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KNOWLEDGE SPILLOVERS AND SOCIAL INTERACTIONS

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(Co-)Working in Close Proximity: 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 random 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.

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1 Introduction

The COVID-19 pandemic affected close to all facets of life, perhaps none more greatly than work life. As offices around the world closed and work shifted to Zoom, the trend towards remote work was greatly accelerated. While remote work has allowed many organizations to continue their day-to-day operations, there is preliminary evidence that the lack of physical proximity has altered the interactions and collaborations that normally would have taken place (Yang et al., 2021). Although the importance of place for innovation, entrepreneurship, and firm performance has been well established in the literature (e.g., Rosenthal and Strange 2004; Michelacci and Silva 2007; Samila and Sorenson 2011; Glaeser et al. 2015), less is known about the level at which geographic proximity matters most. On the one hand, cities may serve as the appropriate focus for understanding the dynamics of labor markets, but it may be at much smaller scales that more nuanced interpersonal interactions – especially those that produce knowledge spillovers – take place.

While physical proximity is one of the more salient dimensions of distance that has been shown to impact knowledge exchange among collaborators (Allen, 1977; Cowgill et al., 2009), numerous other *distances* also facilitate/impede knowledge exchange and learning. For example, social (Blau, 1977; McPherson and Smith-Lovin, 1987), product-market (Wang and Zhao, 2018; Alcácer et al., 2015; Saxenian, 1996), and knowledge-space (Cohen and Levinthal, 1990; Lee, 2019; Lane et al., 2020) distances have all been shown to impact the ability or willingness to exchange knowledge. Although recent work stresses the importance of taking such factors into account when aiming to optimize peer effects (Carrell et al., 2013; Chatterji et al., 2019; Hasan and Koning, 2019), less is known about how the similarity and dissimilarity of startups impacts knowledge transfer in physical proximity. On the one hand, similar startups, due to their common ground and shared understanding, may more effectively exchange knowledge. Conversely, however, the value of this more efficacious knowledge transfer may be diminished due to redundant knowledge that both parties already possess.

Thus, being geographically proximate may be most advantageous to dissimilar startups who can benefit most from diverse and novel knowledge.[1]

In this paper we build upon prior research by applying a micro-geographic lens to deepen our understanding of the relationship between physical proximity and 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).[2] 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 differences among startups play in modulating the effect of distance. 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.

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.). One challenge in examining the relationship between location and knowledge spillovers is that startups and individuals may choose to locate in areas where knowledge exchange is already likely to be high. To deal with this potential endogenous location choice, we rely on the random assignment of office space to the hub's 251 startups. We measure knowledge spillovers as the instance of adopting a component of a peer startup's technology stack. Using floor plans to measure geographic distance, we find that close physical proximity greatly influences the likelihood of these knowledge spillovers. This effect, however, quickly decays with distance

[1]The greatest advancements in understanding the importance of similarity and physical proximity has been evaluated at the individual level. However, due to methodological challenges it has still been difficult to separately distinguish the effects of proximity and homophily on outcomes (Angst et al., 2010; Conley and Udry, 2010).

[2]The size of the mean high-tech startup has decreased to approximately two employees over the past two decades (Ewens and Marx, 2017; Kaplan et al., 2009).

where startup 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. In addition, 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.

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. This is provided that "(...) interpersonal channels are more effective in forming and changing attitudes toward a new idea, and thus in influencing the decision to adopt or reject a new idea (Rogers 2010, p.36)". 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 – joint 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 $1MM 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.

Overall, our findings contribute to prior research in important ways. First, we provide a better understanding of a fundamental decision early stage, high tech ventures face: building their technology infrastructure. Especially in our context of technology-enabled high-growth entrepreneurship, the adoption and integration of upstream production technologies, the startup's technology stack, may be considered comparable to supplier choice in more traditional industries – a crucial decision, which tends to imply significant path dependency (Arthur, 1994; Murray and Tripsas, 2004; Alcácer and Oxley, 2014; Fang et al., 2020). Second, where prior research has emphasized the role of a startup's formal, structural features, such as its size, age and prior social ties in the entrepreneurial process (Elfenbein et al., 2010; Hasan and Koning, 2019), our analyses yield unique insights into knowledge exchange and integration of startups by highlighting the role of diversity among exchange partners and the critical role of proximity. We underscore that understanding which startups and how they respond to their peer startups matters for designing effective environments for early stage startups. Finally, we speak to the literature examining accelerators, bootcamps, incubators and other interventions targeted at early stage entrepreneurs (e.g., Hassan and Mertens 2017; Cohen et al. 2019; Lyons and Zhang 2018) by examining an additional type of entrepreneurial workplace that has received limited attention so far in the literature: the co-working hub (Howell, 2022).[3]

Taken together, this paper informs our understanding of the scale at which knowledge

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

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. 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 empirical estimation strategy and data sources. 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). 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).

One important environment where many interactions occur and information exchange takes place on a daily basis is the workplace. As such, the workplace represents a setting for unexpected influences, and for the serendipitous flow of information and ideas. Here the physical layout of the workplace can play a critical role with early research dating back to Allen (1977) showing the importance of proximity in determining and shaping workplace interactions. Studies have tested the link between proximity and interpersonal interactions in the context of, e.g., science (Boudreau et al., 2017; Catalini, 2018), options exchange (Baker, 1984), technology companies (Cowgill et al., 2009), e-commerce (Lee, 2019), and first responders (Battiston et al., 2020) finding that physical proximity has important implications for sharing information among collaborators and co-workers.

The importance of (work)place for knowledge diffusion also has strong implications for nascent startups. Generally, entrepreneurs gain information from a variety of sources, though one particularly important channel is through fellow entrepreneurs (Nanda and Sørensen, 2010; Lerner and Malmendier, 2013). This is provided that entrepreneurs predominately operate in fast-paced and uncertain environments, making local search (Cyert et al., 1963) based on experimentation and frequent adjustments (Lippman and McCall, 1976; Gavetti and Levinthal, 2000; Gans et al., 2019) a crucial component in the early stages of a venture.

We propose that an important channel through which physical proximity may enable knowledge exchange across startups is through the creation of increased opportunities for social interaction. Social interaction represents an important integration mechanism which enables better understanding of others' specific background, challenges and language. 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 and trust (Granovetter, 1973); all of which facilitate knowledge exchange and integration.

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 proximity/similarity have also been shown 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 level of which two entities are similar (or different) along these dimensions plays 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). What remains to be understood is how these other forms of proximity interact with physical proximity. Since it is particularly challenging to integrate distant knowledge, it is possible that via its impact on frequent and repeated interactions, which help establish trust (Granovetter, 1973) and an understanding of others' skills (Rogers, 2010), physical proximity aids especially in connecting those that are otherwise different. If this is the case, we should detect a positive interaction between physical proximity and diversity in predicting the likelihood of integrating technologies from peer startups.

3 Empirical Strategy and Data

3.1 Estimation Strategy

Estimating the role of physical proximity on knowledge spillovers – 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 random 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 random room assignment assumption (and confirmed by multiple senior staff at the co-working space).[4]

<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.

[4]Please refer to Table A1 of the Appendix for further robustness checks.

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.[5] 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.[6] 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. 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 $Close_{ij}$.

[5] 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).

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

3.2 Data Sources and Construction

The data for our study were collected at one of the five largest technology co-working spaces in the United States (in 2016). Designated as a startup hub where new ventures work side by side, the building consists of five floors, 9,300 m^2 (100,000 sq.ft.) and 207 rooms. The data 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 interactions 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.[7] 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.[8] 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.[9] We measure the distance between rooms from available floor plans using space syntax software (Bafna, 2003; Kabo et al., 2014, 2015).[10] One useful feature of space syntax software is that it calculates distances between rooms as people would walk rather than the shortest

[7]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.

[8]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.

[9]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").

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

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$^{\text{th}}$ percentile of pair-wise distances between all rooms).[11] 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 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

[11] For a summary and description of all variables used in the dyadic model, please refer to Table A2 of the Appendix.

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.[12]

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$_j$

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

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* and *Both B2C Companies* indicate if startup$_i$'s and startup$_j$'s main customers are other businesses (B2B) or individual consumers (B2C).[13]

We additionally identified startup age as a startup's tenure at the co-working hub and the gender composition of startups using information provided by the co-working space. As derived from the entry date into the co-working space, $|age_i\text{-}age_j|$ reflects the absolute value of the age difference between 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

[13] 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.

by sex.[14]

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

3.3 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

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

percent are considered to be successful startups. On average, the startups in our sample have been at the co-working space for approximately one year. The use of web technologies is highly skewed, ranging from a minimum of 0 to a maximum of 255. In Table 2, the variable *Min. Technology Usage* (*Max. Technology Usage*) displays the minimum (maximum) amount of technologies a startup ever hosted while at the co-working space. Over time, the startups in our sample adopt about 7.33 technologies on average, 53 percent adopt at least one new technology.

The main focus of our analyses is on startup dyads. A key component is thereby the characteristics both startups have in common. Of the startup-dyads in the co-working hub, 11 percent operate in the same industry, 48 and 11 percent both have a B2B and B2C business model respectively. The percentage of startup-dyads where the majority of team members are female is 1.3 percent (N = 138), and eight percent of the startup-dyads are considered successful. The average age difference between startups in a dyad is 7.30 months.

4 Results

For the purpose of this study, we operationalize the distinct proximity dimensions as follows. *Physical Proximity* is measured using the geographic distance (in meters) between rooms on one floor. *Social Proximity* captures when both startups possess a salient characteristic that only a minority of the startups in the co-working space have. We identify socially proximate startups as those where both startups are majority female. We measure *Knowledge-Space Similiarity* using the pre-period technology tech-stack overlap between focal $startup_i$ and $startup_j$. The indicator is equal to one if $startup_i$ and $startup_j$ have high overlap in their pre-period tech-stack (above the 75^{th} percentile). In this paper, *Productx-Market Proximity* captures when the consumers of two startups' products are similar. We measure product-market proximity by using a combination of two startup characteristics: a) industry, and b) business model. Two startups are proximate in their product-market if they either operate in the same industry or have the same business model.

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, age and pre-period technology overlap, we find that the doubling of distance between two dyads reduces both the amount of peer technology adoption by 3.5% and the likelihood of any peer technology adoption by 1.7%, with both point estimates significant at the 1% level. As seen, the magnitude and statistical significance of the effect remains largely unchanged with the inclusion of additional controls.[15]

<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 startup 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 20 meters of

[15]Please refer to Tables A4 and A5 of the Appendix for models excluding controls.

each other (and equal to zero for all other dyads) and use this measure for the remainder of our 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 three percentage point higher probability of adopting a peer technology (= 0.025, dyad and floor-neighborhood cluster-robust standard errors 0.011). This finding remains robust to including different covariates. As displayed in Columns 5 and 6, applying an OLS model and estimating the count of adopted peer technologies ($ln(AdoptCount_{ij} + 1)$) provides a similar result. In the full model (Column 6), the point estimate on the coefficient for close proximity is 0.048 (cluster-robust standard errors 0.015). This implies that a switch to a room in close proximity would translate into a five percent increase in the number of peer technologies adopted from the mean.

For robustness 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.[16] 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>

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

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 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^{th} distance quartile as the omitted category).[17] 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 with other proximity dimensions

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

4.2.1 Interplay with social proximity

We first examine how social proximity – the gender composition of the startup dyads – may influence the effect of physical proximity on peer technology adoption. In the case of our setting, female startups represent a minority group. As suggested by Reagans (2011),

[17] Please refer to Table A6 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).

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 4, Column 1, we find that dyads where both startups are predominately female overcome the distance discount suggesting that these startups rely on alternate mechanisms to overcome the negative effects of distance or, as a minority within the co-working space, may have different networking behavior (Kerr and Kerr, 2018).

4.2.2 Interplay with product-market proximity

In Table 4, Column 2, we present the results including an interaction of physical and product-market proximity in order to gauge the role of competition-based dynamics. 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 proximity are substitutes and that being physically close is most beneficial to startup dyads that are dissimilar.

<Insert Table 4 here>

4.2.3 Interplay with knowledge-space similarity

In Table 4, Column 3, we present the results including an interaction of physical and knowledge-space proximity in order to evaluate the role of information-based dynamics. For simplicity, we count a dyad as similar along the knowledge-space dimension if their pre-period technology overlap is over 0.27.[18] As seen earlier across a number of other proximity dimensions, the interaction between technology overlap/similarity and physical

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

proximity is negative, implying that being physically close is less valuable for startups that are already proximate 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.

4.2.4 Interplay with diversity

Thus far, the results suggest that proximity along non-geographic dimensions may substitute for being physically close. This points to possible advantages of co-location for facilitating knowledge spillovers among startups that are otherwise dissimilar. To test this, we create a composite variable called *Diverse* that is equal to one if a startup dyad differs along the social, product-market, and knowledge space dimensions, 0 otherwise. As displayed in Table 4, Column 4, we find that being physically close matters most for knowledge exchange that leads to integration of new technologies among otherwise distant 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.

4.3 The role of social interactions

One potential explanation for our previous set of results is that physical proximity shapes the social interactions of individuals (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 further exploit a joint event – a lunch – hosted at the co-working space on a weekly basis. Table 5, 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, yet 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)*).[19] We present the results from estimating the effect of room proximity on check-in line proximity in Columns 5-6, Table 5. 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, wherein startup pairs that are different/diverse 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 discrepancy and seemingly contradictory finding: startups that are close and different receive more knowledge spillovers from each other yet startups that are close are less likely to socialize (co-attend events) with startups different from them. Of greatest interest then, is to examine the impact of diverse proximity on knowledge spillovers when the startups do socialize. We explore this

[19] In the Appendix, Table A7, 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.

next.

<Insert Table 5 here>

4.4 Proximity, socializing, and diversity

We next 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 age 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 6, 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 4 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 6 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[20] of the location and age. 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 A8. 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

For Katalin Karikó, whose research was critical for creating mRNA-based tharapeutics that do not induce an antiviral immune response, there was a long period when it seemed that her research on messenger RNA would never get funding. Her approach was so different from that of colleagues she struggled to find support. An encounter at the copy machine – a common area – with Drew Weissman brought a new perspective and idea for a potential application laying the foundation for the successful COVID-19 vaccines made by Pfizer-BioNTech and Moderna.

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

Stories like these 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 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 on deepening our understanding of inter-startup knowledge spillovers, the same mechanisms can 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.

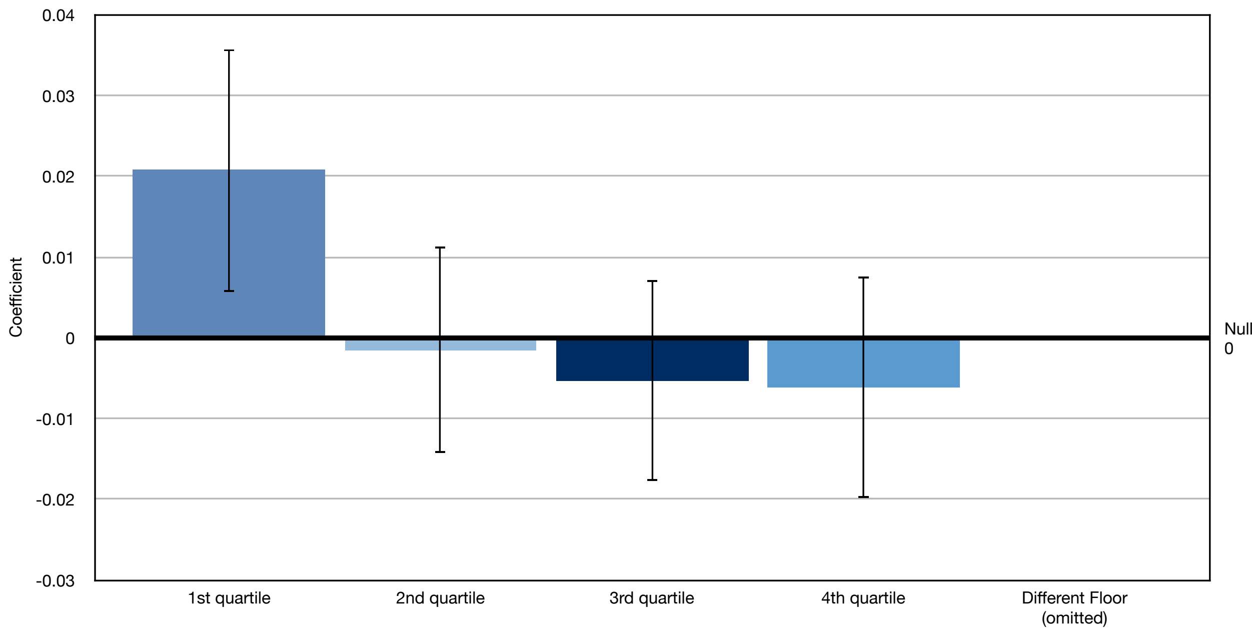


Figure 2: Quartile plots

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.

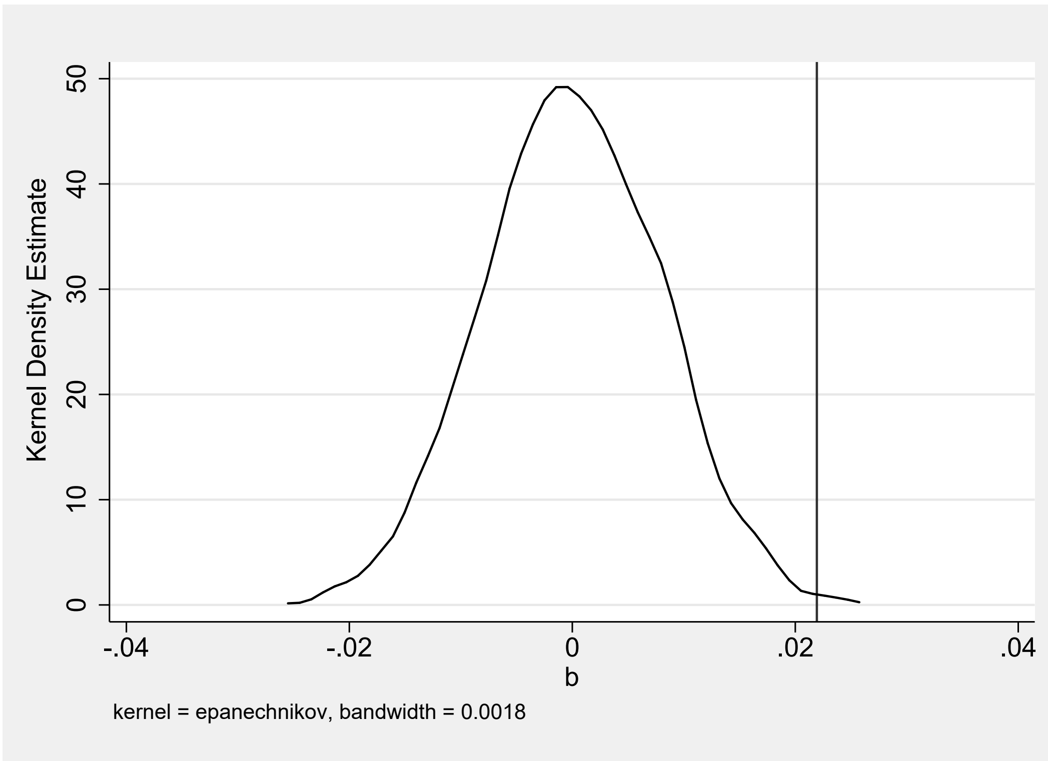


Figure 3: Randomized Inference using Monte Carlo Simulation

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.

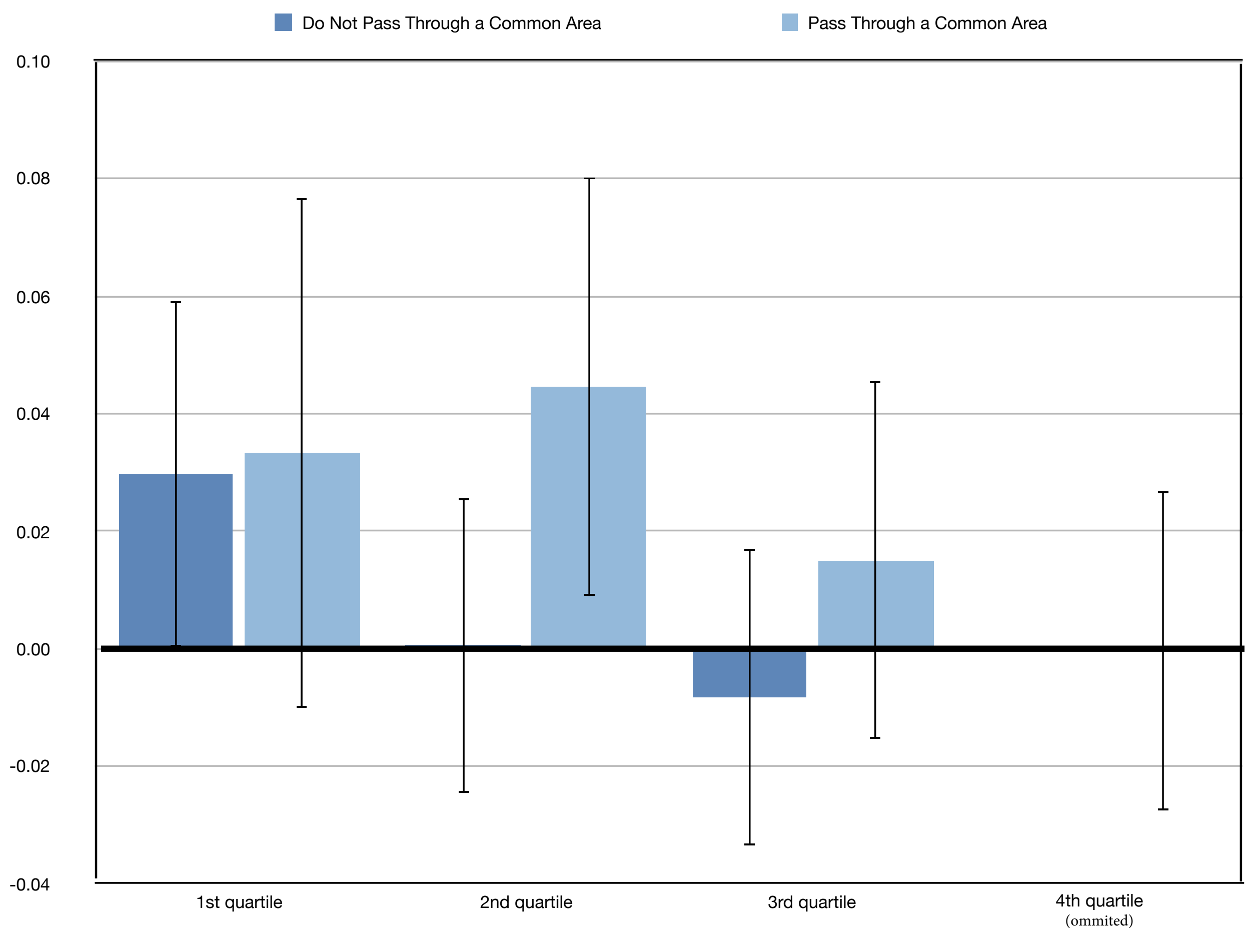


Figure 4: Common area quartile plots

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

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

Table 2: Summary Statistics

Firm level (N = 251)	mean	sd	min	p25	p50	p75	max
Age (in months)	12.24	9.59	0	3	11	20	29
Room size (in sq.feet)	271.18	315.82	50	134	143	255	1878
Room size (in m^2)	25.20	29.34	4.64	12.45	13.29	23.70	174.50
Female CEO (= 0/1)	0.12	0.32	0	0	0	0	1
B2B Company (= 0/1)	0.74	0.44	0	0	1	1	1
B2C Company (= 0/1)	0.39	0.49	0	0	0	1	1
Successful (= 0/1)	0.24	0.43	0	0	0	0	1
Min. Technology Usage	33.15	33.15	0	0	28	54	168
Max. Technology Usage	51.06	49.70	0	0	43	79	255
Dyad level (N = 10840)	mean	sd	min	p25	p50	p75	max
Adopted a Technology (= 0/1)	0.53	0.50	0	0	1	1	1
Number of Adopted Technologies	7.33	10.49	0	0	2	12	76
Distance (in m^2)	32	15.20	4.30	20	30	44	77
Close (= 0/1)	0.28	0.45	0	0	0	1	1
Common Area (= 0/1)	0.38	0.48	0	0	0	1	1
Pre-period Technology Overlap (%)	0.14	0.18	0	0	0	0.27	0.85
Same Industry (= 0/1)	0.11	0.31	0	0	0	0	1
Both B2B Companies (= 0/1)	0.48	0.50	0	0	0	1	1
Both B2C Companies (= 0/1)	0.11	0.31	0	0	0	0	1
Both Female (= 0/1)	0.013	0.11	0	0	0	0	1
Age Difference (in months)	7.30	7.28	0	1	5	12	29
Both Successful (= 0/1)	0.08	0.27	0	0	0	0	1
Non-geographically distant (= 0/1)	0.38	0.49	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.

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 Majority Female		-0.102*		0.013		-0.103*		0.012
		(0.057)		(0.027)		(0.057)		(0.028)
$\lvert$age$_i$-age$_j\rvert$		-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 $\lvert age\_i\text{-}age\_j \rvert$ represents the absolute age difference in months between firm$_i$ and firm$_j$. *Pre-period Technology Overlap* presents the share of firm$_i$'s technologies also used by firm$_j$ in the previous period. We include firm$_i$ x room 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: 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 Female	0.018			
	(0.016)			
Close x 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)
|age_i-age_j|	−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	✓	✓	✓	✓
Dimension	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 age 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 5: 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)	(0.046)	(0.006)	(0.009)
Common Area	0.025**	0.024**	0.010*	0.010*	0.013***	0.013***
	(0.010)	(0.011)	(0.005)	(0.029)	(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 6: Proximity, Socializing, and Diversity - OLS Regressions

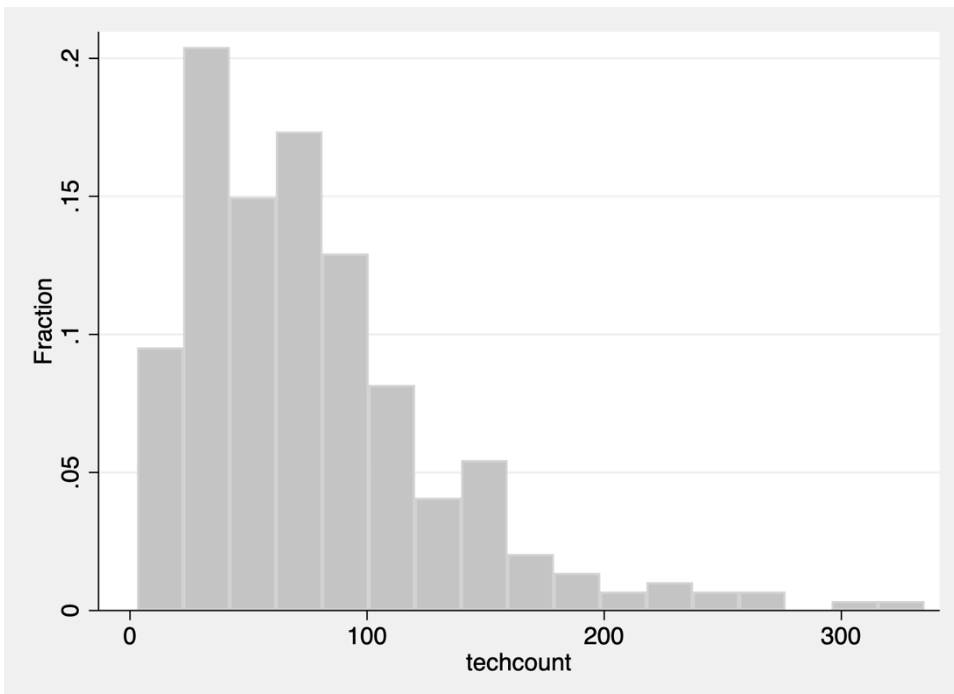
Unit of Analysis	Firm$_i$-Firm$_j$ Dyad			
Dependent Variable	$\mathbb{1}(\text{AdoptTech}_{ij})$			
mean	0.531			
	(1)	(2)	(3)	(4)
Close	0.023***	0.022***		
	(0.009)	(0.009)		
# Events	0.043***	0.037***	0.043***	
	(0.007)	(0.007)	(0.007)	
Diverse		−0.002		
		(0.006)		
# Events x Diverse		0.044***		
		(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, Age 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-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

(Co-)Working in Close Proximity: Knowledge Spillovers and Social Interactions

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: Pairwise characteristics do not predict geographic proximity - OLS Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad	
Dependent Variable	Close	
	(1)	(2)
Same Industry	−0.001	−0.002
	(0.021)	(0.022)
Both B2B Companies	−0.023	−0.023
	(0.029)	(0.028)
Both B2C Companies	−0.005	−0.005
	(0.032)	(0.032)
Both Majority Female	0.022	0.021
	(0.102)	(0.100)
Both Successful	−0.024	−0.025
	(0.035)	(0.034)
$\|age\_i\text{-}age\_j\|$	−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 predominately female, and are both successful. The variable $|age\_i\text{-}age\_j|$ represents the absolute age difference in months between firm$_i$ and firm$_j$. *Pre-period Technology Overlap* presents the share of firm$_i$'s technologies also used by firm$_j$ in the previous period. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Variable Description

Variable	Description
Outcome Variables	
ln(Distance$_{ij}$)	The distance between $firm_i$ and $firm_j$ in steps (log transformed). One step corresponds to 1.8 meters.
ln(AdoptCount$_{ij}$ + 1)	The number of technologies $firm_i$ adopts from $firm_j$ (log transformed and normalized). An adopted technology is a technology used by $firm_i$ in the focal period that $firm_i$ had not implemented in any previous period, but $firm_j$ had.
1(AdoptTech$_{ij}$):	Equals one if $firm_i$ adopts a technology from $firm_j$.
# Event Both$_{ij}$ Attend	The number of events hosted at the co-working space at least one person working for of $firm_i$ and $firm_j$ both attend.
1(Ever within X people in line)	Equals one if at least one team member of $firm_i$ and $firm_j$ appear within X (1, 2, 5, 10, 25) people in line for an event hosted at the co-working space.
Dyad-Level Independent Variables	
Close	Equals to one if $firm_i$ and $firm_j$ are located within 20 meters (14 steps; the 25$^{\text{th}}$ percentile of pair-wise distances between all rooms) of each other on the same floor.
Common Area	Equals one if the shortest path between $firm_i$ and $firm_j$ passes through a common area. Common areas are the kitchens and zone in front of the elevator on each floor as well as the open sitting space provided on the second floor. Please refer to Figure 1 for a visual depiction of the location of these areas.
Same Industry	Equals to one if $firm_i$ and $firm_j$ operate in the same industry. We follow the classification of industries provided by AngelList and BuiltWith. The individual industries are Administration&Management, Data, Design&Development, Digital, Education, Energy&Construction, Entertainment, Finance&Legal Healthcare, Marketing&PR, Real Estate, Retail, Science&Technology, Security, Software&Hardware. For our analyses we use each firm's primary industry, since many operate in more than one. We determined this by conducting extensive web searches on the startups in our sample.
Pre-period Technology Overlap	Percentage of same technologies $firm_i$ and $firm_j$ used in the period prior to the focal period.
Both Majority Female	Equals to one if the team members in both $firm_i$ and $firm_j$ are predominately female (over 50 percent). We determined the gender of founders conducting extensive web searches on the startups as well as by comparing first names with lists provided by the US Census for most common names by sex (https://www2.census.gov/topics/genealogy/1990surnames).
Both B2B Companies	Equals to one if $firm_i$'s and $firm_j$'s main customers are other businesses.
Both B2C Companies	Equals to one if $firm_i$'s and $firm_j$'s main customers are individual consumers.
Both Successful	Equals to one if $firm_i$ and $firm_j$ have received a TAG40 award, have received the Village Verified certificate, have raised a seed round or have ever raised a VC seed investment.
Diverse	Equals to one if a startup dyad differs along the social, product-market and knowledge dimensions. For simplicity, we count a dyad as different along the knowledge space dimension if their pre-period technology overlap is below the mean.
$\lvert age_i\text{-}age_j \rvert$	The age difference between $firm_i$ and $firm_j$ (derived from date of entry at the co-working space).

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: Distance negatively affects peer technology adoption - OLS Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad					
Dependent Variable	$ln(AdoptCount_{ij}+1)$					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(distance$_{ij}$)	-0.073^{**}	-0.044	-0.056^{**}	-0.043^{***}	-0.043^{**}	-0.035^{***}
	(0.037)	(0.043)	(0.027)	(0.017)	(0.018)	(0.010)
Same Industry					0.056	0.021
					(0.034)	(0.029)
Both B2B Companies					0.004	-0.034
					(0.028)	(0.022)
Both B2C Companies					0.007	0.030
					(0.031)	(0.029)
Both Female					-0.095	-0.102^{*}
					(0.098)	(0.057)
|age_i-age_j|					-0.004^{***}	-0.006^{***}
					(0.001)	(0.002)
Pre-period Technology Overlap						3.624^{***}
						(0.146)
Firm$_i$ Fixed Effects		✓				
Firm$_j$ Fixed Effects			✓			
Firm$_i$ X Room Fixed Effects				✓	✓	✓
Firm$_j$ X Room Fixed Effects				✓	✓	✓
Observations	10840	10840	10840	10840	10840	10840
R^2	0.00	0.35	0.44	0.80	0.80	0.86

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

Table A5: Distance negatively affects peer technology adoption - LPM Regressions

Unit of Analysis	Firm$_i$-Firm$_j$ Dyad					
Dependent Variable	$\mathbb{1}$(AdoptTech$_{ij}$)					
mean	0.531					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(distance$_{ij}$)	-0.030^{**}	-0.022	-0.024^{*}	-0.019^{***}	-0.019^{***}	-0.017^{***}
	(0.014)	(0.022)	(0.014)	(0.007)	(0.007)	(0.005)
Same Industry					0.015	0.005
					(0.016)	(0.013)
Both B2B Companies					0.004	-0.007
					(0.014)	(0.011)
Both B2C Companies					-0.002	0.005
					(0.012)	(0.008)
Both Female					0.015	0.013
					(0.019)	(0.027)
$\vert$age_i-age_$j\vert$					-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 predominately female. The variable $|$age_i-age_$j|$ represents the absolute age difference in months between firm$_i$ and firm$_j$. *Pre-period Technology Overlap* presents the share of firm$_i$'s technologies also used by firm$_j$ in the previous period. We include firm$_i$ X room fixed effects. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: 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 A7: 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 A8: Socializing, Diversity Quintiles and Financial Performance Outcomes

Funding raised	Seed (1)	>1M+ (2)
Social = 0 × Diversity Quantiles = 2	−0.045 (0.073)	−0.031 (0.046)
Social = 0 × Diversity Quantiles = 3	0.017 (0.062)	0.003 (0.039)
Social = 0 × Diversity Quantiles = 4	−0.078 (0.070)	0.010 (0.044)
Social = 0 × Diversity Quantiles = 5	−0.104 (0.070)	−0.033 (0.044)
Social = 1 × Diversity Quantiles = 1	−0.035 (0.068)	−0.049 (0.043)
Social = 1 × Diversity Quantiles = 2	−0.131 (0.085)	−0.063 (0.054)
Social = 1 × Diversity Quantiles = 3	0.155** (0.074)	0.107** (0.047)
Social = 1 × Diversity Quantiles = 4	−0.034 (0.101)	0.069 (0.064)
Social = 1 × Diversity Quantiles = 5	−0.152 (0.102)	−0.010 (0.064)
Room Size	0.000 (0.000)	0.000 (0.000)
Female CEO	−0.128 (0.082)	−0.047 (0.052)
Remoteness	−0.004 (0.008)	−0.006 (0.005)
Age	0.004 (0.003)	0.004** (0.002)
No. Firms	0.003 (0.004)	−0.000 (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. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.