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

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Abstract. We examine the influence of physical proximity on between-start-up knowledge spillovers at one of the largest technology coworking hubs in the United States. Relying on the exogenous assignment of office space to the hub's 251 start-ups, we find that proximity positively influences knowledge spillovers as proxied by the likelihood of adopting an upstream web technology already used by a peer start-up. This effect is largest for start-ups within close proximity of each other and quickly decays; start-ups more than 20 meters apart on the same floor are indistinguishable from start-ups on different floors. The main driver of the effect appears to be social interactions. Although start-ups in close proximity are most likely to participate in social coworking space events together, knowledge spillovers are greatest between start-ups that socialize but are dissimilar. Ultimately, start-ups 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

Over the past three years, there has been an unprecedented shift in the nature of work. Between 2020 and 2023, the percentage of days worked from home in the United States surged almost sixfold, from 4.7% to 28.1% (Barrero et al. 2021). Although this shift to remote work has brought some benefits, such as a reduction in employee attrition and an increase in measures of job satisfaction (Bloom et al. 2023), evidence also indicates that the reduction in physical proximity has altered the interactions and collaborations that normally would have taken place (Yang et al. 2022). The observation of such change is much in line with a body of work that has garnered support for the role of physical proximity for knowledge exchange among collaborators over decades of research (Allen 1977, Cowgill et al. 2009).

Beyond the physical dimension, numerous other distances have been found to play critical roles in facilitating/impeding knowledge exchange and learning (Blau 1977, McPherson and Smith-Lovin 1987, Cohen and Levinthal 1990, Saxenian 1996, Alcácer et al. 2015, Wang and Zhao 2018, Lee 2019, Lane et al. 2021), which recent work stresses to take into account when aiming to optimize peer effects (Carrell et al. 2013, Chatterji et al. 2019, Hasan and Koning 2019). Yet, despite these advances, we still have to understand the extent to which the similarity and dissimilarity of organizations impact knowledge transfer in conjunction with physical proximity, a relationship that is typically difficult to estimate provided endogeneity concerns.

The focus of this study is to fill this gap by providing a deeper comprehension of the impact of physical proximity and potential channels driving this relationship. We thereby build upon prior research applying a microgeographic lens to the relationship between physical proximity and knowledge exchange in a particularly relevant context: knowledge exchange between early-stage entrepreneurial firms (start-ups). Shedding light on how start-ups 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 start-ups (Conti et al. 2021). In particular, we examine how geographic distance impacts knowledge spillovers among nascent start-ups located within the same building—a start-up coworking space—and further document the role that nongeographic differences, such as demographic characteristics, and knowledge overlap among start-ups play in modulating the effect of distance. Importantly, we provide evidence suggesting that opportunities for social interactions are a critical channel for knowledge spillovers to occur among proximate (co-)workers.

The setting for our study is one of the largest technology coworking spaces in the United States. The building consists of five floors, covering 9,300 meters squared (m^2; 100,000 square feet (sq. ft.)). To deal with endogenous location choice, we rely on the exogenous assignment of office space to the hub's 251 start-ups. In this paper, we consider the instance of adopting a component of a peer start-up's technology stack as knowledge spillovers, which represents a novel way of capturing potential knowledge flows (Breschi 2011). Using floor plans to measure geographic distance, we find that close physical proximity greatly influences the likelihood of these knowledge spillovers, especially when the potential technology choice set is large. This effect, however, quickly decays with distance, in which start-ups that are more than 20 meters (m; 66 feet) away are no longer influenced by each other. Strikingly, being located more than 20 m apart but on the same floor does not appear to differ from being located on a different floor altogether. Moreover, we find that when start-ups overlap with common areas at the hub (e.g., kitchens), the distance of influence increases, revealing the important role that these spatial features play in extending geographic reach and in promoting knowledge spillovers. In addition, our results indicate a more nuanced role of proximity in fostering knowledge spillovers across nascent firms. We find that physical proximity is less important in promoting knowledge exchange among similar start-ups but in turn, more crucial for start-ups that are dissimilar.

From these findings, the question remains. Why do these microdistances 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, the integration and internal use of externally sourced information. Therefore, to understand the possible dynamics underlying knowledge spillovers at short distances, we examine the role of social interactions in explaining the relationship between physical proximity and knowledge exchange. To do so, we exploit event check-in data that provide information on the temporal overlap of start-up members at events where we would expect social interactions to occur. Our results indicate that proximity predicts joint attendance of these events—our proxy for socializing—and that start-ups that coattend 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 start-up performance (Cohen and Levinthal 1990, Chesbrough 2012). Because external knowledge provides unique insights previously unavailable to the start-up (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 start-up'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 start-up's environment on early-stage start-up performance (raising a seed round or receiving more than $1 million in funding). We find that start-ups embedded in environments that have neither too much nor too little diversity perform better but only if they engage in social interactions.

Taken together, this paper informs our understanding of the scale at which knowledge spillovers among small, nascent firms take place. We thereby highlight important nuances in terms of the benefits accruing from physical proximity depending on how different exchange partners are from each other along nonphysical dimensions. Importantly, we observe that physical proximity is most helpful for supporting knowledge exchange among start-ups 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. Section 3 describes the data sources and empirical estimation strategy. In Section 4, 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 peers 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 colocation.

2. Background

2.1. Physical Proximity and Knowledge Spillovers

The diffusion of ideas has been found to be highly localized (Allen 1977, Arzaghi and Henderson 2008, Roche

2020). In theory, the assumption pervades that knowledge (especially more tacit know-how) transfers via face-to-face interaction between individuals (Jacobs 1969, Gaspar and Glaeser 1998, Rosenthal and Strange 2001, Moretti 2004). 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 (Reagans et al. 2005, Cowgill et al. 2009, Kerr and Kominers 2015, Catalini 2018, Atkin et al. 2022).

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

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

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

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

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

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

2.2. The Interplay of Physical Proximity with Nongeographic Similarity

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

In general and across a range of contexts, scholars have provided empirical evidence to support the notion that individuals tend to affiliate more closely with those who exhibit similarities to themselves. One plausible explanation is that individuals possess an inherent psychological inclination to engage in interactions with others who share similar characteristics. Numerous instances of this phenomenon have been observed, such as in confiding networks among adults (Marsden 1988), social support networks within governmental structures (South et al. 1982), interaction networks among individuals of the same religious beliefs (Fischer 1982), and especially relevant to this study, cofounding networks among entrepreneurs (Ruef et al. 2003).

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

3. Data and Empirical Strategy

3.1. Data Sources and Construction

The data for our study were collected at one of the five largest technology coworking spaces in the United States (in 2016). Designated as a start-up 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 to January 2017, during which 251 unique start-ups had rented an office in the coworking space. For our analyses, we only examine relationships between start-ups on the same floor, resulting in 10,840 unique start-up dyads. Note that the coworking hub is relatively specialized in digital technologies, fintech, software development, and marketing tech.

Approximately 35% of the start-ups ceased operations or left the coworking space each year, which according to senior administrators at the coworking space, typically occurs because start-ups fail, grow out of the space, or occasionally, fall stagnant and do not want to pay for an office when they can work from home.[1] As such, start-ups leave the coworking hub in two ways: either by not renewing their membership or by outgrowing their office space. The vacant office spaces are then assigned to start-ups based off of a waiting list.[2] Start-ups on the waiting list are prioritized as follows: technology start-ups over service providers and local versus nonlocal start-ups.

The layout of the floors we examine (floors 2–5) is depicted in Figure 1.[3] We measure the distance between rooms from available floor plans using space syntax software (Bafna 2003; Kabo et al. 2014, 2015).[4] One useful feature of space syntax software is that it calculates distances between rooms as people would walk rather than the shortest Euclidian distance on a plane or "as the crow flies." For each room dyad, we calculate the shortest walking distance. The variable *Close* is an indicator equal to one if the shortest distance between $startup_i$ and $startup_j$ located on the same floor is within 20 m (the 25th percentile of pairwise distances between all rooms, corresponding to being an average of two offices apart).[5] We flag dyads for which 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.

Our main outcome variable of interest is new web technology adoption, which serves as our proxy for knowledge spillovers (Fang et al. 2021). 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 this 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 content management system) that tracks how technology usage of start-ups changes 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 application is colloquially known as a "technology stack" (and often shortened to "tech stack"). In Table A3

Figure 1. Floor Plan of the Coworking Space

Notes. This figure displays the floor plans of the coworking hub we examine. The legend and scale can be found in the lower right corner.

in the online appendix, we provide examples of the "tech stack" corresponding to three start-ups in our sample. As the table displays, there is much variation between start-ups in terms of technology categories used, but also, there is variation of software components used within those categories.

From this website, we collect information on the web technology usage of the start-ups in our sample, including the exact date of implementation and abandonment. Web technologies are the markup languages and multimedia packages that computers use to communicate and can be thought of as tools at a start-up's disposal 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, for example, 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 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 they have implications that span across various layers of the start-up, including human resources, finance, marketing, and management. Because 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 start-up.[6]

We construct two measures for technology adoption. The first is the number of technologies $startup_i$ adopts from $startup_j$ ($\ln(AdoptCount_{ij} + 1)$). An adopted technology is a technology used by $startup_i$ in the focal period that $startup_i$ had not implemented in any previous period but that $startup_j$ 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 *Preperiod Technology Overlap* corresponds to the percentage of technologies $startup_i$ has adopted from $startup_j$ before both of the two start-ups are active at the coworking 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 start-ups, we conducted extensive web searches to find detailed information regarding start-ups' 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 & public relations, 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) because 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).[7]

We additionally identified a start-up's tenure at the coworking hub and the gender composition of start-ups using information provided by the coworking space. As derived from the entry date into the coworking space, $|tenure_i\text{-}tenure_j|$ reflects the absolute value of the tenure difference between $startup_i$ and $startup_j$. The variable *Both Majority Female* flags start-up dyads where team members in both $startup_i$ and $startup_j$ are predominately female (over 50% female). We have additional information on the CEOs/heads of each start-up, which we use to identify whether a start-up is led by a woman (*Female CEO*) or not. We determined the gender of founders by conducting extensive web searches on the start-ups as well as by comparing first names with lists provided by the U.S. Census for the most common names by sex.[8]

To capture differences in performance outcomes, we construct two measures using information provided by the coworking space and AngelList. These two outcomes are based on prior literature (Nanda and Sørensen 2010, Ewens and Marx 2018) and capture financial performance of start-ups. One is raising a seed round, and the other is raising financial capital in excess of U.S. $1 million.

We further exploit a joint event hosted at the coworking 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 nonmembers is $10) organized by the coworking 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 coworking space keeps track of the exact order individuals (both members and nonmembers) enter to attend the lunch. For a period of time (January 2016 to December 2016), we identify the number of lunches hosted at the coworking 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 each of $startup_i$ and $startup_j$ appears within 1, 2, 5, 10, or 25 people in line for the lunch (1(*Ever within X people in line*)).

3.2. Estimation Strategy

Estimating the role of physical proximity on knowledge spillovers—for the purpose of this study captured through peer technology adoption—not only requires data at a highly granular geographic level but is also likely to yield biased estimates of the effect size. Specifically, as has been well documented in the context of individual-level peer effects by Manski (1993), these biases may be driven by issues of endogenous sorting, contextual effects, and other correlated effects. On the one hand, technology adoption could be a function of characteristics of the group (e.g., industry type), where start-ups that would use similar input factors like to locate close to each other. On the other hand, start-ups that are in physical proximity often experience similar social phenomena, which could drive exposure to certain input factors. To deal with such endogenous geographic clustering, we rely on the exogenous assignment of office space to the hub's 251 start-ups, whereas to deal with contextual contaminants, we specifically examine start-up i's decisions to adopt relevant input factors that are already being used by start-up j. Table 1 shows that pairwise characteristics do not correlate with physical proximity, serving as a validation of our exogenous room assignment assumption (and confirmed by multiple senior staff at the coworking space).[9]

To operationalize knowledge spillovers, we focus our attention on a fundamental decision nascent start-ups 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 start-up dyad as our unit of analysis, we estimate the following specification using OLS:

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

where Y_{ij} represents our web technology adoption measures, X_{ij} is a vector of dyad-specific controls, and θ_i and ϕ_j are $Room_i \times Startup_i$ and $Room_j \times Startup_j$ fixed effects, respectively. The inclusion of the start-up room-specific fixed effects allows us to hold all time-invariant individual start-up 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

Table 1. Pairwise Characteristics Do Not Predict Geographic Proximity—OLS Regressions

Unit of analysis	$Firm_i$-$Firm_j$ dyad			
Dependent variable	ln($distance_{ij}$)			
	(1)	(2)	(3)	(4)
Same Industry	−0.001	0.001	−0.000	0.001
	(0.017)	(0.023)	(0.017)	(0.025)
Both B2B Companies	0.019	0.030	0.021	0.030
	(0.042)	(0.040)	(0.040)	(0.040)
Both B2C Companies	0.031	0.030	0.031	0.030
	(0.028)	(0.044)	(0.028)	(0.044)
Both Female	0.120	0.015	0.125	0.016
	(0.104)	(0.124)	(0.107)	(0.124)
Both Successful	0.046	0.022	0.049	0.023
	(0.041)	(0.058)	(0.042)	(0.059)
$\lvert TechUsage_i\text{-}TechUsage_j \rvert$	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.001)	(0.000)	(0.001)
$\lvert tenure_i\text{-}tenure_j \rvert$	0.001*	0.002	0.001	0.002
	(0.001)	(0.003)	(0.001)	(0.002)
Preperiod Technology Overlap			−0.080	−0.060
			(0.112)	(0.052)
$Firm_i \times Room$ fixed effects		✓		✓
$Firm_j \times Room$ fixed effects		✓		✓
Observations	10,840	10,840	10,840	10,840
R^2	0.00	0.12	0.00	0.12

Notes. This table displays the results from OLS regressions predicting physical distance between two firms as a function of firm-dyad characteristics. These variables (indicated by *Both* and *Same*) equal one if both $firm_i$ and $firm_j$ operate in the same industry, both have a B2B (B2C) business model, both are led by a female, and both are successful. The variable $\lvert TechUsage_i\text{-}TechUsage_j \rvert$ represents the absolute difference in the number of technologies adopted by $firm_i$ and $firm_j$, respectively. The variable $\lvert tenure_i\text{-}tenure_j \rvert$ represents the absolute age difference in months between $firm_i$ and $firm_j$. *Preperiod 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.

$^*p < 0.10$.

geographic proximity affects web technology adoption decisions, then the outcomes of all start-ups in close proximity will be correlated. We resolve this standard clustering problem by clustering at the floor-neighborhood level (15 clusters) to account for correlated outcomes in close proximity.[10] Second, because of the dyadic nature of our data, it is insufficient to solely engage in two-way clustering at the separate $startup_i$ and $startup_j$ level.[11] As an example, the dyad $startup_i$-$startup_j$ will also be correlated with the dyads $startup_i$-$startup_j'$ because a common component of start-up i's web technology adoption decisions will also create correlation across all of start-up 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 (Cameron and Miller 2014, Aronow et al. 2017, Carayol et al. 2019, Harmon et al. 2019) and produce dyadic-robust standard errors using the floor-neighborhood locations of start-ups i and j as the levels of clustering.

In alternate analyses, we estimate the following specification:

$$Y_{ij} = \beta Close_{ij} + X_{ij} + \theta_i + \phi_j + \eta, \qquad (2)$$

where $Close_{ij}$ is equal to one if start-ups i and j are in the first quartile of the $distance_{ij}$ distribution and zero otherwise, and we further extend our analysis by interacting variables with $Close_{ij}$.[12]

3.3. Descriptive Statistics

As displayed in Table 2, on average, each start-up is at risk for spillovers from 53 other start-ups. The average distance between room dyads is approximately 32 m, and the average room size is circa 27 m^2 (288 sq. ft.). Twenty-eight percent of the rooms (by floor) are located close to each other, and 38% of the shortest paths between two rooms pass through a common area. Of the 251 start-ups, 12% are predominately female, and 24% are considered to be successful start-ups. On average, the start-ups in our sample have been at the coworking 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) number of technologies a start-up ever hosted while at the coworking space. Over time, the start-ups in our sample adopt about 7.33 technologies on average, and 53% adopt at least one new technology.

The main focus of our analyses is on start-up dyads. A key component is thereby the characteristics that both start-ups have in common. Of the start-up dyads in the coworking hub, 11% operate in the same industry; 48% of the dyads both have B2B (business-to-business) business models and 11% of the dyads both have B2C (business-to-consumer) business models. The percentage of start-up dyads where the majority of team members are female is 1.3% ($n = 138$), and 8% of the start-up dyads are considered successful. The average tenure difference between start-ups in a dyad is 7.30 months.

4. Results

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

4.1. Baseline Results: Physical Proximity

Table 3 presents the results from assessing the effect of distance on the amount of peer technology adoption (ln($AdoptCount_{ij}$ + 1)) using a standard Ordinary Least

Table 2. Summary Statistics

	Mean	Standard deviation	Min	p25	p50	p75	Max
Firm level (N = 251)							
Tenure (months)	12.24	9.59	0	3	11	20	29
Room size (sq. ft.)	268.95	310.32	50	134	143	255	1,878
Room size (m^2)	25.20	29.34	4.64	12.45	13.29	23.70	174.50
Female CEO (=0/1)	0.12	0.32	0	0	0	0	1
B2B Company (=0/1)	0.74	0.44	0	0	1	1	1
B2C Company (=0/1)	0.39	0.49	0	0	0	1	1
Successful (=0/1)	0.24	0.43	0	0	0	0	1
Min. Technology Usage	33.15	33.15	0	0	28	54	168
Max. Technology Usage	51.06	49.70	0	0	43	79	255
Number Close Firms	11.14	5.73	0	7	10	14	33
Seed Funding	0.084	0.28	0	0	0	0	1
$1M+	0.032	0.18	0	0	0	0	1
Dyad level (N = 10,840)							
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 (m)	32	15.20	4.30	20	30	44	77
Close (= 0/1)	0.28	0.45	0	0	0	1	1
Common Area (=0/1)	0.38	0.48	0	0	0	1	1
Preperiod Technology Overlap (%)	0.14	0.18	0	0	0	0.27	0.85
Same Industry (=0/1)	0.11	0.31	0	0	0	0	1
Both B2B Companies (=0/1)	0.48	0.50	0	0	0	1	1
Both B2C Companies (=0/1)	0.11	0.31	0	0	0	0	1
Both Majority Female (=0/1)	0.013	0.11	0	0	0	0	1
Tenure Difference (months)	7.30	7.28	0	1	5	12	29
Both Successful (=0/1)	0.08	0.27	0	0	0	0	1
Nongeographically distant (=0/1)	0.31	0.46	0	0	0	1	1

Notes. This table displays summary statistics for the start-ups operating at the coworking space we examine. We report summary statistics on both the firm and dyad levels. Please refer to Table A1 in the online appendix for a description of the variables displayed. A total of 110 firms were on the second floor, 53 firms were on the third floor, 29 firms were on the fourth floor, and 59 firms were on the fifth floor. p denotes percentile.

Squares (OLS) model and using a linear probability model to estimate the likelihood of adopting a technology from a peer start-up $\mathbb{1}(AdoptTech_{ij})$. In the full model (columns (2) and (4)), using *start-up* × *room* fixed effects and controlling for industry, business model, gender, tenure, and preperiod 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 remain largely unchanged with the inclusion of additional controls.[13]

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 start-ups 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 start-ups located within 20 m 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, start-up pairs that are not within 20 m of each other on the same floor behave as if they are on different floors altogether.

Having identified that the distance effect is strongest for the most proximate start-ups, we create an indicator equal to one (*Close*) that flags dyads located within the first quartile of the distance distribution (20 m) and zero otherwise. For simplicity, we use this measure for the remainder of our empirical results. In Table 3, columns (5)–(8), we display our findings from estimating Equation (1) using this more nuanced classification of distance. The results indicate that close proximity positively influences the likelihood of adopting an upstream (production) technology also used by a peer start-up. We find that being in close proximity is associated with a 2.5-percentage point higher probability of adopting a peer technology (=0.025, dyad and floor-neighborhood cluster-robust standard errors = 0.011). This finding remains robust to including different covariates. As displayed in columns (5) and (6), applying an OLS model and estimating the count of adopted peer technologies ($\ln(AdoptCount_{ij} + 1)$) provides a similar result. In the full model (column (6)), the point estimate on the coefficient for close proximity is 0.048 (cluster-robust standard errors = 0.015). This implies that a switch to a room in

Table 3. Physical Proximity Positively Affects Peer Technology Adoption

Unit of analysis	$Firm_i$-$Firm_j$ dyad							
Dependent variable	$\ln(AdoptCount_{ij}+1)$		$\mathbb{1}(AdoptTech_{ij})$		$\ln(AdoptCount_{ij}+1)$		$\mathbb{1}(AdoptTech_{ij})$	
Mean	1.275		0.531		1.275		0.531	
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(distance_{ij})$	−0.043*** (0.017)	−0.035*** (0.010)	−0.019*** (0.007)	−0.017*** (0.005)				
Close					0.057** (0.026)	0.048*** (0.015)	0.025** (0.011)	0.022*** (0.007)
Same Industry		0.021 (0.029)		0.005 (0.013)		0.021 (0.029)		0.005 (0.013)
Both B2B Companies		−0.034 (0.022)		−0.007 (0.011)		−0.034 (0.022)		−0.007 (0.011)
Both B2C Companies		0.030 (0.029)		0.005 (0.008)		0.029 (0.029)		0.004 (0.008)
Both Female		−0.102* (0.057)		0.013 (0.027)		−0.103* (0.057)		0.012 (0.028)
$\lvert tenure_i\text{-}tenure_j\rvert$		−0.006*** (0.002)		−0.001** (0.000)		−0.006*** (0.001)		−0.001* (0.001)
Preperiod Technology Overlap		3.624*** (0.146)		1.007*** (0.066)		3.624*** (0.145)		1.007*** (0.065)
$Firm_i \times Room$ fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
$Firm_j \times Room$ fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	10,840	10,840	10,840	10,840	10,840	10,840	10,840	10,840
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 m (the 25th percentile of pairwise 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 both are predominately female. The variable $|tenure_i\text{-}tenure_j|$ represents the absolute tenure difference in months between $firm_i$ and $firm_j$. *Preperiod Technology Overlap* presents the share of $firm_i$'s technologies also used by $firm_j$ in the previous period. We include $firm_i \times room$ and $firm_j \times room$ fixed effects. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level.

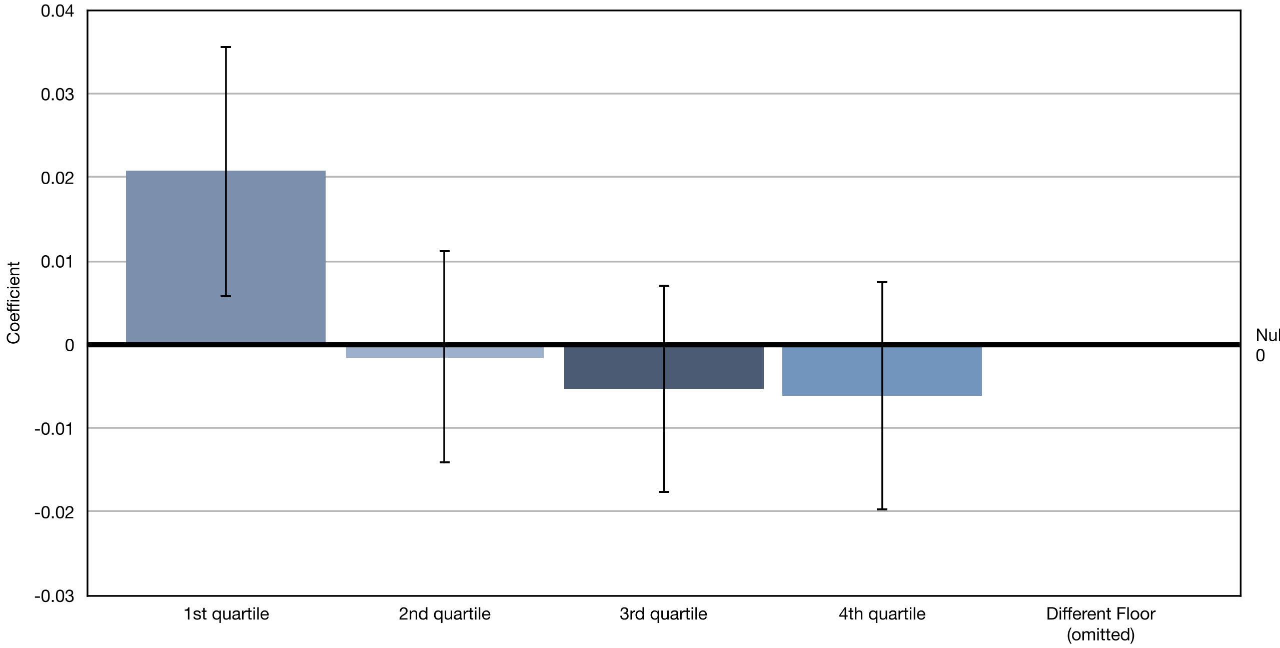
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

close proximity would translate into a 5% increase in the number of peer technologies adopted from the mean.

For robustness and to ensure that the results we present are not because of spurious correlations, we utilize a randomization inference method suggested by Athey and Imbens (2017) and Young (2019) using a Monte Carlo simulation (1,000 runs). In this simulation, we randomly draw closeness (with replacement) for each dyad and then estimate the likelihood of adopting a technology as a function of this random closeness variable. The placebo treatment effect results attained from the simulation are presented in Figure 3.[14] In line with our findings, only 2 of the simulated Monte Carlo draws (from 1,000) had a coefficient greater than the point estimate of our main results (=0.022), resulting in a randomized inference p-value of 0.002—strongly rejecting our null of no relationship between proximity and technology adoption.

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

Figure 2. (Color online) Quartile Plots

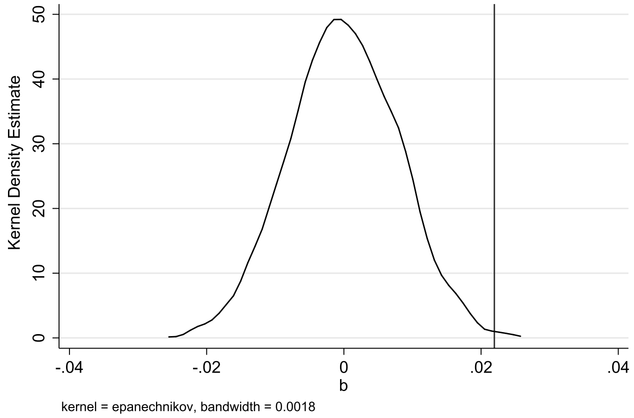


Notes. This figure displays the results from estimating Equation (1) using a quartile regression. We thereby split our distance measure into quartiles instead of using a continuous measure of distance. Our omitted category consists of distances among start-up dyads that span more than one floor.

adoption would weaken. As such, our main results are likely to present a lower bound of our estimate.

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

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.

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

An additional feature of the physical layout of the office space is the common areas provided by the coworking space, such as kitchens on each floor. To examine

Table 4. Physical Proximity Positively Affects Peer Technology Adoption When There Are Many Options or the Technology Category Is New

Unit of analysis	$Firm_i$-$Firm_j$ dyad		
Dependent variable	$\mathbb{1}(AdoptTech_{ij})$		
	Many Options (1)	*Few Options* (2)	*New Category* (3)
Close	0.025**	0.000	0.030***
	(0.011)	(0.002)	(0.011)
Same Industry	0.015	0.003	0.014
	(0.016)	(0.004)	(0.016)
Both B2B Companies	0.004	0.004	0.005
	(0.014)	(0.003)	(0.016)
Both B2C Companies	−0.002	0.008*	−0.002
	(0.010)	(0.004)	(0.007)
Both Female	0.014	−0.003	0.009
	(0.020)	(0.007)	(0.021)
$\lvert tenure_i\text{-}tenure_j \rvert$	−0.001*	−0.000*	−0.001**
	(0.000)	(0.000)	(0.001)
$Firm_i \times Room$ fixed effects	✓	✓	✓
$Firm_j \times Room$ fixed effects	✓	✓	✓
Observations	10,840	10,840	10,840
R^2	0.79	0.13	0.78

Notes. This table displays the results from OLS regressions predicting physical distance between two firms as a function of firm-dyad characteristics. In this table, we include three different outcomes. *Many Options* indicates the adoption of a technology from a technology category with many options to choose from (above median number of technologies > 14). *Few Options* indicates the adoption of a technology from a technology category with few options (below median ≤ 14) to choose from. *New Category* indicates the adoption of a technology from a technology category new to the firm. The variables indicated by *Both* and *Same* equal one if both $firm_i$ and $firm_j$ operate in the same industry, both have a B2B (B2C) business model, and both are predominately female. The variable $\lvert tenure_i\text{-}tenure_j \rvert$ represents the absolute tenure difference in months between $firm_i$ and $firm_j$. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

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* × 4th distance quartile as the omitted category).[16] The results are displayed in Figure 4, which reveals two things. First, being close (first quartile of distance) to a start-up increases technology adoption likelihood independent of whether the two start-ups 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 m apart) is also greater, but this effect only activates for start-up dyads that pass through a common area. In other words, it appears that these common areas extend the colocation premium to start-ups that are more distant from one another.

4.2. Interplay of Physical Proximity and Similarity

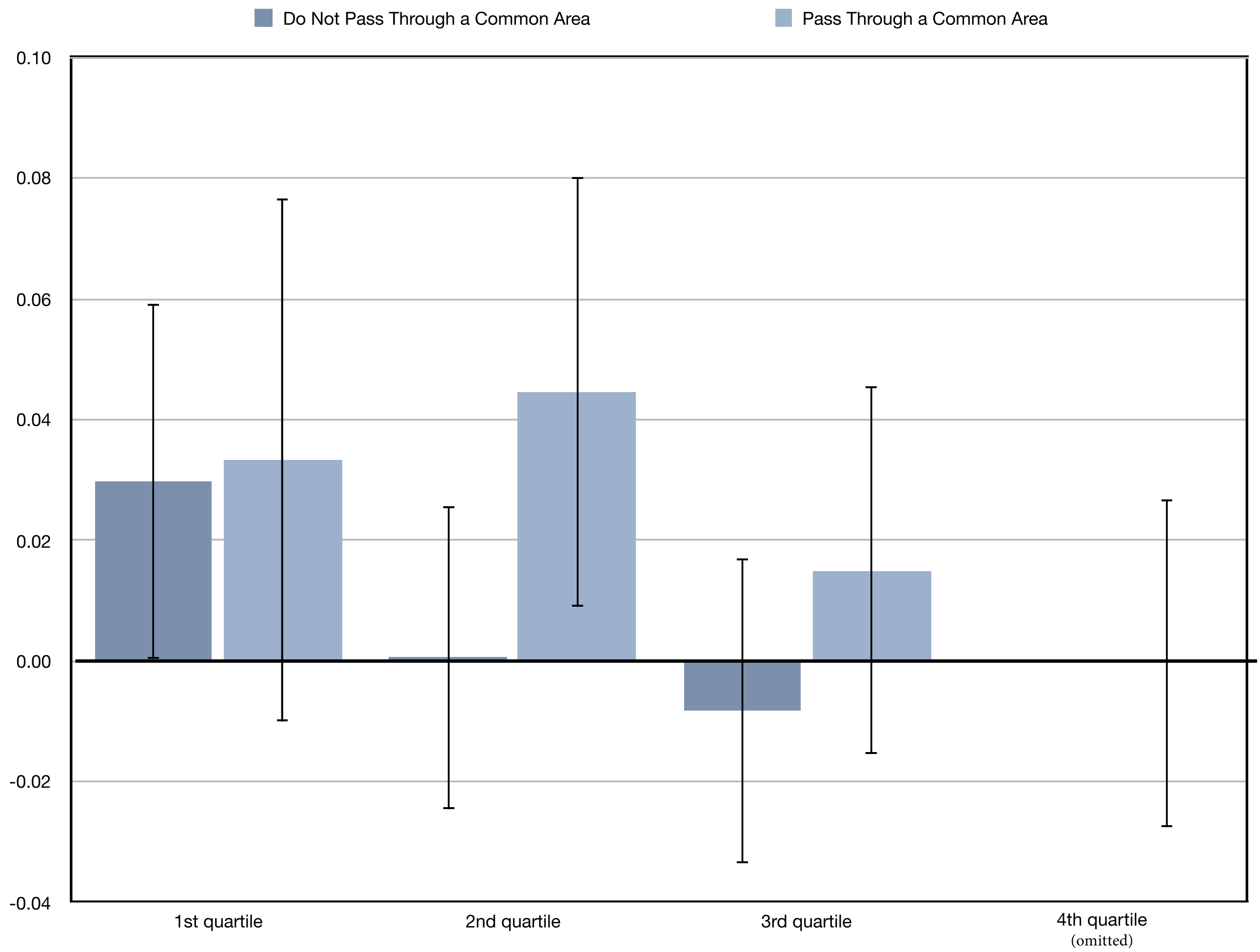
We now turn to the results on the interplay between physical proximity and similarity. To this end, we construct three different measures that may *proxy* for similarity of start-ups in a dyad. These are the gender composition of the start-up dyads, their product-markets, and knowledge overlap. All three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

For example, in our setting, female start-ups represent a minority group. As suggested by Reagans and Zuckerman (2001), demographic characteristics that define minority status are more likely to be salient. Salience is important because entities are more likely to identify with a salient characteristic, and identification with a characteristic generates positive affect for in-group members (Hogg and Turner 1985, Grieve and Hogg 1999). As shown in Table 5, column (1), we find that dyads where both start-ups are predominately female overcome the distance discount, suggesting that these start-ups rely on alternate mechanisms to overcome the negative effects of distance or as a minority within the coworking space, may have different networking behavior (Kerr and Kerr 2018).

In Table 5, column (2), we present the results including an interaction of physical and product-market similarity (if either operates in the same industry or has the same business model). The main effect of physical proximity *Close*—which reflects the benefits of proximity for start-up 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 similarities, as in the case of the gender composition measure, are substitutes and that being physically close is most beneficial to start-up dyads that are dissimilar along this dimension.

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

Figure 4. (Color online) 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* × 4th distance quartile as the omitted category. The darker shaded area represents the results when the dyads do not pass through a common area, the lighter shade when they do.

Thus far, the results suggest that similarity along certain nongeographic dimensions may substitute for being physically close. Using these three available proxies, this points to possible advantages of colocation for facilitating knowledge spillovers among start-ups that are otherwise dissimilar. To test this further, we create a composite variable called *Diverse* that is equal to one if a start-up dyad differs along the three dimensions and is zero otherwise. As displayed in Table 5, column (4), we find that being physically close matters most for knowledge exchange that leads to the integration of new technologies among otherwise dissimilar start-ups. This may indicate that the advantages of close physical proximity lie in supporting more exploratory search by better enabling access to different and nonobvious 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 patterns of social interactions (Allen 1977, Hasan and Bagde 2015, Battiston et al. 2021, Lane et al. 2021). To explore the likelihood of this mechanism in the coworking hub context, we would require a suitable measure for the propensity of members of two start-ups to interact. Albeit not a perfect and complete measure of interactions, we identify a proxy that gets close. To this end, we exploit data on a joint event—a lunch—hosted at the coworking space on a weekly basis. Table 6, columns (1) and (2) present the results using the number of lunches (*#Event*) hosted at the coworking 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

Table 5. Proximity and Diversity

Unit of analysis	$Firm_i$-$Firm_j$ dyad			
Dependent variable mean	$\mathbb{1}(AdoptTech_{ij})$ 0.531			
	(1)	(2)	(3)	(4)
Close	0.024*** (0.007)	0.037*** (0.007)	0.031*** (0.012)	0.014** (0.006)
Both Majority Female	0.018 (0.016)			
Close × *Both Majority Female*	−0.089*** (0.016)			
Same Product Market		0.013*** (0.005)		
Close × *Same Product Market*		−0.023*** (0.008)		
High Tech-Stack Overlap			0.209*** (0.027)	
Close × *High Tech-Stack Overlap*			−0.027** (0.014)	
Diverse				−0.001 (0.007)
Close × *Diverse*				0.029*** (0.005)
Preperiod Technology Overlap	1.007*** (0.066)	1.006*** (0.065)		1.011*** (0.063)
$\lvert tenure_i - tenure_j \rvert$	−0.001** (0.001)	−0.001** (0.000)	−0.001* (0.000)	−0.001** (0.001)
$Firm_i$ × *Room* fixed effects	✓	✓	✓	✓
$Firm_j$ × *Room* fixed effects	✓	✓	✓	✓
Proxies for similarity	Social	Product-market	Knowledge	Composite index
Observations	10,840	10,840	10,840	10,840
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 nongeographic proximity dimensions that we 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 m (the 25th percentile of pairwise 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 are predominately female. *High Tech-Stack Overlap* denotes dyads that have a preperiod tech stack overlap of over 0.27, which represents the 75th percentile. We include controls for tenure differences and $firm_i$ × *room* fixed effects as well as the share of $firm_i$'s technologies that are 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.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

one if both ever attended one together. Because common areas seem to extend the effect of proximity, we include this variable in our model. The main result reinforces a result shown throughout: that proximity matters. Start-up dyads that are within 20 m are more likely to attend a lunch together and attend more lunches together than dyads that are farther apart. Passing through a common area also increases the likelihood of jointly socializing. Further, start-ups that are different are less likely to socialize (i.e., jointly attend these events together). Put differently, homophily—as represented by start-ups that are similar—are much more likely to socialize. Ultimately, however, being close has no differential impact on socializing for start-ups that are different. In other words, the extent to which a start-up is different from the focal start-up 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 start-ups went to the event together. To do so, we create an indicator equal to one if at least one team member of $startup_i$ and $startup_j$ appears within five people in the check-in line for the event (1(*within* 5 *people in line*)).[18] We present the results from estimating the effect of room proximity on check-in line proximity in columns (5) and (6) in Table 6. Similar to our results using

Table 6. Joint Attendance and Check-in Line Proximity—OLS Regressions

Unit of analysis	$Firm_i$-$Firm_j$ dyad					
Dependent variable mean	*#Event Both$_{ij}$ Attend* 0.27		$\mathbb{1}$(*Event*) 0.11		$\mathbb{1}$(*w/in* 5 *people in line*) 0.06	
	(1)	(2)	(3)	(4)	(5)	(6)
Close	0.036**	0.039*	0.010*	0.009*	0.017***	0.023***
	(0.018)	(0.022)	(0.005)	(0.005)	(0.006)	(0.009)
Common Area	0.025**	0.024**	0.010*	0.010*	0.013***	0.013***
	(0.010)	(0.011)	(0.005)	(0.005)	(0.005)	(0.005)
Diverse		−0.028***		−0.013***		−0.009***
		(0.008)		(0.003)		(0.003)
Close × *Diverse*		−0.010		0.003		−0.018*
		(0.021)		(0.010)		(0.011)
$Firm_i$ × *Room* fixed effects	✓	✓	✓	✓	✓	✓
$Firm_j$ × *Room* fixed effects	✓	✓	✓	✓	✓	✓
Observations	10,840	10,840	10,840	10,840	10,840	10,840
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 coworking space that at least one team member each of $firm_i$ and $firm_j$ attends (*#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 appears within five 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 zones in front of the elevator on each floor as well as the open sitting space provided on the second floor. We include $firm_i$ × *room* and $firm_j$ × *room* fixed effects. *Diverse* is an indicator equal to one if the firm dyads differ along all nongeographic proximity dimensions that we in examine. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

the number of events both attended, we see a positive impact of close room proximity on checking in together. Here, however, we observe homophilous behavior that is amplified by proximity, wherein start-up pairs that are different/diverse and proximate are less likely to attend the event together. Although we do not want to overstate this result given the interaction's marginal significance (at conventional levels), we do want to draw attention to this interesting finding. Although on the one hand, start-ups that are close and different receive more knowledge spillovers from each other, left to their own revealed preferences, start-ups that are close are less likely on the margin to socialize (coattend events) with start-ups different from them. We attempt to explore this seeming paradox by examining the impact of diverse proximity on knowledge spillovers when diverse start-ups do socialize. We analyze this next.

4.4. Proximity, Socializing, and Diversity

In this section, we combine physical proximity, socializing, and diversity and examine their joint relationship with technology adoption. As in earlier tables, the outcome $\mathbb{1}$(*AdoptTech$_{ij}$*) equals one if $startup_i$ adopted at least one new technology from $startup_j$. *Close* equals one if $startup_i$ and $startup_j$ are located within 20 m (14 steps; the 25th percentile of pairwise distances between all rooms) of each other on the same floor. The variable *#Event Both$_{ij}$ Attend* equals one if at least one team member of $startup_i$ and $startup_j$ both attends a lunch hosted at the coworking space. The indicator $\mathbb{1}$(*within* 5 *people in line*) equals to one if at least one team member of $startup_i$ and $startup_j$ appears within five people in line for the lunch. *Diverse* is an indicator equal to one if the start-up dyads differ along all nongeographic proximity dimensions that we examine and equal to zero otherwise. We control for tenure differences, preperiod technology overlap, and the passing through a common area en route between $startup_i$ and $startup_i$. We include $startup_i$ × *room* fixed effects. Standard errors are robust to dyadic clustering at the floor-neighborhood level. As displayed in Table 7, column (1), social activity—measured by the number of mutually attended events and check-in line proximity—predicts technology adoption alongside physical proximity. In column (2), we present the result of interacting our measure of social activity with our measure for diversity. The coefficient suggests that although diversity alone does not predict technology adoption (as was also shown in Table 5, column (4)), the more socializing that diverse start-up dyads engage in, the greater the likelihood of technology adoption.

Next, we form all pairwise combinations of our proximity and diverse measures in order to more effectively evaluate their combined effect. These are (1) far and similar (*Close* = 0 and *Diverse* = 0), (2) far and different (*Close* = 0 and *Diverse* = 1), (3) close and similar (*Close* = 1 and *Diverse* = 0), and (4) close and different (*Close* = 1 and *Diverse* = 1). As displayed in column (3) in Table 7 (similar and far serving as the omitted category), technology

Table 7. Proximity, Socializing, and Diversity—OLS Regressions

Unit of analysis	$Firm_i$-$Firm_j$ dyad			
Dependent variable mean	$\mathbb{1}(AdoptTech_{ij})$ 0.531			
	(1)	(2)	(3)	(4)
Close	0.023*** (0.009)	0.022*** (0.009)		
#Events	0.043*** (0.007)	0.037*** (0.007)	0.043*** (0.007)	
Diverse		−0.002 (0.006)		
#Events × *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 × (*Close* = 0 & *Diverse* = 0)				0.034*** (0.006)
#Event × (*Close* = 0 & *Diverse* = 1)				0.077*** (0.010)
#Events × (*Close* = 1 & *Diverse* = 0)				0.041*** (0.010)
#Events × (*Close* = 1 & *Diverse* = 1)				0.093*** (0.021)
Preprd. Tech. Overlap, Tenure Diff., Common Area	✓	✓	✓	✓
$Firm_i$ × *Room* fixed effects	✓	✓	✓	✓
$Firm_j$ × *Room* fixed effects	✓	✓	✓	✓
Observations	10,840	10,840	10,840	10,840
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 $\mathbb{1}(AdoptTech_{ij})$ 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 m (the 25th percentile of pairwise distances between all rooms) of each other on the same floor. The variable *#Event Both*$_{ij}$ *Attend* equals the number of lunches hosted at the coworking space that at least one team member each of $firm_i$ and $firm_j$ attends. *Diverse* is an indicator equal to one if the firm dyads differ along all nongeographic proximity dimensions that we in examine and zero (*Diverse* = 0) otherwise. In columns (3) and (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 $|age_i$-$age_j|$, *Preperiod Technology Overlap*, and *Common Area* are included. Variables including "&" denote categories. We include $firm_i$ × *room* and $firm_j$ × *room* fixed effects. Standard errors (in parentheses) are robust to dyadic clustering at the floor-neighborhood level.
$^*p < 0.10$; $^{***}p < 0.01$.

adoption is especially strong among dyads that are close and different, even when controlling for social activity. In column (4) in Table 7, 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.

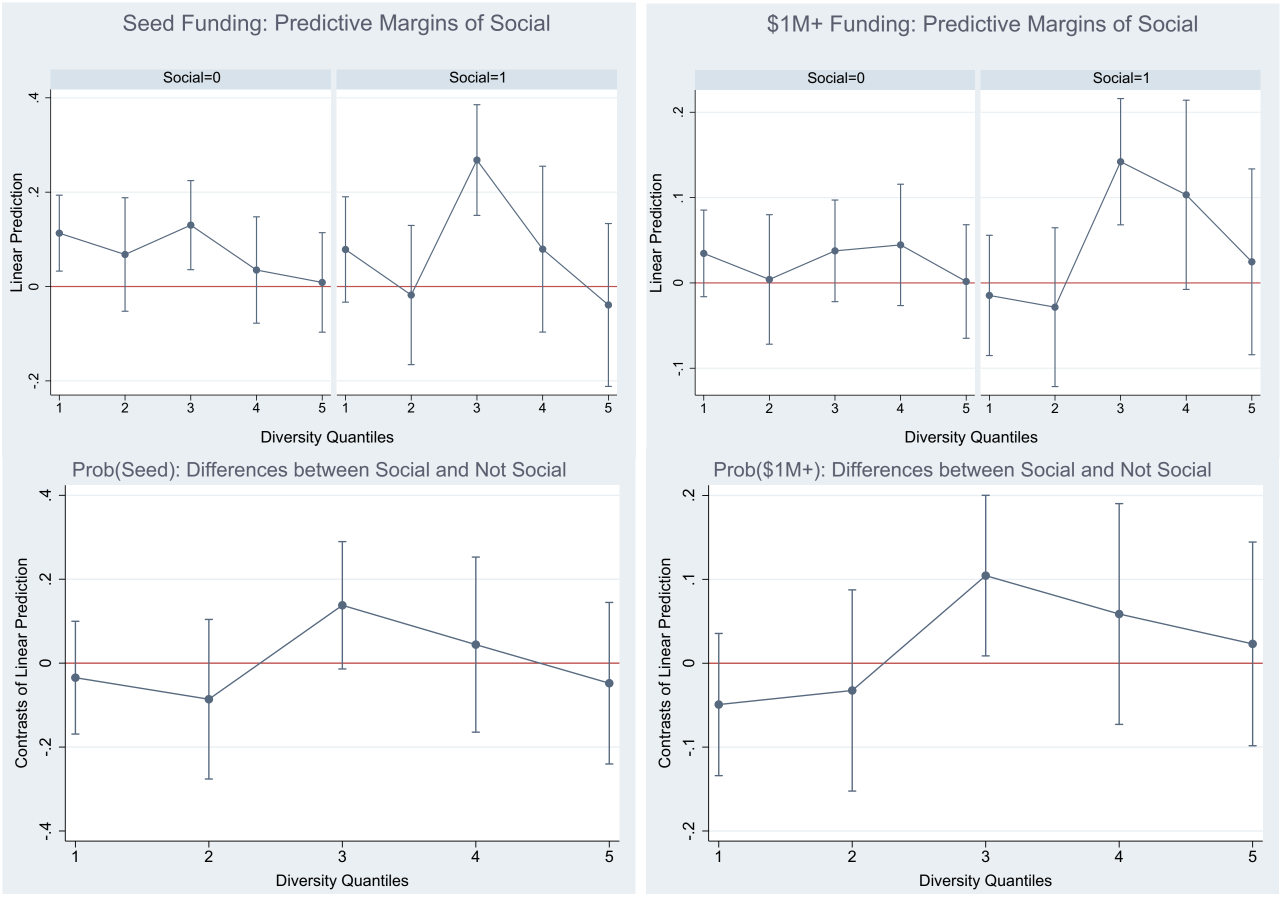
4.5. Performance

The notion that peers influence performance has been demonstrated in a host of different environments, such as retail (Chan et al. 2014a), finance (Hwang et al. 2019), and science (Oettl 2012, Catalini 2018), with the idea being that sharing knowledge, helping, and setting expectations (e.g., Mas and Moretti 2009, Herbst and Mas 2015, Housman and Minor 2016) enhance 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 start-up (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 start-ups) thereby increases the amount of novel information pieces that a start-up has access to.

To provide more insight into the potential role of the immediate environment for start-up performance, we move our analysis away from the start-up-dyad level and aggregate to the start-up level. We then estimate the probability of achieving two important start-up performance milestones as a function of the diversity of the microenvironment (start-ups located within 20 m of each other) and the extent to which start-ups engage in social events. Following prior literature, we use indicators identifying start-ups that raise seed funding and raise funding in excess of U.S. $1 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 U.S. $1 million as a function of the aggregate diversity indicator of start-ups within 20 m of the focal start-up interacted with an indicator equal to one if the focal start-up engages in the lunches hosted at the coworking space (*Social* = 1). We thereby control for the following start-up characteristics: size, gender, remoteness[19] of the location, and tenure. We further include floor fixed effects and cluster standard errors on the floor-neighborhood level. We break our diversity measure into quintiles and then plot the corresponding coefficients (with 95% confidence intervals). Results suggest that start-ups 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 U.S. $1 million. The corresponding regression results can be found in Table A10 in the online appendix. This

Figure 5. (Color online) How a Start-up's Socializing and the Diversity of Proximate Start-ups Predict Raising Funding



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

highlights the importance of not only bringing people together but socializing with each other for promoting better start-up performance outcomes. Moreover, our results provide suggestive evidence that striking a balance between diversity and similarity is especially crucial.

5. Discussion and Conclusions

Recent events have executives pondering what the future of work entails in balancing the flexibility and productivity-enhancing benefits of working from home with the creativity-generating potential of serendipitous encounters that are most commonly formed via face-to-face interactions. We contribute to this discussion in three important ways by examining how physical environments provide knowledge spillovers at the microgeographic level for knowledge workers and entrepreneurs. First, our findings indicate that knowledge spillovers and more specifically, the type that help in the selection of technologies from a large choice set and that lead to the integration of external knowledge occur at very short distances. We show that in one of the largest entrepreneurial coworking spaces in the United States, start-ups are influenced by peer start-ups that are within a distance of 20 m and no longer at greater distances—even if they are located on the same floor. Although the focus of our study has been on deepening our understanding of interstart-up knowledge spillovers, the same mechanisms may be conceptually extended to examine within-organizational knowledge spillovers as in Allen (1977).

Second, we contribute to the literature examining physical proximity and knowledge exchange by incorporating additional dimensions of similarity/diversity and examining their interdependencies. In doing so, we find support for the idea that particularly the integration of external, diverse knowledge is facilitated through physical proximity. We thereby provide evidence for heterogeneity in the effect of physical distance on knowledge integration depending on similarity along other dimensions, highlight the importance of engaging in social activities, and directly respond to the call for a better understanding of structures and processes adopted by start-ups 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 it also may serve as guidance in the design of workplaces that promote knowledge exchange between noncollaborating entities—may they be research groups, teams, or start-ups.

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

We acknowledge that our paper is not without limitations. For one, we restrict our analysis to only one coworking space. In this case, we are trading off a higher level of generalizability for richer data. Furthermore, the sample of start-ups we observe includes primarily digital and web based. These are the types of nascent start-ups that may benefit the most from integrating new knowledge. However, in terms of both current start-up industry trends and technology sophistication, the findings we present should nonetheless be fairly representative for the population of start-ups working in similar coworking spaces around the world. Furthermore, we restrict our focus to one type of decision that entrepreneurs make as a proxy for knowledge integration: web technology adoption. We use this measure because on the one hand, choices regarding the technology of a start-up are especially fundamental for start-ups (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 start-up's 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 start-ups 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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Endnotes

[1] Outgrowing the office space is a celebrated event at the coworking hub akin to a graduation. During the time covered by our data, only

eight start-ups moved out because they "graduated" from (outgrew) the building. Although outside options for these start-ups surely exist, we can interpret our estimates as causal conditional on remaining in the coworking space.

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

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

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

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

[6] In Figure A1 in the online appendix, we present a histogram of the distribution of the number of technologies used by each start-up.

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

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

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

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

[11] In this two-way setup, we would allow arbitrary correlation between the dyad $startup_i$-$startup_j$ and all other dyads $startup_i$-$startup_{j'}$.

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

[13] Please refer to Tables A5 and A6 in the online appendix for models excluding controls. Table A7 in the online appendix presents the results using different clustering variables. In results available upon request, we exclude all "movers" and obtain similar results. Moreover, our results are robust to clustering at different levels (*floor*, $Room_i$ and $Room_j$, $Firm_i$ and $Firm_j$, and $Firm_i \times Room$ and $Firm_j \times Room$). They are also unchanged when we present heteroskedasticity-consistent (Huber–White) standard errors.

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

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

[16] Please refer to Table A8 in the online 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 start-ups are located within 20 m from each other (*Close*) is negative yet not statistically significant ($p > 0.1$).

[17] This is the 75th percentile of this variable's distribution.

[18] In Table A9 in the online appendix, we further create indicators equal to one if at least one team member of $startup_i$ and $startup_j$ appears 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 m) only increases check-in line proximity for the group of people within one to five individuals from each other at check-in and not for those individuals farther away in line. Our results are robust to using log(*distance*) as the main independent variable of interest.

[19] We calculate $Remoteness_i = \frac{1}{N}\sum_j distance_{ij}$ to control for the general location of a start-up.

References

Aggarwal VA, Hsu DH, Wu A (2020) Organizing knowledge production teams within firms for innovation. *Strategy Sci.* 5(1):1–16.

Alcácer J, Oxley J (2014) Learning by supplying. *Strategic Management J.* 35(2):204–223.

Alcácer J, Dezsoő C, Zhao M (2015) Location choices under strategic interactions. *Strategic Management J.* 36(2):197–215.

Allen TJ (1977) *Managing the Flow of Technology: Technology Transfer and the Dissemination of Technological Information Within the R&D Organization* (MIT Press, Cambridge, MA).

Aronow PM, Samii C, Assenova VA (2017) Cluster–robust variance estimation for dyadic data. *Political Anal.* 23(4):564–577.

Arthur WB (1994) *Increasing Returns and Path Dependence in the Economy* (University of Michigan Press, Ann Arbor, MI).

Arzaghi M, Henderson JV (2008) Networking off Madison Avenue. *Rev. Econom. Stud.* 75(4):1011–1038.

Athey S, Imbens GW (2017) *The Econometrics of Randomized Experiments*, vol. 1 (Elsevier, Amsterdam), 73–140.

Atkin D, Chen MK, Popov A (2022) The returns to face-to-face interactions: Knowledge spillovers in Silicon Valley. NBER Working Paper No. 30147, National Bureau of Economic Research, Cambridge, MA.

Azoulay P, Fons-Rosen C, Graff Zivin JS (2019) Does science advance one funeral at a time? *Amer. Econom. Rev.* 109(8):2889–2920.

Bafna S (2003) Space syntax: A brief introduction to its logic and analytical techniques. *Environ. Behav.* 35(1):17–29.

Barrero JM, Bloom N, Davis SJ (2021) Why working from home will stick. NBER Working Paper No. 28731, National Bureau of Economic Research, Cambridge, MA.

Battiston D, Blanes i Vidal J, Kirchmaier T (2021) Face-to-face communication in organizations. *Rev. Econom. Stud.* 88(2):574–609.

Blau PM (1977) A macrosociological theory of social structure. *Amer. J. Sociol.* 83(1):26–54.

Bloom N, Han R, Liang J (2023) How hybrid working from home works out. NBER Working Paper No. 30292, National Bureau of Economic Research, Cambridge, MA.

Borgatti SP, Cross R (2003) A relational view of information seeking and learning in social networks. *Management Sci.* 49(4):432–445.

Breschi S (2011) The geography of knowledge flows. Cooke P, Asheim B, Boschma R, Martin R, Schwartz D, Tödtling F, eds. *Handbook of Regional Innovation and Growth* (Edward Elgar Publishing, Cheltenham, UK).

Burt RS (2004) Structural holes and good ideas. *Amer. J. Sociol.* 110(2):349–399.

Cameron AC, Miller DL (2014) Robust inference for dyadic data. Working paper, University of California, Davis, CA.

Carayol N, Bergé L, Cassi L, Roux P (2019) Unintended triadic closure in social networks: The strategic formation of research collaborations between French inventors. *J. Econom. Behav. Organ.* 163(C):218–238.

Carrell SE, Sacerdote BI, West JE (2013) From natural variation to optimal policy? The importance of endogenous peer group formation. *Econometrica* 81(3):855–882.

Catalini C (2018) Microgeography and the direction of inventive activity. *Management Sci.* 64(9):4348–4364.

Catalini C, Fons-Rosen C, Gaulé P (2020) How do travel costs shape collaboration? *Management Sci.* 66(8):3340–3360.

Chan TY, Li J, Pierce L (2014a) Compensation and peer effects in competing sales teams. *Management Sci.* 60(8):1965–1984.

Chatterji A, Delecourt S, Hasan S, Koning R (2019) When does advice impact startup performance? *Strategic Management J.* 40(3):331–356.

Chesbrough H (2012) Open innovation where we've been and where we're going. *Res. Tech. Management* 55(4):20–27.

Cohen WM, Levinthal DA (1990) Absorptive capacity: A new perspective on learning and innovation. *Admin. Sci. Quart.* 35(1):128–152.

Conti A, Peukert C, Roche M (2021) Beefing IT up for your investor? Open sourcing and startup funding: Evidence from GitHub. Working Paper No. 22-001, Harvard Business School, Cambridge, MA.

Cowgill B, Wolfers J, Zitzewitz E (2009) *Using Prediction Markets to Track Information Flows: Evidence from Google* (Springer, Berlin).

Cyert RM, March JG (1963) *A Behavioral Theory of the Firm* (Prentice Hall, Englewood Cliffs, NJ).

Dingler A, Enkel E (2016) Socialization and innovation: Insights from collaboration across industry boundaries. *Tech. Forecasting Soc. Change* 109(C):50–60.

Ewens M, Marx M (2018) Founder replacement and startup performance. *Rev. Financial Stud.* 31(4):1532–1565.

Fang TP, Wu A, Clough DR (2021) Platform diffusion at temporary gatherings: Social coordination and ecosystem emergence. *Strategic Management J.* 42(2):233–272.

Feld SL (1982) Social structural determinants of similarity among associates. *Amer. Sociol. Rev.* 47(6):797–801.

Festinger L, Schachter S, Back K (1950) Social pressures in informal groups: A study of human factors in housing. Working paper, Stanford University Press, Stanford, CA.

Fichman RG (2004) Going beyond the dominant paradigm for information technology innovation research: Emerging concepts and methods. *J. Assoc. Inform. Systems* 5(8):11.

Fischer CS (1982) What do we mean by "friend?" An inductive study. *Soc. Networks* 3(4):287–306.

Fleming L (2001) Recombinant uncertainty in technological search. *Management Sci.* 47(1):117–132.

Gans JS, Stern S, Wu J (2019) Foundations of entrepreneurial strategy. *Strategic Management J.* 40(5):736–756.

Gaspar J, Glaeser EL (1998) Information technology and the future of cities. *J. Urban Econom.* 43(1):136–156.

Gavetti G, Levinthal D (2000) Looking forward and looking backward: Cognitive and experiential search. *Admin. Sci. Quart.* 45(1):113–137.

Granovetter MS (1973) The strength of weak ties. *Amer. J. Sociol.* 78(6):1360–1380.

Grieve PG, Hogg MA (1999) Subjective uncertainty and intergroup discrimination in the minimal group situation. *Personality Soc. Psych. Bull.* 25(8):926–940.

Harmon N, Fisman R, Kamenica E (2019) Peer effects in legislative voting. *Amer. Econom. J. Appl. Econom.* 11(4):156–180.

Hasan S, Bagde S (2015) Peers and network growth: Evidence from a natural experiment. *Management Sci.* 61(10):2536–2547.

Hasan S, Koning R (2019) Prior ties and the limits of peer effects on startup team performance. *Strategic Management J.* 40(9):1394–1416.

Herbst D, Mas A (2015) Peer effects on worker output in the laboratory generalize to the field. *Science* 350(6260):545–549.

Hochberg YV, Ljungqvist A, Lu Y (2007) Whom you know matters: Venture capital networks and investment performance. *J. Finance* 62(1):251–301.

Hogg MA, Turner JC (1985) Interpersonal attraction, social identification and psychological group formation. *Eur. J. Soc. Psych.* 15(1):51–66.

Housman M, Minor DB (2016) Workplace design: The good, the bad and the productive. Working Paper No. 16-147, Harvard Business School, Cambridge, MA.

Hwang B-H, Liberti JM, Sturgess J (2019) Information sharing and spillovers: Evidence from financial analysts. *Management Sci.* 65(8):3624–3636.

Jacobs J (1969) *The Economy of Cities* (Vintage Books, New York).

Kabo F, Hwang Y, Levenstein M, Owen-Smith J (2015) Shared paths to the laboratory: A sociospatial network analysis of collaboration. *Environ. Behav.* 47(1):57–84.

Kabo FW, Cotton-Nessler N, Hwang Y, Levenstein MC, Owen-Smith J (2014) Proximity effects on the dynamics and outcomes of scientific collaborations. *Res. Policy* 43(9):1469–1485.

Kapoor R, Furr NR (2015) Complementarities and competition: Unpacking the drivers of entrants' technology choices in the solar photovoltaic industry. *Strategic Management J.* 36(3):416–436.

Kerr SP, Kerr WR (2018) *Immigrant Networking and Collaboration: Survey Evidence from CIC* (University of Chicago Press, Chicago).

Kerr WR, Kominers SD (2015) Agglomerative forces and cluster shapes. *Rev. Econom. Statist.* 97(4):877–899.

Kleinbaum AM, Stuart TE, Tushman ML (2013) Discretion within constraint: Homophily and structure in a formal organization. *Organ. Sci.* 24(5):1316–1336.

Koning R, Hasan S, Chatterji A (2019) Experimentation and startup performance: Evidence from A/B testing. NBER Working Paper No. 26278, National Bureau of Economic Research, Cambridge, MA.

Lane JN, Ganguli I, Gaule P, Guinan E, Lakhani KR (2021) Engineering serendipity: When does knowledge sharing lead to knowledge production? *Strategic Management J.* 42(5):1215–1244.

Laursen K, Salter A (2006) Open for innovation: The role of openness in explaining innovation performance among UK manufacturing firms. *Strategic Management J.* 27(2):131–150.

Lee S (2019) Learning-by-moving: Can reconfiguring spatial proximity between organizational members promote individual-level exploration? *Organ. Sci.* 30(3):467–488.

Lerner J, Malmendier U (2013) With a little help from my (random) friends: Success and failure in post-business school entrepreneurship. *Rev. Financial Stud.* 26(10):2411–2452.

Lippman SA, McCall JJ (1976) The economics of job search: A survey. *Econom. Inquiry* 14(2):155–189.

Manski CF (1993) Identification of endogenous social effects: The reflection problem. *Rev. Econom. Stud.* 60(3):531–542.

March JG (1991) Exploration and exploitation in organizational learning. *Organ. Sci.* 2(1):71–87.

Marsden PV (1988) Homogeneity in confiding relations. *Soc. Networks* 10(1):57–76.

Marshall A (1890) *Principles of Economics* (Macmillan, London).

Mas A, Moretti E (2009) Peers at work. *Amer. Econom. Rev.* 99(1): 112–145.

McPherson JM, Smith-Lovin L (1987) Homophily in voluntary organizations: Status distance and the composition of face-to-face groups. *Amer. Sociol. Rev.* 52(3):370–379.

Moretti E (2004) Workers' education, spillovers, and productivity: Evidence from plant-level production functions. *Amer. Econom. Rev.* 94(3):656–690.

Murray F, Tripsas M (2004) The exploratory processes of entrepreneurial firms: The role of purposeful experimentation. Baum J, McGahan A, eds. *Business Strategy Over the Industry Life Cycle (Advances in Strategic Management)*, vol. 21 (Emerald Group Publishing, Bingley, UK), 45–75.

Nanda R, Rhodes-Kropf M (2013) Investment cycles and startup innovation. *J. Financial Econom.* 110(2):403–418.

Nanda R, Sørensen JB (2010) Workplace peers and entrepreneurship. *Management Sci.* 56(7):1116–1126.

Oettl A (2012) Reconceptualizing stars: Scientist helpfulness and peer performance. *Management Sci.* 58(6):1122–1140.

Oh H, Labianca G, Chung M-H (2006) A multilevel model of group social capital. *Acad. Management Rev.* 31(3):569–582.

Porter ME (1996) Competitive advantage, agglomeration economies, and regional policy. *Internat. Regional Sci. Rev.* 19(1–2):85–90.

Reagans R, Zuckerman EW (2001) Networks, diversity, and productivity: The social capital of corporate R&D teams. *Organ. Sci.* 12(4):502–517.

Reagans R, Argote L, Brooks D (2005) Individual experience and experience working together: Predicting learning rates from knowing who knows what and knowing how to work together. *Management Sci.* 51(6):869–881.

Roche MP (2020) Taking innovation to the streets: Microgeography, physical structure, and innovation. *Rev. Econom. Statist.* 102(5):912–928.

Roche MP (2023) Academic entrepreneurship: Entrepreneurial advisors and their advisees' outcomes. *Organ. Sci.* 34(2):959–986.

Rogers EM (2010) *Diffusion of Innovations* (Simon and Schuster, New York).

Romer PM (1986) Increasing returns and long-run growth. *J. Political Econom.* 94(5):1002–1037.

Rosenthal SS, Strange WC (2001) The determinants of agglomeration. *J. Urban Econom.* 50(2):191–229.

Ruef M, Aldrich HE, Carter NM (2003) The structure of founding teams: Homophily, strong ties, and isolation among us entrepreneurs. *Amer. Sociol. Rev.* 68(2):195–222.

Sandvik JJ, Saouma RE, Seegert NT, Stanton CT (2020) Workplace knowledge flows. *Quart. J. Econom.* 135(3):1635–1680.

Saxenian A (1996) *Regional Advantage* (Harvard University Press, Cambridge, MA).

Schilling MA, Fang C (2014) When hubs forget, lie, and play favorites: Interpersonal network structure, information distortion, and organizational learning. *Strategic Management J.* 35(7):974–994.

Singh J (2005) Collaborative networks as determinants of knowledge diffusion patterns. *Management Sci.* 51(5):756–770.

Sorenson O, Audia PG (2000) The social structure of entrepreneurial activity: Geographic concentration of footwear production in the United States, 1940–1989. *Amer. J. Sociol.* 106(2):424–462.

Sørensen JB, Sorenson O (2003) From conception to birth: Opportunity perception and resource mobilization in entrepreneurship. Baum JAC, Sorenson O, eds. *Geography and Strategy (Advances in Strategic Management)*, vol. 20 (Emerald Group Publishing Limited, Bingley, UK), 89–117.

South SJ, Bonjean CM, Markham WT, Corder J (1982) Social structure and intergroup interaction: Men and women of the federal bureaucracy. *Amer. Sociol. Rev.* 47(5):587–599.

Stefano G, King A, Verona G (2017) Too many cooks spoil the broth? Geographic concentration, social norms, and knowledge transfer. *Geography, Location, and Strategy (Advances in Strategic Management)*, vol. 36 (Emerald Publishing Limited, Bingley, UK), 267–308.

Stuart T, Sorenson O (2003) The geography of opportunity: Spatial heterogeneity in founding rates and the performance of biotechnology firms. *Res. Policy* 32(2):229–253.

Todorova G, Durisin B (2007) Absorptive capacity: Valuing a reconceptualization. *Acad. Management Rev.* 32(3):774–786.

Tortoriello M, McEvily B, Krackhardt D (2015) Being a catalyst of innovation: The role of knowledge diversity and network closure. *Organ. Sci.* 26(2):423–438.

Wang S, Zhao M (2018) A tale of two distances: A study of technological distance, geographic distance and multilocation firms. *J. Econom. Geography* 18(5):1091–1120.

Yang L, Holtz D, Jaffe S, Suri S, Sinha S, Weston J, Joyce C, et al. (2022) The effects of remote work on collaboration among information workers. *Nature Human Behav.* 6:43–54.

Young A (2019) Channeling Fisher: Randomization tests and the statistical insignificance of seemingly significant experimental results. *Quart. J. Econom.* 134(2):557–598.

Zahra SA, George G (2002) Absorptive capacity: A review, reconceptualization, and extension. *Acad. Management Rev.* 27(2):185–203.