290)		(0.0253)		(0.0246)		(0.0443)
Quant. GRE		0.00110		-0.00115		-0.00233		0.00328		-0.000491
		(0.00419)		(0.00272)		(0.00306)		(0.00207)		(0.00459)
Start-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of overall sample	0.22	0.22	0.08	0.08	0.10	0.10	0.08	0.08	0.55	0.55
Observations	932	932	932	932	932	932	932	932	932	932
R-sq.	0.0367	0.0376	0.0558	0.0599	0.0395	0.0452	0.0401	0.0483	0.0433	0.0457

Notes: This table displays the results from estimating the likelihood that students find their first position post-PhD as a Postdoc (columns 1 and 2), Professor (columns 3 and 4) or in another Academic/Government or National Lab position (columns 5 and 6) as a function of having been exposed to an entrepreneurial advisor. Columns 7 and 8 display the results for working at a prestigious firm, and columns 9 and 10 report the respective results for all other industry positions. All models are obtained using OLS and the sample includes all students of professors who ever were founders or patent-holders. The results reported in the even-numbered columns present the full model including the amount of highly-cited publications and patents (both log) students produced during their PhDs, as well as their Quantitative GRE scores. Robust standard errors are clustered at the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.9: Long Term Employment Outcomes

	Ever					
	Professor		Prestigious		Founder	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure (=0/1)	-0.113**	-0.110**	-0.0366	-0.0392	0.0423	0.0388
	(0.0442)	(0.0445)	(0.0413)	(0.0420)	(0.0421)	(0.0408)
Highly-Cited Publ. during PhD (log)		0.0256*		-0.00900		-0.00205
		(0.0142)		(0.0130)		(0.00874)
Patents during PhD (log)		0.0264		0.0302		0.0579**
		(0.0270)		(0.0296)		(0.0234)
Quant. GRE		-0.00232		0.00444**		-0.00175
		(0.00320)		(0.00211)		(0.00189)
Start-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes	Yes	Yes
First Job Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.15	0.15	0.10	0.10	0.01	0.01
Observations	1034	1034	1034	1034	1034	1034
R-Squared	0.211	0.216	0.0701	0.0758	0.0325	0.0470

Notes: This table displays the results from estimating the likelihood that students ever work as a professor (columns 1 and 2), ever work at a prestigious firm (*LinkedIN50*, columns 3 and 4), or as a founder (columns 5 and 6) as a function of having been exposed to an entrepreneurial advisor. All models are obtained using OLS and the sample includes students of professors who ever were founders or patent-holders. The results reported in the even-numbered columns present the full model including the amount of highly-cited publications and patents (both log) students produced during their PhDs, as well as their Quantitative GRE scores. Robust standard errors are clustered at the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.10: Mentorship Quality

Graduate Level Teaching	Score			Number	
	$>95^{\text{th}}$	$>90^{\text{th}}$	>Median	Classes	Students
Unit of Analysis: Professor-Year	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}(Found_{p,t})$	-0.0622	-0.0599	0.0426	-0.117*	-0.101
	(0.0530)	(0.0503)	(0.0581)	(0.0600)	(0.123)
Professor FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1226	1226	1226	1226	1226
R-squared	0.479	0.480	0.440	0.526	0.442
Number of Professors	212	212	212	212	212

Notes: This table displays the relationship between a professor's graduate level teaching evaluation scores and transitioning into entrepreneurship. Column 1 displays the results for the likelihood of being among the top 95$^{\text{th}}$ percent of the distribution, column 2 for the top 90$^{\text{th}}$, and column 3 for above the median. Standard errors are reported in parentheses and clustered on the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendices

APPENDIX A

TAKING INTERACTIONS AND INNOVATION TO THE NEIGHBORHOOD

A.0.1 Geographic Hierarchy and Boundaries

To better understand the advantages of using Census Block Groups, I will provide a brief introduction to the hierarchy of established geographic entities and their respective boundaries.

There are numerous geographic entities for which the US Census Bureau collects data. All of these geographic entities can be classified into two larger categories: legal and administrative entities and statistical entities. The former originate from e.g., legal actions, statutes, or historic treaties and are mainly used to meet data demands of authorities. The Nation, States, Counties, Divisions and Voting Districts are considered legal units, school districts and ZIP codes are administrative units. Statistical units are, for example, Census Designated Places (CDPs), Metropolitan Statistical Areas (MSAs), Census Tracts, Block Groups (BGs) and Blocks. They were developed from practice and need. The criteria for the delineation of the respective boundaries were established by the US Census Bureau. In contrast to administrative and legal geographic boundaries, the boundaries for statistical entities were officially instated nationwide following standardized criteria. Since 1990, the geographic hierarchy of units has been consistently applied to decennial census data collection efforts (with few boundary changes) (US Census Bureau, Department of Commerce, 1994).

The geographic hierarchy corresponds to the following structure. The highest entity is the Nation, which consists of 4 Regions (Northeast, Midwest, South and West), 6 Divisions (New England, Mid-Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain and Pacific) and 57 States and territories (including outlying areas). Within each State there are Counties, within each County there are numerous Census Tracts and within these Census Tracts are nested Block Groups that consist of Blocks. Down to every Census Block, a location can be identified via a unique Federal Information Processing Standards (FIPS) Code. MSAs, ZIP codes and Urban Area (UA) distinctions transcend these boundaries and as such do not form part of the traditional geographic hierarchy as they do not correspond completely to the established State-Block boundaries. MSA, ZIP codes and UA boundaries also tend to change over time as they are closely tied to the population and economic growth in an area. Unlike Census Block Group boundaries, which are determined by visible features, such as natural barriers that only very rarely change over time.

Census Tracts were first established as geographic entities for the 1910 Census in the then eight largest US cities. Over time, other large municipalities gradually adopted the Census Tract program. However, it was not until the 1990 US Census that all areas of the USA were assigned a Census Tract number. The size of most Census Tracts was determined based on the 1990 population in a given area, where the objective was to have an initial population size of between 2500 and 8000 residents in a Census Tract. A Census Block Group (hereafter referred to as BG) consists of all blocks that begin with the same digit in a given Census Tract. It is the lowest level of geography for which the US Census has consistently tabulated data in the 1990, 2000 and 2010 census. In the years before 1990, similar to the Census Tract, coverage did not span the entirety of the USA. The Block itself is the smallest entity for which data are collected. Patterns, sizes, and shapes of Census Blocks vary within and between overarching entities. Factors that influence the overall configuration of Census Blocks include topography, such as the type of boundary feature (streets and natural boundaries), the presence of governmental boundaries such as state boundaries and density of urban and rural development. The assignment of Census Block boundaries was automated as far as possible by the US Census Bureau for the 1990 census. The minimum size of a Census Block is 30,000 square feet for areas bounded by roads, and 40,000 square feet for other areas. There is no maximum size for a Census Block, which is why I find strong variation in the size of Census Blocks. For example, the standard block size in Manhattan is 200x500 feet (2.30 acres or 9308 sq. meters) and in Portland 200x200 feet (0.92 acres or 3723 sq.meters) (US Census Bureau, Department of Commerce, 1994).

A.0.2 A Different Approach to Grouping Observations

A widespread approach in the Geography of Innovation literature has been to group observations using the MSA level. An alternative approach is the commuting zone (CZ). The following equation shows how a commuting zone is calculated where r_i is the number of all workers residing in county i and c_{ij} is the number of workers who reside in county i but work in county j. T_{ij} (the commuting tie statistic) divides the flow of workers who commute in either direction between counties i and j by the workers who live in the smaller county. The threshold for inclusion lies at 0.02 (Autor et al., 2013).

$$T_{ij} = (c_{ij} + c_{ji})/argmin(r_i, r_j)$$

In the USA, 741 CZ were determined using 1990 National Household Travel Survey (NHTS) data. CZs in general, cover a smaller geographic area than the corresponding MSA.

A.0.3 Measuring Street Networks

In the SLD the street network measures are calculated using HERE Streets and Zlevels layers to determine facility orientation of each street network feature. The HERE Streets layer displays network links and includes attributes such as functional class, speed category, direction of travel (one-way or two-way), auto or pedestrian restrictions, and tags ramps, tunnels, and bridges. The Zlevels layer displays all points of articulation on the network and elevation fields. Zlevels are vertical coordinates that specify a vertical map space similar to floors of a building. Node features are stacked with each feature representing an endpoint of a specific link in the HERE Streets layer. The street network metrics were derived using several steps. First, streets were grouped into facility categories: auto-oriented, multi-modal, and pedestrian-oriented. These facility categories were then summarized to obtain total facility miles by type for each BG. As taken from the SLD manual, the EPA uses the following criteria to categorize streets (Ramsey and Bell, 2014: 22):

"*Auto Oriented facilities:*

- *Any controlled access highway, tollway, highway ramp, or other facility on which automobiles are allowed but pedestrians are restricted*
- *Any arterial street having a speed category value of 3 or lower (speeds are 55 mph or higher)*
- *Any arterial street having a speed category value of 4 (between 41 and 54 mph) where car travel is restricted to one-way traffic*
- *Any arterial street having four or more lanes of travel in a single direction (implied eight lanes bi-directional – turn lanes and other auxiliary lanes are not counted)*
- *For all of the above, ferries and parking lot roads were excluded*

Multi-modal facilities:

- *Any arterial or local street having a speed category of 4 (between 41 and 54 mph) where car travel is permitted in both directions*
- *Any arterial or local street having a speed category of 5 (between 31 and 40 mph)*
- *Any arterial or local street having a speed category of 6 (between 21 and 30 mph) where car travel is restricted to one-way traffic*
- *For all of the above, autos and pedestrians must be permitted on the link*
- *For all of the above, controlled access highways, tollways, highway ramps, ferries, parking lot roads, tunnels, and facilities having four or more lanes of travel in a single direction (implied eight lanes bi-directional) are excluded*

Pedestrian-oriented facilities:

- *Any arterial or local street having a speed category of 6 (between 21 and 30 mph) where car travel is permitted in both directions*

- *Any arterial or local street having a speed category of 7 or higher (less than 21 mph)*
- *Any local street having a speed category of 6 (between 21 and 30 mph)*
- *Any pathway or trail on which automobile travel is not permitted (speed category 8)*
- *For all of the above, pedestrians must be permitted on the link*
- *For all of the above, controlled access highways, tollways, highway ramps, ferries, parking lot roads, tunnels, and facilities having four or more lanes of travel in a single direction (implied eight lanes bi-directional) are excluded"*

A.0.4 Heterogeneity in Firm Size Composition

With regard to heterogeneity, a reason why I observe larger IV than OLS estimates could be that not all types of firms benefit equally from high levels of *Connectivity*. Moreover, those firms opting out of locating in physically highly connected environments could also be those that would benefit less from physical connectivity in the first place.

Intuitively, smaller firms should be those with most to gain from physical connectivity because they may not, e.g., have all necessary skills in-house or fewer internal knowledge sources. As such, smaller firms are likely to have greater need to access information from outside the firm and may, therefore, engage in more inter-firm communication (Allen et al., 2010). In addition, it is difficult for large firms to locate in areas with more highly connected streets given their size, and large firms' benefits from being in highly connected areas may outweigh their costs of rent and/or land.

To gain more insight on this potential explanation, I create two measures for small firm size and plot these visually. I base one of my measures for firm size on data from County Business Pattern (CBP) information and categorize firms as small if they have nine or fewer employees. Note that the CBP data does not provide information on what these firms do. It could well be that some of the small firms are restaurants, cafes, or bars. The other size measure is based on the number of inventors an assignee had between 2005-2010. I define small firms as those with fewer than ten inventors. The graphs I present are binned scatterplots. To generate a binned scatterplot, the x-axis variable is first grouped into equal-sized bins. Next, the mean of the x- and y-axis variables within each bin is calculated. These data points are then displayed in a scatterplot, the so called binned scatterplot. I obtain the linear fit line using OLS and include the same controls as in the fully saturated model presented in Table 1.2. The resulting coefficients and the corresponding *p*-values for each linear fit plot are displayed in the bottom left corner under each graph.

The results as displayed in Figure A1.4, indicate that in BGs with no small firms, the relationship between *Connectivity* and patenting is not statistically significant, and most of the effect is driven by places with at least one small firm. Similarly, the *Connectivity* effect is not statistically significant in BGs with less than 50 percent small firms using either approach. However, when examining the relationship by BGs with all small firms (=1) the results indicate that the positive relationship between *Connectivity* and patenting may be primarily driven by those BGs with a mix of firms size. Taken together, and with much caution given endogenous location choice, this could be interpreted such that BGs with a representation of at least 50 percent of small firms, but not all small firms "benefit" most from higher levels of *Connectivity*. These patterns are also in line with previous findings, such as Agrawal et al. (2014), who find that innovation output is higher in regions with both small firms and large laboratories.

To further support these findings, I run the OLS regressions from Table 2 in the main manuscript including interactions between firm size and physical connectivity. The results are reported in the Appendix, Table A1.9. I thereby categorize firm size, using historic inventor data and distinguish between very small (<5 inventors), small (5-9 inventors), medium (10-49 inventors), and large assignees (<50 inventors). In the fully saturated model, it appears that the share of small and medium sized assignees in a BG bolsters the impact of *Connectivity*.

However, as per my prior discussion, I cannot definitively disentangle if and how much of the effect can be attributed to smaller firms truly benefiting more from a physically connected environment or smaller firms' higher probability of locating in BGs with elevated *Connectivity* levels. Either reason could explain why the OLS estimates are biased downward in comparison to the results obtained in the IV model.

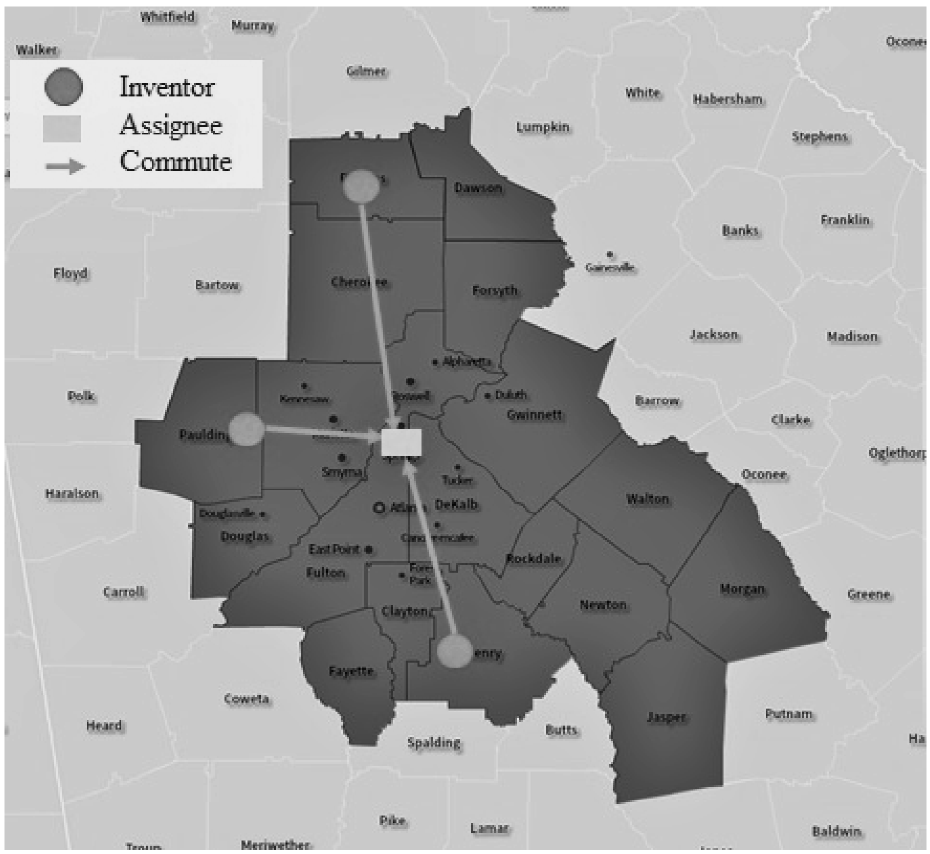


Figure A1.1: Depiction of Sample Selection using CZ 9100 (Atlanta, GA) as an Example

Notes: This image is a stylized depiction of how the sample of patents was selected. I retain only those patents where both assignees (box) and all inventors (circles) are within the same commuting zone (commuting tie is the arrow line). Image created by the authors.

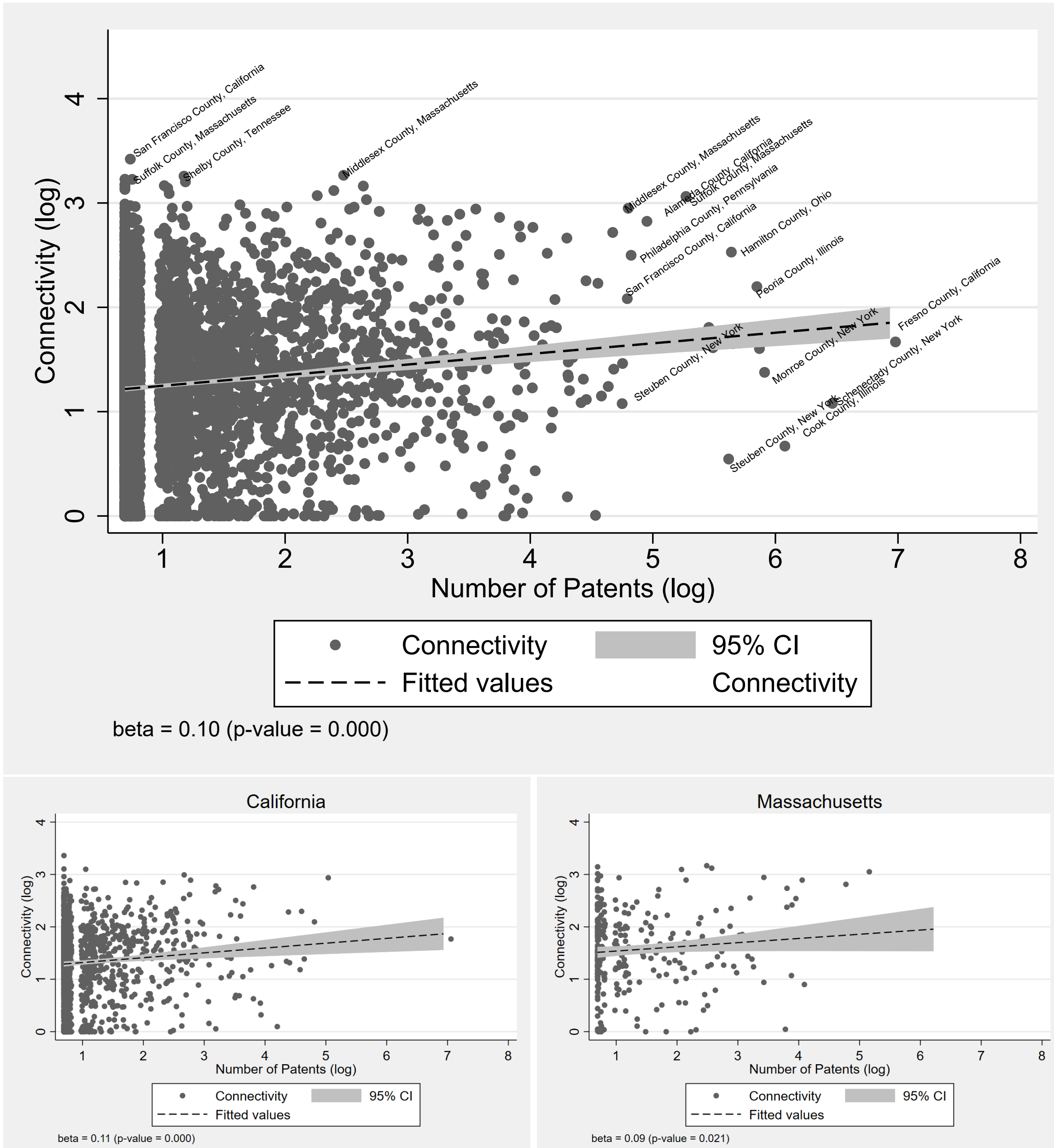


Figure A1.2: Scatterplot of the Relationship between *Connectivity* and Patents

Notes: The top figure plots the relationship between *Connectivity* (y-axis) and *Number of Patents* (x-axis) for the entire sample (with the restriction that there is at least one patent). Both variables are log transformed. The labels list the county and state of the corresponding BGs. Suffolk County, MA and Middlesex County, MA are two major counties in the Boston/Cambridge area, Alameda County, CA covers the Oakland - Fremont area, Hamilton County, OH forms part of the Cincinnati area, Cook County, IL is one of Chicago's main counties. Steuben County and Monroe County, New York belong to the Rochester commuting zone, Schenectady County, New York forms part of the Troy/Albany area, Shelby County, TN is one of the main counties in Memphis. The remaining counties are named after the cities they lie in. The bottom left plot is for California only, and the bottom right plot displays the relationship for BGs in Massachusetts only.

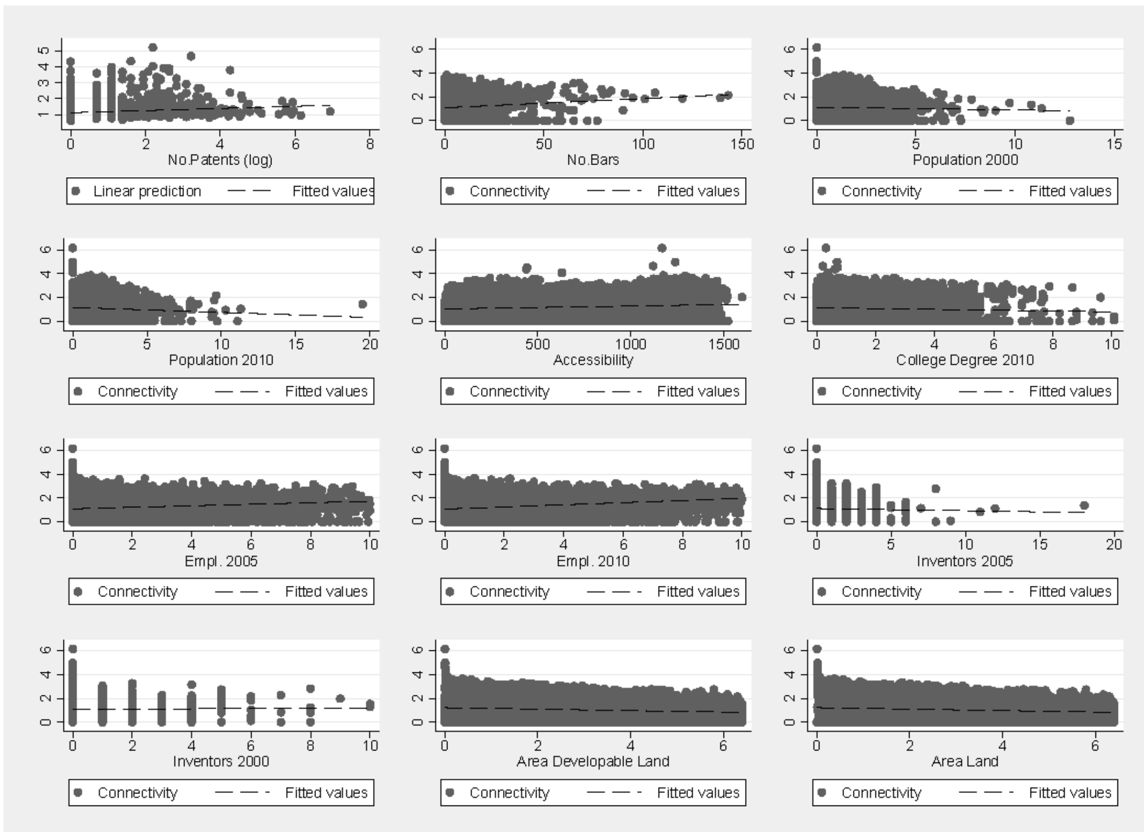


Figure A1.3: The Relationship between *Connectivity* and Controls

Notes: Each scatter plot represents the relationship between *Connectivity* and the variable specified on the x-axis with exception of the top left scatter plot. The top left scatter plot displays the relationship between the residuals obtained from regressing all controls on *Connectivity (log)* and the log *No.of Patents* in a BG. The graphs presenting the relationship between *Connectivity (log)* and employment are without the top 99$^{\text{th}}$ percentile. *No.Bars* is the short form of the measure for number of bars, restaurants and hotels in a BG.

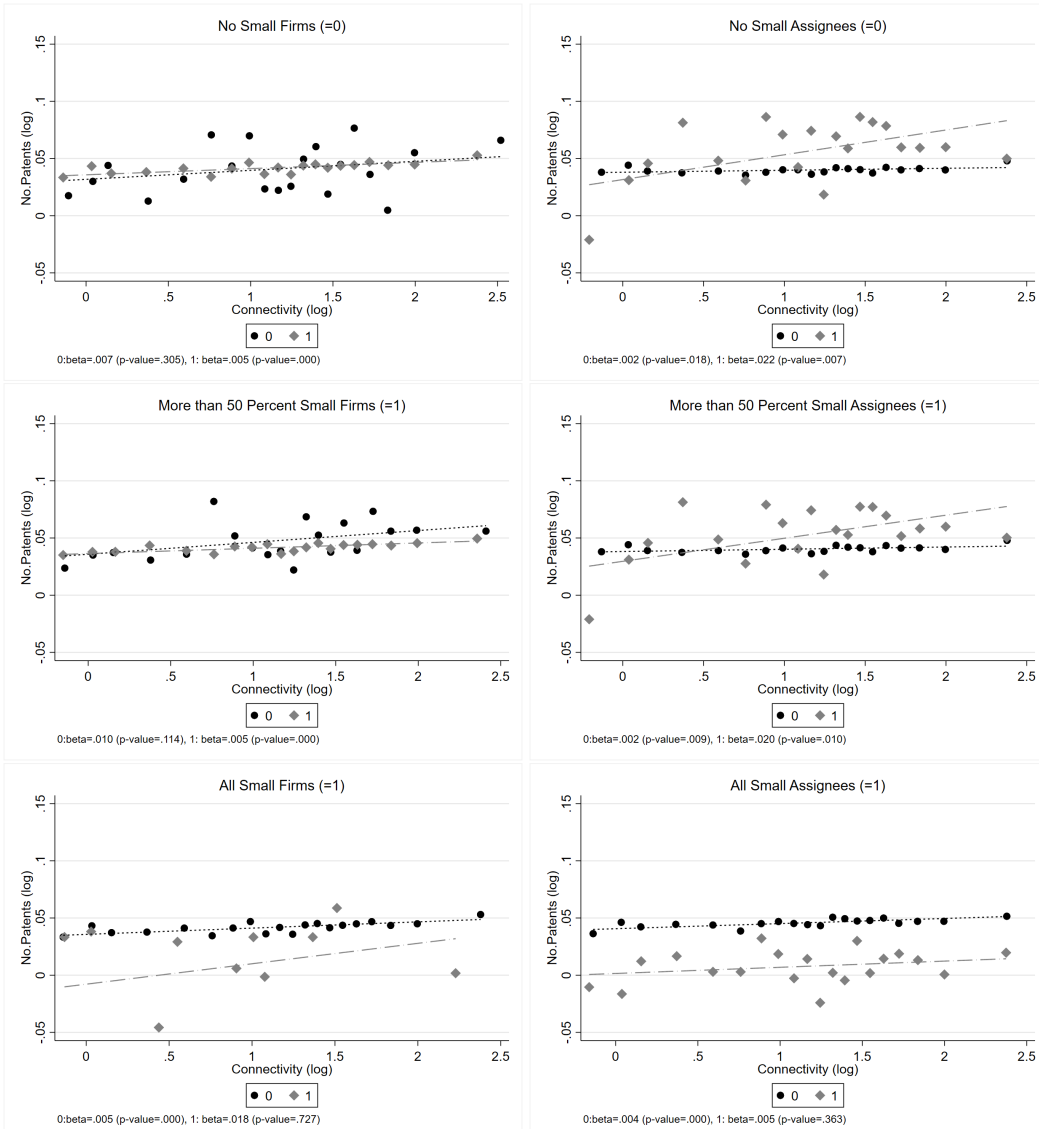


Figure A1.4: *Connectivity* by Percentage of Small Firms

Notes: This figure displays the relationship between the number of patents in a BG (y-axis) and *Connectivity* (x-axis) by the percentage of small firms in a BG. All plots are binned scatterplots with the same controls as in the full OLS model, Table 2 (20 bins, mean average). In the left column, firm size is measured in 2010 using CBP data. The top left captures the outcome using an indicator equal to one if there are no small firms, and is zero otherwise. The middle left plot, captures the outcome using an indicator equal to one if the percentage of small firms is over 50 percent, and is zero otherwise. The bottom left figure captures the outcome using an indicator equal to one if all firms are small, and is zero otherwise. The right column displays results using firm size measures constructed from historic inventor counts by assignee location (2005-2010). Here, I additionally control for the number of assignees in order to obtain graphs comparable to the left column. The top right reports the results by an indicator capturing if there are no (=0) or any small firms (=1), the middle right if the share of small assignees is larger than 50 percent (=1), and the bottom right displays the results by a small firm ratio equal to one. I report the point estimates and corresponding *p*-values in the bottom left corner of each graph.

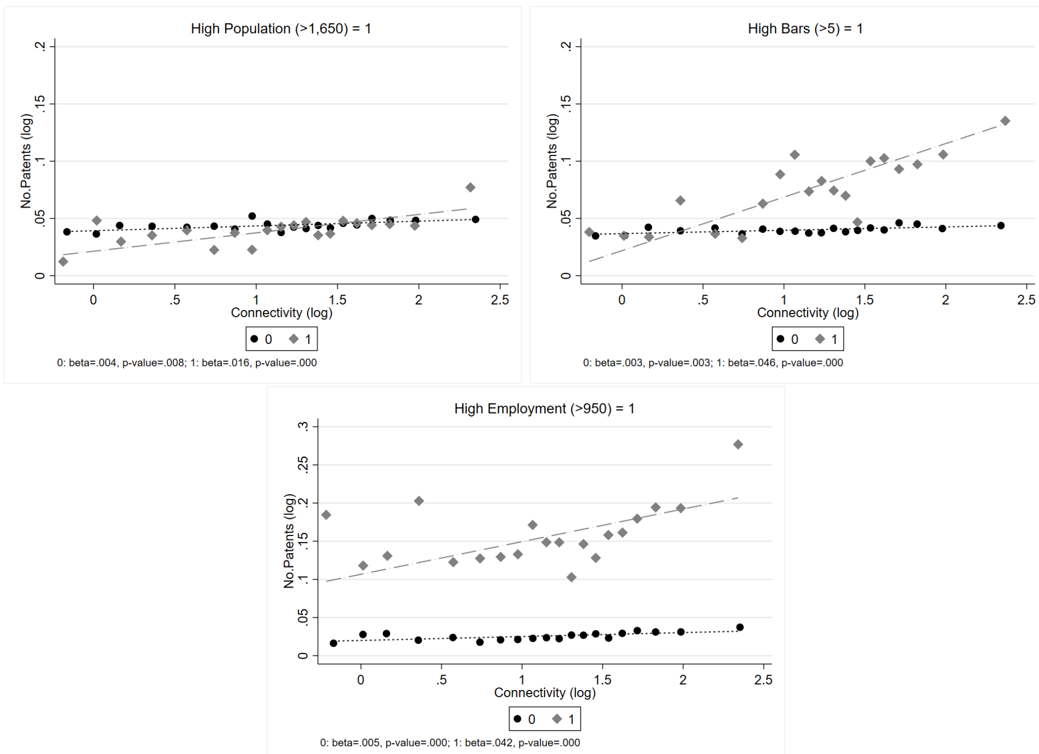


Figure A1.5: Interaction of *Connectivity* (log) with Population, Employment, and No. Bars

Notes: This figure displays the relationship between the number of patents in a BG (y-axis) and *Connectivity* (x-axis) by high levels of population, number of bars, restaurants, and hotels in a BG as well as employment (all measured in 2010). All plots are binned scatterplots (20 bins, mean average). The top left captures the outcome using an indicator equal to one if population is larger than 1,650, and is zero otherwise. The top right figure represents the outcome using an indicator equal to one if the number of bars, restaurants or hotels in a BG exceeds 5, and is zero otherwise. The bottom figure captures the outcome using an indicator equal to one if employment is larger than 950, and is zero otherwise. The controls in each plot correspond to those used in Table 6.

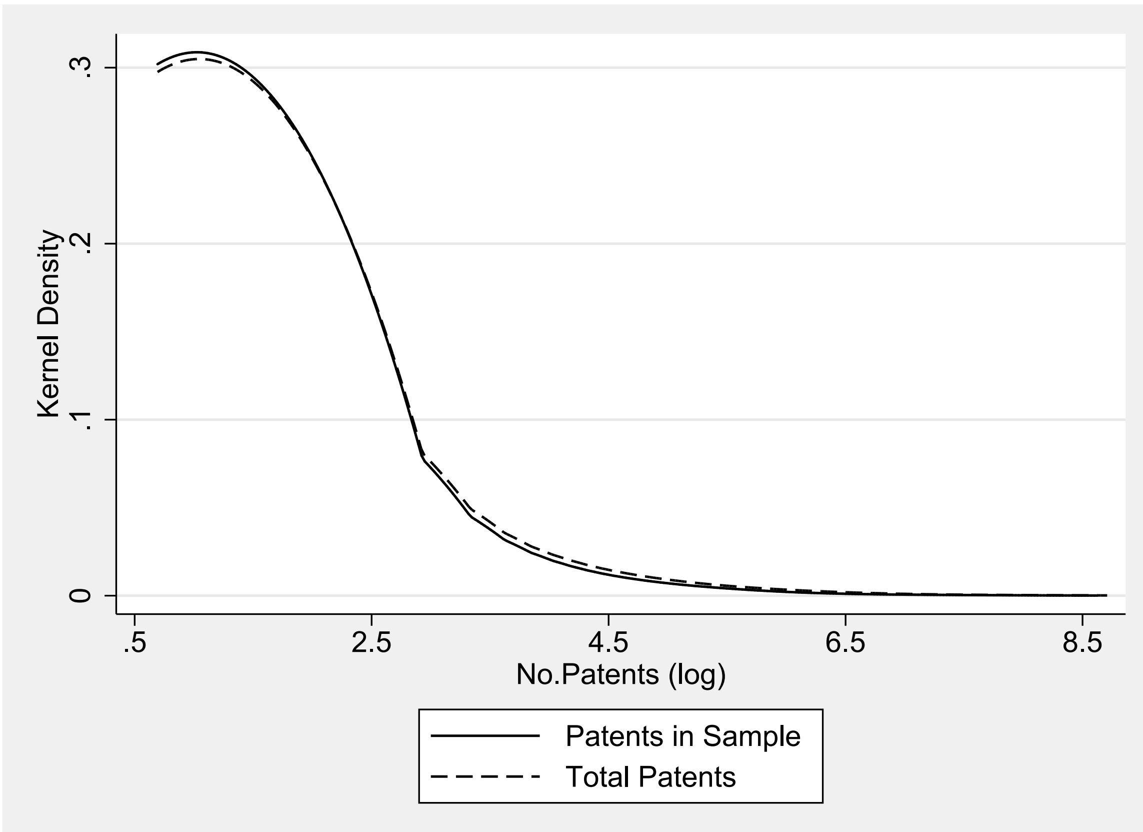


Figure A1.6: Kernel Density Distribution of Assignee Size in the Sample and in Full Data Set

Notes: This figure plots the kernel density distribution of assignee size by those patents that are included in the sample against those in the raw data set (only where a precise location was available). Size is determined by the number of patents an assignee has (ln(*No.Patents* +1)). The bandwidth used is 1.

Table A1.1: Variable Description

Variable	Description	Source
Innovation		
Number of Patents (2011-2013)	The amount of US granted patents located in a BG that had been applied for 2011 - 2013.	Morrison et al. (2017), Disambiguated Patent Data Set (DPDS); TIGER Census Boundaries
Patent	An indicator equal to one if there is at least one patent located in a BG that had been applied for 2011 - 2013.	Morrison et al. (2017), DPDS; TIGER Census Boundaries
Knowledge Exchange		
Total Citations	The amount of same BG patent citation pairs in a BG for patents that had been applied for 2011 - 2013.	Morrison et al. (2017), DPDS; TIGER Census Boundaries
Self Citations	The amount of same BG patent self-citations in a BG for patents that had been applied for 2011 - 2013.	Morrison et al. (2017), DPDS; TIGER Census Boundaries
Non-self Citations	The amount of same BG patent citations in a BG excluding self-citations for patents that had been applied for 2011 - 2013.	Morrison et al. (2017), DPDS; TIGER Census Boundaries
Physical Network Structure		
Connectivity	The total miles of streets oriented towards both car and pedestrian travel (multimodal) in a BG, normalized by total BG area, measured in 2010.	EPA, Smart Location Data-base (SLD)
HUpre1940	The percent of housing units built in a BG before 1940.	IPUMS, Census Demographics
HU1940-1949	The percent of housing units built in a BG between 1940 and 1949.	IPUMS, Census Demographics
Social Activity		
Number of Bars, Restaurants, and Hotels	The number of bars, restaurants, and hotels in a BG.	US Census, County Business Pattern (CBP)
Formal Knowledge		
Campus	Indicator equal to one if the BG has a postsecondary education campus.	US Department of Education, Database of Accredited Postsecondary Institutions and Programs
Human Capital (by work location)		
Accessibility	The number of working age population that is within a 45 minute commute from a focal BG (2010).	EPA, SLD
College 2000/2010	The number of college degree holders in 2000/2010. These values were only available on the census tract level	IPUMS, Census Demographics
Employment 2010/2005	The number of employees in 2010/2005.	US Census, CBP; EPA, SLD
Inventors 2005/2000	The number of inventors in 2005/2000.	Morrison et al. (2017), DPDS; TIGER Census Boundaries
Socio-Demographic		
Population 2010/2000	Population in a BG according to the 2010/2000 US census.	IPUMS Census Demographics; EPA, SLD
Physical Geography		
Area Water	The amount of BG area covered by water.	EPA, SLD
Area Developable Land	The amount of BG area that can be used for development.	EPA, SLD
Area Land	The total amount of land in a BG.	EPA, SLD

Table A1.2: Correlation of Distinct Density Measures with Connectivity

	Connectivity
Pathway and Trail Density (miles/sq.miles)	0.0278
Auto-Only Road Density (miles/sq.miles)	-0.0024
Intersection Density (all)	0.0504
Transit Frequency (h/sq.miles)	0.0473
Residential Density (HU/acre)	0.121
Population Density (people/acre)	0.126
Employment Density (jobs/acre)	0.112
Regional Centrality Index	0.136
Accessibility (workers w/in 45min commute)	0.194

Notes: This table presents the correlation matrix of *Connectivity* with other density measures and accessibility measures. These measures are a) the density of *Pathways and Trails* (constructed using the total amount of pathways and trails divided by total land area), b) the density of *Auto-Only* roads (total amount of automobile only roads divided by total land area), c) *Intersection Density* (using all types of intersections, see SLD for exact calculation), d) *Transit Frequency* (calculated using the transit frequency per square mile of land area, only available for participating GTFS transit service areas), e) *Residential Density* (housing units divided by area of unprotected land), f) *Population Density*, g) *Employment Density* (both divided by area of unprotected land), as well as, h) the *Regional Centrality Index* (*Accessibility* of a BG relative to the maximum in the CBSA), and i) *Accessibility* (the number of working age population that is within a 45 minute commute from a focal BG).

Table A1.3: Different Dependent Variable Construction

	All Inventors in CZ (assignee location)	One Inventor in CZ (assignee location)	Inventor Location (by no.of inventors)
DV: Number of Patents (log)	(1)	(2)	(3)
Connectivity (log)	0.00452***	0.00585***	0.0108*
	(0.00129)	(0.00155)	(0.00576)
Social Activity Controls	Yes	Yes	Yes
Formal Knowledge Controls	Yes	Yes	Yes
Human Capital Controls	Yes	Yes	Yes
Socio-Demogr. Controls	Yes	Yes	Yes
Phys. Geography Controls	Yes	Yes	Yes
Observations	95294	95294	95294
R-squared	0.0996	0.112	0.0689
Fixed Effects	czone	czone	czone
Number of Groups	253	253	253

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

Notes: This table reports the results obtained from using alternative sample selection approaches. The outcome variable is the amount of U.S. granted patents applied for between 2011-2013 in a BG. Column 1 presents the results from the main paper. In Column 2 the sample was obtained including those patents where at least one inventor was in the same commuting zone as the assignee. The location of these patents is the BG of the assignee. The end sample of BGs with at least one patent increases to 5,350 following this approach. In Column 3 the sample was obtained taking the location of each inventor. Before aggregating, each patent was weighted by the number of inventors on a focal patent (e.g., for 2 inventors of the same patent, but in different BGs, the patent count is 0.5 for each inventor-BG). The end sample of BGs with at least one patent increases to 16,272 following this approach. The *SocialActivityCONTROLS* include the number of bars, restaurants, and hotels in a BG. *FormalKnowledgeCONTROLS* is an indicator equal to one if the BG has a postsecondary education campus. The *HumanCaptialCONTROLS* consist of historic inventor counts from 2000, and 2005 as well as employment levels for 2005 and 2010, and the amount of college degree holders in 2000, and 2010 (by work location). *Socio-DemographicCONTROLS* are population counts for 2000 and 2010. *PhysicalGeographyCONTROLS* are the area covered by water, the area of developable land, and total land area. Standard errors (in parentheses) are clustered at the commuting zone level.

Table A1.4: Conditional Fixed-Effects Poisson Model

	Poisson Models		
DV: Number of Patents	(1)	(2)	(3)
	Incidence Rate Ratios		
Connectivity	1.010***	1.053***	1.055***
	(0.00220)	(0.0115)	(0.0100)
Social Activity Controls	No	Yes	Yes
Formal Knowledge Controls	No	Yes	Yes
Human Capital Controls	No	Yes	Yes
Socio-Demogr. Controls	No	Yes	Yes
Phys. Geography Controls	No	Yes	Yes
Observations	119937	93074	84273
Fixed Effects	czone	czone	county
Number of Groups	249	219	410
Std. Errors	Robust	Robust	Robust
LogLikelihood	-23269.6	-16547.5	-15570.2

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

Notes: This table reports the results obtained from estimating equation (1) using a conditional fixed-effects poisson model. The outcome variable is the amount of U.S. granted patents applied for between 2011-2013 in a BG (we exclude the top 1 percentile to ensure that outliers are not driving the results). Reported coefficients are incidence rate ratios. Coefficients greater (smaller) than one indicate that exposure to the independent variable is associated with higher (lower) incidence rate ratio. Columns 1 presents the reduced model without controls. Columns 2 and 3 present the fully saturated model with all controls. The *SocialActivityCONTROLS* include the number of bars, restaurants, and hotels in a BG. *FormalKnowledgeCONTROLS* is an indicator equal to one if the BG has a postsecondary education campus. The *HumanCaptialCONTROLS* consist of historic inventor counts from 2000, and 2005 as well as employment levels for 2005 and 2010, the amount of college degree holders in 2000, and 2010 (by work location), and the amount of working age population that is within a 45 minute commute from a focal BG. *Socio-DemographicCONTROLS* are population counts for 2000 and 2010. *PhysicalGeographyCONTROLS* are the area covered by water, the area of developable land, and total land area. Standard errors (in parentheses) are clustered at the commuting zone (columns 1, and 2) and county (column 3) level.

Table A1.5: OLS - Different Measures of Connectivity

	OLS Models											
DV: Number of Patents (log)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pathways (log)	-0.0277***	0.00188	0.00400									
	(0.00531)	(0.00337)	(0.00324)									
Connectivity incl. Pathways (log)				-0.0193***	0.0293***	0.0106**						
				(0.00537)	(0.00672)	(0.00422)						
Street Intersection Density							-0.00598**	0.0117**	0.00521**			
							(0.00257)	(0.00562)	(0.00215)			
Transit Frequency (log)										0.00354***	0.00995***	0.00333***
										(0.000985)	(0.00123)	(0.000885)
Social Activity Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Formal Knowledge Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Human Capital Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Socio-Demogr. Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Phys. Geography Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	121398	121398	95294	121398	121398	95294	121398	121398	95294	93866	93866	73369
R-squared	0.00190	0.00721	0.0788	0.000712	0.00821	0.0789	0.000214	0.00787	0.0996	0.00111	0.0155	0.108
Fixed Effects	czone	czone	czone	czone	czone	czone	czone	czone	czone	czone	czone	czone
Number of Groups	261	261	253	261	261	253	261	261	253	116	116	113

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

Notes: This table reports the results obtained from using alternative measures of *Connectivity*. These alternative measures are a) the density of pathways and trails (log transformed and constructed using the total amount of pathways and trails divided by total land area), b) the density of streets including pathways and trails (log transformed and divided by total land area), c) *Intersection Density* (log transformed, using all types of intersections, see SLD for exact calculation), and d) *Transit Frequency* (log transformed, calculated using the transit frequency per square mile of land area, only available for participating GTFS transit service areas). The outcome variable is the amount of U.S. granted patents applied for between 2011-2013 in a BG. Columns 1, 4, 7, and 10 represent the overall effect without controls. In columns 2, 5, 8, and 11 I include *PhysicalGeographyCONTROLS*. Columns 3, 6, 9, and 12 present the fully saturated model. The *SocialActivityCONTROLS* include the number of bars, restaurants, and hotels in a BG. *FormalKnowledgeCONTROLS* is an indicator equal to one if the BG has a postsecondary education campus. The *HumanCaptialCONTROLS* consist of historic inventor counts from 2000, and 2005 as well as employment levels for 2005 and 2010, the amount of college degree holders in 2000, and 2010 (by work location), and the amount of working age population that is within a 45 minute commute from a focal BG. *Socio-DemographicCONTROLS* are population counts for 2000 and 2010. *PhysicalGeographyCONTROLS* are the area covered by water, the area of developable land, and total land area. Standard errors (in parentheses) are clustered at the commuting zone level.

Table A1.6: 2SLS Using Different Housing Ages as Instruments

DV: Number of Patents (log)	(1) (1950-59)	(2) (1960-69)	(3) (1970-79)	(4) (1980-89)
Connectivity (log) (= HU19XX)	0.313	0.142***	0.068	-0.037
	(0.2957)	(0.0445)	(0.0475)	(0.0346)
Social Activity Controls	Yes	Yes	Yes	Yes
Formal Knowledge Controls	Yes	Yes	Yes	Yes
Human Capital Controls	Yes	Yes	Yes	Yes
Socio-Demogr. Controls	Yes	Yes	Yes	Yes
Phys. Geography Controls	Yes	Yes	Yes	Yes
First Stage Coef.	-0.061	-0.144***	-0.151***	-0.231***
	(0.0495)	(0.0291)	(0.0293)	(0.0384)
Observations	95097	95097	95097	95097
First Stage Fstats	1.53	24.46	26.53	36.02
Fixed Effects	czone	czone	czone	czone
Number of Groups	252	252	252	252

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

Notes: This table reports the results obtained from instrumenting *Connectivity* with the percentage of housing units built in different time periods *HU19XX*. In column 1 *Connectivity* is instrumented using the percentage of housing units built in the 1950s. The instrument in columns 2, 3, and 4 are the housing units built in the 1960s, the 1970s, and the 1980s. The outcome variable is the log amount of U.S. granted patents applied for between 2011-2013 in a BG. The *SocialActivityCONTROLS* include the number of bars, restaurants, and hotels in a BG. *HigherEducationCONTROLS* is an indicator equal to one if the BG has a postsecondary education campus. The *HumanCaptialCONTROLS* consist of historic inventor counts from 2000, and 2005 as well as employment levels for 2005, and 2010, as well as the amount of college degree holders in 2000, and 2010 (by work location). *Socio-DemographicCONTROLS* are population counts for 2000, and 2010. *PhysicalGeographyCONTROLS* are the area covered by water, the area of developable land, and total land area. Standard errors (in parentheses) are clustered at the commuting zone level.

Table A1.7: Instrumental Variable Estimation - Including Pathways and Trails

DV: Number of Patents (log)	2SLS Models (1)	(2)	(3)	(4)	(5)	(6)
	Second Stage					
Connectivity incl. Pathways (log)	0.0928***	0.0870***	0.0701***	0.0466***	0.0428***	0.0324**
	(0.0159)	(0.0153)	(0.0135)	(0.0170)	(0.0159)	(0.0156)
Social Activity Controls	No	Yes	Yes	Yes	Yes	Yes
Formal Knowledge Controls	No	Yes	Yes	Yes	Yes	Yes
Human Capital Controls	No	No	No	Yes	Yes	Yes
Socio-Demogr. Controls	No	No	Yes	No	Yes	Yes
Phys. Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
	First Stage					
HUpre1940	0.3045***	0.3077***	0.3274***	0.2748***	0.2909***	0.2908***
	(0.0272)	(0.0279)	(0.0309)	(0.0256)	(0.0283)	(0.0259)
HU1940-1949						0.2961***
						(0.0285)
Social Activity Controls	No	Yes	Yes	Yes	Yes	Yes
Formal Knowledge Controls	No	Yes	Yes	Yes	Yes	Yes
Human Capital Controls	No	No	No	Yes	Yes	Yes
Socio-Demogr. Controls	No	No	Yes	No	Yes	Yes
Phys. Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120926	118838	118838	95097	95097	95097
First Stage Fstats	125.5	120.9	111.7	115.1	105.6	77.65
Hansen J Stat. P-val						0.100
Fixed Effects	czone	czone	czone	czone	czone	czone
Number of Groups	260	256	256	252	252	252

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

Notes: This table reports the results obtained from instrumenting *Connectivity* including pathways and trails with *HUpre1940* (column 1-6) and *HU1940-1949* (column 6). In the *Second Stage*, the outcome variable is the log amount of U.S. granted patents applied for between 2011-2013 in a BG. In the *First Stage*, the outcome variable is *Connectivity (log)* including pathways and trails. *HUpre1940*, is the percentage of housing units built before 1940 and *HU1940-1949*, is the percentage of housing units built between 1940-1949. The *SocialActivityCONTROLS* include the number of bars, restaurants, and hotels in a BG. *FormalKnowledgeCONTROLS* is an indicator equal to one if the BG has a postsecondary education campus. The *HumanCaptialCONTROLS* consist of historic inventor counts from 2000, and 2005 as well as employment levels for 2005, and 2010, and the amount of college degree holders in 2000, and 2010 (by work location). *Socio-DemographicCONTROLS* are population counts for 2000, and 2010. *PhysicalGeographyCONTROLS* are the area covered by water, the area of developable land, and total land area. Variation in the number of observations depending on the included controls is due to missing values for the number of bars, restaurants, and hotels, as well as college education. *First Stage* F-statistics are reported in all columns and the *p*-value obtained from the Hansen J Statistic, which tests the validity of the overidentifying restrictions in column 6. Standard errors (in parentheses) are clustered at the commuting zone level.

Table A1.8: Control Function Approach Using FE Poisson in the Second Stage

DV: Number of Patents	(1)	(2)
	Incidence Rate Ratios	
Connectivity	1.528***	1.480***
	(0.177)	(0.177)
Residuals	0.681***	0.704***
	(0.0801)	(0.0851)
Quadratic Residuals	Yes	Yes
Social Activity Controls	Yes	Yes
Higher Ed. Controls	Yes	Yes
Human Capital Controls	Yes	Yes
Socio-Demogr. Controls	Yes	Yes
Phys. Geography Controls	Yes	Yes
First Stage includes	HUpre1940	HUpre1940 HU1940-1949
Observations	92866	92866
Fixed Effects	czone	czone
Number of Groups	218	218
Std. Errors	Bootstrap	Bootstrap
Log Likelihood	-16381.2	-16382.9

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

Notes: This table reports the results obtained from estimating a control function approach. In the first step I predict the endogenous variable *Connectivity* including *HUpre1940* with the full set of controls (in column 2 I also include *HU1940-1949*). I save the residuals and insert them into a conditional fixed-effects poisson model in the second stage. Reported coefficients are incidence rate ratios. Coefficients greater (smaller) than one indicate that exposure to the independent variable is associated with higher (lower) incidence rate ratio. In the first step I predict the endogenous variable *Connectivity* including *HUpre1940* with the full set of controls (in column 2 I also include *HU1940-1949*). The outcome variable is the number of U.S. granted patent that were applied for between 2011-2013 in a BG (I exclude the top 1 percentile to ensure that outliers are not driving the results). I include the quadratic expansion of the residuals. The residuals without change to the functional form are displayed in the table. The *SocialActivityCONTROLS* include the number of bars, restaurants, and hotels in a BG. *FormalKnowledgeCONTROLS* is an indicator equal to one if the BG has a postsecondary education campus. The *HumanCaptialCONTROLS* consist of historic inventor counts from 2000, and 2005 as well as employment levels for 2005, and 2010, the amount of college degree holders in 2000, and 2010 (by work location), and the amount of working age population that is within a 45 minute commute from a focal BG. *Socio-DemographicCONTROLS* are population counts for 2000, and 2010. *PhysicalGeographyCONTROLS* are the area covered by water, the area of developable land, and total land area. Standard errors (in parentheses) are clustered at the commuting zone level.

Table A1.9: Interaction of Connectivity with Assignee Size

Number of Patents (log)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Connectivity (log)	0.0105***	0.00192*	0.0172***	0.00328***	0.0166***	0.00314***	0.0166***	0.00332***
	(0.00208)	(0.00110)	(0.00281)	(0.00104)	(0.00278)	(0.00104)	(0.00285)	(0.00114)
Share Very Small	0.0950***	0.0969***						
	(0.0127)	(0.0113)						
Connectivity × Share Very Small	0.0606***	0.0115						
	(0.00997)	(0.00744)						
Share Small			0.348***	0.296***				
			(0.0556)	(0.0560)				
Connectivity × Share Small			0.146***	0.0978**				
			(0.0440)	(0.0400)				
Share Medium					0.722***	0.728***		
					(0.0984)	(0.103)		
Connectivity × Share Medium					0.230***	0.132*		
					(0.0705)	(0.0698)		
Share Large							2.143***	2.136***
							(0.319)	(0.336)
Connectivity × Share Large							0.551**	0.402
							(0.241)	(0.264)
Social Activity Controls	No	Yes	No	Yes	No	Yes	No	Yes
Formal Knowledge Controls	No	Yes	No	Yes	No	Yes	No	Yes
Human Capital Controls	No	Yes	No	Yes	No	Yes	No	Yes
Socio-Demogr. Controls	No	Yes	No	Yes	No	Yes	No	Yes
Phys. Geography	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	121398	95294	121398	95294	121398	95294	121398	95294
R-squared	0.0466	0.114	0.0395	0.118	0.0756	0.149	0.154	0.226
Fixed Effects	czone	czone	czone	czone	czone	czone	czone	czone
Number of Groups	261	253	261	253	261	253	261	253

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

Notes: This table presents results from interacting *Connectivity* with the share of very small, small, medium, and large assignees in a BG. These values were derived using the sum of inventors of an assignee between 2005-2010. Very small firms have fewer than 5 inventors, small have 5-9 inventors, medium have 10-49 inventors, and large are all firms with 50 or more inventors. The outcome variable is the amount of U.S. granted patents applied for between 2011-2013 in a BG. The columns with uneven numbers represent the overall effect without controls (but incl. *PhysicalGeographyCONTROLS*). The columns with even numbers present the fully saturated model. Please refer to previous tables for a description of the controls. Standard errors (in parentheses) are clustered at the commuting zone level.

Table A1.10: Patent Citation Patterns - Including Pathways and Trails

	Non-self				Self			
DV: Number Citations (log)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Streets incl. Pathways (log)	0.00147***	0.00133***	0.00271**	0.00236**	0.00469***	0.00389***	-0.0000612	-0.00351
	(0.000550)	(0.000481)	(0.00130)	(0.00114)	(0.00166)	(0.00144)	(0.00619)	(0.00482)
Number of Patents (log)				0.0221***				0.214***
				(0.00486)				(0.0203)
Social Activity Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Higher Ed. Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Human Capital Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Socio-Demogr. Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Phys. Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model	OLS	OLS	IV	IV	OLS	OLS	IV	IV
			First Stage				First Stage	
HUpre1940			0.299***	0.299***			0.299***	0.299***
			(0.027)	(0.027)			(0.027)	(0.027)
HU 1940-1949			0.294***	0.294***			0.294***	0.294***
			(0.028)	(0.028)			(0.028)	(0.028)
Number of Patents (log)			No	Yes			No	Yes
Other Controls			Yes	Yes			Yes	Yes
Firststage Fstats			74.65	74.81			74.65	74.81
Hansen J Stat. P-val			0.815	0.549			0.658	0.777
Observations	121398	119159	95097	95097	121398	119159	95097	95097
R-Sq.	0.000509	0.00331	0.00322	0.0416	0.00114	0.00821	0.00812	0.298
Fixed Effects	czone	czone	czone	czone	czone	czone	czone	czone
Number of Groups	261	257	252	252	261	257	252	252
Std. Errors	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust

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

Notes: This table reports the results obtained from estimating the relationship between *Connectivity* (including pathways and trails) and citation patterns. The outcome variable in columns 1-4 is the log amount of same-BG citation pairs between distinct assignees (*Non-self Citations*). The outcome variable in columns 5-8 is the log amount of same-BG citation pairs between the same assignee (*Self Citations*). Columns 1, 2, 5, and 6 report the results estimating the OLS model. Columns 3, 4, 7, and 8 report the results using an instrumental variable approach where we use *HUpre1940* and *HU1940-1949* as instruments for *Connectivity*. For the IV models, we report *First Stage* F-statistics and the p-value obtained from the Hansen J Statistic, which tests the validity of the overidentifying restrictions. Columns 1 and 5, represent the overall effect without controls (but incl. geographic controls). The other columns present the fully saturated model. *SocialActivityCONTROLS* include the number of bars, restaurants, and hotels in a BG. *FormalKnowledgeCONTROLS* is an indicator equal to one if the BG has a postsecondary education campus. The *HumanCaptialCONTROLS* consist of historic inventor counts from 2000, and 2005 as well as the natural log of employment for 2010, and the amount of college degree holders in 2010 (by work location) in a focal BG. *Socio-DemographicCONTROLS* include the natural log of population for 2010. *PhysicalGeographyCONTROLS* are the area covered by water, the area of developable land, and total land area. Standard errors (in parentheses) are clustered at the commuting zone level.

APPENDIX B

TAKING INTERACTIONS AND INNOVATION TO CO-WORKING SPACES

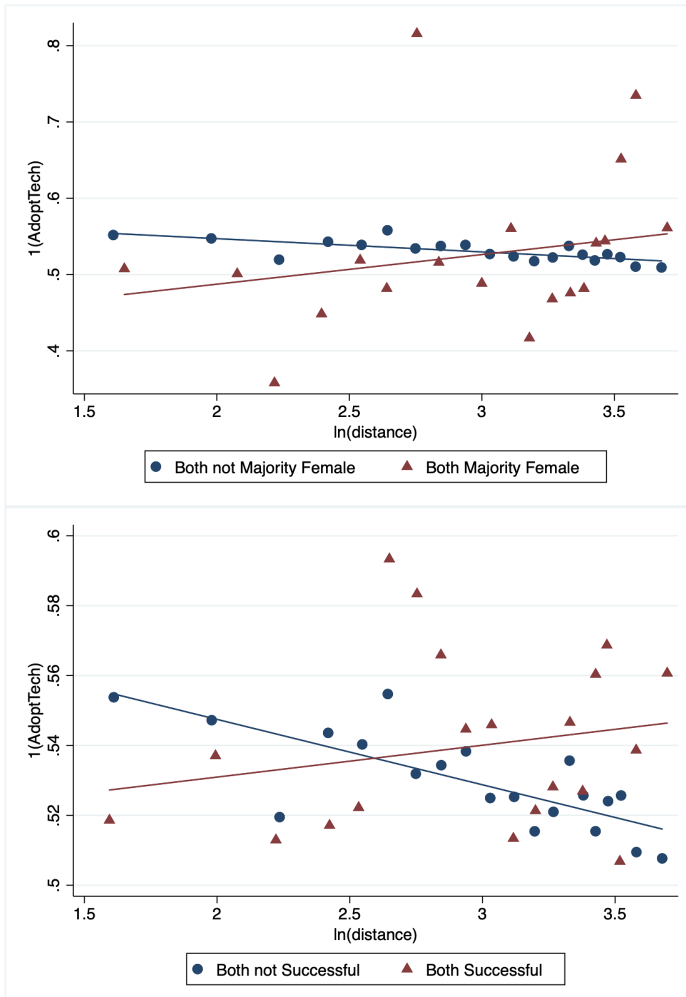


Figure A2.1: Heterogeneous Effects of Physical Proximity: Social Proximity

Notes: This figure displays the results from estimating the interaction between social proximity and physical proximity using binned scatterplots (20 bins, mean average).

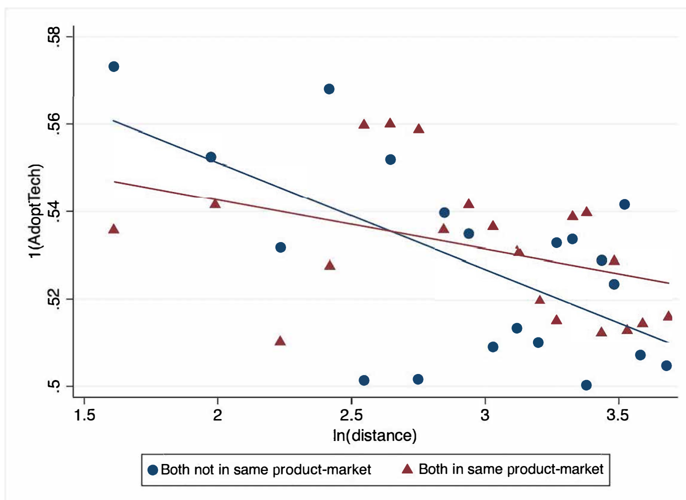


Figure A2.2: Heterogeneous Effects of Physical Proximity: Product-market Proximity

Notes: This figure displays the results from estimating the interaction between product-market proximity and physical proximity using binned scatterplots (20 bins, mean average).

Table A2.1: Variable Description

Variable	Description
Outcome Variables	
ln($Distance_{ij}$)	The distance between $firm_i$ and $firm_j$ in steps (log transformed). One step corresponds to 1.8 meters.
ln($AdoptCount_{ij}$ + 1)	The number of technologies $firm_i$ adopts from $firm_j$ (log transformed and normalized). An adopted technology is a technology used by $firm_i$ in the focal period that $firm_i$ had not implemented in any previous period, but $firm_j$ had.
I($AdoptTech_{ij}$):	Equals one if $firm_i$ adopts a technology from $firm_j$.
# Event $Both_{ij}$ Attend	The number of events hosted at the co-working space at least one person working for of $firm_i$ and $firm_j$ both attend.
I(Ever within X people in line)	Equals one if at least one team member of $firm_i$ and $firm_j$ appear within X (1, 2, 5, 10, 25) people in line for an event hosted at the co-working space.
ln(min line $distance_{ij}$)	Captures the log distance of entry between members of $firm_i$ and $firm_j$ at the event hosted by the co-working hub.
Independent Variables	
Close	Equals to one if $firm_i$ and $firm_j$ are located within 25 meters (14 steps; the 25th percentile of pair-wise distances between all rooms) of each other on the same floor.
Distant	Equals to one if $firm_i$ and $firm_j$ are located further than 56 meters (31 steps; the 75th percentile of pair-wise distance between all rooms) from each other on the same floor.
Common Area	Equals one if the shortest path between $firm_i$ and $firm_j$ passes through a common area. Common areas are the kitchens and zone in front of the elevator on each floor as well as the open sitting space provided on the second floor. Please refer to Figure 1 for a visual depiction of the location of these areas.
Same Industry	Equals to one if $firm_i$ and $firm_j$ operate in the same industry. We follow the classification of industries provided by AngelList and BuiltWith. The individual industries are Administration&Management, Data, Design&Development, Digital, Education, Energy&Construction, Entertainment, Finance&Legal Healthcare, Marketing&PR, Real Estate, Retail, Science&Technology, Security, Software&Hardware. For our analyses we use each firm's primary industry, since many operate in more than one. We determined this by conducting extensive web searches on the startups in our sample.
Pre-period Technology Overlap	Percentage of same technologies $firm_i$ and $firm_j$ used in the period prior to the focal period.
Both Predominately Female	Equals to one if the team members in both $firm_i$ and $firm_j$ are predominately female (over 50 percent). We determined the gender of founders conducting extensive web searches on the startups as well as by comparing first names with lists provided by the US Census for most common names by sex (https://www2.census.gov/topics/genealogy/1990surnames).
Both B2B Companies	Equals to one if $firm_i$'s and $firm_j$'s main customers are other businesses.
Both B2C Companies	Equals to one if $firm_i$'s and $firm_j$'s main customers are individual consumers.
Small (Big) Room	Equals to one if a room is smaller or equal to (larger) than the median room size.
Both Successful	Equals to one if $firm_i$ and $firm_j$ have received a TAG40 award, have received the Village Verified certificate, have raised a seed round or have ever raised a VC seed investment.
$\|age_i$-$age_j\|$	The age difference between $firm_i$ and $firm_j$ (derived from date of entry at the co-working space).
Both Use Roof/Mail/Gym	Equal to one if at least one person working for $firm_i$ and one person working for $firm_j$ has ever accessed the roof/mailroom/gym and zero otherwise. We determine each firm's use of these amenities using information from individual's key-cards for a selected period of time (October 2015 - February 2016, and May 2016 - July 2016).
Mean Technological Similarity to Close Firms	This measure is constructed using the average technology overlap of $firm_i$ technologies with other firms within 20m distance.

APPENDIX C

TAKING INTERACTIONS AND INNOVATION TO THE LAB

C.0.1 Inverse Probability of Treatment Approach

For robustness, I further apply an inverse probability of treatment approach following Azoulay et al. (2017). The inverse probability weighting estimator can be used to demonstrate causality when a controlled experiment is not feasible but fine-grained data is available to model selection. Since treatment to an entrepreneurial advisor may not be randomly assigned, the goal is to estimate the counterfactual or potential outcome if all subjects in the population were assigned either treatment.

Inverse probability weighting refers to weighting the outcome measures by the inverse of the probability of the individual with a given set of covariates being assigned to their treatment (propensity score). In short, the goal is to estimate the potential outcome, that would be observed if a student were assigned treatment to an entrepreneurial advisor and then compare the mean outcome if all students in the population were assigned treatment (Angrist and Pischke, 2008). The equation I estimate is presented below:

$$\omega_s = \frac{1}{PROB(T_s = p|X_s^p)}$$

In the above equation, the denominator of ω_s is the conditional probability that a student was assigned her advisor *p*. Assuming that all relevant factors determining matches are observed and included in X, then, weighting by ω_s effectively creates a pseudo-population of students in which X no longer predicts assignment.

<Insert Table A3.9 here>

I present the results from estimating the above equation in Table A3.9. Column 1 shows the results for patenting outcome, column 2 for overall publication output and columns 3 for highly-cited publications. All outcomes are in log. Overall, the results confirm earlier findings. The estimates in column 3, for example, suggest that exposure to an entrepreneurial professor causes students' highly-cited publications to be reduced by an average of 0.3 from the average of 1.3 for students' who are not exposed. This represents a decrease by one highly-cited publication within five years from starting the PhD. Post-estimation tests indicate that the overlap assumption is not violated.

C.0.2 Student Career Outcomes - Multinomial Logit Approach

To assess if exposure to an entrepreneurial advisor impacts students' career outcomes, I further estimate a multinomial logit model that relates the probability that a student *s* obtains her first position in employment category *j* to exposure to an entrepreneurial advisor. The equation I estimate is:

$$Pr(y_s = j|\boldsymbol{x_s}) = \frac{exp(\boldsymbol{x_s}\boldsymbol{\beta_j})}{\sum_{j=1}^{M} exp(\boldsymbol{x_s}\boldsymbol{\beta_j})}$$

where *j=1,2,3,...,k...,M*, $Pr(y_s = j|\boldsymbol{x_s})$ is the probability that a student *s* obtains her first position in employment category *j*, given $\boldsymbol{x_s}$, $\boldsymbol{x_s}$ is a vector of characteristics and fixed effects related to *s*, and $\boldsymbol{\beta_j}$ is the vector of coefficients pertaining to a student's employment category *j*. In the model presented in Figure 10 and 11, I include student and professor controls, as well as start-year and department fixed effects. Note that I cannot include professor fixed effects in this model given issues with convergence.

Figure A3.10, displays the point estimates from estimating equation (6) with the corresponding 95 percent confidence intervals. Ratios greater than one imply that being exposed to an entrepreneurial advisor leads to a higher probability that a student obtains her first position in a given category *j* over the reference outcome (in this case industry), with the opposite for ratios less than one. As displayed in Figure 10, students of professor-founders are relatively more likely to find their first position in academia and as founders compared to an industry position.

In Figure A3.11, I display the average marginal effects from estimating the above equation with the respective 95 percent confidence intervals. As shown, having an entrepreneurial advisor leads to an increase in the likelihood that a student finds her first position in academia by 6 percentage points (p-value = 0.001) and finds her first position as a founder by 1.3 percentage points (p-value = 0.007), respectively.

As mentioned, using the multinomial logit model, I am not able to apply professor fixed effects. Consequently, the results presented in Figure A3.10 and 11 may merely be picking up differences in entrepreneurial professors' propensity to train students for certain career paths. From this, I interpret my findings such that students of professor-founders are more likely to find their first position in academia and as founders in relation to students of non-founders and not necessarily as a function of engagement in entrepreneurial activity.

<Insert Figures A3.10 and A3.11 here>

Figure A3.1: Number of Startups per Professor-Founder

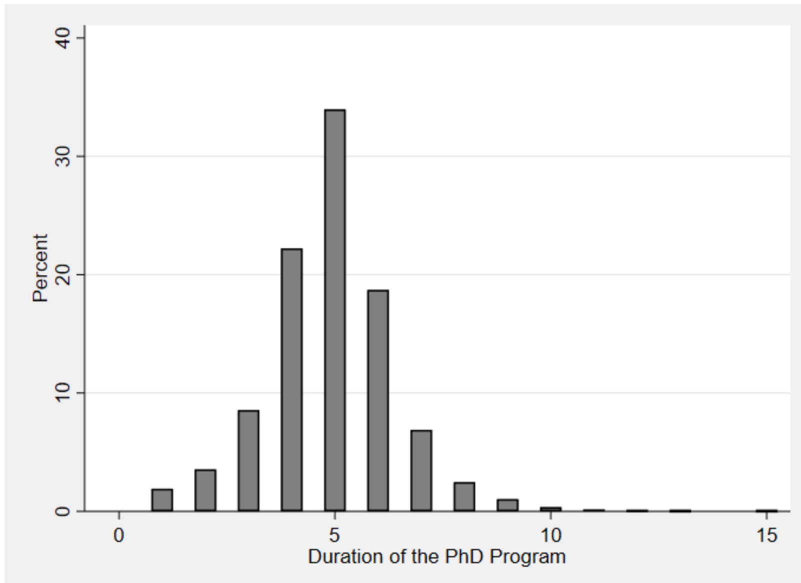


Figure A3.2: Duration of the PhD Program

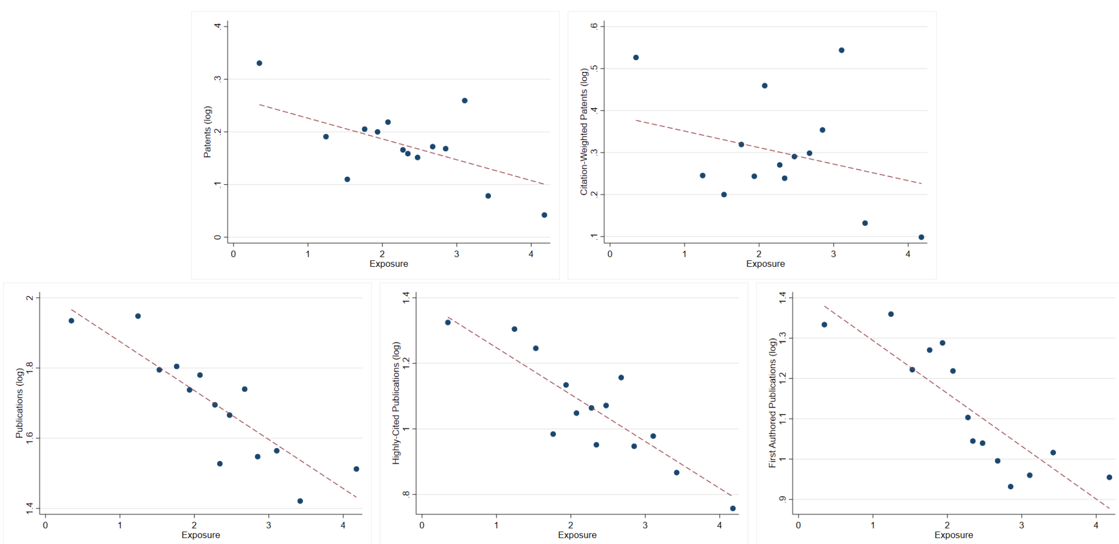


Figure A3.3: Binscatter Plots - Student Outcomes and Exposure

Notes: This graph reports the results from estimating the relationship between exposure (continuous) and student outcomes including professor fixed effects, start-year fixed effects, professor-year trends, and student major fixed effects using binned scatterplots (15 bins, mean average). I obtain the linear fit line using OLS.

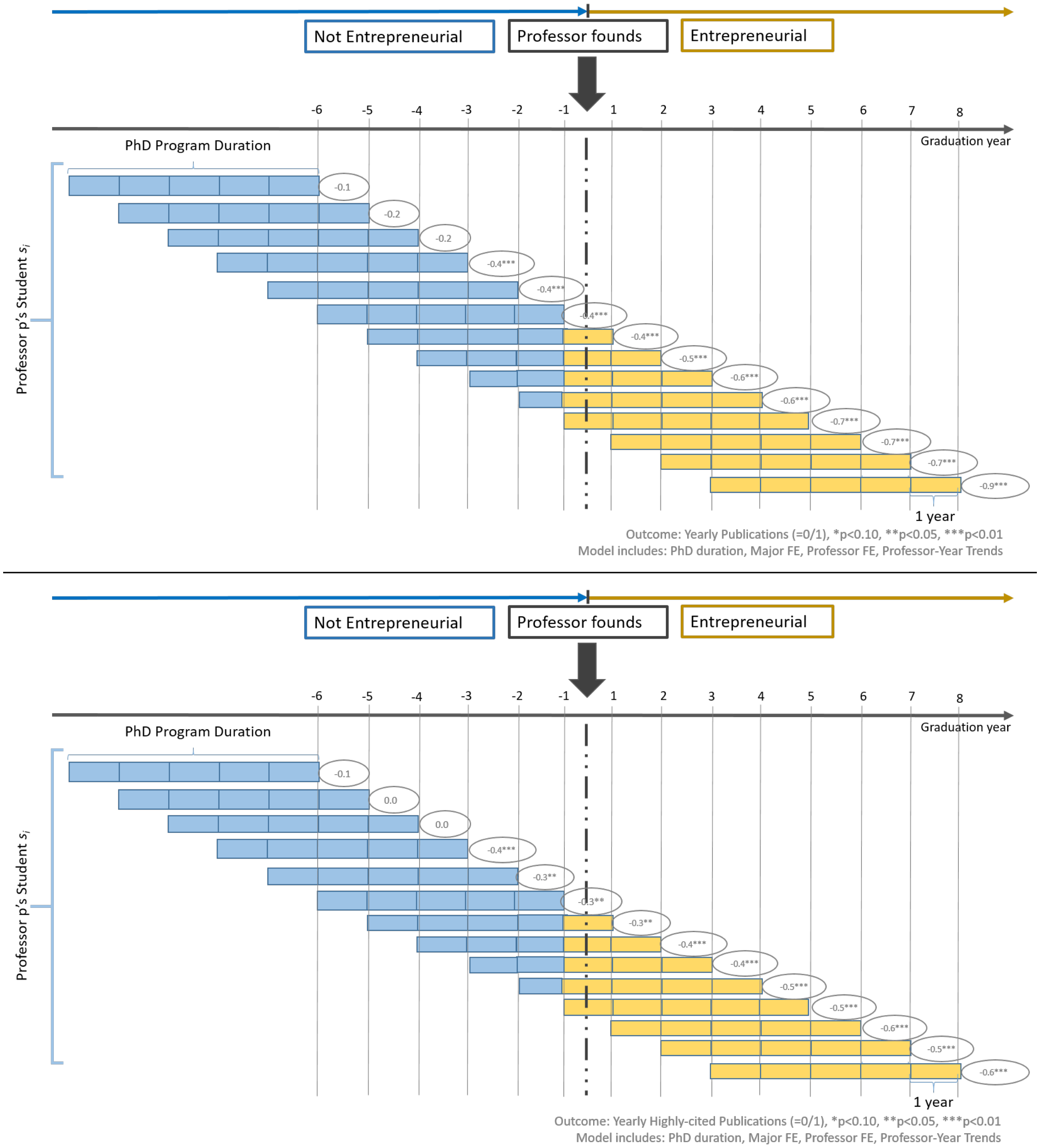


Figure A3.4: Yearly Outcomes for Students by Time of Graduation from Founding - Stylized Approach

Notes: This figure stylistically depicts my empirical approach described in the main text and reports the corresponding coefficients from estimating the model for the likelihood that a student has a publication (top) and a highly-cited publication (bottom) in a given year. The coefficients correspond to those in Figure A5 (C and D).

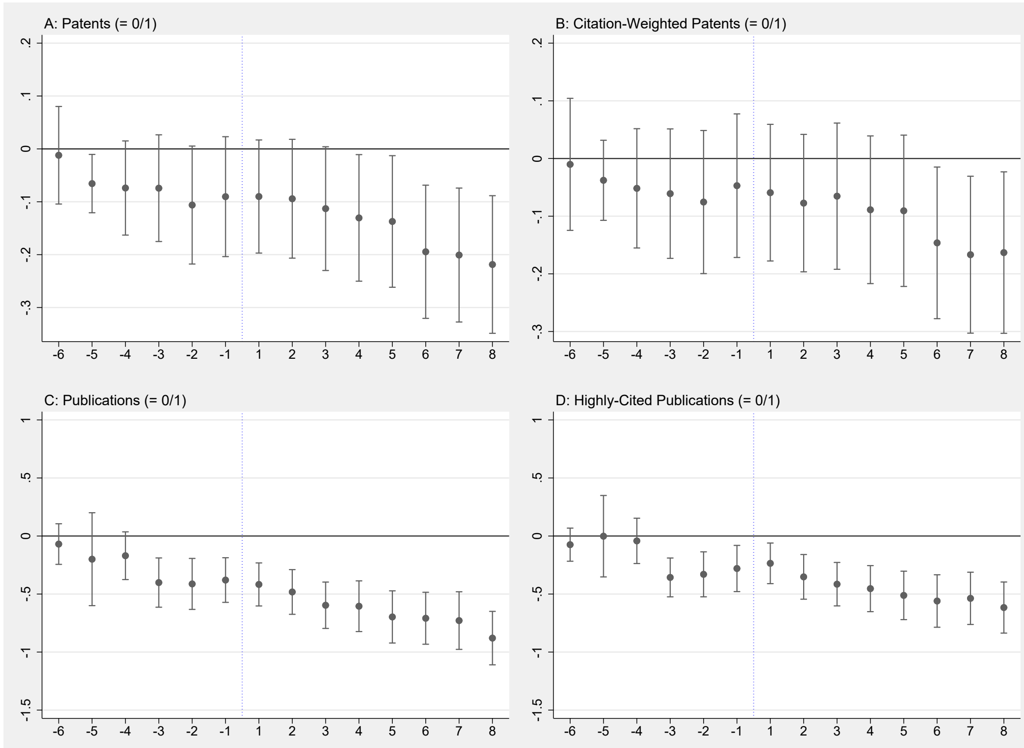


Figure A3.5: Yearly Outcomes for Students by Time of Graduation from Founding

Notes: In this figure, I visually depict the yearly outcomes of PhD students (the x-axis indicates the time a student graduated relative to the time of founding; negative values indicate how many years before founding a student graduated the program) and students' inventive output (y-axis represent coefficients; all outcomes 0 or 1). The omitted category is 7 or more years prior to founding, the values -6 and 8 capture students who graduated 6 years before and 8 or more years after the founding date. The results are obtained using professor and start-year fixed effects and professor-year trends as well as controlling for a student's major. I cluster standard errors on the advisor level. 95 percent confidence intervals are displayed.

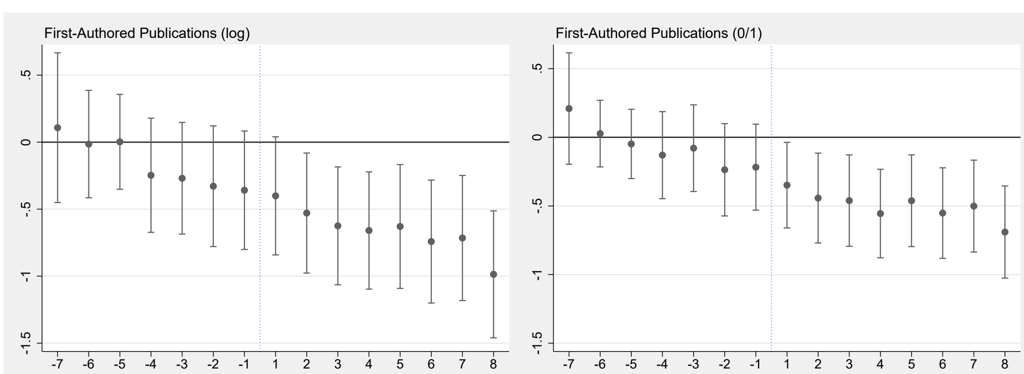


Figure A3.6: First-Authored Publications

Notes: This graph is the equivalent of Figure A5 for students' amount of first-authored publications (log).

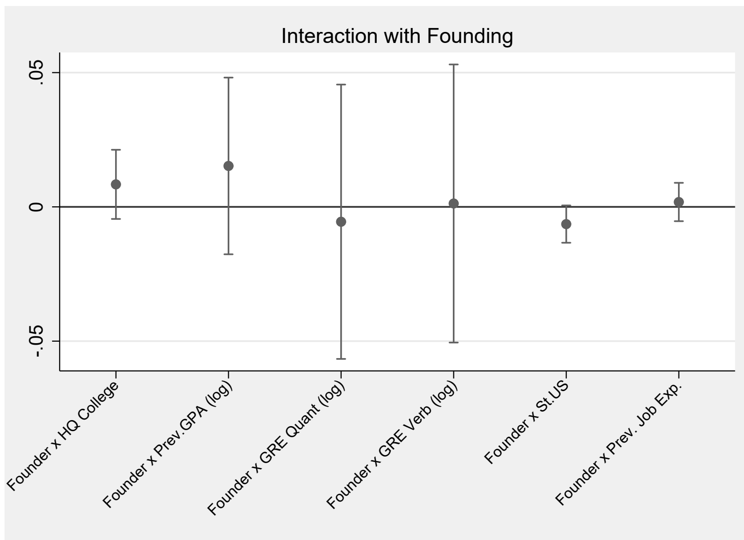


Figure A3.7: Interaction of Student Quality Indicators with Professors' Prior Founding Experience

Notes: This figure displays the interaction coefficients between a professor having founded in the 5 years prior to a student's entry and student quality indicators. The characteristics I examine are the quality of a student's previous degree granting institution, previous GPAs, GRE Scores, US citizenship, and previous work experience as proxies for incoming students quality and characteristics. The model used includes both student and professor fixed effects. 95 percent confidence intervals are displayed.

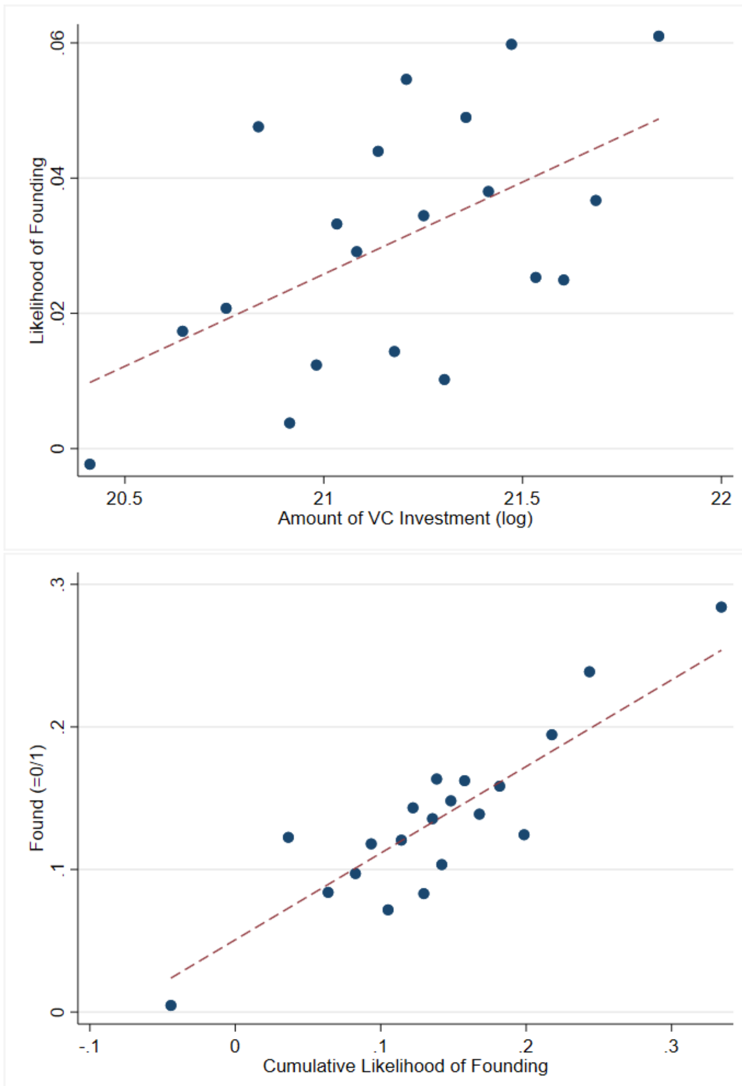


Figure A3.8: Binscatters First Stage(s) IV

Notes: This figure displays the relationships exploited for the instrumental variable approach. All plots are binned scatterplots (20 bins, mean average) including the fixed effects described in Table 4. The top figure presents the likelihood of founding in a given year as a function of the amount of VC investment (log) in a professor's field one year prior. The bottom figure depicts the relationship between founding and the cumulative likelihood of founding.

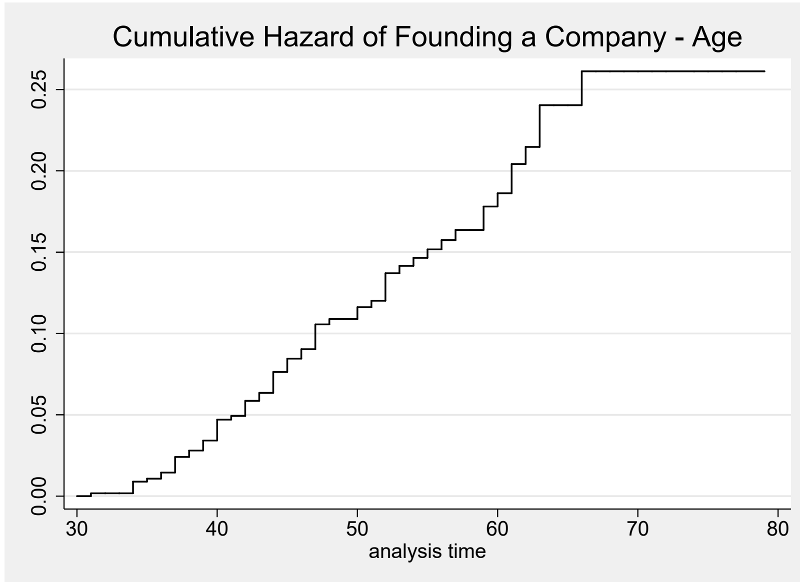


Figure A3.9: Cumulative Hazard of Founding a Company by Professor Age

Notes: This figure displays the results from estimating the hazard of becoming a founder by age using a Cox Proportional Hazard Model.

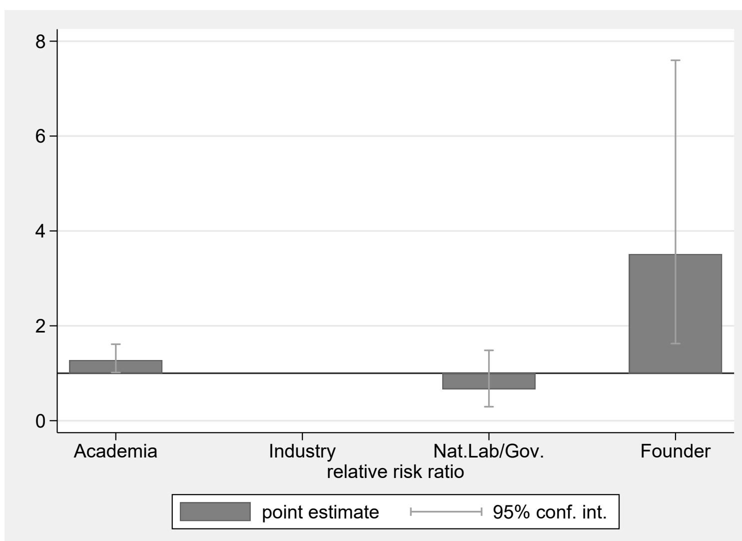


Figure A3.10: Point Estimates of the Effect of Founding on Student Job Outcomes

Notes: This figure displays the relative risk ratios obtained from estimating the multinomial logit approach described in equation (3). In this model, I include student and professor controls, as well as start-year and department fixed effects. Ratios greater than one imply that being exposed to an entrepreneurial advisor leads to a higher probability that a student finds first employment in a given category over the reference outcome (in this case industry), with the opposite for ratios less than one. I report the corresponding 95 percent confidence intervals.

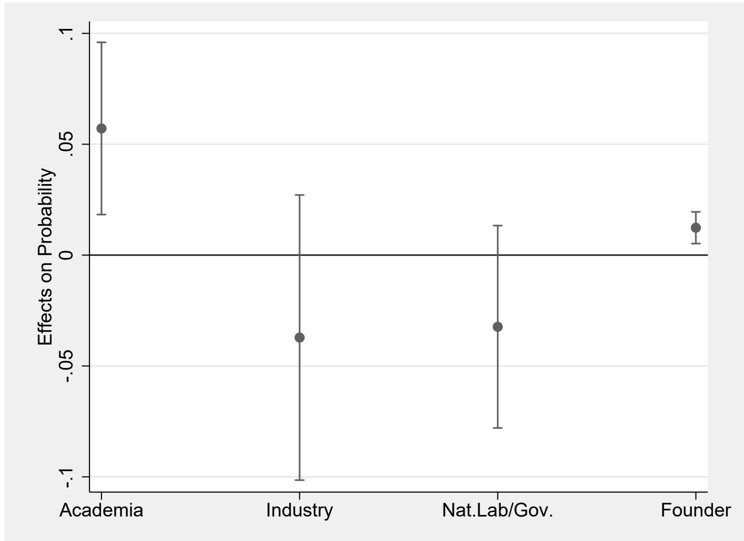


Figure A3.11: Average Marginal Effects of Founding on Student Job Outcomes

Notes: This figure displays results from estimating the average marginal effect of founding on student job outcomes. I report the corresponding 95 percent confidence intervals. These results are obtained running a multinomial logit model including student and professor controls, as well as start-year and department fixed effects.

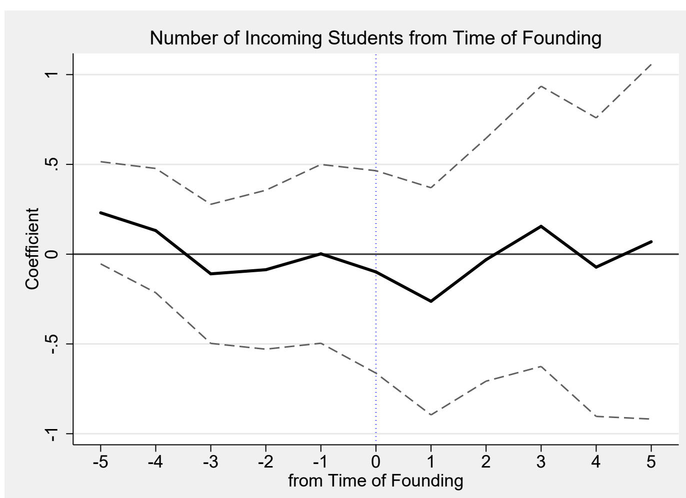


Figure A3.12: Number of Incoming Students from Time of Founding

Notes: This figure displays the coefficients (y-axis) from estimating the relationship between the number of incoming students in a lab and time from founding (x-axis). The unit of analysis is the professor-year level. I obtain the graphs by including professor and year fixed effects. The dashed vertical line indicates the time of founding. Standard errors are clustered on the advisor level to account for intra-group correlation. 95 percent confidence intervals are displayed.

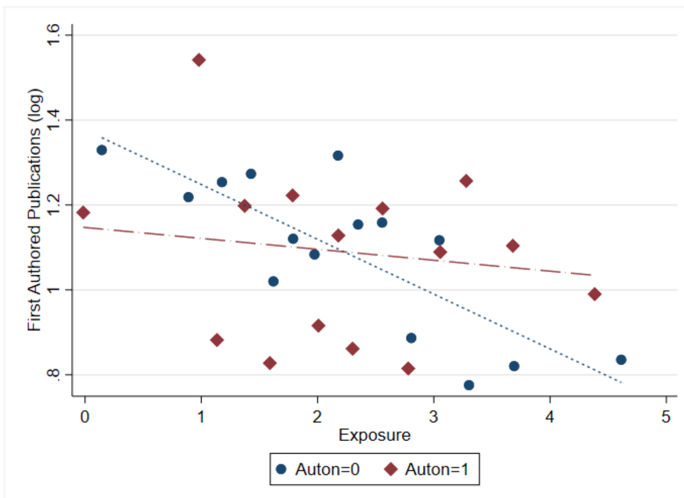


Figure A3.13: First-authored Publications and Exposure by Field of Research Type

Notes: This graph reports the results from estimating the relationship between exposure (continuous) and PhD students' first-authored publications using binned scatter plots (15 bins, mean average) by type of major (autonomous=1 if students are enrolled in biology or chemistry) and including professor and year fixed effects. I obtain the linear fit line using OLS.

Table A3.1: Summary Statistics - By Advisor Type

	Founder	Founder or Patent-holder	All Advisors
	Student Averages		
	(1)	(2)	(3)
Exposure (cont.)	2.46	1.12	0.60
Exposure (=0/1)	0.65	0.29	0.16
Duration of PhD	4.92	4.89	4.90
Departments:			
- AERO	0.03	0.04	0.08
- BIOMED	0.09	0.06	0.07
- CHEME	0.14	0.19	0.14
- CIVIL	0.02	0.03	0.08
- CS	0.09	0.11	0.12
- ECE	0.35	0.33	0.25
- MATERIALS	0.11	0.09	0.09
- ME	0.16	0.15	0.17
Ethnicity:			
- Asian	0.59	0.58	0.54
- Black	0.02	0.03	0.04
- Hispanic	0.03	0.02	0.03
- Two Or More	0.02	0.01	0.01
- White	0.34	0.35	0.39
Other Characteristics:			
- Female	0.20	0.21	0.21
- US citizen	0.37	0.38	0.40
- Previous GPA	3.62	3.61	3.60
- Verbal GRE	155.05	154.55	154.40
- Quant. GRE	163.01	162.69	162.49
- CV Record	0.85	0.82	0.82
First Job:			
- Academia	0.37	0.32	0.35
- Industry	0.57	0.62	0.57
- Gov./Nat. Lab	0.04	0.05	0.07
- Founder	0.02	0.01	0.01
Outcomes During PhD:			
- Patents	0.35	0.33	0.25
- Citation-Weighted Patents	2.02	2.08	1.90
- Publications	7.25	6.44	5.51
- Highly-Cited Publications	3.42	3.13	2.57
Advisor Founder or Patent-holder	1.00	1.00	0.54
Observations	615	1358	2510

Notes: This table displays averages for student characteristics by different types of advisors. Column 1 displays averages for students of advisors who are ever founders, column 2 for those of advisors who are ever founders or patent-holders, and column 3 present averages for students of all advisors.

Table A3.2: Summary Statistics - All Advisors

Professor-Year Level	min	mean	p50	max
All Professors				
Female	0.00	0.15	0.00	1.00
Age at time	25.00	47.61	47.00	88.00
Assistant Professor	0.00	0.22	0.00	1.00
Patents	0.00	0.38	0.00	35.00
Citation-Weighted Patents	0.00	1.82	0.00	698.00
Publications	0.00	5.35	4.00	90.00
Highly-Cited Publications	0.00	2.53	1.00	71.00
Amount Federal Funding (in $million)	0.00	0.09	0.00	20.32
Founder or Patent-holder	0.00	0.44	0.00	1.00
Observations	9661			
Founder or Patent-holder Professors				
Female	0.00	0.12	0.00	1.00
Age at time	25.00	48.03	47.00	82.00
Assistant Professor	0.00	0.18	0.00	1.00
Patents	0.00	0.48	0.00	35.00
Citation-Weighted Patents	0.00	3.85	0.00	698.00
Publications	0.00	7.24	5.00	90.00
Highly-Cited Publications	0.00	3.54	2.00	71.00
Amount Federal Funding (in $million)	0.00	0.12	0.00	20.32
Observations	4195			

Notes: This table displays summary statistics for all professors (*All Professors*) and those professors who ever founded a company or had at least one patent (*Founder or Patent-holder Professors*). The values displayed reflect the characteristics of the advisors by year.

Table A3.3: Robustness: PhD Outcomes Including Student and Professor Controls

	Patents		Publications	
during PhD (in log)	amount	cit.-weighted	amount	highly-cited
	(1)	(2)	(3)	(4)
Panel A				
Exposure (=0/1)	0.0881	0.259*	-0.221**	-0.272***
	(0.0607)	(0.133)	(0.0959)	(0.0970)
Professor FE	Yes	Yes	Yes	Yes
Start-Year FE	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes
StudentCONTROLS	Yes	Yes	Yes	Yes
ProfessorCONTROLS	Yes	Yes	Yes	Yes
R-squared	0.0381	0.0670	0.0777	0.0685
Panel B				
Exposure (cont.)	-0.00878	0.0212	-0.0822***	-0.0816***
	(0.0109)	(0.0265)	(0.0233)	(0.0202)
Professor FE	Yes	Yes	Yes	Yes
Start-Year FE	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes
StudentCONTROLS	Yes	Yes	Yes	Yes
ProfessorCONTROLS	Yes	Yes	Yes	Yes
R-squared	0.0359	0.0623	0.0848	0.0738
Panel C				
Exposure/PhD Dur.	0.000764	0.199	-0.256*	-0.306**
	(0.0715)	(0.174)	(0.140)	(0.138)
Professor FE	Yes	Yes	Yes	Yes
Start-Year FE	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes
StudentCONTROLS	Yes	Yes	Yes	Yes
ProfessorCONTROLS	Yes	Yes	Yes	Yes
R-squared	0.0353	0.0634	0.0767	0.0667
Observations	1248	1248	1248	1248
Number of Professors	183	183	183	183

Notes: This table displays the results from estimating equation (2) without professor-year trends, but including student and professor controls. These are a professor's publication stock in the five years prior to entry, the number of student in a lab at entry of student, rank and age (log) ($ProfessorCONTROLS_{s,t}$). The $StudentCONTROLS_s$ we include are gender, ethnicity, nationality, GRE scores, and previous degree level. *Panel A* reports student outcomes using an indicator equal to one if a student was ever exposed to an entrepreneurial advisor during the PhD. *Panel B* reports student outcomes using a continuous measure of years exposed to an entrepreneurial advisor. *Panel C*, displays outcomes using relative exposure (continuous measure of exposure divided by PhD duration). Standard errors are reported in parentheses and are clustered on the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3.4: Robustness: PhD Outcomes Using IHS Transformation

	Patents		Publications	
during PhD	amount	cit.-weighted	amount	highly-cited
(using IHS transformation)	(1)	(2)	(3)	(4)
Panel A				
Exposure (=0/1)	-0.0182	-0.0586	-0.572**	-0.592***
	(0.102)	(0.173)	(0.236)	(0.208)
Major FE	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes
Start-Year FE	Yes	Yes	Yes	Yes
Prof-X-Year Trends	Yes	Yes	Yes	Yes
R-squared	0.165	0.222	0.181	0.198
Panel B				
Exposure (cont.)	-0.0454*	-0.0362	-0.199***	-0.181***
	(0.0231)	(0.0454)	(0.0463)	(0.0399)
Major FE	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes
Start-Year FE	Yes	Yes	Yes	Yes
Prof-X-Year Trends	Yes	Yes	Yes	Yes
R-squared	0.169	0.222	0.192	0.206
Panel C				
Exposure/PhD Dur.	-0.358	-0.432	-1.079***	-1.237***
	(0.229)	(0.447)	(0.355)	(0.316)
Major FE	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes
Start-Year FE	Yes	Yes	Yes	Yes
Prof-X-Year Trends	Yes	Yes	Yes	Yes
R-squared	0.169	0.223	0.181	0.201
Observations	1248	1248	1248	1248
Number of Professors	186	186	186	186

Notes: This table displays the results from estimating equation (2). *Panel A* reports student outcomes using an indicator equal to one if a student was ever exposed to an entrepreneurial advisor during the PhD. *Panel B* reports student outcomes using a continuous measure of years exposed to an entrepreneurial advisor. *Panel C*, displays outcomes using relative exposure (continuous measure of exposure divided by PhD duration). Standard errors are reported in parentheses and are clustered on the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3.5: Robustness: PhD Outcomes Using IHS Transformation
- Including Individual Controls

	Patents		Publications	
during PhD	amount	cit.-weighted	amount	highly-cited
(using IHS transformation)	(1)	(2)	(3)	(4)
Panel A				
Exposure (=0/1)	0.113	0.305^{*}	-0.260^{**}	-0.345^{***}
	(0.0774)	(0.158)	(0.117)	(0.122)
Start-Year FE	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes
StudentCONTROLS	Yes	Yes	Yes	Yes
ProfessorCONTROLS	Yes	Yes	Yes	Yes
R-squared	0.0385	0.0661	0.0778	0.0696
Panel B				
Exposure (cont.)	-0.0116	0.0254	-0.0982^{***}	-0.103^{***}
	(0.0140)	(0.0318)	(0.0284)	(0.0253)
Start-Year FE	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes
StudentCONTROLS	Yes	Yes	Yes	Yes
ProfessorCONTROLS	Yes	Yes	Yes	Yes
R-squared	0.0359	0.0623	0.0848	0.0738
Panel C				
Exposure/PhD Dur.	-0.000194	0.234	-0.305^{*}	-0.391^{**}
	(0.0917)	(0.206)	(0.169)	(0.172)
Start-Year FE	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes
StudentCONTROLS	Yes	Yes	Yes	Yes
ProfessorCONTROLS	Yes	Yes	Yes	Yes
R-squared	0.0357	0.0627	0.0769	0.0678
Observations	1248	1248	1248	1248
Number of Professors	183	183	183	183

Notes: This table displays the results from estimating equation (2) without professor-year trends, but including student and professor controls. These are a professor's publication stock in the five years prior to entry, the number of student in a lab at entry of student, rank and age (log) ($ProfessorCONTROLS_{s,t}$). The $StudentCONTROLS_s$ we include are gender, ethnicity, nationality, GRE scores, and previous degree level. Student outcomes are log transformed using a inverse hyperbolic sine (IHS) transformation. *Panel A* reports student outcomes using an indicator equal to one if a student was ever exposed to an entrepreneurial advisor during the PhD. *Panel B* reports student outcomes using a continuous measure of years exposed to an entrepreneurial advisor. *Panel C*, displays outcomes using relative exposure (continuous measure of exposure divided by PhD duration). Standard errors are reported in parentheses and are clustered on the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3.6: First-Authored Publications

	First-Authored Publications		
during PhD (in log)	(1)	(2)	(3)
Panel A			
Exposure (=0/1)	-0.474***		
	(0.164)		
Exposure (cont.)		-0.151***	
		(0.0371)	
Exposure/Dur. PhD			-0.777***
			(0.291)
Major FE	Yes	Yes	Yes
Start-Year FE	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes
Prof-X-Year Trends	Yes	Yes	Yes
R-squared	0.221	0.232	0.220
Panel B			
Exposure (=0/1)	-0.218***		
	(0.0814)		
Exposure (cont.)		-0.0760***	
		(0.0198)	
Exposure/Dur. PhD			-0.186
			(0.124)
Major FE	Yes	Yes	Yes
Start-Year FE	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes
StudentCONTROLS	Yes	Yes	Yes
ProfessorCONTROLS	Yes	Yes	Yes
R-squared	0.203	0.210	0.200
Observations	1248	1248	1248
Number of Professors	183	183	183

Notes: This table displays the results from estimating equation (2) with student's first-authored publications as the outcome variable including professor-year trends (*Panel A*) and without professor-year trends, but including student and professor controls (*Panel B*). These are a professor's publication stock in the five years prior to entry, the number of student in a lab at entry of student, rank and age (log) ($ProfessorCONTROLS_{s,t}$). The $StudentCONTROLS_s$ included are gender, ethnicity, nationality, GRE scores, and previous degree level. Standard errors are reported in parentheses and are clustered on the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3.7: Robustness: PhD Student Outcomes - Excluding Students that were never and always exposed

	Patents		Publications			
			amount		highly-cited	
during PhD (in log)	(1)	(2)	(3)	(4)	(5)	(6)
Exposure (=0/1)	-0.0348 (0.0885)		-0.528** (0.228)		-0.482** (0.191)	
Exposure (continuous)		-0.0521 (0.0503)		-0.233*** (0.0801)		-0.245*** (0.0913)
Major FE	Yes	Yes	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes	Yes	Yes
Start-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Prof-X-Year Trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1061	179	1061	179	1061	179
R-squared	0.185	0.496	0.207	0.614	0.230	0.584
Number of Professors	180	61	180	61	180	61
Sample Excluding	Always	Always and Never	Always	Always and Never	Always	Always and Never

Notes: This table displays the results from Table 2, but excluding those students always or never exposed. Standard errors are in parentheses and clustered on the professor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3.8: PhD Student Outcomes by Year of Graduation

PhD Student-Year Level	$\mathbb{1}(Patent_{s,t})$		$ln(Publication_{s,t}+1)$	
	all	cit.-weighted	all	highly-cited
	(1)	(2)	(3)	(4)
Omitted Group: Graduated 7y or more pre-founding				
Graduated 6y pre-founding	-0.0286	-0.0264	-0.0163	-0.0753
	(0.0436)	(0.0474)	(0.142)	(0.111)
Graduated 5y pre-founding	-0.0855**	-0.0444*	0.0836	0.0689
	(0.0391)	(0.0244)	(0.314)	(0.203)
Graduated 4y pre-founding	-0.0792**	-0.0561	-0.113	-0.0288
	(0.0334)	(0.0358)	(0.170)	(0.132)
Graduated 3y pre-founding	-0.0841**	-0.0672*	-0.288*	-0.253*
	(0.0403)	(0.0397)	(0.165)	(0.129)
Graduated 2y pre-founding	-0.102***	-0.0744*	-0.276	-0.209
	(0.0378)	(0.0405)	(0.175)	(0.135)
Graduated 1y pre-founding	-0.0796**	-0.0439	-0.224	-0.167
	(0.0357)	(0.0382)	(0.162)	(0.139)
Graduated year of founding	-0.0686*	-0.0469	-0.199	-0.111
	(0.0352)	(0.0374)	(0.163)	(0.137)
Graduated 1y post-founding	-0.0583	-0.0495	-0.283*	-0.205
	(0.0386)	(0.0366)	(0.155)	(0.135)
Graduated 2y post-founding	-0.0394	-0.00951	-0.416***	-0.256*
	(0.0389)	(0.0409)	(0.156)	(0.131)
Graduated 3y post-founding	-0.0610	-0.0397	-0.343**	-0.244*
	(0.0377)	(0.0393)	(0.169)	(0.133)
Graduated 4y post-founding	-0.0685*	-0.0393	-0.482***	-0.341**
	(0.0408)	(0.0414)	(0.173)	(0.145)
Graduated 5y post-founding	-0.109***	-0.0779*	-0.507***	-0.373**
	(0.0397)	(0.0400)	(0.180)	(0.145)
Graduated 6y post-founding	-0.103**	-0.0926**	-0.444**	-0.317**
	(0.0397)	(0.0402)	(0.177)	(0.140)
Graduated 7y post-founding	-0.116***	-0.0818**	-0.557***	-0.317**
	(0.0400)	(0.0409)	(0.178)	(0.141)
Year FE	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes
Professor FE	Yes	Yes	Yes	Yes
PhD Duration	Yes	Yes	Yes	Yes
Observations	8676	8676	8676	8676
R-squared	0.0211	0.0184	0.143	0.0811
Mean	0.04	0.03	1.13	0.52

Notes: This table displays the results from estimating the likelihood that a PhD student has a patent, a citation-weighted patent, and the amount of publications, and highly-cited publications a student has in a given year. The variables *Graduated Xy pre-/post-founding* indicate a PhD student's time of graduation, where the omitted group is represented by those students who graduated 7 or more years prior to their advisor's transition into entrepreneurship (*pre-founding*). Standard errors are reported in parentheses and are clustered on the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3.9: Robustness: Inverse Probability of Treatment

	Patents	Publications	
during PhD (in log)		amount	highly-cited
	(1)	(2)	(3)
1 vs 0.Exposure (=0/1)	0.0686	-0.324***	-0.300***
	(0.0577)	(0.0567)	(0.0722)
POmean			
1 vs 0.Exposure (=0/1)	0.170***	1.963***	1.310***
	(0.0414)	(0.125)	(0.104)
Stud.-Prof Overlap	Yes	Yes	Yes
Major	Yes	Yes	Yes
Start-Year FE	Yes	Yes	Yes
Department FE	Yes	Yes	Yes
Observations	564	564	564
Cluster Variable	pdpt	pdpt	pdpt
Reported Statistic	ate	ate	ate
Number of Treated	380	380	380

Notes: This table presents the results from estimating the inverse probability of treatment approach described in equation (5). Column 1 shows the results for patenting outcome, column 2 for overall publication output and column 3 for highly-cited publications. Standard errors are reported in parentheses and are clustered on the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3.10: What predicts PhD Student Outcomes?

during PhD (in log)	Patents		Publications		
	amount (1)	cit.-weighted (2)	amount (3)	highly-cited (4)	1^{st}authored (5)
GRE Verbal	-0.00178*	-0.00358**	-0.00322	-0.00281	-0.00310
	(0.000830)	(0.00160)	(0.00192)	(0.00254)	(0.00177)
GRE Quant	0.00475***	0.00744*	0.0172***	0.0116***	0.0128***
	(0.00149)	(0.00379)	(0.00320)	(0.00281)	(0.00361)
Prev GPA	0.0275	0.0275	0.126	0.0495	0.136
	(0.0170)	(0.0349)	(0.0906)	(0.0805)	(0.0764)
Job in 5y before PhD	0.0418**	0.0861***	-0.0362	-0.00861	-0.00341
	(0.0155)	(0.0257)	(0.0606)	(0.0520)	(0.0394)
Prev. Degree from Top Univ.	0.0176	0.0766	0.0967	0.101	0.0272
	(0.0284)	(0.0720)	(0.0754)	(0.0697)	(0.0512)
Master's Pre-PhD	-0.0114	-0.0377	0.0370	0.0402	0.0282
	(0.0223)	(0.0370)	(0.0410)	(0.0415)	(0.0286)
Omitted Major: Algorithms, Combinatorics, and Optimization (ACO)					
Aerospace Engineering (AE)	0.0232	0.0811	-0.0277	-0.0498	0.278*
	(0.0509)	(0.0491)	(0.179)	(0.154)	(0.137)
Bioinformatics (BINF)	-0.0143	0.116**	-0.539**	-0.697***	-0.305
	(0.0441)	(0.0474)	(0.197)	(0.151)	(0.318)
Bioengineering (BIOE)	0.0335	0.122*	-0.177	-0.193	-0.0332
	(0.0494)	(0.0665)	(0.177)	(0.162)	(0.115)
Biology (BIOL)	0.0365	0.132	-0.640*	-0.211	-0.460***
	(0.0344)	(0.0931)	(0.351)	(0.325)	(0.140)
Biomedical Engineering (BMED)	0.0758*	0.182***	-0.400**	-0.240	-0.172
	(0.0387)	(0.0496)	(0.154)	(0.167)	(0.118)
Biomedical Engineering - Joint with Med. School (BMEJ)	0.0151	0.140**	0.206	0.368	-0.165
	(0.0457)	(0.0527)	(0.385)	(0.326)	(0.207)
Computer Engineering (CE)	0.00446	0.0890*	-0.301	-0.220	0.0313
	(0.0424)	(0.0408)	(0.170)	(0.154)	(0.123)
Chemical Engineering (CHE)	0.0558	0.126**	0.00531	-0.0636	0.253*
	(0.0472)	(0.0449)	(0.168)	(0.184)	(0.138)
Chemistry (CHEM)	0.0476	0.0716	0.340	0.437	0.287
	(0.0581)	(0.0404)	(0.444)	(0.405)	(0.239)
Computer Science (CS)	0.222***	0.465***	0.331*	0.290*	0.513***
	(0.0415)	(0.0593)	(0.170)	(0.136)	(0.142)
Computational Science and Engineering (CSE)	0.0681	0.288*	0.121	0.108	0.569*
	(0.0766)	(0.135)	(0.364)	(0.380)	(0.289)
Electrical and Computer Engineering (ECE)	0.186***	0.393***	0.611***	0.487**	0.694***
	(0.0359)	(0.0630)	(0.174)	(0.169)	(0.144)
Environmental Engineering (ENVE)	-0.0232	0.0260	-0.236	-0.199	0.00382
	(0.0428)	(0.0384)	(0.255)	(0.215)	(0.180)
Human-Centered Computing (HCC)	0.0168	0.272**	0.501	0.428	0.788***
	(0.0403)	(0.116)	(0.279)	(0.275)	(0.237)
Industrial Engineering (IE)	-0.0355	0.0367	-0.958***	-0.567**	-0.704***
	(0.0493)	(0.0820)	(0.189)	(0.247)	(0.131)
Mechanical Engineering (ME)	0.0545	0.155***	0.159	0.129	0.476***
	(0.0478)	(0.0466)	(0.171)	(0.152)	(0.134)
Materials Science and Engineering (MSE)	0.165***	0.276***	0.404**	0.293*	0.444***
	(0.0495)	(0.0593)	(0.170)	(0.147)	(0.111)
Nuclear Engineering (NE)	-0.0124	0.0853	-0.00983	-0.155	0.407**
	(0.0407)	(0.0836)	(0.207)	(0.184)	(0.139)
Nuclear and Radiological Engineering (NRE)	-0.00586	0.315	-0.0123	-0.277	0.295*
	(0.0481)	(0.250)	(0.189)	(0.155)	(0.143)
Paper Science and Engineering (PSE)	-0.0283	0.0278	-0.218	-0.444**	0.0898
	(0.0412)	(0.0444)	(0.232)	(0.196)	(0.180)
Polymer, Textile and Fiber Engineering (PTFE)	-0.00498	0.110**	0.338*	0.221	0.357**
	(0.0399)	(0.0410)	(0.179)	(0.249)	(0.147)
Robotics (ROBO)	0.0462	0.107**	0.675***	0.529**	0.941***
	(0.0698)	(0.0444)	(0.188)	(0.175)	(0.227)
Textile Engineering (TE)	0.0723	0.206	-0.126	-0.171	0.114
	(0.0643)	(0.155)	(0.205)	(0.198)	(0.176)
Observations	2254	2254	2254	2254	2254
R-squared	0.0627	0.0478	0.133	0.108	0.138
Fixed Effects	year	year	year	year	year
Number of Groups	12	12	12	12	12

Notes: This table displays the results from estimating what student characteristics predict the amount of patents, citation-weighted patents, publications and highly-cited publications a student produces within 5 years from starting the PhD. Standard errors are reported in parentheses and are clustered on the year-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3.11: Average Student Productivity - Interaction with Age at Founding

Advisor's Students' in 5-year window (log)	Patents	Publications	
		amount	highly-cited
	(1)	(2)	(3)
$\mathbb{1}(Found_{p,t})$	-0.123**	-0.264***	-0.231***
	(0.0486)	(0.0949)	(0.0798)
Age at Founding>49 × $\mathbb{1}(Found_{p,t})$=1	0.127***	0.426**	0.385***
	(0.0488)	(0.175)	(0.129)
Professor FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1630	1630	1630
R-squared	0.427	0.517	0.539

Notes: This table presents the results from estimating equation (5) where the outcomes are a professor's students average patents, publications and top publications within a 5 year time window. In the model, we include the interaction between an indicator equal to one for post-founding period and an indicator equal to one for an age of 50 and older at founding (including all professors). Standard errors are reported in parentheses and are clustered on the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3.12: Average Student Productivity - Interaction With Federal Funding

Advisor's	Fed. Funding (log)	*Average Student Output (5y)* Patents (log)	Publications amount (log)	highly-cited (log)
	(1)	(2)	(3)	(4)
$\mathbb{1}(Found_{p,t})$=1	1.760**	-0.113**	-0.201**	-0.160**
	(0.740)	(0.0480)	(0.0995)	(0.0813)
Fed.Funding$>$90$^{\text{th}}$=1		-0.0188	0.0269	0.0211
		(0.0201)	(0.0608)	(0.0479)
Fed.Funding$>$90$^{\text{th}}$=1 $\times$ $\mathbb{1}(Found_{p,t})$=1		0.0313	-0.0568	0.0160
		(0.0452)	(0.132)	(0.0950)
Professor FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1630	1630	1630	1630
R-squared	0.431	0.426	0.514	0.536

Notes: This table displays the amount of federal funding a professor received (log) as a function of transitioning into entrepreneurship (column 1). Columns 2-4 present the results from predicting a professor's students average outcomes within 5 years including the interaction with an indicator equal to one for the period after a professor transitions into entrepreneurship and an indicator equal to one for federal funding above the 90$^{\text{th}}$ percentile. Standard errors are reported in parentheses and clustered on the advisor-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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