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Knowledge spillover and entrepreneurship: Evidence from BITNET[☆]

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ABSTRACT

In this study, we investigate how knowledge spillovers create entrepreneurial opportunities using the adoption of BITNET, an early predecessor of the Internet, across universities in the U.S. as an exogenous shock to the knowledge base in the county where the university is located. Using County Business Patterns data, we find a positive relationship between entrepreneurship, measured by the increase in the number of establishments in a county, and the adoption of BITNET at a university in that county. Further, this relationship is stronger for establishments in high-tech industries and for smaller establishments. We also find that the number of patents and citations in a county increase after the adoption of BITNET in a county. These results indicate that knowledge spillovers from local universities can have a strong impact on entrepreneurial opportunities in a location, consistent with the knowledge spillover theory of entrepreneurship.

1. Introduction

Entrepreneurship is widely regarded as one of the most potent drivers of economic growth. As a result, substantial research has been devoted to analyzing how entrepreneurship occurs and what policies can foster it. One strand of literature focuses on the entrepreneur's motivation, characteristics, and background to understand the entrepreneurial process. Another strand examines the impact of external constraints on entrepreneurship and entrepreneurial performance, such as financing (e.g., Black and Strahan, 2002; Krishnan et al., 2015) and availability of suppliers and workers (e.g., Glaeser and Kerr, 2009). Both strands of literature take the presence of entrepreneurial opportunities as given.

Another strand of literature, which includes Audretsch and Keilbach (2007), Acs et al. (2009), and Braunerhjelm et al. (2010), takes a distinctly different point of view that entrepreneurial opportunities do not arrive on their own. This literature proposes the idea that knowledge is first created in institutions, such as large firms and universities, through R&D expenditures. These institutions, however, may not be able to take complete advantage of the outcomes of their investments by not commercializing the knowledge from these inventions. Thus, individuals in these organizations (or somehow affiliated or connected with them) rationally create a startup that can create pecuniary returns from this knowledge. According to this theory, knowledge-rich environments will have greater entrepreneurial activity, whereas information-impoverished environments will have lower entrepreneurial activity. Thus, knowledge spills over from the producers of knowledge to startup firms that commercialize the knowledge and appropriate returns from these endeavors. This theory is referred to as the "knowledge spillover theory of entrepreneurship."[1] In this paper, we empirically test the knowledge spillover channel using the adoption of BITNET, an earlier predecessor of the Internet, across U.S. universities as a shock to the local knowledge base.

It is challenging to empirically test the knowledge spillover theory of entrepreneurship due to the difficulties in identifying the causal impact of knowledge spillover on entrepreneurial activity. Causal interpretations between knowledge spillover and entrepreneurship can be confounded by endogeneity and reverse causality concerns. For

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[1] Note that neither this literature nor we assume that the knowledge spillover effect is the only factor driving entrepreneurship. Clearly, the presence of an entrepreneurial culture, skill, and risk-taking ability among individuals, as well as other catalytic factors such as the availability of financing are crucially important in driving entrepreneurship.

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instance, any relation between knowledge spillover and entrepreneurship observed in the data could result from co-location by similar firms, common shocks, or startup firm activity creating new knowledge. In this paper, we address the issue of endogeneity by utilizing a natural experiment, namely, the adoption of BITNET. This network system predated the Internet and was introduced to universities and government agencies in the 1980s. As Agrawal and Goldfarb (2008) explain in careful detail, the adoption of BITNET was exogenous to the extent of R&D activity in universities. They point out that directors of university computing centers, rather than individual researchers, drove the decision to join BITNET. In our context, where the outcome variable of interest is the extent of entrepreneurship in the same location (i.e., county) as the institution adopting BITNET, there is even less reason to expect the choice of BITNET adoption to be driven by local entrepreneurial or economic activity.

Prior research indicates that the adoption of BITNET had a positive impact on both the quantity and quality of local knowledge production through enhancing access to new information that supports knowledge creation and fostering collaborative research (Agrawal and Goldfarb, 2008; Ding et al., 2010; Wernsdorf et al., 2022). Additionally, BITNET likely also increased knowledge flows and absorption into a location from other areas (Forman and Zeebroeck, 2019), creating another channel for new knowledge production. Studies suggest that knowledge spillovers are localized and influenced by the spatial proximity to the source of the knowledge (Audretsch and Feldman, 1996; Audretsch and Lehmann, 2005; Jaffe, 1989; Jaffe et al., 1993; Lee et al., 2013). Therefore, BITNET adoption likely led to an increase in the local knowledge base.

Once the knowledge is produced in a location (higher in quantity and quality after BITNET adoption) or diffused to that location from other areas due to BITNET introduction, the researchers or other people affiliated or connected with the university – including students, post-doctoral students, friends and families of those affiliated with the university - can use this knowledge to commercialize.[2] Thus, we hypothesize that the increase in the local knowledge base due to BITNET adoption leads to an increase in local entrepreneurship.

The adoption of BITNET at research institutions offers us two unique advantages for our empirical analysis. First, it provides us with a clean measure for the spillover of incremental knowledge (that is, in addition to what the local area already possesses). Second, it allows us to identify the causal impact of knowledge spillover on entrepreneurship. Due to the staggered nature of the adoption of BITNET, we can wipe out local area-specific effects (such as entrepreneurial talent pool, culture, local policy and regulations, and access to capital) as well as time trend effects in a difference-in-differences framework.

We use the data provided by Agrawal and Goldfarb (2008) to create county-level measures of BITNET adoption. We define a county as having “adopted” BITNET if a research institution located within the county has adopted BITNET. We then construct county-level measures of the number of establishments from the County Business Patterns data and relate how the adoption of BITNET in a county affects the number of establishments in that county. Consistent with the predictions of the knowledge spillover theory of entrepreneurship, we find that BITNET adoption in a county in a given year is associated with an increase in the number of establishments in that county over the subsequent year. Specifically, BITNET adoption is associated with a 1.9 % increase in the number of establishments in a county. For the median county in our sample, this represents an increase of 23 establishments.

One way to determine if BITNET’s impact on local entrepreneurship is due to knowledge spillover is to examine whether new establishment creation predominantly occurs in high-tech industries. If knowledge spillover from research institutions to entrepreneurs drives startup activity, then our results should be stronger for high-tech firms. Thus, we classify establishments based on their 3-digit SIC codes as “High-tech” and “Low-tech”. High-tech industries include computer and office equipment, computer and data processing services, communications equipment, drugs, scientific and medical equipment manufacturers, among others. Consistent with the knowledge spillover theory of entrepreneurship, we find that BITNET adoption in a county is associated with an economically large 17 % increase in the number of high-tech establishments in a county. On the other hand, BITNET adoption is associated with only a 1.7 % increase in low-tech establishments in a county. The difference between these two effects is statistically significant at the 1 % level. After dividing the high- and low-tech samples by firm size, we find that BITNET’s adoption had the most significant effect on small, high-tech establishments, resulting in a 19 % increase, while it had no significant impact on large, low-tech firms. Interestingly, the difference in the impact of BITNET adoption on small-high-tech vs. small-low-tech establishments is significantly larger than the difference in the impact of BITNET adoption on large-high-tech vs. large-low-tech establishments.

We also test whether our results are impacted by the knowledge richness in a region. If a region is already rich in knowledge, the incremental impact of BITNET adoption on the knowledge base would be smaller for such regions. If a significant proportion of entrepreneurial activity is driven by knowledge-based opportunities present in a region (consistent with the knowledge spillover theory), then the impact of BITNET adoption on startup activity should be weaker in those regions. Consistent with this argument, using patent and citation stock in a county prior to the invention of BITNET as a proxy for knowledge richness, we find that the impact of BITNET adoption on the number of establishments is lower for knowledge-rich regions.

Finally, we complement the results from Agrawal and Goldfarb (2008) and Wernsdorf et al. (2022) by showing that the introduction of BITNET in a county is related to a greater extent of innovation in a county. We find that BITNET introduction in a county is associated with a significant increase in the number of patents filed from a county over the next three years, as well as an increase in the number of citations on those patents. These results, while meant to support our main conjecture and in conjunction with Agrawal and Goldfarb’s (2008) and Wernsdorf et al. (2022) results, are also supportive of our identification assumption that the introduction of BITNET in a county increased the level of knowledge production and knowledge spillover in that county.

Our paper contributes to the existing studies on the knowledge spillover theory of entrepreneurship (e.g., Audretsch and Keilbach, 2007; Acs et al., 2009). While there are several studies that examine the relationship between university research and new venture creation (e.g., Audretsch and Lehmann, 2005; Audretsch et al., 2005; Audretsch and Stephan, 1999), this is one of the first papers in the literature to establish the causal link between knowledge spillover and entrepreneurship.[3] Prior works have primarily focused on examining the causal impact of knowledge spillovers on innovation and growth (e.g., Agrawal and Goldfarb, 2008; Bloom et al., 2013; Forman et al., 2012). We contribute to these studies by showing that BITNET led to greater entrepreneurship by inducing a shock to the local knowledge base. Our results suggest that information flow may be one of the important determinants of high-tech startup activity alongside other factors such as entrepreneurial culture, ability, and skill, and thus generate significant implications for

[2] Our argument related to knowledge spillover does not rely on specific channels through which BITNET can enhance local knowledge. Local knowledge can be enhanced through higher local knowledge production or through higher local access to knowledge produced elsewhere. As we discuss later, we find evidence of an increase in local knowledge production after BITNET adoption. However, we do not rule out that our results are also partly driven by improved local access to knowledge produced elsewhere.

[3] See Ghio et al. (2015) for a review of studies in knowledge spillover theory of entrepreneurship and Agarwal and Shah (2014) for a review of studies on employee and academic entrepreneurship.

policymakers and stakeholders involved in promoting knowledge transfer, economic growth, and innovation.

2. Theory and hypothesis development for empirical tests

In this section, we briefly review the knowledge theory of entrepreneurship, discuss BITNET and its effect on knowledge production and diffusion, and develop hypotheses for our empirical tests.

2.1. The knowledge theory of entrepreneurship

What drives entrepreneurship? The existing literature suggests that both the intrinsic characteristics of entrepreneurs and the external environment (in particular, the knowledge base) play an important role. One strand in the literature argues that the skills or characteristics of entrepreneurs are major conditions that are needed to define entrepreneurship. These characteristics include higher education (Oosterbeek et al., 2010; von Graevenitz et al., 2010), prior experience of having received an inheritance (Blanchflower and Oswald, 1998), the ability to develop general skills (Lazear, 2004) and family background (Djankov et al., 2007), among others.

Another strand in the literature focuses on the external environment, particularly the knowledge pool, and offers a different perspective. Acs et al. (2009) and Audretsch and Keilbach (2007) assume entrepreneurial skills as given and discuss what external conditions can generate entrepreneurial opportunity. They argue that new knowledge and ideas can be a potential source of entrepreneurial opportunity. According to the theory of knowledge spillover of entrepreneurship, knowledge and ideas created within organizations like universities and firms, but not commercialized due to factors such as uncertainty, asymmetries, and transaction costs related to new ideas, can create entrepreneurial opportunities. The entrepreneur can exploit these opportunities arising from this "incomplete commercialization" by starting a new business, facilitating the commercialization and the spillover of knowledge from the organization that it was originally created. Thus, the knowledge spillover of entrepreneurship suggests a richer knowledge base in the local environment would give rise to greater entrepreneurial opportunities.

Acs et al. (2013) introduce the concept of the "Knowledge Incubator" – an organization that develops new knowledge with commercialization potential but chooses not to commercialize it. The incubator provides entrepreneurs with an opportunity to leverage this knowledge and create new businesses without bearing the full costs of this knowledge development. For example, a university lab that discovers a new molecule that has the potential to treat cancer represents valuable knowledge that can be used to create a new business. In this context, the R&D expenditure for the laboratory and the salary for the scientists is not provided by the entrepreneur, who will eventually appropriate the rents from the discovery of the new molecule. Yet, the university is unlikely to start up a firm to obtain economic value from the molecule since business activity is not the primary venture of a university. Therefore, an employee, student, faculty member of the university and/or their family and friends may decide to commercialize this innovation by starting up a firm and creating a product utilizing this innovation.[4]

Acs et al. (2009) argue that this is also true for large firms that engage in R&D investments. The expected return from the commercialization of knowledge generated from the firm's R&D investments can be either sufficiently high for an employee to leave the large firm and start their own firm to reap economic value from knowledge generated by the large firm or may be sufficiently low for the large firm to justify not engaging in the commercialization of the knowledge that its R&D creates. Thus, employees or agents related to those employees (either through business or personal connections) may decide to capture the economic value of the invention by starting up a new firm.[5] In support of these arguments, Audretsch et al. (2021) show that knowledge spillovers have a stronger effect on the innovation performance of startups compared to incumbent firms.

Several studies examine the spatial dimension of knowledge spillovers (Audretsch and Feldman, 1996; Audretsch and Lehmann, 2005; Jaffe, 1989; Jaffe et al., 1993; Lee et al., 2013). Jaffe (1989) finds that university research has a significant impact on corporate patents and R&D investments in a local area. Similarly, Jaffe et al. (1993) find that inventors are more likely to cite patents from neighboring regions than from more distant areas, supporting the notion that knowledge spillovers are localized. In addition, Audretsch and Lehmann (2005) show that the number of firms located near a university is positively impacted by the knowledge capacity of the region and the university's knowledge output. Lee et al. (2013) show that the effects of knowledge spillovers decay rapidly with distance. These studies suggest that knowledge spillovers are localized and influenced by the spatial proximity to the source of the knowledge.

The knowledge spillover theory of entrepreneurship suggests that new knowledge produced in a region is commercialized and spills over through entrepreneurship. Recent research extends this literature by showing that the extent of knowledge spillover effects may depend on the characteristics of potential entrepreneurs and local regions. For example, Kirschning and Mrożewski (2023) and Qian and Jung (2017) show that high levels of entrepreneurial absorptive capacity of the region (i.e., the ability to understand and absorb knowledge) may strengthen the knowledge spillover effects on entrepreneurship. Araki et al. (2024) explore the effect of knowledge diffusion on entrepreneurship and show that strong regional innovation networks characterized by well-connected members and effective knowledge sharing help with the knowledge spillover process and facilitate high-growth entrepreneurship.

In summary, the knowledge theory of entrepreneurship posits that entrepreneurial opportunities that primarily arise from incomplete commercialization by the organizations where the knowledge or ideas originate from give rise to new firm creation. The major empirical prediction of this theory is that, ceteris paribus, environments rich in knowledge will experience greater entrepreneurial activity, whereas environments that are poor in knowledge will experience lower entrepreneurial activity.

2.2. BITNET and its effect on knowledge production and diffusion

BITNET was an early world leader in network communications for the research and education communities, paving the way for the eventual introduction of the Internet.[6,7] The first BITNET connection was from the City University of New York (CUNY) to Yale University in 1981. As of 1982, the network consisted of 20 institutions. By the end of the 1980s, it had expanded to connect approximately 450 universities and research institutions, as well as 3000 computers spanning North

[4] Many universities now have technology transfer and patent licensing offices whose fundamental mission is to enhance the commercialization of research conducted at the university.

[5] A well-known example of this effect is the computer mouse. This device was originally invented in Xerox's labs but never commercialized by Xerox. Steve Jobs visited the Xerox labs and recognized the potential of this technology. Ultimately, it was Apple Computers that refined and commercialized this technology, not Xerox.

[6] The discussion in this section relies heavily on Agrawal and Goldfarb (2008) and http://www.livinginternet.com/u/ui_bitnet.htm.

[7] BITNET was a "store-and-forward" network similar to the Usenet, and coincidentally invented at about the same time, in 1981, by Ira Fuchs and Greydon Freeman at the City University of New York (CUNY), and originally named for the phrase "Because It's There Net", later updated to "**B**ecause **I**t's **T**ime **Net**".

America and Europe. In the early 1990s, BITNET became the world's most widely used research communication network, facilitating email, mailing lists, file transfer, and real-time messaging. It allowed communication via e-mail, access to remote file archives, use of Listserv, file transfer protocol (FTP), and compatibility with other operating systems such as UNIX.

While other networks (e.g., ARPANET, EDUNET, USENET, CSNET) existed at the same time, BITNET is the most suitable for examining the impact of knowledge spillovers. First, rather than being narrowly focused on areas such as defense or computer science like some of the other networks, BITNET was made available to all scholars, and it was consequently adopted more widely than any other network at the time. In addition, unlike other networks, the commercial use of BITNET was not prohibited.[8] Second, the adoption of BITNET was carefully recorded, with available data indicating the precise date of adoption for each institution within the network up until 1990. This is not the case for other networks. Third, BITNET users were able to exchange data through FTPs, which allowed for a more substantive knowledge transfer compared to networks that only allow bulletin board postings and text messages. BITNET also allowed one of the first real-time chat programs called relay, a precursor to Internet relay chat (IRC), which facilitated discussions between researchers at different institutions. Thus, the adoption of BITNET lends itself well suited to the analysis of knowledge spillover, given the significant scope of new knowledge generation and access by users who participated in this network.

Since BITNET made the sharing of data and resources significantly easier across universities, it effectively provided an exogenous boost to knowledge production at these institutions. Evidence suggests that BITNET affected the quantity and quality of local knowledge production through increased access to information that could support knowledge creation and through increased collaborative research. Ding et al. (2010) show that the availability of BITNET at a campus increases research productivity (as measured by the number of publications). Wernsdorf et al. (2022) show that patenting by university-connected inventors increases after the adoption of BITNET by the focal university. Thus, both studies suggest that BITNET positively affected local knowledge production.

Studies also show that BITNET increased research collaborations. For example, Agrawal and Goldfarb (2008) find increased research collaboration at universities in engineering after BITNET adoption. Similarly, Ding et al. (2010) show that the adoption of BITNET increases the collaborative network of life science researchers. Forman et al. (2014) find that advanced internet adoption mediates the increase in geographic concentration of patenting and this effect is strongest for distant collaborations. Research collaborations, in turn, also increase the quantity and quality of knowledge produced. For example, Azoulay et al. (2010) show that the sudden death of a prominent co-author leads to a lasting and significant decline in the publication rates of their collaborators. Additionally, Wutchy et al. (2007) find that collaborative research is more highly cited than individual research, indicating that collaborations lead to the production of higher-quality knowledge. Collectively, these studies indicate that BITNET adoption likely increased both the quantity and quality of local knowledge production.

BITNET could have also increased access to knowledge from other locations and improved knowledge flows and absorption. Forman and Zeebroeck (2019) show that when two locations in the same firm adopt the Internet, the likelihood of citation of a patent between two locations increases, especially when the establishments work in similar fields. These results suggest that internet connectivity increases knowledge flows, thus creating another avenue for new knowledge production.

Thus, evidence suggests BITNET had a positive impact on local knowledge production by providing access to knowledge, increasing research collaborations, and improving knowledge flows.

It is worth noting that these channels are interconnected. For example, as Ding et al. (2010) argue, knowledge is one of the inputs of scientific knowledge production, and by reducing the cost of access to this input, BITNET could have led to an increase in research productivity. Further, since BITNET reduced communication costs, it would increase collaboration among researchers, positively impacting productivity (Ding et al., 2010). Finally, increased collaboration would not only enhance knowledge production but could also lead to greater knowledge absorption from external sources (Forman and Zeebroeck, 2019). In summary, BITNET likely increased the quantity and quality of knowledge produced, and thus, it represents a shock to local knowledge production.

It is also possible that BITNET increased access to knowledge produced elsewhere, increased knowledge flows and absorption, and thus had a broader impact on the knowledge base of the focal county. This, in turn, could increase the ability of individuals to understand and spread new information (a shock to local knowledge absorption and diffusion). All these effects might have led to a richer knowledge base and increased entrepreneurial activity due to knowledge spillover in the local area in which BITNET was adopted.

2.3. Hypothesis development

As discussed above, BITNET likely increased the local knowledge base through several channels. First, knowledge was produced due to greater access to new ideas and information as well as the increased ability of researchers in a given location to collaborate with scholars elsewhere. BITNET also increased access to knowledge produced elsewhere and likely increased knowledge flows and absorption, leading to an exogenous increase in the local knowledge base.

We conjecture the process through which knowledge would diffuse to potential entrepreneurs as follows. Once the knowledge is produced (higher in quantity and quality after BITNET adoption) or diffused, the researchers or other people affiliated or connected with the university (such as students, post-doctoral students, friends and families of those affiliated with the university, etc.) can use this knowledge to commercialize.[9] Thus, we propose the following hypothesis:

H1. The number of establishments in a county increases after the adoption of BITNET by a research institution in that county.

In addition, we expect that the creation of new startup firms will be driven by employees or other agents related to the R&D conducting entity. Consequently, we predict that most newly established startup firms resulting from this knowledge spillover will be relatively small. This is because most employees involved in research for the R&D conducting entity are unlikely to possess significant financial capital, all else equal, given that they are likely to be salary-taking employees. Thus, the primary initial input for their new startup venture is the knowledge these entrepreneurs gained in their previous workplaces. Further, the knowledge spillover theory of entrepreneurship suggests that new startup activity is more likely to be in high tech industries (e.g., computer, software, telecommunications, and medical equipment) that are

[8] ARPANET and NSFNET had an Acceptable Use Policy (AUP), which prohibited the use of the Internet for commercial purposes (see http://www.internetsociety.org/internet/what-internet/history-internet/brief-history-internet#f8).

[9] Some anecdotal examples of such spillovers include Cisco Systems, which was founded by then-partners Leonard Bosack and Sandy Lerner in 1984 while they were working at a computer science lab at Stanford University. They successfully commercialized a router developed at that university. Similarly, Regeneron Pharmaceuticals was founded by Leonard Schleifer, a neurologist at Cornell University, based on his research. Gail Naughton, an academic entrepreneur, developed and patented a technique to grow tissues during her postdoctoral studies at New York University and co-founded Advanced Tissue Sciences based on this invention in 1986.

more knowledge-intensive. These high-tech ventures are also less likely to require a large initial size. Thus, we propose the following two hypotheses:

H2. The number of high-tech establishments in a county increases more than the number of low-tech establishments after the adoption of BITNET by a research institution in that county.

H3. The number of high-tech small establishments in a county increases more than the number high-tech large establishments after the adoption of BITNET by a research institution in that county.

The impact of BITNET adoption might vary depending on the local area's existing knowledge base. In regions already rich in knowledge, the addition of incremental knowledge through BITNET adoption might be less impactful in increasing entrepreneurial activity. Thus, in counties with high quantity and quality of knowledge production, proxied by patent and citation stock in a county prior to the invention of BITNET, the impact of BITNET adoption on the number of establishments might be less pronounced. This leads to our last hypothesis:

H4. The effect of BITNET adoption on the number establishments in a county will be weaker when the BITNET-adopting research institution is in a knowledge-rich area.

3. Identification strategy: the impact of BITNET on knowledge spillover

Our instrument for knowledge spillover is the introduction of BITNET across various research institutions during the 1980s. As discussed in the previous section, we conjecture that BITNET led to an increase in the local knowledge base. This incremental knowledge will, in turn, spill over to the neighboring regions if employees and agents related to the institution decide to monetize this knowledge to start up new firms.

In later tests, we find support for the idea that BITNET adoption by research institutions in a county is also related to greater subsequent innovation in that county, measured by patents applied for from those counties that are eventually granted, and by citations of those patents. In conjunction with the results from Agrawal and Goldfarb (2008) and Wernsdorf et al. (2022), these results provide supporting evidence that BITNET indeed led to greater knowledge spillover within the county where a research institution adopts BITNET. Prior literature finds evidence supportive of the idea that knowledge spillover occurs within a short boundary around the source of the spillover (e.g., Jaffe, 1989; Jaffe et al., 1993). One concern may be the relevance of research institutions such as universities in knowledge spillover and local innovation activities. Fortunately, Jaffe (1989) has argued that university research and research at industrial labs can both drive innovation. Indeed, he finds that university research has a significant impact on corporate patents as well as on corporate R&D investments in a local area.

We then address whether our instrument for knowledge spillover satisfies exclusion restriction conditions. Agrawal and Goldfarb (2008) argue that the BITNET introduction was not related to any omitted variables. They note that the decision to adopt BITNET at universities was made by the directors of computing centers rather than faculty members. In fact, Ira Fuchs, the founder of BITNET, described the many individual university adoption decisions he was familiar with as being made predominantly by computing center directors. Agrawal and Goldfarb (2008) point out that "At the conception of the network, for example, he [Ira Fuchs] personally sent letters to IT administrators (not researchers) at approximately 50 institutions and visited many more on a personal basis to convey the benefits of joining BITNET. In addition, he lectured about the mechanics and attributes of BITNET at public forums, such as EDUCOM, that were primarily attended by administrators. Dr. Fuchs described the 'value proposition' that was used to persuade university administrators to connect as being largely predicated on the argument that 'if nothing else, it will be very useful for aiding your IT staff to communicate with others.'"

The above arguments and additional tests by Agrawal and Goldfarb (2008) are convincing pieces of evidence to show that the relation between the adoption of BITNET by universities and their research collaboration was unlikely to be driven by omitted variables. In our context, which focuses on entrepreneurship in the same county as the institution adopting BITNET (and not even the same institution), these arguments are even more potent. University IT administrators were unlikely to consider local entrepreneurship or economic conditions as a factor in their choice of BITNET adoption for their research institutions. Given that university budgets are not necessarily linked to local economic conditions in a county, it is unlikely that any budget-related issues dictating the choice of BITNET adoption were also related to local economic conditions. This is because universities get their funding from tuition (from students from across the country), alumni (who may reside anywhere in the country), and endowment (which depends more on the performance of assets in their investment portfolio). Thus, we do not expect any omitted variables to drive the relationship between BITNET introduction and local entrepreneurial activity. Moreover, we will provide additional tests in later sections to check whether any potential relationship between BITNET introduction and local entrepreneurship is indeed driven by knowledge spillovers.

A useful feature of institutions where BITNET was adopted was that such institutions did not have a profit motive for conducting R&D. This fact separates the introduction of BITNET even more from local entrepreneurial activity. Moreover, this feature fits in nicely with the conjecture in the knowledge spillover theory of entrepreneurship that knowledge-producing institutions may not want to extract (at least all the) commercial benefits from their inventions and discoveries (which in turn leads to employees bearing such knowledge to start up new firms). Commercial operations are neither the stated goal nor an area of expertise of research institutions like universities. Another source of concern in analyzing knowledge spillover effects, pointed out by Bloom et al. (2013), is that measures of knowledge spillover between firms can also contain the effect of product market competition between firms. However, our methodology is not affected by any product market competition since the knowledge-producing entity is not in the business of producing products or services.

4. Data, sample selection, and construction of variables

4.1. BITNET adoption at research institutions

The information on BITNET adoption comes from the data compiled by Agrawal and Goldfarb (2008). The dataset they provide contains the name of the research institution, the county FIPS code that the institution is in, and the date of BITNET adoption in that institution. Research institutions can be universities as well as government and private labs. About 85 % of the BITNET connections are at universities or colleges. Among the rest, BITNET connections can be at federal institutions and labs (e.g., NASA, NSF, EPA, Fermi National Accelerator Laboratory) or private research institutions (e.g., Cold Spring Harbor Laboratory which is a private, non-profit institution with research programs focusing on cancer, neuroscience, plant biology, genomics, and quantitative biology). Research at both types of institutions fits our requirements of being knowledge-producing, while the institutions themselves are not in the business of selling products or services themselves.[10] Moreover, many laboratories are linked to universities.

We collapse the institution-level BITNET adoption data to the county level and create a dummy variable called *AfterBit* that is one for the years in and after which an institution in a county has adopted BITNET, and zero otherwise. This is our primary independent variable of interest in

[10] Seven out of the 454 institutions are related labs bearing the name of private companies like IBM and Exxon. But this represents <2 % of the sample, and thus should not significantly impact our results.

this study. We also create similar variables separately for whether the BITNET was adopted by a university (*AfterBit* (*Univ*)) or adopted by a research center (*AfterBit* (*Research Ctr*)) in the county. BITNET connection data is available from 1981 to 1990. After 1990, BITNET was overshadowed by the advent of the Internet, and many research institutions switched to the broader Internet. We analyze the impact of BITNET on the number of county establishments up to three years after its adoption. Thus, we end our sample period in 1993. Panel A of Table 1 provides the yearly distribution of BITNET introduction in various counties. The patterns indicate that between 1984 and 1989 there was a consistent level of addition of counties to the BITNET. Panel B of Table 1 reports the first time each state in the U.S. was connected to BITNET. It is notable that tech-heavy states like California and Massachusetts were early adopters.

4.2. County-level establishments

We obtain data on county-level establishments from the County Business Patterns (CBP) data from 1983 to 1993. Although the original CBP is available before 1983, we start measuring the number of establishments in 1983 for several reasons. Since our interest is in the number of establishments, we need to ensure that there is a longitudinal continuity in the way CBP calculates the number of establishments. However, in 1983, there was a distinct jump in the number of establishments reported in the CBP. On further investigation, we discovered that the CBP data collection methodology changed from 1982 to 1983.[11] Moreover, as we see in Table 1, Panel A, only 3 counties had adopted BITNET before 1982. Given these factors, we decided to start our data in 1982 (with establishment data starting in 1983) to reduce potential noise that can be created by any changes in the data collection procedure in the CBP.[12] Consistent with Agrawal and Goldfarb (2008) and Wernsdorf et al. (2022), we also restrict our sample to counties with universities.

We create the variable *County Establishments*, which is the total number of establishments in a county-year. We also obtain *Log county establishments*, defined as the log of one plus *County Establishments*, in order to account for the skewness in the establishment data. In addition to the aggregate number of establishments, we also create the number of establishments by firm size (based on the number of employees) and by whether the industry is "high-tech." We define high-tech industries as those that are in high-technology or biotech areas based on three-digit SIC codes.[13] In our difference-in-differences (DiD) framework (shown in Eq. (1) in Section 5.1), given that we include county fixed effects, we capture entrepreneurship in a county and year effectively using the increase in the number of establishments in a county and year. This is consistent with the existing studies that use the number of establishments (and small establishments particularly) to assess entrepreneurial activity in a region (see, e.g., Samila and Sorenson, 2010; Chang et al., 2011).

Panel A of Table 2 reports the summary statistics of our establishment-level data. The median county in the 1983–1993 sample

[11] The CBP documentation reveals that "Establishment counts are based on a determination of active status as of anytime during the year. Locations for both single and multilocation firms determined to be active anytime during the year (presence of payroll in any quarter) are counted as an establishment. In years prior to 1983, establishment counts were based on the determination of active status in the fourth quarter. This change in definition was necessary to reduce differences in the published number of establishments between the County Business Patterns and the other economic data programs." (County Business Patterns, 1974–1986, Technical Documentation, U.S. Department of Commerce).

[12] In robustness checks, our results relating BITNET introduction to the number of county establishments also held while using pre-1983 data. We decided to start the data in 1983 nevertheless to reduce the noise in the establishment data.

[13] Appendix A lists the industries that we classify as high-tech.

Table 1
Distribution of BITNET adoption over time and across states.
Panel A shows the number of BITNET connections across counties from its inception in 1981 till 1990. Panel B shows the first time each state in the US was connected to BITNET.

Panel A: Yearly distribution of BITNET connections across counties

Year	Counties connected	Number of first-time nodes	Cumulative counties connected	Cumulative number of first-time nodes
1981	3	105	3	105
1982	12	208	15	313
1983	20	215	35	528
1984	32	294	67	822
1985	43	236	110	1058
1986	46	157	156	1215
1987	42	80	198	1295
1988	34	58	232	1353
1989	30	35	262	1388
1990	10	11	272	1399

Panel B: State distribution of BITNET connections

State Name	First year of BITNET connection	Number of BITNET nodes by 1990
Connecticut	1981	20
New York	1981	233
Pennsylvania	1981	114
California	1982	212
Maine	1982	5
Massachusetts	1982	104
New Jersey	1982	45
Ohio	1982	59
Rhode Island	1982	6
District of Columbia	1983	45
Illinois	1983	114
Maryland	1983	80
Missouri	1983	37
North Carolina	1983	47
Virginia	1983	33
West Virginia	1983	26
Arizona	1984	28
Colorado	1984	15
Delaware	1984	2
Florida	1984	31
Indiana	1984	39
Iowa	1984	10
Louisiana	1984	15
Tennessee	1984	38
Texas	1984	114
Wisconsin	1984	25
Alabama	1985	10
Georgia	1985	30
Idaho	1985	4
Kansas	1985	7
Kentucky	1985	19
Michigan	1985	25
Minnesota	1985	16
Nebraska	1985	16
New Mexico	1985	10
North Dakota	1985	4
Oregon	1985	13
South Carolina	1985	8
Utah	1985	12
Washington	1985	39
Wyoming	1985	1
Alaska	1986	1
Nevada	1986	2
New Hampshire	1986	3
Arkansas	1987	5
Hawaii	1987	11
Mississippi	1987	8
Oklahoma	1987	10
South Dakota	1987	2
Vermont	1987	6
Montana	1988	1

Table 2
Summary statistics of main variables.
Panel A shows the summary statistics for the variables used in the study. *AfterBit* takes the value of one for years in and after an institution in a county adopted BITNET, and zero otherwise. *AfterBit* (*Univ*) takes the value of one for years in and after a university in a county adopted BITNET, and zero otherwise. *AfterBit* (*Research Ctr*) takes the value of one for years in and after a non-university research center in a county adopted BITNET, and zero otherwise. *County establishments* is the total number of establishments in a county-year. *State GDP* is the state-level gross domestic product deflated by the consumer price index to 1987 dollars. *State* per capita *income* is defined as the state-level real 1987 income divided by the state's population in a year. *State population* is the state's population in a year. Panel B shows the distribution of the number of county establishments in a county-year by the number of employees. Panel C shows the distribution of county establishments in a county-year by technology classification.

Variable	N	Mean	25th pct	Median	75th pct	SD
Panel A: Summary of variables used in main analyses						
AfterBit	15,705	0.117	0	0	0	0.322
AfterBit (Univ)	15,705	0.111	0	0	0	0.315
AfterBit (Research Ctr)	15,705	0.023	0	0	0	0.149
County establishments	15,705	3535	618	1223	2799	8865
State GDP ($billion)	15,705	130,541	48,470	87,524	179,151	126,372
State per capita income ($thousand)	15,705	15.37	12.73	15.09	17.67	3.40
State population	15,705	7,034,697	2,928,507	4,966,587	10,737,743	5,953,635
Panel B: County establishments by size						
1–19 employees	15,705	3072	559	1093	2475	7576
20–49 employees	15,705	287	38	84	213	785
50–99 employees	15,705	99	12	27	70	290
≥100 employees	15,705	76	8	20	52	228
Panel C: County establishments by technology classification						
High-tech establishments	15,620	52	5	10	28	174
Low-tech establishments	15,620	3502	619	1222	2787	8725

period has 1223 establishments. Panel B reports the number of establishments by breakdowns based on number of employees (i.e., 1–19, 20–49, 50–99, and 100 or more). Consistent with expectations, the median number of small establishments, i.e., those with 1 to 19 employees (1093), is much higher than the median number of large establishments, i.e., those with 100 or more employees (20). In Panel C of Table 2, we see that, consistent with intuition, the median number of high-tech establishments is much smaller at 10 compared to the median number of low-tech establishments at 1222.

4.3. Other variables

We now describe the other variables used in our analysis. *State GDP* is the state-level gross domestic product deflated by the consumer price index to 1987 dollars. *State* per capita *income* is defined as the state-level real 1987 income divided by the state's population in a year. We also use *State population* as a control variable. We take log terms of *State GDP* and *State population* in our regressions to account for their skewness. The summary statistics of these variables are reported in Table 2.

In addition to the above variables, we create the variables *Patent Stock 1971–1980*, which is the total number of patents granted between 1971 and 1980 in a county, and *Citation Stock 1971–1980*, which is the total number of forward citations received by the patents in a county during the same period, as proxies for the knowledge richness of a county. Finally, to analyze the impact of BITNET adoption on knowledge spillover in a county, we use *Log county patents*, which is the log of one plus the number of patents applied for in a year from a given county. In addition, we create *Log county citations*, which is the log of one plus the number of citations of patents applied for in a year from a given county. Data on patents and citations are obtained from Li et al. (2014).

5. Results

5.1. The impact of BITNET adoption on the number of establishments

Our first analysis relates the adoption of BITNET in a county to subsequent levels of entrepreneurship in a location. Exploiting the staggered adoption of BITNET as a shock to the local knowledge base, we use a DiD framework for our baseline regressions as follows:

$$\textit{Log county establishments}_{c,t+1} = \alpha + \beta_1 \textit{AfterBit}_{ct} + \beta_2 X_{ct} + \lambda_c + \eta_t + \varepsilon_{ct} \tag{1}$$

Here, *Log county establishments*$_{c,\ t+1}$ is the number of establishments in a county in the subsequent year. *AfterBit*$_{ct}$ is the main BITNET adoption variable described above in year t in county c. X_{ct} refers to a set of control variables that account for state-level economic activity, as described in Section 4.3. λ_c and η_t are county and year-fixed effects, respectively. The coefficient β_1 is our main test coefficient. In particular, the knowledge spillover theory of entrepreneurship predicts a positive value for β_1. In all our regressions, we cluster standard errors at the county level and report cluster-robust standard errors in parentheses in our tables.

Column (1) in Table 3 reports the results of our baseline regression model in Eq. (1). The coefficient on *AfterBit* is positive and statistically significant at the 1 % level. Economically, the adoption of BITNET by a research institution in a county is associated with a 1.9 % increase in the number of establishments one year later. For the median county in our sample, this represents an increase of 23 establishments. Thus, BITNET adoption has a significantly large economic impact on startup activity in a county. This effect remains when we measure the number of establishments two and three years after BITNET adoption, as shown in Columns (2) and (3) of Table 3.[14]

In Column (4), we examine the effect separately for whether the BITNET-adopting institution is a university or research center. The results indicate that the positive impact of BITNET adoption on the

[14] We have also examined the impact of intensive margin of BITNET adoption on the number of establishments in a county. The results of this test are presented in Panel B of Table B.2 in Internet Appendix B and discussed in Section 5.5.

Table 3
Impact of BITNET adoption on county establishments.
This table shows the results of regressions where the dependent variables are the log of one plus the number of county establishments (Models 1–5, 8, and 9), the number of county establishments (Model 6), and the number of county establishments per thousand people living in the county (Model 7). Models 1 to 8 show the results of OLS regressions. Model 9 shows the average treatment effect using Callaway and Sant'Anna (2021) doubly-robust estimation procedure. All models except Model 5 include county and year fixed effects. Model 5 includes county and state-year fixed effects. *AfterBit* takes the value of one for years in and after an institution in a county adopted BITNET, and zero otherwise. *AfterBit* (*Univ*) takes the value of one for years in and after a university in a county adopted BITNET, and zero otherwise. *AfterBit* (*Research Ctr*) takes the value of one for years in and after a non-university research center in a county adopted BITNET, and zero otherwise. Model 8 reports dynamic staggered DiD estimates. *Bit-3* takes the value of one if the year is 3 years before an institution in a county adopted BITNET, and zero otherwise. *Bit-2* and *Bit-1* are similarly defined. *Bit0* is a dummy variable for the year of adoption. *Bit + 1* takes the value of one if the year is one year after an institution in a county adopted BITNET, and zero otherwise. *Bit + 2* to *Bit + 5* are similarly defined. Model 7 includes the complete set of possible relative-time periods (except the most negative and positive relative-time periods) but not all coefficients are reported for brevity. *Log state GDP* is the log of state-level gross domestic product deflated by the consumer price index to 1987 dollars. *State* per capita *income* is defined as the state-level real 1987 income divided by the state's population in a year. *Log state population* is the log of the state's population in a year. Standard errors clustered at the county level are in parentheses. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	CSDID
	Log county est. (t + 1)	Log county est. (t + 2)	Log county est. (t + 3)	Log county est. (t + 1)	Log county est. (t + 1)	County est. (t + 1)	County est. per population (t + 1)	Log county est. (t + 1)	Log county est. (t + 1)
AfterBit	0.019***	0.017***	0.013***		0.021***	765.653***	0.193***		0.013**
	(0.005)	(0.004)	(0.004)		(0.005)	(99.888)	(0.071)		(0.005)
AfterBit (Univ)				0.017***					
				(0.005)					
AfterBit (Research Ctr)				0.010					
				(0.012)					
Bit-3								0.006	
								(0.016)	
Bit-2								0.011	
								(0.016)	
Bit-1								0.017	
								(0.016)	
Bit-0								0.022	
								(0.016)	
Bit+1								0.025	
								(0.016)	
Bit+2								0.030*	
								(0.016)	
Bit+3								0.032**	
								(0.015)	
Bit+4								0.031**	
								(0.015)	
Bit+5								0.029*	
								(0.015)	
Log state GDP	0.359***	0.403***	0.379***	0.359***		−6.210	7.173***	0.356***	
	(0.034)	(0.032)	(0.029)	(0.034)		(187.926)	(0.517)	(0.034)	
State per capita income	0.009***	−0.001	−0.012***	0.009***		142.762***	0.112***	0.010***	
	(0.003)	(0.003)	(0.003)	(0.003)		(24.161)	(0.041)	(0.003)	
Log state population	0.266***	0.081	−0.033	0.267***		4173.282***	−13.434***	0.268***	
	(0.061)	(0.057)	(0.055)	(0.061)		(752.920)	(0.899)	(0.061)	
County and year FE	Y	Y	Y	Y	N	Y	Y	Y	Y
County and State-year FE	N	N	N	N	Y	N	N	N	N
Observations	15,705	14,271	12,837	15,705	15,705	15,705	15,705	15,705	15,520
R-squared	0.508	0.439	0.388	0.508	0.567	0.261	0.435	0.509	

number of establishments mostly comes from university adoptions.[15]

In Column (5), in addition to county fixed effects, we include state-year fixed effects to rule out any potential impact of local economic conditions on our results. In Column (6), we run our regressions without taking the log of county establishments. In Column (7), we scale the number of county establishments by county population (in thousands). *AfterBit* continues to be positively related to the number of county establishments in these specifications.

To establish that there is no prior trend in *Log county establishments* before BITNET adoption in a county and to alleviate any omitted variables or reverse causality concerns, we perform dynamic DiD regressions in Column (8). Following the recommendations of Baker et al. (2022) and Sun and Abraham (2021), these regressions include the complete set of relative-time indicators, although we report a subset of the coefficient estimates of these indicators for brevity. We drop the relative time indicators for the most positive and the most negative relative time periods to avoid perfect collinearity. We do not find a statistically significant trend effect in *Log county establishments* before BITNET adoption in a county. The coefficient estimates for the relative-time indicator variables become significant two years after the adoption of BITNET and remain significant. This result is consistent with the notion that there may be a lag between knowledge production spurred by BITNET

[15] In untabulated tests, we examine whether the effect of BITNET adoption differs based on whether the university is a top-tier university (defined as the 90 universities that received the most NSF funding during 1977–1980 Following Agrawal and Goldfarb (2008)). Our findings indicate that the positive effect of BITNET adoption on entrepreneurship is generally similar for both top-tier and non-top-tier universities.

Table 4
Impact of BITNET adoption on county establishments by industry type.
This table reports the results of OLS regressions where the dependent variables are the log of one plus the number of county establishments in high-tech industries (Model 1), and the log of one plus the number of county establishments in low-tech industries (Model 2). *AfterBit* takes the value of one for years in and after an institution in a county adopted BITNET, and zero otherwise. *Log state GDP* is the log of state-level gross domestic product deflated by the consumer price index to 1987 dollars. *State* per capita *income* is defined as the state-level real 1987 income divided by the state's population in a year. *Log state population* is the log of the state's population in a year. All models include county and year fixed effects. Standard errors clustered at the county level are in parentheses. The last row reports the difference in coefficient estimates for the two models. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	(1)	(2)
	Log county establishments (t + 1) by industry	
	High-tech	Low-tech
AfterBit	0.173***	0.017***
	(0.017)	(0.005)
Log state GDP	−0.288**	0.368***
	(0.118)	(0.033)
State per capita income	0.053***	0.008***
	(0.009)	(0.003)
Log state population	1.386***	0.240***
	(0.186)	(0.060)
County and year FE	Y	Y
Observations	15,639	15,639
R-squared	0.410	0.513
Diff in coef.	0.0156**	

Table 5
Impact of BITNET adoption on county establishments by establishment size and industry type.
This table shows the results of OLS regressions where the dependent variables are the log of one plus the number of county establishments by size and industry type. *AfterBit* takes the value of one for years in and after an institution in a county adopted BITNET, and zero otherwise. *Log state GDP* is the log of state-level gross domestic product deflated by the consumer price index to 1987 dollars. *State* per capita *income* is defined as the state-level real 1987 income divided by the state's population in a year. *Log state population* is the log of the state's population in a year. All models include county and year fixed effects. Standard errors clustered at the county level are in parentheses. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1–19 employees		20–49 employees		50–99 employees		>100 employees	
	High Tech	Low Tech	High Tech	Low Tech	High Tech	Low Tech	High Tech	Low Tech
AfterBit	0.190***	0.016***	0.140***	0.016**	0.121***	0.007	0.106***	0.006
	(0.019)	(0.005)	(0.026)	(0.007)	(0.025)	(0.009)	(0.019)	(0.010)
Log state GDP	−0.457***	0.328***	0.180	0.620***	−0.014	0.833***	0.150	0.436***
	(0.139)	(0.032)	(0.129)	(0.057)	(0.121)	(0.099)	(0.092)	(0.085)
State per capita income	0.068***	0.011***	0.025**	−0.005	0.043***	−0.028***	−0.009	−0.039***
	(0.011)	(0.003)	(0.011)	(0.005)	(0.012)	(0.007)	(0.009)	(0.006)
Log state population	1.702***	0.298***	0.505**	−0.133	0.347*	−0.402***	−0.193	0.181
	(0.217)	(0.059)	(0.223)	(0.093)	(0.205)	(0.152)	(0.168)	(0.146)
County and year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	15,639	15,639	15,639	15,639	15,639	15,639	15,639	15,639
R-squared	0.403	0.464	0.070	0.423	0.037	0.282	0.012	0.380
Diff in coef.	0.175**		0.124**		0.124**		0.100*	

adoption and new firm formation. It is also consistent with the findings of Wernsdorf et al. (2022), who show that the impact of BITNET on the number of university patents starts in the year following its adoption.

Baker et al. (2022) discuss the biases in two-way fixed effects staggered DiD regressions. They note that such regressions can result in biased estimates when there are relatively few never-treated units in the sample and when treatment effect heterogeneity is likely. It is reassuring to note that such a bias is unlikely to be a concern for us since we have many counties that have never adopted BITNET in our sample. However, it is possible that the impact of BITNET on the number of establishments increases gradually over time. As a result, universities that have only recently started using BITNET could potentially lower the estimated impact of BITNET on the number of establishments for universities that have already adopted it. To alleviate the concern about the second bias, we apply the regression, inverse-probability-weighted, and doubly-robust variants of Callaway and Sant'Anna (2021), as suggested by Baker et al. (2022). We report the average treatment effect using doubly-robust estimation procedure in Column (9) of Table 3. We obtain results consistent with those using other estimation procedures. The coefficient estimate of *AfterBit* remains positive and significant, indicating that our results remain robust after addressing the concerns for potential biases.

5.2. Results by establishment industry and size

To estimate the impact of BITNET introduction on true startup activity, we assess whether the results above are stronger for establishments in high-tech industries. Thus, we estimate regression model (1) for high- and low-tech industries separately. If BITNET adoption impacts startup activity in a county, then our results should be much stronger in high-tech industries, where the impact of knowledge will be much more significant. The results for these regressions are reported in Table 4. Consistent with our expectations, we find that the coefficient estimate on *AfterBit* is much larger for firms in high-tech industries, although the estimates are statistically significant for both high- and low-tech industries. Further, we find that the difference in coefficient estimates on *AfterBit* between high- and low-tech regressions is statistically significant at the 1 % level. In economic terms, BITNET adoption results in a 17.3 % increase in the number of high-tech establishments and a 1.7 %

Table 6

Impact of BITNET adoption on county establishments across areas with different levels of knowledge richness.

This table shows the results of OLS regressions where the dependent variable is the log of one plus the number of county establishments. *AfterBit* takes the value of one for years in and after an institution in a county adopted BITNET, and zero otherwise. *Patent Stock 1971–1980* is the number of patents applied for (that were eventually granted) in a county during 1971–1980. *Citation Stock 1971–1980* is the number of forward citations received by patents filed by a county during 1971–1980. For the ease of interpretation of coefficients, we standardize the raw variables of patent stock and citation stock. *Log state GDP* is the log of state-level gross domestic product deflated by the consumer price index to 1987 dollars. *State* per capita *income* is defined as the state-level real 1987 income divided by the state's population in a year. *Log state population* is the log of the state's population in a year. All models include county and year fixed effects. Standard errors clustered at the county level are in parentheses. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	(1)	(2)
	Log county establishments (t + 1)	
AfterBit	0.021***	0.021***
	(0.005)	(0.005)
AfterBit * Patent Stock 1971–1980	−0.002*	
	(0.001)	
AfterBit * Citation Stock 1971–1980		−0.002**
		(0.001)
Log state GDP	0.358***	0.358***
	(0.034)	(0.034)
State per capita income	0.009***	0.009***
	(0.003)	(0.003)
Log state population	0.266***	0.267***
	(0.061)	(0.061)
County and year FE	Y	Y
Observations	15,705	15,705
R-squared	0.508	0.508

increase in the number of low-tech establishments for a typical median county in our sample. Thus, these findings support the knowledge spillover mechanism through which the introduction of BITNET increases startup activity.

In Table 5, we segment our regressions by both size and industry type. Our findings show that the coefficient estimate on *AfterBit* is consistently statistically significant, with a significantly greater impact on high-tech industry establishments in all size categories as opposed to low-tech establishments. Moreover, the difference in the effect of BITNET on establishment count is most pronounced between high and low-tech industries for establishments with 19 or fewer employees. This difference is much smaller for establishments >100 employees and the difference in these differences is statistically significant at the 5 % level (0.175 vs. 0.10) Economically, the impact of BITNET adoption in a county is very large for small, high-tech establishments (a 19 % increase).[16]

Thus, the results from Tables 4 and 5 suggest that the impact of BITNET is the strongest for smaller, high-tech establishments, and weak for very large, low-tech establishments, consistent with the idea that BITNET-induced knowledge spillovers have a positive impact on entrepreneurial firm starts.

5.3. Impact in areas with different levels of knowledge richness

Next, we test whether the impact of BITNET on entrepreneurial activity in a county is different for knowledge-rich areas. We expect the incremental impact of BITNET in knowledge-rich areas to be weaker. We use the patent and citation stock in a county from 1971 to 1980 (prior to the introduction of BITNET in any US county) as proxies for knowledge richness. These proxies indicate the level of quantity and quality that has already been produced in a county. We conjecture that in counties where there is already a rich knowledge base and a substantial amount of knowledge production, the impact of BITNET adoption might be less pronounced.

The results of this analysis are reported in Table 6. In the regressions here, we interact *AfterBit* with *Patent Stock 1971–1980* and with *Citation Stock 1971–1980*. The coefficient estimates on the interaction terms between *AfterBit* and patent and citation stock variables are negative and significant. Thus, the results show that the impact of BITNET adoption is weaker in knowledge-rich areas consistent with our conjecture.

5.4. BITNET adoption and county-level innovation

In this section, we provide evidence that BITNET adoption in a county led to an increase in knowledge production. As our proxy for knowledge production and spillover, we use patents and citations to patents applied from a county. Thus, we estimate model (1) with dependent variables the log of one plus the number of patents applied in a year from a given county, and the log of one plus the number of citations for the patents in a year from a given county. Table 7 reports the results of these regressions. Columns (1), (2), and (3) report the results with one-year, two-year, and three-year ahead values of *Log county patents* as the dependent variable, and Columns (5), (6), and (7), report the similar period results for *Log county citations*.[17]

Our results are supportive of the conjecture that knowledge spillovers led to an increase in the number of patents and citations in a county. The coefficient estimate on *AfterBit* is positive and statistically significant in all specifications. The results continue to be significant when we use Callaway and Sant'Anna (2021) doubly-robust estimator, reported in Columns (4) and (8). Our results are consistent with those reported by Wernsdorf et al. (2022) who find that university-connected

[16] Results in Table 5 show a small impact of BITNET adoption in low-tech firms with <50 employees. We believe this might be due to the classification of high vs low-tech industries. Some firms that are typically classified as low-tech might still benefit from university innovations (see, for example, Maietta (2015), who documents university-firm R&D collaboration in the food and drink sector). It is also worth noting that the impact of BITNET on the number of small, low-tech establishments is economically much smaller than its impact on the number of small, high-tech establishments.

[17] The results are similar if we do not use log one plus the number of patents and citations as dependent variables but rather scale the number of patents and citations by county population.

Table 7
Impact of BITNET adoption on county-level innovation.
This table shows the results of OLS regressions (Models 1–3, 5–7) where the dependent variables are the log of one plus the number of patents applied in a year and county and the log of one plus the number of citations received by the patents applied in a year and county. Model 4 and 8 show the average treatment effect using Callaway and Sant'Anna (2021) doubly-robust estimation procedure. *AfterBit* takes the value of one for years in and after an institution in a county adopted BITNET, and zero otherwise. *Log county establishments* is the log of one plus the number of establishments in a county-year. *Log state GDP* is the log of state-level gross domestic product deflated by the consumer price index to 1987 dollars. *State* per capita *income* is defined as the state-level real 1987 income divided by the state's population in a year. *Log state population* is the log of the state's population in a year. All models include county and year fixed effects. Standard errors clustered at the county level are in parentheses. *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	CSDID	OLS	OLS	OLS	CSDID
	Log county patents (t + 1)	Log county patents (t + 2)	Log county patents (t + 3)	Log county patents (t + 1)	Log county citations (t + 1)	Log county citations (t + 2)	Log county citations (t + 3)	Log county citations (t + 1)
AfterBit	0.149***	0.152***	0.150***	0.165**	0.245***	0.186***	0.191***	0.173***
	(0.028)	(0.027)	(0.026)	(0.070)	(0.056)	(0.059)	(0.059)	(0.061)
Log state GDP	0.040	0.064	0.136		−0.494	−0.417	0.058	
	(0.150)	(0.166)	(0.166)		(0.336)	(0.366)	(0.360)	
State per capita income	0.015	0.021	0.017		0.047	0.057*	0.022	
	(0.013)	(0.014)	(0.014)		(0.031)	(0.033)	(0.034)	
Log state population	1.255***	1.223***	1.097***		1.968***	1.904***	1.439**	
	(0.267)	(0.281)	(0.296)		(0.573)	(0.600)	(0.643)	
County and year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	15,705	14,271	12,837		15,705	14,271	12,837	
R-squared	0.164	0.157	0.139		0.041	0.035	0.028	

inventors increase patenting after the adoption of BITNET.[18] Our evidence of an increase in citations of local patents after BITNET is introduced in a county also indicates that the new knowledge produced is of higher quality and thus could be a driver for entrepreneurship, given existing evidence that shows higher quality patents (characterized by greater citations) lead to greater success of startups (e.g., Balasubramanian and Sivadasan, 2011; Hsu and Ziedonis, 2013). Overall, these results indicate the spillover of knowledge created in universities in a county into corporate knowledge production.

In Table B.1 of Internet Appendix B, we also conduct a mediation analysis and find that the effect of BITNET adoption on entrepreneurial activity is mediated through increased knowledge creation (as proxied by patenting activities), which supports the argument that the effect of BITNET adoption on entrepreneurship occurs at least partly through knowledge spillovers.

5.5. Robustness tests

We perform a battery of robustness checks and additional analyses and report the results of these tests in Internet Appendix B. First, we test the robustness of our results to the timing of the BITNET adoption. Our main results treat the adoption of BITNET based on the calendar year. For example, whether an institution adopted BITNET in January or December of 1984, it would be coded as adopted in 1984. Naturally, BITNET adoption in January might have different effects than BITNET adoption in December. Thus, we check the robustness of the results by redefining the cutoff period for BITNET adoption. Table B.2 of Internet Appendix B presents the results of these robustness tests. In Panel A of Table B.2, we define *AfterBit* (*Q1*) as a dummy variable that takes the value of one for the year if an institution in a county adopted BITNET in the first quarter of that year and for all the years later on, and zero otherwise. The results are similar to our reported main tests. In unreported tests, we also define the *AfterBit* variable as one if an institution in a county adopted BITNET in the first half of the year and for all the years later on, and zero otherwise. The results remain robust with this definition as well.

Second, we examine the impact of the intensive margin of BITNET adoption on the number of establishments in a county. For this test, we create the variable *Frac Bit Adoption* as the fraction of institutions that have adopted BITNET in a particular year and county. The results of the tests with this variable are presented in Panel B of Table B.2 in Internet Appendix B. We find that the fraction of institutions that have adopted BITNET is also positively related to the number of establishments in the county, indicating that our results hold at the intensive margin.

Third, to address the concern that the establishment definition in County of Business Patterns (CBP) data also captures expansions and relocations of existing firms, we gather data from the Census Bureau's Business Dynamics Statistics (BDS). Although, unlike CBP, this dataset does not provide the number of establishments in a county by size and the industry, it does provide the number of firms (rather than establishments) in a county and the number of firms with age zero. Thus, we repeat our main test using the number of firms in a county (rather than the number of establishments) and report these tests in Columns (1) to (3) of Table B.3. The results continue to show an increase in the number of firms in a county after BITNET adoption. We also use the number of startups (firms with an age of zero) as the dependent variable in regressions presented in Columns (4) to (6) in Table B.3. The results suggest an increase in startup growth after BITNET adoption. These additional tests support our conclusions that BITNET led to an increase in entrepreneurship in the country in which it was adopted.[19]

Fourth, we examine whether the effect of BITNET adoption on the number of establishments is stronger for information and communication technology (ICT) producing industries. Agrawal and Goldfarb (2008) focus on examining the effect of BITNET on electrical engineering publications, arguing that researchers in such technical fields are more inclined to embrace new communications technologies. Thus, it is

[18] Our analysis of the impact of BITNET on county patents is similar to that of Wernsdorf et al. (2022). They examine how BITNET affects patenting by university-connected inventors. We focus on the impact of BITNET on patenting within a county. However, our main analysis centers on the effect of BITNET on the formation of new firms, an area that Wernsdorf et al. (2022) do not investigate.

[19] Business Dynamics Statistics provides the number of firms in a county at the sector level based on a two-digit NAICS code. This classification is too broad to identify high-tech industries, thus we were unable to repeat our tests in Table 4 with this dataset.

plausible that the effect of BITNET adoption on the number of establishments is stronger for ICT-producing industries. We test this conjecture by conducting our regressions separately for the number of establishments in ICT-producing industries, all non-ICT-producing industries, and other non-ICT-producing high-tech industries (e.g., drugs and medical instruments and supplies). We present these results in Table B.4 of Internet Appendix B. Our findings do not show a stronger effect of BITNET adoption in ICT-producing industries compared to other high-tech industries. However, these results are consistent with the evidence of Ding et al. (2010), who show that BITNET adoption also increased productivity and collaborative networks of life scientists.

Fifth, we check the robustness of our results using MSA as a unit of observation, as opposed to using county as a unit of observation in the main tests, since the impact of BITNET adoption can be broader and spill over to neighboring counties. We report these results in Tables B.5, B.6, and B.7 of Internet Appendix B. Our results remain robust when we measure BITNET adoption and the number of establishments at the MSA level.

Finally, we examine the robustness of dynamic DiD regressions (presented in Column (8) of Table 3) to address concerns regarding the truncation of these pre- and post-trend dummies. In Columns (1) to (3) of Table B.8 in Internet Appendix B, we limit the leads and lags to t - 5 to t + 5, t - 3 to t + 3, and t - 2 to t + 2, respectively. Consistent with the main results reported in the paper, we do not observe a significant effect before BITNET adoption. The effect starts mostly in t + 1, although the economic significance is small for that year. The effect becomes statistically and economically significant starting two years after the BITNET adoption. Furthermore, we check the robustness of the results by excluding the counties that adopted BITNET before 1985 and those that adopted BITNET before 1984 in Columns (4) and (5), respectively. This ensures that the same leads and lags are defined for all counties. The results remain similar to the main results presented in the paper.

6. Discussion and conclusion

How do entrepreneurial opportunities arise? We try to answer this question by analyzing the extent to which knowledge spillovers create entrepreneurial opportunities. We exploit the adoption of BITNET, an early predecessor of the Internet, across universities in the U.S. as an exogenous shock to the knowledge base in the county where the university is located. We analyze how the introduction of BITNET in universities impacted local entrepreneurship. Using County Business Patterns data, we document a positive relationship between entrepreneurship (as measured by the increase in the number of establishments in a county) and the adoption of BITNET at a university in that county. Further, this relationship is stronger for establishments in high-tech industries and for smaller establishments. These results indicate that knowledge spillovers from local universities can have a strong impact on entrepreneurial opportunities in a location. Our results are weaker in counties with higher patent and citation stock, suggesting that knowledge spillover is likely to be the mechanism linking BITNET adoption to local entrepreneurship. To provide further support for the knowledge spillover effects, we show that the number of patents and citations in a county increases after the adoption of BITNET in a county. Further, a mediation analysis demonstrates that the effect of BITNET adoption on entrepreneurial activity is mediated through increased knowledge creation (as proxied by patenting activities). Taken together, our results support the notion that the effect of BITNET adoption on entrepreneurship is at least partly due to knowledge spillovers.

Our results are broadly consistent with the knowledge spillover theory of entrepreneurship, which suggests that entrepreneurial opportunities arise when research institutions fail to monetize the knowledge they produce, and employees and other related agents can expropriate economic rents from this knowledge by starting up their own firms. We shed significant novel light on the existing research by showing that BITNET adoption leads to greater entrepreneurship by inducing a positive shock to the local knowledge base. By highlighting the crucial role played by information technology that allows knowledge creation and diffusion in stimulating entrepreneurship, our study also generates important policy implications for improving the prospects of entrepreneurship.

As with all studies, ours has some limitations that provide opportunities for further research. First, we provide somewhat indirect evidence on the potential mechanisms underlying the knowledge spillover effects on entrepreneurship: We documented a positive effect of BITNET adoption on local patents and found local patents (as an imperfect proxy for new knowledge creation) mediated the effect of BITNET adoption on entrepreneurship. However, more research is needed to provide more direct evidence on the exact mechanism(s) through which BITNET adoption affects entrepreneurship through knowledge spillovers using better data and measures. Second, we aim to test the knowledge spillover on entrepreneurship theory by exploiting the exogenous adoption of BITNET in different counties. To identify the casual impact of BITNET adoption, we control for the local entrepreneurial talent pool and culture, local regulation and policies in different regions by including county fixed effects in our empirical framework. Therefore, our findings shed little light on how the spillover effects due to BITNET adoption depend on entrepreneurial culture as well as skills and abilities. We encourage future research to delve deeper into these issues.

CRediT authorship contribution statement

Mine Ertugrul: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Karthik Krishnan:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Qianqian Yu:** Writing – review & editing, Formal analysis, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. High-tech industry classification

SIC code	SIC code description
283	Drugs
357	Computer and office equipment
366	Communications equipment
367	Electronic components and accessories
369	Misc. electrical equipment and supplies
381	Search and navigation equipment
382	Measuring and controlling devices
384	Medical instruments and supplies
385	Ophthalmic Goods
481	Telephone communication
489	Communication services, n.e.c.
737	Computer and data processing services
873	Research and testing services

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.respol.2024.105091.

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