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FROM WIRES TO PARTNERS: HOW THE INTERNET HAS FOSTERED R&D COLLABORATIONS AMONG FIRMS

Completed Research Paper

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Abstract

This paper studies how IT investments shape the geography of firm innovation. We focus on the role of investments by US firms in basic internet technology on the organization of innovation. We combine establishment-level IT investment data with data on US patenting activity at the MSA level. Our difference-in-difference econometric estimation approach compares the citation-weighted count of co-invented patents among two firm locations before basic Internet technology diffused (i.e., 1992) to the count of patents after its diffusion (i.e., 1998). Our results show that when two firm locations adopt Internet technology, the number of cross-location collaborative patents between them increases compared to an otherwise identical pair without Internet technology. We further find that the link between Internet adoption and cross-location patenting is greatest for firm pairs that have previously been successful innovators, have not collaborated before, and which have different research foci.

Keywords: R&D organization, geography of innovation, internet adoption, IT investments

Introduction

How has the diffusion of communication technologies like the Internet influenced research collaborations and innovative activity within firms? This question speaks to two central problems in the economics of and value of information systems as well as the economics of technical change. First, it advances a large IS literature on the business value of IT, in particular recent research on the impact of IT investment on intangible assets such as patents (a proxy for innovation; e.g., Han and Ravichandran 2006; Kleis et al. 2010) and trademarks (a proxy for product variety; e.g., Gao and Hitt 2004).[1] Further, it speaks to a large literature on the organization of innovation within organizations (e.g., Cohen and Levin 1989).

One question of particular interest is how the use of information technology (IT) reshapes the geography of research collaborations within firms. Recent work has shown that IT investments are positively associated with the innovative output within firms (Han and Ravichandran 2006; Kleis et al. 2009). Further, a small body of work has begun to emerge that suggests that IT increases academic research collaborations most among those who are geographically close (e.g., Agrawal and Goldfarb 2008), or who have similar research interests (e.g., Rosenblat and Mobius 2004), however there has been little systematic empirical study of IT investment and its impact on the geography of research within firms. This gap in knowledge is significant, given the longstanding interest in the geography of industrial innovation (e.g., Jaffe, Trajtenberg, and Henderson 1993).

In this paper we take a first step toward studying how IT investments shape the geography of firm innovation. To do this, we focus on the role of investments by firms in a set of Internet technologies that enable basic communication such as Internet access or the development of intranet. The set of technologies we examine require little adaptation or co-invention to be used successfully, and so allow us to focus on the short run changes to collaboration patterns that are made in response to a decline in communication costs. We combine this firm-level IT investment data with data on US patenting activity from the US Patent and Trademark Office (USPTO).

Our econometric approach examines the impact of Internet adoption on the number of patents co-invented by researchers within a firm. We first examine collaborations within pairs of heterogeneous firm locations: we compare the number of patents co-invented by researchers in two firm locations before basic Internet technology diffused (i.e., in 1992) to the number of patents after its diffusion (i.e., in 1998). That is, we use a difference-in-difference econometric estimation approach to identify the relationship between Internet investments and the pattern of research collaborations. For comparison, we also study the effects of Internet investment on co-invented patents within a single firm location. Our sample period addresses a time period over which Internet technology had diffused but before enough time had elapsed for firms to change the internal organization (in particular, the geographic locations) of its research organization.

To identify how IT investments influence research collaborations, we combine two data sources. First, we identify IT investments using a data set compiled by Harte Hanks Market Intelligence, a market research firm. As has been discussed elsewhere (e.g., Forman, Goldfarb, and Greenstein 2005), this data set represents the best set of information on the IT investments of private firms available. We link IT data collected at the establishment level to the number of patents invented within a metropolitan statistical area (MSA). Thus, in our analyses we examine variance over time in the number of patents invented by researchers in pairs of firm-MSA locations and among researchers within a given firm-MSA.

Our first set of results assumes that Internet adoption is exogenous to research collaborations. Our results show that when two locations within a firm both adopt Internet technology, the patents co-invented by researchers in both locations increases significantly compared to an otherwise identical pair without Internet technology. In contrast, we find that adoption of Internet technology has no impact on the number of co-invented patents among researchers within a single firm location. We find that both results remain robust to numerous specifications and changes to controls.

We next address the assumption that Internet adoption is exogenous. We first utilize the timing of Internet adoption as the source of a falsification exercise. We find no evidence that cross-location research collaborations (1990-1994) prior to the diffusion of the commercial Internet were correlated with establishment's later adoption of Internet technology (i.e., in 1998). We next show that our results are robust to the use of instrumental variables estimates.

[1] See also the focus on innovation in the recent book by Brynjolfsson and Saunders (2009).

Next, we examine the characteristics of pairs that experience the largest increase in patenting as a result of Internet adoption. We find that Internet adoption has the greatest impact among location pairs that were already among the most research productive, among those who had not collaborated before, and among these that previously had concentrated on different research fields. That is, Internet adoption had the greatest impact on innovative activity among researchers who had previously not been active collaborators. We find that these results are also robust to the use of instrumental variables.

Our research contributes to prior literature that has examined the impact of computer networks on scientific collaborations. In particular, the paper most closely related to ours is Agrawal and Goldfarb (2008), who show that adoption of an earlier communication technology, Bitnet, facilitated cross-institution university collaboration, particularly among those in the same geographic region. Our work is also related to that of Rosenblat and Mobius (2004), who examine time trends in research collaborations and show that researchers have become increasingly likely to collaborate with others in the same of related fields relative to cross-field collaborations; their hypothesis is that by lowering communication costs, IT reduces the costs of working with those who may be geographically distant but who may have similar research interests.[2] In contrast, we examine a different setting: industrial research collaborations, and find that adoption of basic IT was associated with a disproportionate increase in cross-location collaborations, with little effect on within-location collaborations. Further, we show that collaborations among research locations with different foci were disproportionately affected by IT investment. As we discuss in further detail below, we argue that these results are due to the way that firm and academic research collaborations are formed.

As noted above, we also related to recent research in the IS literature that has demonstrated a relationship between IT investments and innovative output (Han and Ravichandran 2005; Kleis et al. 2009). In contrast to this work that focuses on measuring the value of IT investments for innovative output, we focus on the mechanism through which IT investments influence innovative collaborations.

Internet Investment and the Geography of Knowledge Production

The starting point for the motivation of our analyses will be the innovation production function. If a firm i generates new innovation by investing R&D resources R_i, the innovation production functions is $y_i = R_i^{\beta} s_i$, where y_i is the number of innovations, R_i is the amount of R&D expenditure and s_i is a vector of factors influencing the productivity of R&D investments (e.g., Pakes and Griliches 1987). Our interest is in examining how investments in Internet technology influence the productivity of R&D investments among research groups within a firm, i.e. through shifts in the term s_i.

However, our focus departs from the innovation production function literature in that we examine how Internet adoption influences the number of collaborative innovations developed in research groups within a firm. For our purposes, a research group can either be a location within a firm or a pair of locations. We first motivate how adoption of Internet technology would improve research productivity within research groups. We then motivate when these effects would be strongest.

Did adoption of the Internet improve research productivity?

By lowering communication costs, Internet technology can improve research productivity by facilitating knowledge sharing and lowering the costs to access scare resources. For example, Internet technology can lower communication costs by providing access to Internet protocol (IP)-based email, telephony, and other collaborative tools (Kleis et al. 2009; Lee and Choi 2003; Rice 1994). This will facilitate lower cost access to others, especially to researchers in distant locations.

Internet technology can also facilitate access to codified knowledge (e.g., Ding, Levin, Stephan, and Winkler 2010) by lowering the costs of accessing shared resources such as electronic databases for journals and online repositories

[2] Van Alstyne and Brynjolfsson (2005) similarly present a model demonstrating how IT use can contribute to agents increasingly communicating more with those who have similar preferences.

for data. It has also facilitated the development of more efficient processes for accessing knowledge, as when an institution sets up an online mechanism for accessing books from a library.

Last, Internet technology can aid in providing access to shared resources. Of course, this is most evident in access to computing resources: the original ARPANET was conceived as a means of sharing computing resources. However, laboratory resources can be shared as well. For example, as Ding et al (2010) note, collaborative networks can help laboratories access scarce chemical or biological compounds that may be offsite.

While the benefits of knowledge sharing and access to shared resources will benefit all research collaborations, adoption of Internet technology is likely to have the strongest productivity benefits for those that are geographically dispersed. Prior to the adoption of Internet technology, the costs of knowledge sharing among dispersed establishments was high—the options were to communicate either through telephone or face-to-face communication or through more expensive private networks (Forman 2005). All three of these options were either costly, had limited functionality, or both. In contrast, the costs of face-to-face collaboration among geographically collocated researchers are lower.

While IT may improve the productivity of ongoing distant collaborations more than the productivity of ongoing close collaborations, it is less effective at facilitating the initiation of new collaborations (e.g., Gaspar and Glaeser 1998). The reason is that developing a new research project often involves the communication of tacit information that may be difficult to communicate in any circumstances and are most effectively communicated in person (e.g., von Hippel 1986). Further, the identification of potential collaborators is usually modeled as an activity that requires face-to-face contact (e.g., Charlot and Duranton 2006; Gaspar and Glaeser 1998). As a result, "distance matters" for the initiation of new projects.

To summarize, adoption of Internet technology lowers the costs of conducting ongoing collaborations that are geographically dispersed. However, it is likely to be less successful at lowering the coordination costs of identifying research partners and of initiating new projects. However, firms themselves may develop capabilities in coordinating and initiating research projects (Henderson and Cockburn 1994), even among scientists in different research areas. Further, research programs may be set by higher level management in accordance with the strategy of the firm. Thus, the costs of initiating scientific research collaborations will vary less with distance than in other scientific research settings where collaborators are autonomous, as in academia. Thus, we expect Internet adoption will more strongly influence the productivity of distant industrial research collaborators than those located in the same region.

Where are the benefits of Internet adoption strongest?

In this section we briefly discuss how the returns to Internet adoption will be influenced by economies of scale, economies of scope, and the prior collaboration history of the research group.

Economies of Scale. We study whether the productivity benefits to adopting Internet technology will be greatest among pairs of locations that have large research groups. Prior research has demonstrated that group-level R&D exhibits economies of scale (e.g., Henderson and Cockburn 1994, 1996). If investments in Internet technology facilitate collaborations among scientists in larger research groups or enable formation of larger cross-site research groups, then the productivity of these large interconnected research groups formed through Internet adoption may be greater than an equivalent set of smaller groups. Further, IT may be particularly effective at lowering collaboration costs among very large research groups due to network effects.

Economies of Scope and Prior Collaboration History. We similarly examine whether IT is particularly effective at improving research productivity among sites in different research fields. A related question is whether Internet adoption strengthens the productivity of existing collaborators, or enables new collaborations among previously independent researchers. To the extent that the productivity of research groups exhibit economies of scope (Henderson and Cockburn 1996), the productivity benefits of IT investments may be greatest among sites with different research concentrations and among those that have not collaborated before. However, as noted above, a key open question is whether IT reinforces the propensity to collaborate with researchers with similar interests and capabilities (Rosenblat and Mobius 2004; Van Alstyne and Brynjolfsson 2005) or whether the firm is able to encourage the exchange of information across 'component' boundaries within a firm (Clark and Fujimoto 1991; Hauser and Clausing 1988; Henderson and Cockburn 1994).

Data

We use a variety of data sources to show how adoption of basic Internet influences research productivity within firms. In particular, we match data on IT investment from a well-known private data source on IT expenditures with patenting data from the US Patent and Trademark office. We first describe our patent data, then our IT investment data, and the matching procedure we use to combine them. Last we discuss our construction of control variables. Descriptive statistics are provided in Table 1.

Table 1 – Descriptive Statistics (as of 1998)

Variable	Mean	Standard Deviation	Minimum	Maximum
Log of Weighted Citations	0.0773	0.3534	0	4.6790
Basic Internet in both locations	0.6899	0.4626	0	1
Log of per-establishment R&D spending	3.1763	1.5149	-0.9715	7.7295
Log of establishment employees	7.5909	1.0847	5.2983	11.6315
Share of local employment in manufacturing	0.1973	0.0644	0.0391	0.4861
Local average weekly wages	605.00	87.40	382.68	848.33
Log of local employment	13.8355	0.9511	10.3316	15.7005
Number of local patents (divided by 1000)	1.6827	1.7458	0.0015	9.2400

Patent Data. We use patent data from the US Patent and Trademark Office (USPTO) as a measure of innovative activity. We map patents to firm identifiers using the patent's assignee information and the NBER Patent Data Project's matching data set (Hall et al. 2005).

Our analyses will examine the geographic variance in patenting behavior across firm-Metropolitan Statistical Areas (MSAs). Using the inventor location data in US patents, we map inventors to MSAs using the zip code of the inventor (obtained through the USPTO Patents BIB data product). In cases where Consolidated Metropolitan Statistical Areas (CMSAs) were present, we used those. In regions of the US that are outside of MSAs, we constructed "phantom" MSAs that consisted of the region of a state outside of all of the MSAs.

Patents are dated using the year of application because of the variance in the patent application-grant delay over time, and because application dates are closer to the time when the innovation occurred (e.g., Griliches 1990). Because of the well-known heterogeneity in the value of patents, we weight patents by citations using the procedure described in Hall, Jaffe, and Trajtenberg (2005). Use of citation-weighted patents is common in studies that examine the inventive output of firms like ours (e.g., Kleis et al. 2009; Branstetter 2006); in the absence of some measure of patent importance our dependent variable would weight patents of little scientific or commercial value with those with great value equally, and so would provide a poor measure of inventive output. We consider only citations within five years of the grant to avoid truncation bias, and deflate the citations received by each patent by its International Patent Classification (IPC) 4-year average to control for cross-industry differences in the propensity to patent and cite other patents.

Citation-weighted patents have been used extensively as a measure of inventive output, however there are, of course, significant limitations to their use in this way. As Jaffe and Trajtenberg (2002) note, not all inventions meet the U.S. Patent and Trademark Office (USPTO) criteria for patentability. Further, inventors must make an explicit decision to patent an invention, as opposed to relying on some other method for intellectual property protection. In particular, there may be incremental inventive activity that is not patented and therefore is not reflected in patent statistics (e.g., Cohen, Nelson, and Walsh 2000). Firms may sometimes also choose to use trade secrecy rather than patenting to protect groundbreaking inventions because of incomplete enforcement of property rights. However, citation-weighted patents have been shown to be correlated with a firm's stock market value, and thereby provide one useful measure of a firm's intangible stock of knowledge (Hall, Jaffe, and Trajtenberg 2005). Further, so long as a firm-location's patent propensity does not vary significantly over time in a way that is correlated with Internet adoption, this should not bias our estimates of the key parameters of interest.

IT Data. Our data on IT investment come from the Harte Hanks Market Intelligence Computer Intelligence Technology database (hereafter CI database). Harte Hanks tracks over 300,000 establishments in the United States. Because we focus on industrial research, we exclude government, military, and nonprofit establishments. Our sample from the CI database contains commercial establishments with over 100 employees. While this limits our sample to predominately large establishments, our algorithm for matching our IT data to the firms using Compustat identifiers from the NBER Patent Data Project similarly requires us to focus upon large firms. Further, our primary research question—how the adoption of the commercial Internet affected the geography of research collaborations within firms—also circumscribes our focus to large, multi-establishment research organizations. Thus, our analysis should be viewed as a study of IT and research collaborations within large research organizations. Prior work has compared the Harte Hanks data to the distribution of establishments in the Census County Business Patterns and found that the data include slightly less than half of all establishments with over 100 employees in the United States, and represents roughly one-third of all employment (Forman, Goldfarb, and Greenstein 2002).

Our raw data include at least twenty different specific Internet applications, from basic access to software for Internet-enabled ERP business applications software. As noted earlier, we focus on that set of basic communication technologies that involve little adaptation by users to be implemented successfully. In particular, we define an establishment as a basic Internet adopter if it indicates that it has one of the following: basic access, an intranet, or uses the internet for research purposes. We set the value of basic Internet equal to zero for all establishments in 1992 as this was well before the diffusion of the commercial Internet.

To map our establishment-level IT data to unique firm-MSAs, we map the unique firm identifier included in the Harte Hanks database to the GVKEY from the NBER Patent Data Project. We then assign establishments to MSAs using their zip code. For our analysis data set, we include only firm-MSA-year triplets that are from manufacturing firms (SIC 20-40) and are in firm-MSAs with at least one patent over the period 1992-1998. We have also experimented with an alternative sample that includes only firm-MSA-year triplets that are from manufacturing firms (SIC 20-40) and that are in firm-MSAs with at least one patent in two separate years over the period 1992-1998. Our results are robust to this alternative sample and are in fact stronger. In cases where there are multiple establishments within an MSA we calculate a firm-location as adopting basic Internet when at least one has done so.

Firm-MSA pairs. The focus of our study is on the effects of IT investment on within and cross-location innovative output. For each pair of firm-MSA establishments, we examine whether the adoption of basic Internet technology in both locations increases the number of patents co-invented by inventors located in both locations. That is, we examine the effects of Internet technology adoption on cross-location collaborative output. We further examine whether Internet adoption in a single firm-MSA increases the number of collaborations among inventors located within that MSA. To do this, we form the complete set of pairwise combinations of Firm-MSAs within a given organization. Based upon co-authorship, we identify the number of collaborations that were performed between units in different MSAs in a given patent application year, as well as the number of collaborations by multiple inventors within the same MSA. Thus, the unit of analysis will be a Firm-MSA pair-Year.

Other controls. We combine these data with additional information from a number of sources. The additional data are used to control for time-varying factors that may be correlated with Internet adoption and with patent output. First, to control for variance in R&D inputs across firms, we compute the flow of R&D spending dollars using Compustat and compute the per-location R&D flow dollars by normalizing total spending by the number of Firm-MSA locations in our data. We further compute the log of the total number of employees among establishments in the pair.

Next, we control for a number of local factors that may influence both the likelihood of basic Internet adoption as well as innovation productivity and the propensity to patent. The data sources for these measures are at the county level and are then matched to MSAs. Based on these county-level data, each of these data items are computed for a Firm-MSA-year triplet, and then are averaged across triplets in a pair. We use the percent of manufacturing employment in the MSA, the average weekly wage in the MSA, and the log of MSA employment using County Business Patterns data. Using the USPTO data, we compute the total number of patents in the MSA-year.

Empirical Strategy

To measure the impact of Internet on collaborations within firm-location pairs, we use a difference-in-difference identification strategy, comparing the number of (citation-weighted) collaborations of a time period before basic Internet technology diffused (1992) to those of a period where we observe adoption (1998). Our endogenous variable will be log($Patents_{ijkt}$ + 1), which represents the number of patents applied for in year t with inventors in locations j and k of a particular firm i. To simplify notation going forward we will label this variable log($Patents_{ijkt}$) Internet technology had not diffused among firms prior to 1995 except in very rare cases, so we set the value of this variable to zero in 1992. We utilize a difference-in-difference approach to remove unobserved firm-pair features that may be correlated with Internet adoption and patents. This yields the following regression equation:

$$\log\left(Patents_{ijk1998}\right) - \log\left(Patents_{ijk1992}\right) = \alpha_1 X_{ijk} + \alpha_2 Z_{ijk} + \beta Internet_{ijk} + \varepsilon_{ijk} \qquad (1)$$

The variable $Internet_{ijk}$ measures whether both establishments in the pair adopted basic Internet (we note that because $Internet_{ijk}$=0 in 1992, this is equivalent to the change in Internet usage). We have two types of controls: the variables in X_{ijk} capture changes in firm-pair controls for things like R&D expenditures and establishment size that may affect the volume of collaborations in a firm-pair. The variables in Z_{ijk} capture changes in local characteristics that may influence innovative output. We have assumed that ε_{ijk} is a normal i.i.d. variable, but utilize robust standard errors in our estimation.

Our hypothesis is that the adoption of basic Internet at both locations in the firm-pair will be associated with an increase in the number of collaborative innovations, as proxied by the number of (citation-weighted) co-invented patents: a test of $\beta>0$ against the null of $\beta=0$.

To measure the impact of basic Internet adoption on within-location collaborations, we estimate a variant of the above equation for collaborations within a single MSA. Our endogenous variable will be log($Patents_{ijt}$), which represents the number of patents applied for in year t with at least two inventors in location j of a particular firm i.

$$\log\left(Patents_{ij1998}\right) - \log\left(Patents_{ij1992}\right) = \alpha_1 X_{ij} + \alpha_2 Z_{ij} + \beta Internet_{ij} + \varepsilon_{ij} \qquad (2)$$

Here, $Internet_{ij}$ is a binary indicator of whether basic Internet has been adopted at the location, and X_{ij} and Z_{ij} represent changes in firm-location and location level controls, respectively. Here the hypothesis is that adoption of basic Internet within the firm-location will be associated with an increase in the number of within-location collaborations: again, a test of $\beta>0$ against the null of $\beta=0$.

To start, we assume that there are no unobserved factors in ε_{it} in either equation (1) or (2) that are correlated with Internet adoption. We then explore this assumption: a particular concern is that unobserved features of the firm establishments in the pair or their locations may be correlated both with Internet adoption and patent growth. In particular, we do two things to explore this assumption. First, we present instrumental variable estimates that use measures of local telecommunications costs and programming capabilities in related locations as instruments for Internet investment. Second, we perform two sets of analyses to circumscribe how unobserved factors may influence our results. First, we conduct a falsification test of whether the number of co-invented patents over a period (1990-1994) prior to the diffusion of the commercial Internet were correlated with an establishment's later adoption of Internet technology (i.e., in 1998). Second, we examine whether the adoption of basic Internet by one firm-location in a pair is correlated with patenting output. If the adoption of Internet technology influences patent output through lower costs of knowledge flows, then we should observe no correlation between single-location adoption and collaborative output.

Last to examine how the collaborative benefits of Internet adoption are influenced by economies of scale, scope, and prior collaborations, we estimate the following models:

$$\begin{aligned}\log\left(Patents_{ijk1998}\right) - \log\left(Patents_{ijk1992}\right) \\ = \alpha_1 X_{ijk} + \alpha_2 Z_{ijk} + \beta_1 Internet_{ijk} + \beta_2 Internet_{ijk} \times HighPriorPatents_{ijk} + \varepsilon_{ijk}\end{aligned}$$

$$\begin{aligned}\log\left(Patents_{ijk1998}\right) - \log\left(Patents_{ijk1992}\right) \\ = \alpha_1 X_{ijk} + \alpha_2 Z_{ijk} + \beta_1 Internet_{ijk} + \beta_2 Internet_{ijk} \times NoPriorCollab_{ijk} + \varepsilon_{ijk}\end{aligned}$$

$$\log(Patents_{ijk1998}) - \log(Patents_{ijk1992}) = \alpha_1 X_{ijk} + \alpha_2 Z_{ijk} + \beta_1 Internet_{ijk} + \beta_2 Internet_{ijk} \times DifferentClass_{ijk} + \varepsilon_{ijk}$$

where the variables $HighPriorPatents_{ijk}$ is an indicator of whether the pair is in the top quartile of patenting over 1990-1992, $NoPriorCollab_{ijk}$ is a dummy that indicates whether the pair had collaborated previously over the period 1990-1992 and $DifferentClass_{ijk}$ is a dummy indicating the similarity in USPTO 3-digit patent classes applied to by the two locations over the same period.

Results

We first establish a relationship between the adoption of basic Internet and the number of co-invented patents at geographically dispersed research locations. We then show that there is no significant relationship between adoption and the number of patents co-invented by researchers within a location. We demonstrate that this result is robust to a variety of specifications and robustness checks, and to the use of instrumental variables. Last, we examine evidence on the conditions under which Internet adoption will have the greatest impact on collaborative innovative output. We show that Internet adoption has a particularly strong effect on cross-location research collaborations among pairs that had historically been high patenters (HighPriorPatents), among pairs had not collaborated before (NoPriorCollab), and among those with a different research focus (DifferentClass).

Baseline Results

In Table 2, we show the baseline results across cross-location pairs. In Column 1 we include what we view as our baseline specification, which uses first differences to remove cross-pair unobserved heterogeneity and includes controls for R&D spending and establishment employment, as well as local controls for industry composition, wages, employment, and innovative activity (we have also estimated random effects models, in which the marginal effect of Internet investment is positive and significant at the 1% level, we exclude these results in the interests of brevity and because the assumptions required for our parameters to be identified are stronger than in our other models). The result is statistically (at the 10% level) and economically significant. If both establishments in the pair have basic Internet this translates into a 1.5% increase in the growth of the number of (citation-weighted) patents. As we show below, this point estimate masks considerable heterogeneity on the impact of Internet adoption on collaborative research productivity.

We explore further robustness in columns (2) through (4). Column (2) shows that our results hold when we use the level of patents rather than the log. We use the log of the number of patents in our baseline specification as our model is based on the innovation production function (e.g., Pakes and Griliches 1987). However, in contrast to most prior work in this area, our focus is on the number of (citation-weighted) collaborative patents within two firm locations, rather than the total number of firm patents. Thus, the mean number of patents is relatively low (0.1980, standard deviation=1.7403) with many zeroes. Thus, we examine the robustness of our results to the use of the level of patents and find that they are qualitatively similar, if not stronger. We have also examined whether our results are robust to the use of an unbalanced panel of data over the years 1992, 1994, 1996, and 1998 (not reported). They are.

One potential concern with these estimates is that they may be affected by omitted variable bias. If there exist unobserved features related to a firm pair or its location that are changing over time in a way that is systematically correlated with Internet adoption and with patenting, then our parameter estimates for Internet adoption will be biased. Though we discuss our instrumental variable estimates below, here we describe two tests that will help to circumscribe the way in which omitted variable bias may influence our estimates.

First, following Agrawal and Goldfarb (2008), we examine whether Internet adoption at one firm location is correlated with the number of collaborative patents. If Internet adoption influences research productivity by lowering the costs of cross-unit collaborations, then adoption at one location should have no impact on the growth in the number of patents. Column (3) shows that Internet adoption at one location has no impact on the growth in the number of patents co-invented by researchers in the pair. While Internet adoption could still potentially influence research productivity by lowering the costs of obtaining shared resources, these results suggest that if omitted variable bias is influencing our results, it must do so only when both establishments adopt Internet technology.

Table 2 – Baseline Results – Different CMSAs

	(1)	(2)	(3)	(4)	(5)
	Baseline	Levels	Only One Adopter	1990-1994	Poisson†
Basic Internet in both locations	0.0153	0.1055	0.0166	0.0040	0.5298
	(0.0085)+	(0.0459)*	(0.0089)+	(0.0082)	(0.2927)+
Change in log of per-establishment R&D spending	0.0337	0.0785	0.0338	0.0246	0.1724
	(0.0085)**	(0.0479)	(0.0085)**	(0.0081)**	(0.0673)**
Change in log of establishment employees	-0.0336	-0.1687	-0.0336		0.7648
	(0.0186)+	(0.0945)+	(0.0186)+		(0.0747)**
Change in the share of local employment in manufacturing	-0.1735	1.5550	-0.1703	0.0313	-0.4710
	(0.3488)	(1.4916)	(0.3491)	(0.4848)	(1.7515)
Change in local average weekly wages	0.0006	0.0024	0.0006	0.0009	0.0073
	(0.0003)*	(0.0013)+	(0.0003)*	(0.0006)	(0.0021)**
Change in log of local employment	-0.0513	-0.1936	-0.0507	0.0845	-0.5011
	(0.0883)	(0.4851)	(0.0883)	(0.0764)	(0.1246)**
Change in number of local patents	0.0021	0.0998	0.0022	0.0237	0.1933
	(0.0104)	(0.0632)	(0.0104)	(0.0265)	(0.0841)*
Internet in only one location			-0.0120		
			(0.0173)		
Constant	-0.0691	-0.2935	-0.0585	-1.6078	-5.0990
	(0.0263)**	(0.1526)+	(0.0294)*	(1.0638)	(2.0039)*
Observations	5878	5878	5878	5488	11756

Robust standard errors in parentheses . + significant at 10%; * significant at 5%; ** significant at 1%. † Column 5 displays the results of a two-period Poisson regression using 1992 and 1998 data. For this column, variables represent levels rather than changes.

In column (4) we show the results of a falsification test that utilizes the timing of Internet adoption. As has been reported extensively elsewhere, the commercial Internet diffused rapidly beginning in the end of 1995. Prior to that time, Internet access existed only in a few academic research institutions. If we observe an effect of Internet adoption on patenting behavior prior to 1995, then there exist serious concerns that our results may be influenced by omitted variable bias. If we only observe the "right" timing for our Internet variable, then this adds additional confidence to our results and circumscribes the way in which omitted variable bias may be influencing our results. Column (4) shows that there is little impact on Internet adoption over the period 1990-1994: the coefficient on Internet adoption is small (0.0040) and insignificantly different from zero.

Column 5 shows the results of pooled Poisson quasi-maximum likelihood (QML) regression estimates using the count of citation-weighted patents. Our results are robust to the use of these models. While we have experimented with QML Poisson models with conditional fixed effects, for many of our pairs the number of patents in both periods is equal to zero and so are dropped from the estimation sample, as is typical in Poisson conditional fixed effects with no variance in the dependent variable. Thus, these conditional fixed effects results are qualitatively similar to our baseline model but not statistically significant.

As a further robustness check, we also investigated the impact of Internet adoption on growth in the count of patents (not adjusting for citations). The qualitative results remain similar—pairs that adopt Internet experience a 1.1% higher rate of growth in patenting—however some significance is lost (p-value 0.148).

Table 3 – Baseline Results – Same CMSA

	(1)	(2)	(3)	(4)
	Baseline	Levels	1990-1994	Poisson†
Basic Internet in both locations	-0.0303	-1.7418	-0.0086	-0.4452
	(0.0767)	(3.3033)	(0.0680)	(0.4158)
Change in log of per-establishment R&D spending	0.3716	6.8315	0.2566	0.3486
	(0.0554)**	(1.4869)**	(0.0627)**	(0.1043)
Change in log of establishment employees	0.0594	2.7932		0.1834
	(0.1242)	(2.2441)		(0.1831)
Change in the share of local employment in manufacturing	-1.5324	40.1995	0.9738	2.2118
	(1.7523)	(31.7639)	(2.2192)	(2.5959)
Change in local average weekly wages	-0.0007	0.0263	0.0004	0.0015
	(0.0013)	(0.0630)	(0.0023)	(0.0026)
Change in log of local employment	0.9210	44.6011		0.2930
	(0.4984)+	(20.1975)*		(0.2147)
Change in number of local patents	0.0524	2.9280	0.0852	0.0316
	(0.0408)	(2.5294)	(0.0898)	(0.0621)
Constant	-0.1597	-9.3267	-9.3521	-5.5958
	(0.1516)	(6.8742)	(6.1045)	(3.0098)
Observations	1210	1210	1192	2420

Robust standard errors in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%. † Column 4 displays the results of a two-period Poisson regression using 1992 and 1998 data. For this column, variables represent levels rather than changes.

In Table 3 we show the results of our model that explores the correlation between Internet adoption and within location collaborative patents. We do not find a relationship between Internet adoption and within-location patenting in any of our models. As a result, we do not examine the relationship between Internet adoption and within-location patenting for the remainder of the paper.

To further examine the robustness of our results, in Tables 4 we report the (second stage) results of two stage least squares instrumental variable estimates. (In first stage results, all of our instruments are significant at above the 1 percent significance level.) We have three instruments in total for one endogenous variable. We include two variables to proxy for local deployment costs: the year in which the local state capped prices that incumbent local exchange carriers (ILECs) could charge entrants and the year in which they switched to rate of return regulation. By influencing the local costs of deployment, these variables should be correlated with local Internet adoption. However, it is very unlikely they will be correlated with growth in patenting among establishments in the pair. We compute these instruments for each location in the pair and take the average. Finally, we use the multi-establishment nature of the firms in our data to construct one additional instrument. Forman, Goldfarb, and Greenstein (2008) show that establishments that are part of firms with many programmers in other locations adopt faster (even if there are few programmers at the focal establishment). They argue for a causal interpretation, partly because these programmers would have been hired for reasons other than Internet investment. In other words, programmers elsewhere in the firm make internet investment at the focal establishment more likely. In particular, in our setting, the presence of IT capabilities (as proxied by programmers) could aid in the set-up of an intranet or developing and configuring applications that could aid inventors in using the Internet for research purposes. However, as it reflects the presence of IT skills in linked counties, it is unlikely to be correlated with innovative output in the pair. As with the other two instruments, we take the average of this measure of IT capabilities across the pair as our instrument.

Table 4 – Instrumental Variable Estimates – Second Stage

	(1)	(2)	(3)	(4)
	All Instruments, 2SLS	Firm Capabilities Only	Rate of Return Instrument Only	All Instruments, LIML
Basic Internet in both locations	0.2196	0.3582	0.1335	0.2226
	(0.0811)**	(0.1944)+	(0.1042)	(0.0824)**
Change in log of per-establishment R&D spending	0.0253	0.0196	0.0288	0.0252
	(0.0091)**	(0.0123)	(0.0093)**	(0.0091)**
Change in log of establishment employees	-0.0397	-0.0439	-0.0371	-0.0398
	(0.0193)*	(0.0208)*	(0.0192)+	(0.0194)*
Change in the share of local employment in manufacturing	-0.2174	-0.2472	-0.1989	-0.2181
	(0.3648)	(0.3971)	(0.3533)	(0.3653)
Change in local average weekly wages	0.0005	0.0005	0.0006	0.0005
	(0.0003)+	(0.0003)	(0.0003)*	(0.0003)+
Change in log of local employment	-0.0577	-0.0621	-0.0550	-0.0578
	(0.0910)	(0.0961)	(0.0891)	(0.0911)
Change in number of local patents	0.0050	0.0069	0.0037	0.0050
	(0.0108)	(0.0118)	(0.0106)	(0.0108)
Constant	-0.1996	-0.2881	-0.1446	-0.2015
	(0.0600)**	(0.1290)*	(0.0731)*	(0.0608)**
Observations	5878	5878	5878	5878

Robust standard errors in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%

Column (1) of Table 4 shows our second stage results with our full set of instruments; the effects of Internet adoption on the growth of collaborative patent output remain statistically and economically significant. We also present estimates using our single best instrument in column (2); examining just-identified regressions is useful because they are median unbiased and less likely to be subject to a weak instruments critique (Angrist and Pischke 2009). Here the second stage results continue to show that the effects of Internet adoption are again economically and statistically (at the 10% level) significant. Column (3) of Table 4 shows the results of our second best instrument: the second stage results remain qualitatively similar, however are no longer significant at traditional thresholds. While columns (1) through (3) use 2SLS, column (4) shows that the results with the complete set of instruments are also robust to LIML estimation.

Where were the effects of Internet on research collaborations strongest?

In this section, we examine when Internet adoption was associated with the strongest growth in patenting among inventors in dispersed locations. In particular, we show that Internet adoption has a particularly strong effect on cross-location research collaborations among pairs that had historically been high patenters (HighPriorPatents), among pairs had not collaborated before (NoPriorCollab), and among those with a different research focus (DifferentClass). We compute each of these measures based upon the distribution of patenting behavior over 1990-1992. To reduce the extent of unobserved heterogeneity in our sample, we drop firm-pairs that include locations with no patents over this period.

Column (1) of Table 5 replicates the results in column (2) of Table 3 using only establishments with patents over the period 1990-1992. Over this sample our original results remain qualitatively similar, however less statistically significant because of the smaller sample size and lower power of the test.

Table 5 – Where Is the Effect of Internet Adoption Strongest?

	(1)	(2)	(3)	(4)	(5)
	Baseline, Prior Patenters	Prior Patenting High	No Prior Collaborations	Different Primary Patenting Class	Different Primary Patenting Class, Those with High Patents
Basic Internet in both locations	0.0183	-0.0007	-0.0865	-0.0532	-0.0534
	(0.0138)	(0.0119)	(0.0511)+	(0.0481)	(0.0481)
Basic Internet X High Prior Patents		0.0271			
		(0.0126)*			
Basic Internet X No Prior Collaborations in Pair			0.1227		
			(0.0502)*		
Basic Internet X Different Primary Patenting Class				0.0781	0.0515
				(0.0475)+	(0.0471)
Basic Internet X Different Primary Patenting Class X High Prior Patenting					0.0385
					(0.0119)**
Change in log of per-establishment R&D spending	0.0437	0.0443	0.0423	0.0450	0.0460
	(0.0126)**	(0.0126)**	(0.0124)**	(0.0126)**	(0.0126)**
Change in log of establishment employees	-0.0591	-0.0553	-0.0704	-0.0589	-0.0537
	(0.0348)+	(0.0348)	(0.0345)*	(0.0346)+	(0.0346)
Change in the share of local employment in manufacturing	0.0971	0.0314	0.2265	0.0738	-0.0232
	(0.6263)	(0.6273)	(0.6294)	(0.6268)	(0.6287)
Change in local average weekly wages	0.0006	0.0005	0.0007	0.0006	0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Change in log of local employment	-0.0187	-0.0078	-0.0364	-0.0334	-0.0206
	(0.1409)	(0.1412)	(0.1403)	(0.1412)	(0.1412)
Change in number of local patents	0.0120	0.0124	0.0142	0.0118	0.0125
	(0.0153)	(0.0153)	(0.0152)	(0.0153)	(0.0154)
Constant	-0.0813	-0.0771	-0.0892	-0.0801	-0.0745
	(0.0424)+	(0.0424)+	(0.0429)*	(0.0423)+	(0.0423)+
Observations	3586	3586	3586	3586	3586

Robust standard errors in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%. Note: Sample in this case is only places who have patented between 1990-1992

Table 6 Where is the Effect of the Internet Strongest? Second Stage of IV Estimates

	(1)	(2)	(3)
	High Prior Patenting	No Prior Collaboration s	Different Primary Patenting Class
Basic Internet in both locations	0.2444	0.0534	0.1689
	(0.1070)*	(0.1129)	(0.1176)
Basic Internet X High Prior Patents	0.0107		
	(0.0160)		
Basic Internet X No Prior Collaborations in Pair		0.2196	
		(0.0561)**	
Basic Internet X Different Primary Patenting Class			0.0714
			(0.0530)
Change in log of per-establishment R&D spending	0.0284	0.0264	0.0305
	(0.0140)+	(0.0138)+	(0.0142)*
Change in log of establishment employees	-0.0642	-0.0857	-0.0650
	(0.0356)+	(0.0351)*	(0.0352)+
Change in the share of local employment in manufacturing	0.1527	0.4066	0.1512
	(0.6452)	(0.6513)	(0.6427)
Change in local average weekly wages	0.0006	0.0008	0.0006
	(0.0004)	(0.0004)+	(0.0004)
Change in log of local employment	-0.0474	-0.0818	-0.0627
	(0.1436)	(0.1421)	(0.1423)
Change in number of local patents	0.0098	0.0137	0.0096
	(0.0155)	(0.0157)	(0.0155)
Constant	-0.2402	-0.2487	-0.2287
	(0.0839)**	(0.0883)**	(0.0884)**
Observations	3586	3586	3586

Robust standard errors in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%

Column (2) shows how the results differ for pairs in that were in the top quartile of patenting over 1990-1992. The results show that firm locations that were in the top quartile of patenting who adopt Internet experience a 2.6% faster rate of patenting growth than other pairs. In contrast, those who were not in the top quartile experience no additional growth in patenting from adoption. These results are consistent with the interpretation offered in section 2 that Internet adoption will have the strongest impact among research locations that already exhibit some economies of scale in innovative output.

Column (3) compares how the effects of basic Internet varies for location pairs who had and who had not collaborated during 1990-1992. Pairs who had not collaborated before and who adopt basic Internet have on average a 3.6% faster rate of growth in patenting than those without Internet (1% significance). In contrast, pairs who had collaborated before and who adopt Internet experience no additional growth in patenting from Internet adoption; in fact, the results suggest that they may experience some decline as researchers apparently shift to new collaborations. This result suggests that Internet adoption may influence the margin of whether locations collaborate or not; we explore this in more detail below.

Column (4) examines whether the marginal effect of Internet adoption is different for locations engaging in similar research activities. To identify similarity in research areas, we identify the three-digit USPTO class for each patent invented at the location over the application years 1990-1992. We then identify the most popular three-digit class for the location over this period. We set the dummy DifferentClass equal to one if the three digit classes differ for the locations in the pair. This was true for 91.7% of pairs in our sample. We find that pairs with different primary patenting classes experience a 2.5% greater increase in patenting as a result of Internet adoption (significant at the 10% level), while those with similar patenting classes experience no such gain. Unfortunately, most popular classes are estimated more precisely for high patenting locations. As a robustness check, we allow the marginal effect of "Different Primary Patenting Class" to differ for high and low patenting locations. In this case, high patenting pairs with different primary classes experienced a 3.7% increase in patenting from Internet adoption (significant at the 5% level), while those that were low patenting or who had the same primary class experienced no gain.

We have also investigated whether the marginal effect of Internet adoption on cross-location collaborations was moderated by the distance between firm-MSA locations (these results are available from the authors upon request), however we found no evidence of such a moderating relationship. We believe that this finding is consistent with a large literature that has demonstrated that knowledge flows tend to be localized within regions that are within a day's commuting distance or less (e.g., Jaffe, Trajtenberg, and Henderson 1993). For our purposes, this suggests that collaboration costs—and the marginal effect of Internet on reducing collaboration costs—are similar for inventors located in two separate MSAs, regardless of the distance between them.

To further address concerns about omitted variable bias, Table 6 provides instrumental variable estimates for columns (2) through (4) of Table 5. We interact each of our original instruments –programmer capabilities, the indicator for the price cap or freeze, and the first to change to rate of return regulation—with each of our binary variables measuring pair heterogeneity (HighPriorPatents, NoPriorCollab, and DifferentClass). The results are shown in Table 7. For all three types of pairs—those with high prior patents, those with no prior collaborations, and those with different primary patenting classes—the marginal effect of Internet remains statistically significant at the 5% level.

Effects of the Internet on the likelihood of collaboration

Table 7 shows how Internet adoption influenced the likelihood of any collaboration between firm location pairs: the dependent variable here is the binary decision of whether or not there are any co-invented patents among inventors during an application year. Several factors about the sample and model used in Table 7 are of note. We use a linear probability model here instead of a probit or logit model for several reasons. First, use of a linear probability model allows us to control for cross-pair heterogeneity with pair fixed effects, which would be more difficult in nonlinear models due to the incidental parameters problem. Second, our interest is on the interaction of Internet with pair characteristics, and in nonlinear models the cross-partial may have a different sign than the coefficient on the interaction term (Ai and Norton 2003). As always, we utilize robust standard errors which adjust for the heteroskedasticity issue that arises with the use of the linear probability model, so the main drawback to this choice is reduced efficiently.

A second feature of Table 7 to note is that we use the entire panel of data, every other year from 1992-1998. While entry and exit of locations in our data makes this less appealing than the use of our baseline difference-in-difference estimator, inadequate variance in the dependent variable over two periods makes estimation of the key parameters difficult using a difference-in-difference estimation strategy.

The estimation results in Table 7 are qualitatively similar to those elsewhere in Table 2 and Tables 5 and 6. Namely, Internet adoption is positively associated with an increased likelihood of collaboration, however the effects are strongest for pairs that had already been frequent patenters, had no prior collaborations, and had different areas of research focus.

Table 7 How Does Internet Affect the Likelihood of Any Collaboration?

	(1)	(2)	(3)	(4)	(5)
	Baseline	Prior Patenting High	No Prior Collaborations	Different Primary Patenting Class	Different Primary Patenting Class, Those with High Patents
Basic Internet in both locations	0.0116	0.0005	-0.0611	0.0015	0.0011
	(0.0066)+	(0.0059)	(0.0236)*	(0.0100)	(0.0100)
Basic Internet X High Prior Patents		0.0171			
		(0.0073)*			
Basic Internet X No Prior Collaborations in Pair			0.0838		
			(0.0233)**		
Basic Internet X Different Primary Patenting Class				0.0136	-0.0012
				(0.0100)	(0.0095)
Basic Internet X Different Primary Patenting Class X High Prior Patenting					0.0214
					(0.0080)**
Log of per-establishment R&D spending	0.0196	0.0201	0.0187	0.0199	0.0203
	(0.0059)**	(0.0059)**	(0.0058)**	(0.0059)**	(0.0059)**
Log of establishment employees	0.0011	0.0032	-0.0045	0.0013	0.0031
	(0.0155)	(0.0155)	(0.0156)	(0.0155)	(0.0156)
Share of local employment in manufacturing	-0.3526	-0.3729	-0.3172	-0.3573	-0.3804
	(0.2618)	(0.2619)	(0.2581)	(0.2618)	(0.2621)
Local average weekly wages	0.0002	0.0001	0.0002	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log of local employment	-0.0331	-0.0296	-0.0389	-0.0340	-0.0304
	(0.0652)	(0.0652)	(0.0644)	(0.0652)	(0.0652)
Number of local patents	0.0098	0.0098	0.0113	0.0098	0.0098
	(0.0072)	(0.0072)	(0.0071)	(0.0072)	(0.0072)
Constant	0.4334	0.3865	0.5288	0.4499	0.3994
	(0.8770)	(0.8771)	(0.8661)	(0.8774)	(0.8771)
Observations	24298	24298	24298	24298	24298
Number of corpmsaindex	6877	6877	6877	6877	6877

Robust standard errors in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%

Conclusion

This study focuses on the effect of basic Internet adoption on geography of industrial research collaborations. We match local (MSA) business IT investment data with local firm patenting activity and, using a difference-in-difference econometric estimation approach, find robust empirical evidence that Internet adoption is associated with increased growth of citation-weighted co-invented patents in geographically dispersed firm locations. On the contrary, we find no evidence of such a link between Internet adoption and within-location collaborative patents. We further find that the link between Internet adoption and cross-location patenting is greatest for firm pairs that have previously been successful innovators, have not collaborated before, and which have different research foci. These results stand in contrast to recent work on IT and academic research that has found that IT adoption leads to a disproportionately greater increase in cross-institution close collaborations (Agrawal and Goldfarb 2008) and to an increase in collaborations among researchers with similar research interests (Rosenblat and Mobius 2004).

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