Proximate (Co-)Working: Knowledge Spillovers and Social Interactions*

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Abstract

We examine the influence of physical proximity on between-startup knowledge spillovers at one of the largest technology co-working hubs in the United States. Relying on the exogenous assignment of office space to the hub's 251 startups, we find that proximity positively influences knowledge spillovers as proxied by the likelihood of adopting an upstream web technology already used by a peer startup. This effect is largest for startups within close proximity of each other and quickly decays: startups more than 20 meters apart on the same floor are indistinguishable from startups on different floors. The main driver of the effect appears to be social interactions. While startups in close proximity are most likely to participate in social co-working space events together, knowledge spillovers are greatest between startups that socialize but are dissimilar. Ultimately, startups that are embedded in environments that have neither too much nor too little diversity perform better, but only if they socialize.

Keywords: *Startups*, *Knowledge Integration*, *Technology Adoption*, *Co-working Hub*, *Micro-Geography*

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1 Introduction

Over the past three years, there has been an unprecedented shift in the nature of work. Between 2020 and 2023, the percentage of days worked from home in the US surged almost sixfold, from 4.7% to 28.1% (Barrero et al., 2021). While this shift to remote work has brought some benefits such as a reduction in employee attrition and an increase in measures of job satisfaction (Bloom et al., 2023), evidence also indicates that the reduction in physical proximity has altered the interactions and collaborations that normally would have taken place (Yang et al., 2021). The observation of such change is much in line with a body of work that has garnered support for the role of physical proximity for knowledge exchange among collaborators over decades of research (Allen, 1977; Cowgill et al., 2009).

Beyond the physical dimension, numerous other *distances* have been found to play critical roles in facilitating/impeding knowledge exchange and learning (Blau, 1977; McPherson and Smith-Lovin, 1987; Wang and Zhao, 2018; Alcácer et al., 2015; Saxenian, 1996; Cohen and Levinthal, 1990; Lee, 2019; Lane et al., 2020), which recent work stresses to take into account when aiming to optimize peer effects (Carrell et al., 2013; Chatterji et al., 2019; Hasan and Koning, 2019). Yet despite these advances, we have still to understand the extent to which the similarity and dissimilarity of organizations impacts knowledge transfer in conjunction with physical proximity; a relationship that is typically difficult to estimate provided endogeneity concerns.

The focus of this study is to fill this gap by providing a deeper comprehension of the impact of physical proximity and potential channels driving this relationship. We thereby build upon prior research applying a micro-geographic lens to the relationship between physical proximity and knowledge exchange in a particularly relevant context: knowledge exchange between early-stage entrepreneurial firms (startups). Shedding light on how startups interact with their environment is of particular importance given that dependence on external resources (e.g., compute power, labor platforms, manufacturing, knowledge, etc.) has become increasingly crucial for startups (Conti et al., 2021). In particular, we examine how geographic distance impacts knowledge spillovers amongst nascent startups located within the same building – a startup co-working space – and further document the role that non-geographic differences, such as demographic characteristics, and knowledge overlap among startups play in modulating the effect of distance. Importantly, we provide evidence suggesting that opportunities for social interactions are a critical channel for knowledge spillovers to occur among proximate (co-)workers.

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 exogenous assignment of office space to the hub's 251 startups. In this paper, we consider the instance of adopting a component of a peer startup's technology stack as knowledge spillovers, which represents a novel way of capturing potential knowledge flows (Breschi, 2011). Using floor plans to measure geographic distance, we find that close physical proximity greatly influences the likelihood of these knowledge spillovers, especially when the potential technology choice set is large. This effect, however, quickly decays with distance where startups 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. Moreover, we find that when startups 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 spillovers. In addition, our results indicate a more nuanced role of proximity in fostering knowledge spillovers across nascent firms. We find that physical proximity is less important in promoting knowledge exchange amongst similar startups, but, in turn, more crucial for startups that are dissimilar.

From these findings, the question remains: Why do these micro-distances matter? As suggested by Tortoriello et al. (2015), frequent and repeated interactions may help promote fine-grained information sharing and allow for a better understanding of a neighbor's knowledge and skill. Via its impact on the likelihood and frequency of interacting with others, physical proximity may thereby play an especially fundamental role in not only enabling access and awareness of distinct knowledge pieces (Borgatti and Cross, 2003), but also for the integration and internal use of externally sourced information. Therefore, to understand the possible dynamics underlying knowledge spillovers at short distances, we examine the role of social interactions in explaining the relationship between physical proximity and knowledge exchange. To do so, we exploit event check-in data that provides information on the temporal overlap of startup members at events where we would expect social interactions to occur. Our results indicate that proximity predicts joint attendance of these events – our proxy for socializing – and that startups who co-attend these events produce the largest technology adoption peer effects when they are dissimilar from one another.

The broader innovation literature stresses the importance of external knowledge in promoting innovation and startup performance (Cohen and Levinthal, 1990; Chesbrough, 2012). Because external knowledge provides unique insights previously unavailable to the startup (Zahra and George, 2002; Laursen and Salter, 2006) and provides access to information from a wide range of skills and experiences, it aids in maximizing a startup's capacity for creativity, knowledge-generation, and effective action (Reagans and Zuckerman, 2001; Aggarwal et al., 2020). Building on this research, we further examine the impact of a startup's environment on early-stage startup performance (raising a seed round or receiving more than $1 million in funding). We find that startups embedded in environments that have neither too much nor too little diversity perform better, but only if they engage in social interactions.

Taken together, this paper informs our understanding of the scale at which knowledge spillovers among small, nascent firms take place. We thereby highlight important nuances in terms of the benefits accruing from physical proximity depending on how different exchange partners are from each other along non-physical dimensions. Importantly, we observe that physical proximity is most helpful for supporting knowledge exchange among startups that are otherwise distant. A feasible explanation for our findings is that spatial proximity increases the likelihood and frequency of social interaction, which facilitates the integration of diverse knowledge. As such, our results carry fundamental implications for the design of work spaces that cross the boundaries of collaboration, may they be of physical or virtual nature, for innovation and entrepreneurial communities.

This paper is structured as follows. In the next section, we briefly discuss findings established in the existing literature. The third section describes the data sources and empirical estimation strategy. In section four, we present our main results, provide suggestive evidence in support of social interactions as a feasible mechanism, and unveil potential consequences of knowledge spillovers from proximate, but different peer for 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 Background

2.1 Physical Proximity and Knowledge Spillovers

The diffusion of ideas has been found to be highly localized (Allen, 1977; Arzaghi and Henderson, 2008; Roche, 2020). 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 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; Atkin et al., 2022).

For the last decades, the office was the default way to organize workers. A major benefit attributed to this type of workplace is the provision of a setting for unexpected influences, and for the serendipitous flow of information and ideas to take place. Most recently, however, the office format has been called into question making understanding how to organize workspace for a highly digitized world and global workforce, a front and center question that many firms are grappling with. To this purpose, leading technology companies have created units, such as Google's People Innovation Lab, Meta's Global Workplace Research Group, and Microsoft's Future of Work Group.

The significance of the (work)place for knowledge diffusion holds substantial implications for nascent startups. Generally, entrepreneurs acquire information from a wide array of sources, a notably vital one being fellow entrepreneurs (Nanda and Sørensen, 2010; Lerner and Malmendier, 2013). Given that entrepreneurs primarily function within fast-paced and unpredictable environments, this necessitates a local search strategy (Cyert et al., 1963) that hinges on continuous experimentation and frequent adjustments (Lippman and McCall, 1976; Gavetti and Levinthal, 2000; Gans et al., 2019). This strategy is crucial during the early stages of a venture.

However, the extent to which physical proximity influences knowledge exchange in this context, and in an increasingly digital work environment, remains under-explored. The benefits of proximity, as suggested in previous studies, are often grounded in the theory that a startup's physical environment affects the costs tied to problem-solving, the search for solutions, and access to resources (Stuart and Sorenson, 2003; Sorenson and Audia, 2000; Sørensen and Sorenson, 2003). While it is known that the physical environment plays a pivotal role in many scenarios (Jacobs, 1969; Porter, 1996), our understanding is less comprehensive when it comes to how these mechanisms function in more digital and data-driven environments. In these digital contexts, the advantages of proximity may have less significance, which underscores the need for further study in this area.

Why, then, may proximity matter? As suggested by prior literature, the workplace – a function of organizational structures and geography – may delimit the opportunities available for interaction (Kleinbaum et al., 2013; Feld, 1982). In fact, canonical work by Festinger et al. (1950) examining Westgate West housing communities, detects a high relationship between friendship formation and physical distance, where 22 feet to 88 feet apart (7 - 27 meters) "... seem to be major determinants of whether or not friendships will form" (p.39) in the first place. Results from this study suggest that proximity and the subsequently afforded opportunities to bump into each other on a daily basis increase chances for friendships, especially with people who live next door. Building on this work, the empirical question remains if such patterns akin to friendship formation in housing projects also translate to technology adoption decisions between (potentially competing) nascent firms. Moreover, to what degree could this facilitate the reduction of obstacles associated with knowledge transfer?

In our context, there is one particularly salient type of friction that may hinder transmission of relevant task-specific knowledge that proximity could help overcome: initiation costs (Sandvik et al., 2020). Initiation costs are defined as such frictions that prevent (co-)workers from gathering information, may they be associated with social concerns, coordination difficulties, and/or search frictions. Similarly, Catalini et al. (2020) stress the role of such frictions associated with identifying ideal collaborators, especially given that the transfer of complex, and more novel (distant) knowledge relies on face to face interactions. From this, the relationship between proximity and technology adoption may be a result of increasing the odds that social interaction among proximate firms is initiated (by reducing frictions associated with establishing a relationship) in the first place.

In addition, technology adoption choices require a deep understanding of complex knowledge that may not be apparent from a web search, and may be more quickly and efficiently transferred face to face (Roche, 2023; Atkin et al., 2022). Importantly, social interaction represents an integration mechanism which enables better understanding of others' specific background, challenges, language, and skills (Rogers, 2010). This understanding facilitates the processing of external knowledge and the development of absorptive capacity (Todorova and Durisin, 2007; Dingler and Enkel, 2016), which influences the decision to adopt or reject a new idea (Rogers, 2010). Moreover, frequent interaction with partners may help establish emotional closeness, intimacy, trust (Granovetter, 1973). The technology in question may be accepted more readily when information comes from a trustworthy source of information, especially when there are many potential options to choose from and the type of technology is new to the firm.

2.2 The Interplay of Physical Proximity with Non-Geographic Similarity

While physical proximity has been shown to be an important condition for knowledge exchange, other dimensions of similarity have also been suggested to impact knowledge transfer. For example, social (e.g., Blau 1977; McPherson and Smith-Lovin 1987; Hasan and Koning 2019), product-market (e.g., Wang and Zhao 2018; Alcácer et al. 2015; Saxenian 1996), and knowledge-space (e.g., Cohen and Levinthal 1990; Lee 2019) proximity are important facilitators of knowledge spillovers as established by the literature. The extent to which two entities are similar (or different) along these dimensions may play a crucial role in governing exchange between actors (Granovetter, 1973; McPherson and Smith-Lovin, 1987; Singh, 2005), in reducing or creating barriers for knowledge spillovers (Marshall, 1890; Stefano et al., 2017; Saxenian, 1996), in influencing the ability to absorb (Cohen and Levinthal, 1990), and the amount of non-redundant and relevant information available between actors (Azoulay et al., 2019; Burt, 2004; Oh et al., 2006; Schilling and Fang, 2014; Rogers, 2010).

In general, and across a range of contexts, scholars have provided empirical evidence to support the notion that individuals tend to affiliate more closely with those who exhibit similarities to themselves. One plausible explanation is that individuals possess an inherent psychological inclination to engage in interactions with others who share similar characteristics.

Numerous instances of this phenomenon have been observed, such as in confiding networks among adults (Marsden, 1988), social support networks within governmental structures (South et al., 1982), interaction networks among individuals of the same religious beliefs (Fischer, 1982), and, especially relevant to this study, co-founding networks among entrepreneurs (Ruef et al., 2003).

What remains to be understood is how other forms of similarity interact with physical proximity. If the advantage of geographical closeness is anchored in the reduction of initiation expenses and the complexities associated with transferring more abstract and distant knowledge, it is plausible that physical proximity is most beneficial when similarity along other dimensions – factors that should foster social interaction and trust – is low. In this scenario, we would anticipate a negative interaction between measures of non-geographic similarity and physical proximity. Conversely, a positive interaction would be expected when peers are different.

3 Data and Empirical Strategy

3.1 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 cover a period of 30 months from August 2014 – January 2017, during which 251 unique startups had rented an office in the co-working space. For our analyses, we only examine relationships between startups on the same floor resulting in 10,840 unique startup dyads. Note that the co-working hub is relatively specialized in digital technologies, fintech, software development, and marketing tech.

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.[1] As such, startups leave the co-working hub in two ways: either by not renewing their membership or by outgrowing their office space. The vacant office spaces are then assigned to startups based off a wait-list.[2] Startups on the wait-list are prioritized as follows: technology startups over service providers, and local vs. non local startups.

The layout of the floors we examine (floors two - five), is depicted in Figure 1.[3] We measure the distance between rooms from available floor plans using space syntax software (Bafna, 2003; Kabo et al., 2014, 2015).[4] 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 startup_i and startup_j located on the same floor is within 20 meters (the 25^{th} percentile of pair-wise distances between all rooms, and corresponding to being an average of two offices apart).[5] 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.

<Insert Figure 1 here>

Our main outcome variable of interest is new web technology adoption, which serves as our proxy for knowledge spillovers (Fang et al., 2020). Prior studies have predicted a nascent

[1] 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. While outside options for these startups surely exist, we can interpret our estimates as causal conditional on remaining in the co-working space.

[2] One threat to our assumption of exogeneity is the possibility that some startups may wish to remain on the wait-list in hopes of securing a space they believe to be "better". We do not detect this phenomenon in our data nor did the co-working space administrators observe this taking place.

[3] 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 startup entities (so called "hotdesks").

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

[5] For a summary and description of all variables used in the dyadic model, please refer to Table A1 of the Appendix. Table A2 of the Appendix displays the corresponding correlation matrix.

firm's inherent propensity to adopt as a function of organizational factors and traits such as size, structure, and resources (Fichman, 2004) and highlights that, especially for new web-tech based ventures, technology choice is a fundamental decision (Kapoor and Furr, 2015) as it sets the building block(s) for the future. To construct this variable, we exploit a novel data set (`www.builtwith.com`), covering over 25,000 web technologies (e.g., analytics, advertising, hosting, and CMS) that tracks how technology usage of startups change on a weekly basis (Koning et al., 2019). Builtwith is used by large and small companies alike to learn about the adoption of software components used to build web applications. The set of elements used to develop a web applications are colloquially known as a "technology stack" (and often shortened to "tech stack"). In the Appendix Table A3, we provide examples of the "tech stack" corresponding to three startups in our sample. As the table displays, there is much variation between startups in terms of technology categories used, but also variation of software components used within those categories.

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 startup'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 "tech stacks" 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 startup, 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.[6]

We construct two measures for technology adoption. The first is the number of technologies startup$_i$ adopts from startup$_j$ ($ln(AdoptCount_{ij} + 1)$). An adopted technology is a technology used by startup$_i$ in the focal period that startup$_i$ had not implemented in any previous period, but startup$_j$ had already put to use. The second measure is $1(AdoptTech_{ij})$, which equals one if startup$_i$ adopts a technology from startup$_j$. The control variable *Pre-period Technology Overlap* corresponds to the percentage of technologies startup$_i$ has adopted from startup$_j$ before both of the two startups 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 startup$_i$ and startup$_j$ operate in the same primary industry. Similarly, the variables *Both B2B Companies*

[6]In Figure A1, we present a histogram of the distribution of the number of technologies used by each startup.

and *Both B2C Companies* indicate if startup$_i$'s and startup$_j$'s main customers are other businesses (B2B) or individual consumers (B2C).[7]

We additionally identified 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, $|tenure_i\text{-}tenure_j|$ reflects the absolute value of the tenure difference between startup$_i$ and startup$_j$. The variable *Both Majority Female* flags startup dyads where team members in both startup$_i$ and startup$_j$ are predominately female (over 50 percent female). We have additional information on the CEOs/heads of each startup, 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.[8]

To capture differences in performance outcomes, we construct two measures using information provided by the co-working space and AngelList. These two outcomes are based on prior literature (Nanda and Sørensen, 2010; Ewens and Marx, 2017) and capture financial performance of startups. One is raising a seed round, and the other is raising financial capital in excess of US$ 1 million.

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

[7] We recognize that firms that operate in the same industry or that focus on the same customer type may potentially operate quite differently and employ distinct business models. As such, we may not entirely capture the level of competition between dyad members in the same industry. However, we are still reassured to observe meaningful co-variation between technology adoption and operating in the same industry. Consequently, we should view these effects as lower bounds given the potential measurement error (which thus introduces attenuation bias) making it more difficult to detect an effect.

[8] *https://www2.census.gov/topics/genealogy/1990surnames*

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 startup$_i$ and startup$_j$ both attend (*# Event Both$_{ij}$ Attend*). The average is 0.27. We further exploit the order of entry to create an indicator equal to one if at least one team member of startup$_i$ and startup$_j$ appear within 1, 2, 5, 10, or 25 people in line for the lunch (*1(Ever within X people in line)*).

3.2 Estimation Strategy

Estimating the role of physical proximity on knowledge spillovers – for the purpose of this study captured through peer technology adoption – 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 effects 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 startups that would use similar input factors like to locate close to each other. On the other hand, startups 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 exogenous assignment of office space to the hub's 251 startups, while to deal with contextual contaminants we specifically examine startup i's decisions to adopt relevant input factors that are already being used by startup j. Table 1 shows that pairwise characteristics do not correlate with physical proximity, serving as a validation of our exogenous room assignment assumption (and confirmed by multiple senior staff at the co-working space).[9]

[9] Please refer to Table A4 of the Appendix for further robustness checks. Note that firms can move once assigned to a space. This most frequently happens because the firm is growing and needs larger space. When this occurs, we do not double-count previous dyad alters. As such, all firm1-firm2 dyads are unique and are never associated with multiple rooms. Furthermore, results are robust to the exclusion of within- and between-floor movers. While understanding the causes and consequences of firm relocation is both important

<Insert Table 1 here>

To operationalize knowledge spillovers, we focus our attention on a fundamental decision nascent startups have to make pertaining to their web infrastructure that entails considerable path-dependency (Arthur, 1994; Murray and Tripsas, 2004; Alcácer and Oxley, 2014): web technology stack choices. Specifically, we examine a) the count of web technologies startup$_i$ adopts that startup$_j$ has already adopted, and b) the probability that startup$_i$ adopts a web technology that startup$_j$ has already adopted. Using the unique startup 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 $Room_i \times Startup_i$ and $Room_j \times Startup_j$ fixed effects, respectively. The inclusion of the startup-room specific fixed effects allows us to hold all time-invariant individual startup characteristics constant so that estimation of γ solely arises from dyad-level variation in distance. The nature of our error term, η, is more complicated. First, if geographic proximity affects web technology adoption decisions, then the outcomes of all startups 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.[10] Second, because of the dyadic nature of our data, it is insufficient to solely engage in 2-way clustering at the separate startup$_i$ and startup$_j$ level.[11] As an example, the dyad startup$_i$-startup$_j$ will also be correlated with the dyads startup$_i$-startup$'_j$ since a common component of startup i's web technology adoption decisions will also create correlation across all of startup i's web technology decisions from each other dyad alter.

and interesting, it is beyond the scope of this study and we leave it to future research to explore.

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

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

However, dyad startup$_i$-startup$_j$ will also be correlated with dyads startup$_j$-startup$'_i$, that is, any dyad that shares a common connection, i.e., has either startup$_i$ or startup$_j$ 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 startups i and j as the levels of clustering.

In alternate analyses 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 startups 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 $Close_{ij}$.[12]

3.3 Descriptive Statistics

As displayed in Table 2, on average, each startup is at risk of spillovers from 53 other startups. 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

[12]One threat to our assumption of exogeneity is the possibility that some startups may exit because of worse room conditions. To provide further robustness, we calculate a remoteness measure for each room (defined as the mean distance between the focal startup's room and all other rooms on the same floor) and interact it with *Close*. While the main effect of *Close* remains the same as in our specification, the interaction with remoteness, while positive, is statistically indistinguishable from 0. In addition, using a firm-level data structure, we create an "exit" dummy variable that corresponds to 1 if the startup had left during our sample period and 0 otherwise. We regress this exit dummy on a variety of measures, including the remoteness measure described above. In a similar vein we also explore the extent to which room location may influence socializing. Neither the size nor the remoteness of the room correlate with exiting early.

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.

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 tenure difference between startups in a dyad is 7.30 months.

4 Results

For the purpose of this study, we operationalize *Physical Proximity* using the geographic distance (in meters) between rooms on one floor.

4.1 Baseline Results: Physical Proximity

Table 3 presents the results from assessing 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 to estimate the likelihood of adopting a technology from a peer startup $\mathbb{1}(\text{AdoptTech}_{ij})$. In the full model (Columns 2 and 4), using startup-x-room fixed effects and controlling for industry, business model, gender, tenure 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 seen, the magnitude and statistical significance of the effect remains largely unchanged with the inclusion of additional controls.[13]

[13] Please refer to Tables A5 and A6 of the Appendix for models excluding controls. Table A7 presents the results using different clustering variables. In results available upon request, we exclude all "movers" and obtain similar results. Moreover, our results are robust to clustering at different levels (floor, Room_i and Room_j, Firm_i and Firm_j, and Firm_i x Room and Firm_j x Room). They are also unchanged when we present

<Insert Table 3 here>

We next loosen the (log)linearity assumption of distance on technology adoption by breaking our distance measure into quartiles and estimate equation (1) using these indicators rather than the continuous measure of distance. Figure 2 displays these regression results graphically. We construct our omitted category as startups that are on different floors allowing us to estimate the full set of (same-floor) distance quartiles. The results obtained from this approach suggest that startups located within 20 meters of each other are those most influenced by each other. Being more distant, however, greatly reduces the influence of peers. Put differently, for technology adoption influence, startup pairs that are not within 20 meters of each other on the same floor behave as if they were on different floors altogether.

<Insert Figure 2 here>

Having identified that the distance effect is strongest for the most proximate startups, we create an indicator equal to one (*Close*) that flags dyads located within the first quartile of the distance distribution (20 meters), and 0 otherwise. For simplicity, we use this measure for the remainder of our empirical results. In Table 3, 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 startup. We find that being in close proximity is associated with a 2.5 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 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

heteroskedasticity-consistent (Huber-White) standard errors.

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 and 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) using a Monte Carlo simulation (1,000 runs). In this simulation, we randomly draw closeness (with replacement) for each dyad and then estimate the likelihood of adopting a technology as a function of this random closeness variable. The placebo treatment effect results attained from the simulation are presented in Figure 3.[14] 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 - strongly rejecting our null of no relationship between proximity and technology adoption.

<Insert Figure 3 here>

A further concern may arise around overestimating the relationship between proximity and technology adoption provided "contextual effects" and "reflection" issues (Manski, 1993). For example, multiple firms could be falsely credited with initiating a single adoption. To address this concern, we construct an alternative outcome variable that only includes those technologies adopted by $Startup_i$ that $Startup_j$ had adopted before joining the co-working space. Results from using this approach indicate an increase in the point estimate from 0.025 (as displayed in Table 3, column 7) to 0.033 ($p < 0.01$). The higher point estimate may, indeed, arise from contextual effects such as sales associates pitching software at common events, where multiple firms may adopt technologies advertised to them that had also been previously adopted by other firms. However, since startups from across the building attend these events, the correlation between distance and technology adoption would weaken. As

[14]As expected from this randomization exercise, the mean correlation is close to 0, and 5% of the results were significant at the 5% level.

such, our main results are likely to present a lower bound of our estimate.

Next, we explore the potential heterogeneity around the types of technologies adopted. Given that the choices related to technology adoption require a deep comprehension of complex knowledge, which is not readily gleaned from a web search and might be more effectively transferred through face-to-face interactions, it is plausible that a technology may gain quicker acceptance if information about it is sourced from a physically proximate peer. This is particularly relevant when there are many potential options to choose from and when the technology type is novel to the firm.

To provide insight into this potential, we reconstruct our outcome variable in three different ways. The first outcome, *Many Options*, captures the adoption of a technology from a technology category where numerous viable options exist (above median).[15] The second outcome, *Few Options*, indicates the adoption of a technology from a technology category with few options (below median) to choose from and where technology adoption may be more straightforward (less choice). The final outcome, *New TechCategory*, indicates the adoption of a technology from a technology category new to the firm, which may encompass new and unfamiliar knowledge terrain for the adopting firm. Our results from applying this approach can be found on Table 4. As displayed, our baseline results are stronger for decisions around technologies selected from a pool of many options or when originating from a category new to the firm. In the case of technologies emanating from categories with few choices, we find no relationship.

<Insert Table 4 here>

An additional feature of the physical layout of the office space are common areas provided by the co-working space, such as kitchens on each floor. To examine the extent to which common areas may help extend the effect of proximity and the precise spatial distances this

[15] We construct this measure by looking at the number of technologies in each technology category and coding as 1 if the number in that technology category is above the median. This corresponds to a technology category as having more than 14 technologies/products in it.

applies to, we again 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).[16] The results are displayed in Figure 4, which reveals two things. First, being close (first quartile of distance) to a startup increases technology adoption likelihood independent of whether or not the two startups 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 startup dyads that pass through a common area. In other words, it appears that these common areas extend the co-location premium to startups that are more distant from one another.

<Insert Figure 4 here>

4.2 Interplay of physical proximity and similarity

We now turn to the results on the interplay between physical proximity and similarity. To this end, we construct three different measures that may *proxy* for similarity of startups in a dyad. These are the gender composition of the startup dyads, their product-markets, and knowledge overlap. All three measures are suitable proxies for different ways startup dyads may be similar.

For example, in 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

[16] Please refer to Table A8 of the Appendix for the results from estimating equation (1) including a variable equal to one that indicates if the shortest path between startup$_i$ and startup$_j$ 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).

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).

In Table 5, Column 2, we present the results including an interaction of physical and product-market similarity (if either operate in the same industry or have the same business model). The main effect of physical proximity, *Close* – which reflects the benefits of proximity for startup dyads in different product-markets – increases the likelihood of peer technology adoption by 3.7%. The interaction between product-market and physical proximity, however is negative and reduces the aforementioned proximity benefits by 2.3 percentage points (or over 60% of the total effect, 2.3/3.7). This indicates that physical and product-market similarity, as in the case of the gender composition measure, are substitutes and that being physically close is most beneficial to startup dyads that are dissimilar along this dimension.

In Table 5, Column 3, we present the results including an interaction of physical and knowledge similarity. For simplicity, we count a dyad as similar along the knowledge-space dimension if their pre-period technology overlap is over 0.27.[17] As seen earlier across a the other similarity dimensions, the interaction between technology overlap and physical proximity is negative, implying that being physically close is less valuable for startups that are already similar in knowledge/technology space. We omit our pre-period technology overlap measure in Column 3 as it is highly correlated with the knowledge-space similarity measure.

Thus far, the results suggest that similarity along certain non-geographic dimensions may substitute for being physically close. Using these three available proxies, this points to possible advantages of co-location for facilitating knowledge spillovers among startups that are otherwise dissimilar. To test this further, we create a composite variable called *Diverse* that is equal to one if a startup dyad differs along the three dimensions and is 0 otherwise. As

[17]The 75^{th} percentile of this variables distribution.

displayed in Table 5, Column 4, we find that being physically close matters most for knowledge exchange that leads to the integration of new technologies among otherwise dissimilar startups. This 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.

<Insert Table 5 here>

4.3 The role of social interactions

One potential explanation for our previous set of results is that physical proximity shapes patterns of social interactions (Battiston et al., 2020; Hasan and Bagde, 2015; Allen, 1977; Lane et al., 2020). To explore the likelihood of this mechanism in the co-working hub context, we would require a suitable measure for the propensity of members of two startups to interact. Albeit, not a perfect and complete measure of interactions, we identify a proxy that gets close. To this end, we exploit data on 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 startup_i and startup_j both attend ($Both_{ij}$ *Attend*). Columns 3 and 4 present the results using an indicator equal to one if both ever attended one together. Since common areas seem to extend the effect of proximity, we include this variable in our model. The main result reinforces a result shown throughout: proximity matters. Startup dyads that are within 20 meters are more likely to attend a lunch together and attend more lunches together than dyads that are further apart. Passing through a common area also increases the likelihood of jointly socializing. Further, startups that are different are less likely to socialize, i.e., jointly attend these events together.

Put differently, homophily – as represented by startups that are similar – are much more likely to socialize. Ultimately, though, being close has no differential impact on socializing for startups that are different. In other words, the extent to which a startup is different from the focal startup has no bearing on the likelihood of socializing when they are both close.

We further provide evidence for the effect of proximity on socializing by exploring the extent to which the two startups *went* to the event together. To do so we create an indicator equal to one if at least one team member of startup$_i$ and startup$_j$ appears within five people in the check-in line for the event (*1(within 5 people in line)*).[18] We present the results from estimating the effect of room proximity on check-in line proximity in Columns 5-6, Table 6. Similar to our results using the number of events both attended, we see a positive impact of close room proximity on checking-in together. Here, however, we observe homophilous behavior that is amplified by proximity, wherein startup pairs that are different/diverse and proximate are less likely to attend the event together. While we do not want to overstate this result, given the interaction's marginal significance (at conventional levels), we do want to draw attention to this interesting finding. While on the one hand, startups that are close and different receive more knowledge spillovers from each other, left to their own revealed preferences, startups that are close are less likely on the margin to socialize (co-attend events) with startups different from them. We attempt to explore this seeming paradox by examining the impact of diverse proximity on knowledge spillovers when diverse startups do socialize. We analyze this next.

<Insert Table 6 here>

[18] In the Appendix, Table A9, we further create indicators equal to one if at least one team member of startup$_i$ and startup$_j$ appear within 1, 2, 5, 10, or 25 people in line for the lunch (*1(Ever within X people in line)*). 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. Our results are robust to using log(distance) as the main independent variable of interest.

4.4 Proximity, socializing, and diversity

In this section, we combine physical proximity, socializing, and diversity and examine their joint relationship with technology adoption. As in earlier tables, the outcome $\mathbb{1}(\text{AdoptTech}_{ij})$ equals one if *startup*$_i$ adopted at least one new technology from *startup*$_j$. *Close* equals to one if *startup*$_i$ and *startup*$_j$ 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 variable (# *Event Both*$_{ij}$ *Attend* equals one if least one team member of *startup*$_i$ and *startup*$_j$ both attend a lunch hosted at the co-working space. The indicator $\mathbb{1}$*(within 5 people in line)* equals to one if at least one team member of *startup*$_i$ and *startup*$_j$ appear within 5 people in line for the lunch. *Diverse* is an indicator equal to one if the startup dyads differ along all non-geographic proximity dimensions we in examine and equal to zero otherwise. We control for tenure differences, pre-period technology overlap, and the passing through a common area en route between *startup*$_i$ and *startup*$_i$. We include startup$_i$ x room fixed effects. Standard errors are robust to dyadic clustering at the floor-neighborhood level. As displayed in Table 7, Column 1, social activity – measured by number of mutually-attended events and check-in line proximity – predicts technology adoption alongside physical proximity. In Column 2, we present the result of interacting our measure of social activity with our measure for diversity. The coefficient suggests that although diversity alone does not predict technology adoption (as was also shown in Table 5 Column 4), the more socializing diverse startup dyads engage in, the greater the likelihood of technology adoption.

Next, we form all pair-wise combinations of our proximity and diverse measures in order to more effectively evaluate their combined effect. These are 1) far and similar (*Close=0 & Diverse =0*); 2) far and different (*Close=0 & Diverse =1*); 3) close and similar (*Close=1 & Diverse =0*); and 4) close and different (*Close=1 & Diverse =1*). As displayed in Column 3 (similar and far serving as the omitted category), technology adoption is especially strong among dyads that are close and different, even when controlling for social activity. In Column

4, we examine how dyad properties amplify the benefits of socializing. Dyads that socialize, are in close physical proximity, and are different, experience that largest boost to technology adoption particularly relative to those dyads that are similar.

<Insert Table 7 here>

4.5 Performance

The notion that peers influence performance has been demonstrated in a host of different environments such as retail (Chan et al., 2014*a*,*b*), finance (Hwang et al., 2019) and science (Oettl, 2012; Catalini, 2018). 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. Moreover, the broader innovation literature stresses the importance of external knowledge in promoting innovation and performance (Cohen and Levinthal, 1990; Chesbrough, 2012). External knowledge introduces novelty with respect to the knowledge available inside a startup (Zahra and George, 2002; Laursen and Salter, 2006), and access to information from a wide range of skills and experiences aids in maximizing a group's capacity for creativity, knowledge-generation, and effective action (Reagans and Zuckerman, 2001; Aggarwal et al., 2020). Diversity of external knowledge sources (in our case peer startups) thereby increases the amount of novel information pieces a startup has access to.

To provide more insight into the potential role of the immediate environment for startup performance, we move our analysis away from the startup-dyad level and aggregate to the startup-level. We then estimate the probability of achieving two important startup performance milestones as a function of the diversity of the micro-environment (startups located within 20m of each other) and the extent to which startups engage in social events. Following prior literature, we use indicators identifying startups that raise seed funding and raise funding in excess of US$ million as measures for new venture financial performance (e.g., Hochberg et al. 2007; Nanda and Rhodes-Kropf 2013).

In Figure 5, we display results from estimating the relationship between the likelihood of raising a seed round and raising funding in excess of US$ million as a function of the aggregate diversity indicator of startups within 20 meters of the focal startup interacted with an indicator equal to one if the focal startup engages in the lunches hosted at the co-working space (*Social=1*). We thereby control for the following startup characteristics: size, gender, remoteness[19] of the location and tenure. We further include floor fixed effects and cluster standard errors on the floor-neighborhood level. We break our diversity measure into quintiles and the plot the corresponding coefficients (with 95% confidence intervals). Results suggest that startups located within a balanced environment (middle level of diversity) and that engage in social activity are most likely to receive seed funding and funding in excess of US$ 1 million. The corresponding regression results can be found in Appendix Table A10. This highlights the importance of not only bringing people together, but socializing with each other for promoting better startup performance outcomes. Moreover, our results provide suggestive evidence that striking a balance between diversity and similarity is especially crucial.

<Insert Figure 5 here>

5 Discussion and Conclusions

Recent events have executives pondering what the future of work entails in balancing the flexibility and productivity enhancing benefits of working from home with the creativity-generating potential of serendipitous encounters that are most commonly formed via face-to-face interactions. We contribute to this discussion in three important ways by examining how physical environments provide knowledge spillovers at the micro-geographic level for knowledge workers and entrepreneurs. First, our findings indicate that knowledge spillovers, and more specifically the type that help in the selection of technologies from a large choice set and that lead to the integration of external knowledge, occur at very short distances. 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. While the focus of our study has been

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

on deepening our understanding of inter-startup knowledge spillovers, the same mechanisms may be conceptually extended to examine within-organizational knowledge spillovers as in Allen (1977).

Second, we contribute to the literature examining physical proximity and knowledge exchange by incorporating additional dimensions of similarity/diversity and examining their interdependencies. In doing so, we find support for the idea that particularly the integration of external, diverse knowledge is facilitated through physical proximity. We thereby provide evidence for heterogeneity in the effect of physical distance on knowledge integration depending on similarity along other dimensions, highlight the importance of engaging in social activities, and directly respond to the call for a better understanding of structures and processes adopted by startups to facilitate or impede learning (Alcácer and Oxley, 2014). This finding not only presents a possible avenue to reconcile Marshall-Arrow-Romer specialization externalities (Romer, 1986) and Jacobs-style diversification externalities (Jacobs, 1969), but also may serve as guidance in the design of workplaces that promote knowledge exchange between non-collaborating entities – may they be research groups, teams or startups.

Third, we provide insight on how micro-environments can be leveraged to enhance startup performance. Our findings suggest that environments that strike a balance between diversity and similarity can contribute to achieving important startup milestones. However, our results suggest an important caveat. This boost to performance only occurs if startups socially engage with their environment.

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 startups that may benefit the most from integrating new knowledge. 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 knowledge integration: web technology adoption. We use this measure since, on the one hand, choices regarding the technology of a startup 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 and the technology was integrated into a startups tech stack.

Taken together, our findings provide fundamental insights for the design of workplaces that support knowledge production, entrepreneurship, and innovation. We highlight important trade-offs and stress that understanding which startups 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 who benefits more from presented opportunities.

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Figure 1: 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.

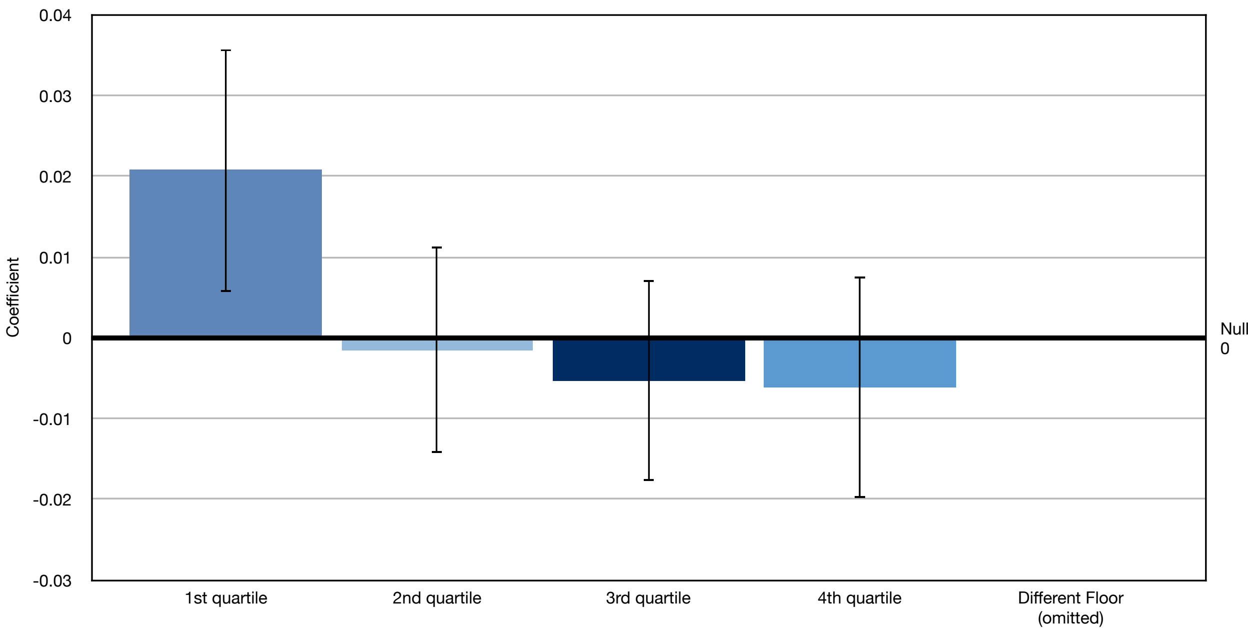

Figure 2: Quartile plots

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 startup dyads that span more than one floor.

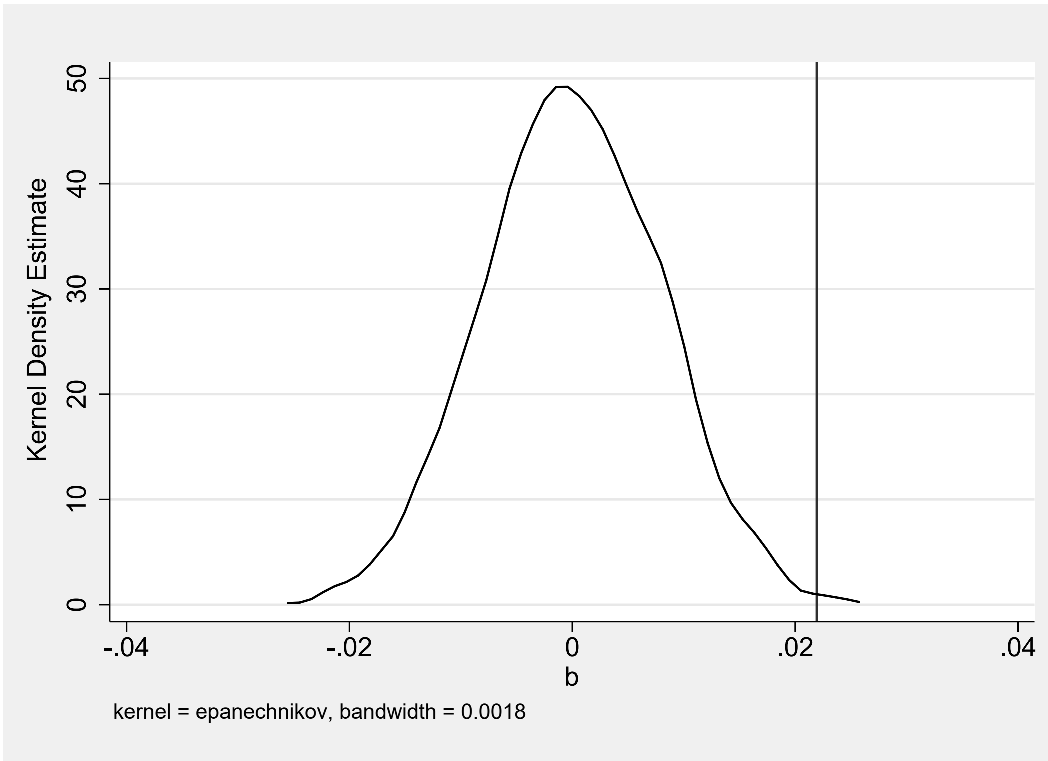

Figure 3: Randomized Inference using Monte Carlo Simulation

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.

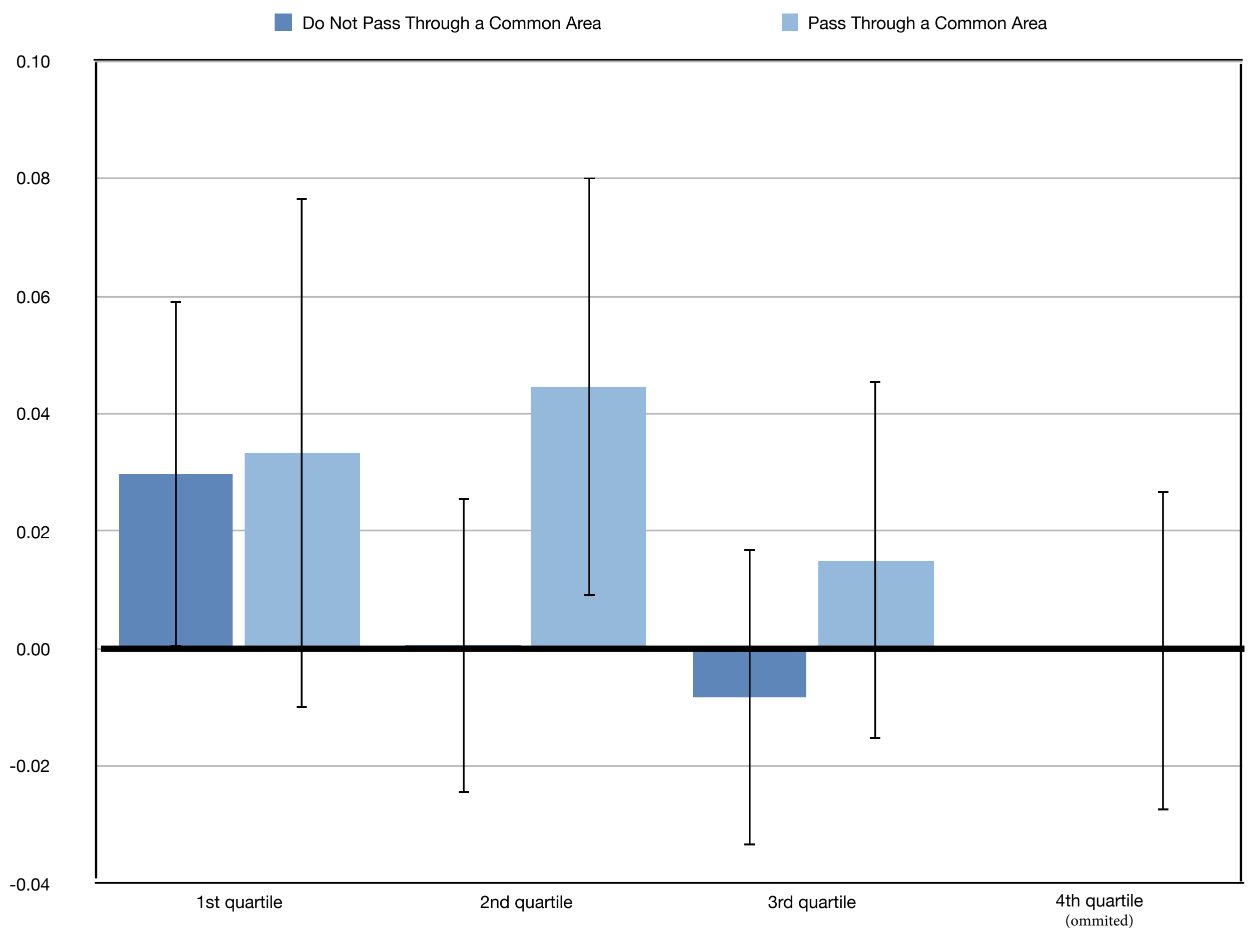

Figure 4: Common area quartile plots

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 5: How a startup's socializing and the diversity of proximate startups predicts raising funding

Notes: This figure displays margins plots for the results from estimating the likelihood of raising a seed round (left)/$1M+ or more (right) as a function of the aggregate diversity index of startups within 20 meters of the focal startup interacted with an indicator equal to one if the focal startup engages in social events (*Social=1*). We thereby control for startup characteristics (industries, age, size) and the number of startups in the immediate environment. 95% confidence intervals are displayed.

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)	(3)	(4)
Same Industry	−0.001	0.001	−0.000	0.001
	(0.017)	(0.023)	(0.017)	(0.025)
Both B2B Companies	0.019	0.030	0.021	0.030
	(0.042)	(0.040)	(0.040)	(0.040)
Both B2C Companies	0.031	0.030	0.031	0.030
	(0.028)	(0.044)	(0.028)	(0.044)
Both Female	0.120	0.015	0.125	0.016
	(0.104)	(0.124)	(0.107)	(0.124)
Both Successful	0.046	0.022	0.049	0.023
	(0.041)	(0.058)	(0.042)	(0.059)
$\|\text{TechUsage}_i\text{-TechUsage}_j\|$	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.001)	(0.000)	(0.001)
$\|\text{tenure}_i\text{-tenure}_j\|$	0.001*	0.002	0.001	0.002
	(0.001)	(0.003)	(0.001)	(0.002)
Pre-period Technology Overlap			−0.080	−0.060
			(0.112)	(0.052)
Firm$_i$ X Room Fixed Effects		✓		✓
Firm$_j$ X Room Fixed Effects		✓		✓
Observations	10840	10840	10840	10840
R^2	0.00	0.12	0.00	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, both are led by a female, and are both successful. The variable $|TechUsage_i\text{-}TechUsage_j|$ represents the absolute difference in the number of technologies adopted by firm$_i$ and firm$_j$, respectively. The variable $|tenure_i\text{-}tenure_j|$ 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 2: Summary Statistics

Firm level (N = 251)	mean	sd	min	p25	p50	p75	max
Tenure (in months)	12.24	9.59	0	3	11	20	29
Room size (in sq.feet)	268.95	310.32	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
Number Close Firms	11.14	5.73	0	7	10	14	33
Seed Funding	0.084	0.28	0	0	0	0	1
$1M+	0.032	0.18	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 (in m)	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 Majority Female (= 0/1)	0.013	0.11	0	0	0	0	1
Tenure 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
Non-geographically distant (= 0/1)	0.31	0.46	0	0	0	1	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. A total of 110 firms were on the 2nd floor, 53 on the 3rd, 29 on the 4th, and 59 on the 5th.

Table 3: Physical proximity positively affects peer technology adoption

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad							
Dependent Variable mean	$ln(AdoptCount_{ij}+1)$ 1.275		$\mathbb{1}$(AdoptTech$_{ij}$) 0.531		$ln(AdoptCount_{ij}+1)$ 1.275		$\mathbb{1}$(AdoptTech$_{ij}$) 0.531	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(distance$_{ij}$)	-0.043***	-0.035***	-0.019***	-0.017***				
	(0.017)	(0.010)	(0.007)	(0.005)				
Close					0.057**	0.048***	0.025**	0.022***
					(0.026)	(0.015)	(0.011)	(0.007)
Same Industry		0.021		0.005		0.021		0.005
		(0.029)		(0.013)		(0.029)		(0.013)
Both B2B Companies		-0.034		-0.007		-0.034		-0.007
		(0.022)		(0.011)		(0.022)		(0.011)
Both B2C Companies		0.030		0.005		0.029		0.004
		(0.029)		(0.008)		(0.029)		(0.008)
Both Female		-0.102*		0.013		-0.103*		0.012
		(0.057)		(0.027)		(0.057)		(0.028)
|tenure$_i$-tenure$_j$|		-0.006***		-0.001**		-0.006***		-0.001*
		(0.002)		(0.000)		(0.001)		(0.001)
Pre-period Technology Overlap		3.624***		1.007***		3.624***		1.007***
		(0.146)		(0.066)		(0.145)		(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 $\mathbb{1}$(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 (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 $|tenure_i\text{-}tenure_j|$ represents the absolute tenure 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 and firm$_j$ 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 4: Physical proximity positively affects peer technology adoption when there are many/few options or the technology category is new

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad		
Dependent Variable	$\mathbb{1}$(AdoptTech$_{ij}$)		
	Many Options	Few Options	New Category
	(1)	(2)	(3)
Close	0.025**	0.000	0.030***
	(0.011)	(0.002)	(0.011)
Same Industry	0.015	0.003	0.014
	(0.016)	(0.004)	(0.016)
Both B2B Companies	0.004	0.004	0.005
	(0.014)	(0.003)	(0.016)
Both B2C Companies	−0.002	0.008*	−0.002
	(0.010)	(0.004)	(0.007)
Both Female	0.014	−0.003	0.009
	(0.020)	(0.007)	(0.021)
|tenure_i-tenure_j|	−0.001*	−0.000*	−0.001**
	(0.000)	(0.000)	(0.001)
Firm$_i$ X Room Fixed Effects	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓
Observations	10840	10840	10840
R^2	0.79	0.13	0.78

Notes: This table displays the results from OLS regressions predicting physical distance between two firms as a function of firm-dyad characteristics. In this table, we include three different outcomes. *Many Options* indicates the adoption of a technology from a technology category with many options to choose from (above median number of technologies >14). *Few Options* indicates the adoption of a technology from a technology category with few options (below median ≤ 14) to choose from. *New TechCategory* indicates the adoption of a technology from a technology category new to the firm. The 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, and are both predominately female. The variable $|tenure_i\text{-}tenure_j|$ represents the absolute tenure difference in months between firm$_i$ and firm$_j$. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Proximity and Diversity

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad			
Dependent Variable	$\mathbb{1}$(AdoptTech$_{ij}$)			
mean	0.531			
	(1)	(2)	(3)	(4)
Close	0.024***	0.037***	0.031***	0.014**
	(0.007)	(0.007)	(0.012)	(0.006)
Both Majority Female	0.018			
	(0.016)			
Close x Both Majority Female	−0.089***			
	(0.016)			
Same Product Market		0.013***		
		(0.005)		
Close x Same Product Market		−0.023***		
		(0.008)		
High Tech-Stack Overlap			0.209***	
			(0.027)	
Close x High Tech-Stack Overlap			−0.027**	
			(0.014)	
Diverse				−0.001
				(0.007)
Close x Diverse				0.029***
				(0.005)
Pre-period Technology Overlap	1.007***	1.006***		1.011***
	(0.066)	(0.065)		(0.063)
$\lvert$tenure$_i$-tenure$_j\rvert$	−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	✓	✓	✓	✓
Proxies for Similarity	Social	Product-Market	Knowledge	Composite Index
Observations	10840	10840	10840	10840
R^2	0.8305	0.8306	0.8063	0.8306

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. *Diverse* 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 (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, or both predominately female. *High Tech-Stack Overlap* denotes dyads that have a pre-period tech-stack overlap of over 0.27, which represents the 75$^{\text{th}}$ percentile. We include controls for tenure differences and firm$_i$ X room fixed effects as well as the share of firm$_i$'s technologies also used by firm$_j$ in the previous period in columns 1, 2, and 4. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad					
Dependent Variable mean	*# Event Both$_{ij}$ Attend* 0.27		$\mathbb{1}$*(Event)* 0.11		$\mathbb{1}$(w/in 5 people in line) 0.06	
	(1)	(2)	(3)	(4)	(5)	(6)
Close	0.036**	0.039*	0.010*	0.009*	0.017***	0.023***
	(0.018)	(0.022)	(0.005)	(0.005)	(0.006)	(0.009)
Common Area	0.025**	0.024**	0.010*	0.010*	0.013***	0.013***
	(0.010)	(0.011)	(0.005)	(0.005)	(0.005)	(0.005)
Diverse		-0.028***		-0.013***		-0.009***
		(0.008)		(0.003)		(0.003)
Close x Diverse		-0.010		0.003		-0.018*
		(0.021)		(0.010)		(0.011)
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	10840	10840	10840	10840	10840	10840
R^2	0.5443	0.5444	0.5141	0.5142	0.3525	0.3532

Notes: This table displays the results from OLS regressions predicting 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* and the likelihood of attending ($\mathbb{1}$*(Event)*). The indicator $\mathbb{1}$*(w/in 5 people in line)* equals to one if at least one team member of $firm_i$ and $firm_j$ ever appear within 5 people in line for the lunch. 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 and firm$_j$ x room fixed effects. *Diverse* is an indicator equal to one if the firm dyads differ along all non-geographic proximity dimensions we in examine. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Proximity, Socializing, and Diversity - OLS Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad			
Dependent Variable	$\mathbb{1}$(AdoptTech$_{ij}$)			
mean	0.531			
	(1)	(2)	(3)	(4)
Close	0.023***	0.022***		
	(0.009)	(0.009)		
# Events	0.043***	0.037***	0.043***	
	(0.007)	(0.007)	(0.007)	
Diverse		−0.002		
		(0.006)		
# Events x Diverse		0.044***		
		(0.006)		
Close = 1 & Diverse = 1			0.041***	
			(0.007)	
Close = 0 & Diverse = 1			−0.002	
			(0.007)	
Close = 1 & Diverse = 0			0.013*	
			(0.008)	
# Events x (Close = 0 & Diverse = 0)				0.034***
				(0.006)
# Events x (Close = 0 & Diverse = 1)				0.077***
				(0.010)
# Events x (Close = 1 & Diverse = 0)				0.041***
				(0.010)
# Events x (Close = 1 & Diverse = 1)				0.093***
				(0.021)
Pre-prd. Tech. Overlap, Tenure Diff., Common Area	✓	✓	✓	✓
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓
Observations	10840	10840	10840	10840
R^2	0.8325	0.8330	0.8326	0.8325

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 $\mathbb{1}(\text{AdoptTech}_{ij})$ 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 (the 25$^{\text{th}}$ percentile of pair-wise distances between all rooms) of each other on the same floor. The variable *# Event Both$_{ij}$ Attend* equals the number of lunch hosted at the co-working space that at least one team member of $firm_i$ and $firm_j$ both attend. *Diverse* is an indicator equal to one if the firm dyads differ along all non-geographic proximity dimensions we in examine and zero (*Diverse = 0*) otherwise. In Columns 3-4, we include categories that indicate whether a dyad is 1) far and similar (*Close=0 & Diverse =0*); 2) far and different (*Close=0 & Diverse =1*); 3) close and similar (*Close=1 & Diverse =0*); and 4) close and different (*Close=1 & Diverse =1*). In Column 3, the omitted category is Close=0 & Diverse = 0. The variables $|age\_i\text{-}age\_j|$, *Pre-period Technology Overlap* and *Common Area* are included. Variables including "&" denote categories. We include firm$_i$ x room and firm$_j$ x room fixed effects. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

Proximate (Co-)Working: Knowledge Spillovers and Social Interactions

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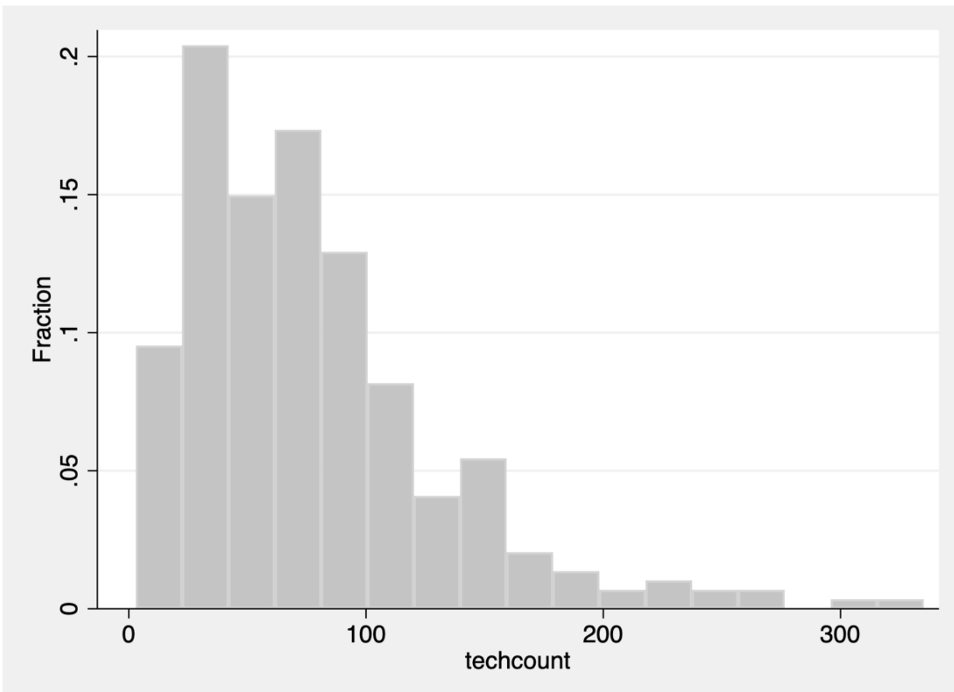
Figure A1: Technology Adoption Counts - Histogram



Notes: This figure displays the relative distribution of technology adoption (*techcount*) by the startups in our sample.

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^{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.
$\|tenure_i - tenure_j\|$	The difference in tenure at the co-working space between $firm_i$ and $firm_j$ (derived from date of entry at the co-working space).

Table A2: Correlation Matrix - Dyad Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) 1(AdoptTech)	1										
(2) ln($AdoptCount_{ij}$)	0.896	1									
(3) ln($Distance_{ij}$)	-0.0347	-0.0317	1								
(4) Close	0.0374	0.0364	-0.820	1							
(5) Pre-period Technology Overlap	0.699	0.769	-0.0198	0.0253	1						
(6) Same Industry	0.0279	0.0336	0.000534	0.00491	0.0342	1					
(7) Both B2B Companies	0.0594	0.0788	0.0115	-0.00882	0.0965	0.105	1				
(8) Both B2C Companies	0.0251	0.0104	0.0111	-0.00747	-0.0140	-0.0126	-0.332	1			
(9) Both Female CEOs	0.0171	0.0205	0.0116	-0.00349	0.0267	0.0369	0.0299	-0.00802	1		
(10) Both Successful	0.0886	0.107	0.0214	-0.0250	0.0965	-0.0148	0.0266	0.0192	-0.0161	1	
(11) |tenure_i-tenure_j|	0.0376	0.0198	0.0162	-0.00402	0.110	-0.0127	0.0229	0.00604	0.0346	0.0123	1

Table A3: Example Tech-Stacks (only including first 90 in category alphabetic order)

Technology Category	**Firm A:** *created and hosts an automated scheduling tool. Founded in 2013.*	**Firm B:** *hosts a platform for sellers to execute digital selling tasks, communicate with buyers, and get coaching. Founded in 2012.*	**Firm C:** *runs a marketing platform used to target companies, decision-makers, and accelerate pipeline speed. Founded in 2014.*
A/B Testing	Mixpanel; Optimizely; KISSmetrics	Optimizely	Mixpanel, Optimizely
Ad Analytics			AdStage; Advertising.com; ContextWeb
Ad Exchange	AppNexus		Facebook Exchange FBX; BlueKai; IponWeb BidSwitch; Eyeota
Ad Network	Bizo		Burst Media; Tribal Fusion; AdRoll; Twitter Ads
Ad Server			AppNexus Openads/OpenX
Ads	AdsNative; LinkedIn Ads; DoubleClick.Net; AppNexus Segment Pixel	DoubleClick.Net	Index Exchange; Adap.TV; Yahoo Small Business; Yield Manager; SpotXchange; DoubleClick.Net; Aggregate Knowledge; Rubicon Project; eXelate; AppNexus Segment Pixel; Tapad; Simpli.fi; Ad Tech Japan AOL; Adbrain; RUN Ads; Arbor Marketplace; Uberflip
Advertiser Tracking	Bizo Insights		Bombora; Krux Digital; comScore; Datalogix
Affiliate Programs			adingo
Analytics	Google Universal Analytics; Google Analytics Classic	Google Universal Analytics	Google Universal Analytics; Lotame Crowd Control; Twitter Website Universal Tag; Tynt Tracer; Facebook Signal; Facebook Pixel; Marketo Real Time Personalization
Animation			GSAP
Application Performance	New Relic; Heap	New Relic; Google Analytics	VisiStat; Google Analytics
Audience Measurement		FullStory	FullStory; Shareaholic
Audience Targeting			Turn; DemDex
Business Email Hosting	Google Apps for Business; UserVoice Mail; Intercom Mail	Google Apps for Business	Google Apps for Business
Call Tracking		CallRail	CallRail
CAPTCHA			Are You a Human
Charting, UI			D3 JS
Campaign Management		MailChimp SPF	
Cloud Hosting, Cloud PaaS	Amazon	Amazon	Google Cloud; Google
Content Delivery Network	CloudFront; Twitter CDN; Bootstrap CDN; AJAX Libraries API; CDN JS; GStatic Google Static Content	Akamai; CDN	Bootstrap CDN; GStatic Google Static Content; AJAX Libraries API; CloudFront; Max CDN; CDN JS; jQuery CDN; Amazon S3 CDN
Compatibility	Modernizr; html5shiv		Modernizr; html5shiv
Comment System		Disqus	
Content Curation			Taboola
Conversion Optimization	Google Conversion Tracking; Twitter Analytics; LinkedIn Insights; Bing Universal Event Tracking	LinkedIn Insights	Twitter Analytics; Twitter Conversion Tracking; Google Conversion Tracking; BrightFunnel; G2 Crowd Conversion
Cookie Sync			Adobe Audience Manager Sync
CRM	Zendesk	Salesforce SPF; Zendesk	
Data Management Platform	Segment		BlueKai DMP
Dedicated Hosting			Rackspace
Demand-side Platform			The Trade Desk; DoubleClick Bid Manager
Dynamic Creative Optimization			Pubmatic
Enterprise DNS	Amazon Route 53; Microsoft Azure DNS	Wistia; Amazon Route 53	Amazon Route 53
Error Tracking			Sentry; Bugsnag; Rollbar
Feedback Forms and Surveys	Wufoo; Intercom	Intercom	Contact Form 7
Feeds	RSS	RSS; Pingback Support; Really Simple Discovery; Live Writer Support	Really Simple Discovery; RSS; Live Writer Support; Pingback Support
Fonts	Font Awesome; Google Font API		Font Awesome; Google Font API; jQuery Form
Framework	Ruby on Rails Token; Heroku Proxy; AMP Project; Handlebars	Ruby on Rails Token	Ruby on Rails Token
JavaScript	jQuery; Marionette.js; Moment JS; Backbone.js	jQuery; CryptoJS	CryptoJS; Froogaloop; Angular JS v1; Raven JS; punycode; Isotope; jQuery Waypoints; Webpack; Facebook Graph API; jQuery; lodash; Moment JS; jQuery Masonry
Lead Generation			LiveRamp; Insightera
Lightbox			Magnific Popup
Live Chat		SnapEngage	SnapEngage; Drift
Live Stream			YouTube
Marketing Automation		Pardot; Captora; Bizible; Hubspot	Pardot; Rapleaf; Marin Software; Bizible; OwnerIQ, Terminus; Marketo
Marketing Platform		Pardot Mail	
Media			SundaySky
Multi-Channel			Crosswise
Open Source, Blog		WordPress	WordPress
Plugins		Yoast WordPress SEO Plugin; Yoast SEO Premium; Disqus Comment System for WordPress	Yoast Plugins; Yoast WordPress SEO Plugin; Yoast SEO Premium; jQuery UI; Click To Tweet for WordPress; Lazy Load for WordPress; SiteOrigin Panels; WP Super Cache
Payments Processor	Stripe		
Programming Language	Ruby on Rails	PHP	PHP; Ruby on Rails
Retargeting / Remarketing	Twitter Ads	AdRoll	Perfect Audience; Facebook Custom Audiences; Google Remarketing
Root Authority		Comodo SSL	GeoTrust SSL; LetsEncrypt; DigiCert SSL
Server			Ubuntu
Site Optimization			CrazyEgg
Site Search	Algolia	Sitelinks Search Box	Sitelinks Search Box
Social Management	Facebook Domain Insights		
SSL	SSL by Default; Heroku SSL; GoDaddy SSL	Comodo PositiveSSL; SSL by Default	RapidSSL; SSL by Default
Standard	SPF	SPF	SPF; DMARC
Tag Management	Google Tag Manager		Google Tag Manager
Toolbar		Hello Bar	Hello Bar
Transactional Email		Sendgrid	Mandrill
US hosting	Amazon Virginia Region	Amazon Virginia Region	
Video Analytics		Mux	Vidyard
Video Players			MediaElement.js
Web Master		Google Webmaster	Google Webmaster
Web Server	Cowboy; nginx	nginx	Apache; nginx
Widgets		Typekit; Wordpress Plugins; Twemoji; Gravatar Profiles	Wordpress Plugins
Wildcard		Comodo PositiveSSL Wildcard	Typekit; Twemoji; Ipify; Lever; ZeroClipboard; TurboLinks; Facebook Sharer; Pinterest

Table A4: 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 Female	0.022	0.021
	(0.102)	(0.100)
Both Successful	−0.024	−0.025
	(0.035)	(0.034)
|age_i-age_j|	−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 led by a 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 A5: 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)
$\|$tenure$_i$-tenure$_j\|$					-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 $|$tenure$_i$-tenure$_j|$ represents the absolute tenure 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 A6: 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)	(0.022)	(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)
$\lvert$tenure$_i$-tenure$_j\rvert$					-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 $\mathbb{1}$(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 led by a female. The variable $\lvert$tenure$_i$-tenure$_j\rvert$ represents the absolute tenure 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 A7: Table 3, column 8, using different clustering

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad					
Dependent Variable	$\mathbb{1}$(AdoptTech$_{ij}$)					
mean	0.531					
	(1)	(2)	(3)	(4)	(5)	(6)
Clustering	original	robust	floor	Firm$_i$ and $_j$	Room$_i$ and $_j$	Firm$_i$ x Room$_i$ Firm$_j$ x Room$_j$
Close	0.022***	0.022***	0.022*	0.022***	0.022***	0.022***
	(0.007)	(0.005)	(0.008)	(0.007)	(0.007)	(0.007)
Same Industry	0.005	0.005	0.005	0.005	0.005	0.005
	(0.013)	(0.007)	(0.010)	(0.009)	(0.010)	(0.010)
Both B2B Companies	−0.007	−0.007	−0.007	−0.007	−0.007	−0.007
	(0.011)	(0.011)	(0.013)	(0.012)	(0.013)	(0.013)
Both B2C Companies	0.004	0.004	0.004	0.004	0.004	0.004
	(0.008)	(0.010)	(0.016)	(0.012)	(0.011)	(0.011)
Both Female	0.012	0.012	0.012	0.012	0.012	0.012
	(0.028)	(0.033)	(0.033)	(0.036)	(0.041)	(0.039)
|tenure_i-tenure_j|	−0.001*	−0.001***	−0.001***	−0.001**	−0.001**	−0.001**
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Pre-period Technology Overlap	1.007***	1.007***	1.007***	1.007***	1.007***	1.007***
	(0.065)	(0.024)	(0.068)	(0.080)	(0.095)	(0.083)
Firm$_i$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓
Firm$_j$ X Room Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	10840	10840	10840	10840	10840	10840

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 $\mathbb{1}$(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 (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 female led. The variable |*tenure_i-tenure_j*| represents the absolute tenure 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 and firm$_j$ x room fixed effects. Standard errors (in parentheses) are robust to clustering as indicated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: 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 × 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Socializing, Diversity Quintiles and Financial Performance Outcomes

Funding raised	Seed (1)	>1M+ (2)
Social = 0 × Diversity Quantiles = 2	−0.045	−0.031
	(0.073)	(0.046)
Social = 0 × Diversity Quantiles = 3	0.017	0.003
	(0.062)	(0.039)
Social = 0 × Diversity Quantiles = 4	−0.078	0.010
	(0.070)	(0.044)
Social = 0 × Diversity Quantiles = 5	−0.104	−0.033
	(0.070)	(0.044)
Social = 1 × Diversity Quantiles = 1	−0.035	−0.049
	(0.068)	(0.043)
Social = 1 × Diversity Quantiles = 2	−0.131	−0.063
	(0.085)	(0.054)
Social = 1 × Diversity Quantiles = 3	0.155**	0.107**
	(0.074)	(0.047)
Social = 1 × Diversity Quantiles = 4	−0.034	0.069
	(0.101)	(0.064)
Social = 1 × Diversity Quantiles = 5	−0.152	−0.010
	(0.102)	(0.064)
Room Size	0.000	0.000
	(0.000)	(0.000)
Female CEO	−0.128	−0.047
	(0.082)	(0.052)
Remoteness	−0.004	−0.006
	(0.008)	(0.005)
Age	0.004	0.004**
	(0.003)	(0.002)
No. Firms	0.003	−0.000
	(0.004)	(0.002)
Floor FE	✓	✓
Observations	248	248
R^2	0.10	0.11

Notes: This table displays the results from OLS regressions predicting the likelihood of raising a seed round (*Seed*) and $ million or more (*>1M+*) as a function of the aggregate diversity of firms within 20 meters of the focal firm interacted with an indicator equal to one if the focal firm engages in social events (*Social=1*). The aggregate diversity index ins split into quintiles. We thereby control for firm characteristics (industries, age, size) and the number of firms in the immediate environment. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.