(Co-)Working in Close Proximity: Heterogeneous Impacts on Peer Learning and Startup Performance Outcomes*

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Abstract

In this paper, we examine the influence of physical proximity on firm-level production input decisions and subsequent startup performance outcomes at one of the largest technology co-working hubs in the United States. 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 proximity greatly influences the likelihood of adopting an upstream web technology already used by a peer firm. This effect quickly decays where startups more than 20 meters apart no longer influence each other. Our results further suggest that other social, informational, and competition-based dimensions alter the effect of distance. In particular, physical proximity appears most crucial for promoting exchange among otherwise different firms.

Keywords: *Entrepreneurial Learning*, *Technology Adoption*, *Co-working Hub*, *Micro-Geography*, *Performance*

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1 Introduction

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 in general, and knowledge diffusion in particular (e.g., Rosenthal and Strange 2004; Michelacci and Silva 2007; Samila and Sorenson 2011; Glaeser et al. 2015). Insights from this literature suggest that while geography matters, it may matter at a scale much more granular than has traditionally been measured (<500 meters). However, difficulties arising from measurement and the non-random geographic placement of firms and individuals, have hampered the ability to make causal claims (Arzaghi and Henderson, 2008; Hanson, 2001) and to examine more micro-geographic interactions.

To address these issues, another stream of research has turned their focus on examining the relationship between physical proximity and knowledge sharing within the boundaries of the organization and between individuals. Following work by Allen (1977), who proposed the fundamental role of proximity in determining and shaping workplace interactions, studies have since then tested the link between proximity and individual interactions in a host of different contexts including options exchange (Baker, 1984), technology companies (Cowgill et al., 2009), e-commerce (Lee, 2019), and public sector organizations (Battiston et al., 2020). The empirical evidence provided suggests that physical proximity strongly influences collaboration patterns and the transmission of information among individuals within the same organizational boundary.

In this paper we build upon this prior work by applying a micro-geographic perspective to understanding the relationship between physical proximity and knowledge transfer *outside* the traditional boundaries of the firm. In particular, we examine how geographic distance facilitates/hinders peer learning amongst nascent firms located within the same building – a startup co-working space. As the size of the mean high-tech startup has decreased to approximately two employees over the past two decades (Ewens and Marx, 2017; Kaplan et al., 2009), a startup's ability to access critical external resources (e.g., compute, labor platforms, manufacturing, knowledge, etc.) has never been greater. Yet, our understanding of if and how startups learn from their environments is incomplete.

While physical proximity is one of the more salient dimensions of distance that affects knowledge exchange (Allen, 1977; Cowgill et al., 2009; Agrawal et al., 2017; Roche, Forthcoming), numerous other *distances* also facilitate/impede knowledge exchange and learning. Social (Blau, 1977; McPherson and Smith-Lovin, 1987), product-market (Wang and Zhao, 2018; Alcácer et al., 2015; Saxenian, 1996), and knowledge-space (Cohen and Levinthal, 1990; Lee, 2019; Lane et al., 2020) distance have all been shown to impact the ability or desire to exchange knowledge. Yet are these dimensions more important for knowledge exchange than geographic proximity? Further, how do these dimensions diminish or augment the value of geographic proximity? In this paper we directly examine how social, product-market, and knowledge-base proximity complement or substitute for being geographically close. In light of recent work stressing the importance of taking such factors into account when aiming to engineer peer effects (Carrell et al., 2013; Chatterji et al., 2019; Hasan and Koning, 2019), these dynamics are likely to have critical implications for fostering knowledge exchange, especially among peer firms.

The setting for our study is 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 location choice, 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 learning from 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. Strikingly, being located more than 20 meters apart, but on the same floor does not appear to differ from being located on a different floor altogether. 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 additionally exploit individual characteristics of the startups in the co-working space to examine the interplay between physical proximity and a) social proximity, b) product-market proximity, and c) knowledge-space proximity. This approach allows us to further our understanding of the importance of *micro*-geography for peer firm learning and by including other non-geographic features provides a more complete picture of possible boundary conditions. Examining each non-geographic dimension in detail, we detect that both social and product-market proximity serve as substitutes for physical proximity, and that mid-levels of knowledge-space proximity maximize the impact of physical proximity on peer learning, which we measure using a focal firm's adoption of upstream production technologies already used by a neighboring firm. Taken together, our results indicate that physical proximity is less important in promoting knowledge exchange amongst similar firms, but, in turn, more crucial for firms that are distant along non-geographic dimensions. This suggests that physical proximity may play an especially fundamental role in enabling more exploratory search. Using an instrumental variable approach, where the predicted probability of adopting a web technology from a proximate firm serves as our instrument for actual adoption, we further find evidence for a positive link between peer learning and startups' financial performance outcomes. Finally, our results provide support for the non-negligible role of interpersonal interaction as a channel that facilitates peer learning.

Overall, our findings contribute to previous research in important ways. For one, we provide insight into a fundamental decision early stage, high tech ventures face: building their web-infrastructure. Especially in our context (of predominately digital, web-based startups), the adoption of upstream production technologies may be considered similar to supplier adoption in more traditional industries - a crucial decision, which tends to imply significant path dependency (Arthur, 1994; Murray and Tripsas, 2004; Alcácer and Oxley, 2014; Fang et al., 2020). for another, where previous research has emphasized formal, structural features 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 peer learning 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 thereby focus on proximity to other firms and not individual team members or co-workers. As such, we examine organizational learning in the context of startups, which may differ from individual learning (e.g., in terms of knowledge retention as suggested by March (1991)) and lead to distinct conclusions. Finally, 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.[1]

Taken together, this paper informs our understanding of the scale at which peer learning among small, entrepreneurial firms takes place. We thereby highlight important nuances in terms of the benefits accruing from physical proximity depending on other structural, social, knowledge-based, and competition-related dimensions. Importantly, we detect that physical proximity is most crucial for supporting learning among firms that are otherwise distant. As such, our findings carry fundamental implications for the design of work spaces, may they be of physical or virtual nature, for innovation and entrepreneurial communities.

This paper is structured as follows. In the next section, we develop a basic conceptual framework to guide our predictions. The third section describes the empirical estimation strategy and data sources. In section four, we present our main results on technology adoption and startup performance outcomes. We conclude this paper with a discussion of our findings, including limitations, and broader implications for designing collaborative work environments and for developing technologies that mimic co-location.

2 Conceptual Framework

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

[1] We intentionally use the term hub as described in e.g., Schilling and Fang (2014), since - similar to hubs "who have significantly more connections than does the average member"(p.974) in an interpersonal network - co-working spaces are designed to create more connections between entities in a shared environment.

layout of the workplace, early research dating back to Allen (1977), has proposed the fundamental role of proximity in determining and shaping workplace interactions. Studies have tested the link between proximity and *individual* interactions in the context of, e.g., science (Boudreau et al., 2017; Catalini, 2018), options exchange (Baker, 1984), technology companies (Cowgill et al., 2009), e-commerce (Lee, 2019), and first responders (Battiston et al., 2020) 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 nascent firms and, especially, for firm-level 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). From this, our baseline prediction is: *Physical proximity will increase the likelihood that a startup learns from another startup.* (P1)

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 predict: *Common areas will extend the reach of physical proximity.* (P1.1)

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 1, a) the social (e.g., Blau 1977; McPherson and Smith-Lovin 1987), b) the product-market dimensions (e.g., Wang and Zhao 2018; Alcácer et al. 2015; Saxenian 1996), and c) the knowledge-space (e.g., Cohen and Levinthal 1990; Lee 2019). Although most recent research has pushed on extending our knowledge about 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 or iatrogenic recommendations (Carrell et al., 2013) for the design of entrepreneurial workplaces. In what follows, we hone in on the interplay between these dimensions in relation to physical proximity. Our goal is to thereby assess the role of other social-, information- and competition-based dynamics in shaping the effect of co-location.

2.2.1 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), manufacturing (Kato and Shu, 2016), and emergency relief (Battiston et al., 2020) 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 incentives of with whom information is exchanged. We, therefore, predict: *Social proximity will substitute for physical proximity in promoting learning from peer firms.* (P2.1)

2.2.2 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 peer firms in the same or similar product-market space may not share information, and exercise heightened secrecy precisely because they are co-located competitors. Physical proximity would thereby serve as a barrier 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 we predict: *Product-market space proximity will extenuate the impact of* *physical proximity on peer learning.* (P2.2a)

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 we predict: *Product-market space proximity will bolster the impact of physical proximity on peer learning.* (P2.2b)

2.2.3 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 studies, 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; Schilling and Fang, 2014). 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 predict: *The interaction between physical and knowledge-space proximity has a curvilinear relationship with peer learning. Having both high and low levels of knowledge-space proximity will extenuate the effect of physical proximity whereas having a medium level of knowledge-space proximity will bolster the effect of physical proximity.* (P2.3)

<Insert Figure 1 here>

3 Empirical Strategy and Data

In what follows, we turn to a description of our estimation strategy. We highlight important challenges associated with the role of physical proximity on entrepreneurial peer learning and how we address these. We further provide a detailed overview of how the data are constructed and the context of this study.

3.1 Estimation Strategy

Estimating the role of physical proximity on peer learning 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 individual-level 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, learning could be a function of characteristics of the group (e.g., industry type) where firms that would use similar input factors 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 exposure to certain input factors. 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 decisions to adopt relevant input factors that are already being used by firm j. Table 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).[2]

<Insert Table 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 learning. To operationalize peer learning, we focus our attention on a fundamental decision nascent firms have to make pertaining to their web-infrastructure, which entails considerable path-dependency (Arthur, 1994; Murray and Tripsas, 2004; Alcácer and Oxley, 2014): web technology adoption. Specifically, we examine a) the count of web technologies firm_i

[2] Please refer to Table A2 of the Appendix for further robustness checks.

adopts that firm$_j$ has already adopted, and b) the probability that firm$_i$ adopts a web technology that firm$_j$ has already adopted. Applying the unique firm dyad as our unit of analysis, we estimate the following specification using OLS:

$$Y_{ij} = \gamma ln(distance_{ij}) + X_{ij} + \theta_i + \phi_j + \eta \tag{1}$$

where Y_{ij} represents our web technology adoption measures, X_{ij} is a vector of dyad-specific controls, and θ_i and ϕ_j are $Room_i \times Firm_i$ and $Room_j \times Firm_j$ fixed effects, respectively. The nature of our error term, η, is more complicated. First, if geographic proximity affects web technology adoption decisions, then the outcomes of all firms in close proximity will be correlated. We resolve this standard clustering problem by clustering at the floor-neighborhood level (15 clusters) to account for correlated outcomes in close proximity.[3] Second, because of the dyadic nature of our data, it is insufficient to solely engage in 2-way clustering at the firm$_i$ and firm$_j$ level.[4] As an example, the dyad firm$_i$-firm$_j$ will also be correlated with the dyads firm$_i$-firm$'_j$ as a common component of firm i's web technology adoption decisions and will create correlation across all of firm i's web technology decisions from each dyad alter. However, dyad firm$_i$-firm$_j$ will also be correlated with dyads firm$_j$-firm$'_i$, that is, any dyad that shares a common connection, i.e., has either firm$_i$ or firm$_j$ in common. To correct for these two issues we follow recent work (Aronow et al., 2017; Cameron and Miller, 2014; Carayol et al., 2019; Harmon et al., 2019) and produce dyadic-robust standard errors using the floor-neighborhood locations of firms i and j as the levels of clustering.

In alternate explanations we estimate the following specification:

$$Y_{ij} = \beta Close_{ij} + X_{ij} + \theta_i + \phi_j + \eta \tag{2}$$

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 and further extend our analysis by interacting variables with $Close_{ij}$.

[3] Based on the spatial layout of the co-working building, we attain these floor-neighborhoods by splitting each floor into four quadrants (with exception of the fifth floor which we split into three).

[4] In this 2-way setup, we would allow arbitrary correlation between the dyad firm$_i$-firm$_j$ and all other dyads firm$_i$-firm$_{j'}$.

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. For our analyses, we only examine interactions between firms on the same floor resulting in 10,840 unique firm dyads. Note, that the co-working hub is relatively specialized in digital technologies, fin-tech, software development and marketing.

Approximately 35 percent of the startups ceased operations or left the co-working space each year, which according to senior administrators at the co-working space, typically occurs either because startups 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 prioritized as follows: technology startups over service providers, and local vs. non local startups. Startups leave the co-working hub in two ways: either by not renewing their membership or by outgrowing their office space.[5]

The layout of the floors we examine (floors two - five), is depicted in Figure 2.[6] We measure the distance between rooms from available floor plans using space syntax software (Bafna, 2003; Kabo et al., 2014, 2015).[7] 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 flies". 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).[8] We 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.

[5] Outgrowing the office space is a celebrated event at the co-working hub akin to a graduation. During the time covered by our data, only eight startups moved out because they "graduated" from (outgrew) the building.

[6] 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").

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

[8] For a summary and description of all variables used in the dyadic model, please refer to Table A1 of the Appendix.

<Insert Figure 2 here>

Our main outcome variable of interest is new web technology adoption, which serves as our proxy for peer learning (Fang et al., 2020). To construct this variable, we exploit a novel data set (*builtwith.com*), covering over 25,000 web technologies (e.g., analytics, advertising, hosting, and CMS) that tracks how technology usage of firms change on a weekly basis (Koning et al., 2019). From this website we collect information on the web technology usage of the startups in our sample, including the exact date of implementation and abandonment. Web technologies are the markup languages and multimedia packages computers use to communicate and can be thought of as tools at a firm's disposition to ensure the functionality and efficiency of their websites. Functionalities include interacting with users, connecting to back-end databases, and generating results to browsers, which are updated continuously. When choosing web technologies and web "stacks" (distinct combinations of web technologies) there are different aspects developers need to consider. These are, e.g., the type of project, the team's expertise and knowledge base, time to market, scalability, maintainability, and overall cost of development. As an example, in the subcategory of the Analytics and Tracking category, Error Tracking, at the time of our study, the three most prominent technologies were Rollbar (used by Salesforce, Uber, and Kayak), Bugsnag (used by Airbnb, Lyft, and Mailchimp), and Honeybadger (used by Ebay, Digitalocean, and Heroku). Each technology has their unique advantages and disadvantages, that may only become apparent after learning about peers' experience using them. Similarly, peers can share their experience applying other tools or combinations, specifically in terms of if there was a notable boost in user attraction, conversion, sales, functionality, security or efficiency in running the website. These aspects do not necessarily become palpable until implemented on the website, but have implications that span across various layers of the firm, including HR, finance, marketing, and management. Since implementation entails costs associated with labor, user turnover and embeddedness with other existing technologies reducing these types of frictions should come at the benefit of the startup.

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. We include this variable in order to control, as far as possible, for the fact that some technologies may be adopted as packages.

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 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 firm age as a startup's tenure at the co-working hub and the gender composition of 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). We have additional information on the CEOs/heads of each firm, which we use to identify whether a startup is led by a woman (*Female CEO*) or not. 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.[9]

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 $1 million (Seven Figure Club),

[9](*https://www2.census.gov/topics/genealogy/1990surnames*)

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 and based on prior literature (Nanda and Sørensen, 2010; Ewens and Marx, 2017), 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*.

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; the price for non-members is $10) organized by the co-working space every Friday at noon. The average number of people who attend the lunch is approximately 250 every week. This shared meal is intended to give members the opportunity to "network with other startups" and to "meet, greet and chowdown." The co-working space keeps track of the exact order individuals (both members and non-members) enter to attend the lunch. For a period of time (January 2016 - December 2016), we identify the number of lunches hosted at the co-working space that at least one team member of firm_i and firm_j both attend (*# Event Both$_{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 Descriptive Statistics

On average, each firm is at risk of learning from 53 other firms. The average distance between room dyads is approximately 32 meters 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, 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 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), and eight percent of the startup-dyads are considered successful. The average age difference between startups in a dyad is 7.30 months.

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 3.[10] *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 (within 20m). 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 3 here>

4.1 Baseline Results: Physical Proximity

4.1.1 Average effects of distance

Table 4 presents the results from estimating the effect of distance on the amount of peer technology adoption ($ln(AdoptCount_{ij} + 1)$) using a standard OLS model and using a linear probability model

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

to estimate the likelihood of adopting a technology from a peer firm $\mathbb{1}(\text{AdoptTech}_{ij})$. In the full model (columns 2 and 4) using firm-x-room fixed effects and controlling for industry, business model, gender, age and pre-period technology overlap, we find that the doubling of distance between two dyads reduces both the amount of peer technology adoption by 3.5% and the likelihood of any peer technology adoption by 1.7%, with both point estimates significant at the 1% level. As presented, the magnitude and statistical significance of the effect remains robust to the inclusion of different covariates and confirms our prediction (P1).[11]

<Insert Table 4 here>

To get a better understanding of the precise spatial distances that predict technology adoption, we break our distance measure into quartiles and estimate equation (1) using these indicators rather than the continuous measure of distance.his figure displays the results from estimating equation (1) using a quartile regression. The omitted category consists of the furthest distance, namely being located on different floors. Figure 3 displays the results obtained from this approach suggesting that startup firms located within 20 meters of each other are those most influenced by each other. Firm dyads that are further apart, but on the same floor exhibit the same patterns as those located on different floors.

<Insert Figure 3 here>

Having identified that the distance effect is strongest for the most proximate firms, we create an indicator equal to one (*Close*) that flags dyads located within 20 meters of each other (and equal to zero for all other dyads) and use this measure for the remainder of our results. In Table 4, columns 5-8, we display our findings from estimating equation (1) using this more nuanced classification of distance. The results indicate that close proximity positively influences the likelihood of adopting an upstream (production) technology also used by a peer firm. We find that being in close proximity is associated with a three percentage point higher probability of adopting a peer technology (= 0.025, dyad and floor-neighborhood cluster-robust standard errors 0.011). This finding remains robust to including different covariates. As displayed in columns 5 and 6, applying an OLS model

[11]Please refer to Tables A3 and A4 of the Appendix for models excluding controls.

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 0.048 (cluster-robust standard errors 0.015). This implies that a switch to a room in close proximity would translate into a five percent increase in the number of peer technologies adopted from the mean.

For robustness, to ensure that the results we present are not due to spurious correlations, we utilize a randomization inference method suggested by Athey and Imbens (2017) and Young (2019) and implement a Monte Carlo simulation (1,000 runs). In this simulation, we randomly assigned closeness of each dyad and then estimate the likelihood of adopting a technology as a function of closeness (*Close*) using the simulated strata. The placebo treatment effect results attained from the simulation are presented in Figure 4. Reassuringly, 5% of results were significant at the 5% level. Further, and in line with our findings, only 2 of the simulated Monte Carlo draws (from 1,000) had a coefficient greater than the point estimate of our main results (=0.022), resulting in a randomized inference p-value of 0.002.

<Insert Figure 4 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 order to get a deeper understanding of whether common areas may help extend the effect of proximity and 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 $CommonArea \times 4^{\text{th}}$ distance quartile as the omitted category).[12] The results are displayed in Figure 5, 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

[12]Please refer to Table A5 of the Appendix for the results from estimating equation (1) including 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, common area overlap is associated with a higher likelihood of technology adoption. The interaction of common area overlap with an indicator equal to one if startups are located within 20 meters from each other (*Close*) is negative, yet not statistically significant (p-value>0.1).

to firms that are more distant from one another. As such, these findings confirm our prediction (P1.1).

<Insert Figure 5 here>

4.2 Interplay of physical proximity with other proximity dimensions

We now turn to the results on the interplay between physical proximity and other proximity dimensions.

4.2.1 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 entities 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 5, column 1, 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).

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 5, column 2 displays the results from examining how quality differences impact the effect of physical proximity. 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. Taken together, these results confirm our prediction (P2.1).

4.2.2 Interplay with product-market proximity

In Table 5, column 3, we present the results including an interaction of physical and product-market proximity in order to gauge the role of competition-based dynamics. The interaction between product-market and physical proximity is negative. In addition, the main effect of physical proximity is positive and statistically significant on a level of p-value<0.01. This, again, 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.[13] This result confirms our prediction (P2.2a), and not (P2.2b).

<Insert Table 5 here>

4.2.3 Interplay with knowledge-space proximity

In Figure 6, 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 display a curvilinear relationship with peer technology adoption. Our findings suggest that the strongest interaction is between being physically close and the 2$^{\text{nd}}$ quintile in terms on knowledge-space proximity. The size of the interaction coefficient almost halves from the 2$^{\text{nd}}$ to 3$^{\text{rd}}$, more than halves from the 3$^{\text{rd}}$ to 4$^{\text{th}}$, and is close to zero for the 1$^{\text{st}}$ and 5$^{\text{th}}$ quintiles. Put differently, firms do not learn from firms in close proximity that have very little or very much knowledge overlap, but rather from those with some to moderate levels of knowledge-space proximity. This suggests that informational processes are important factors determining the effect of distance, as predicted in (P2.3)

<Insert Figure 6 here>

4.2.4 Interplay with non-geographic distance

Thus far, the results suggest that proximity along non-geographic dimensions may substitute for being physically close. This points to possible advantages of co-location for peer learning among firms that are otherwise distant. To test this, we create a variable that is equal to one if a firm dyad differs along the social, product-market, and knowledge space dimensions. For simplicity, we count a dyad as different along the knowledge-space dimension if their pre-period technology overlap is below the mean. As displayed in Table 5, column 4, we find that being physically close matters most for knowledge exchange among otherwise distant firms (*Non-geographically Distant*). This

[13] We visually display the results for social and knowledge-space proximity using binned scatterplots (Starr and Goldfarb, Forthcoming; Chetty et al., 2014) in the Appendix, Figures A1 and A2.

may indicate that the advantages of close physical proximity lie in supporting more exploratory search by better enabling access to different and non-obvious sources of knowledge (Fleming, 2001). In contrast to the exploitation of more proximate knowledge, the exploration of new information - an important feature of innovation - typically entails substantial search costs (especially with regard to speed), risk taking, and experimentation (March, 1991). Shorter distances and more immediate feedback may reduce such barriers to both more efficiently transmit and adopt distant knowledge.

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 (Battiston et al., 2020; Hasan and Bagde, 2015; Allen, 1977; Lane et al., 2020). To explore the extent to which this is the case in the co-working hub context, we further exploit a joint event - a lunch - hosted at the co-working space on a weekly basis. Table 6, columns 1 and 2, present the results using the number of lunches (*# Event*) hosted at the co-working space that at least one team member of firm$_i$ and firm$_j$ both attend ($Both_{ij}$ *Attend*) and an indicator equal to one if at least one member of firm$_i$ and firm$_j$ both attend (*1(Event)*) as the outcome variables. As shown, startup dyads that are within 20 meters attend 0.24 more lunches together than the other startup dyads.

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)*). We present the results from estimating the effect of room proximity on check-in line proximity, conditional on jointly attending the event in columns 3-7, Table 6. 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. The results also indicate a higher likelihood of repeat interaction, which may facilitate the development of trust necessary to establish a neighbor's credibility as a source of information.

<Insert Table 6 here>

4.4 Performance

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 sharing knowledge, helping, and setting expectations (e.g., Mas and Moretti, 2009; Herbst and Mas, 2015; Housman and Minor, 2016) enhances performance. To provide more insight into whether this also applies to the context of the co-working hub, we examine the potential performance implications of proximity and resulting peer technology adoption. We thereby move our analysis to the firm-level and estimate the probability of achieving two important startup performance milestones as a function of technology adoption from proximate peer firms. Following prior literature, we use indicators identifying startups that raise seed funding (*Seed Funding*) and raise funding in excess of $million (*>$Million Funding*) as measures for new venture financial performance (e.g., Hochberg et al. 2007; Nanda and Rhodes-Kropf 2013).

The choice to adopt a technology may be driven by unobservable characteristics that are also correlated with achieving startup performance milestones. Consequently, estimating performance as a function of technology adoption may lead to biased results. To address this concern, we implement an instrumental variable approach. The instrument we apply is constructed using the dyadic model as described in equation (1). We then restrict the sample to those j firms in close proximity (20m or less) to firm$_i$ and take the sum of the predicted values for each firm$_i$ as our instrument in the first stage. As displayed in Table 7, column 1, the instrument strongly predicts technology adoption on the firm level.

In column 2, we display OLS results from estimating the likelihood of receiving seed funding as a function of the count of technologies new to firm$_i$ adopted from proximate firms. We include floor fixed effects and cluster on the floor-neighborhood level. The magnitude of the effect remains similar when we include controls for room size, gender of leadership (*Female CEO*), general location (*Remoteness*)[14], age of the focal startup, and the number of firms in close proximity (column 3). Columns 4 and 5 present the equivalent of 2 and 3 using the instrumental variable approach. The reported F-statistics of over 40, indicate that our instrument is sufficiently strong. Our results imply

[14] We calculate Remoteness$_i = \frac{1}{N}\sum_j$ distance$_{ij}$ to control for the general location of a startup.

that a doubling of a firm's technology adoption from proximate firms increases the likelihood of receiving seed funding by about six percentage points - indicating a 66 percent increase from the mean. Table 7, columns 6-9 present the results for our second startup performance measure, raising funding in excess of one million US dollars (*>$Million Funding*). As shown, and similar to seed funding, there is a positive impact of technology adoption from proximate firms on raising funds of over one million US dollars.

<Insert Table 7 here>

The results reported in Table 7 further suggest that technology adoption from proximate firms explains about four percent of variation in the likelihood of achieving important startup milestones. While the R-squared may appear small, this level of model fit is in line with other studies that examine startup outcomes (Guzman and Stern, 2015). Generally, a reconciliation of the magnitudes of our results with those provided by previous related research may be useful at this point. For one, our findings indicate an even smaller distance at which peer learning among firms activates - 20 meters - than has been proposed in the literature thus far (Arzaghi and Henderson, 2008; Rosenthal and Strange, 2008). In the context of an entrepreneurial bootcamp (Hasan and Koning, 2019) detect that distance reduces the likelihood of, amongst others, seeking advice by a magnitude of -0.028. Our most stringent model using the natural log of distance suggests a magnitude of -0.035 for the number and -0.017 for the likelihood of adopting a peer technology. In the context of venture performance, our study fills an important gap, as to our knowledge, there is no published work linking technology adoption from proximate peers to startup performance. The closest study we identified, in order to give a better sense of the magnitude of our results, is by Hochberg et al. (2007). The authors find that a one-standard deviation increase in their measure of network-based VC proximity is associated with a 2.4–2.5 percentage point increases in the likelihood that a venture experiences an exit event. Both the magnitudes of our results on receiving seed funding and > $ million in funding are larger.

5 Discussion and Conclusions

"*We are so thankful for our time at the [co-working hub]. We started out as a small team (...) in the office and all working like crazy to try and build a product that* *[customers] would see the value of and want to use. We found many companies that we could learn from, and were able to establish some key relationships that provided timely advice (...). These relationships directly contributed to the significant growth of [our startup] (...). I can definitively say that we would not be where we are today without our time and the relationships formed at [the co-working hub]" (CEO of a graduating startup at the co-working space, from a published blog post).*

We contribute to the discussion on workplace design for knowledge workers and entrepreneurs as well as the micro-geography of technology diffusion in three important ways. First, our findings indicate that very small distances matter for entrepreneurial learning, and more specifically, for technology adoption. Our results suggest that working in close proximity has clear benefits for the performance of nascent firms via the exchange of knowledge enabled by interaction with peer startups. 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 - even if they are located on the same floor. Our results further highlight the important role of common areas in extending geographic reach and in promoting knowledge exchange. When designing spaces that promote knowledge exchange, areas where individuals can congregate or run into each other in an unplanned manner may be especially important spatial features. Furthermore, given the recent push towards more work from home policies (Choudhury et al., 2018) and the development of technologies that mimic co-location, the importance of common areas presents an interesting finding provided that these spaces and the associated advantages for learning may be lost using at-a-distance work arrangements. It appears that in working from home arrangements especially "creative combustion" (Bloomberg, 2020) may take a toll.

Second, we contribute to the literature examining proximity and knowledge exchange, 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 and directly respond to the call for a better understanding of structures and processes adopted by firms to facilitate or impede learning (Alcácer and Oxley, 2014). Here, for example, our results provide suggestive evidence that socially proximate peers may be able to overcome the distance discount possibly 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 and converges as a result (March, 1991). Further, we find that mid-levels of knowledge-space proximity maximize 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. Overall, our findings highlight that physical proximity may be more crucial for promoting exchange among otherwise distant firms. This finding not only presents a possible avenue to reconcile Marshall-Arrow-Romer specialization externalities (Romer, 1986) and Jacobs' type diversification externalities (Jacobs, 1969), but also may serve as guidance in the allocation of space. Particularly keeping our context in mind, administrators of co-working spaces and other workplaces should consider that the characteristics of their members may influence the overall benefits to co-location. For example, given the constraint that not everyone can sit beside everyone, our results suggest that placing socially proximate actors or startups that compete in the same product-market space further apart may increase the returns from physical proximity for the overall space.

Third, we provide insight on the implications of technology adoption for startup performance highlighting how micro-environments can be leveraged to enhance startup performance by promoting peer learning. Our findings suggest that technology adoption from proximate peers contributes to achieving important startup performance milestones. It is, however, quite feasible that our measure for technology adoption is thereby serving as a proxy for the broader influence of proximate peers on learning and subsequent startup outcomes rather than technology adoption per se.

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. Furthermore, the sample of startups we observe are primarily digital and web-based. These are the types of nascent firms that may benefit the most about learning of new technologies. However, both in terms of current startup industry trends and technology sophistication, 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 as a proxy for peer learning: web 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.

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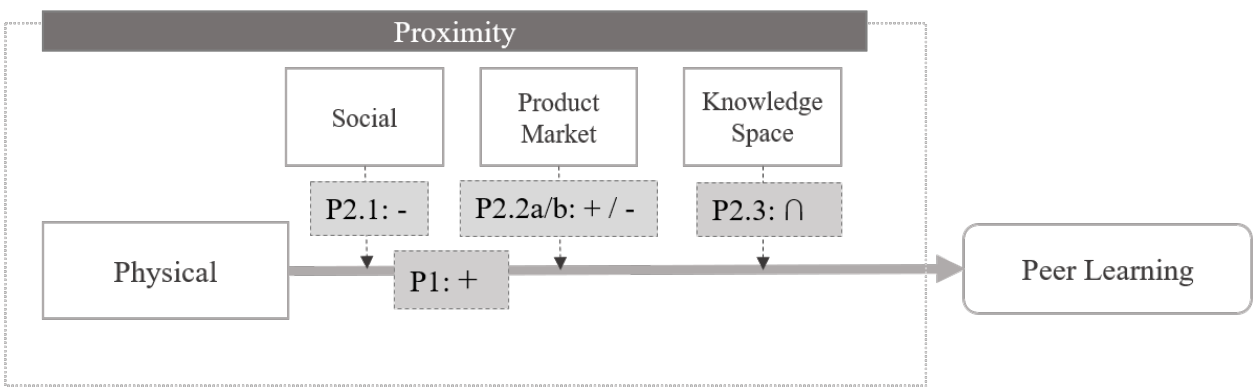


Figure 1: Conceptual Approach

Notes: This figure stylistically displays our conceptual approach. P denotes the corresponding prediction as elaborated in the main text. Each symbol represents the direction of predicted relationship.

Figure 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.

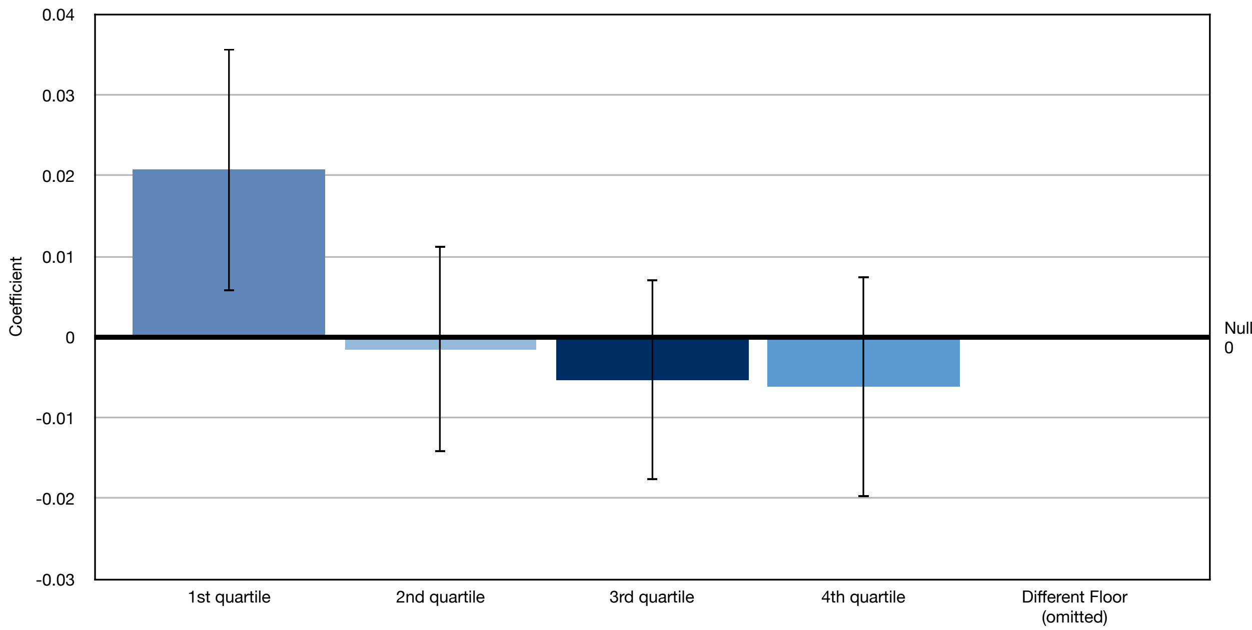


Figure 3: Quartile plots

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. Our omitted category consists of distances among firm dyads that span more than one floor.

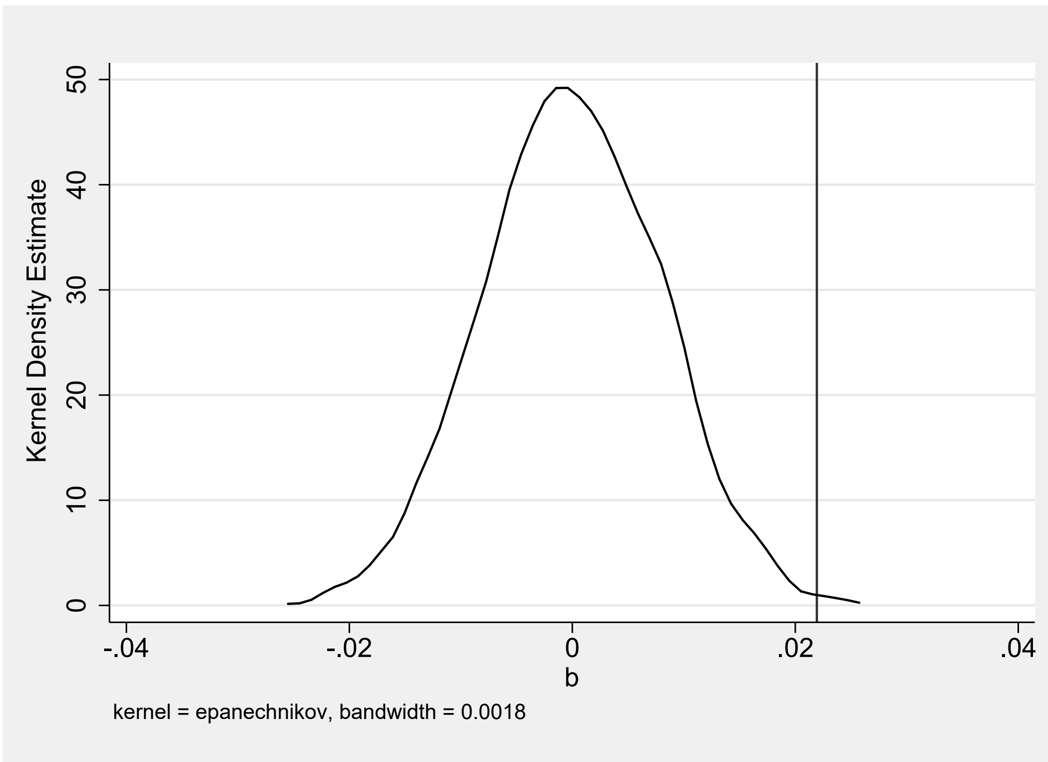


Figure 4: Randomized Inference using Monte Carlo Simulation

Notes: This figure presents the kernel density distribution of coefficients from simulated Monte Carlo draws (1,000 runs). In the simulation, we randomize closeness between each dyad and subsequently estimate the likelihood of adopting a technology as a function of closeness (*Close*) using the simulated strata. The vertical line indicates the point estimate of our main results ($\beta = 0.022$). Only 2 of the simulated Monte Carlo draws (from 1,000) had a coefficient greater than the point estimate of our main results, resulting in a randomized inference p-value of 0.002.

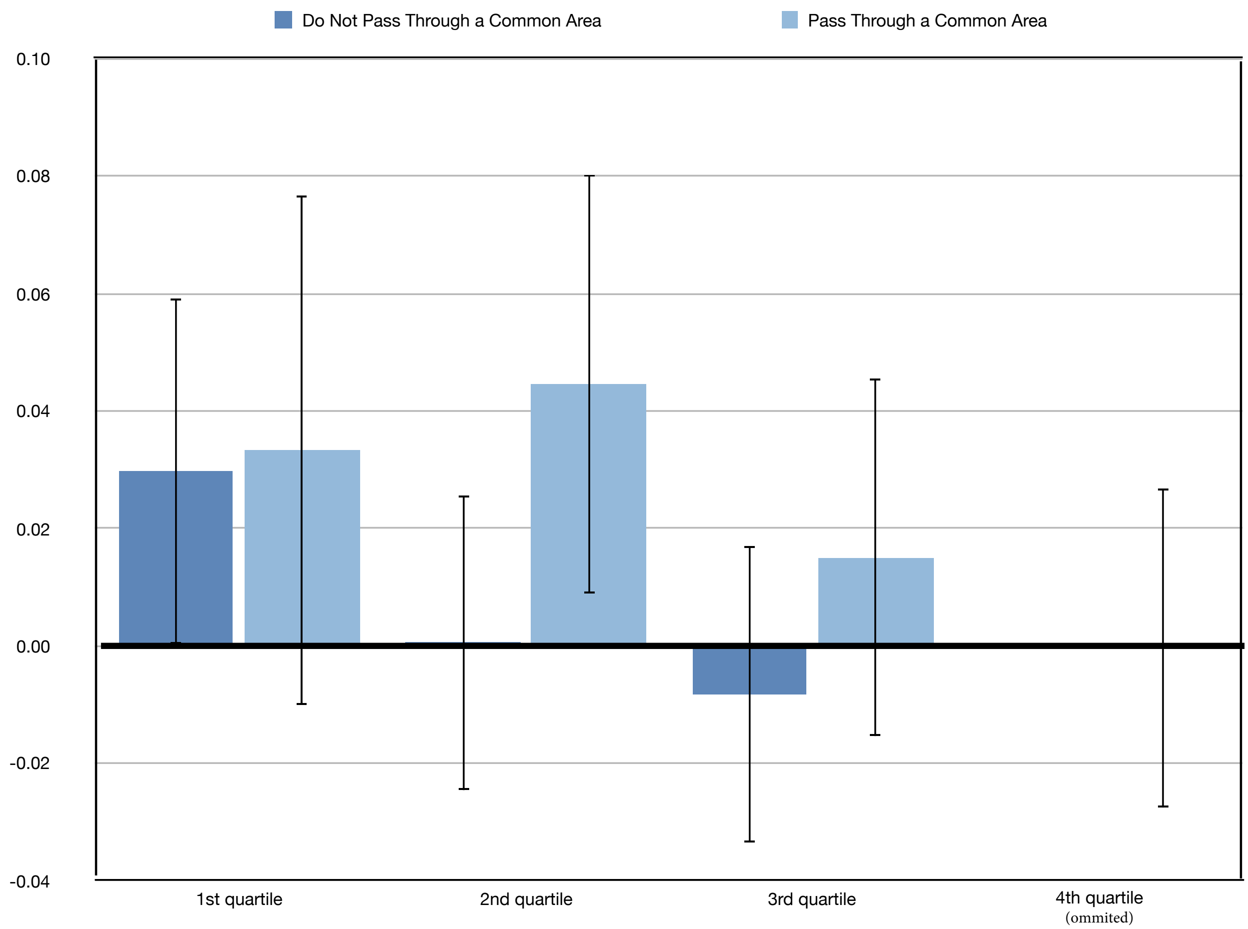


Figure 5: Common area quartile plots

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.

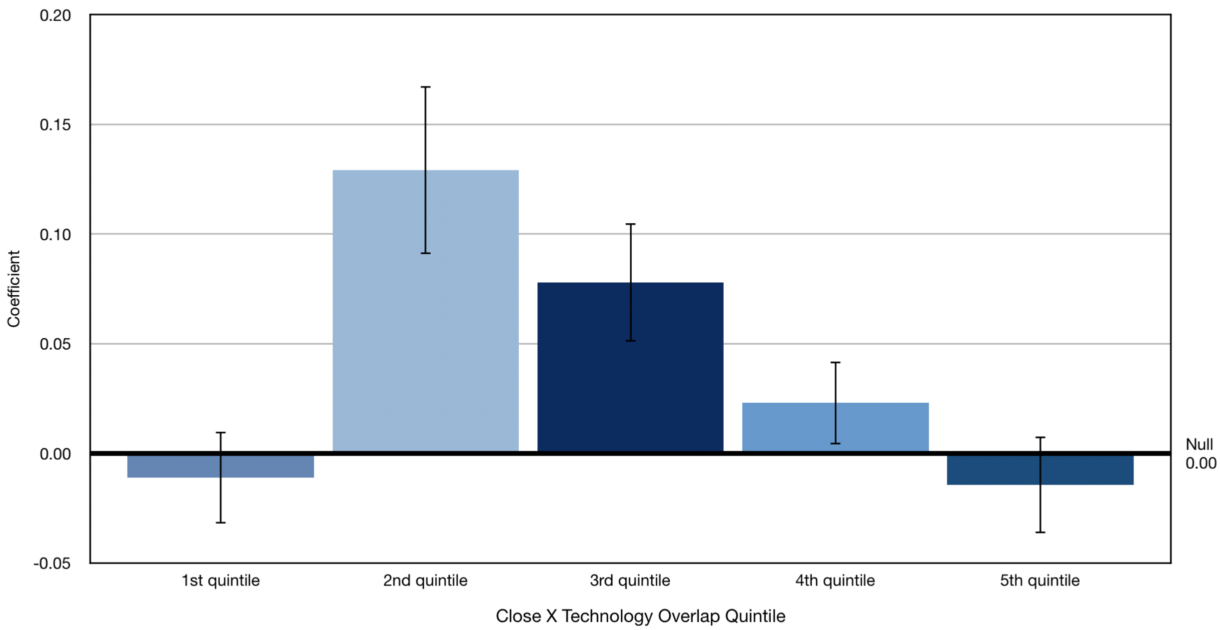


Figure 6: Adoption by technology overlap quintiles

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.

Table 1: Pairwise characteristics do not predict geographic proximity - OLS Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad	
Dependent Variable	ln(distance$_{ij}$)	
	(1)	(2)
Same Industry	0.000	0.001
	(0.023)	(0.023)
Both B2B Companies	0.029	0.030
	(0.041)	(0.039)
Both B2C Companies	0.030	0.030
	(0.045)	(0.044)
Both Majority Female	0.015	0.015
	(0.126)	(0.124)
Both Successful	0.021	0.022
	(0.059)	(0.058)
$\|age\_i\text{-}age\_j\|$	0.001	0.001
	(0.003)	(0.003)
Pre-period Technology Overlap		-0.074
		(0.082)
Firm$_i$ X Room Fixed Effects	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓
Observations	10840	10840
R^2	0.12	0.12

Notes: This table displays the results from OLS regressions predicting physical distance between two firms as a function of firm-dyad characteristics. These variables (indicated by *Both* and *Same*) equal one if both firm$_i$ and firm$_j$ operate in the same industry, both have a B2B (B2C) business model, are both predominately female, and are both successful. The variable $|age\_i\text{-}age\_j|$ represents the absolute age difference in months between firm$_i$ and firm$_j$. *Pre-period Technology Overlap* presents the share of firm$_i$'s technologies also used by firm$_j$ in the previous period. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level.

Table 2: Summary Statistics

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)	271.18	315.82	50	134	143	255	1878
Room size (in m^2)	25.20	29.34	4.64	12.45	13.29	23.70	174.50
Female CEO (= 0/1)	0.12	0.32	0	0	0	0	1
B2B Company (= 0/1)	0.74	0.44	0	0	1	1	1
B2C Company (= 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
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 (in m^2)	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 Companies (= 0/1)	0.48	0.50	0	0	0	1	1
Both B2C Companies (= 0/1)	0.11	0.31	0	0	0	0	1
Both Female (= 0/1)	0.013	0.11	0	0	0	0	1
Age Difference (in months)	7.30	7.28	0	1	5	12	29
Both Successful (= 0/1)	0.08	0.27	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. Please refer to Table A1 in the Appendix for a description of the variables displayed.

Table 3: 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, b) successful, and c) room size.
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.
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.

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

Table 4: Physical proximity positively affects peer technology adoption

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad							
Dependent Variable mean	$ln(AdoptCount_{ij}+1)$ 1.275		$\mathbb{1}(\text{AdoptTech}_{ij})$ 0.531		$ln(AdoptCount_{ij}+1)$ 1.275		$\mathbb{1}(\text{AdoptTech}_{ij})$ 0.531	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(distance$_{ij}$)	-0.043 (0.017)	-0.035 (0.010)	-0.019 (0.007)	-0.017 (0.005)				
Close					0.057 (0.026)	0.048 (0.015)	0.025 (0.011)	0.022 (0.007)
Same Industry		0.021 (0.029)		0.005 (0.013)		0.021 (0.029)		0.005 (0.013)
Both B2B Companies		-0.034 (0.022)		-0.007 (0.011)		-0.034 (0.022)		-0.007 (0.011)
Both B2C Companies		0.030 (0.029)		0.005 (0.008)		0.029 (0.029)		0.004 (0.008)
Both Majority Female		-0.102 (0.057)		0.013 (0.027)		-0.103 (0.057)		0.012 (0.028)
|age_i-age_j|		-0.006 (0.002)		-0.001 (0.000)		-0.006 (0.001)		-0.001 (0.001)
Pre-period Technology Overlap		3.624 (0.146)		1.007 (0.066)		3.624 (0.145)		1.007 (0.065)
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	10840	10840	10840	10840	10840	10840	10840	10840
R^2	0.80	0.86	0.79	0.83	0.80	0.86	0.79	0.83

Notes: This table displays the results from OLS regressions predicting technology adoption as a function of physical distance (proximity) and other dyad characteristics. The outcome $ln(AdoptCount_{ij}+1)$ is the natural logarithm of the number of new to $firm_i$ technologies $firm_i$ adopts from $firm_j$. The outcome $\mathbb{1}(\text{AdoptTech}_{ij})$ equals one if $firm_i$ adopted at least one new technology from $firm_j$. Distance is captured using the natural logarithm of step distance between two firms (ln(distance$_{ij}$)). *Close* equals to one if $firm_i$ and $firm_j$ are located within 20 meters (14 steps; the 25$^{\text{th}}$ percentile of pair-wise distances between all rooms) of each other on the same floor. The variables denoted by *Both* and *Same* equal one if both firm$_i$ and firm$_j$ operate in the same industry, both have a B2B (B2C) business model, and are both predominately female. The variable $|age\_i\text{-}age\_j|$ represents the absolute age difference in months between firm$_i$ and firm$_j$. *Pre-period Technology Overlap* presents the share of firm$_i$'s technologies also used by firm$_j$ in the previous period. We include firm$_i$ x room fixed effects. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level.

Table 5: Proximity Dimensions

	(1)	(2)	(3)	(4)
Unit of Analysis	Firm$_i$-Firm$_j$ Dyad			
Dependent Variable	$\mathbb{1}$(AdoptTech$_{ij}$)			
mean	0.531			
Close	0.024	0.025	0.037	0.013
	(0.007)	(0.008)	(0.007)	(0.005)
Both Female	0.018			
	(0.016)			
Close x Both Female	−0.089			
	(0.016)			
Both Successful		0.025		
		(0.0151)		
Close x Both Successful		−0.036		
		(0.016)		
Same Product Market			0.013	
			(0.005)	
Close x Same Product Market			−0.023	
			(0.008)	
Non-geographically Distant				−0.068
				(0.013)
Non-geographically Distant x Close				0.042
				(0.010)
Pre-period Technology overlap	1.007	1.006	1.006	0.976
	(0.066)	(0.065)	(0.065)	(0.063)
$\lvert$age_i-age_$j\rvert$	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.000)	(0.000)	(0.001)
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓
Proximity Dimension	Social	Social	Product-Market	Composite Index
Observations	10840	10840	10840	10840
R^2	0.83	0.83	0.83	0.83

Notes: This table displays the results from linear probability models predicting technology adoption as a function of physical proximity (close) and the interaction with other proximity dimensions. *Non-geographically Distant* is an indicator equal to one if the firm dyads differ along all non-geographic proximity dimensions we in examine. The outcome $\mathbb{1}$(AdoptTech$_{ij}$) equals one if $firm_i$ adopted at least one new technology from $firm_j$. *Close* equals to one if $firm_i$ and $firm_j$ are located within 20 meters (14 steps; the 25$^{\text{th}}$ percentile of pair-wise distances between all rooms) of each other on the same floor. The variables denoted by *Both* and *Same* equal one if both firm$_i$ and firm$_j$ operate in the same product market, are both successful, or both predominately female. The variable $|age\_i\text{-}age\_j|$ represents the absolute age difference in months between firm$_i$ and firm$_j$. *Pre-period Technology Overlap* presents the share of firm$_i$'s technologies also used by firm$_j$ in the previous period. We include firm$_i$ X room fixed effects. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level.

Table 6: Joint Attendance and Checkin-line Proximity - OLS Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad						
	Both$_{ij}$ Attend		$\mathbb{1}$(Ever within X people in line)				
Dependent Variable	# Events (1)	$\mathbb{1}$(Event) (2)	1 person (3)	2 people (4)	5 people (5)	10 people (6)	25 people (7)
Close	0.240	0.010	0.064	0.091	0.093	0.010	−0.027
	(0.142)	(0.006)	(0.035)	(0.047)	(0.046)	(0.039)	(0.036)
Common Area$_{ij}$	0.147	0.010	0.019	0.061	0.057	0.047	0.056
	(0.064)	(0.005)	(0.040)	(0.036)	(0.029)	(0.041)	(0.007)
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Observations	10840	10840	1398	1398	1398	1398	1398
R^2	0.47	0.51	0.42	0.45	0.48	0.51	0.47

Notes: This table displays the results from OLS regressions predicting the number of lunches (likelihood of attending at least two 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*/$\mathbb{1}$*(Event)*). The indicator $\mathbb{1}$*(Ever within X people in line)* equals 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 conditional on jointly attending the event. The variable *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. We include firm$_i$ X room fixed effects. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level.

Table 7: Technology adoption predicts performance outcomes

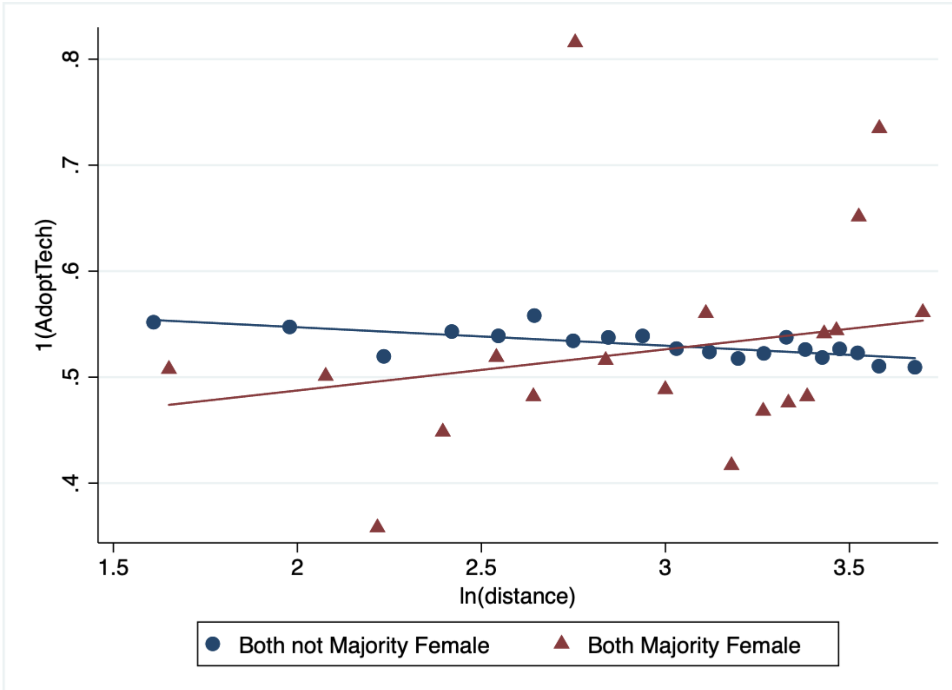
Unit of Analysis	Firm$_i$								
Dependent Variable	ln(AdoptCount$_i$)	$\mathbb{1}$(Seed Funding) (mean = 0.09)				$\mathbb{1}$(>\$Million Funding) (mean = 0.03)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\ln(\sum \widehat{AdoptCount}_{ij})$	1.146								
	(0.127)								
ln(AdoptCount$_i$)		0.0368	0.0371	0.0456	0.0608	0.0145	0.0125	0.0224	0.0204
		(0.0112)	(0.0112)	(0.0194)	(0.0193)	(0.00638)	(0.00548)	(0.0102)	(0.0100)
Room Size			0.0000664		0.0000599		0.0000389		0.0000368
			(0.0000877)		(0.0000792)		(0.0000645)		(0.0000599)
Female CEO			-0.105		-0.108		-0.0405		-0.0418
			(0.0290)		(0.0303)		(0.0137)		(0.0144)
Remoteness			-0.00234		-0.00238		-0.00338		-0.00339
			(0.00576)		(0.00527)		(0.00375)		(0.00351)
Age			-0.000568		-0.0000402		0.000121		0.000297
			(0.00249)		(0.00235)		(0.00121)		(0.00122)
No. Firms			-0.000108		-0.00201		0.000731		0.0000948
			(0.00284)		(0.00297)		(0.00203)		(0.00232)
Floor Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Model	OLS	OLS	OLS	IV	IV	OLS	OLS	IV	IV
First Stage F-stat				81.25	40.37			81.25	40.37
Clusters	15	15	15	15	15	15	15	15	15
Observations	248	248	248	248	248	248	248	248	248
R^2	0.422	0.0219	0.0337	0.0209	0.0284	0.0230	0.0379	0.0208	0.0370

Notes: This tables reports results on the firm-level from estimating the probability of raising seed funding (*Seed Funding*) and raise funding in excess of \$million (>*\$Million Funding*). Column 1 presents the first stage estimates using an instrument constructed from the dyadic model as described in equation (1) including only proximate - within 20m or less - firms. Columns 2, 3, 6, and 7 display results using OLS, columns 4, 5, 8, and 9 present the corresponding IV results. We include controls for room size, leadership gender (*Female CEO*), location (*Remoteness*), age of the focal startup, and the number of firms in close proximity. All models include floor fixed effects. Standard errors (in parentheses) are robust to clustering at the floor-neighborhood level.

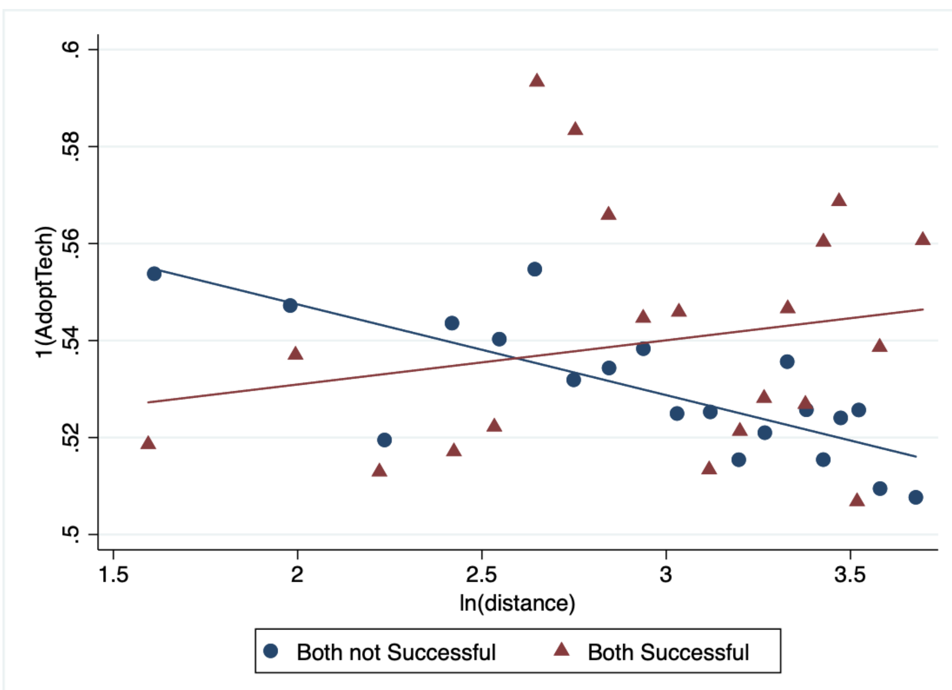
Appendix

Entrepreneurs (Co-)Working in Close Proximity: Heterogeneous Impacts on Peer Learning and Startup Performance Outcomes

Figure A1: Heterogeneous effects of physical proximity: Social proximity



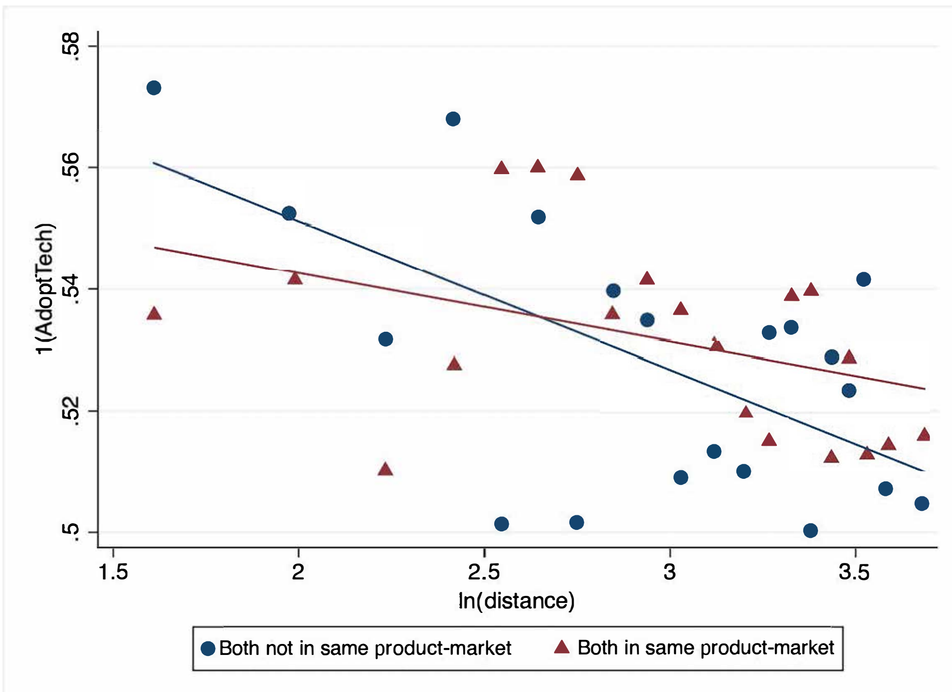
(a) Both Majority Female



(b) Both Successful

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: 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 A1: 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.
1(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.
1(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.
Dyad-Level Independent Variables	
Close	Equals to one if $firm_i$ and $firm_j$ are located within 20 meters (14 steps; the 25$^{\text{th}}$ percentile of pair-wise distances between all rooms) of 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 Majority 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.
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.
Diverse	Equals to one if a startup dyad differs along the social, product-market and knowledge dimensions. For simplicity, we count a dyad as different along the knowledge space dimension if their pre-period technology overlap is below the mean.
$\|age_i\text{-}age_j\|$	The age difference between $firm_i$ and $firm_j$ (derived from date of entry at the co-working space).

Table A2: Pairwise characteristics do not predict geographic proximity - OLS Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad	
Dependent Variable	Close	
	(1)	(2)
Same Industry	-0.001	-0.002
	(0.021)	(0.022)
Both B2B Companies	-0.023	-0.023
	(0.029)	(0.028)
Both B2C Companies	-0.005	-0.005
	(0.032)	(0.032)
Both Majority Female	0.022	0.021
	(0.102)	(0.100)
Both Successful	-0.024	-0.025
	(0.035)	(0.034)
$\lvert$age_i-age_$j\rvert$	-0.000	-0.000
	(0.001)	(0.001)
Pre-period Technology Overlap		0.054
		(0.076)
Firm$_i$ X Room Fixed Effects	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓
Observations	10840	10840
R^2	0.10	0.10

Notes: This table displays the results from OLS regressions predicting that two firms are located within 20m as a function of firm-dyad characteristics. These variables (indicated by *Both* and *Same*) equal one if both firm$_i$ and firm$_j$ operate in the same industry, both have a B2B (B2C) business model, are both predominately female, and are both successful. The variable $|age\_i\text{-}age\_j|$ represents the absolute age difference in months between firm$_i$ and firm$_j$. *Pre-period Technology Overlap* presents the share of firm$_i$'s technologies also used by firm$_j$ in the previous period. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Distance negatively affects peer technology adoption - OLS Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad					
Dependent Variable	$ln(AdoptCount_{ij}+1)$					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(distance$_{ij}$)	-0.073^{**}	-0.044	-0.056^{**}	-0.043^{***}	-0.043^{**}	-0.035^{***}
	(0.037)	(0.043)	(0.027)	(0.017)	(0.018)	(0.010)
Same Industry					0.056	0.021
					(0.034)	(0.029)
Both B2B Companies					0.004	-0.034
					(0.028)	(0.022)
Both B2C Companies					0.007	0.030
					(0.031)	(0.029)
Both Female					-0.095	-0.102^{*}
					(0.098)	(0.057)
|age_i-age_j|					-0.004^{***}	-0.006^{***}
					(0.001)	(0.002)
Pre-period Technology Overlap						3.624^{***}
						(0.146)
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

Notes: This table displays the results from OLS regressions predicting technology adoption as a function of physical distance (proximity) and other dyad characteristics. The outcome $ln(AdoptCount_{ij}+1)$ is the natural logarithm of the number of new to $firm_i$ technologies $firm_i$ adopts from $firm_j$. Distance is captured using the natural logarithm of step distance between two firms (ln(distanceij)). *Close* equals to one if $firm_i$ and $firm_j$ are located within 20 meters (14 steps; the 25$^{\text{th}}$ percentile of pair-wise distances between all rooms) of each other on the same floor. The variables denoted by *Both* and *Same* equal one if both firm$_i$ and firm$_j$ operate in the same industry, both have a B2B (B2C) business model, and are both predominately female. The variable \|age_i-age_j\| represents the absolute age difference in months between firm$_i$ and firm$_j$. *Pre-period Technology Overlap* presents the share of firm$_i$'s technologies also used by firm$_j$ in the previous period. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Distance negatively affects peer technology adoption - LPM Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad					
Dependent Variable	$\mathbb{1}(\text{AdoptTech}_{ij})$					
mean	0.531					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(distance$_{ij}$)	-0.030^{**}	-0.022	-0.024^{*}	-0.019^{***}	-0.019^{***}	-0.017^{***}
	(0.014)	(0.022)	(0.014)	(0.007)	(0.007)	(0.005)
Same Industry					0.015	0.005
					(0.016)	(0.013)
Both B2B Companies					0.004	-0.007
					(0.014)	(0.011)
Both B2C Companies					-0.002	0.005
					(0.012)	(0.008)
Both Female					0.015	0.013
					(0.019)	(0.027)
|age_*i*-age_*j*|					-0.001	-0.001^{**}
					(0.000)	(0.000)
Pre-period Technology Overlap						1.007^{***}
						(0.066)
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

Notes: This table displays the results from predicting the likelihood of technology adoption as a function of physical distance (proximity) and other dyad characteristics. The outcome $\mathbb{1}(\text{AdoptTech}_{ij})$ equals one if $firm_i$ adopted at least one new technology from $firm_j$. Distance is captured using the natural logarithm of step distance between two firms (ln(distanceij)). *Close* equals to one if $firm_i$ and $firm_j$ are located within 20 meters (14 steps; the 25$^{\text{th}}$ percentile of pair-wise distances between all rooms) of each other on the same floor. The variables denoted by *Both* and *Same* equal one if both firm$_i$ and firm$_j$ operate in the same industry, both have a B2B (B2C) business model, and are both predominately female. The variable |age_*i*-age_*j*| represents the absolute age difference in months between firm$_i$ and firm$_j$. *Pre-period Technology Overlap* presents the share of firm$_i$'s technologies also used by firm$_j$ in the previous period. We include firm$_i$ X room fixed effects. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Common-area overlap increases technology adoption

Dependent Variable	$\mathbb{1}(\text{AdoptTech}_{ij})$	
	(1)	(2)
Close	0.029**	0.032***
	(0.012)	(0.012)
Common Area_{ij}	0.010*	0.011**
	(0.005)	(0.005)
Close $\times$ Common Area_{ij}		-0.036
		(0.027)
Firm_i X Room Fixed Effects	✓	✓
Firm_j X Room Fixed Effects	✓	✓
Observations	10840	10840
R^2	0.79	0.79

Notes: This table displays the results from OLS regressions the likelihood of technology adoption as a function of physical proximity and common areas. The variable *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. We include firm_i X room fixed effects. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.