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## Abstract

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JEL Classification: N/A

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# ICT, Collaboration, and Innovation: Evidence from BITNET*

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Does access to technologies that reduce information and communication costs 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 closely related to science. In contrast, we neither find an effect on patents not closely related to science nor on corporate inventors unconnected to universities.

**JEL codes:** H54, L23, L86, O30, O32, O33

**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 knowledge of others. ICT could thus provide governments with a tool to boost regional development and innovation. For example, President Biden has made it a priority to "ensure that science and technology hubs flourish in every part of the country" (Office of the President-Elect, 2021).

Does access to ICT increase local innovation? Answering this question is important as significant economic resources are spent to extend access to ICT to every region in the developed world. 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 because 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 1,400 member organizations in 1991. BITNET greatly facilitated the exchange of knowledge by reducing communication costs. It allowed written communication through e-mail, real-time messages, and featured e-mail lists and discussion groups. Because of these characteristics, our results largely speak towards other ICTs or policies reducing the costs of communication in written form. In contrast, other features of modern ICT such as access to large databases or real-time video telephony as well as other effects of lower communication costs in face-to-face settings are not part of BITNET (Catalini, 2018; Furman et al., 2021). 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 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, a sizable effect. If we weight each patent with its forward citations to account for quality, we find an increase of around 1.4 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 knowledge that is otherwise unavailable locally, we find that the impact is entirely driven by universities in non-urban areas. After BITNET adoption, universities also use more prior art from universities that themselves are already connected to BITNET. The effects are robust to a wide range of robustness and plausibility checks. For instance, there is no significant impact of BITNET on patents by non-university corporate inventors.

In additional analyses, we provide evidence that collaboration among new inventor teams is the mechanism behind our effects. We first show that our results are driven by inventor teams (Agrawal and Goldfarb, 2008). Second, investigating this result further we show that new inventor teams, i.e., those that had not yet collaborated before BITNET adoption, increase their patenting most. Third, we show that collaborations between inventors at different BITNET-connected universities is increasing the most in relative terms. These results are in line with the notion that BITNET facilitated the exchange of knowledge among collaborators with access to BITNET.

We then show that the patents induced by BITNET are closely related 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 or that cite other patents that directly cite research articles. In contrast, patents that are not closely related to science 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. However, we also find that patents become longer, use more figures, and are more similar to already existing patents. Thus, the marginal patents induced by BITNET may be less novel than the average patent that is closely related to science.

Our findings contribute to the literature on ICT and knowledge production by showing a large positive effect of ICT on the translation of science to patents. 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. In contrast to our results, 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 a specific form of ICT on the productivity of inventors in a setting where the change in communication costs due to the 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. We provide evidence that not only scientific publications but also patenting increased after the introduction of BITNET at a university. Agrawal and Goldfarb (2008) examine the effect of BITNET on collaboration among university scientists in top electrical engineering journals between 1981 and 1991 and find a positive impact. Complementing their paper, we show that collaborations also increased among inventors. Most importantly, we show that these new collaborations seem to translate scientific insights into innovation. Patents close to science are particularly valuable on average (Poege et al., 2019; Watzinger et al., 2021; Arora et al., 2022) and we do not yet understand well under which circumstances they emerge (e.g., Bikard, 2018; Bikard and Marx, 2020).

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., 2022; 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.[1] Extending this literature to innovation is important since innovation, and especially innovation closely related to science, is a key driver of economic growth and long-run productivity.

[1] 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., Akerman et al., 2015; Dettling et al., 2018; Bhuller et al., 2021), on political outcomes (e.g., Falck et al., 2014; Campante et al., 2018; Gavazza et al., 2019; Zhuravskaya et al., 2020), and on social capital (e.g., Bauernschuster et al., 2014; Geraci et al., 2022).

# 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.[2] BITNET became the most widely used network for communication in scientific research. The network featured e-mail communication, real-time messages, transmission of text files and programs. The most popular feature were mailing lists on almost 3,000 different topics. For example, BITNET featured an Organic Chemistry mailing list. It was intended "[t]o facilitate the interchange of ideas, information, computer programs, papers, to announce opportunities for doing collaborative efforts (teaching and/or research activities) between specialists in Organic Chemistry and related areas." (NetMonth, 1987).[3] Besides e-mail lists, BITNET also featured other collaboration tools, such as *LifeSci*, a computer program intended "to enhance interaction and cooperation among researchers and scientists working far from each other" (Zakai, 1988).[4] These ways of communicating permitted active discussions and knowledge exchange even among geographically separated scientists.

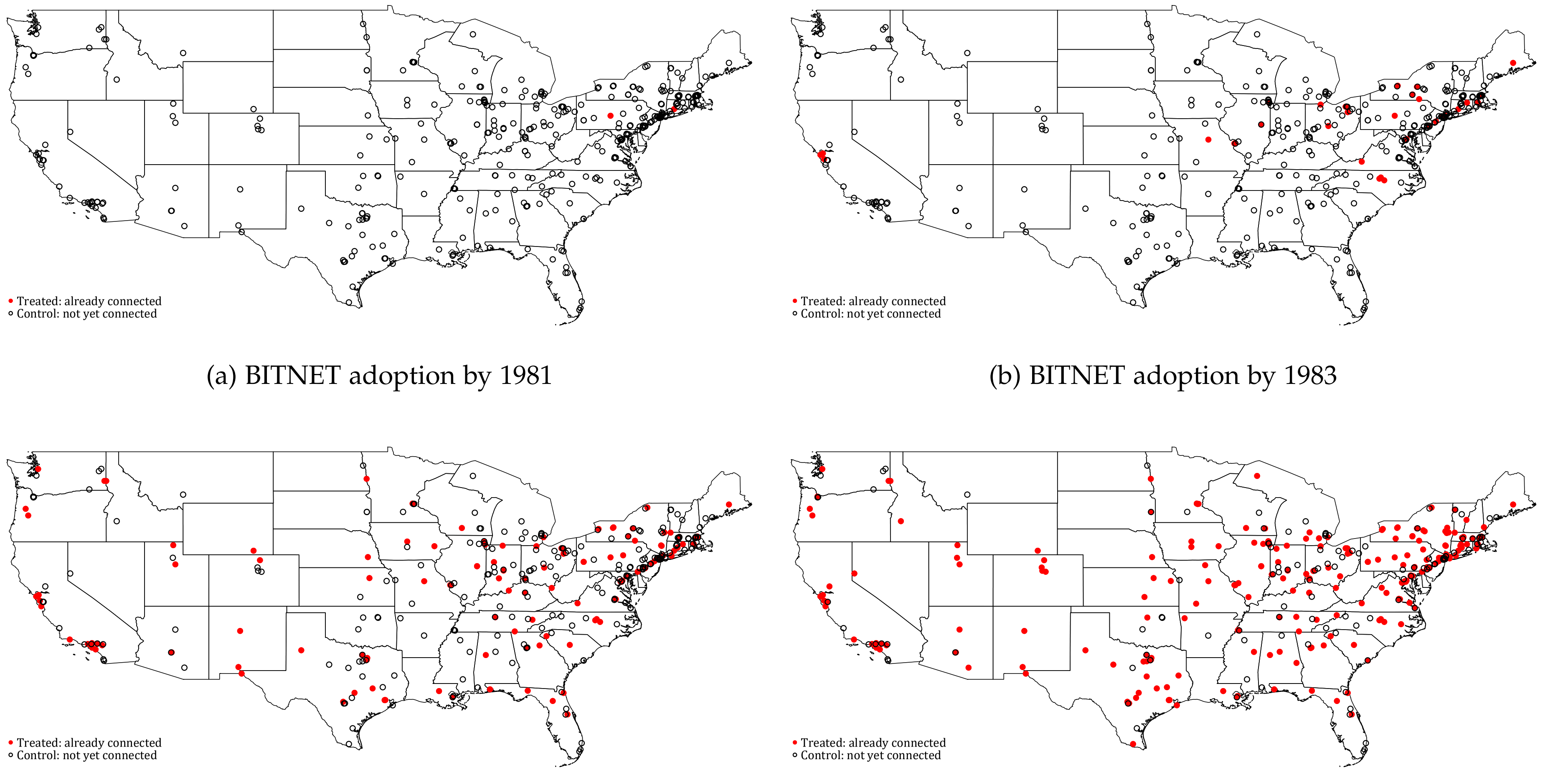
In the beginning, Ira H. Fuchs and Greydon Freeman directly approached IT administrators via letters and phone calls to outline the benefits of joining the network. Institutions could join BITNET if they fulfilled several requirements: First, they had to lease a phone line which allowed them to connect 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.

[2]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).

[3]See `https://ia803109.us.archive.org/10/items/bitnet_documents/nm8711.txt`, last accessed February 11th, 2022.

[4]See `https://ia803109.us.archive.org/10/items/bitnet_documents/nm8802.txt`, last accessed February 11th, 2022.




(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.

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.[5]

# 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. 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 an estimate of 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 therefore 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.[6] 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 changes in 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).[7] 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. Because the network spread fast, it is also unlikely that adopting BITNET was part of a strategic plan that involved investments into innovation capabilities that would have generated higher patenting even in the absence of BITNET adoption. In line with this, we show in the Online Appendix that there do not seem to be concurrent funding shocks or effects of the Bayh-Dole Act that can plausibly explain our results.

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

[6] Note that, for the validity of the control group, it is fine that those universities with a higher treatment effect join BITNET first, as long as the parallel trends assumption holds.

[7] 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.

In our main specification, we estimate an event-study difference-in-differences specification. Specifically, we quantify the impact of adopting BITNET on patenting by estimating the following equation:

$$y^i_{j\tau} = \beta_1 \cdot Post^i_\tau + \beta_2 \cdot BITNET^i_j \cdot Post^i_\tau + \mu_t + \gamma^i_j + \varepsilon^i_{j\tau} \tag{1}$$

where superscript $i$ denotes the treated university along with the associated control universities assigned to the treated university. $j$ denotes the university under consideration, $\tau$ indexes the time relative to the BITNET adoption of university $i$ in years, and $t$ are the calendar years. $y^i_{j\tau}$ corresponds to the outcome of interest, $Post^i_t$ is an indicator which equals one in the years after BITNET was introduced and $BITNET^i_j$ is an indicator equal to one for the treated university (i.e., $i = j$) and zero otherwise. In all specifications, we include calendar year fixed effects ($\mu_t$) and a seperate fixed effect for each combination of university $j$ and treated university $i$. We adjust for the different number of control observations for each treated university by using weights (Iacus et al., 2012). The standard errors allow for clustering at the treated university $i$ level. $\beta_2$ measures the average increase in the outcome variable in the year of BITNET introduction and in the four years thereafter for treated universities.[8]

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.[9] For patents with multiple inventors, we allocate an equal share of the patent to each inventor. If there are multiple universities less than 15 miles from an inventor, we divide the inventor's patent share equally among them to avoid double counting. To factor in quality differences between patents, we use the number of citation-weighted patents. To this end, we determine for each patent the number of forward citations received within 5 years of the filing date (including the year of filing). To account for 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.[10] We use *university patents with an inventor localized in the region of*

[8]Note that, upon BITNET adoption, some universities drop from the control group. This does not drive our effects: In Appendix A.2, we show that an approach similar to our approach, but leveraging only control universities that adopt BITNET after the treatment period of the focal universities (Cengiz et al., 2019) provides similar results. In Appendix A.3, we additionally show that alternative difference-in-differences specifications such as those suggested by Callaway and Sant'Anna (2021) and Borusyak et al. (2021) provide qualitatively identical results.

[9]This distance approximately corresponds to the average commuting distance in the United States, which is roughly 15 miles according to polls (ABC News, 2005). Rapino and Fields (2013) find a mean commuting distance of around 19 miles (including extreme commutes).

[10]In Figure A3 in Appendix A.4, we show the treatment effects around BITNET adoption using the number of patents as the dependent variable. The results are qualitatively identical to our time-varying results in the main specification, but larger by around the average population in the data. In the same Appendix, we also show that scaling university patents per faculty yields qualitatively identical results.

*the university* instead of *patents assigned to the university* because from the name of the assignee it is often unclear which university is meant. For example, patents of all universities in the University of California System are assigned to "The Regents of the University of California" and not to the individual universities.[11]

For our empirical analysis, we combine data from various sources. The information on universities and their BITNET status is from the Atlas of Cybergeography.[12] The data covers 1,054 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 (U.S. Department of Education, 2019). 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 (European Patent Office, 2016). 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.1 shows summary statistics for the universities in our sample in the year before their respective BITNET adoption. The average university has around 0.39 university patents and 1.35 citation-weighted patents per 100,000 population in the year before BITNET adoption.

# 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. 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. The impact starts in the year after BITNET adoption and increases over time.[13]

[11] Similar problems appear with patents assigned to universities throughout the United States.

[12] The file including information on BITNET institutions is available at `https://personalpages.manchester.ac.uk/staff/m.dodge/cybergeography/atlas/bitnet\_topology.txt`, last accessed February 10th, 2022.

[13] This increase over time is consistent with several explanations. For once, effects may take time to develop, for instance because producing the invention takes time. However, it could also be driven by network effects with more and more universities connecting to BITNET and thus the network becoming more useful over time.

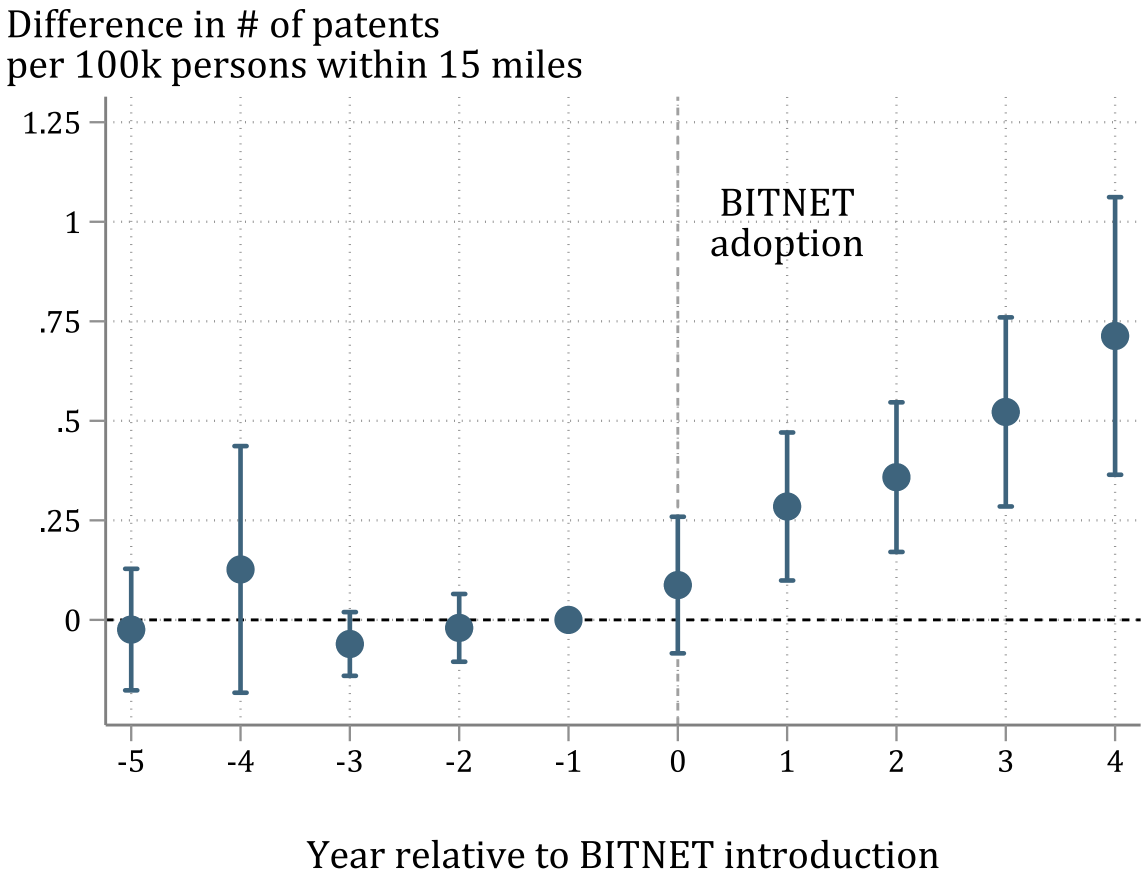



Figure 2: Effects of BITNET on Local Patenting Relative to the Connection Date

Note: This figure shows the yearly average treatment effects on the treated 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).

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 0.3. This is around 34% of the average number of university patents around treated universities in the post period.[14] 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

[14]Note that this large effect is also due to many universities not patenting much. This is illustrated when estimating our main model with a Poisson maximum likelihood model following Correia et al. (2020). Using this approach, we obtain an estimate for the increase in local per capita patenting after BITNET adoption of around 11%.

patents resulting from the adoption of BITNET are 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 13% fewer citations after BITNET introduction, relative to the average of the outcome variable among treated universities in the post period.[15] 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. Figure A6 in Appendix A.5 shows that this is independent of the exact measure of patent quality that we use.

Because BITNET lowered the cost of communicating with other universities, we would expect the impact of BITNET to be greater in remote, non-urban areas. In Columns (4) and (5), we thus split the sample by population density. We find that universities with below-median population densities (labeled "non-urban") largely drive the effect.[16] For universities in urban environments, we only find a small effect of BITNET on local innovation. This is in line with the idea that ICT facilitates communication and collaboration in particular in non-urban regions. In Table A4 in Appendix A.6, we show further heterogeneity analyses for our results. We find that the effect is driven by universities that already showed above median patenting levels before the introduction of BITNET. This could point to a complementarity between ICT and local inventive capacity. We also show a split by adoption year and find that the effect is larger for early adopters (until 1984), but is also substantial for late adopters. We show time-varying treatment effects of all of the above heterogeneities in Figure A7 in Appendix A.6.[17]

Do these effects plausibly stem from BITNET? We investigate this question directly by leveraging the "paper trail of ideas" embedded in citations. We weight all university patents around treatment and control universities by whether they cited inventors at other already connected BITNET universities or inventors that are not close to a BITNET-connected university. That is, we use backward citations to BITNET-connected or non-BITNET-connected universities as our dependent variable. Columns (6) to (9) show the results of this analysis. Column (6) uses the patents' total backward citations per 100,000 population as dependent variable. Relative to baseline, inventors around BITNET-adopting universities start citing more prior art than inventors around control group universities. Columns (7) and (8) then show that this is largely due to patents

[15] This result also only appears after BITNET adoption, as Figure A5 in Appendix A.5 shows.

[16] When we split the sample by quartiles of population densities, we find that the effect is strongest for the bottom quartile and decreases subsequently, with no effect in the most populated regions. Results are available on request.

[17] In unreported regressions, we estimate interaction effects to formalize inference. We find that non-urban universities experience significantly higher treatment effects than urban universities. In contrast, the results on above vs. below median patenting universities as well as on early vs. late adopters are not significant at conventional levels.

citing inventors close to other BITNET-connected universities. This suggests that BITNET primarily increased patenting based on inputs from other BITNET universities. This is true both in absolute terms and relative to baseline citation rates to both sets of universities. In addition, this is not driven by increased self-citations, as Column (9) shows.

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 company inventors unconnected to universities as the dependent variable. Column (10) shows the result from this analysis. The impact of BITNET on company inventors unconnected to universities is very small (less than 1% of the variable mean in 1980) and statistically not significantly different from zero. We acknowledge however that the standard errors are wide such that the 95% confidence bounds of this analysis include the effect on university patents.

## Further Analyses in the Online Appendix

In Online Appendix A we show the results from several auxiliary analyses. Using data from Hausman (2021), from Fleming et al. (2019), and from Microsoft Academic, we provide evidence that it is not likely that concurrent funding shocks can fully explain our results in Appendix A.7. In Appendix A.8 we provide evidence that we do not confound the impact of BITNET with the impact of the 1980 Bayh-Dole Act and the subsequent establishment of technology transfer offices (TTOs) by universities (see, e.g., Henderson et al., 1998; Mowery et al., 2001; Mowery and Ziedonis, 2002). BITNET seems to have an independent effect on local innovation, which also appears at universities without TTOs. However, we do find that universities with TTOs benefit more from BITNET than universities without and that TTOs are directly associated with more university patenting.[18] We also use data from Ouellette and Tutt (2020) to investigate whether the introduction of royalty payments biases our estimates of the BITNET effect. This does not seem to be the case.

[18] We thank Arvids Ziedonis for providing us with data on TTOs.

| Dep. Var.: | Univ. patents p.c. | Cit.-wght. univ. patents p.c. | Average citations | University patents p.c. | | Backward citations univ. patents p.c. | | | | Company patents |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Non-urban | Urban | All | BITNET | Other | Self | p.c. |
| | | | | Area | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| BITNETxPost | 0.30*** | 1.43*** | -0.62*** | 0.58*** | 0.05*** | 2.44*** | 1.74*** | 0.70*** | 0.04 | 0.08 |
| | (0.08) | (0.35) | (0.13) | (0.15) | (0.01) | (0.49) | (0.37) | (0.23) | (0.04) | (0.27) |
| Mean Dep. | 0.30 | 1.01 | 4.17 | 0.48 | 0.12 | 1.78 | 0.66 | 1.12 | 0.09 | 9.28 |
| R2 (within) | 0.00 | 0.01 | 0.05 | 0.00 | 0.15 | 0.01 | 0.02 | 0.01 | 0.00 | 0.05 |
| Obs. | 531063 | 531063 | 307858 | 125306 | 139950 | 531063 | 531063 | 531063 | 531063 | 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) and (5) 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 5-year forward citations per patent among university-connected inventors as the dependent variable. Columns (4) and (5) split the sample by median local population density. Columns (6) to (9) use backward citations per capita as the dependent variable. Columns (7) and (8) distinguish between citations to patents where at least one inventor is around a BITNET-connected universities vs. not. Column (9) uses patents with self-citations as the dependent variable, a subset of BITNET-connected patents. Column (10) uses patents per 100,000 population by company 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

In Appendix A.9 we show that results are not driven by a particular university. In Appendices A.10 we show the results of alternative control groups that rely on more stringent matching strategies and find similar results. In Appendix A.11, we estimate different plausible alternative versions of the main specification, accounting for the skewed nature of patenting, and find similar results. In Appendix A.12 we show that results are not driven by a particular region.

Finally, in Online Appendix A.13, we find that the effect of BITNET is largely proportional to baseline patenting levels across fields. We show that the largest absolute effects in Chemistry and in Instruments, followed by Electrical Engineering. The largest relative results are in Electrical Engineering, however, in line with the impact of BITNET on collaboration in this category reported by Agrawal and Goldfarb (2008).

# 5 Mechanism: Collaboration and Patenting Closely Related to Science

## 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 also have productivity effects that go beyond its impact on collaboration and new team formation. In Columns (6) and (7), we split the collaborative patents into those that were filed with other inventors around universities that already adopted BITNET (labeled "BITNET collaborations") and into all other team patents. Both BITNET collaborations and other collaborative patents contribute to our finding that BITNET positively impacts collaborative patents, with the latter contributing more in absolute terms. However, relative to baseline levels, collaborations that are joint with inventors close to universities that already connected to BITNET rise substantially more than other team patents. Relative to baseline levels, Column (6) suggests that collaborative patents with other BITNET universities increase sevenfold. Finally, in Column (8) we show only a small positive effect on team size, suggesting that our results rather reflect a change in team composition. We show time-varying treatment effects of these effects in Figure A11 in Appendix B.1.[19] 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 Patenting Closely Related to Science

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 closely related to science the excess patents are. Columns (2) through (4) leverage the data on patent-to-article citations by Ahmadpoor and Jones (2017). We distinguish between patents that (i) directly cite scientific papers and patents that (ii) either do this or cite a patent directly citing an article. Thus, the latter is a superset of the former category. All other patents are interpreted as not being closely related to science. Column (2) shows that the effect is largely driven by increases in patents directly citing scientific articles. Columns (3) and (4) show that it is entirely driven by patents that at least indirectly cite scientific articles. In contrast, patents that are not closely related to science show no effect at all.

In Figure A12 in Online Appendix B.2, we show the time-varying version of these results. In line with our identification assumption, patents of all types do not differ between treatment and control group before BITNET adoption. After BITNET adoption, patents that directly or indirectly cite research articles increase around treated universities. In contrast, patents that are not closely connected to science are unaffected. It seems plausible that patents closely connected to science are most affected by the introduction of BITNET, since BITNET was a communication system between scientists.

[19]These figures again show that the impact on team size is small and hardly detectable, suggesting a change in team composition as the likely driver behind our results.

| Dep. Var.: | University patents p.c. | | | Collaborative univ. patents p.c. | | | | Average team size |
|---|---|---|---|---|---|---|---|---|
| | Baseline | Single-authored | Collab-orative | New Team | Old Team | BITNET Collaboration | Other Collaboration | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| BITNETxPost | 0.30*** | 0.07** | 0.23*** | 0.18*** | 0.05** | 0.10*** | 0.13*** | 0.06* |
| | (0.08) | (0.03) | (0.06) | (0.04) | (0.02) | (0.01) | (0.05) | (0.03) |
| Mean Dep. | 0.30 | 0.13 | 0.17 | 0.14 | 0.03 | 0.01 | 0.16 | 2.27 |
| R2 (within) | 0.00 | 0.00 | 0.01 | 0.01 | 0.00 | 0.03 | 0.00 | 0.05 |
| Obs. | 531063 | 531063 | 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). In Column (6) we use the number of patents that involve inventors from different BITNET universities. In Column (7) we use all patents of teams that are not included in (6) as outcome. This means inventors teams exclusively at one university or where inventors are at different non-BITNET universities. Column (8) 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

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) those containing words that are new to the U.S. patent system (i.e., that were previously not used in any USPTO patent), (ii) those containing words that are not new, but new to the region around the treated university, and into those 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.[20]

In Figure A13 in Appendix B.3, we investigate this result further by analyzing more dimensions of patent content. We find that the patents driving our results, namely those closely connected to science, change in content. They increase in length, use more figures, show somewhat higher originality (Hall et al., 2001), and their text is more similar to existing patents using the measure of Kelly et al. (2021).

Overall, our findings show that BITNET induced more and different patenting. Our results are especially relevant since patents closely connected to science are particularly valuable on average (Poege et al., 2019; Watzinger et al., 2021) 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 research to patenting. At the same time, our additional results caution that the marginal patent translating scientific insights to actual innovation may be less novel than the average patent doing so.

[20]In unreported regressions, we estimate interaction effects on stacked datasets to formalize inference. We find that all differences that we report above are significant at conventional levels.

| Dep. Var.: | University patents p.c. | | | | University patents p.c. with words... | | |
|---|---|---|---|---|---|---|---|
| | Baseline | Close to Science | | Not Close | new to | new to region, | old |
| | | Direct | (In)direct | to Science | the world | not the world | words |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| BITNETxPost | 0.30*** | 0.14*** | 0.29*** | 0.01 | 0.11*** | 0.18*** | -0.00 |
| | (0.08) | (0.03) | (0.06) | (0.07) | (0.03) | (0.05) | (0.00) |
| Mean Dep. | 0.30 | 0.06 | 0.10 | 0.20 | 0.09 | 0.21 | 0.01 |
| R2 (within) | 0.00 | 0.03 | 0.03 | 0.00 | 0.00 | 0.00 | 0.01 |
| 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 ("Direct"). The next two columns distinguish between patents that directly cite research articles or that cite patents based on scientific articles ("(In)direct", Column 3); and patents not closely connected to scientific articles (Column 4). Column (5) uses patents that include 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 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 specific ICTs 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 larger among universities in non-urban areas and is linked to increased knowledge flows between universities already connected to BITNET. 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.

Because BITNET largely reduced the costs of communication in written form, our results mainly speak towards related ICTs or policies. In contrast, the innovation impacts of modern ICTs that allow for more extensive communication as well as access to large scale databases and online search remain to be studied.

# References

ABC News (2005): "Poll: Traffic in the United States," Retrieved August 21, 2019 from abcnews.go.com.

Agrawal, A. and A. Goldfarb (2008): "Restructuring Research: Communication Costs and the Democratization of University Innovation," *American Economic Review*, 98, 1578–90.

Ahmadpoor, M. and B. F. Jones (2017): "The dual frontier: Patented inventions and prior scientific advance," *Science*, 357, 583–587.

Akerman, A., I. Gaarder, and M. Mogstad (2015): "The Skill Complementarity of Broadband Internet," *Quarterly Journal of Economics*, 130, 1781–1824.

Andersen, T. B., J. Bentzen, C.-J. Dalgaard, and P. Selaya (2012): "Lightning, IT Diffusion, and Economic Growth Across U.S. States," *Review of Economics and Statistics*, 94, 903–924.

Arora, A., S. Belenzon, and J. Suh (2022): "Science and the Market for Technology," *Management Science*, forthcoming.

Arts, S., B. Cassiman, and J. C. Gomez (2018): "Text matching to measure patent similarity," *Strategic Management Journal*, 39, 62–84.

Bauernschuster, S., O. Falck, and L. Woessmann (2014): "Surfing alone? The internet and social capital: Evidence from an unforeseeable technological mistake," *Journal of Public Economics*, 117, 73–89.

Bhuller, M., A. R. Kostol, and T. C. Vigtel (2021): "The Internet, Search Frictions and Aggregate Unemployment," *Working Paper, University of Oslo*.

Bikard, M. (2018): "Made in Academia: The Effect of Institutional Origin on Inventors' Attention to Science," *Organization Science*, 29, 818–836.

Bikard, M. and M. Marx (2020): "Bridging Academia and Industry: How Geographic Hubs Connect University Science and Corporate Technology," *Management Science*, 66, 3425–3443.

Borusyak, K., X. Jaravel, and J. Spiess (2021): "Revisiting Event Study Designs: Robust and Efficient Estimation," *Mimeo*.

Callaway, B. and P. H. Sant'Anna (2021): "Difference-in-Differences with Multiple Time Periods," *Journal of Econometrics*, 225, 200–230.

Campante, F., R. Durante, and F. Sobbrio (2018): "Politics 2.0.: The multifaceted effect of broadband internet on political participation." *Journal of the European Economic Association*, 16, 1094–1136.

Catalini, C. (2018): "Microgeography and the Direction of Inventive Activity," *Management Science*, 64, 4348–4364.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer (2019): "The effect of minimum wages on low-wage jobs," *Quarterly Journal of Economics*, 134, 1405–1454.

Correia, S., P. Guimaraes, and T. Zylkin (2020): "ppmlhdfe: Fast Poisson Estimation with High-Dimensional Fixed Effects," *Stata Journal*, 20, 95–115.

CREN (1997): "CREN History and Future," Retrieved August 08, 2019 from cren.net.

Czernich, N., O. Falck, T. Kretschmer, and L. Woessmann (2011): "Broadband Infrastructure and Economic Growth," *Economic Journal*, 121, 505–532.

Dettling, L. J., S. Goodman, and J. Smith (2018): "Every Little Bit Counts: The Impact of High-Speed Internet on the Transition to College," *Review of Economics and Statistics*, 100, 260–273.

Ding, W. W., S. G. Levin, P. E. Stephan, and A. E. Winkler (2010): "The Impact of Information Technology on Academic Scientists' Productivity and Collaboration Patterns," *Management Science*, 56, 1439–1461.

European Patent Office (2016): "PATSTAT Global, Autumn Edition," .

Falck, O., R. Gold, and S. Heblich (2014): "E-lections: Voting Behavior and the Internet," *American Economic Review*, 104, 2238–65.

Fleming, L., H. Greene, G. Li, M. Marx, and D. Yao (2019): "Government-funded research increasingly fuels innovation," *Science*, 364.

Forman, C. and K. McElheran (2019): "Firm Organization in the Digital Age: IT Use and Vertical Transactions in U.S. Manufacturing," *Working Paper, University of Toronto*.

Forman, C. and N. van Zeebroeck (2012): "From Wires to Partners: How the Internet Has Fostered R&D Collaborations Within Firms," *Management Science*, 58, 1549–1568.

——— (2019): "Digital technology adoption and knowledge flows within firms: Can the Internet overcome geographic and technological distance?" *Research Policy*, 48, 103697.

Furman, J. L., M. Nagler, and M. Watzinger (2021): "Disclosure and Subsequent Innovation: Evidence from the Patent Depository Library Program," *American Economic Journal: Economic Policy*, 13, 239–270.

Gale Encyclopedia of E-Commerce (2019): "Bitnet," Retrieved August 08, 2019 from Encyclopedia.com.

Gavazza, A., M. Nardotto, and T. Valletti (2019): "Internet and Politics: Evidence from U.K. Local Elections and Local Government Policies," *Review of Economic Studies*, 86, 2092–2135.

Geraci, A., M. Nardotto, T. Reggiani, and F. Sabatini (2022): "Broadband Internet and Social Capital," *Journal of Public Economics*, 206, 104578.

Gurbaxani, V. (1990): "Diffusion in Computing Networks: The Case of BITNET," *Commun. ACM*, 33, 65–75.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg (2001): "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools," *NBER Working Paper No. 8498*.

Harhoff, D., F. M. Scherer, and K. Vopel (2003): "Citations, family size, opposition and the value of patent rights," *Research Policy*, 32, 1343–1363.

Hausman, N. (2021): "University Innovation and Local Economic Growth," *Review of Economics and Statistics*, forthcoming.

Henderson, R., A. B. Jaffe, and M. Trajtenberg (1998): "Universities as a Source of Commercial Technology: A Detailed Analysis of University Patenting, 1965–1988," *Review of Economics and Statistics*, 80, 119–127.

Huang, P., M. Ceccagnoli, C. Forman, and D. J. Wu (2022): "IT Knowledge Spillovers, Absorptive Capacity, and Productivity: Evidence from Enterprise Software," *Information Systems Research*, forthcoming.

Iacus, S. M., G. King, and G. Porro (2012): "Causal Inference without Balance Checking: Coarsened Exact Matching," *Political Analysis*, 20, 1–24.

Jones, B. F. (2009): "The Burden of Knowledge and the "Death of the Renaissance Man": Is Innovation Getting Harder?" *Review of Economic Studies*, 76, 283–317.

Kellerman, A. (1986): "The diffusion of BITNET: a communications system for universities," *Telecommunications Policy*, 10, 88 – 92.

Kelly, B., D. Papanikolaou, A. Seru, and M. Taddy (2021): "Measuring Technological Innovation over the Long Run," *American Economic Review: Insights*, 3, 303–320.

Kleis, L., P. Chwelos, R. V. Ramirez, and I. Cockburn (2012): "Information Technology and Intangible Output: The Impact of IT Investment on Innovation Productivity," *Information Systems Research*, 23, 42–59.

Lach, S. and M. Schankerman (2008): "Incentives and invention in universities," *RAND Journal of Economics*, 39, 403–433.

Living Internet (2000): "BITNET History," Retrieved August 08, 2019 from livinginternet.com.

Morrison, G., M. Riccaboni, and F. Pammolli (2017): "Disambiguation of patent inventors and assignees using high-resolution geolocation data," *Scientific Data*, 4.

Mowery, D. C., R. R. Nelson, B. N. Sampat, and A. A. Ziedonis (2001): "The Growth of Patenting and Licensing by US Universities: An Assessment of the Effects of the Bayh–Dole Act of 1980," *Research Policy*, 30, 99–119.

Mowery, D. C. and A. A. Ziedonis (2002): "Academic Patent Quality and Quantity Before and After the Bayh-Dole Act in the United States," *Research Policy*, 31, 399–418.

NBER (2010): "U.S. Census Intercensal County Population Data, 1970-2014," .

NetMonth (1987): "New Mailing Lists," in *NetMonth - The guide to BITNET servers and services*, vol. 2, 14–17.

Office of the President-Elect (2021): "Letter to Eric S. Lander in Press Release on "President-elect Biden Announces Key Members of his White House Science Team","
.

Ouellette, L. L. and A. Tutt (2020): "How Do Patent Incentives Affect University Researchers?" *International Review of Law and Economics*, 61, 105883.

Pakes, A. (1986): "Patents as Options: Some Estimates of the Value of Holding European Patent Stocks," *Econometrica*, 54, 755–784.

Poege, F., D. Harhoff, F. Gaessler, and S. Baruffaldi (2019): "Science Quality and the Value of Inventions," *Science Advances*, 5, eaay7323.

Putnam, J. D. (1996): "The value of international patent rights," Ph.D. thesis, Yale University.

Ramirez, A. (2014): "BITNET," Encyclopædia Britannica, retrieved August 08, 2019 from britannica.com.

Rapino, M. A. and A. K. Fields (2013): "Mega Commuters in the U.S. - Time and Distance in Defining the Long Commute using the American Community Survey," *U.S. Census Bureau Working Paper SEHSD-WP2013-03*.

Romer, P. M. (1990): "Endogenous Technological Change," *Journal of Political Economy*, 98, S71–S102.

Saunders, A. and E. Brynjolfsson (2016): "Valuing IT-Related Intangible Assets," *MIS Quarterly*, 40, 83–110.

Schankerman, M. and A. Pakes (1986): "Estimates of the Value of Patent Rights in European Countries During the Post-1950 Period," *Economic Journal*, 96, 1052–1076.

U.S. Department of Education (2019): "National Center for Education Statistics, Integrated Postsecondary System (IPEDS)." Retrieved April 11, 2019.

Watzinger, M., J. L. Krieger, and M. Schnitzer (2021): "Standing on the Shoulders of Science," *CEPR Discussion Paper No. 13766*.

Winkler, A. E., S. G. Levin, and P. E. Stephan (2010): "The Diffusion of it in Higher Education: Publishing Productivity of Academic Life Scientists," *Economics of Innovation and New Technology*, 19, 481–503.

Zakai, A. (1988): "LifeSci - Coming Soon," in *NetMonth - The independent guide to BITNET*, ed. by C. Condon, vol. 2, 19.

Zhuravskaya, E., M. Petrova, and R. Enikolopov (2020): "Political Effects of the Internet and Social Media," *Annual Review of Economics*, 12, 415–438.

# Appendix

## Table of Contents

# A Appendix to Sections 3 and 4

## A.1 Descriptive Statistics

Table A1: Summary Statistics in the Year before BITNET Adoption

| *Main sample* | | | | |
|---|---|---|---|---|
| | Mean | Standard deviation | Minimum | Maximum |
| # univ. patents/100k | 0.39 | 1.56 | 0.00 | 53.20 |
| # cit.-wght. univ. patents/100k | 1.35 | 5.73 | 0.00 | 117.42 |
| Average cit. per univ. patent | 3.98 | 3.51 | 0.00 | 34.00 |
| *Backward citations* | | | | |
| | Mean | Standard deviation | Minimum | Maximum |
| # backward citations/100k | 2.28 | 8.75 | 0.00 | 194.01 |
| # backward citations to BITNET unis/100k | 0.93 | 3.85 | 0.00 | 105.22 |
| # backward citations to other unis/100k | 1.35 | 5.96 | 0.00 | 173.15 |
| # backward citations to own uni/100k | 0.11 | 0.86 | 0.00 | 33.82 |
| *Collaboration* | | | | |
| | Mean | Standard deviation | Minimum | Maximum |
| # single-authored univ. patents/100k | 0.17 | 0.87 | 0.00 | 26.30 |
| # collaborative univ. patents/100k | 0.22 | 0.97 | 0.00 | 37.55 |
| # collab. univ. patents/100k with new inventors | 0.18 | 0.72 | 0.00 | 21.90 |
| # collab. univ. patents/100k with existing teams | 0.04 | 0.34 | 0.00 | 15.65 |
| # collab. univ. patents/100k with BITNET inventors | 0.01 | 0.09 | 0.00 | 2.35 |
| # collab. univ. patents/100k with other inventors | 0.21 | 0.95 | 0.00 | 37.55 |
| Average team size | 2.22 | 0.76 | 1.00 | 6.00 |
| *Patent content* | | | | |
| | Mean | Standard deviation | Minimum | Maximum |
| # directly science-related univ. patents/100k | 0.09 | 0.31 | 0.00 | 4.39 |
| # indirectly science-related univ. patents/100k | 0.14 | 0.49 | 0.00 | 7.44 |
| # not directly science-related univ. patents/100k | 0.25 | 1.35 | 0.00 | 52.15 |
| # univ. patents with words new to world/100k | 0.11 | 0.47 | 0.00 | 15.65 |
| # univ. patents with words new to region/100k | 0.27 | 1.24 | 0.00 | 37.55 |
| # univ. patents with old words/100k | 0.01 | 0.10 | 0.00 | 2.83 |

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. Patents are (in)directly related to science if they directly cite a scientific article (or cite a patent that does so).

## A.2 Alternative Control Group Specification

In our current specification, we use later-adopting universities as the control group for earlier adopting universities. This implies that some control universities drop from the control group when they connect to BITNET in the post period of the focal university. We think this is a sensible approach because a university that adopts BITNET shortly after the treated university might be a better control than a control university that adopts BITNET many years later.

Yet, our results stay qualitatively and quantitatively very similar if we use "clean controls", that is, if we use only those universities as control observations for any focal university that adopt BITNET after the end of the treatment period for the focal university. This is the approach used in Cengiz et al. (2019). Table A2 replicates the main table and Figure A1 replicates the main figure of our paper. In line with our identification assumption that the timing of BITNET adoption is not related to trends in university patenting, the results are similar if we do or do not use clean controls. If anything, the results in this analysis are larger.

| Dep. Var.: | Univ. patents p.c. | Cit.-wght. univ. patents p.c. | Average citations | University patents p.c. | | Backward citations univ. patents p.c. | | | | Company patents |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Non-urban Area | Urban | All | BITNET | Other | Self | p.c. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| BITNETxPost | 0.30*** | 1.59*** | -0.30** | 0.57*** | 0.05*** | 2.56*** | 2.04*** | 0.51** | 0.04 | 0.33 |
| | (0.08) | (0.35) | (0.14) | (0.14) | (0.01) | (0.49) | (0.38) | (0.23) | (0.04) | (0.27) |
| Mean Dep. | 0.19 | 0.69 | 4.15 | 0.26 | 0.10 | 1.17 | 0.48 | 0.68 | 0.06 | 7.19 |
| R2 (within) | 0.02 | 0.03 | 0.09 | 0.02 | 0.26 | 0.02 | 0.04 | 0.01 | 0.01 | 0.05 |
| Obs. | 91690 | 91690 | 49896 | 21800 | 25200 | 91690 | 91690 | 91690 | 91690 | 91690 |

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 after the treatment period of the treated university. All specifications include year fixed effects and institution group fixed effects. Column (1) as well as Columns (4) and (5) 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 5-year forward citations per patent among university-connected inventors as the dependent variable. Columns (4) and (5) split the sample by median local population density. Columns (6) to (9) use backward citations per capita as the dependent variable. Columns (7) and (8) distinguish between citations to patents where at least one inventor is around a BITNET-connected universities vs. not. Column (9) uses patents with self-citations as the dependent variable, a subset of BITNET-connected patents. Column (10) uses patents per 100,000 population by company 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 A2: Main Results Using “Clean Controls”

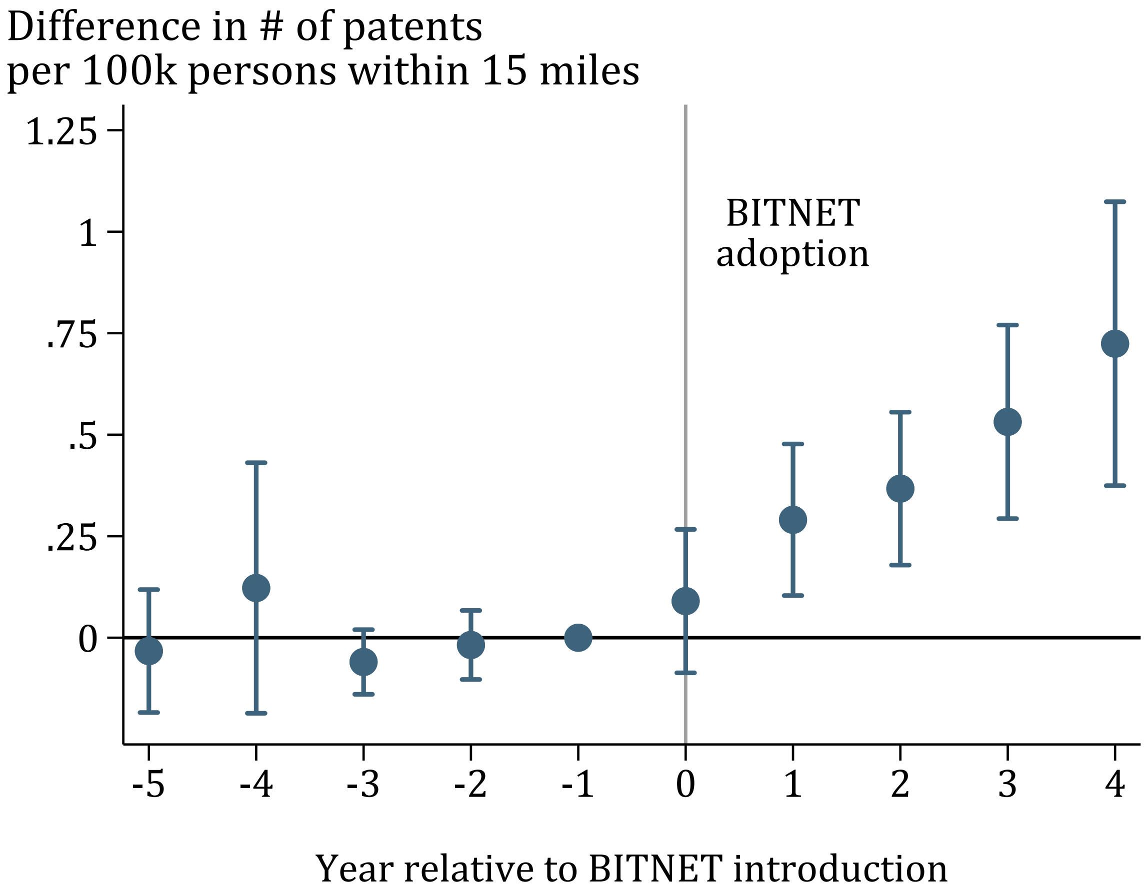



Figure A1: Effects of BITNET on Local Patenting Relative to the Connection Date Using Clean Controls

Note: This figure shows the yearly average treatment effects on the treated 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 after the treatment period of the focal university. 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).

## A.3 Alternative Difference-in-differences Methods

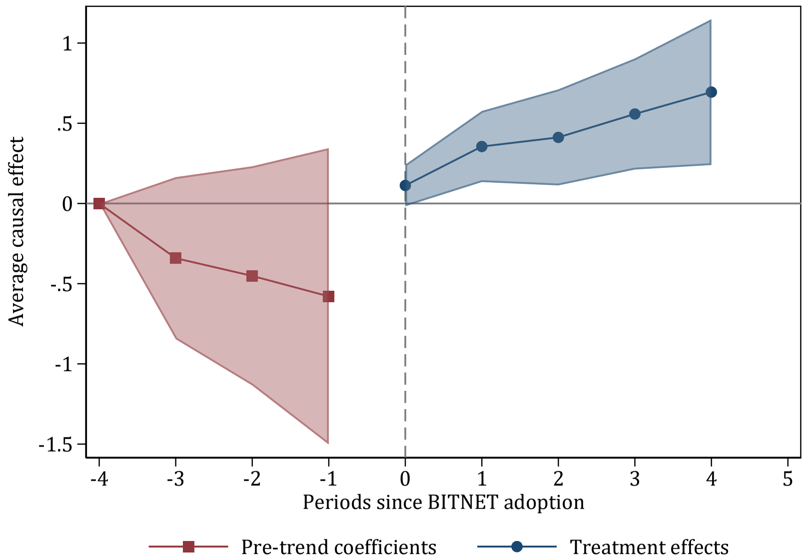
Table A3 reports estimates from alternative specifications using novel methods for difference-in-differences estimation with variations in treatment timing (Callaway and Sant'Anna, 2021). The first column shows average treatment effect on the treated (ATT) when using a simple weighted aggregation of the treatment effect. The second column shows the ATT when using the group-specific aggregation. The third column shows the ATT when averaging over the dynamic effects. In all columns, the effects are sizable and significantly different from zero. They are qualitatively identical with the results from our event-study design.

| Dep. Var.: | Numer of patents p.c. | | |
|---|---|---|---|
| Spec.: | Callaway and Sant'Anna | | |
| Aggregation: | Simple weighted | Group-specific | Dynamic |
| | (1) | (2) | (3) |
| ATT | 0.41** | 0.34** | 0.38** |
| | (0.11) | (0.08) | (0.11) |

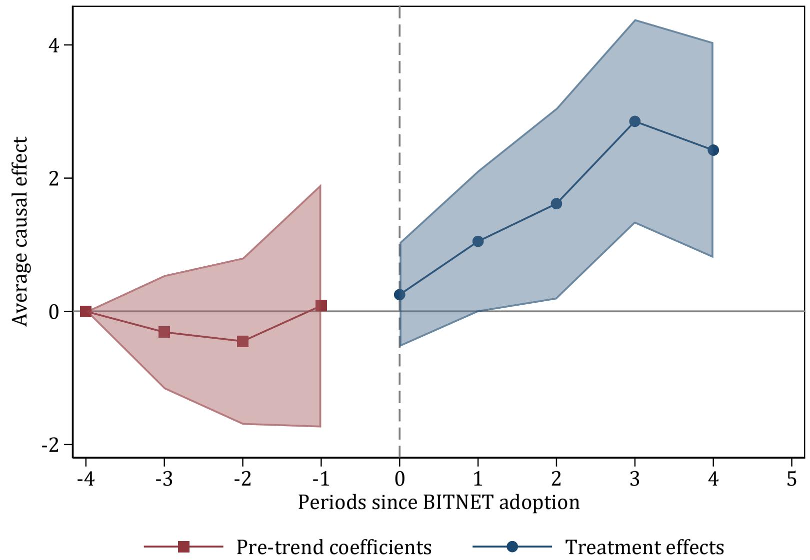
Note: This table shows difference-in-differences specifications of the impact of BITNET on local patenting with the number of patents per capita in the 15 miles around the university as the dependent variable. We use the methods suggested by Callaway and Sant'Anna (2021). All specifications include year fixed effects and institution fixed effects. Columns (1), (2), and (3) use the simple weighted, the group-specific, and the dynamic aggregation methods suggested by Callaway and Sant'Anna (2021) using their doubly-robust estimation procedure, respectively. Bootstrapped standard errors in parentheses, ** $p < 0.05$

Table A3: Main Results Using Difference-in-Differences Specifications

We also report the results from the estimator suggested by Borusyak et al. (2021). Figure A2 shows that in line with our main estimates, the estimated treatment effects in the period before BITNET adoption are insignificantly different from zero and do not show a clear or strong pre-trend. After BITNET adoption, both the number of patents and citation-weighted patents per capita increase in the treated relative to the control universities.




(a) Patents per 100,000 Population




(b) Citation-weighted Patents per 100,000 Population

Figure A2: Treatment effects analysis following Borusyak et al. (2021)

Note: These figures show the yearly average treatment effects on the treated of BITNET adoption on universities adopting BITNET relative to universities that only adopt BITNET after the treatment period of the focal university. We use the methodology proposed by Borusyak et al. (2021) to estimate these graphs. Panel (a) uses the number of university patents per 100,000 population within 15 miles as dependent variable. Panel (b) uses citation-weighted patents per 100,000 population within 15 miles as dependent variable. The shaded areas represent 95% confidence bounds that allow for clustering at the treated institution level.

## A.4 Estimates With a Different or Without Scaling of the Outcome Variable

In Figure A3 below, we show the treatment effects around BITNET adoption using the number of patents as the dependent variable. The results are qualitatively identical to our time-varying results in the main specification.

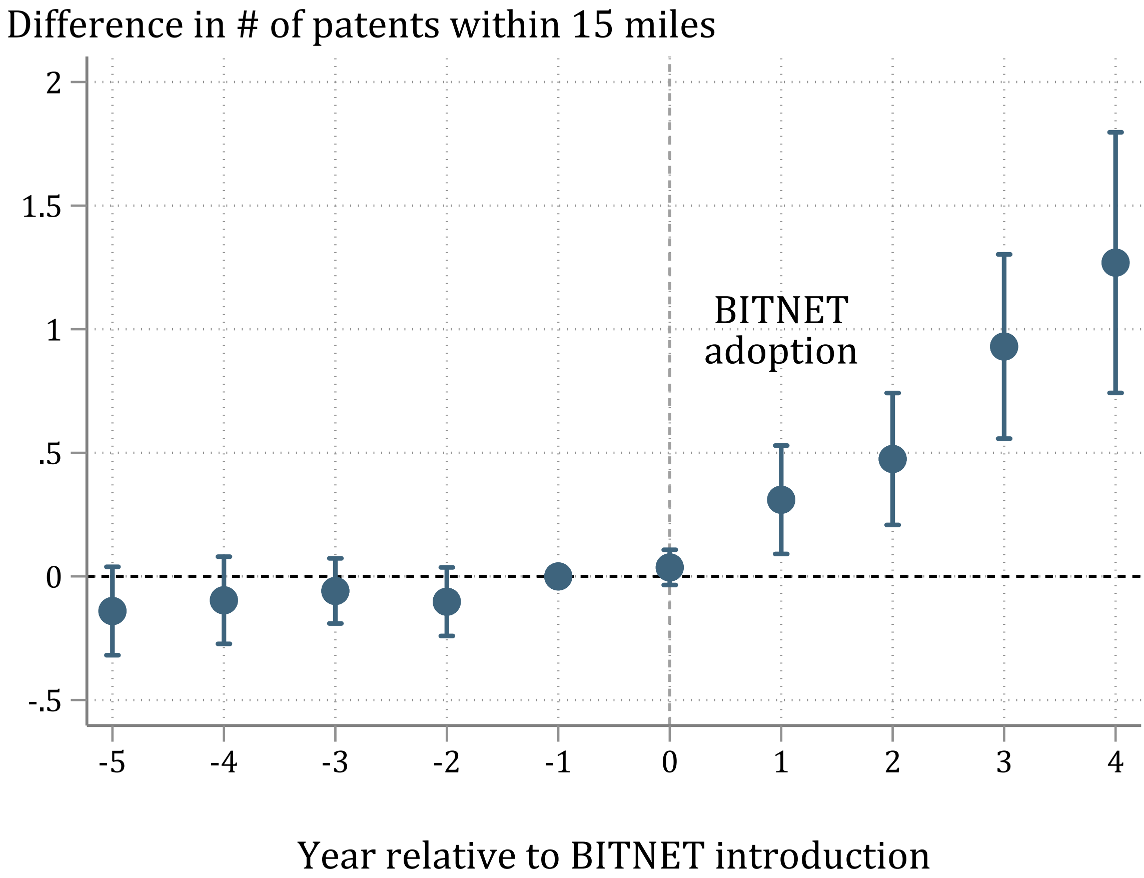



Figure A3: The Impact of BITNET on the Local Number of Patents

Note: This figure shows the yearly average treatment effects on the treated of BITNET adoption on the number of university patents 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).

We additionally show a specification where we use the number of patents assigned to the respective universities scaled by a measure of university size as outcome. To construct a measure of university size, we count the number of active faculty at patenting universities using data from Microsoft Academic. We define an author as faculty if she published for an institution at least twice in the top 10,000 highest impact journals with a gap of five or more years. To count the number of patents directly assigned to a university we use the direct match between patents and universities provided by Microsoft Academic to identify the right assignee name for the university. Then, we count all patents of the identified assignee. Figure A4 shows the results from this analysis. We find qualitatively identical results to our main analysis, suggesting that using population as scaling of the dependent variable does not drive our results.

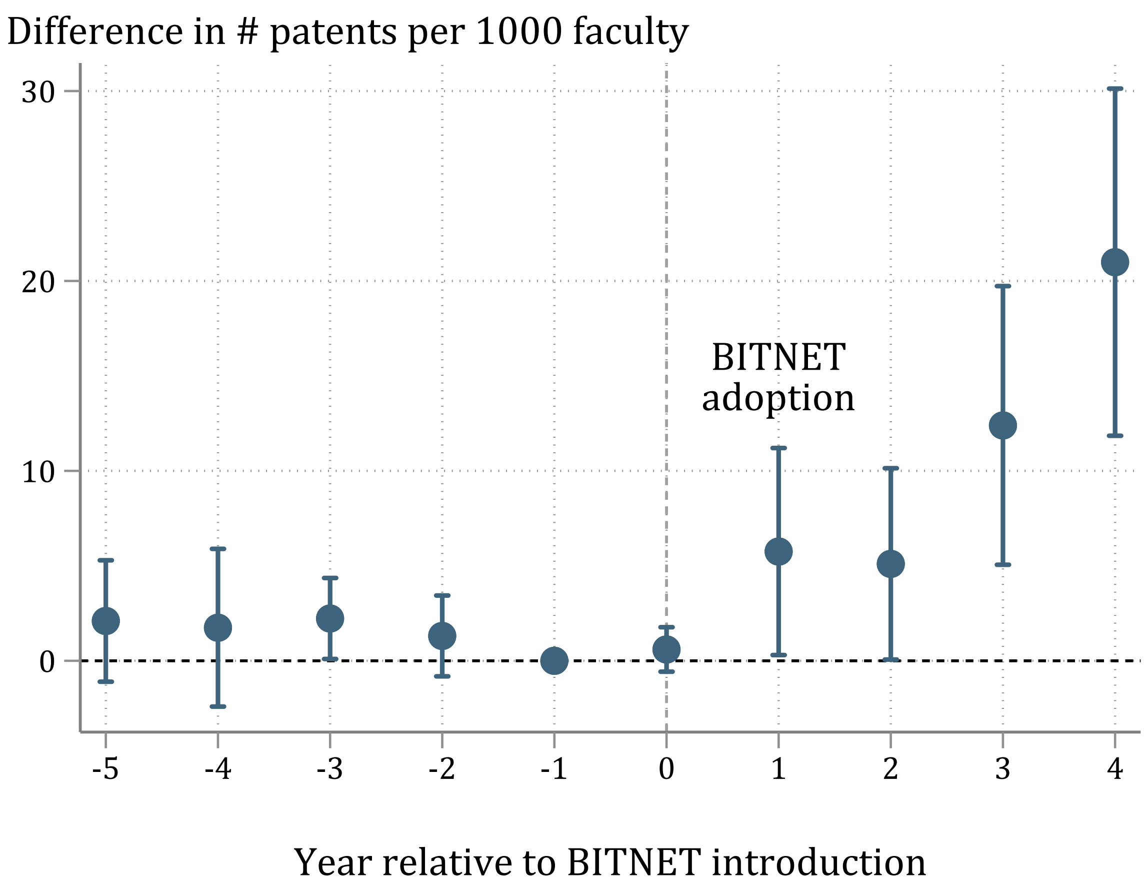



Figure A4: Treatment effects analysis normalized by university faculty

Note: This figure shows the yearly average treatment effects on the treated of BITNET adoption on the number of directly assigned university patents per faculty of universities adopting BITNET relative to universities that only adopt BITNET later. We take the number of faculty and the patent assignments from Microsoft Academic. We define an author as faculty if she published for an institution at least twice in the top 10000 highest impact journals with a gap of five or more years. 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).

## A.5 Additional Results on Patent Quality

Figure A5 shows how the introduction of BITNET relates to the average number of citations per patent. As in our main graphs, there is no difference in the average citations per patent between treatment and control groups in the time period before the introduction of BITNET. After the introduction, the negative effect on average citations appears soon, becoming statistically significantly different from zero around two years after the introduction of BITNET.

Figure A6 shows the results from difference-in-differences regressions around BITNET introduction using different quality measures as dependent variables. We translate the point estimates to percent changes for better interpretability. The upper part of the figure shows results for all university patents, while the lower part shows results for university patents closely related to science only, the main driver of our effects. Row (1) shows that average forward citations decrease around treated universities relative to control universities, as just shown above. Row (2) shows that also the share in the top 1% of the citation distribution decrases. Row (3) uses patent renewals as alternative measure of patent quality (e.g., Pakes, 1986; Schankerman and Pakes, 1986). The effect is negative but not statistically different from zero. Row (4) uses the size of the patent family as a quality measure (Putnam, 1996; Harhoff et al., 2003) and finds a negative effect. Finally, Row (5) uses the patent quality measure by Kelly et al. (2021) as dependent variable and finds no effects. Thus, average patent quality seems to have at least not increased, no matter which measure we look at. This is broadly in line with our finding of a negative impact on average citations.

Is this finding also true for patents closely related to science, the main driver of our effects on patenting? Rows (6) through (10) repeat the analysis using the same quality measures, but focusing on patents closely related to science instead of all university patents. The effects are more pronounced and negative, suggesting that the patents induced through BITNET were indeed of lower quality than the average patent filed in the control group.

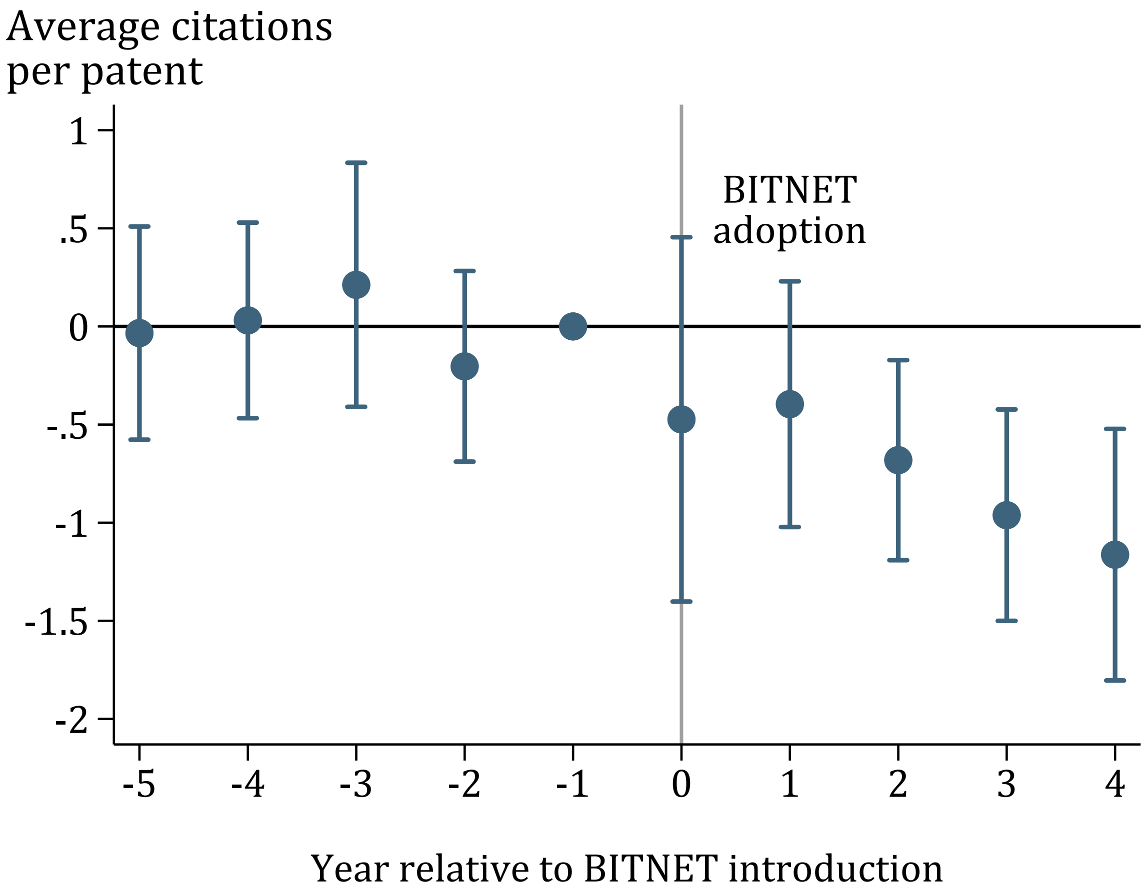



Figure A5: The Impact of BITNET on the Average Citations to Local Patents

Note: This figure shows the yearly average treatment effects on the treated of BITNET adoption on the average forward citations to university patents 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).

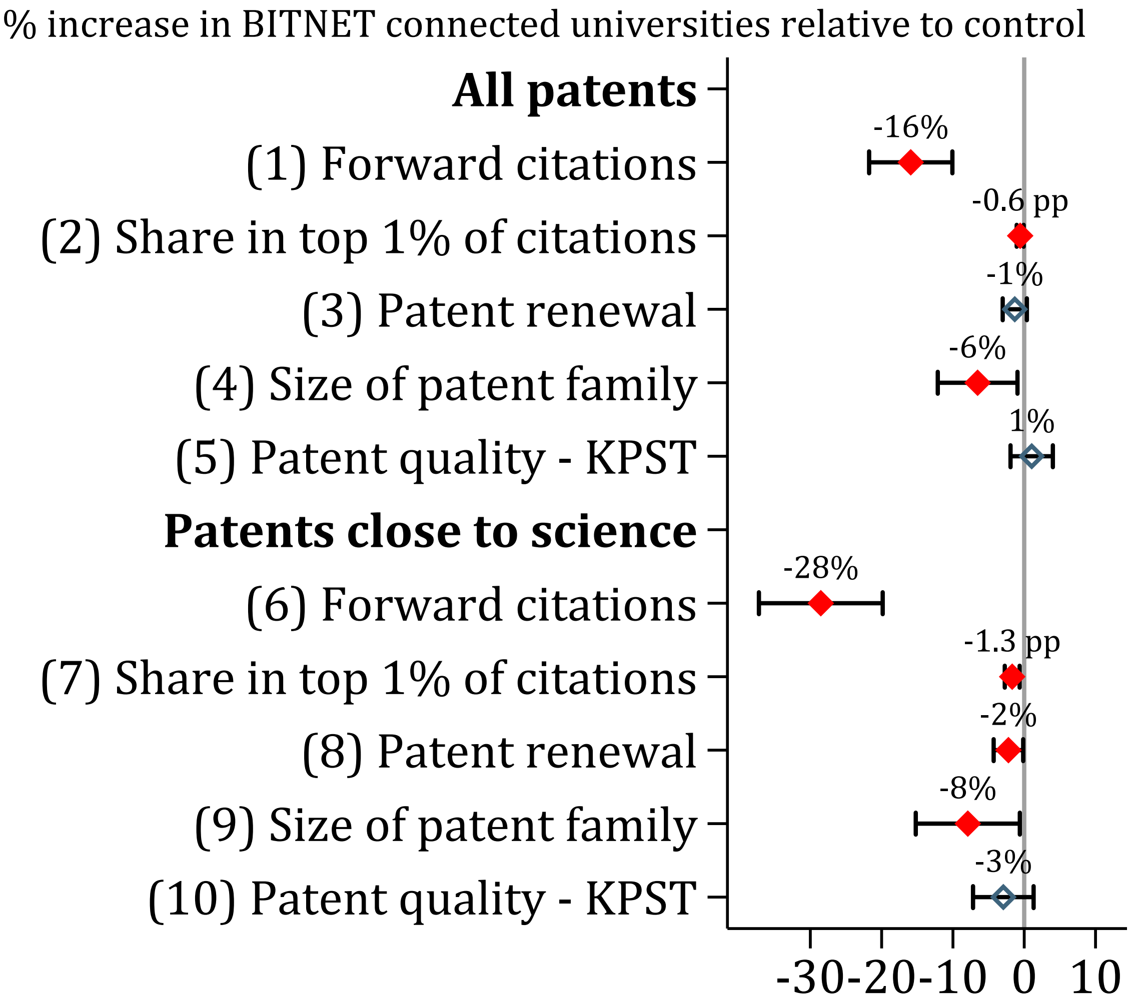



Figure A6: The Impact of BITNET Different Measures of Patent Quality

Note: Note: This figure shows the results from a difference-in-differences estimation with measures of quality of university patents in the 15 miles region around a university 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 connect to BITNET later. All specifications include year fixed effects and institution group fixed effects. The bars indicate 90% 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.

## A.6 Additional (Time-Varying) Heterogeneity of Effects

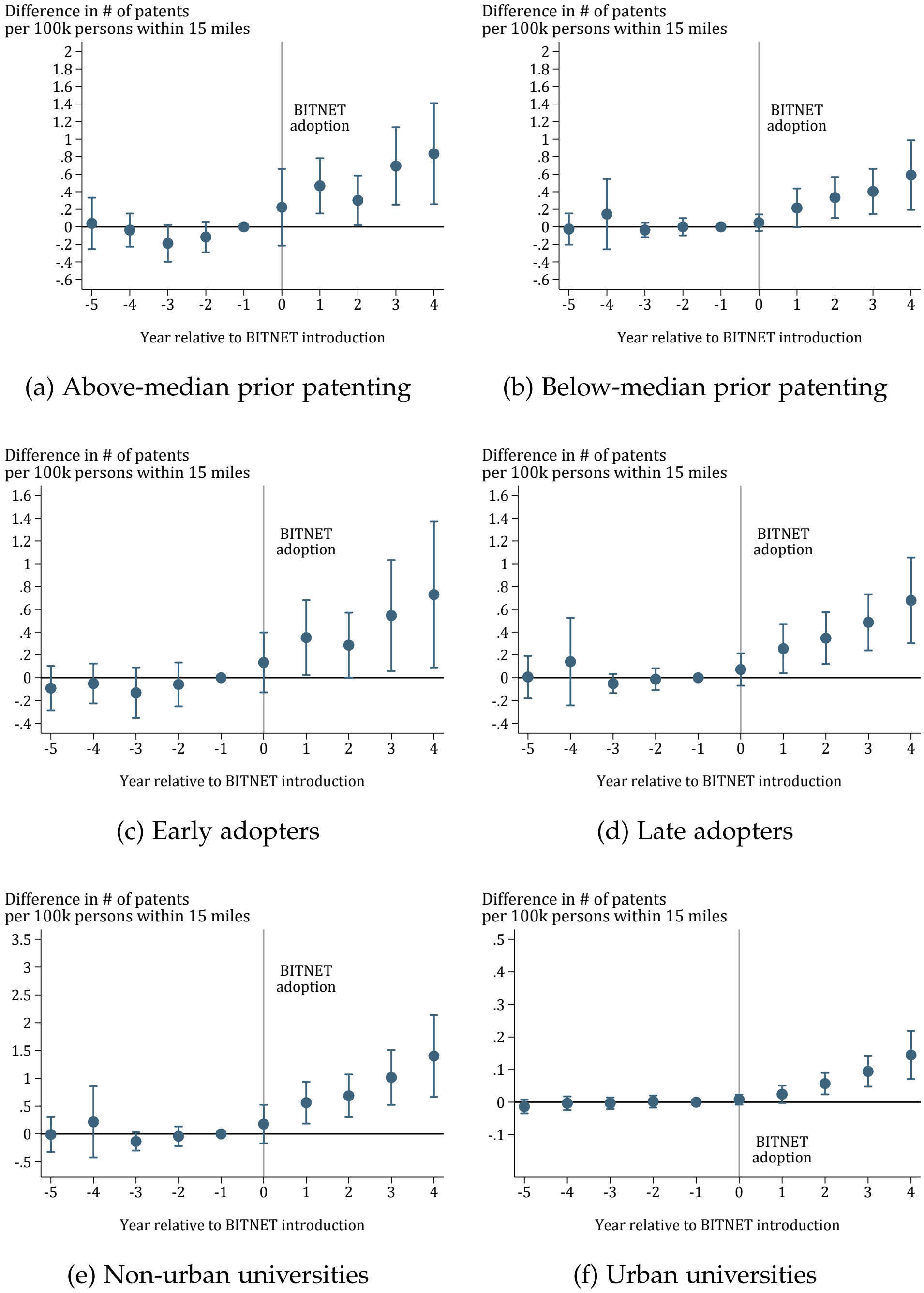
In Table A4 below, we show more heterogeneity results. In Column (1), we repeat our baseline estimate for comparison. In Columns (2) and (3), we split the sample by the treated university's patenting levels before BITNET existed, i.e., in 1980. We find that the effect is largely driven by universities that already showed above median patenting levels in 1980. This could point to a complementary between ICT and local inventive capacity. In Columns (4) and (5), we show a split by adoption year and find that the effect is larger for early adopters (until the end of 1984), but is also substantial for late adopters.

| Dependent Variable: | University patents p.c. | | | | |
|---|---|---|---|---|---|
| Split: | Baseline | Above Median Patenting | Below Median Patenting | Early Adopters | Late Adopters |
| | (1) | (2) | (3) | (4) | (5) |
| BITNETxPost | 0.30*** | 0.56*** | 0.20** | 0.48*** | 0.24*** |
| | (0.08) | (0.17) | (0.08) | (0.18) | (0.08) |
| Mean Dep. | 0.30 | 0.70 | 0.23 | 0.42 | 0.27 |
| R2 (within) | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| Obs. | 531063 | 102175 | 264225 | 200777 | 330286 |

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) and (3) split the sample by median patenting rates per 100,000 population in the 15 miles region around universities in 1980, the year before the first BITNET adoption. Columns (4) and (5) split the sample into early and late BITNET adopters. Early adopters are those universities that are connected by the end of 1984. 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: Impact on Number of University Patents p.c. Across Different Types of Universities

In panels (a) and (b) of Figure A7, we show the effects by above- and below-median patenting before BITNET adoption. In both figures, the difference between treatment and control universities is insignificant in the time period before BITNET adoption. After BITNET adoption, patenting increases around universities that had above-median patenting in 1980, while we only see smaller effects arising around universities with historically low patenting rates. In panels (c) and (d) of the Figure, we split our sample into early and late adopters. We again find that before BITNET adoption, there is no differential trend between treatment and control group both for early and for late adopters. After BITNET adoption, both sets of universities see increases in patenting. This increase is larger for early adopters than for late adopters. In panels (e) and (f), we split the sample into non-urban and urban universities (by median population density). Again, in line with our identification assumption, there is no difference in patenting between treatment and control group both for non-urban and for urban universities before BITNET adoption. After BITNET adoption, patenting substantially increases around non-urban universities. Around urban universities, there is only a small increase in patenting around treated universities that also sets in later. Note the difference in scales that is necessary such that any impact is visible for urban universities. This reinforces our finding that non-urban universities benefit from BITNET while urban universities do not.




(a) Above-median prior patenting (b) Below-median prior patenting

(c) Early adopters (d) Late adopters

(e) Non-urban universities (f) Urban universities

Figure A7: Treatment effects analysis by sub-groups

Note: This figure shows the yearly average treatment effects on the treated 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 across sub-groups. Panels (a) and (b) split the sample by median per capita patenting in 1980. Panels (c) and (d) split the sample by whether the focal university adopted BITNET before or after 1984. Panels (e) and (f) split the sample by median population around universities. 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).

## A.7 Funding Shocks as Potential Explanation

If there is a funding increase concurrent to the BITNET introduction, this might bias our results. We use two complementary approaches to provide evidence that this is likely not an issue in our setting.

First, we directly control for the funding that universities have at their disposal by using federal funding per university and an estimate of the number of faculty as controls. The federal funding data per university is from Hausman (2021), which Naomi Hausman thankfully shared with us. Unfortunately, this data is available only for a subset of our universities. To estimate the number of faculty, we use data from Microsoft Academic. We define an author as faculty if she published for an institution at least twice in the top 10,000 highest impact journals with a gap of five or more years.

We show the results of this analysis using the number of patents as outcomes in Table A5. The results are qualitatively identical when estimating this in per capita terms. Column (1) shows our baseline estimate for comparison. Column (2) controls for the number of faculty in the respective year. Column (3) adds the funding measure from Hausman (2021). Column (4) includes both measures. The table shows that our results are qualitatively unaffected by these additional controls.

Figure A8 shows the time-varying treatment effects on patents within 15m of the respective university around BITNET adoption when controlling for both measures of university funding. Again, the estimates are very similar to the estimates without controlling for these variables. This analysis suggests that concurrent funding shocks are unlikely to explain our results. Note, however, that data limitations make this analysis not entirely conclusive. Thus, we cannot entirely rule out funding shocks as a partial confounder.

| Dep. Var.: | University patents | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| BITNETxPost | 0.50*** | 0.35*** | 1.34*** | 1.51*** |
| | (0.12) | (0.13) | (0.33) | (0.32) |
| Faculty (in 100) | | 0.30*** | | -0.28*** |
| | | (0.02) | | (0.05) |
| Total funding (in 10,000 USD) | | | 0.09*** | 0.12*** |
| | | | (0.02) | (0.02) |
| Mean Dep. | 1.24 | 1.35 | 2.33 | 2.33 |
| R2 (within) | 0.10 | 0.12 | 0.04 | 0.05 |
| Obs. | 531063 | 365537 | 19791 | 19791 |

Note: This table shows difference-in-differences estimates of BITNET adoption on local university 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. All columns use university patenting in 15 miles around the universities as dependent variable. Column (2) controls for the number of faculty that we take from Microsoft Academic. We define an author as faculty if she published for an institution at least twice in the top 10,000 highest impact journals with a gap of five or more years. In Column (3) we control for total funding from all government agencies, using the data from Hausman (2021). 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: Impact on Number of University Patents p.c. Controlling for Funding Shocks

In a second, complementary, approach, we also directly investigate the possibility that concurrent funding shocks by the government induce both BITNET adoption and higher patenting, without a direct effect of BITNET. We leverage that patents that rely on U.S. government funding must acknowledge that they do. Using the data by Fleming et al. (2019), we can thus split the dependent variable into whether patents rely on U.S. government funding, either directly or indirectly. If government funding increased at the same time as BITNET was introduced we would expect that patents acknowledging government funding grow faster than patents that do not acknowledge funding. In particular - if there is no BITNET effect and we only see a funding shock - we would expect little reaction from patents that do not acknowledge funding.

We show the results from the analysis in changes relative to post period means using the margins command in Stata in Figure A9. The first line shows our baseline

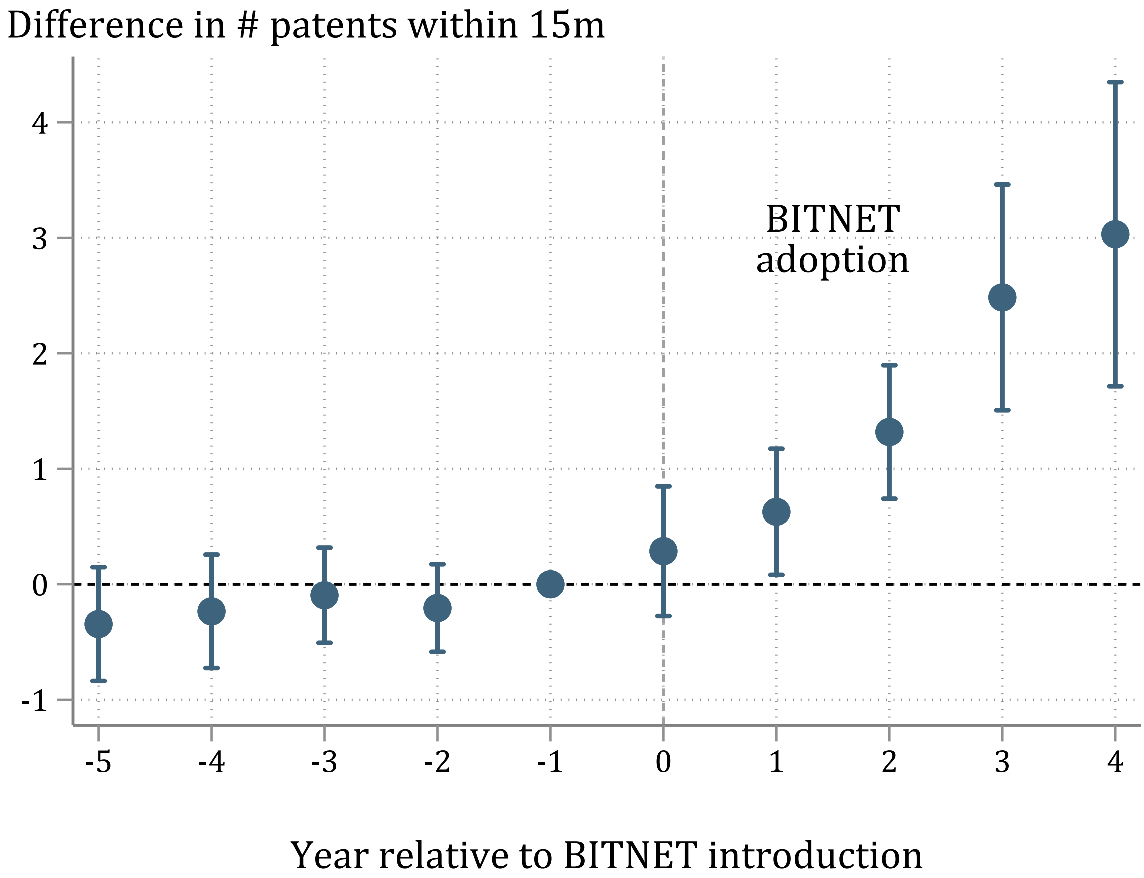



Figure A8: Innovation impact controlling for funding

Note: This figure shows the yearly average treatment effects on the treated of BITNET adoption on the number of patents in 15m around universities adopting BITNET relative to universities that only adopt BITNET later. In the graph, we control for faculty members and total funding support available at the universities. We count faculty members by identifying authors in Microsoft Academic. We define an author as faculty if she published for an institution at least twice in the top 10,000 highest impact journals with a gap of five or more years. For the funding data, we rely on a name matching to the data from Hausman (2021). 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).

effect for comparison. It amounts to an around 50% increase in local per capita patenting. In the second line, we show the impact of BITNET on patenting per capita for patents that directly acknowledge U.S. government funding. Relative to the mean of the control group in the year before BITNET adoption, this is an effect of around 50%, proportional to the main result. In the third line, we repeat the analysis using those patents as dependent variable that do not directly rely on government funding but cite either a patent or an article that acknowledges government funding ("indirect government funding"). We find a somewhat larger effect (68%). We show the impact on patents without direct or indirect funding from the U.S. government in line (4). In relative terms, the effect is by far the largest, with an increase of 77%. Many patents in the data by Fleming et al. (2019) do not contain positive or negative information on their reliance on U.S. government funding. In this group, the relative effect is around 41% (line 5). All in all, it does not seem as if our effects are exclusively driven by increases in funding that occur at the same time as the introduction of BITNET. All categories see increases in patenting that are roughly proportional to the categories' baseline patenting levels. If anything, the largest relative effect occurs among patents for which we know that they do not rely on U.S. government funding.

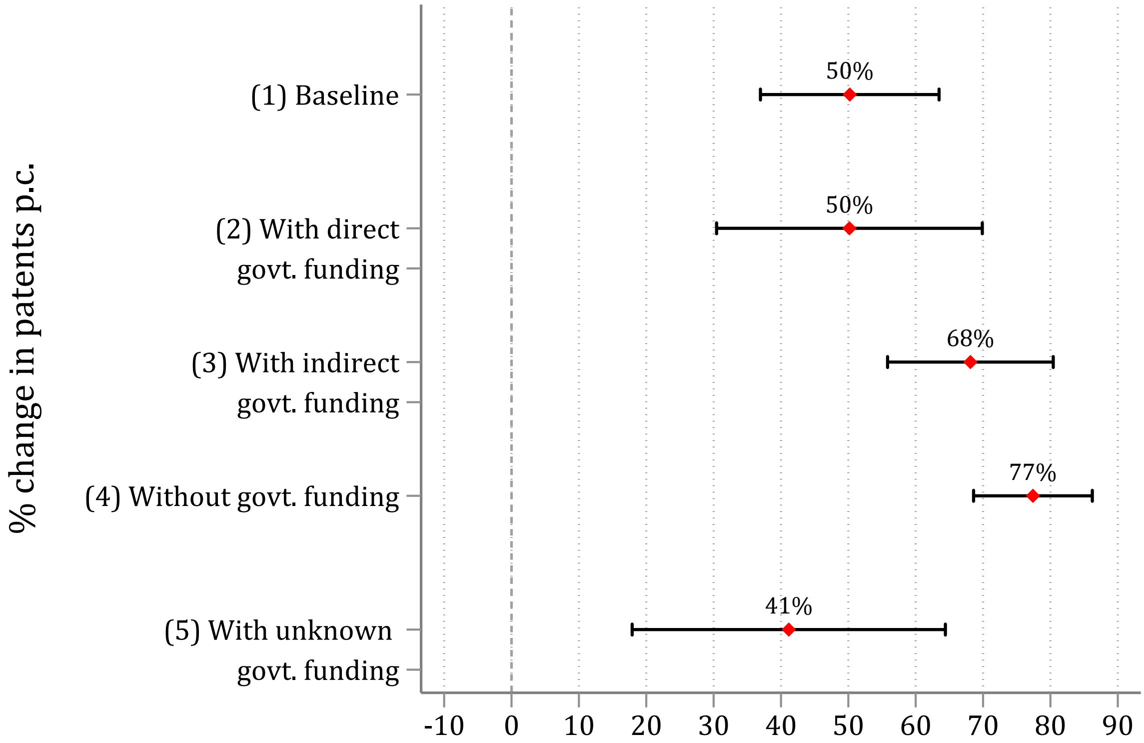



Figure A9: Treatment effect by acknowledgment of U.S. government funding

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 first line and university patents with the respective characteristic per 100,000 population in the 15 miles region around a university as the dependent variable in all subsequent lines. We show the results from the analysis in changes relative to post period means using the margins command in Stata. 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. To adjust for the different number of control universities, we use the weights suggested by Iacus et al. (2012).

## A.8 Relation to Bayh-Dole Act

The Bayh-Dole Act was an important step in inducing more innovation closely connected to science and local economic activity around universities (Hausman, 2021). But while the Bayh-Dole Act greatly changed the nature of university patenting, we think it did so for all universities, i.e., treatment and control universities alike. For example, looking at a treated university that joined BITNET in 1984, it is difficult to understand how Bayh-Dole (enacted in 1980) led to an increase in patents in 1985 only at the treated university but not at the control universities, and how it did not increase patents at either the treated or control universities in 1983.

This seems possible only if Bayh-Dole had an impact on patenting that is synchronized both in location (at treated but not at control universities) and time (after BITNET but not before) with the introduction of BITNET. There are, therefore, two key concerns related to the Bayh-Dole Act. Universities adopting BITNET earlier might also have been more keen to increase technology transfer by (i) introducing TTOs and by (ii) incentivizing their faculty with royalty payments.

In this subsection, we show that we arguably do not confound the impact of BITNET with the impact of the 1980 Bayh-Dole Act and the subsequent establishment of technology transfer offices or the introduction of royalties by universities (e.g., Henderson et al., 1998; Mowery et al., 2001; Mowery and Ziedonis, 2002).

To this end, we first leverage data on the number of full-time equivalent staff at universities devoted to technology transfer, e.g., in a technology transfer office. We thank Arvids Ziedonis for providing us with this data. Column (1) repeats our baseline estimate. Column (2) controls for an indicator whether the university employs staff devoted to technology transfer (i.e., a technology transfer office, TTO) in a given year. Our main result is unaffected, while we do see positive impacts of TTOs on university patenting. In Columns (3) and (4), we split our sample into whether the treated university ever had staff devoted to technology transfer or not. The impacts of BITNET are somewhat larger for universities that had a TTO, suggesting a complementarity between BITNET and TTOs. However, even in universities without a TTO, we see positive and significant effects of BITNET adoption on university patenting. Our analyses thus suggest that the establishment of TTOs and the introduction of BITNET had independent effects on local university innovation.

Second, we extend this analysis to universities' licensing regimes. A key part of the Bayh-Dole Act was that universities could now incentivize their research staff to translate research findings to inventions by allowing researchers to benefit from subsequent royalty payments (Lach and Schankerman, 2008; Ouellette and Tutt, 2020). We therefore use the data provided by Ouellette and Tutt (2020) to investigate whether we confound these potential royalty payments with our estimates of BITNET.

We show the results of our main specification controlling for royalty payments in Table A7. The first column repeats our baseline estimate. In Column (2) we additionally control for whether the university grants its researchers shares of the royalties resulting from their patents. Note that the royalty variable is time-varying since the data contain information on when the universities introduced royalties. Our estimate is unaffected. Columns (3) and (4) then divide the sample according to whether the university has ever granted its researchers royalty shares from its patents. The table shows that royalties do not materially affect our estimate for the impact of BITNET on local university patenting. While royalty-granting universities benefit somewhat more, the effect on universities that do not is also sizable.

Overall, we believe that these results show that the Bayh-Dole Act does not confound our estimates on the patenting impact of BITNET adoption.

| Dep. Var.: | University patents p.c. | | | |
|---|---|---|---|---|
| Sample | Baseline | Baseline | TTO Univ. | Non-TTO Univ. |
| | (1) | (2) | (3) | (4) |
| BITNETxPost | 0.30*** | 0.29*** | 0.60*** | 0.18*** |
| | (0.08) | (0.08) | (0.18) | (0.06) |
| TTO | | 0.08*** | | |
| | | (0.02) | | |
| Mean Dep. | 0.30 | 0.30 | 0.82 | 0.22 |
| R2 (within) | 0.00 | 0.00 | 0.02 | 0.01 |
| Obs. | 531063 | 518154 | 43907 | 265600 |

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. Column (2) controls for an indicator whether the university employs staff devoted to technology transfer in a given year. Columns (3) and (4) split our sample into whether the treated university ever had staff devoted to technology transfer (i.e., a technology transfer office) or not. 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: Impact on Number of University Patents p.c.: Relation to University Technology Transfer Offices

| Dep. Var.: | University patents p.c. | | | |
|---|---|---|---|---|
| Sample: | Baseline | | Royalties | |
| | | | Yes | No |
| | (1) | (2) | (3) | (4) |
| BITNETxPost | 0.30*** | 0.31*** | 0.59*** | 0.15*** |
| | (0.08) | (0.08) | (0.18) | (0.06) |
| Royalty Fee | | -1.64*** | | |
| | | (0.03) | | |
| Mean Dep. | 0.30 | 0.30 | 0.37 | 0.27 |
| R2 (within) | 0.00 | 0.01 | 0.00 | 0.00 |
| Obs. | 531063 | 531063 | 219265 | 311798 |

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. All columns use patents by university-connected inventors adjusted by the population in the 15 miles region around the university as the dependent variable. The royalty data stems from Ouellette and Tutt (2020). We label those universities without information on royalties as not granting them. Column (2) controls for whether the treated university every pays royalties to university inventors. Columns (3) and (4) split the sample by this 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 A7: Impact of BITNET accounting for royalty payments

## A.9 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) |
| BITNETxPost | 0.30*** | 0.31*** | 0.30*** | 0.26*** | 0.25*** |
| | (0.08) | (0.08) | (0.08) | (0.06) | (0.06) |
| Mean Dep. | 0.30 | 0.30 | 0.30 | 0.30 | 0.29 |
| R2 (within) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Obs. | 531063 | 518512 | 505660 | 478728 | 464855 |

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 A8: Impact on Number of University Patents p.c. without Top X Universities

## A.10 Matching

In Table A9, we show that our results are robust when we use a more detailed matching strategy. In particular, we show that additionally matching on the number of patents in the year before BITNET adoption as well as matching on number of patents and on 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) |
| BITNETxPost | 0.30*** | 0.29*** | 0.29*** | 1.43*** | 1.40*** | 1.40*** |
| | (0.08) | (0.08) | (0.08) | (0.35) | (0.35) | (0.35) |
| Mean Dep. | 0.30 | 0.29 | 0.29 | 1.01 | 0.98 | 0.97 |
| R2 (within) | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 |
| Obs. | 531063 | 530326 | 439080 | 531063 | 530326 | 439080 |

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 A9: Results Using Additional Matching Strategies

## A.11 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) |
| BITNETxPost | 0.30*** | 1.43*** | 0.09*** | 0.13*** |
| | (0.08) | (0.35) | (0.02) | (0.03) |
| Mean Dep. | 0.30 | 1.01 | 0.19 | 0.44 |
| R2 (within) | 0.00 | 0.01 | 0.03 | 0.07 |
| Obs. | 531063 | 531063 | 531063 | 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. Columns (1) and (2) repeat our baseline specification using patents and citation-weighted patents in levels as dependent variable. Columns (3) and (4) repeat our baseline specification using a inverse hyperbolic sine transformation as 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 A10: Main Results Using Different Specifications

## A.12 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) |
| BITNETxPost | 0.30*** | 0.50*** | 0.21** | 0.13* | 0.68** |
| | (0.08) | (0.15) | (0.09) | (0.08) | (0.31) |
| Mean Dep. | 0.30 | 0.31 | 0.31 | 0.31 | 0.28 |
| R2 (within) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 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 A11: Results across Regions: Impact on Number of University Patents p.c.

## A.13 Effects by Technology Category

We show the effects by technology category in Figure A10. Each line is the difference-in-difference coefficient on the interaction between time and BITNET in a different regression that uses patents in the respective field as the dependent variable. The absolute effects on the number of patents per capita are most pronounced in Chemistry and Instruments, but these effects are proportional to baseline patenting levels. We find the largest relative effects in Electrical Engineering, but effects are hardly distinguishable (not shown). This suggests that the adoption of BITNET might have had a productivity-enhancing effect on inventors in several technology areas.

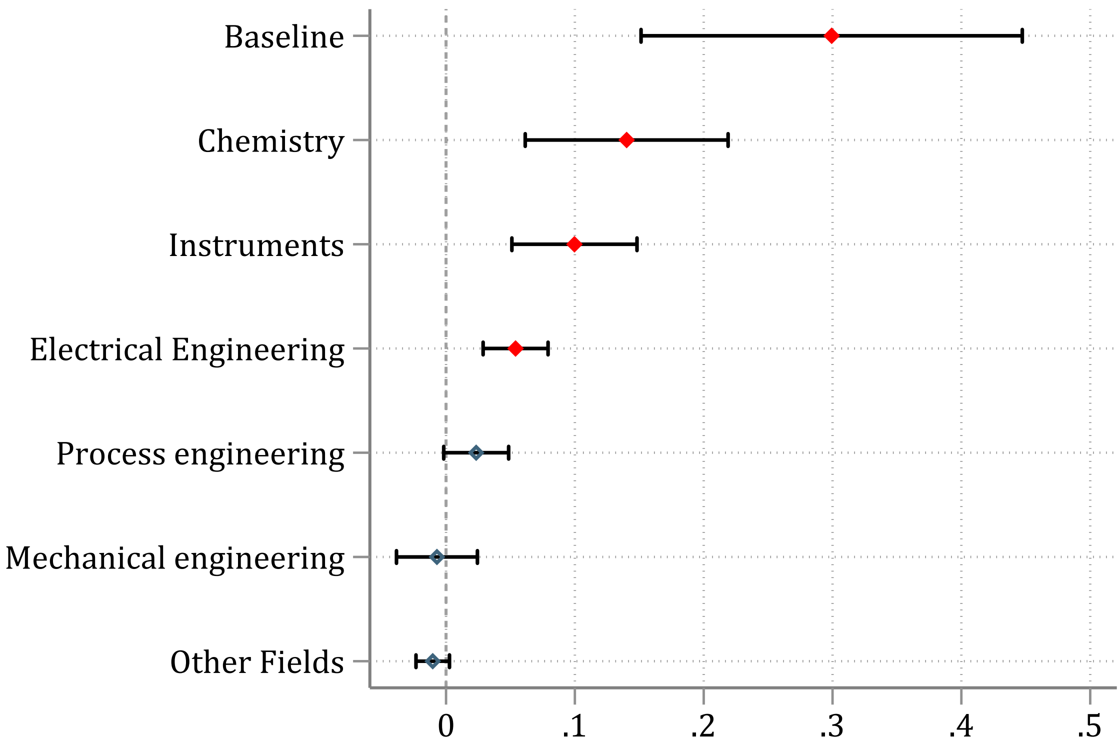


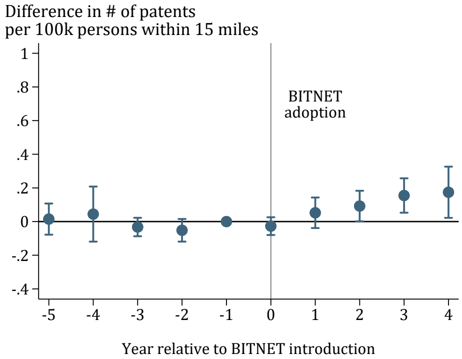

Figure A10: Innovation Effects of BITNET by Technology Category

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 first line and university patents in the denoted field per 100,000 population in the 15 miles region around a university as the dependent variable in all subsequent lines. Thus, the coefficients in the next lines add up to the first line. 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.

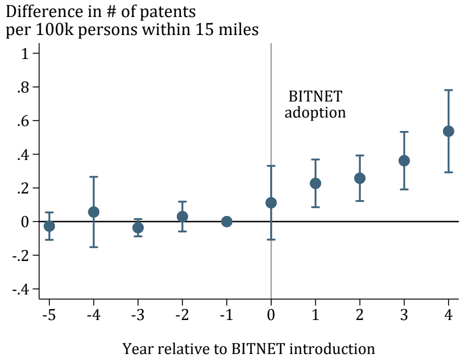
# B Appendix to Section 5

## B.1 Time-varying Effects on Team Formation

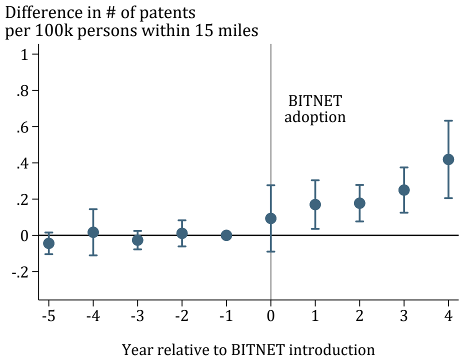
Figure A11 shows the time-varying impacts of BITNET on team formation. Panels (a) and (b) show estimates using single-authored and team patenting as dependent variables, respectively. In line with our identification assumption, outcomes do not differ between treatment and control universities before BITNET adoption. After BITNET adoption, all types of inventors become somewhat more productive, but inventor teams increase their patenting substantially more than single inventors. Panels (c) and (d) show patenting by new and by old teams, respectively. We define new teams as teams that had at least one new team member (including entirely new teams that had not patented together before), whereas teams that had patented in the same composition before count as old teams. Again, in line with our identification assumption, outcomes do not differ between treatment and control universities before BITNET adoption. After BITNET introduction, we find that both types of teams increase their patenting but new teams increase their patenting substantially more than old teams. Finally, Panel (e) shows the impact of BITNET adoption on average team size. The positive impact observed in Table 2 is visible, but it is much more noisily estimated than the other results.



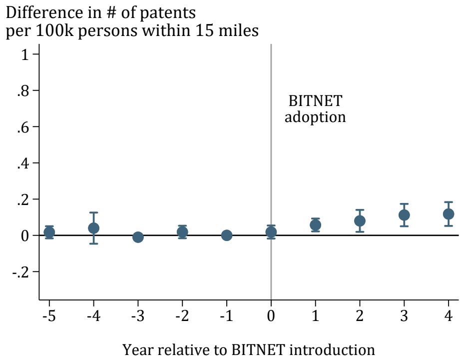

(a) Single-authored patents



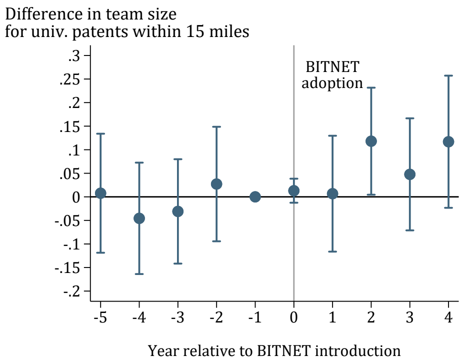

(b) Patenting by teams




(c) Patenting by new teams




(d) Patenting by old teams



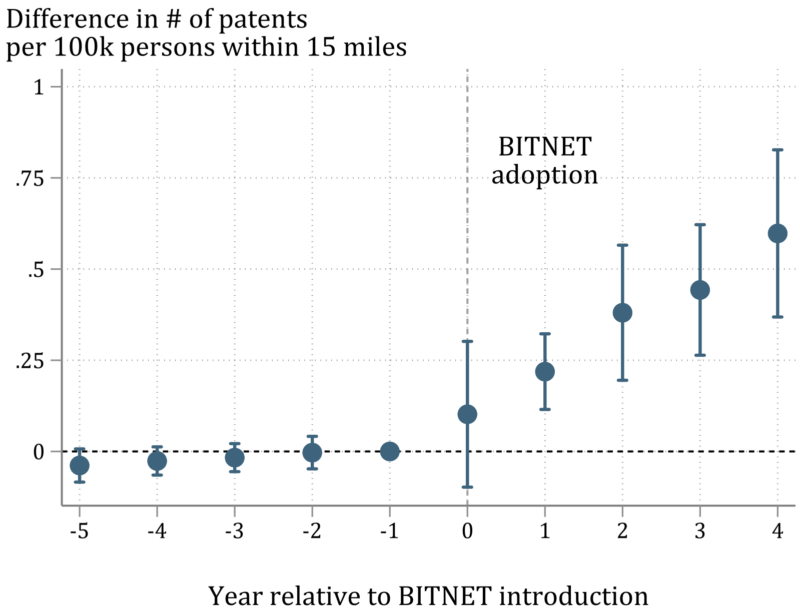

(e) Average team size

Figure A11: Time-varying effects on team formation

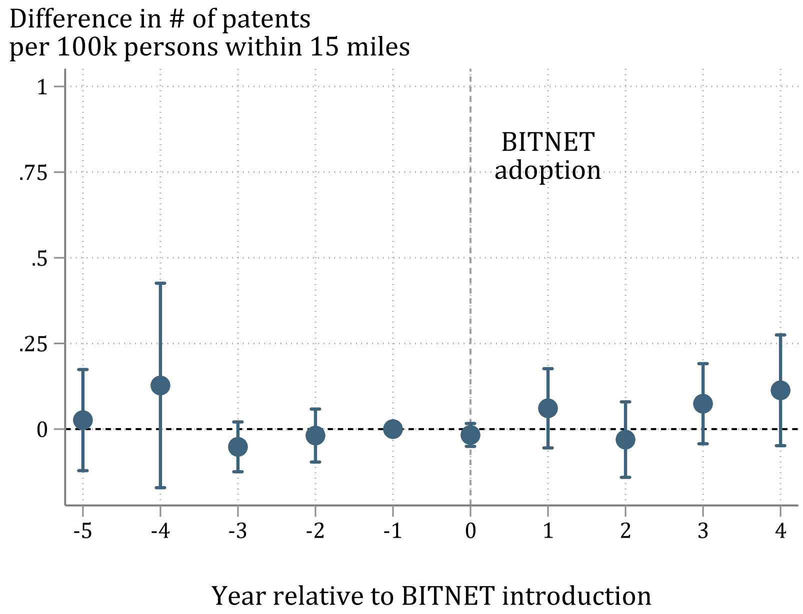
Note: This figure shows the yearly average treatment effects on the treated of BITNET adoption on different outcomes of universities adopting BITNET relative to universities that only adopt BITNET later. Panels (a) to (d) use the number of university patents filed by different types of inventors per 100,000 population within 15 miles around the universities. Panels (a) and (b) use single-authored and team patents as dependent variables, respectively. Panels (c) and (d) use patenting by new teams and by existing teams, respectively. Panel (e) uses average team size on university patents filed within 15 miles around the universities as dependent variable. 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).

## B.2 Time-varying Effects on Patents Closely Related to Science

In Figure A12, we show the time-varying version of our results on patents closely connected to science. Closely connected patents are those which either directly cite academic articles or cite patents that directly cite academic articles. Patents not closely connected to science are all other patents. The data is from Ahmadpoor and Jones (2017). In line with our identification assumption, both types of patents do not differ between treatment and control group before BITNET adoption. After BITNET adoption, patents closely connected to science increase around treated universities. In contrast, other patents are unaffected.




(a) Patents Closely Related to Science per 100,000 Population




(b) Other Patents per 100,000 Population

Figure A12: 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 cite a scientific article directly or that cite another patent which directly cites a scientific article. Panel (b) uses the number of patents p.c. that neither directly cite a scientific article nor cite 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.

## B.3 Other Margins of Patent Content

In Figure A13 we analyze various measures of patent content. We show our results for all university patents as well as for patents closely related to science only. We find that patents seem to have more information, draw on a wider range of prior art (originality), but are less widely used (generality) and more similar to prior work.

In Rows (1) to (5) we look at all patents and do not find a strong pattern. If at all, the number of sheets, the length of the patents, appears to go down. We find much stronger effects when we restrict our analysis to patents closely connected to science, the drivers of our effect. These patents become longer (Row 6) and use more figures (Row 7) after BITNET adoption. Following the adoption of ICT, they show lower generality (Row 8, measuring the range in technologies that cite the patent - Hall et al. 2001) and higher originality (Row 9, measuring the range in technologies that are cited by a patent - Hall et al. 2001), but are also substantially more similar to prior US patents (Row 10 - Kelly et al. 2021). Overall, after the adoption of BITNET, patents closely related to science around adopting universities seem to have more, but less impactful content.

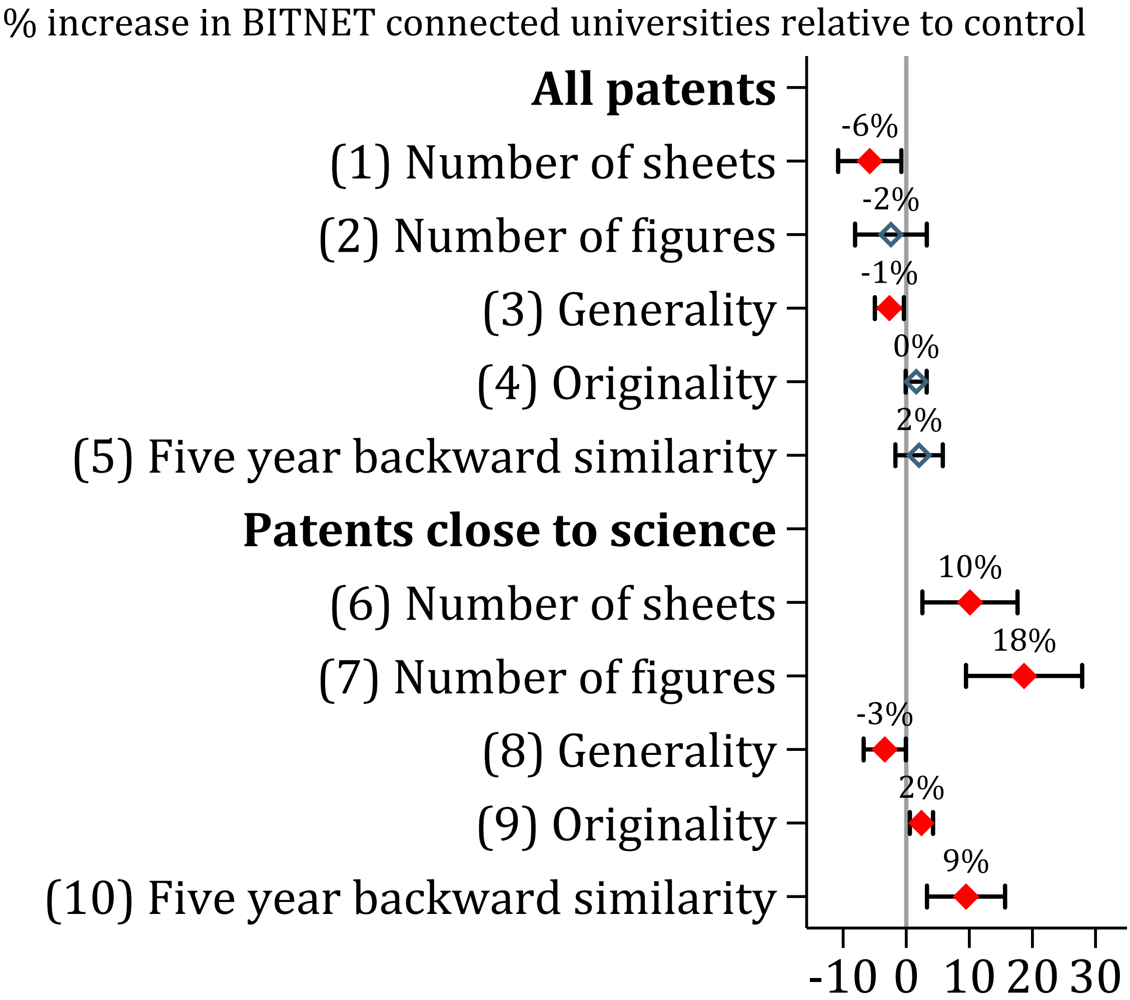



Figure A13: The Impact of BITNET on the Content of Patents

Note: This figure shows the results from a difference-in-differences estimation with measures of content of university patents in the 15 miles region around a university 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 connect to BITNET later. All specifications include year fixed effects and institution group fixed effects. We show the results from the analysis in changes relative to post period means using the margins command in Stata. The bars indicate 90% 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.