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ICT, Collaboration, and Science-Based Innovation: Evidence from BITNET

Abstract

Does access to information and communication technologies (ICT) increase innovation? We examine this question by exploiting the staggered adoption of BITNET across U.S. universities in the 1980s. BITNET, an early version of the Internet, enabled e-mail-based knowledge exchange and collaboration among academics. After the adoption of BITNET, university-connected inventors increase patenting substantially. The effects are driven by collaborative patents by new inventor teams. The patents induced by ICT are exclusively science-related and stem from fields where knowledge can be codified easily. In contrast, we neither find an effect on patents not building on science nor on inventors unconnected to universities.

JEL-Codes: H540, L230, L860, O300, O320, O330.

Keywords: ICT, communication, knowledge diffusion, science-based innovation, university-patenting.

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1 Introduction

Scientific and technological advances are thought to be critical drivers of economic growth. Modern theories put cumulative innovation, i.e., that inventors stand on the proverbial shoulders of prior innovations, and collaboration at the heart of the ideas production function (Romer, 1990; Jones, 2009). If these theories are true, information and communication technologies (ICT) could supercharge the innovation process, as they greatly facilitate collaborating with other researchers and learning from and building on the codified knowledge of others.

Does access to ICT increase innovation? Answering this question is important as significant economic resources are spent to extend access to ICT to every region in the developed world. For example, the British government has pledged £5 billion in its 2020 budget to ensure high-speed broadband internet across the UK until 2025.[1] However, it is far from obvious that there should be strong effects of ICT on innovation. On the one hand, ICT gives inventors easier access to a wider range of ideas and potential collaborators which can potentially lead to new inventions. On the other hand, ICT might have no effect at all because relevant information for inventions is difficult to codify, people are reluctant to share valuable information, or collaborations are costly.

This paper exploits the staggered adoption of BITNET, an early version of the Internet, among U.S. universities between 1981 and 1990 to provide evidence whether access to ICT affects local innovation. BITNET was initiated in 1981 with the aim of setting up a messaging network for students. At its start, it only connected three universities, but it quickly became the most widely adopted network in academic institutions worldwide, with about 1400 member organizations in 1991. BITNET greatly facilitated the exchange of knowledge by reducing communication costs. For the first time, it allowed written communication through e-mail, real-time messages, and also featured e-mail lists and discussion groups. BITNET was only discontinued in 1996, when the World Wide Web became dominant.

To estimate the impact of BITNET adoption on innovation in a region, we focus on patents assigned to universities ("university patents") as only university affiliates had access to BITNET. In our empirical specification, we compare the change in the number of university patents in a region before and after the local university adopted BITNET with changes in the number of university patents around universities that are not yet connected to BITNET. Thus, we compare the change in innovative activity around treated universities to the change in not-yet-treated universities that eventually

[1] For example (last accessed 2020-10-15):
https://www.bloomberg.com/news/articles/2020-03-08/johnson-announces-6-5-billion-boost-for-u-k-broadband-service

adopt BITNET in later periods. Our analysis focuses on the years between 1981 and 1990, the time period during which the network was rolled out.

We find that the introduction of BITNET results in an average increase of 0.3 university patents per 100,000 population relative to control universities. This corresponds to an around 50% rise in university patenting. If we weigh each patent with its forward citations to account for quality, we find an increase of around 1.8 citation-weighted university patents per 100,000 population. However, we also find that the average university patent receives fewer citations after BITNET introduction. In line with the idea that ICT can facilitate communication and improves the transmission of codified knowledge that is otherwise unavailable locally, we find that the impact is entirely driven by universities in rural areas. While the effects are somewhat stronger for early adopters, we see positive impacts of BITNET adoption on inventor productivity throughout the sample. The effect is driven by universities with an above-average patenting activity before BITNET adoption, suggesting complementarity of information access with local innovative capabilities. The effects are also robust to a wide range of robustness and plausibility checks. Most importantly, there is no impact of BITNET on non-university patents.

In additional analyses, we provide evidence that collaboration among new inventor teams in areas where knowledge can be codified is the mechanism behind our effects. We first show that our results are driven by inventor teams (Agrawal and Goldfarb, 2008). Second, we then dig deeper and show that new inventor teams which had not yet collaborated before increase their patenting most. Third, we show that the size of the effect differs across technology categories. The effect is strongest in fields such as Chemistry and Instruments, where knowledge is more easily codifiable (Gambardella et al., 2011). These results are in line with the notion that BITNET facilitated the exchange of knowledge in written form among collaborators.

We then show that the patents induced by ICT are patents that are close to science. Using data on patent-to-article citations by Ahmadpoor and Jones (2017), we show that the effect is entirely driven by patents that either directly cite research articles ("science-based") or at least cite other patents that are science-based ("science-related"). In contrast, patents that are not science-related are unaffected by the adoption of BITNET. In line with the transmission of scientific information as mechanism behind our result, we show that the excess patents induced by ICT use words that are either completely new (i.e. used for the first time in a U.S. patent) or are new in the region around the university. Patents that do not contain words in either of these two categories again show no change after BITNET adoption.

Our findings contribute to the literature on ICT and knowledge production by showing a large positive effect of ICT on science-based patenting. The most closely related paper is Forman and van Zeebroeck (2012) that analyzes the effect of basic internet on the productivity of inventors in firms. They do not find any effect. In line with our results, Kleis et al. (2012) find a positive effect of general IT investments on firm innovation. We provide new evidence for a positive impact of ICT on the productivity of inventors in a setting where the change in communication costs due to ICT is likely larger than in the later years studied in Forman and van Zeebroeck (2012).

Our work is also related to several studies that look at the effect of BITNET on scientific publications. For example, Winkler et al. (2010) and Ding et al. (2010) focus on academic life scientists and find some evidence that BITNET increased the publication rates of life scientists. Agrawal and Goldfarb (2008) examine the effect of BITNET on collaboration among university scientists in electrical engineering between 1981 and 1991 and find a positive impact. Our paper finds that there is a positive effect of ICT on patenting, likely due to increased collaboration among new inventor teams. Most importantly, these new collaborations seem to translate scientific insights into innovation. Since patents close to science are particularly valuable (Poege et al., 2019; Watzinger and Schnitzer, 2019; Arora et al., 2019) and we do not completely understand under which circumstances they emerge (e.g., Bikard, 2018; Bikard and Marx, 2020), this is a valuable contribution.

This paper also extends the literature on the effect of ICT on productivity and growth to innovation. Recently, there have been contributions on the impacts of ICT on knowledge spillovers, firm productivity, and firm organization (Huang et al., 2016; Saunders and Brynjolfsson, 2016; Forman and McElheran, 2019; Forman and van Zeebroeck, 2019). On the macro level, Czernich et al. (2011) show that increases in broadband penetration raise annual per capita growth in OECD countries.[2] Extending this literature to innovation is important since innovation, and especially science-based innovation, is a key driver of economic growth and long-run productivity.

2 Institutional Background: BITNET

Ira H. Fuchs and Greydon Freeman initiated BITNET ("**B**ecause **I**t's **T**here **NET**work") in 1981 as a communication network between students of different universities.[3] BITNET became the most widely used network for communication in scientific research.

[2]See also Andersen et al. (2012). Other strands of the literature on the impacts of ICT for example study the impacts of internet access on education and labor market outcomes (e.g., Machin et al., 2007; Akerman et al., 2015; Dettling et al., 2018; Bhuller et al., 2019), on political participation (e.g., Falck et al., 2014; Campante et al., 2018; Gavazza et al., 2019), and on social capital (e.g., Bauernschuster et al., 2014; Geraci et al., 2019).

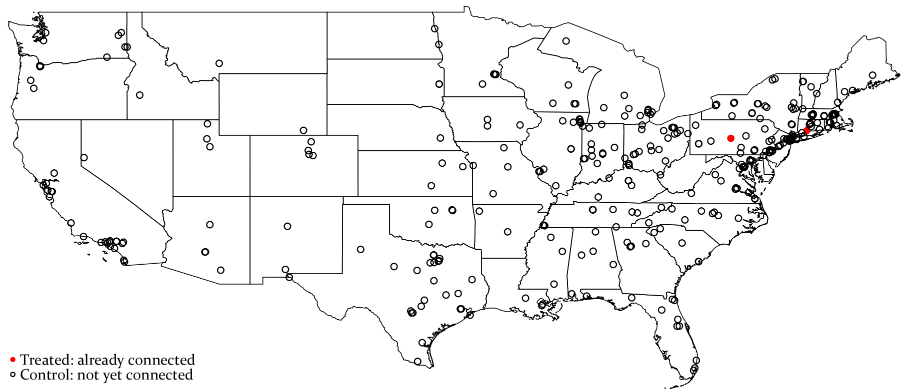
[3]The information summarized in this paragraph is based on Gale Encyclopedia of E-Commerce (2019), Ramirez (2014), Gurbaxani (1990), Agrawal and Goldfarb (2008), CREN (1997), Living Internet (2000).

The network featured email communication, real-time messages, transmission of text files and programs. The most popular feature were mailing lists on almost 3,000 different topics. These at the time novel ways of communication permitted active discussions and knowledge exchange even among geographically separated scientists.

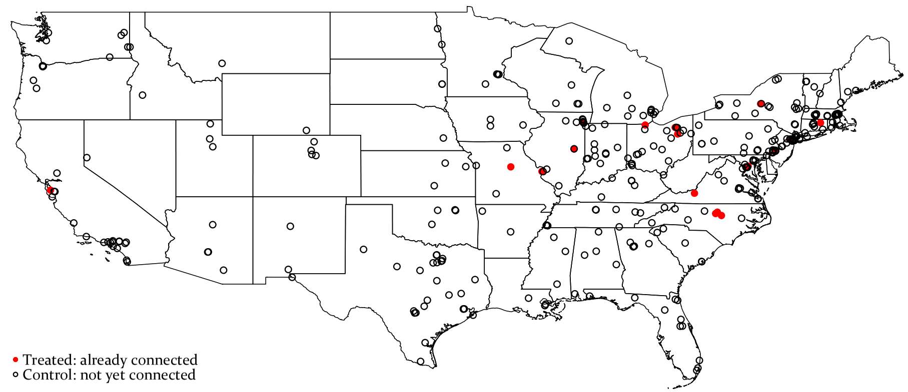
In the beginning, Ira H. Fuchs and Greydon Freeman directly approached IT administrators via letters and phone calls to outline the benefits of joining the network. Institutions could join BITNET if they fulfilled several requirements: First, they had to lease a phone line which allowed them to connect to the network. Second, each institution had to serve as entry point for a new potential member. Third, each institution contributed intermediate storage and computer processing power. Membership was initially free. Yet, each institution had to lease the phone lines to connect to the network. Leasing these lines could be quite costly, depending on the distance between the potential new member and the already existing members of the network. In 1986, a membership fee was implemented which was dependent on the annual budget of the institution.

BITNET spread quickly across the United States and around the world. The first connection was established between the City University of New York and Yale University in May 1981. Figure 1 displays the geographical dissemination of BITNET in the continental United States for the years 1981, 1983, 1985, and 1987. Universities which adopted BITNET up until the respective year are shown as red dots. Universities connecting to BITNET that were not yet connected are shown in black hollow circles. In 1981 only three universities were connected to the network. In 1983 the number of members was 36, 133 in 1985, and 248 in 1987. By 1990, 365 U.S. universities had joined the network. In 1991, at the peak of its popularity, the network had connected about 1,400 organizations in almost 50 countries. BITNET was discontinued in 1996 as the number of BITNET members declined due to the rise of the internet.[4]

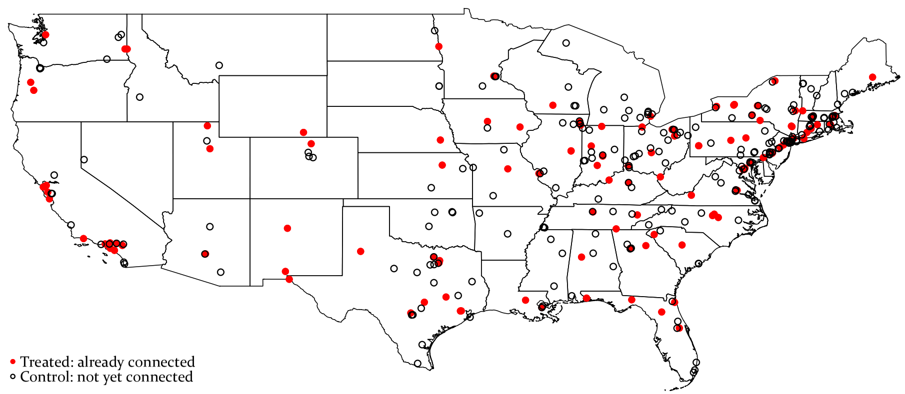
[4]The network formation has been studied by Kellerman (1986).



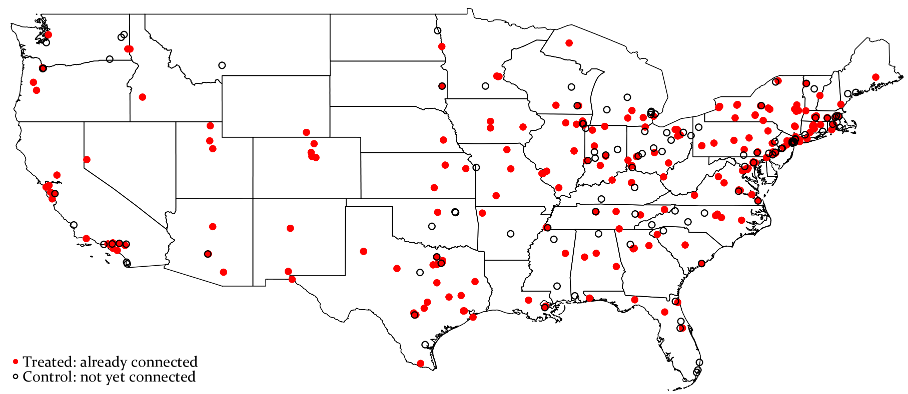
(a) BITNET adoption by 1981



(b) BITNET adoption by 1983



(c) BITNET adoption by 1985



(d) BITNET adoption by 1987

Figure 1: Location of Treated and Control Universities

Note: Universities connecting to BITNET prior to or in the respective year are displayed by red dots and constitute the treatment group in our analysis. Universities adopting BITNET later than the considered year are depicted by black hollow circles and constitute the control group. Universities located in Hawaii and Alaska are omitted from the figure for better visibility.

3 Empirical Setup and Data

In the empirical analysis we aim to estimate the impact of adopting BITNET at a university on university patenting in proximity to the institution.[5] To do this, we need an estimate of how patenting activity in that region would have evolved had the university not received BITNET access. To construct this counterfactual, we exploit the staggered adoption of BITNET between 1981 and 1990. Our control group consists of regions around universities that received BITNET at a later point in time. Figure 1 shows the treatment and control universities for the years 1981, 1983, 1985, and 1987.

Regions that have not yet connected to BITNET are a useful control group if patenting in these regions follows the same trend as patenting in regions with BITNET access would have, had the institution not connected to BITNET. Although we cannot verify the validity of this assumption, historical evidence suggests that the time of connection to BITNET was probably not systematically related to any factor that could also influence patenting. In particular, the decision to adopt BITNET was the responsibility of the directors of university computing centers and not undertaken by individual scientists (Agrawal and Goldfarb, 2008). For that reason, Ira H. Fuchs, one of the founders of the network, targeted IT administrators by sending out letters and by advocacy in public forums of IT professionals to persuade new member institutions to join. As IT administrators are not regularly involved in research efforts, it seems unlikely to us that individual scientists were aware of the potential benefits of joining the network. In line with this, we show below that prior to the actual adoption of BITNET, regions around treatment and around control universities are on parallel trends in terms of per-capita patenting.

In our main specification, we estimate the following difference-in-differences specification to quantify the impact of adopting BITNET on patenting:

$$y_{ijt} = \beta_1 \cdot Post_{it} + \beta_2 \cdot BITNET_{ij} \cdot Post_{it} + \mu_t + \gamma_{ij} + \varepsilon_{ijt} \tag{1}$$

where i is the group of treated university, j is the university under consideration (with $i = j$ for the treated university) and it indexes the time relative to the event (BITNET adoption of university i) in years. y_{ijt} corresponds to the outcome of interest, $Post_{it}$ is an indicator which equals one in the years after BITNET was introduced and $BITNET_{ij}$ is an indicator equal to one for the treated university. In all specifications, we include year and institution fixed effects. We adjust for the different number of

[5] We use *university patents with an inventor localized in the region of the university* instead of *patents assigned to the regional university*. The reason is that it is often unclear from the name of assignee which university is meant. For example, patents of all universities of the University of California System are assigned to "The Regents of the University of California". Similar problems appear with patents assigned to public universities throughout the United States.

control observations for each treated university by using weights (Iacus et al., 2012). Standard errors are clustered at the treated institution level (i). β_2 measures the average increase in the outcome variable in the four years after the introduction of BITNET.

In our main analysis, the outcome of interest is the number and quality of university-assigned patents. We capture patent quantity by the yearly overall number of patents assigned to a university and filed by inventors within 15 miles around the university. This distance approximately corresponds to the average commuting distance in the United States.[6] For patents with multiple inventors, we allocate an equal share of the patent to each inventor's location. To factor in quality differences between patents, we use the number of citation-weighted patents.[7] To account for the regionally varying population, in all analyses we divide the number of patents and citation-weighted patents by the population within 15 miles of the university.

For our empirical analysis, we combine various data sources. The information on universities and their BITNET status is from the Atlas of Cybergeography.[8] The data covers 1054 institutions worldwide, among them universities, government institutions and companies, which connected to BITNET between 1981 and 1990. It includes the exact adoption date as well as information on the number of connections (nodes) to other institutions. Of these institutions, we keep only U.S. universities. The exact university geolocations are from the Integrated Postsecondary Education Data System.[9] Finally, the U.S. Census in 2010 provides information on the population within a certain region around each university (NBER, 2010). The patent data is from PATSTAT. To obtain the geographic location of the inventors, we use the geolocated patent data from Morrison et al. (2017).

Table A1 in Online Appendix A shows summary statistics for the universities in our sample in the year before their respective BITNET adoption. The average university has around 0.7 university patents and 2.8 citation-weighted patents per 100,000 population in the year before BITNET adoption. Most of these patents are in the areas of Chemistry and Instruments.

[6] Information from a poll reveal an average commuting distance of roughly 15 miles (ABC News, 2005). Rapino and Fields (2013) find a mean commuting distance of around 19 miles (including extreme commutes).

[7] To this end, we determine the number of forward citations received within 5 years after its application date (including the year of application) for each patent.

[8] The file including information on BITNET institutions is available at https://personalpages.manchester.ac.uk/staff/m.dodge/cybergeography/atlas/bitnet_topology.txt.

[9] Source: U.S. Department of Education (2019).

4 The Impact of BITNET on Patenting

We start our examination of the innovation effects of BITNET by estimating a variant of equation (1) with time-varying treatment effects. Figure 2 displays the yearly treatment effects for the number of university patents per 100,000 persons in the 15 miles region around a university. We use the year before BITNET adoption as baseline period. Consistent with the parallel trends assumption, the estimates are very small and statistically insignificant prior to BITNET adoption. This speaks in favor of the parallel trends assumption. After BITNET adoption, the number of patents increases around treated universities relative to universities that have not yet adopted BITNET.[10] The impact starts in the year after BITNET adoption and increases over time.

Table 1 presents the difference-in-differences estimation results for equation (1). In line with the figure, Column (1) shows a positive impact of BITNET on the number of patents per 100,000 population relative to universities that gain access to BITNET later. On average, the number of patents increases by 0.34. Relative to the average of the outcome variable, this is an increase of around 50%. These results suggest that BITNET spurred local innovation close to adopting universities. In Column (2) we use citation-weighted patents as the dependent variable and find a positive and significant effect on citation-weighted patents. This suggests that the patents resulting from the adoption of BITNET are somewhat useful. However, when we analyze the impact of BITNET on the number of forward-citations per patent, we find that the average patent around treated universities receives around 15% fewer citations in the four years after BITNET introduction, relative to patents in the control group. Thus, the marginal patents induced by the adoption of BITNET seem to be of somewhat lower quality than an average patent in the control group.

In the remainder of the table, we investigate the heterogeneity of these results. In Columns (4) and (5), we split the sample by population density. We find that universities with below-median population densities (labeled "rural") drive the entire effect. For universities in urban environments, we do not find an effect of BITNET on local innovation. This is in line with the idea that ICT facilitate communication and collaboration in particular in rural regions. In Columns (6) and (7), we split the sample by the treated university's pre-BITNET patenting levels. We find that the effect is entirely driven by universities that already showed elevated patenting levels before the introduction of BITNET. This could point to a complementary between ICT and local inventive capacity. In Columns (8) and (9), we show that the effect is larger for early adopters, but is also substantial for late adopters.

[10] Figure A1 in Online Appendix B shows the analogous figure using citation-weighted patents as outcome.

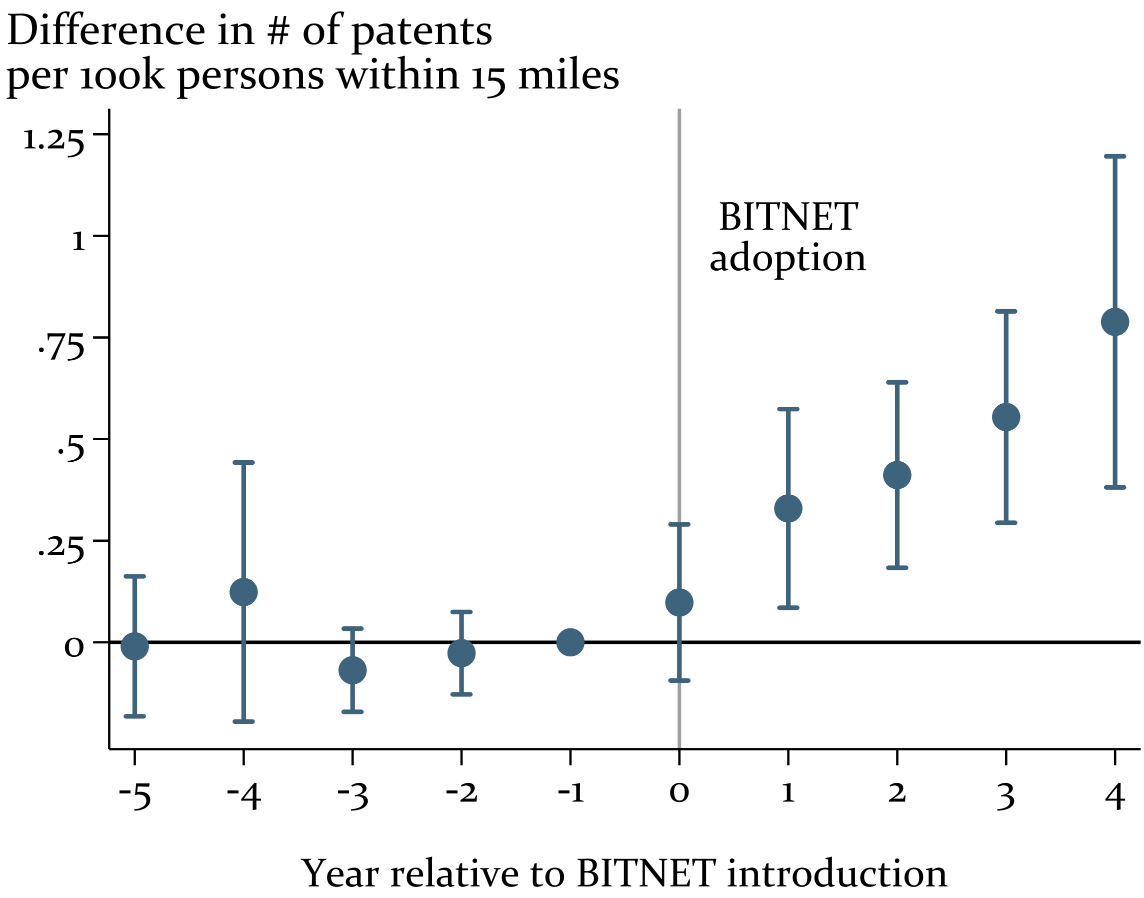


Figure 2: Effects of BITNET on Local Patenting Relative to the Connection Date

Note: This figure shows the yearly average treatment effects of BITNET adoption on the number of university patents per 100,000 population within 15 miles of universities adopting BITNET relative to universities that only adopt BITNET later. The blue bars represent 95% confidence bounds that allow for clustering at the treated institution level. To adjust for the different number of control universities, we use the weights suggested by Iacus et al. (2012).

Dep. Var.:	Univ. patents p.c.	Cit.-wght. univ. patents p.c.	Average citations	University patents p.c.						Non-univ. patents p.c.
				Rural Area	Urban Area	High Patenting	Low Patenting	Early Adopters	Late Adopters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Post	-0.00	0.00	-0.04***	-0.00	0.00	-0.02***	-0.00***	-0.00	0.02***	-0.14***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
BITNETxPost	0.34***	1.78***	-0.36***	0.72***	0.03	0.40***	-0.00	0.46***	0.22*	-0.16
	(0.09)	(0.53)	(0.11)	(0.18)	(0.05)	(0.14)	(0.00)	(0.13)	(0.12)	(0.42)
Mean Dep.	0.64	2.51	2.39	0.66	0.61	1.33	0.02	0.68	0.61	23.30
R2 (within)	0.02	0.03	0.04	0.01	0.17	0.03	0.03	0.01	0.02	0.14
Obs.	531063	531063	531063	266195	264868	245809	285254	327352	203711	531063

Note: This table shows difference-in-differences estimates of BITNET adoption on local patenting. The treatment group are universities that are already connected to BITNET. The control group consists of universities that are not yet connected to BITNET but that are connected to BITNET later. All specifications include year fixed effects and institution group fixed effects. Column (1) as well as Columns (4) through (9) use patents by university-connected inventors adjusted by the population in the 15 miles region around the university as the dependent variable. Column (2) uses forward citations to these patents per population as the dependent variable and Column (3) uses average citations per patent among university-connected inventors as the dependent variable. Columns (4) and (5) split the sample by median local population density in the year before BITNET adoption. Columns (6) and (7) split the sample by median patenting rates per 100,000 population in the 15 miles region around universities in the year before BITNET adoption. Columns (8) and (9) split the sample into early and late BITNET adopters. Early adopters are those universities that are connected by the end of 1985. Column (10) uses patents per 100,000 population by inventors not connected to universities as the dependent variable. To adjust for the different number of control universities, we use the weights suggested by Iacus et al. (2012). Robust standard errors, adjusted for clustering at the treated institution level, are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 1: Main Results and Heterogeneity of Effects

So far, our analysis has focused on patents filed by universities. This is because BITNET was designed as an academic network and consisted almost entirely of academic institutions. If the parallel trends assumption holds, it is reasonable to expect effects on university patenting but less so on the patenting of other inventors. In contrast, if unobservable regional shocks were driving our effects, we would expect to see similar productivity effects for other inventors as well. To test this, we rerun our analysis using patents filed by inventors unconnected to universities as the dependent variable. We combine those assignees who invent for companies, government non-profit organizations, individuals, and hospitals; and other unassigned inventors. Column (10) shows the result from this analysis. The impact of BITNET on inventors unconnected to universities is negative and statistically not significantly different from zero.

4.1 Further Analyses in the Online Appendix

In Online Appendix C we show that the effect of BITNET is most pronounced in fields where knowledge can be easily codified. A field for which knowledge transmission in written form is likely to matter is Chemistry, as chemical knowledge can be entirely described in formulas. For example, patented inventions in this area disclose the formula of the chemical compound and therefore the full invention. This makes codified knowledge particularly useful for future inventors. In other areas, such as Mechanical Engineering, inventors are less enthusiastic about technical descriptions (Gambardella et al., 2011). We would therefore expect the effect to be strongest in fields where information can be more easily transmitted in written form if access to codified knowledge is the underlying driver of our results. When we split the dependent variable into patenting in different fields, this is exactly what we find (see the results in Online Appendix C). We observe a positive and significant effect in Chemistry and in Instruments, followed by Electrical Engineering. Fields such as Mechanical Engineering, where codified knowledge is less useful, do not show any effects.

In addition, in Online Appendix D we show the results from several auxiliary analyses. In Appendix D.1 we show that results are not driven by a particular university or region. In Appendix D.2 we show the results of alternative control groups that rely on more stringent matching strategies and find similar results. In Appendix D.3, we estimate different plausible alternative versions of the main specification, accounting for the skewed nature of patenting, and find similar results.

5 Mechanism: Collaboration and Science-Based Patenting

5.1 Effects are Driven by Collaborative Patents by New Inventor Teams

One reason why BITNET may lead to more patenting is easier team formation (Agrawal and Goldfarb, 2008; Ding et al., 2010; Forman and van Zeebroeck, 2012). For example, e-mail and discussion forums made it easier to identify potential collaborators with complementary capabilities.

Table 2 shows the results of our analysis. Column (1) repeats our baseline estimate for comparison. In Columns (2) and (3), we split the dependent variable by whether the patent was filed by multiple inventors ("collaborative patents") or whether the patent was single-authored. Both in absolute and in relative terms, the impact on collaborative patents is substantially stronger. This is in line with prior research that found impacts of BITNET on collaboration among academics (Agrawal and Goldfarb, 2008). Columns (4) and (5) investigate this result further. In this analysis, we split the result on collaborative patents by whether the inventor team is newly formed (i.e., has at least one new team member) or whether the inventor team has patented before. We find that the effect on collaborative patents is larger both in absolute and in relative terms among new inventor teams. These results point to a leading role of new collaborations in explaining the effect of BITNET on patenting. Incumbent inventor teams are less affected, but still benefit from the adoption of BITNET. In combination with Column (2), this suggests that ICT may have productivity effects over and beyond its large effects on collaboration and new team formation. Finally, in Column (7) we show a slight positive effect on team size, suggesting that the results found in Columns (4) and (5) largely reflect a change in team composition. Overall, while direct productivity effects may well be possible, our effects seem to largely be driven by increases in collaborative patents by new inventor teams.

5.2 BITNET Induced Science-Based Patenting

What kind of patents were induced by BITNET? We investigate this question in Table 3. Column (1) repeats our baseline specification for comparison. We start by investigating how science-related the excess patents are. Columns (2) through (4) leverage the data on patent-to-article citations by Ahmadpoor and Jones (2017). We label patents that directly cite scientific papers as "science-based" and patents that are science-based or directly cite a science-based patent as "science-related". Thus, science-related patents are a superset of science-based patents. All other patents are labeled as non-science-related. Column (2) shows that the effect is largely driven

Dep. Var.:	University patents p.c.			Collaborative univ. patents p.c.		Average team size
	Baseline	Single-authored	Collab-orative	New	Old	
				Team		
	(1)	(2)	(3)	(4)	(5)	(6)
post	-0.00	0.00	-0.00**	-0.00	-0.00***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(post==1)*treat_indic	0.34***	0.07**	0.27***	0.22***	0.05**	0.06*
	(0.09)	(0.03)	(0.07)	(0.05)	(0.02)	(0.03)
Mean Dep.	0.64	0.25	0.39	0.30	0.08	2.27
R2 (within)	0.02	0.01	0.02	0.02	0.01	0.05
Obs.	531063	531063	531063	531063	531063	307858

Note: This table shows difference-in-differences estimates of BITNET adoption on collaboration. The treatment group are universities that are already connected to BITNET. The control group consists of universities that are not yet connected to BITNET but that are connected to BITNET later. All specifications include year fixed effects and institution group fixed effects. Columns (1) to (5) use patents by university-connected inventors adjusted by the population in the 15 miles region around the university as the dependent variable. Columns (2) and (3) distinguish between patents involving only one inventor and patents involving multiple inventors. Columns (4) and (5) distinguish between teams involving some inventors that are new to the team and teams consisting only of inventors who patented together before. The results thus sum up to Column (3). Column (6) uses the average number of inventors on a university-connected patent as the dependent variable. To adjust for the different number of control universities, we use the weights suggested by Iacus et al. (2012). Robust standard errors, adjusted for clustering at the treated institution level, are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 2: Impact on Collaboration

by increases in science-based patents. Columns (3) and (4) show that it is entirely driven by science-related patents. In contrast, non-science-related patents show no effect at all. In Figure A4 in Online Appendix E, we show the time-varying version of these results. In line with our identification assumption, neither science-related nor non-science-related patents differ between treatment and control group before BITNET adoption. After BITNET adoption, science-related patents increase around treated universities. In contrast, non-science-related patents are unaffected. It seems plausible that science-related patents are most affected by the introduction of BITNET, since BITNET was a communication system between scientists.

In Columns (5) through (7) we analyze the patent text of the affected patents further. We use the data of Arts et al. (2018) that gives us the set of words used in the abstract and title of each U.S. patent from 1976 to 2013 and add to this data all words of the first independent claim from the PatentsView database. We split patents into (i) containing words that are new to the U.S. patent system (i.e., that were previously not used in any USPTO patent), (ii) containing words that are not new, but new to the region around the treated university, and into patents (iii) containing only words that do not fall in these two categories. As the results show, the effects are largely driven by patents containing words that are either entirely new or that are new to the region around the adopting university. The strongest relative effect of BITNET is on patents new to U.S. patenting. This is in line with the idea that patents that use novel concepts, such as concepts derived from science, are the most affected.

Overall, our findings show that BITNET induced more science-related patenting. This is an interesting result since science-based patents are particularly valuable on average (Poege et al., 2019; Watzinger and Schnitzer, 2019) but there are many barriers to translating scientific insights to actual innovation (e.g., Bikard, 2018). The types of collaborations that BITNET induced seem to produce knowledge that directly translates to patenting.

Dep. Var.:	University patents p.c.				University patents p.c. with words...		
	Baseline	Science-based	Science-related	Non-science-related	new to the world	new to region, not the world	old words
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post	-0.00	-0.00***	-0.01***	0.00	-0.00	-0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BITNETxPost	0.34***	0.18***	0.34***	-0.00	0.13***	0.21***	-0.01
	(0.09)	(0.04)	(0.08)	(0.07)	(0.04)	(0.07)	(0.00)
Mean Dep.	0.64	0.18	0.28	0.35	0.20	0.39	0.04
R2 (within)	0.02	0.06	0.07	0.00	0.01	0.01	0.02
Obs.	531063	531063	531063	531063	531063	531063	531063

Note: This table shows difference-in-differences estimates of BITNET adoption on patent types. The treatment group are universities that are already connected to BITNET. The control group consists of universities that are not yet connected to BITNET but that are connected to BITNET later. All specifications include year fixed effects and institution group fixed effects. All columns use patents by university-connected inventors adjusted by the population in the 15 miles region around the university as the dependent variable. Column (2) estimates the effect for patents that directly cite scientific articles ("science-based patents"). The next two columns distinguish between patents that are science-based or that cite patents based on scientific articles ("science-related patents", Column 3); and patents unrelated to scientific articles (Column 4). Column (5) uses patents that includes words never used before in U.S. patenting as the dependent variable. Column (6) uses patents containing no new words, but containing words that are new to the region. Column (7) uses patents only containing words that have been used in U.S. patents and patents around the treated university before as the dependent variable. To adjust for the different number of control universities, we use the weights suggested by Iacus et al. (2012). Robust standard errors, adjusted for clustering at the treated institution level, are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 3: Types of Patents

6 Conclusion

Many observers have argued that ICT facilitates the exchange of codified knowledge which in turn improves productivity and inventive activity. While there exists some evidence that shows a research-enhancing role of information technology in academic research, evidence on the impacts of these technologies on innovation and patenting is scarce.

We exploit the staggered adoption of BITNET across U.S. universities between 1981 and 1990 to study whether access to ICT affects (local) innovation. We document a strong effect of BITNET on patenting around adopting institutions. We provide evidence that this effect is driven by an increase in collaborative patents by new inventor teams. Our effect is driven by universities in rural areas and by universities that showed high patenting activity already before BITNET adoption. Patenting by assignees outside of universities is unaffected by BITNET.

We finally show that the patents induced by ICT are closely connected to science. Thus, BITNET seems to have facilitated the translation of scientific insights to innovation by inducing productive collaborations.

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Appendix: For Online Publication Only

A Descriptive Statistics

Table A1: Summary Statistics in the Year before BITNET Adoption

Main sample				
	Mean	Standard deviation	Minimum	Maximum
# univ. patents/100k	0.71	2.03	0.00	53.20
Citation-weighted univ. patents/100k	2.79	8.33	0.00	117.42
Average number of citations/patent	2.39	3.31	0.00	34.00
Population within 15 miles/100k	11.83	20.62	0.12	106.48
Patents by field				
	Mean	Standard deviation	Minimum	Maximum
Electrical Engineering	0.07	0.39	0.00	8.49
Instruments	0.18	0.53	0.00	7.22
Chemistry	0.35	1.02	0.00	28.18
Process Engineering	0.06	0.40	0.00	11.47
Mechanical Engineering	0.03	0.54	0.00	31.29
Other Fields	0.02	0.19	0.00	5.22
Citation-weighted patents by field				
	Mean	Standard deviation	Minimum	Maximum
Electrical Engineering	0.40	2.50	0.00	67.92
Instruments	0.95	4.11	0.00	110.16
Chemistry	1.09	3.40	0.00	78.91
Process Engineering	0.20	1.76	0.00	36.51
Mechanical Engineering	0.09	0.85	0.00	31.22
Other Fields	0.05	0.51	0.00	20.86
Collaboration				
	Mean	Standard deviation	Minimum	Maximum
# single-authored univ. patents/100k	0.28	1.02	0.00	26.30
# collaborative univ. patents/100k	0.43	1.29	0.00	37.55
# collab. univ. patents/100k with new inventors	0.35	0.99	0.00	21.90
# collab. univ. patents/100k with only old inventors	0.08	0.40	0.00	15.65
Average team size	2.22	0.76	1.00	6.00

Note: This table displays the averages of the outcomes of interest for treated universities and associated control universities in the year before the introduction of BITNET. Patents are collaborative if they were filed by more than one inventor. Inventor teams have new inventors if the team had not previously patented in this constellation.

B Further Results for Citation-weighted Patents

Figure A1 displays the yearly treatment effects for the number of citation-weighted patents per 100,000 persons in the 15 miles region around a university analogous to Figure 2 in the main text. We normalize the effect to the period before BITNET adoption. Consistent with the parallel trends assumption, the estimates are very small and statistically indistinguishable from zero prior to BITNET adoption. After BITNET adoption, the number of citation-weighted patents increases around treated universities relative to universities that will only receive BITNET access in the future. The effect gets more pronounced over time. Table A2 shows the difference-in-differences results analogously to Table 1 in the main text using citation-weighted patents as the dependent variable. The results are qualitatively unaffected.

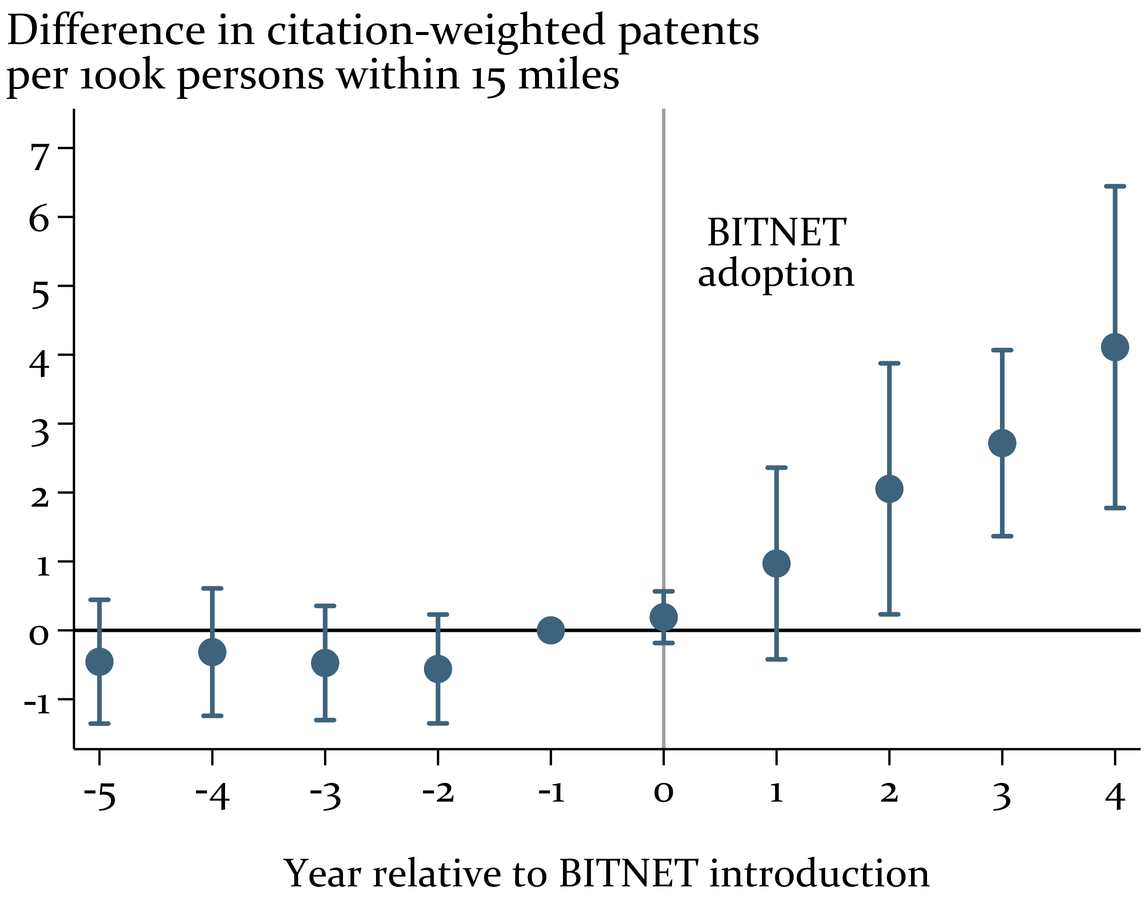


Figure A1: Effect of BITNET Relative to Connection Date

Note: This figure shows the yearly average treatment effects of BITNET adoption on the number of citation-weighted patents per 100,000 population within 15 miles of universities adopting BITNET relative to universities that only adopt BITNET later. The blue bars represent 95% confidence bounds that allow for clustering at the treated institution level. To adjust for the different number of control universities, we use the weights suggested by Iacus et al. (2012).

Dep. Var.:	Citation-weighted patents p.c.							
	Baseline	Rural	Urban	High	Low	Early	Late	Non-uni
		Area		Patenting		Adopters		Assignee
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	0.00	0.07***	-0.04***	0.02	-0.01***	-0.01	-0.09***	0.04
	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)	(0.08)
BITNETxPost	1.78***	3.95***	0.08	2.19**	-0.08***	2.29***	1.32	1.31
	(0.53)	(1.03)	(0.29)	(0.88)	(0.02)	(0.60)	(0.87)	(2.85)
Mean Dep.	2.51	2.12	2.87	5.23	0.09	2.45	2.55	76.83
R2 (within)	0.03	0.01	0.16	0.06	0.04	0.02	0.04	0.26
Obs.	531063	266195	264868	245809	285254	327352	203711	531063

Note: This table shows difference-in-differences estimates of BITNET adoption on local patenting. The treatment group are universities that are already connected to BITNET. The control group consists of universities that are not yet connected to BITNET but that are connected to BITNET later. The dependent variable is the number of citation-weighted patents per 100,000 population in the 15 miles region around a university. All specifications include year fixed effects and institution group fixed effects. Column (1) uses our baseline sample and repeats Column (2) of Table 1. Columns (2) and (3) split the sample by median local population density in the year before BITNET adoption. Columns (4) and (5) split the sample by median patenting rates per 100,000 population in the 15 miles around universities in the year before BITNET adoption. Columns (6) and (7) split the sample into early and late BITNET adopters. Early adopters are those universities that are connected by the end of 1985. Column (8) uses citation-weighted patents per 100,000 population by inventors unconnected to universities as the dependent variable. To adjust for the different number of control universities, we use the weights suggested by Iacus et al. (2012). Robust standard errors, adjusted for clustering at the treated institution level, are in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A2: Heterogeneity of Effects: Citation-weighted University Patents p.c.

C Effects by Technology Category

We show the results by technology category in Figure A2. Each line is the difference-in-difference coefficient on the interaction between time and BITNET (β_2 above) in a different regression that uses patents in the respective field as the dependent variable. We thus split the dependent variable and the individual effects sum to the total effect. Consistent with our conjecture, the effects on the number of patents per capita are most pronounced in Chemistry and Instruments. We find smaller positive effects in Electrical Engineering and Process Engineering. This suggests that the adoption of BITNET might have had a productivity-enhancing effect on inventors in several technology areas. The picture for patent quality is slightly more nuanced (Figure A3). We observe a positive and significant effect in Instruments and in Chemistry, followed by Electrical Engineering. Again, fields such as Mechanical Engineering, where codified knowledge is less useful, do not show any effects.

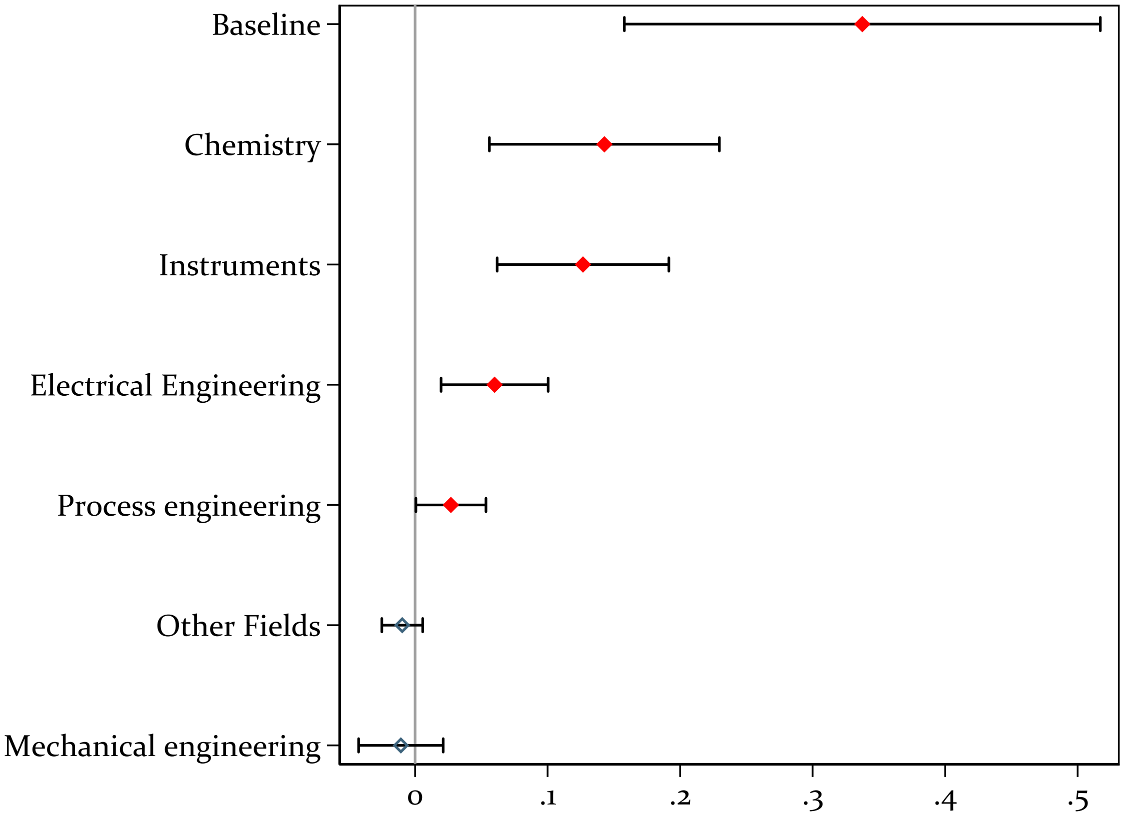


Figure A2: Innovation Effects of BITNET by Technology Category

Note: This figure shows the results from a difference-in-differences estimation with university patents per 100,000 population in the 15 miles region around a university in the respective field as the dependent variable. The treatment group are universities that are already connected to BITNET. The control group consists of universities that are not yet connected to BITNET but that are connected to BITNET later. All specifications include year fixed effects and institution group fixed effects. The bars indicate 95% confidence intervals using standard errors that allow for clustering at the treated institution level. Coefficients plotted as a hollow diamond indicate coefficients not significantly different from zero at this level. Full (red) diamonds indicate coefficients that are significantly different from zero.

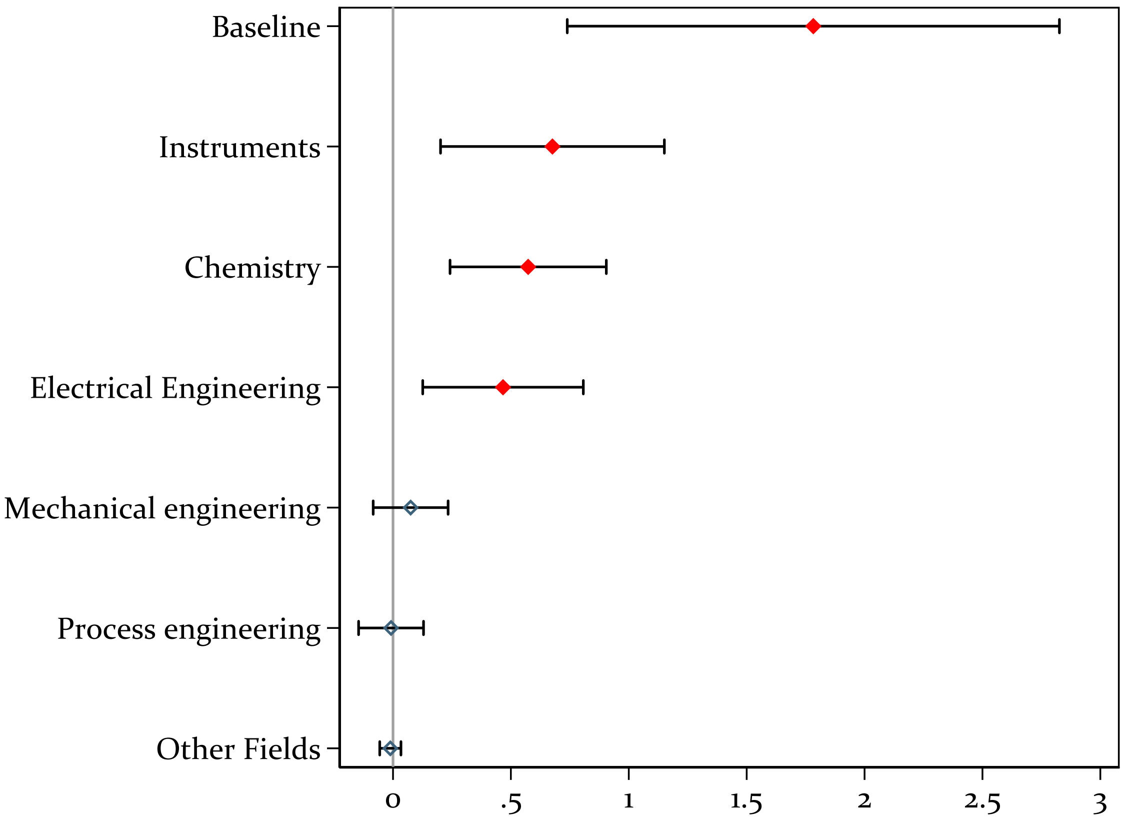


Figure A3: Innovation Effects of BITNET by Technology Category: Citation-weighted Patents

Note: This figure shows the results from a difference-in-differences estimation with university patents weighted by their forward citations per 100,000 population in the 15 miles region around a university in the respective field as the dependent variable. The treatment group are universities that are already connected to BITNET. The control group consists of universities that are not yet connected to BITNET but that are connected to BITNET later. All specifications include year fixed effects and institution group fixed effects. The bars indicate 95% confidence intervals using standard errors that allow for clustering at the treated institution level. Coefficients plotted as a hollow diamond indicate coefficients not significantly different from zero at this level. Full (red) diamonds indicate coefficients that are significantly different from zero.

D Additional Robustness

D.1 Results without Top X Universities

To provide evidence that our results are not driven by few selected universities, we show in this section that our results are robust to dropping the top 5, top 10, top 20, and top 25 universities in terms of pre-BITNET patenting.

Dep. Var.:	University patents p.c.				
Sample	Baseline	w/o Top 5	w/o Top 10	w/o Top 20	w/o Top 25
	(1)	(2)	(3)	(4)	(5)
Post	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BITNETxPost	0.34***	0.26***	0.24***	0.18***	0.15***
	(0.09)	(0.08)	(0.08)	(0.05)	(0.05)
Mean Dep.	0.64	0.64	0.64	0.63	0.63
R2 (within)	0.02	0.02	0.02	0.02	0.02
Obs.	531063	523830	518856	500184	492942

Note: This table shows difference-in-differences estimates of BITNET adoption on local patenting. The treatment group are universities that are already connected to BITNET. The control group consists of universities that are not yet connected to BITNET but that are connected to BITNET later. The dependent variable is the number of patents per 100,000 population in the 15 miles region around a university. All specifications include year fixed effects and institution group fixed effects. Column (1) uses our baseline sample and repeats Column (1) of Table 1. Columns (2) to (5) drop the top 5, 10, 20, and 25 universities in terms of patenting per population before the introduction of BITNET. To adjust for the different number of control universities, we use the weights suggested by Iacus et al. (2012). Robust standard errors, adjusted for clustering at the treated institution level, are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A3: Impact on Number of University Patents p.c. without Top X Universities

D.2 Matching

To provide evidence that our results are not driven by regional shocks affecting overall patenting in the area around adopting universities, we show that the effects are robust to using more detailed matching strategies below. In particular, we show that additionally matching on patenting in the year before BITNET adoption as well as patenting and population before BITNET adoption does not affect our results.

Dep. Var.:	University patents p.c.			Cit.-wght. univ. patents p.c.		
Matching:	Baseline	+ Patenting	+ Patenting & Population	Baseline	+ Patenting	+ Patenting & Population
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.00	0.02***	0.02***	0.00	0.10***	0.07***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)
BITNETxPost	0.34***	0.30***	0.30***	1.78***	1.33***	1.33***
	(0.09)	(0.08)	(0.08)	(0.53)	(0.35)	(0.35)
Mean Dep.	0.64	0.59	0.59	2.51	2.33	2.32
R2 (within)	0.02	0.02	0.02	0.03	0.04	0.04
Obs.	531063	527912	436855	531063	527912	436855

Note: This table shows difference-in-differences estimates of BITNET adoption on local patenting. The treatment group are universities that are already connected to BITNET. The control group consists of universities that are not yet connected to BITNET but that are connected to BITNET later. The dependent variable is the number of patents per 100,000 population in the 15 miles region around a university in Columns (1) through (3). All specifications include year fixed effects and institution group fixed effects. Column (1) uses our baseline sample and repeats Column (1) of Table 1. Columns (2) and (3) additionally match on patenting in the year before BITNET adoption and patenting before BITNET and population, respectively. To match control universities to treatment universities, we use Coarsened Exact Matching (Iacus et al., 2012) with 5 bins on patenting and on population. We repeat this analysis in Columns (4) through (6) using citation-weighted patents as the dependent variable. To adjust for the different number of control universities, we use the weights suggested by Iacus et al. (2012). Robust standard errors, adjusted for clustering at the treated institution level, are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A4: Results Using Additional Matching Strategies

D.3 Specification

Below, we show that our results are robust to accounting for the skewed nature of patenting outcomes. We first repeat our baseline specifications for the number of patents per population and the number of citation-weighted patents per population. We then use inverse hyperbolic sine transformations of these outcomes. Our results are qualitatively unaffected.

Spec.:	Levels		IHS	
Dep. Var.:	Univ. patents p.c.	Cit.-wght. univ. patents p.c.	Univ. patents p.c.	Cit.-wght. univ. patents p.c.
	(1)	(2)	(3)	(4)
Post	-0.00	0.00	0.00**	-0.00***
	(0.00)	(0.01)	(0.00)	(0.00)
BITNETxPost	0.34***	1.78***	0.10***	0.11***
	(0.09)	(0.53)	(0.02)	(0.03)
Mean Dep.	0.64	2.51	0.38	0.79
R2 (within)	0.02	0.03	0.06	0.10
Obs.	531063	531063	531063	531063

Note: All specifications include year fixed effects and institution group fixed effects. Columns (1) and (2) repeat our baseline specification using patents and citation-weighted patents in levels. Columns (3) and (4) repeat our baseline specification using a inverse hyperbolic sine transformation for the respective dependent variable. All variables are weighted with the population in the 15 miles region around the university. To adjust for the different number of control universities, we use the weights suggested by Iacus et al. (2012). Robust standard errors, adjusted for clustering at the treated institution level, are in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A5: Main Results Using Different Specifications

D.4 Results across Regions

To provide evidence that our results are not driven by regional shocks affecting overall patenting in the area around adopting universities, we show that the effects are similar across different regions in the United States. To this end, we repeat our baseline specification splitting the U.S. into four broad regions.

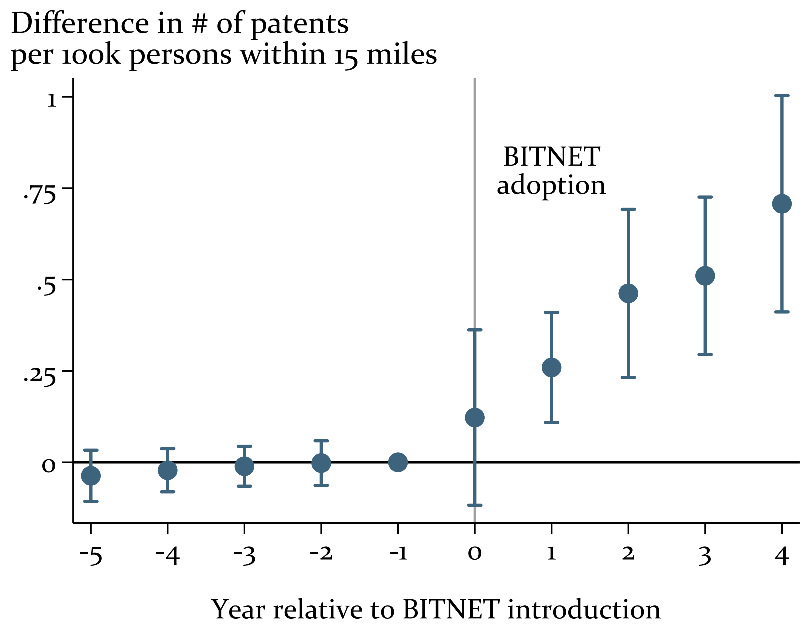
Dep. Var.:	University patents p.c.				
Sample:	Baseline	Northwest	Northeast	Southwest	Southeast
	(1)	(2)	(3)	(4)	(5)
Post	-0.00	0.00	-0.00	-0.01	0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
BITNETxPost	0.34***	0.52**	0.34***	-0.00	0.57*
	(0.09)	(0.25)	(0.12)	(0.08)	(0.31)
Mean Dep.	0.64	0.64	0.63	0.64	0.63
R2 (within)	0.02	0.01	0.02	0.02	0.02
Obs.	531063	56545	322260	79085	73173

Note: This table shows difference-in-differences estimates of BITNET adoption on local patenting. The treatment group are universities that are already connected to BITNET. The control group consists of universities that are not yet connected to BITNET but that are connected to BITNET later. The dependent variable is the number of patents per 100,000 population in the 15 miles region around a university. All specifications include year fixed effects and institution group fixed effects. Column (1) uses our baseline sample and repeats Column (1) of Table 1. Columns (2) to (4) split the sample according to the region in which the university is located. To adjust for the different number of control universities, we use the weights suggested by Iacus et al. (2012). Robust standard errors, adjusted for clustering at the treated institution level, are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

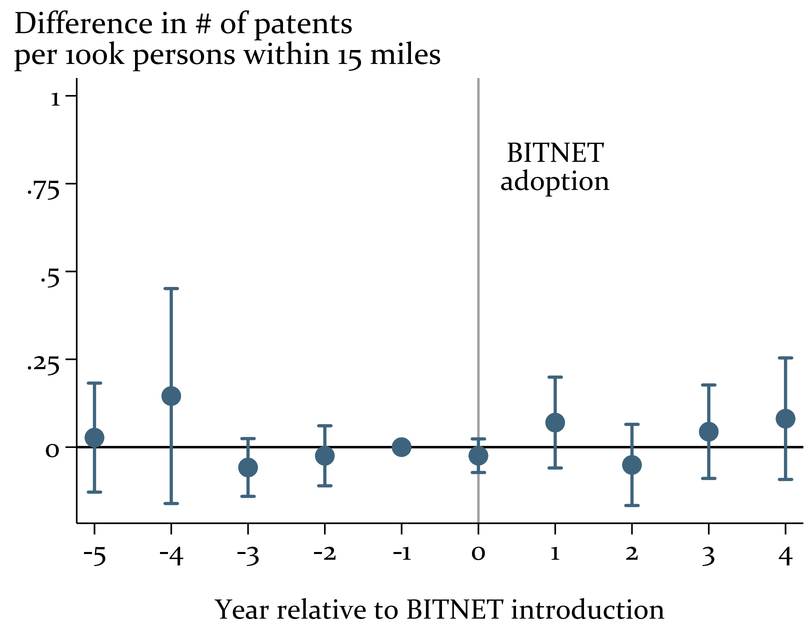
Table A6: Results across Regions: Impact on Number of University Patents p.c.

E Additional Results on Science-related Patents

In Figure A4, we show the time-varying version of our results on science- and non-science-related university patents. Science-related patents are those which either directly cite academic articles or cite patents that directly cite academic articles. Non-science-related patents are all other patents. The data is from Ahmadpoor and Jones (2017). In line with our identification assumption, neither science-related nor non-science-related patents differ between treatment and control group before BITNET adoption. After BITNET adoption, science-related patents increase around treated universities. In contrast, non-science-related patents are unaffected.



(a) Science-related Patents per 100,000 Population



(b) Non-science-related Patents per 100,000 Population

Figure A4: Patent types

Note: These figures show the yearly average treatment effects on the treated of adopting BITNET relative to institutions adopting BITNET at a later point in time. Panel (a) uses the number of patents p.c. that either cites a scientific article directly or that cites another patent which directly cites a scientific article. Panel (b) uses the number of patents p.c. that neither directly cites a scientific article nor cites a patent which directly cites a scientific article. We use the weights of Iacus et al. (2012) to arrive at the average treatment effect on the treated.