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Do makerspaces affect entrepreneurship? If so, who, how, and when?

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Abstract

Research Summary: Makerspaces are physical spaces that offer individuals fabrication tools and materials (e.g., 3D printers) to make artifacts. Although not designed specifically for entrepreneurs, these spaces offer affordable access to rapid prototyping infrastructure. This study examines whether makerspaces affect entrepreneurship and, if so, *who*, *how*, and *when*. Leveraging hand-collected data on US makerspaces and large archival data on Kickstarter projects, I show that makerspaces positively affect entrepreneurial participation and subsequent commercialization outcomes. However, these effects are mostly specific to hardware (vs. nonhardware) activities that typically involve physical prototypes. I find that the effect on entry is driven more by new (vs. established) but intentional (vs. accidental) entrepreneurs and that the effect on commercialization comes from two operating and complementary channels—resource provision and social facilitation.

Managerial Summary: Despite a few high-profile anecdotal entrepreneurial successes that emerged from the increasingly popular makerspaces, whether these spaces have large-scale effects on entrepreneurship remains unclear. Do makerspaces encourage entrepreneurial participation, if so, who? Do makerspaces benefit entrepreneurial commercialization, if so, how? Are there any conditions determining when these effects would occur? This study demonstrates meaningful broad-based impacts of makerspaces on particular types of entrepreneurship with growth potential. The findings suggest that competitive, prominent accelerators and incubators are not the only avenues for entrepreneurs to achieve commercialization success. Useful insights are discussed for entrepreneurial program managers and policy makers designing systems and structures that support inclusive prosperity for entrepreneurs.

KEYWORDS

entrepreneurship, intermediary organizations, knowledge spillover, makerspaces, technological infrastructure

1 | INTRODUCTION

An extensive literature has established the importance of intermediaries for promoting entrepreneurship, such as government agencies (Sine et al., 2007), science parks (Armanios et al., 2017), and educational programs (Eesley & Lee, 2021). Later advancements in strategy and entrepreneurship research investigated prominent types of intermediary organizations: incubators and accelerators, which specifically target high-growth startups (Assenova, 2020; Hallen et al., 2020; Yu, 2020). At the same time, scholars have started examining other burgeoning intermediary organizations that are *not* specifically designed for entrepreneurs but have also cultivated notable cases of well-known startups. For instance, coworking spaces have sparked the successes of Instagram, Uber, and Spotify (Howell, 2022; Roche et al., 2024). More recently, a new type of intermediary has gained significant attention: makerspaces, the physical spaces that provide fabrication tools and materials (e.g., 3D printers and laser cutters). Makerspaces have experienced rapid growth in the last decade, allowing Square, PebbleTec, URB-E, and other ventures to produce their initial prototypes for achieving later commercialization.

Despite successful entrepreneurial anecdotes, research on the broad impacts of makerspaces on entrepreneurship has largely been theoretical (Van Holm, 2015). Empirical studies have focused mainly on the educational benefits of makerspaces (Keune & Peppler, 2019) and nurturing an entrepreneurial mindset among students (Van Holm, 2021). In fact, makerspaces have their roots in the so-called maker movement—a growing trend for individuals interested in "creating something new and learning new skills" to interact and build communities for sharing information about how to tinker (Dougherty, 2012b). Thus, makerspaces are not designed for entrepreneurs specifically and are most often used by hobbyists and students. These community-based environments may actually discourage commercialization activities (Mollick, 2016). Survey results have suggested that entrepreneurs make up a meager percentage of participants at makerspaces, with only 11% of makers considering themselves entrepreneurs (Dougherty, 2012a) and only 5% indicating commercial intent (Halbinger, 2018). The little overall makerspace usage by entrepreneurs with commercialization endeavors contrasts with the high-profile anecdotal successes, and whether makerspaces have large-scale effects on entrepreneurship therefore remains an open question.

Even if makerspaces do foster entrepreneurial activities, it is still unclear who are encouraged to participate. On the one hand, makerspaces can significantly lower the technological entry barrier for *intentional* entrepreneurs by providing them with affordable access to the fabrication tools and materials needed to engage in prototyping. On the other hand, makers with no initial entrepreneurial intention may discover opportunities in these spaces if they realize their creations have a market, thus promoting *accidental* entrepreneurs. These two types of prospective entrepreneurs differ in their commercial intent and may launch projects that vary in scale, therefore pointing to distinct interpretations of the value of makerspaces in the pre-entry stage.

Also unclear are the specific channels through which makerspaces may affect subsequent entrepreneurial performance. Two mechanisms can both potentially contribute to a positive effect, if there is one, on commercialization outcomes. First, entrepreneurs may benefit from a *resource provision* channel, as makerspace resources that lower initial startup costs/time also bring down recurring costs/time of experimentation, which can support product iterations for better addressing customer pain points to increase the likelihood of commercialization success. The resulted concrete working prototypes may also signal preparedness and boost the effectiveness of pitches during fundraising and securing purchase commitments. Second, entrepreneurs may improve the quality of their idea and reduce their failure rate through a *social facilitation* channel, because makerspaces create the common foci of fabrication that can strongly connect individuals with diverse backgrounds and promote knowledge spillovers and learning from social interactions. While pointing to the same positive effect on entrepreneurial commercialization, the two mechanisms have different implications for when the value of makerspaces can be maximized in the post-entry stage depending on the needs of entrepreneurs.

This article addresses the above ambiguities by asking three questions through a phenomenological approach without imposing specific hypotheses (Pongeluppe, 2022). First, do makerspaces encourage entrepreneurial participation, if so, *who*? Second, do makerspaces benefit entrepreneurial commercialization, if so, *how*? Third, are there any boundary conditions for *when* these effects would occur?

Empirically, demonstrating the causal links between makerspaces and entrepreneurship faces two challenges. First, datasets on makerspaces are underdeveloped and incomprehensive. Second, disentangling the treatment effects of makerspaces on entrepreneurship is difficult because makerspaces may endogenously emerge in areas with heightened or successful entrepreneurial activities or may be associated with other omitted variables that affect entrepreneurship. As a result, empirical research is largely descriptive (Halbinger, 2018), and case studies exploring the makerspace phenomenon more deeply have mostly relied on a few idiosyncratic instances and qualitative insights (Gahagan & Calvert, 2020).

I address these challenges by systematically constructing a hand-collected dataset on US makerspaces. I establish the macro-level effects of makerspaces on entrepreneurship with an instrumental variable (IV) design, leveraging the weather on the day of the first, field-configuring Maker Faire in each US metropolitan statistical area (MSA) as an instrument for the number of makerspaces subsequently established in the MSA. Specifically, a rainy first

Maker Faire can reduce public attendance (Negro & Olzak, 2019), inhibit the local maker movement, and decelerate the establishment of new makerspaces in the MSA. By contrast, MSAs with a first Maker Faire on a day that did not rain have more subsequent local makerspaces because of greater public engagement early on. The dataset includes 173,063 Kickstarter projects launched by 141,188 individuals during 2009–2020 in 205 US MSAs. I exploit the exogenous variation in MSA-level makerspace quantities induced by the instrument in 94 MSAs that were Maker Faire sites to estimate the effect of makerspaces on entrepreneurial participation and commercialization outcomes. I examine activities on Kickstarter, the world's largest crowdfunding platform (Burtch et al., 2015), because they are considered important entrepreneurial activities (Burtch et al., 2018; Peterson & Wu, 2021). Further, most makerspace participants with business intent have indicated involvement in crowdfunding, and Kickstarter is the most popular site used (Dougherty, 2012a).

Analyses at the MSA-year and project levels show that makerspace establishments have strong and robust positive effects on entrepreneurial entry, as measured by the number of new local Kickstarter projects, and on the success of entrepreneurial commercialization, as measured by the success of crowdfunding campaigns whose backers are both investors and first users. However, these positive effects are mostly specific to hardware activities that typically involve physical prototypes: while spillover effects leading to the launch of more nonhardware activities cannot be fully ruled out, the commercialization benefits do not extend to software or nontechnology activities. The findings are robust to alternative empirical designs, including propensity score matching on observables, stacked event study using the staggered establishments of the first makerspace across MSAs, and models leveraging more nuanced within-MSA variation in makerspace access based on actual distances.

Interestingly, while one may expect accidental entrepreneurs to be driving most of the increased entrepreneurial activities (because makerspaces are community-based entities utilized more by the broad non-entrepreneur maker population), post hoc analyses suggest that the effect on entry is in fact driven more by new but intentional entrepreneurs. Additionally, mechanism tests exploring the effect on commercialization provide evidence in support of both the resource provision and the social facilitation channels. The two operating channels also appear to be complementary, indicating that effects from physical amenities and effects from social encounters do not operate in a vacuum and that technological infrastructure supporting common foci might be an antecedent and enabler for proximity to give rise to meaningful social interactions that can produce knowledge spillovers. Finally, recognizing important heterogeneities in the definition of entrepreneurship, I extend the study by examining two alternative settings—self-employment and venture capital (VC)-backed startups; I do not find makerspace effects on the former low-tech type of entrepreneurship but indeed discover meaningful impacts on the growth-oriented latter type that has important economic implications.

2 | RESEARCH CONTEXT: US MAKERSPACES

2.1 | The emergence of makerspaces: Maker movement, *Make* magazine, and Maker Faire

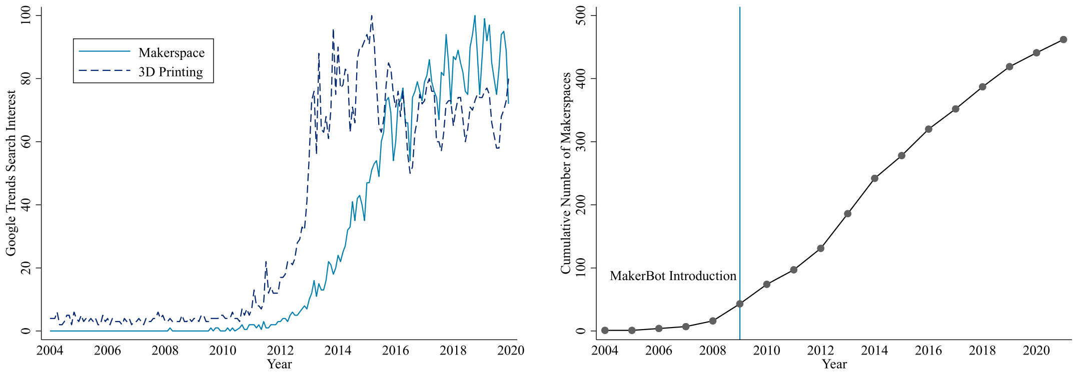
In 2001, the Massachusetts Institute of Technology opened a university-run digital fabrication laboratory called Fab Lab at its Media Lab in Boston to help faculty, staff, and students develop related skills (Konopek et al., 2018). The Fab Lab cultivated "the pragmatic approach of Makers toward repair, self-taught skill acquisition, innovation, and prototyping" (Gorbatai et al., 2021, p. 47)—values and practices that soon spread to general communities. In 2005, Dale Dougherty, the vice president of O'Reilly Media (a publisher in the San Francisco Bay Area), coined the term "maker" to describe individuals interested in "creating something new and learning new skills," founding *Make* magazine to publish information about maker-related projects; this effort marked the start of the maker movement (Dougherty, 2012b). *Make* magazine, which helped hobbyists learn new skills to tinker and find like-minded tinkerers, has been recognized as the catalyst for the growing community of makers.

Another pivotal event in the maker movement was the 2006 launch of the first Maker Faire by *Make* magazine in the San Francisco Bay Area. The event attracted more than 20,000 attendees and was followed by hundreds of local Maker Faires (licensed by Maker Media, a spin-off of O'Reilly Media) in different US cities in the next decade (Dougherty, 2016). Maker Faires provide opportunities for makers to demonstrate in person the artifacts they make and engage the public to join the maker movement (Browder et al., 2019). Maker Faires highlight the importance of the colocation of makers for learning, socializing, and accessing resources. They also inspire interest in self-organized gatherings in physical locations, creating makerspaces to share fabrication tools (e.g., 3D printers and laser cutters) and knowledge about using these tools. Consequently, local Maker Faires are considered field-configuring events for local maker movements (Gorbatai et al., 2021) and often spur local makerspace establishments.

2.2 | Makerspaces, fabrication tools, and potential impacts on entrepreneurial successes

Most makerspaces are primarily community- and volunteer-based nonprofits funded by sponsorships, grants, and donations, although many makerspaces adopt a for-profit model by charging membership fees. Despite the various business models, the core of makerspaces is access to fabrication tools. Real momentum for makerspaces started in 2009, when MakerBot started to sell desktop 3D printers that cost only $2500, compared with $30,000–$40,000 for other models (Clark, 2014). Consequently, 3D printers became one of the most common tools at makerspaces. In other words, the technological advancement in 3D printing was a key antecedent for makerspace emergence. Figure 1 illustrates that the development of 3D printing technology preceded the rise of makerspaces and that the MakerBot invention sparked subsequent makerspace growth. Other common tools makerspaces provide are laser cutters, textile/sewing machines, woodworking/metalworking tools, electronics and robotics tools, and computer access to enable digital fabrication. Previously available only at large organizations or at exorbitant prices, these tools are now accessible to the average maker via makerspaces, significantly reducing the financial and time costs of making (Corsini et al., 2019).

Improved technology accessibility can potentially help entrepreneurs engage in rapid and affordable prototyping in the early stage, ultimately allowing them to achieve product commercialization. Prototyping costs reaching $100,000 before makerspaces emerged are now as low as a few thousand dollars (National League of Cities, 2016). The time required to build a prototype has also declined from weeks or months to days or even hours (Rayna & Striukova, 2016). Over the last decade, high-profile anecdotal accounts have pointed to the possible effects of makerspaces on entrepreneurial successes. The most prominent case is Square, which built a payment platform allowing businesses to use tablet computers as payment registers. The two founders, Jim McKelvey and Jack Dorsey, had the idea of converting a mobile phone into a point-of-sale device for completing credit card transactions but struggled to articulate their



(a) Google Trends Search Interest (b) Cumulative Number of U.S. Makerspaces

FIGURE 1 Technological advancement in 3D printing as an antecedent for the emergence and growth of makerspaces. Panel a presents Google search interests over time in the keywords, "Makerspace" and "3D Printing," respectively, using data from Google Trends. Panel b shows the cumulative number of US makerspaces over time based on the hand-collected dataset used for analyses in this article.

business model and attract funding. After developing a square-shaped working prototype at a makerspace, the team eventually advanced their idea and secured $10 million of VC funding (Anderson, 2012).[1] Selected examples of entrepreneurial successes via makerspaces are presented in Table OA1 (Online Appendix), illustrating the diverse range of projects emerging from makerspaces. The list of such instances keeps growing (Maker Nexus, 2022).

Despite these idiosyncratic success stories, whether makerspaces have broad-based impacts on entrepreneurship remains unclear. Survey results have found that entrepreneurs represent a meager percentage of makerspace participants: only 11% of makers consider themselves entrepreneurs (Dougherty, 2012a), and only 5% of makers indicate having commercial intent (Halbinger, 2018). This lack of overall uptake by entrepreneurs (relative to the entire maker population) is unsurprising because makerspaces are not designed specifically for entrepreneurs. Since makerspaces emerge from community efforts resulting from local maker movements, these spaces are most often used by hobbyists and students focusing on tinkering and learning fabrication skills. The strong community engagement for involved individuals may not be the best condition for commercialization activities (Mollick, 2016).

In this article, I investigate whether makerspaces have large-scale effects on entrepreneurship. In what follows, I first discuss how, in the *pre-entry* stage, makerspaces may encourage two types of prospective entrepreneurs who differ in their commercial intent. I then consider two possible mechanisms for how makerspaces can benefit the *post-entry* performance in entrepreneurial commercialization. These discussions provide insights into additional tests that would help pinpoint *who* and investigate *how*. Finally, I present a key boundary condition for these effects to shed light on *when*.[2]

[1]Two other entrepreneurial successes are noteworthy. First, URB-E, a firm designing foldable personal electric transportation, developed its prototype at a makerspace (CNC West, 2019) and received $5 million in series A funding in 2021. Second, Pebble Watch took its makerspace-developed prototype to the crowdfunding platform Kickstarter and raised $10.3 million in 2012, the most funded project on the platform then (Metzarchive, 2016).

[2]All my arguments focus on the early stages of ventures, when entrepreneurs use makerspaces for prototyping. Although makerspaces can support entrepreneurs in later-stage product manufacturing and distribution, these uses are less common and are beyond the scope of the paper.

3 | THEORETICAL BACKGROUND

3.1 | Pre-entry effects of makerspaces on entrepreneurial participation

3.1.1 | Makerspaces lower technological entry barrier for intentional entrepreneurs

A substantial barrier to entrepreneurship entry is insufficient financial resources for startup costs in pursuing new business ideas. Given that entrepreneurial businesses have become increasingly technology-based over the last decade, one major cost obstacle for founders interested in pursuing a venture idea is the physical capital investment required to build the technological capacity for implementing the idea (Moeen, 2017). Access to technological infrastructure has historically been limited for individual entrepreneurs because procuring tools and materials needed for prototyping can often be expensive (Van Holm, 2015).

Makerspaces can significantly lower the technological entry barrier for *intentional entrepreneurs* by providing them with affordable access to the fabrication tools and materials needed to engage in the initial prototyping of their venture ideas. Specifically, the availability of tools such as 3D printers and laser cutters at many makerspaces radically reduces product design and manufacturing costs and time (Corsini et al., 2019). Instead of making a hefty payment to engineering and design firms for developing product prototypes or purchasing costly tools, an entrepreneur can use makerspace-provided tools for rapid prototyping at a much lower price, reducing the costs of prototyping a new product 25- to 50-fold (National League of Cities, 2016). The time of building a prototype is also reduced from weeks and months to just days or hours (Rayna & Striukova, 2016). Therefore, through the provision of technological resources, makerspaces can considerably lower the startup financial and time costs for prospective entrepreneurs, thus leading to increased entrepreneurial participation. Because entrepreneurs who intentionally seek to overcome technological resource hurdles via makerspaces typically would have preconceived business ideas that are opportunity-driven, the encouraged entrepreneurial activities should largely be commercially oriented and aiming for growth.

3.1.2 | Makerspaces spark opportunity discovery for accidental entrepreneurs

While intentional entrepreneurs may reap significant pre-entry benefits, previous discussions indicate that they may only make up a small percentage of makerspace participants. Theoretical work on makerspaces has thus suggested another possible type of prospective entrepreneurs that can emerge from these spaces—*accidental entrepreneurs* (Browder et al., 2019; Van Holm, 2015). The idea of accidental entrepreneurs is not new. Shah and Tripsas (2007) introduced the phenomenon of "user entrepreneurship" and described a distinct accidental path to entrepreneurship during which individuals first experienced a need in their day-to-day lives, looked to create a solution to that need, then shared their solution with others, and eventually commercialized the solution. Makerspace establishments can be particularly impactful for sparking such accidental opportunity discoveries by providing people with easier access to technological infrastructure. Makers, who are often hobbyists who tinker for fun, students who create and learn, or product users who make modifications to address their tailored needs, may realize that others are also interested in purchasing their creations and that their products actually have a market. Hence, makerspace establishments may broaden entrepreneurial participation by inspiring new entrepreneurs who initially had no entrepreneurial intent.

The increased entrepreneurial activities through the accidental pathway, however, can differ from those intentional ones in important aspects. First, community-based environments often foster values that discourage commercialization (Mollick, 2016). The transition from a maker identity of creating value to an entrepreneur identity of capturing value may not be easy (Shah & Tripsas, 2007), suggesting that accidental entrepreneurs who gradually realize the commercial values of their creations may be initially reluctant to gain from these creations at a large scale. Second, because accidental entrepreneurs tend to have less systematic prelaunch business evaluation processes and spend less time on developing key strategies (Greul et al., 2018), they often do not embark on entrepreneurial activities with explicit growth considerations, thus further limiting the scale of these activities at first.

Together, makerspaces can encourage two types of prospective entrepreneurs in the pre-entry stage, both contributing to a positive effect on entrepreneurial participation. However, due to their varying initial commercial intents, the implications for the encouraged entrepreneurial activities are different, offering a potential angle for investigating *who* are primarily driving the effects of makerspaces on entry, if there are any. The discussion thus far suggests that the heightened entrepreneurial activities due to makerspaces would likely be larger (smaller) in scale if intentional (accidental) entrepreneurs are the driving force.

3.2 | Post-entry effects of makerspaces on entrepreneurial commercialization

The previous arguments on entry have yet to unpack how makerspaces may affect subsequent entrepreneurial performance. Here, I consider two possible mechanisms that can both contribute to a positive effect on entrepreneurial outcomes. It is important to note that the proposed mechanisms are not mutually exclusive—they may act in combination or be complementary to one another. I focus on entrepreneurial commercialization success as an important measure of performance for early-stage ventures, which is typically characterized by a product's first sales (Moeen & Agarwal, 2017) or the receipt of external investor funding (Lin & Maruping, 2022).

3.2.1 | Resource provision channel: Makerspaces support continued experimentation

A critical element for successful entrepreneurial commercialization is continued experimentation and iteration for achieving product-market fit (Contigiani & Levinthal, 2019). This involves a process of creating workable prototypes, testing with target users, incorporating user feedback, and iteratively developing products or sometimes pivoting to a different idea—an experimenting process that is often nonlinear and can reoccur multiple times before the entrepreneur finds *the* solution to the problem. Central to widely adopted entrepreneurial practices, such as Agile Development (Highsmith & Cockburn, 2001), Design Thinking (Dam &

Siang, 2018), and Lean Startup (Ries, 2011), this process has been viewed as the canonical model for entrepreneurial successes. However, experimentation can be costly and time-consuming (Kerr et al., 2014). As most nascent ventures face severe resource constraints (Yang et al., 2020), entrepreneurs may be cautious about spending time/money on new experiments, preventing them from generating sufficient product iterations to create the best product.

As noted, makerspaces can provide prospective entrepreneurs with the technological resources that lower the initial *one-time* startup costs and time; these spaces may similarly offer the technological resources for reducing the *recurring* experimentation costs and time that can add up very quickly. Fabrication tools in makerspaces, such as 3D printers, allow entrepreneurs to quickly produce inexpensive one-offs for gathering user feedback (Corsini et al., 2019). Therefore, entrepreneurs may be more likely to adopt iterative designs and experience faster cycles of trial-and-error learning because of easier access to toolkits for inexpensive rapid prototyping (Von Hippel & Katz, 2002). Through encouraging product iterations, makerspaces can help entrepreneurs improve the quality of their venture idea and better address customer pain points, which may in turn give rise to more successful commercialization outcomes. In addition to reducing technological uncertainty, as entrepreneurs experiment with makerspace tools, they can also easily create concrete working prototypes as a proof of concept to gain legitimacy. The resulted high-resolution prototypes may boost the effectiveness of pitches to investors and first users by signaling preparedness, which can further improve the likelihood of funding successes and purchase commitments in the stage of commercialization (Chen et al., 2009).

This resource provision channel generates several predictions. First, the makerspace effect on commercialization should be larger when resource considerations are more paramount, such as (1) when the entrepreneurial project is large in scale and has greater resource needs or (2) when the entrepreneur is away from supportive entrepreneurial ecosystems and faces greater resource constraints. Second, an intermediate outcome of the proposed experimentation process is that makerspace establishments should increase the number of iterations for a given venture project.

3.2.2 | Social facilitation channel: Makerspaces promote knowledge spillovers

The literature on venture development programs, such as those in incubators and accelerators, has recognized the importance of learning in contributing to the performance of early-stage ventures (Assenova, 2020; Hallen et al., 2020). These programs, mostly targeting inexperienced entrepreneurs, often involve structured training modules, assigned mentorship, and orchestrated social events that aim to improve the quality of participating startups. Recent research suggests that learning may also occur in less formal and structured settings due to the close spatial proximity of nascent ventures (Roche et al., 2024). As the majority of US makerspaces provide coworking spaces for participants in addition to the tools (roughly 62%, based on data used for analyses in this article), the colocation of makers in these spaces can potentially facilitate serendipitous social encounters that would lead to knowledge spillovers, that is, learning informally.

Two factors in the makerspace context are particularly favorable to knowledge spillovers. First, individuals in these spaces *share* the common foci of fabrication. The overlapping knowledge domains around the technological infrastructure generate the knowledge proximity that is crucial for learning and collaboration (Lane et al., 2021). This "connectedness" can be an important enabler for "proximity" to work in favor of learning (Dutta et al., 2021), highlighting how makerspaces are markedly different from traditional coworking spaces. Second, entrepreneurs in makerspaces often *differ* in the end goals for their tool use and may want to prototype very different products even when the same tools are used. For instance, 3D printing is versatile in creating products with a wide spectrum of market applications (Shane, 2000). This diversity, coupled with knowledge overlap, may be optimal for creating knowledge spillovers (Roche et al., 2024; Ter Wal et al., 2016).

As a result, entrepreneurs can improve the quality of their entrepreneurial ideas during prototyping. Information acquisition from people with diverse backgrounds but similar prototyping needs can help entrepreneurs overcome technical hurdles more easily, avoid false paths and unproductive approaches, and engage in more effective exploration and creation (Sheridan et al., 2014). Through promoting knowledge spillovers, makerspaces can reduce the failure rate of venture ideas and increase the average likelihood of successful entrepreneurial commercialization.

This social facilitation channel has several implications. First, the effect of makerspaces on commercialization should be more prominent under conditions that are more conducive to knowledge spillovers, such as (1) when the entrepreneur spans multiple knowledge domains that can broaden the scope of learning or (2) when the local environment breeds homophily for stronger social ties (Ingram & Morris, 2007), for example, when there is more homogeneity in race or ethnicity (McPherson et al., 2001). Second, an intermediate consequence from the learning logic is that makerspace establishments should lead to more knowledge similarity among entrepreneurial activities sharing similar needs for prototyping tools.

In sum, the two proposed mechanisms both point to a positive effect of makerspaces on entrepreneurial commercialization, albeit with distinct insights into key moderating conditions and intermediate outcomes for ruling in/out *how* entrepreneurs can benefit, if they benefit at all.

3.3 | Boundary condition

Finally, all my arguments for the effects of makerspaces on entrepreneurial entry and commercialization hinge on entrepreneurs' prototyping needs for using fabrication tools in makerspaces. Therefore, I conjecture that an important boundary condition for *when* these effects occur is whether the venture idea involves physical products. In my analyses, I investigate this possible boundary condition by comparing how makerspace establishments differentially affect hardware versus nonhardware entrepreneurial activities.

4 | METHODOLOGY

4.1 | Data

I constructed a unique, hand-collected dataset on US makerspaces by first systematically searching several historical makerspace directories and news articles to generate a comprehensive list of US makerspaces established as of November 2021.[3] I then examined each potential makerspace, searching for detailed information, such as location, founding year, tools available, membership structure, and status (i.e., whether it remained open). Following Mersand (2021), I adopted a broad definition of makerspaces as places providing tools and materials to encourage individuals/groups to make things; such spaces needed to (1) occur in a physical place, (2) provide fabrication tools, (3) target the public, and (4) self-identify as a makerspace.[4]

My initial dataset included 462 US makerspaces founded in 2004–2021 in 47 states (and the District of Columbia). I determined the founding year by examining the makerspace's website and social media pages, as well as the Wayback Machine.[5] To balance between exploring fine-grained geographical variation for identification and capturing broader diffused impacts of makerspaces in regions with shared economic ties, I used MSAs as the geographical unit. My analytical data leveraged 404 makerspace establishments in 195 MSAs in the United States. Figure 2 illustrates the geographical distribution of the cumulative number of makerspaces established across MSAs. I used this dataset to construct the main independent variable measuring the quantity of total makerspace establishments at the MSA-year level, as well as measures of more nuanced variation in makerspace access for robustness tests.

I used an IV design to identify the causal effects of makerspace establishments on entrepreneurship, leveraging the weather on the day of the first, field-configuring Maker Faire in an MSA as an instrument for the number of makerspaces subsequently established in the MSA. I collected data on the timing and location of the first Maker Faire in each MSA based on issues of *Make* magazine up to November 2021.[6] Between 2006 and 2019, 94 MSAs experienced their first local Maker Faire. I obtained precipitation data on the Maker Faire event days from the National Centers for Environmental Information.[7]

To measure entrepreneurial participation and commercialization, I used data from Kickstarter. Entrepreneurs launch their project campaigns on the platform with a specific funding goal; backers, who are often first users and investors, fund these projects by pre-purchasing products that entrepreneurs promise to deliver.[8] The Kickstarter platform offers

[3]I used the following historical makerspace directories and news article outlets as sources for constructing the initial list of makerspaces: (1) MakerSpaces (https://makerspaces.make.co/), (2) Makerspace Directory (https://makerspacedir.com/), (3) Maker Camp (https://makercamp.com/explore), (4) hackerspaces (https://wiki.hackerspaces.org/List_of_Hacker_Spaces), (5) Google Maps (performing searches of "makerspace" keywords for each US state), and (6) Google News (performing searches of "makerspace" keywords plus keywords for each state to identify more recently founded makerspaces).

[4]I excluded makerspaces affiliated with universities, colleges, and libraries from the data collection; these makerspaces typically serve specific populations for educational purposes and may be less relevant for studying the effects on entrepreneurship. Although my dataset may exclude makerspaces that are not publicly searchable, these makerspaces might be less visible to entrepreneurs and have negligible effects on entrepreneurs' behavior. Thus, my dataset may closely approximate the universe of makerspaces that ordinary US entrepreneurs can find and access.

[5]The Wayback Machine is a digital archive of internet web pages since 1996. When a makerspace's website and social media did not contain founding date information, I considered the founding year to be the first historical appearance of the makerspace's website on the Wayback Machine.

[6]Maker Faires were identified in the Calendar of Events section. For MSAs without a Maker Faire featured in the magazine, I conducted an additional internet search to uncover historical information on licensed Maker Faires.

[7]The National Centers for Environmental Information is a US government agency that manages one of the world's largest archives of environmental data. When historical data were unavailable for the ZIP code of the Maker Faire location, I used data for the closest ZIP code.

[8]Other research has used the number of Kickstarter projects as a measure of entrepreneurial participation (Agrawal et al., 2018; Burtch et al., 2018) and has exploited the platform for studying entrepreneurial behavior and processes in the commercialization stage (Peterson & Wu, 2021).

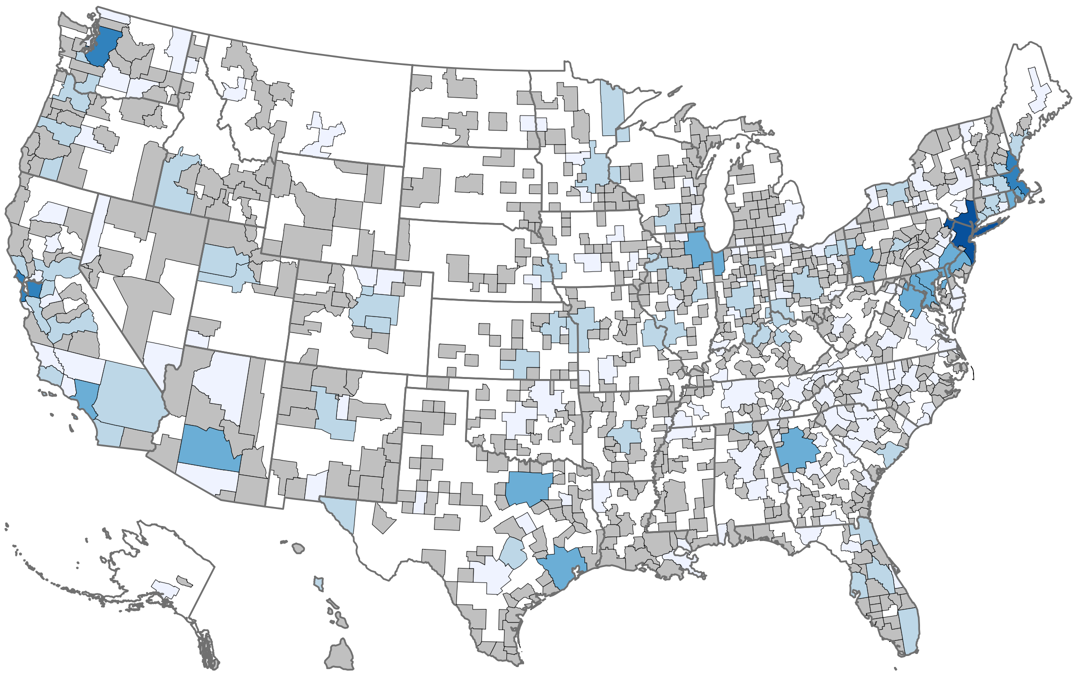


FIGURE 2 Geographical distribution of the cumulative number of US makerspaces established across MSAs as of November 2021 (white regions are non-MSA areas).

several desirable features for my inquiry. First, makers have acknowledged the importance of crowdfunding platforms for obtaining funds for their projects, and Kickstarter is the most popular of these sites (Dougherty, 2012a). Therefore, Kickstarter activities are more likely to capture maker entrepreneurs' early-stage commercialization endeavors than alternative measures of entrepreneurship (e.g., self-employment and business registrations). Second, the platform captures a wide array of project categories, including different types of hardware, software, and nontechnology projects, allowing comparisons for investigating the boundary conditions for makerspace effects. Third, Kickstarter projects typically contain detailed text information and are updated regularly on the platform when pivots and modifications occur. This rich information offers a potential lens for examining intermediate outcomes during the entrepreneurial processes to reveal underlying mechanisms.

I collected project-level Kickstarter data from Web Robots. My data include all Kickstarter projects launched from its founding in 2009–2020. I restricted the sample to 173,063 projects in 146 categories launched by 141,188 entrepreneurs in 205 MSAs. I used the full dataset in robustness checks with alternative empirical designs. In the main analyses, I leveraged an IV approach and thus restricted the sample to observations for which the instrument could be created: projects occurring after the first Maker Faires in MSAs. The main analytical sample included 134,055 projects created by 109,075 entrepreneurs in 94 MSAs. Additionally, the project-level data were aggregated to 649 MSA-year observations for MSA-year analyses.

4.2 | Variables

I used the number of entrepreneurial activities on Kickstarter at the MSA-year level to measure macro-level entrepreneurial participation. To explore the boundary conditions for the effects of makerspaces, I distinguished between projects that were more versus less likely to involve physical products and thus differed in entrepreneurs' needs for accessing fabrication tools for prototyping. Because 3D printers are the most common makerspace tools, hardware projects involving complex designs and production are more likely to benefit from these tools than non-technology craft work. Therefore, leveraging 146 detailed project categories specified by Kickstarter, I categorized projects into three broad types: hardware, software, and non-technology. *Number of Hardware Projects*, *Number of Software Projects*, and *Number of Nontechnology Projects* respectively represent the number of new Kickstarter hardware, software, and nontechnology projects launched on the platform in an MSA in a year.

To capture commercialization success at the project level, I created a binary indicator, *Success*, which equals 1 if the crowdfunding campaign of a Kickstarter project is successful (i.e., meets or exceeds the fundraising goal) and 0 otherwise. I also considered two alternative dependent variables to ensure the robustness of the findings. The logged amount (in dollars) raised for a project, *Pledged Amount* (*logged*), is a continuous measure of commercialization success.[9] Additionally, *Number of Backers* (*logged*) measures interests from investors/first users who pre-purchased products. In the project-level boundary condition analyses, *Hardware Project* is a binary indicator that equals 1 for hardware projects and 0 otherwise; *Technology Project* is a binary indicator that equals 1 for technology projects (software and hardware) and 0 otherwise.

The independent variable is the *Cumulative Number of Makerspaces Established to Date* in an MSA by the time of observation, which represents the time-varying overall makerspace access.

Rainy Maker Faire is the IV. It is a binary indicator equal to 1 if it rained on the day of the first Maker Faire in the focal MSA and 0 otherwise.

To test the mechanisms outlined in the commercialization stage, for each channel, I constructed a project-specific moderator, a region-specific moderator, and an intermediate outcome based on the corresponding theoretical arguments.[10] First, the resource provision channel implies that entrepreneurs with larger projects should benefit more from makerspaces because they have greater resource needs. Because high funding goals generally negatively predict funding successes (Calic & Mosakowski, 2016), entrepreneurs should not overshoot unless they in fact have such a resource need. Therefore, I used a project's fundraising goal to proxy for the entrepreneur's resource need. I created a binary indicator, *Above Median Goal* (*logged*), equal to 1 for projects with a goal (in dollars, logged) above the median level, and 0 otherwise. Another prediction under this channel is that entrepreneurs in regions more constrained in entrepreneurial resources will benefit more. I used an *Entrepreneurial Ecosystem Index* from Andrews et al. (2022) to proxy for access to entrepreneurial resources; the measure captures new for-profit firm formation, and a high value indicates better local entrepreneurial ecosystem

[9]I used logged value for this variable and others in the analyses to mitigate outlier effects.

[10]For full disclosure, Web Robots does not provide detailed project data for creating the intermediate outcomes. Because of data unavailability and technical challenges in scraping Kickstarter data at a large scale, I scraped information directly from the Kickstarter project webpages to create these measures for hardware projects only, as my empirical results show that the effects on commercialization are specific to hardware projects only.

performance and thus resource support.[11] Finally, as the channel suggests that entrepreneurs use makerspace tools for rapid prototyping and thus will experience more iterations for their projects, I used information on an entrepreneur's *Number of Updates* (*logged*) over time for a specific project to proxy for the number of iterations as an intermediate outcome; these updates typically involve product pivots and modifications.

Second, the social facilitation channel indicates that entrepreneurs spanning multiple Kickstarter project categories should reap greater benefits from makerspaces because the multiple knowledge domains can broaden the scope of learning and support more knowledge spillovers. I created a binary indicator, *Category Spanning*, equal to 1 if the focal entrepreneur of a project launched projects in more than one category, and 0 otherwise. Additionally, the channel predicts that regions that are more prone to breed homophily for social interaction may see greater commercialization benefits. I constructed a *Racial Homogeneity* measure at the MSA-year level following the Herfindahl index method in Greve and Yue (2017); a high value of the measure represents high racial homogeneity that encourages homophily. I used *Above Median Racial Homogeneity* as a moderator to distinguish between cases above versus below the median value of *Racial Homogeneity*. Finally, the channel suggests that knowledge spillovers occur and would result in learning and knowledge (text) similarity between otherwise unrelated projects (Feng, 2020). Following Carlson (2023), I leveraged detailed text descriptions of the projects to construct a measure of *Text Similarity* as an intermediate outcome to represent how similar a project is to prior projects in the same category that shares similar needs for prototyping tools.[12]

MSA-year-level analyses included a number of MSA-year controls to account for time-varying regional differences in population density, demographics, innovation intensity, economic condition, and alternative infrastructure: (1) *Population* (*logged*); (2) *Average Age*; (3) *% Female*; (4) *Number of Inventors* (*logged*); (5) *GDP* (*logged*); and (6) *Cumulative Number of Coworking Spaces to Date* (*logged*).[13] I also included (7) *% College Educated*, the state-year-level percentage of individuals in the labor force with a college degree or more, based on CPS data to control for regional human capital. To address the concern that MSAs likely to experience more rainfall might share unobserved characteristics that affect both makerspace establishments and entrepreneurship, I controlled for (8) *Historical Probability of Rain* for each MSA, calculated as the number of rainy days divided by the total number of days around the same date of the MSA's first Maker Faire (±1 week) in the prior 10 years. These eight control variables are henceforth referred to as "region-specific controls" for MSA-year-level analyses.

[11]Specifically, I used the Startup Formation Rate (SFR) from Andrews et al. (2022).

[12]The text similarity measure was calculated using an unsupervised word embedding approach: the sentence-BERT technique (Reimers & Gurevych, 2019), which determines meanings of sentences and documents based on pretrained natural language processing models. Standard preprocessing steps were taken: lowercase conversion and lemmatization were performed; and punctuation, special characters, stop words, location words, and words used in more than 25% of text descriptions of projects were removed. After preprocessing, the pairwise cosine distance between each project and each of its prior Kickstarter projects in the same Kickstarter category was calculated. The average of all pairwise cosine distances was calculated to produce a dissimilarity score. *Text Similarity* equals 1 minus the dissimilarity score.

[13]*Population* (*logged*) was constructed using county-level data from the National Cancer Institute. Data for *Average Age* and *% Female* were obtained from the CPS and constructed using weighted averages of county-level data based on the county-level population. *Number of Inventors* (*logged*), the logged number of individuals filing patents, was obtained from the United States Patent and Trademark Office records on granted patents. *GDP* (*logged*) was constructed using a weighted average of county-level data from the US Bureau of Economic Analysis based on the size of the county population. *Cumulative Number of Coworking Spaces to Date* (*logged*) was created with data from Coworker.com.

Project-level analyses examining the likelihood of successful entrepreneurial commercialization after entry included one additional time-varying region-specific control, *Project Competition* (*MSA-Month*), which is the number of projects in the MSA in the month, to account for local competition from other concurrent Kickstarter activities vying for funding. Several project-specific controls were included for project-level models. *Goal Amount* (*logged*), the entrepreneur's proposed fundraising goal (in dollars) for a Kickstarter project, controlled for the expected size of the project. *Project Sequence*, the sequence number of an entrepreneur's Kickstarter project, controlled for an individual's entrepreneurial experience (i.e., the number of projects the entrepreneur has launched). *Number of Successes to Date* controlled for an entrepreneur's past ability to commercialize venture ideas successfully. To account for intercategory differences in the likelihood of fundraising success, I added category fixed effects.

Summary statistics are presented in panels a and b of Table OA2 at the MSA-year level and project level, respectively. Pairwise correlations are reported in Table OA3. Since the mechanism tests leverage different subsamples due to data availability of the moderators and examine intermediate outcomes that are only created for hardware projects, I report the summary statistics for these additional variables separately in Table OA4.

4.3 | Empirical strategy

Disentangling the treatment effect of makerspace establishment on entrepreneurship is challenging due to potential reverse causality or omitted variables. To mitigate these biases, I tested my hypotheses with an IV design, leveraging whether it rained on the day of the first Maker Faire in an MSA as an instrument for the number of makerspaces subsequently established in the MSA. Focusing on MSAs where Maker Faires occurred, I exploited exogenous variation in the MSA-level number of makerspaces induced by the instrument to estimate the effect of makerspaces on entrepreneurial participation and commercialization.

Research has shown rainfall to be a relevant instrument for examining the success and impact of social movements (Madestam et al., 2013; Negro & Olzak, 2019). Rain on the day of the first Maker Faire in an MSA, which marks the start of the local maker movement, might reduce public attendance, slow the local maker movement, and decelerate new makerspace establishments in the MSA. By contrast, MSAs without rain on the day of a first Maker Faire could subsequently see more local makerspaces because of greater public engagement early on. The relevance of rainfall for Maker Faire engagement is supported by anecdotal comments from attendees who complained about rain-related scheduling and booth issues and early departures of exhibitors, given that most Maker Faires are outdoor (Kelly, 2016). Figure 3 illustrates the geographical variation in the first Maker Faire rainfall across MSAs. See the Results section for a formal examination of the relevance condition (first stage).

A valid instrument must also be exogenous. The key identifying assumption of the IV approach in this study is that whether the first MSA Maker Faire was held on a rainy day does not directly affect subsequent local entrepreneurship. Although I cannot test this assumption, random weather conditions on specific days are generally assumed to be uncorrelated with, and not likely affected by, local unobserved heterogeneity in social and economic forces (Madestam et al., 2013; Negro & Olzak, 2019). Using short-term weather while controlling for long-term weather helps alleviate concerns about the exclusion restriction condition of the instrument (Mellon, 2022). I therefore controlled for the historical probability of rain in all analyses and verified that results were robust to different parameter selections. Table OA5 compares the

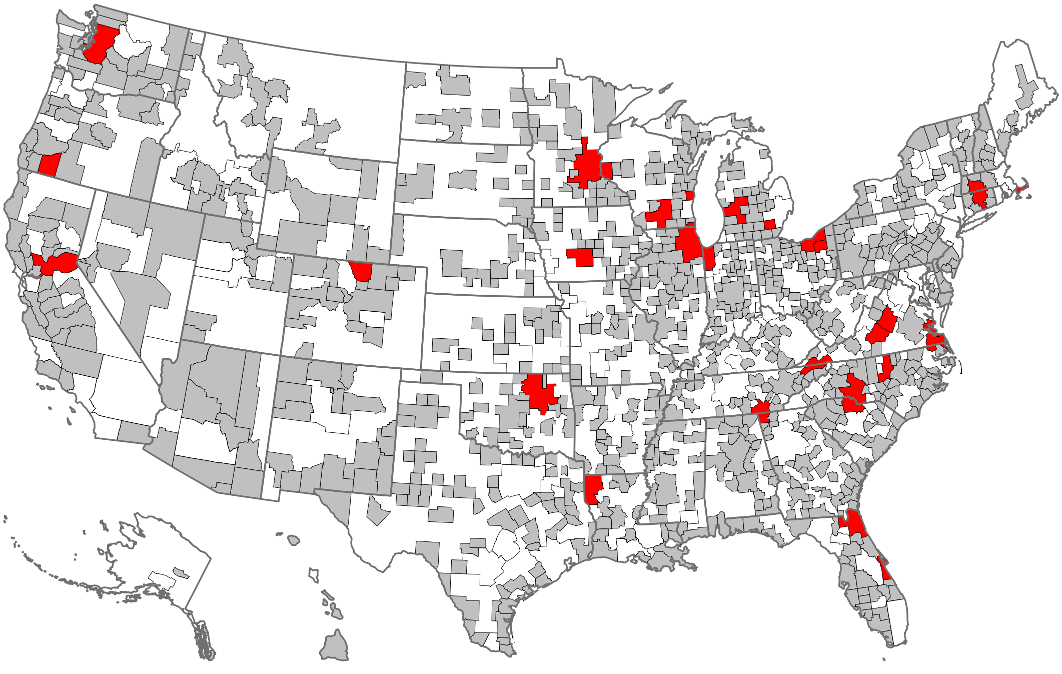


FIGURE 3 Weather of the first Maker Faire in each MSA (white regions are non-MSA areas).

region-specific controls for MSAs with a first Maker Faire on a rainy versus not rainy day. These MSAs do not differ substantively: a higher historical likelihood of rain does not predict a higher event-day likelihood of rain, confirming that the weather on the day of the first Maker Faire is highly random. The only statistically significant difference is the average age of the population; although the difference is small in magnitude, I included this control in all analyses.

The primary model specifications for estimating the effect of makerspace establishments are two-stage least squares (2SLS) models. Analyses examining the effects of makerspaces on entrepreneurial participation were conducted at the MSA-year level. I also report the results from ordinary least squares (OLS) regression for comparison. Additionally, to address potential concerns about weak instruments, I present results from the Fuller-k estimator ($b = 1$), which is more robust to weak instruments than 2SLS models because of its substantially smaller bias and mean squared error (Stock et al., 2002). To address within-MSA serial correlations, I present results with robust standard errors clustered at the MSA level. I added region-specific controls and year fixed effects in sequential specifications. Analyses examining the effects of makerspaces on entrepreneurial commercialization were conducted at the project level. Region-specific controls, project-specific controls, year fixed effects, project category fixed effects, and state fixed effects were added in sequential specifications.[14] I also considered different choices

[14]I could not add MSA fixed effects because variation in the instrument comes from inter-MSA variation. Adding state fixed effects in project-level analyses at least controlled for unobservable, time-invariant, state-level differences that may have affected local Kickstarter fundraising successes. I did not add state fixed effects in MSA-year level analyses because of the lack of statistical power when the number of observations is small.

for standard error clustering; findings were robust when standard errors were not clustered, were clustered by MSA, or were two-way clustered by MSA and project category.

5 | RESULTS

Table OA6 presents the first-stage results for the IV analyses, demonstrating the relevance condition of the instrument. Across all models, *Rainy Maker Faire* is negatively correlated with subsequent makerspace establishments.

5.1 | Entrepreneurial participation

5.1.1 | Main results

Table 1 reports the results for entrepreneurial participation. Models 1–2 suggest a positive relationship between makerspace establishments and hardware entrepreneurial activities from OLS regressions. Model 3 further demonstrates the positive causal link using 2SLS regression ($p = .001$). The first-stage F-statistic from a weak instrument test is 10.28, which is greater than the recommended value of 10 for instrument relevance (Stock et al., 2002). This positive effect holds when robust standard errors are clustered by MSA (Model 4, $p = .062$).[15] To address potential concerns about the finite sample bias of the IV estimator, Model 5 reports a consistent result from the Fuller-k estimator ($b = 1$) that is more robust to weak instruments ($p = .044$).

However, Models 6–9 show that nonhardware projects do not experience a statistically significant makerspace effect (in 2SLS models, $p = .150$ for software projects, and $p = .409$ for nontechnology projects). While one may argue that a larger sample size could potentially also lead to a statistically significant positive effect on the number of software projects launched, I note that the makerspace effect is nevertheless still more pronounced for hardware projects—a post hoc comparison suggests that the 2SLS estimate from Model 4 is larger than that from Model 6 ($p = .077$ for the comparison).[16] Two explanations may behind a "potential" positive effect on nonhardware projects also. First, some nonhardware projects can also involve physical elements and thus be impacted. If this is the case, we should later observe a similar potential effect on commercialization. Second, it is possible that a surge in hardware entrepreneurial activities may have spillover effects on encouraging other nonhardware activities if a lot of hype is generated in local communities for opportunity discovery. In this case, any effects of on subsequent

[15]The magnitude of the estimate gradually reduces when the project count is winsorized at different levels to mitigate the impact of extreme values, but across different specifications, the evidence for a positive makerspace effect on entrepreneurial entry is robust (Table OA7). For instance, at the 5% level of winsorization, one additional makerspace established in the MSA increases the MSA's number of hardware Kickstarter projects by 2.35 projects in a year, which is a 35% increase from the winsorized mean value of hardware activity level. Winsorizing the dependent variable at the 5% level means that I recoded the lowest 5% of values to the value of the 5th percentile and recoded the highest 5% of values to the value of the 95th percentile of the empirical distribution. Table OA7 presents the estimates for Model 4 in Table 1 when the dependent variable is winsorized at different levels. The table also presents the estimates using winsorized dependent variables for alternative research designs that will be discussed later in the paper. All results remain robust in the case of winsorization. I chose to report the estimates from the nonwinsorized models in the main text to avoid underestimating the effects of makerspace—the extreme values can be still highly relevant if makerspaces disproportionately impact the most affected regions (Meager, 2022).

[16]I recast the IV estimations with generalized method of moments (GMM) estimations for the comparison.

TABLE 1 Effects of makerspaces on entrepreneurial entry.

Dependent variable	Number of hardware projects					Number of software projects		Number of nontechnology projects	
	OLS		2SLS		Fuller-k estimator (*b* = 1)	2SLS	Fuller-k estimator (*b* = 1)	2SLS	Fuller-k estimator (*b* = 1)
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Cumulative Number of Makerspaces Established to Date	4.873	3.542	6.639	6.639	6.379	4.147	4.098	43.553	44.070
	[.000]	[.000]	[.001]	[.062]	[.044]	[.150]	[.120]	[.409]	[.362]
Region-specific controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	No	No	No	MSA	MSA	MSA	MSA	MSA	MSA
Observations	649	624	624	624	624	624	624	624	624
R^2	.446	.538	.470	.470	.481	.624	.625	.651	.651

Note: Analyses were conducted at the MSA-year level. Robust standard errors are used for the analyses. *p*-Values are reported in brackets.

commercialization should be rather limited to hardware activities because only these projects benefit from actually using the tools. As I will show later, the commercialization benefits from makerspaces are specific to hardware projects only, implying that the second explanation of spillover effects is more likely. At this stage, I conclude that there is insufficient evidence for the effects of makerspaces on nonhardware activities, whereas the evidence for a positive and larger effect on hardware activities is definitive.[17]

Overall, the 2SLS results indicate a positive effect of makerspace establishments on entrepreneurial participation that is only conclusive for hardware activities. Considering that the 2SLS estimates provide the local average treatment effect (LATE) that may be capturing the most responsive entrepreneurs, I do not focus on interpreting the exact *effect size* but aim to reproduce the *effect itself* across alternative empirical designs in later robustness analyses.

5.1.2 | Post hoc analyses: Who are encouraged to participate?

One remaining question is who are primarily driving the observed increase in hardware activities. This question is twofold. First, are the increased Kickstarter projects in fact launched by new entrepreneurs? For instance, established entrepreneurs/organizations may also leverage makerspaces to launch projects that can appear on the crowdfunding website. Second, even if these Kickstarter activities are indeed representing new entrepreneurial attempts, are intentional or accidental entrepreneurs driving the effect? These two types of prospective entrepreneurs differ in their commercial intent; accidental entrepreneurs are less likely to already have a startup and typically would start with less serious projects at a smaller scale.

First, to verify whether the encouraged hardware activities are from new entrepreneurs, I examine how makerspace establishments respectively affect *Number of First Hardware Projects*, that is, first attempts by new entrepreneurs, and *Number of Subsequent Hardware Projects*, that is, subsequent attempts by the established (Table OA9). The estimates suggest that makerspaces lead to increases in both types of projects, but the effect for first projects is much larger than that for subsequent projects ($p = .008$ comparing Models 1 and 3). Therefore, *new entrepreneurs* are primarily contributing to the observed makerspace effect on Kickstarter activities.

Second, to pinpoint whether intentional or accidental entrepreneurs are encouraged, I focus on first projects (because they mainly differ in *initial* commercial intent) and examine how makerspace establishments respectively affect *Number of First Hardware Projects with Goal > $10,000*, that is, large projects, and *Number of First Hardware Projects with Goal < $10,000*, that is, small projects.[18] Table OA10 suggests that makerspaces lead to increases in both types, but the effect for large projects is greater than that for small projects ($p = .040$ comparing Models 1 and 3). I also leveraged the detailed text description on each project's webpage to directly categorize intentional versus accidental entrepreneurs, defining a project to be launched by an accidental entrepreneur if the founder(s) had personal exposure to a problem in day-to-day life that inspired the focal product/service (Shah & Tripsas, 2007). Results confirm that makerspaces encourage first hardware projects by both types of entrepreneurs but the effect on accidental

[17]In Appendix A of the Online Appendix, I discuss two possible reasons for the differential magnitudes of the OLS and 2SLS estimates for the affected hardware projects, including potential downward bias of the OLS estimates due to omitted variables and the LATE nature of the 2SLS estimates.

[18]$10,000 is a key threshold for project size according to Kickstarter, as most successful projects raise less than this amount: https://www.kickstarter.com/help/stats.

entrepreneurs is smaller (p = .014 comparing Models 5 and 7). Therefore, among new entrepreneurs, *intentional entrepreneurs* are likely driving more of the makerspace effect on entry.

Unpacking who are encouraged to participate sheds light on the value of makerspaces in the pre-entry stage. If accidental entrepreneurs are the driving force, then makerspaces may be powerful in settings such as community centers for cultivating entrepreneurial mindsets and broadening entrepreneurial participation. If intentional entrepreneurs are mostly encouraged, then makerspaces can be particularly useful when integrated into programs that intentionally target new aspiring entrepreneurs who strive to overcome technological entry barriers. The post hoc analyses support both views but point to a more substantial role of the latter.

5.2 | Entrepreneurial commercialization

5.2.1 | Main results

Table 2 estimates makerspace effects on entrepreneurial commercialization. Model 3 indicates that makerspace establishments improve commercialization success for the average hardware project (p = .010). The first-stage F-statistic from the weak instrument tests is 37.52, well above the recommended value of 10 for instrument relevance. Consistent patterns emerge from the OLS estimate (Model 1), the 2SLS model without controls (Model 2), and different choices of standard error clustering (Models 4–5). The observed positive effect, however, do not apply to nonhardware projects. Models 6–7 show that makerspace establishments do not statistically significantly affect the software or nontechnology subsamples (p = .770 and p = .795, respectively). Moderation analyses further confirm that the observed benefit on commercialization is specific to hardware projects when compared with all nonhardware projects (Model 8) or with software projects (Model 9): no main effects are observed (p = .798 and p = .349, respectively) while interaction terms are positive (p = .087 and p = .027, respectively).[19]

All of the above patterns are consistent when alternative continuous measures of commercialization success, including the pledged amount and the number of backers, are used (Tables OA11 and OA12).[20] In a robustness test, I also included state-category fixed effects instead of state and category fixed effects to control for the possibility that certain project categories are more successful in some regions for other reasons. All results remain robust (Table OA14).

Together, the results indicate that makerspace establishments positively affect entrepreneurial commercialization with an important boundary condition: whether the venture idea involves physical products. The effects are specific to hardware projects requiring fabrication tools during prototyping. By providing validity for the relevance of the need for fabrication tools in driving the observed effects, the findings also mitigate concerns about potentially

[19]The 2SLS estimates of the effects on hardware activities continue to be larger than the OLS estimates across the previous project-level analyses. The two potential contributors to the differential magnitudes discussed earlier in the pre-entry stage continue to apply here (see Appendix A).

[20]The two continuous measures of commercialization success capture both potentially large increases in their values from failed projects to successful projects and potentially more moderate increases in their values from less successful projects to more successful projects. In a robustness check, I included the binary indicator *Success* as a control variable when using *Pledged Amount* (*logged*) and *Number of Backers* (*logged*) as dependent variables. The makerspace effects on commercialization outcomes remain positive and specific to hardware projects (Table OA13).

TABLE 2 Effects of makerspaces on entrepreneurial commercialization (likelihood of success).

Subsample	Dependent variable: Success								
	Hardware					Software	Nontechnology	All	Technology
	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Cumulative Number of Makerspaces Established to Date	0.010	0.083	0.090	0.090	0.090	0.010	−0.008	−0.007	0.031
	[.012]	[.009]	[.010]	[.099]	[.043]	[.770]	[.795]	[.798]	[.349]
Goal Amount (logged)			−0.068	−0.068	−0.068	−0.039	−0.060	−0.059	−0.051
			[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Project Sequence			−0.034	−0.034	−0.034	−0.002	−0.049	−0.045	−0.025
			[.002]	[.007]	[.000]	[.848]	[.000]	[.000]	[.000]
Number of Successes to Date			0.116	0.116	0.116	0.085	0.069	0.065	0.110
			[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Cumulative Number of Makerspaces Established to Date × Hardware Project								0.045	0.034
								[.087]	[.027]
Hardware Project								−0.188	0.135
								[.056]	[.027]
Region-specific controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State and category fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	No	No	No	MSA	MSA and category				
Observations	5404	5404	5404	5404	5404	6246	107,339	119,625	11,650
R^2	.059	.004	.115	.115	.115	.126	.232	.245	.222

Note: Analyses were conducted at the project level. Robust standard errors are used for the analyses. *p*-Values are reported in brackets.

confounding local ecosystem conditions that could be conducive to all kinds of entrepreneurial activities.

5.2.2 | Mechanism testing: How do entrepreneurs benefit?

Focusing on the affected hardware projects, Table 3 assesses how the makerspace effect is moderated by the factors predicted by the respective proposed mechanism. First, the resource provision channel indicates that the positive effect on commercialization success should be amplified for larger projects and for entrepreneurs in regions with less developed entrepreneurial ecosystems. Consistent with this mechanism, projects with a larger goal are affected more positively

TABLE 3 Testing mechanisms for entrepreneurial commercialization success (hardware projects).

	Dependent variable: Success			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Cumulative Number of Makerspaces Established to Date	0.086	0.301	0.091	0.048
	[.050]	[.063]	[.058]	[.072]
Cumulative Number of Makerspaces Established to Date × Above Median Goal (logged)	0.006			
	[.097]			
Cumulative Number of Makerspaces Established to Date × Entrepreneurial Ecosystem Index		−0.036		
		[.050]		
Entrepreneurial Ecosystem Index		0.146		
		[.242]		
Cumulative Number of Makerspaces Established to Date × Category Spanning			0.055	
			[.090]	
Category Spanning			−0.242	
			[.136]	
Cumulative Number of Makerspaces Established to Date × Above Median Racial Homogeneity				0.013
				[.095]
Racial Homogeneity				−0.023
				[.789]
Region-specific and project-specific controls	Yes	Yes	Yes	Yes
Year, state, and category fixed effects	Yes	Yes	Yes	Yes
Observations	5404	2769	5404	5172
R^2	.116	.086	.099	.147

Note: Results from project-level 2SLS regressions are reported. Main effects of moderators are omitted for moderators that are already included as controls or have no variation conditional on the controls. Robust standard errors are clustered by MSA and category. *p*-Values are reported in brackets.

TABLE 4 Testing mechanisms: Effects on intermediate outcomes (hardware projects).

Dependent variable	Number of updates (logged) Model 1	Text similarity Model 2	Text similarity Model 3	Model 4
Cumulative Number of Makerspaces Established to Date	0.280	0.007	0.006	0.014
	[.046]	[.037]	[.063]	[.072]
Cumulative Number of Makerspaces Established to Date × Above Median Goal (logged)			0.002	
			[.042]	
Cumulative Number of Makerspaces Established to Date × Cumulative Number of Coworking Spaces to Date (logged)				−0.002
				[.360]
Region-specific and project-specific controls	Yes	Yes	Yes	Yes
Year, state, and category fixed effects	Yes	Yes	Yes	Yes
Observations	5375	5222	5222	5204
R^2	.033	.122	.123	.130

Note: Results from project-level 2SLS regressions are reported. Model 4 focuses on regions with coworking spaces to rule out the possibility that makerspaces are the only available coworking spaces. Robust standard errors are clustered by MSA and category. *p*-Values are reported in brackets.

by makerspace establishments (Model 1, $p = .097$), and the entrepreneurial ecosystem index that proxies for available entrepreneurial resources negatively moderates the makerspace effect (Model 2, $p = .050$). Second, the social facilitation channel implies that the observed effect should be greater for entrepreneurs who span multiple project categories and for those in regions with high racial homogeneity. The results also substantiate this mechanism, as category spanning entrepreneurs reap more gains than those who don't (Model 3, $p = .090$), and high racial homogeneity in the local region positively moderates the effect (Model 4, $p = .095$). These findings suggest that both channels are at play.

Evidence on intermediate outcomes in Table 4 further supports the importance of both mechanisms. First, the resource provision channel predicts use of technological infrastructure for rapid prototyping and experimentation, which should lead to more iterations of venture ideas. Model 1 confirms that makerspace establishments increase the number of updates (logged) over time for the same hardware project ($p = .046$), which suggests more project iterations; these updates are the primary communication pathways for entrepreneurs to inform backers of minor modifications or major pivots. Second, the social facilitation channel predicts knowledge spillovers through social interactions, which should lead to shared knowledge among different projects. Model 2 corroborates this mechanism and shows that makerspace establishments increase text similarity among local hardware projects ($p = .037$), which suggests learning.[21]

[21] I view text similarity as measuring knowledge similarity (Arts et al., 2018). While text dissimilarity might indicate differentiation and radical innovations, incremental innovations that build on prior knowledge are also important improvements and appear to be more likely to emerge from makerspaces.

These results suggest that the resource provision and social facilitation channels are both contributing to how entrepreneurs benefit from makerspaces. The two operating mechanisms also appear to be complementary, as larger projects that have greater resource needs experience larger increases in knowledge/text similarity from makerspaces (Model 3 of Table 4, $p = .042$). In other words, the needs for using the fabrication tools can impact how much entrepreneurs gain from the knowledge spillovers that take place in the coworking areas. Therefore, makerspaces differ markedly from traditional coworking spaces due to the interplay of the technological and the social components. The common fabrication foci can foster the connectedness among individuals that is crucial for learning to occur. If makerspaces purely serve the same purpose as coworking spaces, then the effect of makerspaces on knowledge spillovers would be greater when there are simply more coworking spaces around. However, Model 4 suggests that the number of surrounding coworking spaces does not appear to matter, highlighting the distinctiveness of makerspaces. These findings point to makerspaces as a case illustrating that effects from physical amenities and social encounters do not operate in a vacuum. Because the positive makerspace effects on commercialization are specific to hardware entrepreneurial activities, technological infrastructure that supports common foci might be an antecedent and enabler for proximity to lead to meaningful social interactions for knowledge spillovers.

Unpacking how entrepreneurs benefit provides rich insights into the value of makerspaces in the post-entry stage and when the value can be maximized. As entrepreneurs choose what intermediaries to use, those with commercialization objectives should carefully evaluate whether accessing makerspaces for prototyping is a key priority depending on the specific venture needs.

5.3 | Robustness analyses

I conducted several robustness analyses to further mitigate concerns about unobserved confounders potentially correlating with the instrument and driving the results. A detailed description of all robustness analyses and findings is included in Appendix B. I first performed propensity score matching to achieve balance on relevant controls and replicated the main findings (Tables OA15 and OA16). Even though I cannot rule out possible spillovers in the pre-entry stage, any effects on commercialization success from makerspaces should still be rather limited to hardware activities because only these projects benefit from actually using the tools. This is indeed the case here. To be more rigorous, I abductively revise my claim on the boundary condition henceforth by focusing on the post-entry stage and by showing that the found commercialization benefits are specific to hardware projects.

I then leveraged a larger dataset containing observations before MSA-level Maker Faires. I employed a stacked event study using the staggered establishments of the first makerspace across MSAs. Table OA17 presents the estimates for $Treat \times Post$, which gives the average treatment effect across all events, showing that the positive effects for hardware projects found in the IV analyses are robust under an alternative empirical design. Figure 4 plots the estimates for the year-specific treatment effects relative to the year before the first MSA makerspace establishment and further confirms that the commercialization benefits are specific to hardware projects that do not exhibit differential trending patterns before treatments.[22] I also examined

[22]One caveat for interpreting the stacked event-study estimates is that the first makerspace establishment in an MSA could be followed by more establishments in subsequent years, leading to variation in subsequent treatment intensity in the long term. I used a narrow time window to focus on the immediate effects of makerspace establishments to mitigate this complication. Therefore, these results largely reflect short-term effects that supplement the estimates capturing longer-term implications in the main analyses.

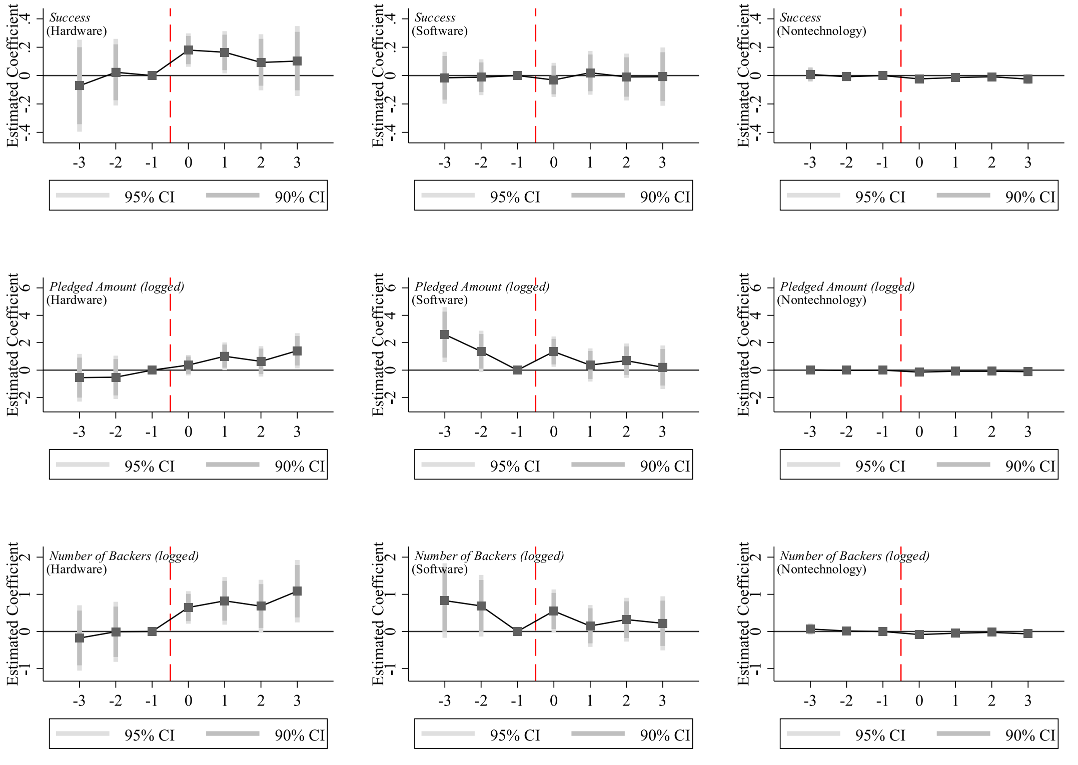


FIGURE 4 Stacked event-study results examining how first MSA makerspace establishments affect entrepreneurial commercialization outcomes.

models leveraging more nuanced within-MSA variation in makerspace access based on actual distances. Tables OA18 and OA19 show that being closer to a makerspace is associated with better commercialization outcomes, but only for hardware projects.[23]

Finally, I performed robustness checks that consider other alternative explanations and sensitivity of the observed effects to different design choices. All results remain robust.

5.4 | Alternative entrepreneurial settings

The empirical inquiry thus far focuses on the context of Kickstarter projects. These crowdfunding activities have been used in many studies as a measure of entrepreneurship and have been acknowledged by makers as their go-to for commercialization. However, to understand the broader implications of makerspaces, it is important to characterize what crowdfunding projects represent and how they relate to alternative types of entrepreneurship.

Existing studies provide two insights. First, crowdfunding activities represent very early-stage entrepreneurial endeavors, such as developing product prototypes and validating demand

[23]These associations should not be interpreted as causal, but they supplement the main results by validating the correlation between makerspace access and entrepreneurial commercialization at a more fine-grained level of geography.

(Mollick & Robb, 2016). Through the campaigns, entrepreneurs often aim to raise the very initial capital for founding ventures (Mollick, 2014). Second, this type of tentative entrepreneurial activities often subsequently result in high-tech, high-growth entrepreneurship that indicates real firm and job creation. Mollick and Robb (2016) note that a very high percentage of successful Kickstarter campaigns remained ongoing ventures and continued to add employees following the campaign. Yu and Fleming (2022) find that commercially oriented crowdfunding activities preceded regional increases in the establishments of high-growth startups, which was also accompanied by decreases in more conventional nontechnology entrepreneurship due to the shifted entrepreneurial focus. Therefore, the makerspace effects on crowdfunding activities potentially would carry over to other types of high-tech (but not low-tech) entrepreneurship.

To examine this conjecture and the scope conditions of the makerspace effects, I extend the study by examining two alternative entrepreneurial settings: (1) generic self-employment (primarily low-tech) reported in the US Census Bureau's Current Population Survey (CPS); and (2) US VC-backed firms (primarily high-tech) reported in the Preqin database (a leading commercial data provider for venture deal information). These two distinct types of entrepreneurial activities represent the two ends of the technology intensity spectrum. Adopting the same IV design with the same set of region-specific controls in the Kickstarter setting, I found no effect of makerspace establishments on the likelihood of individuals entering CPS self-employment or on their likelihood of earning business income; however, I found that makerspaces positively affect the creation of new VC-backed firms and the number of successful first-time VC deals (see Appendix C for a detailed description of the analyses and findings).

Insights from the two alternative settings highlight important heterogeneities in the definition of entrepreneurship. The main analyses focus on crowdfunding projects, which is in itself an important type of entrepreneurial activity—a total of $7.82 billion has been pledged to 618,253 Kickstarter projects as of February 2024 based on Kickstarter's website. The projects, especially the technology ones, can also be indicative of high-tech startups in nascent incubation. Here, I provide preliminary evidence that makerspaces may have meaningful impacts on growth-oriented entrepreneurship with important economic implications (e.g., VC-backed startups).

6 | DISCUSSION AND CONCLUSION

Despite a few high-profile anecdotal entrepreneurial successes that emerged from the increasingly popular makerspaces and theoretical conjectures on how these spaces foster entrepreneurship, empirical evidence on their causal effects is scant. Makerspaces are not designed specifically for entrepreneurs, and overall usage by commercially oriented entrepreneurs (vs. other makers) appears to be low. This article studies whether makerspaces affect entrepreneurship on a large scale by asking: (1) Do makerspaces encourage entrepreneurial participation, if so, who? (2) Do makerspaces benefit entrepreneurial commercialization, if so, how? (3) Are there any boundary conditions for when these effects would occur?

I used hand-collected datasets on US makerspaces and Maker Faires and archival data on Kickstarter projects and leveraged an IV design in which the weather (rain vs. no rain) on an MSA's first Maker Faire was an instrument that exogenously influenced the subsequent local makerspace establishments. I found that makerspace establishments positively affect entrepreneurial participation and subsequent commercialization outcomes, but these effects are mostly specific to hardware activities that involve physical prototypes: while spillover effects leading to the launch of more nonhardware activities cannot be fully ruled out, the commercialization benefits do not extend to software or nontechnology activities. These results are robust to alternative empirical designs addressing the limitations of the main IV approach. Post hoc analyses discover that the makerspace effect on entry is driven more by new (vs. established) but intentional (vs. accidental) entrepreneurs. Mechanism tests further reveal that the makerspace effect on commercialization comes from two operating channels—resource provision and social facilitation—and that they appear to be complementary to one another.

While entrepreneurs account for only a small percentage of the entire *maker population*, my findings point to meaningful large-scale effects of makerspaces on the (*prospective*) *entrepreneur population* (mostly those with prototyping needs). The limited impacts observed for nonhardware activities validate the relevance of fabrication tools in driving the effects. I thus highlight technological infrastructure as an important antecedent and enabler for proximity (e.g., in coworking spaces or through events) to give rise to meaningful social interactions—common foci (e.g., fabrication tools in the context of makerspaces) can create the connectedness for knowledge spillovers to take place and benefit entrepreneurial commercialization.

The study makes three major theoretical contributions. First, it adds to the literature on institutions and entrepreneurship (Tolbert et al., 2011), particularly on the sociocultural environments that shape entrepreneurship (e.g., Eesley et al., 2016). Emerging research has begun investigating the effects of recent social movements on entrepreneurship, creativity, and innovation—for example, the growing gig economy (Burtch et al., 2018), social liberalization issues (Vakili & Zhang, 2018), and Black Lives Matter (Agarwal & Sen, 2022) movements. Adding to this work, I demonstrate that makerspaces emerging from the community-based maker movement encouraged entrepreneurial participation and facilitated subsequent commercialization for certain types of activities. My study thus confirms the important role of grassroots social movements on business activities and outcomes.

Second, the study contributes to the organization and strategy literature on factors reducing entrepreneurial barriers, which has focused primarily on regulatory environments affecting entry costs (e.g., Castellaneta et al., 2020), risk of business failures (e.g., Eberhart et al., 2017), potential litigation risks from prior employers (e.g., Marx, 2022), and labor mobility constraints (e.g., Agarwal et al., 2022). Focusing on the nonlegal contextual factor of local makerspace establishment, I propose that makerspaces provide entrepreneurs with the necessary technological infrastructure to develop early prototypes, mitigating another crucial entrepreneurial barrier: the lack of technology accessibility.

Third, the study extends work on how entrepreneurship intermediaries aid venture development. Whereas researchers have extensively explored accelerators and incubators targeting high-growth ventures (e.g., Assenova, 2020; Hallen et al., 2020; Yu, 2020), my findings reveal how intermediary organizations not specifically designed for entrepreneurs can also promote specific types of entrepreneurial endeavors, especially for entrepreneurs intentionally seeking alternative avenues for overcoming technological resource hurdles. My findings also contribute to work highlighting how physical amenities benefit business formation and organizing (Dutta et al., 2021; Howell, 2022) and their role in facilitating social interactions based on overlapping knowledge domains for learning to occur.

The study has a few practitioner implications. First, for entrepreneurs, competitive and prominent accelerators/incubators are not the only avenues to achieve commercialization success. Accelerators and incubators focus on helping more developed ventures achieve accelerated growth through structured learning, networking, and signaling. For early-stage entrepreneurial ideas involving physical products, though, makerspaces can create environments conducive to iterated improvements, serendipitous learning, and potentially small-scale manufacturing by offering both affordable access to technological infrastructure and social interactions facilitated by common fabrication foci. Second, for managers of entrepreneurial programs, recognizing the boundary condition for makerspace effects is important as they consider adding fabrication tools to existing resources. For instance, programs that typically attract software startups will not likely benefit much from investments in developing technological infrastructure for prototyping. However, programs focusing on certain industry challenges or customer problems that tend to involve physical solutions (e.g., hardware, gadgets, wearables) may disproportionately benefit from the provision of environments conducive to hands-on prototyping experiences. Third, for policy makers, understanding the makerspace effects is crucial for designing systems and structures that support inclusive prosperity for entrepreneurs who otherwise lack access to technological infrastructure or knowledge spillovers. Government funds may be channeled to underserved regions to encourage makerspace establishments for reviving regional entrepreneurial activities and economic development. My findings suggest that fabrication tools create the common foci for social interactions to lead to knowledge spillovers. Investments aiming for future technological development that improves accessibility to alternative tools (e.g., scientific equipment for biolabs) may create similar common foci for learning to occur in other types of entrepreneurial clusters.

To conclude, I discuss the limitations and point to future research directions. First, data on individuals' actual makerspace participation and usage are limited. I focused on providing macro-level estimates to explore the average effects of makerspaces on a large scale and therefore cannot offer direct evidence on makerspace engagement, tool utilization, or social encounters. Instead, I drew on mechanism tests to derive inferences to rule in/out the theorized channels. Future studies can construct more detailed data by tracking and aggregating participation and usage data across multiple major makerspaces to deepen our understanding of how entrepreneurs benefit from makerspaces. Second, this article focuses on the early entrepreneurial stages, which are very likely affected by the technological capacity for prototyping. Data limitations prevented me from examining how makerspaces affect Kickstarter projects' delivery outcomes (i.e., whether entrepreneurs could eventually manufacture and deliver their pre-sold products). Future studies can investigate the long-term performance implications by exploring the growth and scaling stages, for example, local fabrication facilities may improve manufacturing capabilities by reducing the supply chain length.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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