Information Technology and the Distribution of Inventive Activity[*]

Chris Forman
Scheller College of Business
Georgia Institute of Technology
800 West Peachtree St. NW
Atlanta, GA 30308
chris.forman@scheller.gatech.edu

Avi Goldfarb
Rotman School of Management
University of Toronto
105 St George St
Toronto, ON M5S 3E6
agoldfarb@rotman.utoronto.ca

Shane Greenstein
Kellogg School of Management
Northwestern University
2001 Sheridan Road
Evanston IL 60208
greenstein@kellogg.northwestern.edu

July 2013

Abstract
We examine the relationship between the diffusion of advanced internet technology and the geographic concentration of innovation, as measured by patents. First, we show that patenting became more concentrated from the early 1990s to the early 2000s and, similarly, that counties that were leaders in patenting in the early 1990s produced relatively more patents by the early 2000s. Second, we compare the extent of invention in counties that were leaders in internet adoption to those that were not. We see little difference in the growth rate of patenting between leaders and laggards in internet adoption, on average. However, we find that the rate of patent growth was faster among counties who were not leaders in patenting in the early 1990s but were leaders in internet adoption by 2000, suggesting that the internet helped stem the trend towards more geographic concentration. We show that these results are largely driven by patents filed by distant collaborators rather than non-collaborative patents or patents by non-distant collaborators, suggesting low cost long-distance digital communication as a potential mechanism.

Keywords: patenting, innovation, convergence, divergence, information technology, internet
JEL Classification: O31, O33, R11

[*] We thank participants at the pre-conference, Adam Jaffe and Ben Jones for comments. We think Yasin Ozcan for outstanding research assistance. We also thank Harte Hanks Market Intelligence for supplying data. All opinions and errors are ours alone.

1. Introduction

The spatial agglomeration of innovation has many causes. It is widely accepted that innovation generates geographically local positive externalities, reinforcing more innovation in the same location (Jaffe, Trajtenberg, Henderson, 1993). A body of literature has also documented that communication technology can affect how the costs and benefits to innovation vary by location (Agrawal and Goldfarb, 2008, Forman and van Zeebrook, 2012).

In this chapter, we ask whether innovation, as measured in patent data, has become more agglomerated between the early 1990s and the early 2000s. We also explore the potential role of internet technology in explaining this pattern. Either an increase or decrease in the geographic concentration of innovation is possible. By increase in concentration, we mean that the places that served as the location for the majority of the inventions in the past serve as a source for an even greater share in the future. The places rich with inventions become richer. By decrease, we mean the opposite, that the places that are not rich with invention become richer.

This chapter builds on our research agenda examining how the diffusion of the internet altered the geographic concentration of activity (Forman, Goldfarb and Greenstein, 2002, 2005, 2008, 2012). The approach of this study resembles our approach in Forman, Goldfarb, and Greenstein (2012), which examined how geographic variation in business internet adoption shaped US wage growth over the late 1990s. This chapter examines a different outcome, and, hence, a different question, namely, whether those counties that were leading innovators (as measured by patents) between 1990 and 1995 increased or decreased their relative rate of patenting between 2000 and 2005. Then we explore how internet adoption correlates with this change, and whether it increases or decreases the rate of concentration in patenting.

We undertake this exercise with the view that economic theory does not give clear guidance to the expected result. There are good reasons to expect the internet to have increased the geographic concentration of innovation or to have decreased it.

On the side of increasing concentration: The literature on the economics of IT often finds a localization of the adoption of IT (Forman, Goldfarb, Greenstein (2008) and Forman and Goldfarb (2006) reviews the literature). The effective use of advanced internet technology draws on frontier IT skills that are found mostly in urban areas, and it builds on existing links between business use of IT, support services, and specialized labor markets in urban areas. Furthermore, while the internet reduces communication costs for both local and distant communication, most communication and most social contacts are local (Wellman 2001, Hampton and Wellman 2002). Much of the literature on internet adoption and usage, including much of our own prior work, shows a high geographic concentration of economic activity in the areas where the internet is most frequently adopted (Blum and Goldfarb 2006; Sinai and Waldfogel 2004; Forman, Goldfarb, and Greenstein 2005; Kolko 2002; Glaeser and Ponzetto 2007; Arora and Forman 2007; Forman, Goldfarb, and Greenstein 2012; Agrawal, Catalini, and Goldfarb 2011; etc.).

On the side of decreasing concentration: the internet is a communications technology, and it can allow people in isolated areas to plug in to the rest of the economy. Communications scholars and others have long argued that the internet might overcome geographic barriers to economic (and political) activities. Cairncross (1997) and Friedman (2005) provide popular summaries of these ideas, emphasizing the "death of distance" and the "flat world". Moreover, in the specific context of knowledge production and innovation, the internet can reduce collaboration costs and, potentially, the importance of collocation in inventive activity. The empirical literature also has some findings suggesting that the internet might increase cross-institutional and cross-regional collaboration over time (Jones, Wuchty, and Uzzi 2008; Agrawal and Goldfarb 2008; Ding, Levin, Stephan, and Winkler 2012). The setting most closely resembling the one we study in this chapter (Forman and van Zeebroeck, 2012) also shows that internet adoption leads to increased distant collaboration for patents issued to researchers in a given multi-establishment firm.

Our findings generally favor the view that the internet worked against the concentration of innovation. Studying the growth rate of patenting across counties, we show this in several steps. First, we show that invention became more geographically concentrated over this period, suggesting a general trend towards increasing concentration of invention. Specifically, our raw data suggest that patenting grew 27% during this period. For the top quartile of patenting counties from 1990-95, patenting grew 50%. For those below the median, patenting did not grow at all.

We next demonstrate how county-level growth in patenting is shaped by business internet adoption and the prior concentration of patents. While the geographic concentration of patenting increased over the time period we study, the internet appears to have mitigated, rather than exacerbated, that trend. In particular, the overall concentration of invention rose but, among counties that were leading internet adopters, we see little change in the concentration of innovation. Furthermore, our results suggest that this relationship is strongest for long-distance collaboration. Although it is important to recognize that we cannot rule out the possibility that an omitted factor caused both internet adoption and growth in patenting in the set of internet-adopting counties with that were behind in patenting in the early 1990s, our results are more consistent with the internet reducing the geographic concentration of innovation than with the internet increasing that concentration.

This chapter fits into a broader agenda outlined in Vannevar Bush's publication *Science: The Endless Frontier,* which frames a range of questions around the localization of innovation. Recent literature has shown that scientific collaboration across institutions has increased over time and that IT is partly responsible. We contribute the first direct evidence that the diffusion of the internet is correlated with a reduction in the geographic concentration of inventive activity, suggesting that the diffusion of the internet has the potential to weaken the longstanding importance of the geographic localization of innovative activity. Our results also raise intriguing questions about whether the internet's impact on the geographic concentration of invention is distinct from its impact on the geographic concentration of other economic activity, such as wages, business adoption of IT, hospital productivity, and so on. That is, the internet may be a force for weakening the links between the geography of inventive activity.

2. Data

We use a variety of data sources to examine how adoption of advanced internet among firms will affect local inventive activity. We match data on IT investment from the Harte Hanks Market Intelligence Computer Intelligence Database with patent data from the USPTO between 1990 and 2005. We further combine this with data from the US decennial Census. Our sample construction is shaped by key features of our data and the setting. First, we expect a significant lag between the time when IT investments are made and when they influence the creation of new invention. Second, there is significant year-to-year variability in patent output at the county level and particularly at the industry-county level. Third, as with our prior work, we exploit the historical circumstances that led to the deployment of the internet. Instead of creating a gradual deployment and adoption, circumstances created a rather abrupt change in a short time span, leading to a period "before the internet diffused" and a period "after the internet diffused." As a result, in our core analyses our base period and reference period both include six years—that is, we look at the difference in patent output between 1990 and 1995 (before the diffusion of the internet) and 2000 and 2005 (after its diffusion).[1]

[1] We have experimented with alternative specifications for the base and reference years. Our results are robust to these changes, though we do sometimes lose significance for some results in some years.

2.1 Patent Data

Our data on local inventive output are measured using patent data from the USPTO. We use application rather than grant date to measure the timing of inventive activity because the application-to-grant delay varies over time, and because the application date is closer to the time when the invention occurred.[2]

To measure the effect that internet adoption will have on local inventive activity, we match patents to counties using inventor locations.[3] For patents with multiple inventors that reside in multiple counties, we allocate patents to all of the counties where inventors reside. We use county as the unit of observation rather than MSA to facilitate comparison with prior work that has studied the implications of internet investment on local economic outcomes (Forman, Goldfarb, and Greenstein 2012). Our procedure will accurately assign patent output to the correct county to the extent that inventors work where they reside, but may make some errors in assignment when inventors commute between counties.[4]

In our analyses we use a combination of raw patent counts and five year citation-weighted patents as our measure of inventive output. As is well known, not all inventions meet the U.S. Patent and Trademark Office (USPTO) criteria for patentability (Jaffe and Trajtenberg 2002). Further, inventors must make an explicit decision to patent an invention, rather than relying on some other method to appropriate the value of their invention. There will be incremental inventive activity that is not patented and therefore is not reflected in patent statistics (e.g., Cohen, Nelson, and Walsh 2000). However, so long as the propensity of firms in a location to patent 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

[2] See, for example, Griliches (1990).
[3] Specifically, we match the city and state of the inventor location to ZIP codes, and then match the ZIP codes to counties.
[4] We also believe that using inventor locations, which is often the location of their residence, is superior to the alternative of using the location of the assignee, which is the location of a firm or corporate building in the vast majority of patents. The latter does not necessarily correspond with the location of the invention, particularly in corporations that assign all patents to headquarters, irrespective of their origins.

interest. It is also well known that patent values are very skewed. Weighting by citations is one way to address this problem; citation-weighted patents have been shown to be correlated with a firm's stock market value above and beyond the information provided by patent counts (Hall, Jaffe, and Trajtenberg 2005).

Our baseline analyses explore whether internet adoption is associated with changes in the growth of total patents and citation-weighted patents over time. However, we also explore how our results vary by county-industry group. To do this, we utilize the 2011 USPTO concordance between patent classes and NAICS manufacturing industries.[5] In these analyses, our unit of analysis is county-industry-year rather than county-year. To facilitate comparisons between our county and county-industry analyses, all of our patents have a primary class that can be mapped to NAICS using the 2011 concordance. Thus, our measures of patent growth will miss some inventive activity that cannot be used downstream in manufacturing.

We perform several additional analyses over different subsets of the patent data. First, we re-estimate our models over the set of patents with more than one inventor. We label these as collaborative patents. Second, we define distant collaborative patents as ones in which there exists a pair of inventors for whom the distance between the centroids of the inventors' home counties are greater than 50 miles apart.

We further explore differences based upon the type of institution to which the patent is assigned. We identify educational institutions based upon a search of key phrases in the assignee name field of the patent.[6] We further use the assignee role field in the patents to identify whether the patent is from a U.S. private company or corporation or a U.S. government agency.[7]

---

[5] For more details on the correspondence, see http://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/naics_conc/2011/read_me.txt. To perform the correspondence, we use the primary USPTO class in the patent document. In cases where a given USPTO class is related to several industries, we weight the patent equally across the industries to which it is related.

[6] Specifically, we define educational institutions as those which have any of the following phrases in the assignee name (not case sensitive): "university"; "institute of technology"; "college"; "school of medicine"; "school of mines"; "school of

A primary question in this paper is whether internet investments by firms contribute to changes in the distribution of inventive activity. In particular, our interest is in exploring whether internet investments have contributed to more or less concentration in outcomes. To facilitate this, we construct measures of the total number of patents in the county between 1990 and 1995 to measure concentration in innovative activity prior to the diffusion of the internet.

2.2 Information Technology Data

As mentioned above, our IT data come from the Harte Hanks Market Intelligence Computer Intelligence Database (hereafter CI database).[8] [9] The database contains rich establishment- and firm-level data including the number of employees, the number of personal computers and servers, and adoption of internet applications. Harte Hanks collects these data to resell to the marketing divisions of technology companies. Interview teams survey establishments throughout the calendar year; our sample contains the most current information as of December 2000.

Harte Hanks tracks over 300,000 establishments in the U.S. We exclude government, military, and nonprofit establishments because the availability of advanced internet for these establishments and the relationship between advanced internet adoption and patent output may be different than for private firms. Our sample contains nonfarm business establishments with over 100 employees, and includes a total of 86,879 establishments. Prior work has demonstrated that these data are among the best establishment-level data about the use of IT in the US, and include half of all establishments with 100 or more employees in the US (Forman, Goldfarb, and Greenstein 2005). While our sample includes

---

engineering"; and some permutations on these phrases. Further, we identified several specific research active institutions for which these key words were not accurate predictors of educational status. As a result, we also added the following phrases: "georgia tech"; "cornell research foundation"; "wisconsin alumni"; "board of regents for education"; "oregon graduate center"; "iowa state research foundation"; and "board of governors for higher education, state of rhode island"

[7] We also explored whether our results differed for private firms who were small (below 500 employees) and large using the small entity status field on USPTO data on maintenance fee payments. We found that many of our main results were qualitatively similar for small and larger entities, though the economic magnitudes were somewhat weaker among small firms.

[8] These data have been used in a variety of previous studies (including our own) studying the adoption of IT (Bresnahan and Greenstein 1997; Forman, Goldfarb, and Greenstein 2005), the productivity of IT investments (Bresnahan, Brynjolfsson, and Hitt 2002; Brynjolfsson and Hitt 2003; Bloom, Sadun, and Van Reenen 2012), and the effects of IT investments on local wage growth (Forman, Goldfarb, and Greenstein 2012).

[9] This section draws heavily from Forman, Goldfarb, and Greenstein (2012).

only relatively large establishments, this is not a significant problem because very few small establishments adopted advanced internet technology during this time.

The construction of our measure of advanced internet is identical to that used in our previous study of the effects of advanced internet adoption on local wage growth (Forman, Goldfarb, and Greenstein 2012). It includes those facets of internet technology that became available after 1995 in a variety of different uses and applications. The raw data in the CI database include at least 20 different specific applications, from basic internet access to software for internet-enabled enterprise resource planning (ERP) business applications.

Our measure of advanced internet adoption involves investment in frontier technologies, often with significant adaptation costs. As we have done in our prior work, we use substantial investments in e-commerce or e-business to identify advanced internet investment. Specifically, we looked for evidence of investment in two or more of the following internet-based applications: ERP, customer service, education, extranet, publications, purchasing, and technical support. Not all of these applications are directly involved in the production of new inventions, however all support intra- or inter-establishment communication and coordination, and often involve significant changes to business processes. Our measure of advanced internet investment should be viewed as a proxy for a firm's propensity to invest in frontier IT that facilitates communication and collaboration, rather than a direct measure of IT investments that are used as part of the production process in science. As a result, it is possible this will generate some attenuation bias in our estimates.[10]

We aggregate our establishment-level indicators of advanced internet investment to the county to obtain location-level measures of the extent of advanced internet investment. Because the distribution of establishments over industries may be different in our sample of firms from that of the population, as we have done in prior work we weight the number of establishments in our database

[10] Unfortunately, the CI database collects little information on applications that directly facilitate knowledge sharing or knowledge management. See Forman and van Zeebroeck (2012) for further details.

using the number of establishments by two-digit NAICS industry in the Census Bureau's 1999 County Business Patterns data.

This measure has several attractive properties.[11] For one, industry-level measures of this variable correlate with Bureau of Economic Analysis measures of industry-level differences in IT investments. The measure also highlights significant regional differences in advanced internet use (Forman, Goldfarb, and Greenstein 2005). Advanced internet adoption is high in locations that include internet-intensive and IT-intensive industries, such as the San Francisco Bay Area, Seattle, Denver, and Houston. In such regions, advanced internet adoption is high even for establishments that are not producing in traditionally IT-intensive industries.

As noted above, variance in our IT measure will come from differences in adoption rates among large nonfarm business establishments at the county level. Because we do not directly measure the IT investment behavior of public and educational institutions, our analyses of the effects of IT investment on patenting behavior in these institutions must be treated with some caution.

2.3 Controls

We combine these IT and patent data with additional county-level information from a variety of sources. First, we use information from the 1990 US Census on population, median income, and percentage of population with a university education, high school education, below the poverty line, African American, and above 64 years old. We further use the 2000 US Census to control for changes in factors such as population and change in percent African American, university education, high school education, and over 64 years old. We obtain county-level information on additional factors that will influence the propensity of a county to innovate such as enrollment in Carnegie tier 1 research universities in 1990; the fraction of students enrolled in engineering programs; and the 1990 percentage

[11] Here we summarize some highlights. For further details, see Forman, Goldfarb, and Greenstein (2012).

of the county's workforce in professional occupations.[12] To control for differences in growth rates based on the scale of economic activity, we also include controls for employment, establishments, and weekly wages in the country from 1999 County Business Patterns Data.

Table 1 provides the descriptive statistics. While our Census data include the population and demographic data of over 3100 counties, as in our prior work we drop several hundred counties for which we have no IT data. Generally, these are very low population counties with few firms and patents. There are 2734 counties for which we have IT data. There are also some counties that we drop from our analysis because there are no patents in either the 1990-95 or 2000-05 period, though results are robust to assuming that these are zero growth counties. If there are no patents in both periods, we set growth in patenting to zero. Across our different dependent variables we have between 2519 and 2854 observations. As a result, we have between 2235 and 2833 observations in our combined IT- and patent data set.

The top part of table 1 shows the average percent change in our dependent variable across different categories. The average percent change is decreasing for some variables. Because these variables are the average of the percent changes across counties, this does not mean that total patenting in the US for that category is decreasing. Some counties in our data have a large percent change but, due to their small size, do not have a large impact on the total amount of patenting.

3. Empirical strategy and results

Our empirical analysis proceeds in four steps. First, we establish the relationship between patent levels in the 1990-95 period and growth in patenting between 1990-95 and 2000-05. We show an increased concentration in patenting. Second, we show that there is no significant relationship between advanced internet adoption by firms and growth in patenting. Third, we show that the relationship between prior patent levels and growth in patenting is weaker for counties with high levels of internet

[12] Downes and Greenstein (2007) showed that these three help explain the availability of internet service providers.

adoption. Fourth, we demonstrate that the effect of internet on weakening the trend to increased geographic concentration of patenting is driven by changes in distant collaborative patents and private firms.

3.1 Increased concentration of patenting

Figure 1 shows a Lorenz curve for patenting by county comparing 1990-95 to 2000-05. The size of the area under the 45 degree line measures the degree of inequality across counties in their patenting behavior. As the curve moves away from the 45 degree line, it suggests that the geographic concentration of patenting rises in general. Thus, the curve suggests that patenting was somewhat more geographically concentrated in the 2000-05 period than in the 1990-95 period.

In Table 2, we show the related result that those counties that had a large number of patents in the 1990-95 period had a relatively large increase in their level of patenting. In particular, column 1 contains the following regression:

$$(1) \qquad Log(Patents_{i0005}) - Log(Patents_{i9095}) = \alpha + \gamma X_i + \beta_1 Patents_{i9095} + \varepsilon_i,$$

Where $Patents_{i9095}$ and $Patents_{i0005}$ are the number of cumulative patents in county i from 1990-95 and 2000-2005, X_i is a vector of controls including county-level business and demographic data (as listed in Table 1), and ε_i is a normal i.i.d. error. The positive and significant coefficient in the first row shows that those counties with higher levels of patenting from 1990-95 had higher rates of patent growth.

The remaining columns of the table show robustness to various alternative specifications. Column 2 weights the patents by citations over five years. Columns 3 and 4 use only collaborative patents to define the dependent variable.[13]

[13] We maintain total patents 1990-95 as the key covariate as we believe the key measure is the rate of overall patenting in the pre-period. That said, results are robust to using collaborative patents as the key covariate.

Columns 5 through 8 show robustness to switching the unit of observation to the industry-county. This enables the analysis to account for differences across industries in where agglomeration takes place. The industry-level data is challenging to work with as there are many zeros. Therefore, the simple logged difference growth equation cannot be used as it will lead to many missing observations. In addition, the data are highly skewed, with a long positive tail and a fatter-than-normal negative tail in the difference. Instead of the logged difference, we use an ordered probit, splitting the dependent variable into nine groups: (∞,-5), [-5,-2), [-2,-1), [-1,0), 0, (0,1], (1,2], (2,5], (5, ∞). The results show that this alternative specification does not yield qualitatively different results: Those counties that were leading in patenting from 1990-95 had relatively rapid growth in patenting.

The controls also yield some interesting, though perhaps unsurprising, correlations. The level of education, and changes in the level of education, are strongly and positively correlated with growth in patenting. In addition, the fraction of the local students in engineering is highly correlated with growth in patenting. An increased population is associated with increased growth in patenting while an increased elderly population is associated with decreased growth in patenting.

3.2 Business adoption of the internet and growth in patenting

Before assessing whether the internet might enhance or reduce the rate of concentration in patenting, it is important to establish the baseline relationship between internet adoption and growth in patenting. Table 3 shows that there is no significant correlation between internet adoption and growth in patenting. Column (1) shows the results of the following regression:

(2) $Log(Patents_{i\ i0005})- Log(Patents_{i9095}) \ =\alpha+\gamma X_i+\beta_2 AdvancedInternet_i+\varepsilon_i,$

Where $AdvancedInternet_i$ measures the extent of advanced internet investment by businesses in county *i* in 2000. Columns (2) through (8) mirror the columns in Table 2, and while the coefficients are positive, there is no significance in any specification. In this table, and in all remaining tables, we do not report the coefficients on the controls because they are not the focus on the analysis and the signs and significance are similar to those found in Table 2.

3.3 Business adoption of the internet and the concentration of patenting

Table 4 examines whether internet adoption increases or reduces the rate of concentration in patenting. Column (1) shows the results of the following regression:

$$(3)\quad Log(Patents_{i0005}) - Log(Patents_{i9095}) = \alpha + \gamma X_i + \beta_1 Patents_{i9095} + \beta_2 AdvancedInternet_i + \beta_3 Patents_{i9095}\, AdvancedInternet_i + \varepsilon_i,$$

The core coefficient of interest is β_3, the interaction between pre-period patenting and internet adoption. The result suggests that internet adoption is correlated with a reduction in the growth in concentration of patenting (as measured by the correlation between growth in patenting and patenting in the pre-period). The quantitative importance is not apparent from the coefficient, so we separately calculate the implied marginal effect. It suggests that an increase in advanced internet by one standard deviation reduces the increase in concentration by 57%, which is quite substantial. In other words, among counties that were leaders in internet adoption, the rate of patent growth between the early 1990s and the early 2000s is only weakly correlated with the level of patenting in the 1990 to 1995 period.

Put another way, for a county in the 25th percentile of internet adoption, moving from the 25th percentile in patenting to the 90th percentile in patenting in the early 1990s yields an implied increase in the growth of patenting of 5.4 percent. For a county in the 75th percentile of internet adoption, the same move yields an implied increase in patenting of 2.3 percent. For a county in the 90th percentile of internet adoption, the same move yields an implied increase in patenting of just 0.4 percent.[14] Thus,

[14] The increase estimated from the regression is substantially smaller than might be suggested by the descriptive statistics presented in the introduction because the regressions include controls for county-level demographics that are highly correlated with growth in patenting, such as education and population growth.

internet adoption is correlated with a reduction in this divergence: High internet adopting locations that were not leaders in patenting did not fall behind.

As in Tables 2 and 3, the alternative specifications in Columns 2 through 8 are broadly consistent with column 1. The qualitative results are similar if patents are weighted by five year citation rates, if only collaborative patents are used, and if the unit of observation is the county-industry.

One potential concern with this analysis is that $AdvancedInternet_i$ and $Patents_{i9095}$ are highly correlated and therefore the interaction term captures an unusual part of the distribution. Figure 2 addresses this concern. It presents a scatter plot of $AdvancedInternet_i$ on the horizontal axis and $Patents_{i9095}$ on the vertical axis. Figure 2 shows that, while $AdvancedInternet_i$ and $Patents_{i9095}$ are indeed highly correlated, there is plenty of variation. There are many locations with high levels of $AdvancedInternet_i$ and low levels of $Patents_{i9095}$ and there are many with low levels of $AdvancedInternet_i$ and high levels of $Patents_{i9095}$.

Broadly, Table 4 is suggestive that internet overcomes isolation in innovation, though we need to be cautious as it also could be an omitted variable driving both increased innovation and increased internet. Next we provide some suggestive evidence that the internet facilitated communication by inventors, providing some support for a causal interpretation of Table 4.

3.4 Collaboration, firm type, and local growth in patenting

Table 5 reproduces the first four columns of Table 4, but with alternative dependent variables. Instead of measuring patents and collaborative patents, Column 1 looks at the growth in the number of distant collaborators, as defined in section 2.1. Column 2 looks at the growth in the number of collaborative patents by county in which none of the collaborators are distant from each other. Column 3 looks at non-collaborative patents. Columns 4 through 6 show the same analysis but with citation-weighted patents.

In our previous results we documented that advanced internet adoption was associated with decreasing concentration in innovative activity. One possible explanation for this result is that advanced internet adoption made innovative activity in less innovative places relatively more attractive through a decline in the costs of collaboration. Another possibility is that the internet increased the productivity of innovative activity in less innovative regions relative to more innovative ones by, for example, more easily accessing labor, consultants, or ideas developed elsewhere. While we are unable to identify between these hypotheses, we view the results of Table 5 as suggestive that advanced internet adoption reduced the extent of geographic concentration for inventions developed through distant collaborations more than other types of inventions.

In particular, the internet is primarily a communications technology that reduces the cost of both distant and local communication, but the impact of patenting by firms is largest for distant collaborations (Forman and van Zeebroeck 2012). As in Table 4, Columns 1 and 4 (row 3) of Table 5 show that, for counties with low rates of advanced internet adoption, leading counties in the pre-period increased distant collaborations much faster than other counties. For counties with high rates of advanced internet adoption, leading counties in the pre-period did not increase distant collaborations much faster.

In contrast, for non-distant collaborations (columns 2 and 5 row 3) and for non-collaborative patents (columns 3 and 6 row 3) we see no difference between counties with high and low rates of advanced internet adoption, leading counties in the pre-period, and the increase in patenting. Thus, the correlation in Table 4 between patenting in the pre-period, advanced internet, and patent growth does not hold for non-collaborative patents and short-distance collaborative patents even though it holds for long-distance collaborative patents.

Because the role of the internet is likely to facilitate distant collaboration, and because prior work suggested that the internet increased distant patenting between firms (Forman and van Zeebroeck

2012), this suggests that the results of Table 4 may suggest a causal relationship rather than only a spurious relationship measuring counties that were becoming more innovative overall (and therefore becoming more innovative in terms of both patenting and internet adoption).

Table 6 separates patents assigned to US-based private firms, patents assigned to educational institutions, and patents assigned to governments. Consistent with the suggested mechanism, and consistent with the fact that our data on advanced internet represents US-based private firms and not educational institutions or government, our results are strongest for US-based private firms.

We have conducted a number of additional robustness checks on our main results. While not shown here to save space, qualitative results are robust to several alternative specifications including slightly different years, dropping controls, assigning a value of 1 to counties with zero patents in a given period to avoid dropping missing values, and to using alternative threshold choices for the ordered probit in the results at the industry-county level.

4 Conclusion

We have explored the geographic concentration of innovation. We first documented that the geographic concentration of patenting increased from 1990-95 to 2000-05. Then we showed that advanced internet adoption by businesses works against the general increase in the geographic concentration of patenting, leading to different experiences across the regions of the United States. We find that the correlation is strong for distant collaborations and disappears for nearby collaborations and for non-collaborative patents, which suggests that the internet's availability and growth drove at least part of the overall reduction in the growth in concentration of innovation.

Our analysis suffers from a number of limitations that limit the generalizability of our findings. First, we study one type of innovation, patenting, in a particular time period. The internet might have increased patenting but not invention, for example by simplifying the process of applying for a patent through internet lawyers rather than causing any increase in innovation per se. Hence, our results beg questions about whether other measures of innovation – e.g., non-patented inventions, new product development, entrepreneurial founding in technologically intensive markets – follow a similar pattern.

In addition, and as mentioned, our results are consistent with two different explanations. First, it could be the causal explanation, perhaps by allowing relatively isolated inventors to collaborate with inventors located elsewhere. Second, it could be driven by an omitted variable that caused both increased patenting and internet adoption. For example, for counties that were not leaders in patenting in the early 1990s, internet adoption might be a symptom rather than a cause of increased attention to innovation and a growth in the rate of internet adoption by firms. While the results on distant collaboration vs non-collaborative patents are suggestive, they are not definitive. Hence, our findings beg questions about how to instrument for internet adoption to identify truly exogenous variation across the US.

Notwithstanding these limitations, our results here, combined with prior work on the impact of the internet on the concentration of economic activity, suggest that the impact can depend on the particular activity and context being studied. It seems to lead to increased concentration in wages (Forman, Goldfarb, and Greenstein 2012) and hospital efficiency (Dranove, Forman, Goldfarb, and Greenstein 2013), but a decreased concentration in retailing (Choi and Bell 2011), and, as suggested above, in patenting and innovation. Those findings also raise intriguing questions about whether the internet's impact on the geographic concentration of invention is distinct from its impact on the geographic concentration of other economic activity, such as wages, business adoption of IT, hospital productivity, and so on. If that is the case, then the internet could act as a broad force for weakening the links between the geography of inventive activity and spatial patterns of downstream use of it. We speculate that such a broad trend, if sustained for a long time period, would manifest in numerous measurable economic activities. Hence, our results also beg questions comparing changes in the geographic concentration of different parts of the value chain over the very long run.

References

Agrawal, Ajay, and Avi Goldfarb. 2008. Restructuring Research: Communication Costs and the Democratization of University Innovation. *American Economic Review* 98(4):1578-1590.

Agrawal, Ajay, Christian Catalini, and Avi Goldfarb. 2011. "The Geography of Crowdfunding," NBER Working Paper No. 16820, http://www.nber.org/papers/w16820.

Arora, Ashish and Chris Forman. 2007. Proximity and Information Technology Outsourcing: How Local are IT Services Markets? *Journal of Management Information Systems* 24(2): 73-102.

Blum, Bernardo, and Avi Goldfarb. 2006. Does the internet defy the law of gravity? *Journal of International Economics* 70(2), 384-405.

Bloom, Nicholas, Luis Garicano, Raffaella Sadun, and John Van Reenen. 2009. The Distinct Effects of Information Technology and Communication Technology on Firm Organization. NBER Working Paper #14975.

Brensnahan, Timothy, and Shane Greenstein. 1997. Technical Progress and Co-Invention in Computing and in the Use of Computers. *Brookings Papers on Economics Activity: Microeconomics*: 1-78.

Bresnahan, Timothy, Erik Brynjolfsson, and Lorin Hitt, 2002. Information Technology, Work Organization, and the Demand for Skilled Labor: Firm-Level Evidence. *Quarterly Journal of Economics* 117(1): 339-376.

Brynjolfsson, Erik and Lorin Hitt. 2003. Computing Productivity: Firm-Level Evidence. *Review of Economics and Statistics*, 85(4): 793-808.

Cairncross, Frances. 1997. *The Death of Distance*. Cambridge, MA: Harvard University Press.

Choi, Jeonghye and David Bell. 2011. Preference Minorities and the Internet. *Journal of Marketing Research*, 58, 670 - 682.

Cohen, Wesley M., Richard R. Nelson and John P. Walsh. 2000. Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Firms Patent (Or Not). NBER Working Paper #7552.

Ding, Waverly, Sharon Levin, Paula Stephan, and Anne Winkler, 2010. The Impact of Information Technology on Academic Scientists' Productivity and Collaboration Patterns. *Management Science* 56(9): 1439-1461.

Downes, Tom and Shane Greenstein. 2007. Understanding Why Universal Service Obligations May be Unnecessary: The Private Development of Local Internet Access Markets. *Journal of Urban Economics*, 62(1): 2–26.

Dranove, David, Chris Forman, Avi Goldfarb, and Shane Greenstein. 2013. The Trillion Dollar Conundrum: Complementarities and Health Information Technology. NBER Working paper 18281.

Forman, Chris and Avi Goldfarb. 2006. Diffusion of Information and Communication Technologies to Businesses. In *Handbook of Information Systems, Volume 1: Economics and Information Systems*, ed. Terrence Hendershott, 1–52. Amsterdam: Elsevier.

Forman, Chris, Avi Goldfarb, and Shane Greenstein. 2002. Digital Dispersion: An Industrial and Geographic Census of Commercial Internet Use. NBER Working Paper #9287.

Forman, Chris, Avi Goldfarb, and Shane Greenstein. 2005. How Did Location Affect the Adoption of the Commercial Internet? Global Village vs Urban Density. *Journal of Urban Economics*, 58(3): 389–420.

Forman, Chris, Avi Goldfarb, and Shane Greenstein. 2008. Understanding the Inputs into Innovation: Do Cities Substitute for Internal Firm Resources? *Journal of Economics and Management Strategy*, 17(2): 295–316.

Forman, Chris, Avi Goldfarb, and Shane Greenstein. 2012. The Internet and Local Wages: A Puzzle. *American Economic Review* 102(1): 556-575.

Forman, Chris, and Nicholas van Zeebroeck. 2012. From wires to partners: How the Internet has fostered R&D collaborations within firms. *Management Science* 58(8): 1549-1568.

Friedman, Thomas L. 2005. *The World is Flat: A Brief History of the Twenty-First Century*. New York, NY: Farrar, Straus, and Giroux.

Glaeser, Edward L. and Giacomo A. M. Ponzetto. 2007. Did the Death of Distance Hurt Detroit and Help New York? NBER Working Paper #13710.

Griliches, Zvi. 1990. Patent statistics as economic indicators: A survey. *Journal of Economic Literature* 28(4): 1661-1707.

Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg. 2005. Market value and patent citations. *RAND Journal of Economics* 36(1): 16-38.

Hampton, K., B. Wellman. 2002. Neighboring in Netville: How the Internet supports community and social capital in a wired suburb. *City and Community*, 2(3), 277-311.

Jaffe, Adam. and Manuel Trajtenberg. 2002. *Patents, Citations, and Innovations: A Window on the Knowledge Economy.* MIT Press, Cambridge, MA.

Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson. 1993. Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *Quarterly Journal of Economics* 108(3): 577-598.

Jones, Benjamin F., Stefan Wuchty, and Brian Uzzi. 2008. Multi-University Research Teams: Shifting Impact, Geography, and Stratification in Science. *Science* 322(21): 1259-1262.

Kolko, Jed. 2002. Silicon Mountains, Silicon Molehills: Geographic concentration and convergence of internet industries in the US. *Information Economics and Policy* 14(2): 211–32.

Sinai, T. and Waldfogel, J., 2004. Geography and the Internet: Is the Internet a Substitute or a Complement for Cities? *Journal of Urban Economics* 56(1): 1-24.

Wellman, B. 2001. Computer Networks As Social Networks. *Science* 29, 2031-2034.

Table 1: Summary Statistics (County-level data)

Variable	Mean	Std. Dev.	Min	Max	# obs.
DEPENDENT VARIABLES					
Growth in patenting	0.2655	0.7319	-2.4849	3.6376	2807
Growth in citation-weighted patenting	-0.1126	0.9946	-4.804	4.92	2714
Growth in collaborative patenting	-0.1814	0.7166	-2.9444	3.4553	2792
Growth in citation-weighted collaborative patenting	-0.532	1.0105	-4.804	4.3407	2705
Growth in distant collaborative patenting	-0.5559	0.7558	-3.7612	2.8332	2840
Growth in citation-weighted distant collaborative patenting	-0.7729	1.0616	-5.7004	3.6109	2793
Growth in non-distant collaborative patenting	0.4442	0.6072	-2.5649	3.4553	2631
Growth in citation-weighted non-distant collaborative patenting	0.3449	0.8391	-3.4965	4.3758	2519
Growth in non-collaborative patenting	0.4843	0.3386	-1.6094	2.4849	2709
Growth in citation-weighted non- collaborative patenting	0.4820	0.5041	-2.9957	3.3202	2598
Growth in patenting by educational institutions	0.1082	0.4243	-2.1972	2.7726	2631
Growth in citation-weighted patenting by educ. institutions	-0.0236	0.5276	-4.0775	4.2341	2719
Growth in patenting by private firms	0.3789	0.7717	-2.4849	3.7136	2644
Growth in citation-weighted patenting by private firms	0.0175	1.0018	-4.2485	4.7095	2604
Growth in patenting by government institutions	-0.0117	0.317	-3.1499	2.3979	2793
Growth in citation-weighted patenting by govt. institutions	-0.0681	0.4791	-5.3083	3.434	2854
CORE COVARIATES					
Advanced Internet	0.0888	0.1329	0	1	2734
Patenting 1990-1995	7786.7	46544	0	1808028	3131
Citation-Weighted Patenting 1990-1995	24998	184073	0	7905438	3131
CONTROLS					
Log employment	8.832	1.6851	2.77259	15.051	3125
Log estabs.	6.4598	1.4594	1.94591	12.742	3125
Log weekly wages	6.2084	0.2267	5.32301	7.335	3125
Log pop.	10.137	1.3681	4.67283	15.997	3122
% black	0.0859	0.1434	0	0.8624	3122
% university education	0.1356	0.0659	0.03692	0.5366	3122
% high school education	0.6979	0.1039	0.31682	0.962	3122
% below poverty line	0.1667	0.0794	0	0.6312	3122
Median HH income	23978	6599.6	8595	59284	3122
Carnegie tier 1 enrollment	0.0073	0.0651	0	2.6154	3124
Fraction in engineering	0.0009	0.0055	0	0.1125	3124
Fraction professional	0.3522	0.0659	0.16019	0.6744	3124
% > 64 years old	0.1486	0.0442	0.00865	0.3409	3122
Change population	0.0959	0.1337	-0.5506	1.0683	3122
Change % black	0.0014	0.0175	-0.0994	0.2724	3122
Change % univ. educ.	-0.0265	0.021	-0.1461	0.0748	3122
Change % high school educ.	-0.1873	0.0523	-0.3237	-0.026	3122
Change % > 64 years old	-0.0011	0.0145	-0.0919	0.0851	3122

Table 2: Patenting grew fastest in counties that patented more in 1990

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	County-Level Data				County-Industry Level Data			
	All patents		Collaborative Patents		All patents		Collaborative Patents	
	Patents	Citation-weighted patents	Patents	Citation-weighted patents	Patents	Citation-weighted patents	Patents	Citation-weighted patents
Patenting 1990-1995 (000s)	0.00064	0.00017	0.00070	0.00020	6.4951	0.3930	5.6169	0.1929
	(0.00021)***	(0.00008)**	(0.00029)**	(0.00011)*	(1.2580)***	(0.0828)***	(1.0899)***	(0.0389)***
Log emp.	-0.0182	-0.0790	-0.1116	-0.1127	0.0565	0.0798	0.0439	0.0711
	(0.0536)	(0.0749)	(0.0537)**	(0.0730)	(0.0253)**	(0.0234)***	(0.0264)*	(0.0239)***
Log estabs.	-0.0724	0.0312	-0.0122	0.0665	-0.0933	-0.0522	-0.0924	-0.0436
	(0.0695)	(0.0975)	(0.0676)	(0.0923)	(0.0339)***	(0.0314)*	(0.0358)***	(0.0328)
Log weekly wages	0.1504	0.0779	0.2131	0.1349	0.0234	-0.0722	0.0552	-0.0668
	(0.1062)	(0.1405)	(0.1004)**	(0.1333)	(0.0499)	(0.0428)*	(0.0513)	(0.0467)
Log pop.	0.1118	0.0096	0.0644	-0.1095	0.0857	-0.1188	0.0846	-0.1292
	(0.0528)**	(0.0735)	(0.0528)	(0.0718)	(0.0249)***	(0.0223)***	(0.0260)***	(0.0233)***
% black	-0.0194	0.0416	0.1000	0.1466	-0.1225	0.0312	-0.1416	0.0165
	(0.1269)	(0.1750)	(0.1182)	(0.1682)	(0.0452)***	(0.0383)	(0.0470)***	(0.0404)
% university education	2.9157	2.2826	2.4571	0.9879	1.0905	0.0347	1.2201	-0.1427
	(0.6190)***	(0.9073)**	(0.6045)***	(0.8314)	(0.3017)***	(0.2913)	(0.3177)***	(0.3008)
% high school education	1.8525	1.6619	1.1996	0.6376	0.5779	0.5606	0.4234	0.5101
	(0.4937)***	(0.6886)**	(0.4732)**	(0.6723)	(0.2011)***	(0.1831)***	(0.2071)**	(0.1892)***
% below poverty line	-0.2586	-0.0262	0.2511	0.9880	-0.4638	-0.3626	-0.5436	-0.4562
	(0.4012)	(0.5577)	(0.3946)	(0.5431)*	(0.2175)**	(0.1819)**	(0.2277)**	(0.1892)**
Median HH income (000s)	-0.0038	-0.0022	0.0029	0.0089	-0.0029	-0.0110	-0.0055	-0.0134
	(0.0045)	(0.0063)	(0.0045)	(0.0062)	(0.0041)	(0.0033)***	(0.0043)	(0.0035)***
Carnegie tier 1 enrollment	-0.2523	-0.0382	-0.1646	-0.0056	0.0189	0.0745	0.0059	0.0128
	(0.2225)	(0.2382)	(0.2236)	(0.2473)	(0.1981)	(0.1350)	(0.1824)	(0.1040)
Fraction in engineering	3.4605	1.5517	3.5690	2.2435	6.3165	0.9030	5.8570	0.6267
	(1.7789)*	(2.5829)	(1.8096)**	(2.5279)	(1.4945)***	(2.2487)	(1.5666)***	(1.9420)
Fraction professional	-1.1209	-0.5737	-0.2308	0.6745	0.6484	-0.1359	0.7066	-0.0646
	(0.3978)***	(0.5796)	(0.3790)	(0.5234)	(0.1720)***	(0.1600)	(0.1780)***	(0.1666)
% > 64 years old	0.4407	-0.0513	0.4280	0.5431	-0.4569	-0.8157	-0.7806	-1.0565
	(0.4674)	(0.6705)	(0.4679)	(0.6480)	(0.2470)*	(0.2196)***	(0.2563)***	(0.2189)***
Change population	1.0615	0.7248	0.6967	0.2912	0.7874	0.5550	0.6854	0.5021
	(0.1244)***	(0.1819)***	(0.1276)***	(0.1772)	(0.0634)***	(0.0584)***	(0.0663)***	(0.0593)***
Change % black	-1.7615	-0.9647	-0.0603	-0.3806	-0.3149	-0.5353	-0.3086	-0.5910
	(0.7871)**	(1.0774)	(0.7255)	(1.1084)	(0.3954)	(0.3123)*	(0.3864)	(0.3423)*
Change % univ. educ.	6.1112	6.3952	5.5920	4.5995	4.3261	2.4595	4.2466	1.9685
	(1.2503)***	(1.8072)***	(1.2086)***	(1.6587)***	(0.5688)***	(0.5201)***	(0.5965)***	(0.5358)***
Change % high school educ.	2.7721	2.1909	2.1569	0.7946	0.7276	0.5131	0.5669	0.4838
	(0.9188)***	(1.2664)*	(0.8461)**	(1.2148)	(0.3362)**	(0.3108)*	(0.3428)*	(0.3161)
Change % > 64 years old	-2.5195	-3.2211	-3.1657	-3.9618	-1.0473	-0.3929	-1.4842	-0.4454
	(1.2037)**	(1.6021)**	(1.1581)***	(1.5700)**	(0.4805)**	(0.4431)	(0.4906)***	(0.4550)
Constant	-1.8417	-0.9027	-1.8901	-0.7248	N/A	N/A	N/A	N/A
	(0.7104)***	(0.9607)	(0.6664)***	(0.8975)				
Observations	2793	2700	2776	2689	80892	80892	80892	80892
R-squared	0.10	0.04	0.06	0.06	N/A	N/A	N/A	N/A
Log Likelihood	N/A	N/A	N/A	N/A	-121013	-117261	-115144	-112603

Columns 1-4 are ordinary least squares regressions with county as the unit of observation. Columns 5-8 are ordered probit regressions with county-industry as the unit of observation and include industry fixed effects. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Internet adoption is not significantly correlated with growth in patenting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	County-Level Data				**County-Industry Level Data**			
	All patents		**Collaborative Patents**		**All patents**		**Collaborative Patents**	
	Patents	**Citation-weighted patents**	**Patents**	**Citation-weighted patents**	**Patents**	**Citation-weighted patents**	**Patents**	**Citation-weighted patents**
Advanced Internet	0.1722 (0.1371)	0.2598 (0.2153)	0.1575 (0.1431)	0.3260 (0.2108)	0.0565 (0.0378)	0.0508 (0.0344)	0.0583 (0.0392)	0.0509 (0.0363)
Observations	2540	2448	2509	2409	72576	72576	72576	72576
R-squared	0.10	0.04	0.06	0.05	N/A	N/A	N/A	N/A
Log Likelihood	N/A	N/A	N/A	N/A	-115059	-110747	-109970	-106638

Columns 1-4 are ordinary least squares regressions with county as the unit of observation. Columns 5-8 are ordered probit regressions with county-industry as the unit of observation and include industry fixed effects. All regressions include the same set of controls as Table 2. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Internet adoption mutes the correlation between prior patents and growth in patenting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	County-Level Data				**County-Industry Level Data**			
	All patents		**Collaborative Patents**		**All patents**		**Collaborative Patents**	
	Patents	**Citation-weighted patents**	**Patents**	**Citation-weighted patents**	**Patents**	**Citation-weighted patents**	**Patents**	**Citation-weighted patents**
Advanced Internet	0.1852 (0.1376)	0.2799 (0.2161)	0.1715 (0.1437)	0.3466 (0.2117)	0.1273 (0.0373)***	0.0726 (0.0354)**	0.1167 (0.0373)***	0.0588 (0.0365)
Patenting 1990-1995 (000s)	0.0037 (0.00081)***	0.0016 (0.00039)***	0.0040 (0.00074)***	0.0018 (0.00044)***	16.410 (2.871)***	1.6063 (0.2629)***	13.5045 (2.3167)***	0. 6584 (0.1600)***
Patenting 1990-95 (000s) x Advanced Internet	-0. 0160 (0.0039)***	-0. 0075 (0.0019)***	-0. 0178 (0.0036)***	-0. 0086 (0.0021)***	-70.815 (14.826)***	-7.4655 (1.3657)***	-55.989 (12.323)***	-2.8652 (0.8818)***
Observations	2540	2448	2509	2409	72576	72576	72576	72576
R-squared	0.10	0.04	0.07	0.05	N/A	N/A	N/A	N/A
Log Likelihood	N/A	N/A	N/A	N/A	-113555	-110289	-108544	-106469

Columns 1-4 are ordinary least squares regressions with county as the unit of observation. Columns 5-8 are ordered probit regressions with county-industry as the unit of observation and include industry fixed effects. All regressions include the same set of controls as Table 2. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Comparing patents with distant collaborators, patents with non-distant collaborators, and non-collaborative patents

	(1)	(2)	(3)	(4)	(5)	(6)
		Patents			**Citation-weighted patents**	
	Patents with distant collaborators	**Patents with non-distant collaborators**	**Non-collaborative patents**	**Patents with distant collaborators**	**Patents with non-distant collaborators**	**Non-collaborative patents**
Advanced Internet	0.0827	0.0664	-0.0115	0.0370	0.2951	-0.1152
	(0.1262)	(0.1121)	(0.0610)	(0.1816)	(0.1478)**	(0.0773)
Patenting 1990-95 (000s)	0.0047	0. 00002	0.00013	0.0021	0.00003	-0.00002
	(0.00096)***	(0.00069)	(0.00038)	(0.00052)***	(0.00024)	(0.00013)
Patenting 1990-95 (000s) x Advanced Internet	-0.0216	0. 00038	0.000014	-0. 0099	0.00005	0.00021
	(0.0046)***	(0.00333)	(0.00180)	(0.0025)***	(0.0011)	(0.00063)
Observations	2498	2370	2469	2445	2244	2348
R-squared	0.13	0.09	0.04	0.14	0.06	0.05

Ordinary least squares regressions with county as the unit of observation. Distant is defined as more than 50 miles apart. Regressions include the same controls as in Table 2. Robust standard errors in parentheses.
*significant at 10%; **significant at 5%; ***significant at 1%

Table 6: Results by type of patenting institution

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Private Firms				**Educational Institutions**				**Government Institutions**			
	Patents	**Citation-weighted patents**	**Patents**	**Citation-weighted patents**	**Patents**	**Citation-weighted patents**	**Patents**	**Citation-weighted patents**	**Patents**	**Citation-weighted patents**	**Patents**	**Citation-weighted patents**
Patenting 1990-95 (000s)	0.00026 (0.00013)**	0.00012 (0.00006)**	0.0016 (0.00080)**	0.0013 (0.00035)***	-0.00013 (0.00013)	0.00005 (0.00005)	0.0011 (0.00096)	0.00083 (0.00043)*	-0.00074 (0.00019)***	-0.00025 (0.00011)**	-0.0016 (0.0014)	-0.0012 (0.00045)***
Advanced Internet			0.4061 (0.1612)**	0.3349 (0.2280)			-0.0261 (0.0306)	0.0110 (0.0385)			-0.0488 (0.0232)**	-0.0537 (0.0300)*
Patenting 1990-95 (000s) x Advanced Internet			-0.0066 (0.0039)*	-0.0062 (0.0017)***			-0.0069 (0.0052)	-0.0041 (0.0021)*			0.0048 (0.0069)	0.0053 (0.0022)**
Observations	2631	2591	2356	2302	2610	2699	2235	2325	2773	2833	2399	2457
R-squared	0.10	0.03	0.10	0.03	0.21	0.01	0.21	0.01	0.03	0.14	0.03	0.15

Ordinary least squares regressions with county as the unit of observation. Regressions include the same controls as in Table 2. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1: Lorenz curves for concentration of patenting 1990-95 vs 2000-05

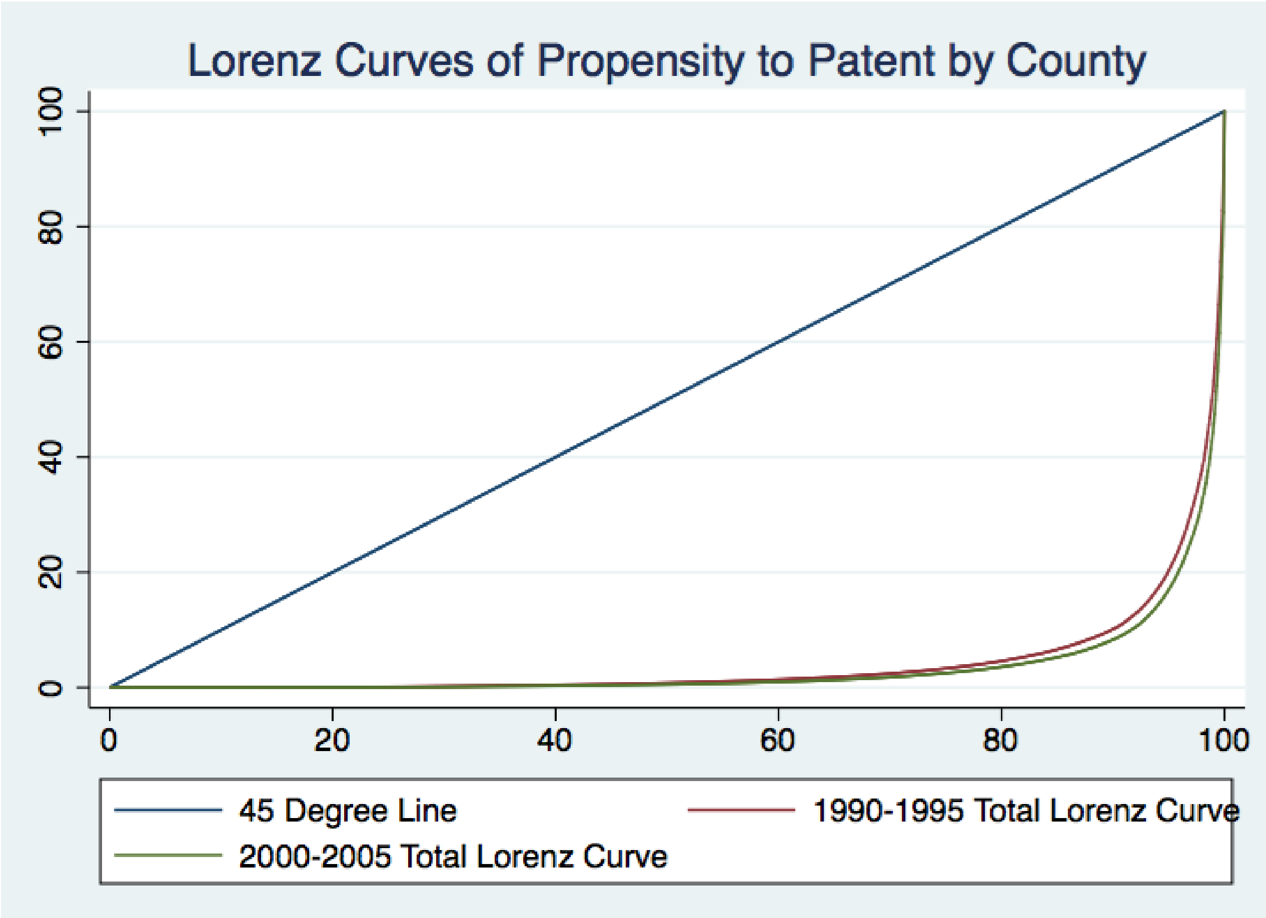

Figure 2: Internet adoption and patenting 1990-95