The Effect of High-Tech Clusters on the Productivity of Top Inventors

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Abstract

The high-tech sector is increasingly concentrated in a small number of expensive cities, with the top ten cities in "Computer Science", "Semiconductors" and "Biology and Chemistry", accounting for 70%, 79% and 59% of inventors, respectively. Why do inventors tend to locate near other inventors in the same field, despite the higher costs? I use longitudinal data on top inventors based on the universe of US patents 1971 - 2007 to quantify the productivity advantages of Silicon-Valley style clusters and their implications for the overall production of patents in the US. I relate the number of patents produced by an inventor in a year to the size of the local cluster, defined as a city $\times$ research field $\times$ year. I first study the experience of Rochester NY, whose high-tech cluster declined due to the demise of its main employer, Kodak. Due to the growth of digital photography, Kodak employment collapsed after 1996, resulting in a 49.2% decline in the size of the Rochester high-tech cluster. I test whether the change in cluster size affected the productivity of inventors outside Kodak and the photography sector. I find that between 1996 and 2007 the productivity of non-Kodak inventors in Rochester declined by 20.6% relative to inventors in other cities, conditional on inventor fixed effects. In the second part of the paper, I turn to estimates based on all the data in the sample. I find that when an inventor moves to a larger cluster she experiences significant increases in the number of patents produced and the number of citations received. Conditional on inventor, firm, and city $\times$ year effects, the elasticity of number of patents produced with respect to cluster size is 0.0662 (0.0138). The productivity increase follows the move and there is no evidence of pre-trends. IV estimates based on the geographical structure of firms with laboratories in multiple cities are statistically similar to OLS estimates. In the final part of the paper, I use the estimated elasticity of productivity with respect to cluster size to quantify the aggregate effects of geographical agglomeration on the overall production of patents in the US. I find macroeconomic benefits of clustering for the US as a whole. In a counterfactual scenario where the quality of U.S. inventors is held constant but their geographical location is changed so that all cities have the same number of inventors in each field, inventor productivity would increase in small clusters and decline in large clusters. On net, the overall number of patents produced in the US in a year would be 11.07% smaller.

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We know from ordinary experience that there are group interactions that are central to individual productivity. We know this kind of external effect is common to all the arts and sciences - the 'creative professions' (Lucas, 1988)

1 Introduction

Firms in the innovation sector display a strong tendency to cluster geographically by research field (Carlino et al., 2012). Prominent examples include the internet and software clusters in Seattle anchored by Amazon and Microsoft, respectively; the medical research and biotech clusters in Boston; the software and telecommunication clusters in Austin; the Raleigh-Durham Research Triangle, with its large concentration of pharmaceutical firms; the nascent autonomous vehicles cluster in Pittsburgh; and the biotech cluster and medical devices clusters in San Diego. The San Francisco-Silicon Valley region has the largest agglomeration of innovative firms in the US, with important clusters in most research fields.

The geographic concentration of high-tech sectors is not just a curiosity—it has important implications for cities and states. The presence of a high-tech sector has been shown to be a key driver of local economic growth as innovation-oriented industries have taken on larger roles (Glaeser-Saiz, 2004; Buera-Kaboski, 2012). In the period 1980 to 2010, mean wages and mean income in cities with large high-tech clusters have increased significantly more than in cities without high-tech clusters (Moretti, 2012; Diamond, 2016a). Thus, it is probably not surprising that competition has emerged among localities to attract high-tech employers, with states and counties offering increasingly generous subsidies designed to spur high-tech clusters in their jurisdiction. The prospect of winning Amazon's second headquarters recently generated intense competition among US cities, with some of finalist cities offering incentives as high as $5 billion. Tesla received incentives worth $1.3 billion from Nevada in 2014 to locate its new Gigafactory in Reno, while Foxxcom received $3 billion from Wisconsin to locate its electronic components factory in the state. In biotech, 11 states provide incentives to relocating firms and the average subsidy has grown four-fold since 1990 (Moretti and Wilson, 2013). It is rare for high-tech firms to open large new facilities in the United States today without receiving some type of local subsidy, with areas with limited high-tech presence typically offering the most aggressive subsidies.

Quantitatively, the amount of spatial concentration observed in high tech by research field is remarkable. (In this paper, I will use the term "high tech" broadly, to include any firm that produces innovation.) In my patent data, the 10 cities with largest number of inventors in "Computer Science" account for 70% of all inventors in 2007. In "Semiconductors" and "Biology and Chemistry", the corresponding shares are 79% and 59%, respectively. These shares are not declining over time. Indeed, they are larger in 2007 than in 1971, suggesting that despite the diffusion of Internet, Skype and other forms of cheap communication, high-tech inventors are more geographically concentrated today than they were in the past. A similar amount of concentration is observed in other countries (Duranton et al, 2010; Kerr, 2018). Agglomeration in manufacturing, meanwhile, is much lower on average (Ellison and Glaeser, 1997).

The agglomeration of innovative activity by research field raises important questions about the economic geography of the high-tech sector, especially since high-tech clusters tend to be located in cities with high labor and real estate costs—cities like San Francisco, Boston or Seattle—rather than in cities where costs are low. Why do high-tech inventors tend to locate near other inventors in the same field, despite the higher costs? What are the effects on innovation? One view of Silicon Valley-style clusters—which can be traced to Marshall (1890)—is that agglomeration economies make workers inside large clusters more productive. To use Marshall's words, in industrial clusters "the mysteries of the trade become no mysteries." In his seminal paper on economic growth quoted above, Lucas (1988) explicitly posits a *productivity* effect of agglomeration and argues that it is particularly important in the innovation sector and "creative professions." This productivity effect could reflect localized knowledge spillovers or the fact that the quality of worker-firm matches may be better in larger clusters due to labor pooling.

Empirically determining the productivity advantage of Silicon Valley-style clusters is difficult. First, location is endogenous, since workers and firms decide where to locate based on a number of observed and unobserved factors. Comparing the productivity of inventors in large clusters to the productivity of inventors in small clusters may yield biased estimates of agglomeration effects if particularly productive inventors select into large clusters. Second, direct worker-level measures of productivity are rare. Most existing papers on the effect of agglomeration on innovation rely either on wages—under the assumption that they reflect the marginal product of labor—or on analyses of patent citations (Jaffe, Trajtenberg, and Henderson 1993).[1]

In this paper I use longitudinal data on top inventors based on the universe of patents filed in the US between 1971 to 2007 to investigate two related questions: (1) Are there productivity benefits for inventors who locate in Silicon Valley-style clusters? (2) What are the aggregate effects of geographical agglomeration on overall innovation in the US? In my analysis, I define a cluster as city $\times$ research field $\times$ year. I estimate how inventors' productivity varies with the size of the relevant cluster, measured by the number of other inventors in the same city, field, and year excluding the focal inventor. As measures of worker-specific productivity, I use the number of patents produced in a year and the number of subsequent citations these patents receive. While these measures have some limitations, they are arguably a more direct measure of inventor productivity than wages. I focus on top inventors—defined as those above the 90th percentile in the total number of patents over the sample period—since the panel is longer for this group.

The analysis proceeds in three parts. I first study the experience of inventors in Rochester NY, where the high-tech cluster declined due to the demise of its main employer, Kodak. Kodak was the market leader in films for cameras and the fifth most prolific patenter in the US. At its peak in 1996, Kodak employed more than half of all the inventors in Rochester. But due to the diffusion of digital photography and the decline of physical film, Kodak stock price and employment collapsed after 1996. Essentially, demand for Kodak's main product evaporated due to a global technology shock. By 2007, the number of Kodak inventors in Rochester had declined by 83.7%.

Kodak's decline had a profound effect on the broader Rochester high-tech cluster. Measured by the number of inventors in all fields, its size declined by 49.2% relative to other cities, dragged down by Kodak's downsizing. The shock was large and arguably exogenous, as it was caused by the advent of digital photography and not factors specific to Rochester's local economy. The experience of Rochester therefore offers an interesting case study for testing the hypothesis that high-tech clusters' size affects inventors' productivity. In particular, examining how the sudden collapse of Rochester high tech cluster affected inventors *outside Kodak* offers a direct test of the effects of cluster size on productivity. I focus on non-Kodak inventors outside the photography sector, since the photography sector may have been exposed to the same negative demand shock as Kodak. Finding that their productivity did not change following the demise of the local high-tech cluster would cast doubt on the hypothesis that productivity depends on cluster size.

I compare productivity changes in Rochester with changes in other cities between 1996—the year when Kodak stock price peaked—and 2007. Specifically, I compare the within-inventor change in productivity between 1996 to 2007 for non-Kodak inventors who were in Rochester in 1996 (irrespective of their 2007 location) to the within-inventor change for non-Kodak inventors who were in other cities in 1996. I find that the log productivity of non-Kodak inventors in Rochester declined by 0.206 (0.077) relative to other cities. This estimate is not driven by changes

[1]Greenstone, Hornbeck and Moretti (2010) and Moretti (2004) study productivity spillovers on firm-level TFP.

in unobserved quality of inventors and it is robust to controlling for field $\times$ city and field $\times$ year effects. Thus, following the decline in the Rochester high-tech cluster, non-Kodak inventors in Rochester experienced large productivity losses relative to non-Kodak inventors in other cities. While this is by no means direct proof of productivity spillovers, it is consistent with the hypothesis that cluster size affects inventor productivity.

In the second part of the paper, I present estimates based on all the data in the sample. The sample includes 823,359 inventors observed between 1971 and 2007, located in 32,220 clusters (179 cities $\times$ 5 research fields $\times$ 36 years). In the baseline specification, I regress inventor's log productivity on log cluster size, conditioning on inventor, firm, city $\times$ year, and research field $\times$ city effects, as well as other controls. Inventor and firm effects account for sorting due to permanent differences in productivity across workers and firms. City $\times$ year effects control for sorting driven by time varying characteristics of cities—local amenities, infrastructure, local policies, housing costs, taxes, subsidies, etc. Estimates are identified because multiple clusters exists within a city-year pair. Research field $\times$ city effects absorb time-invariant productivity shifters that are specific to a city-field pair, such as proximity to a university that is strong in a specific field.

I find that when an inventor moves to a larger cluster, she experiences significant increases in the number of patents produced and the number of subsequent citations. Estimates appear robust to different assumptions on sorting. Models that include five leads and lags allow me to estimate the dynamic response to a change in cluster size and reveal that the productivity increase follows the move with no evidence of pre-trends.

The elasticity of number of patents in a year with respect to cluster size is 0.0662 (0.0138). The estimated elasticity implies that a computer scientist moving from the median cluster in computer science (Gainesville, FL) to the cluster at the 75th percentile of size (Richmond, VA) would experience a 12.0% increase in productivity, holding constant the inventor and the firm. In biology and chemistry, a move from the median cluster—Boise, ID—to the 75th percentile cluster—State College, PA—is associated with a productivity gain of 8.4%, holding constant the inventor and the firm. The magnitude of the implied agglomeration economies is in line with existing estimates in the literature. 2SLS models that use an instrumental variable based on the geographical structure of firms with laboratories in multiple cities yield an elasticity that is statistically similar to the OLS elasticity.

A number of additional specifications are estimated to probe the robustness of the baseline estimates to different assumptions. Alternative measures of cluster size yield similar estimates. Estimates for stayers—defined as inventors who do not change city or field—are larger than baseline estimates. Overall, I can't completely rule out the possibility that my estimates are biased by the presence of unobserved shocks to the productivity of inventors, but the weight of the available evidence lends credibility to my estimates.

Estimates of the elasticity of productivity with respect to cluster size can be used to quantify the spillover effects that a firm generates within a cluster. These estimates indicate that the size of the spillover varies enormously across firms. The spillover effect generated by the average firm in the average city is 0.3% and 0.24% in computer science and biology and chemistry, respectively. But it is much larger for firms that account for a large number of inventors in the local cluster. For example, the productivity of non-Microsoft computer scientist in Seattle is estimated to be 8.06% higher because of the presence of Microsoft in the local computer science cluster. This large effect reflects Microsoft remarkable size in this field in Seattle. Having estimates of the productivity spillover that a specific firm generates in a specific cluster may prove useful to local and state governments that offer subsidies to attract high-tech firms to their jurisdiction.

In the final part of the paper, I seek to quantify the macro-economic benefits of agglomeration for the US as a whole. I use the estimated elasticity of productivity with respect to cluster size to ask how much geographical clustering contributes to the overall production of patents in the US. In particular: Is the total number of patents produced each year in the country made larger by the fact that inventors in each field concentrate in a handful of locations, compared to the case where inventors are spread more equally across locations?

I compare the observed total number of patents produced annually in each field in the US to the number of patents that would be produced if inventor quality and firm quality did not change but some inventors were spatially reallocated from large clusters to small clusters up to the point where clusters size within each field is equalized across cities. Because of the effect of agglomeration on productivity, such spatial redistribution would increase the productivity of inventors in clusters smaller than average and lower the productivity of inventors in clusters larger than average. My estimate of the elasticity of productivity with respect to cluster size implies that the average productivity of computer scientists in the San Francisco-Silicon Valley region, for example, would be 22.52% lower than the observed productivity in 2007 because the size of the San Francisco-Silicon Valley Computer Science would be made significantly smaller. The corresponding losses for New York, Seattle, Austin, and Boston would be -16.91%, -16.47%, -14,56%, and -13.30%, respectively. On the other hand, the average productivity of computer scientists in Kansas City would be 3.18% higher than the observed productivity in 2007, because the Kansas City Compute Science cluster is smaller than average. The corresponding gains for Buffalo, Omaha, Portland ME, and Memphis would be 6.37%, 13.23%, 17.50%, and 23.02%, respectively.

On net, the magnitude of the aggregate effect for the country as a whole of such spatial redistribution depends on the relative magnitude of the gains in small clusters compared to the losses in large clusters. Empirically, I find significant aggregate efficiency gains from clustering. The total number of patents created in the US in Computer Science would be 13.18% lower in 2007 if computer scientists were uniformly distributed across cities. The corresponding losses in biology and chemistry, semiconductors, other engineering, and other sciences would be -9.92%, -14.68%, -7.62%, and -9.64%, respectively. The change in the total number of patents in the US would be -11.07%.[2]

Thus while the spatial clustering of high-tech industries may exacerbate earning inequality across US communities, it is also important for overall production of innovation in the US. The unequal distribution of earnings growth across cities is a source of policy concern and has spurred a wealth of policy proposals to help struggling cities and regions, especially those in the Rust Belt (Gruber and Johnson, 2019). Policies that seek to attract high-tech investment to communities that do not have any—like the incentives offered by some local and state governments—might help reduce earning differences but are costly in the aggregate, creating a classic case of an equity-efficiency trade-off.

This study relates to an extensive literature on the link between agglomeration and innovation (Audretsch and Feldman, 1996). The local nature of knowledge flows and productivity spillovers is frequently noted in the literature. For example, Kantor and Whalley (2014 and forthcoming) find significant spillovers from academic R&D on local firms. Helmers and Overman (2017) find that the establishment of the Diamond Light Source synchrotron in the UK induced a clustering of related research in its geographic proximity and raised research output within a 25 kilometer radius. Peri (2004 and 2005) uncovers significant localized spillovers from knowledge flows in sectors at the frontier of technology. Bloom, Schankerman, and Van Reenen (2013) find evidence of large spillovers from R&D, implying that that the social returns to R&D are larger than the private returns. Akcigit et al (2018) develop a model where an inventor's own knowledge is an input in the innovation process and this knowledge can be increased by interacting with and learning from others.[3] See Carlino and Kerr (2015) for a comprehensive survey of this literature.

[2]Of course, there could be some gains to decentralizing clusters that should be counted against productivity losses. Such gains may come from decreases in congestion or housing prices and may affect welfare. The main focus of this paper is productivity, not welfare. While the question of the magnitude of the utility gains from lower congestion of housing prices is an interesting one, it is not the question I address in this paper. A complete welfare analysis is well outside the scope of this study.

[3]Guzman (2019) finds that startups that move to Silicon Valley patent more and introduce more products. Additional examples include, but are not limited to, Duranton and Overman (2005); Lychagin, Pinkse, Slade, and Van Reenen (2016); Bosquet and Combes (2017); and Acemoglu, Akcigit, and Kerr (2016).

Not all papers in this literature find evidence of spillovers. Waldinger (2012), for example, finds that the publishing activity of the scientists in German universities whose departments suffered losses due to the dismissal of peers by the Nazi government did not decline, while Moser, Voena, and Waldinger (2014) find that the arrival of Jewish émigrés in the U.S. did not increase the productivity of incumbent American inventors. Azoulay et al. (2010) find that the death of a superstar scientist reduces coauthor productivity, but the declines in output does not depend on the geographic distance among collaborators.[4]

This paper is also part of a much broader literature on agglomeration economies, where most of the focus has been on measures of size at the city level, rather than cluster level.[5] Finally, my estimates complement the recent results in Bell et al (2019), who find that growing up in a high-innovation area raises the probability of becoming an inventor and this exposure effect is technology class specific.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 reports the estimates based on the Rochester case study. Section 4 reports the estimates based on the full sample. Section 5 discusses the aggregate implications. Section 6 concludes.

2 Data

I use data on the universe of U.S. patents filed between 1971 and 2007 and ultimately granted. Unsuccessful applications are not included. The source of the data is the COMETS patent database. It is described in detail by Zucker, Darby, and Fong (2014). It is the same data used in a recent paper by Moretti and Wilson (2017).

2.1 Patents, Inventors, and Their Location

The data include 4,229,818 patents. 91.5% of patents in the sample are filed by inventors employed in private firms, 4.1% by inventors employed by universities, with the remainder are filed by inventors working in national labs, government, nonprofit institutions, or for themselves. Table 1 shows the names of the 25 patent assignees—private or public—with the largest number of patents in my sample period. IBM is by far the most prolific patenter, with 155,708 patents filed between 1971 and 2007, followed by General Electric, Microsoft, Intel and Kodak with 69,019, 43,550, 42,087 and 41,553 patents filed respectively. The U.S. Navy and the University of California are the only non-corporate organizations in the Table.[6]

The geographical units of analysis I employ are the Bureau of Economic Analysis's (BEA) "Economic Areas." There are 179 Economic Areas in the US and they cover the entire country. In most cases, "Economic Areas" are similar to an MSA. For large areas like the San Francisco Bay Area, Boston or New York, they tend to be larger than the corresponding MSAs, since they include the entire economic region. For example, the Economic Area for the San Francisco Bay Area includes the entire area between Santa Rosa to the North and San Jose to the South. In the rest of the paper, I will refer to Economic Areas as "cities".[7]

[4]Zacchia (2018) finds that when superstar inventors relocate to a new city there is a positive effect on the productivity of collaborators in the city of destination, but no city-wide spillovers.

[5]The literature on agglomeration economies is too large to be summarized here. For surveys, see Behrens and Robert-Nicoud, 2015; and Combes and Gobillon, 2015; Rosenthal and Strange (2004, 2006 and 2008); and Duranton and Kerr (2018).

[6]In the COMETS data, patent assignees (organizations) are identified by a unique code. Different recorded names that standardize to the same name have been assigned the same code. For example: IBM, IBM Corp., IBM Corporation have the same code FI2651. Moreover, organization names were hand cleaned to determine the variant names that a certain organization uses. For example: International Business Machines Corporation has been assigned the code FI2651 as well. Likewise, UCLA, University of California Los Angeles, Univ Calif Los Angeles have all been assigned the same code.

[7]Kerr and Kominers (2015) model cluster shapes. Buzard et al (2017) examine the spatial clustering of about 1,700 R&D labs and identify four major clusters in the Northeast corridor (Boston, New York–Northern New Jersey, Philadelphia–Wilmington, and Washington, D.C.) and three

Each patent is assigned to an Economic Area based on the inventor's *residential address.* Patenters must report their home address on their patent application and have no economic incentive to misreport it. There is no legal link between where a patent's inventor lives and the taxation of any income generated by the patent for the patent assignee/owner. In many cases both the inventor's residential address and the assignee address (typically the company that first owned the patent) are available. I do not use the latter because it may not reflect the location where the research was conducted, as in many cases it is the address of the corporate headquarters and not the R&D facility.[8]

In the COMETS data, patents are assigned to one of five main "research fields" and 579 "technology classes." The five research fields are: Semiconductors, Integrated Circuits and Superconductors (which accounts for 4.25% of all patents—for brevity, in the rest of the paper, I will refer to this field as "semiconductors"); Computing and Information Technology (8.75%—for brevity: "computer science"); Biology, Chemistry and Medicine (23.15%—for brevity: "biology and chemistry"); "Other Engineering" (54.26%); and "Other Science" (9.59%). Technology classes are more detailed. Examples include "hybrid electric vehicles", "nanotechnology", "X-ray or gamma ray systems or devices", "exercise devices", and "electrical computers and digital processing systems: memory."

I aggregate the patent-level data to the inventor-year level data by counting the number of patents created by an inventor in a year and the number of subsequent citations received by those patents, where year is defined as year of the patent application, not the year when the patent is granted. For citations, year is defined as the year of the cited patent's application, not the year of the citing patent's application. If a patent has multiple inventors, I assign equally weighted fractions of the patent and citations to each of its inventors. For example, if a patent has four inventors, each inventor is credited with one-quarter of a patent and a quarter of the subsequent citations. If an inventor has multiple patents with multiple addresses in a single year, I use the modal city for that inventor-year pair. If an inventor has patents in more than one research field or technology class in an year, I use the modal research field or technology class for that inventor-year pair. In case of ties (for example, if there are two cities or research fields or technology classes with the same frequency in a given inventor-year pair), I pick randomly.

In the main analysis of the paper, I follow Moretti and Wilson (2017) and focus on the productivity of star inventors, defined as those who are at or above the ninetieth percentile in the total number of patents over the sample period. The main motivation for focusing on stars is the length of the panel that they provide: They are in the sample for an average 7.01 years. The ninetieth cutoff is arbitrary, but I also show results for top 0.5%, 1%, 5%, 25% and the full sample.

The sample of star inventors includes 109,846 inventors and 932,008 inventors x years observations with non missing information on field, class, and city. Of these, 823,359 also have non-missing employer (patent assignee) identifier. The mean number of patents per year in the sample is 1.08 patents. The tenth, twenty-fifth percentile, median, seventy-fifth and ninetieth percentiles are .25, .5, 1, 1.2 and 2 respectively.

2.2 Clusters

Clusters are defined as the combination of city $\times$ research field $\times$ year. Recall that there are 179 cities, 5 research fields and 36 years. Cluster size is defined as number of inventors of any productivity level (not just stars) in a city$x$field$x$year, excluding the focal inventor, as a share of all inventors in field$x$year.

For example, Table 2 shows the largest clusters in the computer science in 2007. The San Jose-San Francisco-Oakland region is by far the largest cluster in this field, accounting for 26.1% of all inventors in the field. Second

major clusters in California (Bay Area, Los Angeles, and San Diego).

[8]It is possible in principle that an inventor's home lies outside a cluster while his professional work takes place inside a cluster. However, given the large size of BEA Economic Areas, this is unlikely to be a common problem.

on the list is the New York region, which accounts for 9.1% of all the inventors in the field. Seattle, Austin, and Boston follow, with cluster sizes equal to 8.3%, 5.9%, and 4.7%, respectively. The geographical concentration of inventors in computer science is very pronounced. The top ten cities account for 69.33% of all inventors in the field in 2007. The ratio between the the size of the largest cluster—San Jose-San Francisco-Oakland—and median cluster—Gainesville, FL—is 865.5, indicating that the Bay Area had 865.5 times the number of inventors in computer science than Gainesville did in 2007. The ratios between the 99th and median and 95th percentiles and median are equal to 300.9 and 78.6, respectively.

Table 3 shows the largest clusters in two other research fields. The top panel is for biology and chemistry in 2007. The top five clusters are New York (11.3%), San Jose-San Francisco-Oakland (11.1%), Boston (6.9%), Philadelphia (6.3%) and Los Angeles (5.9%). With the total share of top ten cities equal to 59.05%, the overall concentration in this research field is lower than in computer science, but it remains quite pronounced. The max / median and the 99th percentile / median ratios are 126.8 and 124.4, respectively.

The bottom panel shows the largest clusters in the semiconductors field. The top five clusters are San Jose-San Francisco-Oakland (25.5%), New York (14.9%), Los Angeles (6.1%), Dallas (5.0%) and Phoenix (4.9%). The overall concentration in this research field is even higher than in computer science, with the share of top ten cities equal to 77.16%. Both the max / median ratio and the 99th percentile / median ratio are undefined since the median city had no inventors in this field in 2007. The tenth, twenty-fifth percentile, median, seventy-fifth and ninetieth percentiles across all fields and years are 0.00356, 0.01106, 0.02951, 0.06332, 0.10786, respectively.

Figure 1 shows how the share of inventors in top ten cities has changed over time in computer science (top), biology and chemistry (center), and semiconductors (bottom). The share in computer science has increased monotonically. The share in semiconductors and biology and chemistry has also tended to increase, but not monotonically. Overall, geographical concentration of inventors is very high and it has been generally increasing over time.

Alternative definitions of cluster size are possible. In particular, one could measure size of a cluster not based on the number of inventors in a city-field, but based on the number of *firms* (patent assignees). Based on this measure, the picture that emerges is also one of significantly concentrated patenting activity. In the main part of the paper I focus on a definition of clusters size based on number of inventors, but in a robustness table I show estimates that use a definition of clusters size based on number of firms.

2.3 Data Limitations

There are three main limitations of the data.

(A) First, patent count is an imperfect measure of the amount of innovation created by an inventor. Not all patents are equal, in the sense that not all patents embody the same amount of innovation. While some patents represent important innovations in a field, others represent trivial innovation. In the extreme, some patents do not represent any innovation and are filed for defensive purposes only. To account for these limitations, I use subsequent citations to measure patent quality. In particular, I estimate models where the dependent variable is an inventor's number of citations per year or an inventor's number of citations per patent per year.[9]

In addition, not all innovation is patented and the fraction of innovation that is patented varies across fields and technology classes. Cohen et al. (2000) report that firms in the chemicals, drugs, mineral products, and medical equipment industries applied for patents for more than two-thirds of their innovations. In contrast, firms in the food,

[9]Bernstein McQuade and Townsend (2018) and Akcigit et al (2018) are examples of other papers that use number of patents and citations to measure inventor productivity. On the other hand, Williams (2013) is an example of a paper that measures scientific research and product development directly rather than via patent activity.

textiles, glass, and steel and other metals industries applied for patents on fewer than 15 percent of their product innovations. Moreover, the forms of technologies that are patented change over time. For example, the rate of innovation in software appears to accelerate in the 1990's, but this reflects at least in part changes in the legal practice of patenting software (Carlino and Kerr, 2015). Lerner and Seru (2017) highlight the importance of controlling for the sectoral composition of inventive activity. For this reason, my models include research field $\times$ year and technology class $\times$ year effects. The assumption is that the fraction of innovation that is patented does not vary across cities within a field $\times$ year pair and technology class $\times$ year pair.

A concern is the possibility that the propensity to patent a given innovation may vary geographically as a function of cluster size, even within a field $\times$ year pair and technology class $\times$ year pair. This could be the case, for example, if firms located in larger clusters are more likely to patent a given innovation than firms in the same field and class located in smaller clusters, possibly due to a higher concern of being scooped by competitors.[10] This possibility would imply that marginal innovations patented in large clusters are less valuable than the ones patented in small clusters, everything else equal. As I discuss below, this is inconsistent with the evidence on patent citations. Models based on number of citations per patent show a positive association between patent quality and cluster size.

(B) A second limitation of the data stems from the fact that not every inventor applies for a patent every year, so I don't observe the productivity and location of every inventor in every year. This generates sample selection, as inventors are in the sample only when they patent. This selection problem is conceptually not unlike the sample selection that exists in wage data due to the fact that wages are observed only in years when a worker is employed.

Since I do not observe inventors in years when their number of patents is 0's, a regression of number of patents on cluster size quantifies the effect of cluster size on inventor productivity *given a patent* (intensive margin), but it misses the effect of cluster size on probability of patenting (extensive margin). As a consequence, my estimates should be interpreted as a lower bound of total effect of cluster size on patenting (assuming intensive and extensive margin effects go in the same direction). To minimize this problem I focus my analysis on the population of star inventors. Star inventors are by construction prolific patenters and the typical individual is observed patenting in most years (over the period in which they patent at all).

To empirically probe the direction and magnitude of the sample selection bias, I provide three pieces of evidence.

First, I add some of the missing zeros by interpolating the data when one missing year is immediately preceded and followed by two non-missing years. That is, if an inventor is observed in years $t-1$ and $t+1$, but is missing in year t, I assign her to the cluster in which she was located at $t-1$. For example, if an inventor is observed in 2003 and 2005 but not in 2004, I assign her 0 patents in 2004 and I assign her to the cluster where she is observed in 2003. Estimates in the sample that includes these interpolated zeros are larger than the baseline estimates that do not include interpolation, because they include (part of) the extensive margin. If I interpolate data when two missing years are immediately preceded and followed by non-missing years, estimates are even larger.

Second, I test whether my estimates are sensitive to different definition of the temporal unit of analysis. Specifically, I re-estimate my models using samples where inventor productivity is measured over 1 month, 2 month, 3 month, 6 month, 1 year (the baseline), 2 year, and 3 year periods. When the temporal unit of analysis is short (1 or 2 months), the problem of missing zeros and the resulting downward bias should be particularly pronounced. In the extreme, if one could measure patent creation second by second, virtually all of the inventor-second pairs would be missing. By contrast, when the temporal unit of analysis is long (2 or 3 years), the problem of the missing zeros

[10] It could also happens because high tech clusters tend to have high tech lawyers who help in the patenting activity, which reduces the cost of obtaining advice.

and the downward bias should be less pronounced. In the extreme, if I were to use a temporal unit that includes all the years in the sample, there would be no selection and both the intensive margin and extensive margin would be reflected in my estimates. Empirically, I find that my estimates are increasing with the length of the unit of analysis.

Third, I find that estimates are larger if more stringent definitions of star patenters are adopted. In particular, estimates for the top 0.5%, 1%, and 5% of inventors are larger than the baseline estimates that use the top 10%. In turn, the baseline estimates are larger than estimates for the top 25% and for the full population of inventors. This is due to the fact that the more stringent the definition of star patenters the longer an inventor is in the data and therefore the smaller the downward bias stemming from selection.[11]

(C) A third concern is the possibility that my measure of cluster size is *mechanically* correlated with my measure of inventor productivity in the presence of shocks that affect both the measured number of patents filed in a year and measured number of inventors in that year. This would be the case, for example, if an earthquake or a hurricane in a city lowers the number of patents filed by local inventors in a year and also the measured number of local inventors in that year. Empirically, estimates are robust to using measures of cluster size that should not be affected by this issue, such as cluster size lagged by one or two years, or the average, maximum or minimum size over the previous 3 years.

3 The Rochester High-Tech Cluster and Kodak

The experience of Rochester, NY over the past 25 years represents an interesting case study because of the large, arguably exogenous change in the size of its high-tech cluster due to the demise of its main high-tech employer, Kodak.

In the 1980s and the 1990s, Kodak was the leading producer of films for cameras. The firm was one of the most prolific patenters in the US. Indeed, as we saw in Table 1, Kodak had the 5th largest number of patents filed between 1971 and 2007. Kodak patents are not concentrated in one research field, but span all five fields. Kodak was headquartered in Rochester and it was the largest patenter in the city by a vast margin. At its peak in 1996, Kodak accounted for 51.06% of all the inventors in Rochester. But after 1996, Kodak entered a period of dramatic decline caused by the diffusion of digital photography and the collapse in the demand for physical film (Dickinson, 2017). In essence, Kodak experienced a large negative shock caused by a technological innovation that made its main product obsolete.

Kodak demise can be seen in the top panel in Figure 2, which shows the firm's stock price since 1990. The price grew in the first half of the 1990s, reached a peak in 1996 and then began declining, as digital photography spread and the market for physical films shrank. Between 1996 and 2007, Kodak stock price declined by 82%. Shrinking product demand led to less investment in R&D. The bottom panel in Figure 2 shows that the number of Kodak inventors in Rochester reached a peak in 1997, with 1254 inventors, and then began a steep decline. By 2007 there were only 204 Kodak inventors in Rochester. The size of the overall Rochester high-tech cluster measured by the number of inventors in all fields, declined by 50.5% in this period, dragged down by the collapse of Kodak.

The experience of inventors in Rochester can be used to test the hypothesis that the size of a high-tech cluster affects inventor productivity. Specifically, I test whether the change in the size of the Rochester high-tech cluster

[11] One concern is the possibility that moving lowers the probability of patenting—either because it is distracting and time consuming or because it coincides with a job spell with a new employer and the inventor may be restricted from using intellectual property created while working for a previous employer. This could lead me to underestimate productivity following a move, but there is no obvious reason to expect that this effect is different for those moving from small to large clusters compared to those moving from large to small clusters.

caused by Kodak's demise affected the productivity of inventors *outside Kodak*. The shock was large and arguably exogenous, as it had little to do with what was happening to the Rochester local economy. Finding that the productivity of inventors outside Kodak did not change following the large negative shock to Rochester high-tech cluster would cast doubt on importance of productivity benefits stemming from cluster size.

Figure 3 shows visually what happened to the mean productivity of *non-Kodak* patenters in Rochester in the period 1990-2007. Specifically, it plots the mean log productivity of inventors who do not work for Kodak, after controlling only for research field dummies.[12] The vertical red line marks 1996, which was the peak of Kodak's stock price. While log mean productivity appears generally flat before 1996, it declines after 1996. Excluding Kodak, the main patent producing firms in Rochester in 1996 were Coring (99 patents), Bausch Lomb (42), General Motors (41), Tenneco Chemical (38), Mobil Oil (33), Johnson and Johnson (28), Osram Sylvania (24), PSC (20), and IBM (16).

Tables 4 and 5 present corresponding differences-in-differences estimates comparing the 1996-2007 change experienced by non-Kodak inventors in Rochester to the change experienced by non-Kodak inventors in other cities. The two tables differ because Table 4 is based on a cross-sectional comparison, while Table 5 uses the longitudinal nature of the data and focuses on within-inventor productivity change for a fixed set of inventors. (Since in 1996 Kodak had a presence in all five main research fields, no field can be considered unaffected by its demise. In the next section, where I use all cities and years, I will be able to identify field-specific changes in cluster size.) In both tables, the sample includes years 1996 and 2007. I use 1996 as the initial year because it is the year when Kodak stock prices peaked. I use 2007 as the final year because it is the last year available in the data.

The level of observation in the regressions is inventor-year. I drop all Kodak inventors from the analysis, whether in Rochester or in other cities. I also drop inventors in the photography sector, identified as those with patents in at least one of the following technology classes: "396, Photography"; or "399, Electrophotography", irrespective of their location. They are dropped because although they do not work for Kodak, they may be directly affected by the same negative shock. Thus, they may experience a productivity loss not due to agglomeration economies, but due to a decline in product demand for traditional photographic film.[13]

In column 1 of Table 4 inventor log productivity is regressed on a 2007 dummy, a Rochester dummy and the interaction. In this and the next table, standard errors are clustered by city. The coefficient on the Rochester dummy indicates that in 1996, the mean productivity of non-Kodak inventors in Rochester was not statistically different from the productivity in other cities. The coefficient of interest is the one on the interaction, which indicates that the mean number of patents filed in a year by non-Kodak inventors in Rochester declined by 6.58% between 1996 and 2007 relative to other cities.

In columns 2 to 4, I add field, field $\times$ year and field $\times$ city effects as controls. The coefficient on the interaction becomes more negative and suggests a productivity loss in Rochester between 6.96% and 9.84% relative to other cities, depending on the controls. Column 5 drops Xerox inventors, both in Rochester and other cities. Xerox had a presence in Rochester, although smaller than Kodak in terms of inventors and experienced negative shocks in this period. It is not clear whether one should consider the Xerox shock in Rochester as exogenous or as an endogenous

[12]In practice, I plot the mean residual from a regression of log productivity on research field dummies.

[13]It is possible that Kodak's suppliers might have clustered in Rochester and that product demand that they face declined following Kodak demise. A decline in product demand may result in downsizing on the part of the suppliers. If downsizing resulted in lower inventor productivity, it could in principle explain part of the decline in inventor productivity after Kodak decline. Note that this issue arises only with suppliers that engage in patenting—a subset of Kodak's suppliers. Suppliers with patents in the "Photography" and "Electrophotography" classes—probably a sizable share of Kodak suppliers—are excluded from the sample by construction. I contacted Kodak and requested a list with the names of their suppliers in the 1996 or 1997 with the intent to match their names with patent data, but failed to obtain the data from the company. On the other hand, it is also possible that the decline in supplier productivity—if it took place—was the endogenous effect of the demise of Kodak. Geographical agglomeration of specialized suppliers is one of the mechanisms that the literature on agglomeration effects has identified as possible explanations of productivity spillovers.

effect of Kodak's decline. After dropping Xerox, the sample size is 193,194 and the difference-in-difference estimate is -0.0760 (0.0059).

Since the estimates in Table 4 are based on cross-sectional comparisons, one obvious concern is the possibility of unobserved quality changes due to inventor selection. In particular, it is possible that the quality of non-Kodak inventors in Rochester in 1996 is not the same as the quality in 2007, although the direction of the bias is a priori unclear. On the one hand, it is possible that the decline in the local high-tech cluster induced some of the best non-Kodak inventors to leave Rochester. On the other, it is also possible that Kodak's downsizing allowed other firms in Rochester to hire good inventors laid off by the firm. If former Kodak inventors hired by non-Kodak employers are on average better than incumbent inventors, the average unobserved ability of inventors working outside Kodak may increase.

In Table 5, I present estimates that use the longitudinal structure of the data. I use a balanced panel made up of the inventors who are observed both in 1996 and in 2007 and I add inventor fixed effects to my models. Thus, Table 5 reports estimates where I compare within-inventor productivity changes in Rochester to within-inventor productivity changes in other cities for a fixed set of inventors. The sample includes 8213 inventors observed twice, for a total sample size of 16,426, as shown in the bottom row.

In Panel A, I assign Rochester status to an inventor based on her 1996 location. For a given inventor, the Rochester dummy is set equal to 1 if the inventor is in Rochester in 1996. That is, I compare within-inventor productivity changes of inventors who in 1996 were located in Rochester to within-inventor productivity changes of inventors who in 1996 were located in other cities, *irrespective of their 2007 location*. This is my preferred specification, because 2007 location is potentially endogenous. It estimates the effect of the shock to the Rochester high-tech cluster on inventors who were there at the beginning of the shock, allowing inventors to optimally choose their 2007 location.

In column 1 the only set of controls used is inventor fixed effects. The difference in difference estimate in the first row suggests that inventors who were in Rochester in 1996 experienced a change in productivity that was 20.6% more negative than inventors who were not in Rochester in 1996, after controlling for inventor fixed effects.[14] When I add field, field $\times$ year, and field $\times$ city effects as controls in columns 2, 3 and 4, the coefficient on the interaction become more negative and suggests a productivity loss in Rochester between 22.0% and 32.1% relative to other cities. A comparison with the corresponding cross-sectional estimates in Table 4 indicates that within-inventor estimates are more negative than cross-sectional estimates, suggesting that unobserved quality of non-Kodak inventors biases cross-sectional estimates toward zero. This is consistent with the possibility that some of the best Kodak inventors laid off by Kodak are hired by other Rochester employers.

For completeness, in Panel B I estimate similar models where the Rochester dummy is set equal to 1 if the inventor is in Rochester both in 1996 and in 2007. This specification estimates the effect of the shock to Rochester on inventors who were there at the beginning of the shock and are still there in 2007. The difference in difference estimates are between -0.313 (0.0189) and -0.399 (0.0233).

Overall, I conclude that following the decline in the Rochester high-tech cluster, non-Kodak inventors in Rochester experienced large productivity losses relative to non-Kodak inventors in other cities. While this is by no means direct proof of productivity spillovers, this finding is consistent with the hypothesis that cluster size affects inventor productivity.[15]

[14]The average change for inventors who were in Rochester in 1996 is -.412 (0.0153)—as can be seen by adding the coefficients in row 1 and 2—significantly more negative than the decline for inventors who were not in Rochester in 1996, which is -.206 (0.0190).

[15]One potential concern is that precisely because Kodak was so important to Rochester, Kodak's decline led to property value declines. Bernstein, McQuade and Townsend (2018) find that following a negative wealth shock, innovative workers become less productive. I lack data on individual inventors' housing equity.

4 Inventor Productivity and Cluster Size

I now turn to estimates of the relationship between inventor productivity and cluster size based on all cities, fields, and years in my sample. I assume that the log of productivity of an inventor in a cluster depends upon her skills, location fundamentals, agglomeration effects, and an idiosyncratic component:

$$\ln y_{ijfkct} = \alpha \ln S_{-ifct} + d_{cf} + d_{ck} + d_{ft} + d_{kt} + d_{ct} + d_i + d_j + u_{ijfkct} \tag{1}$$

where y_{ijfct} is the number of patents produced (or citations received) in year t by inventor i working in firm j in research field f, technology class k and located in city c; S_{-ifct} is the size of the cluster in the relevant field, city and year, excluding inventor i; d_{cf} and d_{ck} are city $\times$ field and city $\times$ class effects included in order to absorb time invariant factors that may make specific fields or specific technology classes particularly productive in some locations; d_{ft} and d_{kt} are field $\times$ year and technology class $\times$ year effects and are included to absorb nationwide time-varying technological and sectoral changes; d_{ct} represent city $\times$ year effects and are included to absorb city-wide changes in the determinants of productivity shared by all fields in a location; and d_i and d_j are inventor and firm effects. To account for possible serial correlations in the residual, I report standard errors clustered by city $\times$ research field.

Equation 1 assumes that agglomeration effects vary as a function of cluster size. If cluster size raises inventor productivity due to productivity spillovers, α should be greater than zero. In the absence of spillovers α should be zero. α is identified by inventors who move across cities or across fields and by changes over time in clusters size in a given city and field pair. For OLS to identify α, the unobserved determinants of productivity u_{ijfkct} need to be orthogonal to S_{-ifct}. There are two identification concerns: sorting (or endogenous quality of labor); and simultaneity (or endogenous quantity of labor).

The first concern stems from the fact that inventors *choose* their cluster. An inventor's choice of location likely depends on a number of factors, including earnings, cost of living, local amenities and idiosyncratic preferences for specific locations. Some forms of sorting do not violate the orthogonality condition. For example, it is possible that highly productive scientists tend to locate in large clusters. Sorting based on the permanent component of productivity does not introduce bias in OLS estimates, since equation 1 conditions on the inventor fixed effects. The equation also controls for firm effects, and thus is identified by within firm differences in cluster size across inventors.

Sorting driven by local amenities also does not violate the orthogonality condition. Dummies for the interaction of city $\times$ year—d_{ct}—absorb all characteristics of a city that may affect its attractiveness, both permanent and time-varying, including cultural amenities, restaurants, entertainment, school quality, crime, congestion, costs of living, and local taxes. Endogenous changes in local amenities of the type discussed by Diamond (2016b) are also absorbed by d_{ct}. City-wide productive amenities—i.e., factors that affect the the productivity of all inventors, irrespective of field, such as local infrastructure, productive public goods and regulations—are also absorbed. Identification relies on the fact that there are multiple fields within each city.

Sorting due to time invariant factors that shift the productivity of scientists in specific fields and locations is also accounted for. As an example, consider cases where particularly productive computer scientists are attracted to the San-Francisco Silicon Valley area by the proximity to top engineering departments in Stanford or Berkeley, or, alternatively, where the engineering departments of Stanford and Berkeley produce top computer scientists who after graduation tend to stay in the area. City $\times$ field effects control for this type of productivity differences, to the extent that they are time-invariant.

Sorting into large clusters caused by time-varying unobserved productivity shocks, on the other hand, is a potentially important concern. Consider, for example, the case of inventors in a small cluster whom employers in large clusters expect to become more productive in the future. These expectations are of course not observed in my data. If employers in large clusters systematically hire promising inventors from small clusters, equation 1 will overestimate the effect of cluster size, because it would attribute to cluster size productivity increases that arise because of sorting. In this case, productivity might be increasing even before the move. To assess the importance of this type of sorting, I study the timing of productivity changes relative to changes in cluster size, and test for the existence of pre-trends.

A second identification concern is simultaneity: the existence of unobserved time-varying productivity shocks at the city-field level that attract more inventors to a city field. In practice, some of the localized shocks that affect firms productivity are likely to be city-wide—for example: a new airport, or other form of improved infrastructure—and therefore are controlled for in equation 1. But the city $\times$ year effects do not control for time-varying productivity shocks that are both city and field specific. One example might be changes in local subsidies, to the extent that they target specific fields. This could be the case if city or county adopts subsidies for, say, biotech firms, causing an increase in the size of the local biotech cluster. If subsidies directly affect biotech firms productivity, equation 1 will overestimate the effect of cluster size. This could happen if subsidies allow local biotech firms to buy equipment that they could not afford in the absence of a subsidy. (There is of course no bias if subsidies affect productivity only indirectly by increasing cluster size—which is the case if subsidies increase the number of local inventor and that in turns affects inventor productivity.) To assess the importance of this type of bias, I consider models based on two instrumental variables.[16]

4.1 Baseline Estimates

Figure 4 shows a binned scatter plot of the correlation between log number of patents and log cluster size, conditioning only on year effects, research field effects and city effects. The positive slopes indicate that larger clusters appear to be associated with a higher number of patents generated per year. The estimated slope is 0.053 (0.008).

Table 6 reports estimates of variants of equation 1. Column 1 reports estimates from a model that includes year, research field, technology class and city effects. Thus, the controls are the same as those used in Figure 4, with the addition of technology class effects. The estimated coefficient is similar: 0.0514 (0.0081). In columns 2 and 3, I add dummies for the interaction of city $\times$ field and city $\times$ class. While the field and class effects in column 1 absorb nationwide productivity differences across fields and class, the interactions in columns 2 and 3 absorb features of an area that may make specific fields or specific technology classes particularly productive. The coefficient in column 3 increases to 0.0870 (0.0186). In columns 4 and 5, I add dummies for the interaction of field $\times$ year and class $\times$ year. The coefficient in column 5 is 0.0668 (0.0086).

In column 6, I add inventor fixed effects. This specification absorbs time-invariant quality differences between inventors. The coefficient is 0.0910 (0.00980). A comparison with column 5 indicates that the coefficient in column 6 is larger. Thus, conditional on all the controls included in the model in column 5, larger clusters appear to attract inventors with lower mean unobserved quality.[17] In column 7, I add dummies for the interaction of city $\times$ year. The coefficient drops to 0.0514 (0.0116). Finally, in the last column I add firm effects. Firm identifiers are not available for

[16]Kerr (2010) investigates the speed at which clusters of invention for a technology migrate spatially following breakthrough inventions, defined as inventions in the top one percent in terms of subsequent citations. He finds that patenting growth is significantly higher in cities where breakthrough inventions are located. The result confirms the mechanism of industry migration proposed by Duranton (2007). In his model, centers of innovation are dictated by where frontier inventions occur, and production follows the location of invention to achieve agglomeration economies.

[17]This is consistent with findings by Mitchell (2019), who uses data on prominent authors in the UK and Ireland to estimate the productivity gains associated with agglomeration of writers. She too finds evidence of negative selection into larger clusters.

all patents, since not all inventors are employed by firms and as a consequence sample size drops from 932,008 to 823,359. The coefficient is 0.0662 (0.0138).

In Table 7 I focus on subsequent patent citations. The dependent variable in Panel A is the log number of patents that cite any patent filed by inventor i in year t. The citing patents include any patent filed between year t and the end of the sample, not just patents filed in t. The dependent variable in Panel B is the log of number of subsequent patents that cite patents filed by inventor i in year t divided by the number of patents filed by inventor i in year t. The former is a measure of overall impact of patents produced by an inventor in a given year, while the latter is a measure of the mean quality of patents filed by an inventor in a given year. Estimates in column 8 suggest that the elasticities for the overall number of citations and citations per patent are equal to 0.156 (0.043) and 0.089 (0.040), respectively.

Table 8 reports estimates for models that replicate the models in Table 6, but are based on a sample of "stayers." In Panel A, stayers are defined as inventors who do not change city during the sample period. For this sample, estimates in columns 7 and 8 are identified only by inventors who change research field within a city and by changes over time in cluster size in a given cluster. Estimates in columns 7 and 8 are, respectively, 0.0912 (0.0157) and 0.110 (0.0193) and are larger than the corresponding baseline estimates in Table 6. In Panel B stayers are defined as inventors who do not change field during the sample period. Estimates in columns 7 and 8 are identified by inventors who change city, and by changes over time in cluster size in a given cluster. In Panel C stayers are defined as inventors who do not change city or field during the sample period. Estimates in columns 7 and 8 are identified by changes over time in cluster size in a given cluster. Estimates in Panel B and C are larger than the corresponding baseline estimates. For example, the elasticities in column 8 are 0.219 (0.035) and 0.246 (0.042), respectively.

Appendix Table A.1 reports estimates for models where cluster size is defined based on the number of firms in a city-research field, as opposed to number of inventors. Estimated elasticities in columns 7 and 8 are 0.0203 (0.00989) and 0.0238 (0.0119), respectively.

Magnitude of the Effect. The elasticity of productivity with respect to cluster size estimated in column 8 of Table 6 indicates that a 10% increase in cluster size is associated with a 0.66% increase the number of patents produced by a scientist in a year. To help interpret the magnitude of the estimated effect, consider an inventor in the computer science field who in 2007 moves from the median cluster—Gainesville, FL—to the cluster at the 75th percentile—Richmond, VA. Based on the coefficient in column 8, such inventor would experience a 12.0% increase in the number of patents produced in a year, holding constant the inventor and the firm. In biology and chemistry, a move from the median cluster—Boise, ID—to the 75th percentile cluster—State College, PA—would be associated with a productivity gain of 8.4%, holding constant the inventor and the firm. The estimated productivity gain is smaller than in computer science because the difference in cluster size is smaller.

The magnitude of the implied agglomeration economies is in line with existing estimates in the literature on agglomeration economies. A meta-analysis of 34 different studies (Melo et al., 2009) indicates that my estimated elasticity is below the middle of the distribution of existing estimates but within the range of elasticities reported in several of the most prominent recent studies.[18]

[18]For example, Henderson (2003) obtains an elasticity of productivity with respect to density of 0.01-0.08. Estimates for France in Combes et al. (2010) and Combes et al. (2012) imply elasticities of 0.029 and 0.032, respectively. Kline and Moretti (2014) find an elasticity of 0.2 for US manufacturing. At the other extreme, Greenstone, Hornbeck and Moretti (2010)'s estimates imply an elasticity in the range 1.25-3.1. Of course, part of the variation in these estimates is due to the fact that the models, data, time periods and industries used in the studies are vastly different. The elasticity estimated in this paper is also consistent with estimates based on wages (for example: Ciccone and Hall, 1996; Ciccone and Peri, 2005; Combes et al.; 2008; Rosenthal and Strange; 2008).

4.2 Pre-Trends and Dynamic Response

In this Section, I study the dynamic response of productivity following a change in cluster size. I estimate a version of equation 1 that includes the current cluster size and five leads and five lags:

$$\ln y_{ijfct} = \sum_{s=-5}^{-1} \beta_s \ln S_{-ifc(t+s)} + \beta_0 \ln S_{-ifc(t)} + \sum_{s=1}^{5} \beta_s \ln S_{-ifc(t+s)} + d_{cf} + d_{ck} + d_{ft} + d_{kt} + d_{ct} + d_i + d_j + u_{ijfkct} \quad (2)$$

where the five leads and five lags—$S_{-ifc(t+s)}$ for $s = -5, ..., -1, 1, ..., 5$—refer to the cluster where the focal inventor i is at time $t + s$. The coefficients on the lead terms, β_1 through β_5, allow me to determine how an inventor productivity responds to a future changes in size and therefore are useful for investigating pre-trends. The coefficients on the lag terms, β_{-5} through β_{-1}, allow me to examine how a change in cluster size propagates over time and in particular whether the effect is short lived or permanent.

In the top panel of Figure 5, I plot the coefficients β_5 through β_{-5}. The left most coefficient, β_5 represents the change in the focal inventor's productivity in response to a change in cluster size five years into the future. The rightmost coefficient, β_{-5} represents the focal inventor's change in productivity in response to a change in size 5 years in the past. The dotted lines are a 95 percent confidence bands based on standard errors clustered by city $\times$ field. The sample size is only 21,787 because for a inventor to be in this sample, the five leads and lags need to be non-missing, which implies that only inventors observed in 11 consecutive years are included.

In the bottom panel, I present the cumulative estimates corresponding to equation 2. Specifically, the figure displays $\mu_n = \beta_5 + \beta_4 + ... + \beta_n$ for $n = -5$ through 5, along with an accompanying error band. To interpret this figure, suppose that a change in cluster size takes place at time $t = 0$. For example, the change could be caused by the focal inventor moving from a small cluster to a large cluster at $t = 0$. The point that is farthest to the left, μ_5, represents the productivity response 5 years prior to the move. The next point moving to the right, μ_4, is the estimated cumulative productivity response up to 4 years before the move ($\beta_5 + \beta_4$). The point μ_{-5} is the cumulative productivity response from 5 years before the move through 5 years after the move.

Three features of Figure 5 are worth highlighting. First, the lead terms β_1 through β_5 test for pre-trends. Cluster size in the future should have no effect on productivity in the current period, conditional on current cluster size. Finding positive coefficients on the lead terms would cast doubt on the causal interpretation of my estimates, because it would suggest that the productivity of inventors who are about to move to a larger cluster increases in the years leading up to the move. This would be consistent with the concern of selection on unobservables discussed above, in which promising inventors in small clusters who are experiencing productivity gains tend to be systematically hired by employers in large clusters. In practice, there appears to be little evidence in Figure 5 of pre-trends. I cannot reject that any of the coefficients on the lead terms are equal to zero.

Second, the estimates reveal that in the year when cluster size changes, there is an immediate rise in the focal worker's productivity, with a further increase in the following year. The increase in productivity may appear surprisingly fast. Recall, however, that I use the date of patent *filing*, not the date when the patent is granted. Griliches (1998) points out that in many fields the timing of patent application and R&D are close, often measured in months or even weeks. Indeed, industry studies report average length of R&D projects of less than 12 months for semiconductors, 3 to 6 months for information and communication technologies (ICT) and even shorter for software (Griss, 1993; Krasner, 2003; Wu, 2011; Kapoor, 2012; Haran, 2011; Mansfield, 1972). In addition, there is evidence that in some cases, patents are applied for not at the end of the R&D process but at an early stage (Cohen 2010). Consistent with

Figure 5, Hall, Griliches, Hausman (1986) find a "strong contemporaneous relationship between R&D expenditures and patenting" in a sample of manufacturing firms.

In principle, one exception should be pharmaceutical R&D, where it likely takes several years and sometimes decades to invent and patent new drugs.[19] Figure 6 replicates Figure 5 limiting the sample to inventors working in technology classes for drug development ("drug, bio-affecting and body treating composition"; class codes 424 and 514). While the confidence intervals are inevitably larger, there appears to be no evidence of an immediate effect in this case. In fact, we see no effect within five years.

A third feature of Figure 5 worth highlighting is that the effect appears persistent. After the initial increase in the first two years, productivity declines slightly over the next three years, as inferred from the downward drifting cumulative response in the bottom panel, but most of the effect persists.[20]

4.3 Robustness to Data Limitations

In this subsection I probe the robustness of my baseline estimates to the concerns discussed in Section 2.3.

Sample Selection. I start with the sample selection caused by the fact that not every inventor applies for a patent every year. In Section 2.3, I argued that a regression of number of patents on cluster size captures the intensive margin—namely the effect of cluster size on number of patents, given a positive number of patents—but misses the extensive margin—namely the effect of size on the probability of patenting. As a consequence, the elasticities estimated so far should be interpreted as a a lower bound of total effect of cluster size on patenting.

Here I present three pieces of evidence intended to empirically probe the direction and magnitude of the sample selection bias.

Appendix Table A.2 shows what happens when I use interpolation to impute some of the inventor-year pairs that are missing due to lack of patenting by an inventor in a given year. For convenience, column 1 reproduces the baseline estimate (Table 6, column 8). In column 2, I interpolate the data when one missing year is immediately preceded and followed by non-missing years. If a scientist is missing in year t but observed in years $t-1$ and $t+1$, she is assigned to the cluster in which she is at $t-1$. For example, this would be the case of an inventor observed patenting in 2003 and 2005, and not observed in 2004 due to the lack of patenting. In this case, I assume that the inventor is located in 2004 in the same cluster as the one where I observe her in 2003. Since the dependent variable is in logs, and log(0) is undefined, I set it equal to log(.0001). When I do this interpolation, I do not change the measure of cluster size on the right hand side.

The sample increases to 860,753 observations, indicating that 37,394 observations are interpolated. The estimated coefficient is 0.186 (0.0196), significantly larger than the baseline coefficient in column 1. Intuitively, by including some of inventor-year pairs when an inventor does not patent, the estimate in column 2 reflects not only the the effect of size on number of patents, but also part of the effect of cluster size on the probability of patenting. In column 3, I interpolate the data when 2 missing years are immediately preceded and followed by non-missing years. For example, this would be the case of an inventor observed patenting in 2003 and 2006, and not observed in 2004 and 2005. In this case, I assume that the inventor is located in 2004 and 2005 in the same cluster as the one in 2003. The sample increases to 873,331 observations and the estimated effect increases to 0.218 (0.0212).

[19]Some pharmaceutical patents are secondary. That is, they are modifications of the original idea, and have short research times.

[20]Glaeser and Mare (2001) find that the effect of city size on wages is not immediate but manifest itself over time. De La Roca and Puga (2017) find that Spanish workers in bigger cities obtain an immediate static wage premium and also accumulate valuable experience over time. They also discus the biases that arise if the benefits of bigger clusters take time to realize and show that if all workers move from small (large) to large (small) clusters, there is positive (negative) bias. On net, the sign of the overall bias depends on the share of workers moving in each direction and the portability of the effect.

Appendix Table A.3 reports estimates obtained with different temporal units of analysis. Specifically, I re-estimate my baseline models using measures of productivity defined over 1 month, 2 months, 3 months, 6 months, 2 years and 3 years. I expect that when the temporal unit of analysis is short (months), the problem of sample selection and the downward bias are more pronounced. In the extreme, if I was to measure productivity second by second, very few inventor-second pair would be non-missing and the selection bias would be large. By contrast, when the temporal unit of analysis is long (2 or 3 years), I expect the problem of sample selection and the downward bias to be less pronounced. In the extreme, if I was to have just one observation per inventor with productivity defined as the number of patents created in all the years in the sample, there would be no selection and both the intensive margin and extensive margin would be reflected in my estimates.[21] Empirically, the Table indicates that the estimated coefficient is monotonically increasing with the length of the unit of analysis. In columns 1 and 2, it is negative. In column 3 it is close to 0. In column 4 it is positive, although half of the size of the baseline coefficient. In columns 6 and 7, the estimated coefficient is significantly larger than the baseline coefficient.

Appendix Table A.4 reports estimates based on different cutoff for the definition of star inventors. Column 1 includes all inventors, while columns 2 to 6 include increasingly stringent definitions of star inventors based on the total number of patents over their lifetime. In the top row, I report the average number of years that inventors are in the sample. It is clear that the more stringent the criterion, the larger the number of years. At one extreme, column 1 indicates that if all inventors are included, the average inventors in present in the sample only 2.1 years. At the other extreme, if only the top 0.5% of inventors are used, the mean inventor is in the sample for an average of 13.60. The problem of sample selection and the downward bias should be more pronounced in columns to the left of the Table, and less and less pronounced the more we move to the right. Intuitively, the more stringent the definition of starts the longer an inventor is in the data and therefore the smaller the downward bias stemming from selection is.

The coefficients confirm that estimates are larger if more stringent definitions of starts are adopted. In particular, the estimate for the top 0.5% of inventors (column 6) is larger than estimate for the top 1% (column 5), which in turn is larger than the estimate for the top 5% (column 4) which is larger than the baseline (column 3), and so on. The estimate for the full population of inventors (column 1) is the smallest and it is indistinguishable from zero.

Overall, findings in Appendix Tables A.2 to A.4 suggest that the baseline estimates should be interpreted as a lower bound. These findings are consistent with the notion that the baseline estimates capture only part of the overall effect and that including the extensive margin leads to larger estimates.

Mechanical Correlation. I now turn to the last concern discussed in Section 2.3, namely the possibility that my measure of cluster size is *mechanically* correlated with inventor productivity due to common shocks that affect both the measured number of patents in a given cluster and year and the number of inventors in that cluster and year.

In Appendix Table A.5, I probe the extent of the problem. Column 1 reproduces the baseline estimate (Table 6, column 8). Columns 2 and 3 show that using cluster size lagged by one year or two years, the estimated coefficients are 0.0799 (0.0103) and 0.0531 (0.0106), respectively. To be clear: if the focal inventor is in cluster c in year t, lagged cluster size here is measured as the size of cluster c in year $t-1$ (in column 2) and $t-2$ (in column 3), irrespective of the inventor's location at $t-1$ and $t-2$. This is conceptually different from the model in equation 2 where lagged cluster size refers to the cluster where the focal inventor is at time $t-1$ or $t-2$.

In column 4, I use the average cluster size over the the last 3 years. More precisely, if the focal inventor is in cluster c in year t, cluster size is measured as the average size of cluster c in year t, $t-1$ and $t-2$, irrespective of the

[21] In practice, having only one observation per inventor is not feasible, since models with inventor fixed effects would not be identified. Moreover, the longer the unit of analysis the more measurement error is introduced in inventor location.

inventor's location at t, $t-1$ and $t-2$. The coefficient increases to 0.100 (0.0150). In columns 5 and 6, I use the min and max cluster size over the the last 3 years. If the focal inventor is in cluster c in year t, cluster size is measured as the min or max size of cluster c in years t, $t-1$ and $t-2$. The coefficients are 0.0637 (0.0114) and 0.105 (0.015).

Overall, I conclude that there is limited evidence of a mechanical bias. If anything, using lagged measures of cluster size or average measures leads to larger estimates of the productivity effect in most specifications.

4.4 Instrumental Variable Estimates

I have found that the relationship between inventor productivity and cluster size is robust to a rich set of controls. I have also found limited evidence of pre-trends. As discussed above, one possible identification concern is simultaneity, namely the possible existence of unobserved time-varying productivity shocks at the city-field level that are correlated with variation in cluster size. In this Section, I consider models based on two instrumental variables.

(A) Rochester. First, I re-visit the Rochester case study. The difference in difference estimates uncovered in Section 3 can be interpreted as reduced form estimates in a model where the excluded instrument is the Rochester $\times$ 2007. The 2SLS estimates can be obtained by re-scaling the reduced form estimates by the relevant first stage estimates.

The identifying assumption is that the change in the number of inventors in Rochester caused by the demise of Kodak after 1996 is uncorrelated with unobserved productivity shocks of non-Kodak inventors outside the Photography sector, conditional on controls. The first stage estimates are presented in Panel (A) of Appendix Table A.6. They are obtained by estimating models similar to those in Table 4, where the dependent variable is the log of cluster size. Estimates range from -.492 (.128) in column 1 to -.396 (.0455) in column 4. This last coefficient, for example, indicates that in a model that conditions on field $\times$ year and field $\times$ city effects, the cluster size in Rochester declined by 39.6 percent relative to other cities. (As discussed above, this is the mean across the five fields in Rochester.)

2SLS estimates are shown in Panel B. They are the ratio of the reduced form coefficients (Table 4) and the corresponding first stage coefficients. The 2SLS estimates of the elasticity of inventor productivity with respect to cluster size range from 0.134 (0.038) in column 1 to .249 (.0398) in column 4.

(B) Firm Spatial Networks. Next, I use the geographical structure of firms with multiple locations to build an instrumental variable that isolates variation in local cluster size that originate elsewhere. The idea is that changes over time in the number of inventors employed in other cities by firms other than the focal inventor's firm but that have a presence in the focal inventor's city and field are predictive of changes in the local cluster size but are unlikely to be systematically correlated with unobserved shocks to the focal inventor's productivity. Specifically, let $N_{jf(-c)t}$ be the number of inventors that firm j has in field f, year t in all the cities excluding city c, so that $\Delta N_{jf(-c)t} = N_{jf(-c)t} - N_{jf(-c)(t-1)}$ is the change between year $t-1$ and t. The instrumental variable for inventors in firm j in cluster fct is defined as

$$IV_{jfct} = \sum_{s \neq j} D_{sfc(t-1)} \frac{\Delta N_{sf(-c)t}}{\Delta N_{ft}}$$

where $D_{scf(t-1)}$ is an indicator equal to 1 if firm s has at least 1 inventor in city c in field f in year $t-1$; and ΔN_{ft} is the nationwide change in inventors in the field. Note that the summation is across all firms that have a presence in the city *excluding* the focal firm j.

Identification comes from changes over time in the number of inventors employed in other cities by local firms besides the focal inventor's own firm. To see the intuition, consider as an example Boston and Minneapolis. In 1996, Microsoft has a presence in Boston, with 3 inventors in the computer science field. Between 1996 and 1997 Microsoft is generally expanding its overall R&D investment in the US and the total number of its inventors in all cities outside Boston is growing. Now take a computer scientist in Boston employed by a firm other than Microsoft. The first stage captures whether the size of the cluster that this inventor is exposed to in Boston increases as the number of Microsoft computer science inventors outside Boston increases between 1996 and 1997. The idea is that the growth of Microsoft inventors outside Boston may affect the size of the cluster that non-Microsoft inventors in Boston are exposed to but it is arguably not correlated with productivity shocks of non-Microsoft inventors in Boston, since it is driven by Microsoft's growth elsewhere.

By contrast, consider Minneapolis in 1996, where Kodak had a presence, with two inventors in the computer science field. Between 1996 and 1997, Kodak's total number of inventors in all cities outside Minneapolis is declining. For a computer scientist in Minneapolis employed by a firm other than Kodak, the instrument will likely capture a decrease in cluster size. The decrease arguably reflects Kodak's overall demise rather than unobserved productivity shocks in Minneapolis. (In practice, the instrument is not based only on one firm per city, but instead reflects the sum across all firms that have a presence there. It also includes all years, not just 1996 and 1997).

More explicitly, the assumption is that for focal inventor i variation in the number of inventors in i's field who are located outside i's city and work for firms other than i's firm that have a presence in i's city is orthogonal to unobserved factors that affect i's productivity, after conditioning on covariates. In the Boston example, the assumption is that conditional on the controls, unobserved productivity shocks experienced by an inventor in computer science in Boston who is not employed by Microsoft are orthogonal to changes in the number of computer scientists who work for Microsoft outside Boston. Since the econometric model includes field $\times$ year and class $\times$ year effects, identification is not driven by the sectoral mix of employers in a city. Rather, it is driven by the identity of the firms that exist in a cluster at $t-1$—other than the one where the focal inventor is employed—and by changes in their number of inventors outside the focal inventor cluster.

One limitation is that this instrument predicts changes in cluster size, not its level. I estimate a version of equation 1 in first differences, precluding a direct comparison with the baseline models:

$$\Delta \ln y_{ijfkct} = \alpha \Delta \ln S_{-ifct} + d_t + d_f + d_k + d_j + d_{ft} + d_{kt} + u_{ijfkct} \tag{3}$$

Columns 1-6 of Table 9 report OLS estimates of equation 3. The sample in Panel A includes inventors who are observed in two consecutive years. Standard errors in this table are clustered by city $\times$ firm. The OLS estimates range between 0.0144 (0.00255) and 0.0169 (0.0028), depending on the set of controls, and are significantly smaller that the corresponding models in levels in Table 6. Models that include the contemporaneous change in log size and lagged changes yield larger long run estimates (not shown in the table, but available on request).[22] Columns 7-12 report 2SLS estimates and the corresponding first stage estimates. The F-stats, reported at the bottom of the Table, are between 358.91 and 811.90. The 2SLS estimates range from 0.0291 (0.0120) to 0.0475 (0.0144). The entry in column 12 is equal to 0.0307 (0.0122). While the 2SLS point estimates are larger than the corresponding OLS estimate, they are generally not statistically different from the OLS estimates. Based on a Durbin–Wu–Hausman test for the null of exogeneity of the OLS regressors, I reject the null only in column 2. The p-values for the models in columns 1 to 6 are, respectively: 0.212; 0.025; 0.183; 0.217; 0.235; and 0.235.

The sample in Panel B includes inventors who are observed in two consecutive years and do not change city or field while in the sample. The OLS estimate in column 6 is 0.0415 (0.00944), larger than the estimate in Panel A, and

[22] For example, in a model that has the contemporaneous change in log size and two lagged changes, and all the same controls as column 6, the sum of the three coefficients is 0.036 (0.006), still significantly smaller than the corresponding estimates in levels.

smaller than the estimate from the model in levels. The 2SLS estimates range from 0.0897 (0.0714) to 0.131 (0.0696) and are less precise than the ones for the full sample in panel A. The entry in column 12 is equal to 0.124 (0.0683). The 2SLS estimates are not statistically different from the OLS estimates: The p-values from a Durbin–Wu–Hausman test for the models in columns 1 to 6 are, respectively: 0.202; 0.164; 0.444; 0.184; 0.327; 0.227.

While I can't completely rule out the possible existence of unobserved time-varying productivity shocks at the city-field level that are correlated with variation in cluster size, the instrumental variable estimates based on the Rochester shock and the ones based on firm spatial networks, taken together, appear to allay concerns about simultaneity.

4.5 Heterogeneous Elasticities

My baseline estimates are based on a log-log specification that assumes a constant elasticity. In Figure 4, the relationship between log productivity and log cluster size appeared generally linear, after controlling for a limited set of controls. Here I test whether the estimated elasticity is constant across clusters of different size. In particular, I seek to determine whether the effect of log cluster size on log productivity in large clusters is different from the effect of log cluster size on log productivity in small clusters.

Appendix Table A.7 shows estimates where the I allow the coefficient on log size to vary across size quartiles and the vector of controls includes all the controls that are included in the baseline model. Thus, the coefficients in the table give the elasticity of productivity with respect to size for the relevant size. Estimates in column 1 condition on all the effects excluding firm effects. They appear to quantitatively similar, ranging from 0.0523 (0.0113) to 0.0571 (0.0137). A test for equality, reported at the bottom of the table, has p-value equal to 0.224, indicating that the coefficients are statistically not different from each other. In column 2, I add firm effects. Here the p-value for the test for equality is 0.094. The elasticities remain quantitatively similar. The smallest is the one for the first quartile, which is equal to 0.0685 (0.0136), while the largest is the one for the fourth quartile, which is equal to 0.0776 (0.0162) and the relationship is not monotonic.

Overall, I conclude that there is limited evidence of large heterogeneity in elasticities. This is consistent with Kline and Moretti (2014), who find that the elasticity of manufacturing productivity with respect to density of labor in a county is similar in counties with low density and high density.

4.6 Magnitude of Firm-Specific Productivity Spillovers

Estimates of the elasticity of productivity with respect to cluster size can be used to quantify the spillover effect that a given firm generates in a given cluster. The spillover reflects the impact that a specific firm is estimated to have on the productivity of scientists in other firms in the same cluster in a given year. For each firm in the sample, I estimate the firm-specific productivity spillover generated in each of the clusters where the firm is present. Estimates are based on the elasticity of productivity with respect to cluster size estimated in the baseline model in Table 6, column 8. For a given firm j, field f and city c, the estimated spillover is obtained as $\hat{\alpha}\Delta S_{-jfct}$ where $\hat{\alpha} = 0.066$ is the estimated elasticity and $\Delta \ln S_{-jfct}$ is the difference in log cluster size with and without a given firm: $\Delta \ln S_{-jfct} = [\ln(N_{fct}/N_{ft}) - \ln(N_{jfct}/N_{ft})]$, where N_{fct} is the number of scientists in cluster fct, N_{ft} is number of scientists in field f and year t, N_{jfct} is number of scientists in firm j in cluster fct, and $t = 2007$. Thus, the estimate for a given firm and cluster quantifies the percent gain in the productivity of local scientists in other firms due to the presence of the firm in the cluster relative to the case where the firm was not present in the cluster and everything else in the cluster was unchanged. The estimate is a function of the number of inventors that the firm has in the cluster relative to the overall number of inventors in the cluster.

Table 10 shows examples of estimated firm-specific productivity spillovers for selected firms and clusters in 2007. The top panel is for computer science. The entry in the top row indicates that Microsoft productivity spillover on the Seattle computer science cluster is estimated to be 8.06%. This large effect reflects Microsoft remarkable size in the Seattle computer science cluster. With 1389 inventors in computer science in Seattle in 2007, Microsoft was the largest firm in the cluster by a vast margin. IBM's spillover effect on Minneapolis is estimated to be very large as well (4.15%). Although IBM's headquarter is not in Minneapolis, the firm has a large R&D presence in the city. On the other hand, Cisco's spillover effect on the San Francisco-Silicon Valley cluster is only 0.2%. The external effect of Dell in Austin, Texas Instruments in Dallas, Caterpillar in Peoria, and Motorola in Chicago are, respectively, 0.61%, 1.84%, 10.47%, 0.88%. The estimated external effect of Hewlett-Packard in San Francisco-Silicon Valley is only 0.07%. The last row in the panel indicates that the spillover effect generated by the average firm in the average city in computer science was 0.32%. Thus, Microsoft and Caterpillar are outliers and the more typical case is closer to that of Cisco or Motorola.

The bottom panel shows examples for the biology and chemistry field. Du Pont has a very large presence in Philadelphia, with 986 scientists in 2007. It generates a productivity spillover equal to 1.17%. Two examples of firms with a dominant position in their local cluster and a very large estimated productivity spillover are Procter and Gamble in Cincinnati, OH, and 3M in Duluth, MN, with productivity spillovers estimated to be 3.47% and 8.99%, respectively. More typical cases are Bristol-Myers in New York, Amgen in Los Angeles, Chevron in the Bay Area, and Exxon in Washington DC, with spillovers in the 0.14% - 0.65% range. The spillover for the average firm in the average city reported in the last row is 0.24%.

Overall, the examples in Table 10 indicate that the size of the spillover varies enormously across firms. Having estimates of the productivity spillover that a specific firm generates in a specific cluster may prove useful to local and state governments that offer subsidies to attract high-tech firms to their jurisdiction or to retain incumbent firms. In theory, one economic rationale for offering subsidies to attract or retain high-tech firms is the existence of localized productivity spillovers. (See Greenstone et al. 2010, for a discussion of firm specific subsidies and productivity spillovers in manufacturing). Local and state governments interested in offering subsidies proportional to the spillover effects that a firm may generate in their jurisdiction could use an approach similar to the one used in Table 10 together with information on the expected number of local inventors in the firm they are targeting. The estimates in Table 10 reflect productivity gains scaled in terms of number of additional patents and therefore are not directly informative about the dollar value of the spillover. Local government interested in the corresponding dollar value would need to make an assumption on the expected monetary value of the marginal patent generated.

5 Implications of Agglomeration for the Aggregate Production of Innovation

In the previous sections I found that inventors tend to cluster geographically in a small number of areas. I also found that inventors in large clusters enjoy productivity gains relative to those in small clusters. A natural question is therefore how much geographical clustering contributes to the overall production of patents in the US. Put differently, is the total number of patents produced each year in the country made larger by the fact that inventors in each field concentrate in a handful of locations, compared to the case where inventors are spread more equally across locations?

In this section, I use my estimates of the elasticity of inventor productivity with respect to cluster size to quantify the macro-economic benefits of agglomeration for the US as a whole. I seek to estimate what would happen to the total number of patents produced annually in each field in the US if inventor quality and firm quality did not change but some inventors were spatially reallocated from large clusters to small clusters up to the point where clusters size within each field is equalized across cities. In the presence of productivity spillovers, one would expect that such spatial redistribution would increase the productivity of inventors in clusters smaller than average and lower the productivity of inventors in clusters larger than average. On net, the magnitude of the aggregate effect for the country as a whole of such spatial redistribution depends on the relative magnitude of the gains in smaller clusters compared to the losses in larger clusters. In turn, this depends on the strength of agglomeration economies and how unequal is the initial spatial distribution.

Complete equalization of cluster size is of course an extreme counterfactual. It is intended to be a useful benchmark to assess the aggregate benefits of agglomeration, rather than a specific policy objective.

5.1 How Spatial Agglomeration Affects the Aggregate Number of Patents

Consider the following simplified example. Assume there are only two clusters, A and B, and cluster A is initially larger: $S_A > S_B$. Assume that inventor i's output is only a function of cluster size S_c: $y_{ic} = g(S_c)$, with $g' > 0$. (In equation 1 there are of course many other terms that affect an inventor productivity which I ignore in this example to keep notation as simple as possible.) Aggregate output in this economy is the sum of output in location A and location B: $Y^1 = S_A g(S_A) + S_B g(S_B)$ where the total number of patents produced in a location is simply the product of inventor output times the number of inventors in that location.

Consider a counterfactual where some inventors are moved from cluster A to B so that the number of inventors is equalized: $S_A = S_B = \frac{S}{2}$. The total number of inventors in the economy, S, does not change, but cluster A becomes smaller and cluster B larger. Aggregate output in this counterfactual is $Y^2 = Sg(\frac{S}{2})$. The change in the aggregate output is

$$Y^2 - Y^1 = S_A[g(\frac{S}{2}) - g(S_A)] + S_B[g(\frac{S}{2}) - g(S_B)] \quad (4)$$

The first term is the change in number of patents in A: it is the product of the change in inventor productivity in A times the initial number of inventors in A. This term is negative because cluster A has become smaller, and as a consequence the change in inventor productivity is negative: $[g(\frac{S}{2}) - g(S_A)] < 0$. By contrast, the second term, which measures the change in number of patents in B, is positive because B has become larger and therefore $[g(\frac{S}{2}) - g(S_B)] > 0$.

The effect of redistribution on aggregate output depends on the magnitude of the output losses in the cluster that was initially larger, A, and the output gains in the cluster that was initially smaller, B. Equation 4 clarifies that the aggregate effect depends on the change in inventor productivity in each cluster weighted by the initial cluster size. Intuitively, a certain change in inventor productivity in a cluster that is initially large has a larger aggregate impact on total number of patents produced than the same change affecting a cluster that is initially small.

Extending equation 4 to the case of many cities, fields and years, the difference between counterfactual and observed aggregate number of patents in field f and year t, $Y^2_{ft} - Y^1_{ft}$, can be estimated by summing across all cities the estimated change in inventor productivity in each cluster multiplied by the relevant cluster size:

$$Y^2_{ft} - Y^1_{ft} = \sum_c S_{cft}[g(\overline{S_{ft}}) - g(S_{cft})] \quad (5)$$

where $\overline{S_{ft}}$ is the average cluster size in the relevant field and year across all cities; S_{cft} is the actual cluster size; and the change in inventor productivity $[g(\overline{S_{ft}}) - g(S_{cft})]$ can be quantified empirically as $[g(\overline{S_{ft}}) - g(S_{cft})] = \overline{S_{ft}}^{\hat{\alpha}} - S_{cft}^{\hat{\alpha}}$

where $\hat{\alpha} = 0.0662$. The reason is that equation 1 assumes that $\ln g(S) = \alpha S$, so that $g(S) = S^{\alpha}$, and the elasticity of productivity with respect to cluster size was estimated to be $\hat{\alpha} = 0.0662$ in the baseline estimates in column 8 of Table 6. The elasticity α was found to be constant across clusters of different sizes.[23]

Three points are worth emphasizing. First, this analysis is deliberately a partial equilibrium analysis. In the counterfactual, only cluster size changes, while everything else in the economy is kept unchanged. While in reality it is possible that changes in cluster size induce general equilibrium effects, these are well outside the scope of this paper. A proper analysis of general equilibrium effects would be a paper in itself.

Second, and related, there could be some utility gains to decentralizing clusters that would need to be counted against productivity losses. Such gains may come from decreased congestion or housing prices and may affect welfare. The main focus of this paper is productivity, not welfare. While the question of the magnitude of the utility gains from lower congestion of housing prices is an interesting one, it is not the question I address in this paper. A complete welfare analysis is well outside the scope of this study.[24]

Third, although it may not be immediately obvious, equation 4 is analogous to the expression for aggregate effects derived by Kline and Moretti (2014). To see the analogy, rewrite equation 4 as

$$Y^2 - Y^1 = -g(S_A)\alpha_A + g(S_B)\alpha_B = -(Y_A/S_A)\alpha_A + (Y_B/S_B)\alpha_B \tag{6}$$

where Y_c is the total number of patents produced in a cluster and α_c is the elasticity, which is allowed to vary across locations. This is equivalent to the expression in Section IV.B of Kline and Moretti (2014) for the effect of redistribution from one county to another. They write their expression in terms of elasticity of output with respect to density and show that under the assumption of perfect mobility and homogeneous tastes for locations, when both the elasticity and per-worker output are the same in all locations, reallocating workers has no aggregate effects, as the benefits in the areas that gain activity are identical to the costs in areas that lose it. In this paper, elasticity of agglomeration is found to be constant across cities, but per inventor productivity is not assumed to be the same in all cities. This is the reason why spatial redistribution is found to have aggregate effects even with constant elasticity.[25] See also Glaeser and Gottleib (2008) and Gaubert (2018).

5.2 Estimates of the Effect of Agglomeration on the Aggregate Number of Patents

To gain a concrete idea of which cities may gain and which may lose in the counterfactual scenario, Table 11 reports examples of the estimated effect of size equalization on mean inventor productivity for computer science in 2007. Specifically, for a city c, I am showing $[g(\overline{S_{ft}}) - g(S_{cft})]$ estimated as $\overline{S_{ft}}^{\hat{\alpha}} - S_{cft}^{\hat{\alpha}}$ where f = "computer science" and $t = 2007$. My estimate of $\hat{\alpha} = 0.0662$ from column 8 of Table 6 implies that under size equalization, the average productivity of computer scientists in the San Francisco-Silicon Valley region would be 22.52% lower than the observed productivity in 2007. This productivity loss stems from the fact that the size of the San Francisco-Silicon Valley cluster

[23]A log log model with $\alpha < 1$ implies that the relationship between number of patents and cluster size *in levels* is concave. The magnitude of coefficient α governs the degree of concavity: the smaller the coefficient the more concave the function in levels. My estimate of α equal to 0.0662 points to a very concave function.

[24]Note that my analysis focuses on the size of clusters, which is not identical to the size of a city. For the effects on local congestion or land prices, what is relevant is the magnitude of the entire city. Moreover, the spatial equilibrium is complicated by the fact that while productivity, and therefore wages, are assumed to depend on cluster size, costs of living in a location should be the same irrespective of field.

[25]In a model with homogenous tastes for location and perfect mobility, Kline and Moretti (2014) argue that the welfare effects are the same as the output effects. Put differently, if wage differences are only a function of local amenities, cities with low wages are larger and have better amenities than cities with high wages. Thus, redistributing workers from larger to smaller cities implies a utility loss, as more workers end up living in less desirable locations. This is not true in a more general setting with idiosyncratic preferences for location. When labor supply to a locality is upward sloping, equilibrium wages will reflect both local amenities and local productivity.

is larger than the average, so that in the counterfactual the cluster is made smaller. The corresponding figures for other large clusters like New York, Seattle, Austin, and Boston are -16.91%, -16.47%, -14.56% and -13.30%.

On the other hand, the bottom panel shows that the average productivity of computer scientists in clusters that are originally below average increase, since their counterfactual size is larger. For example, the average productivity of computer scientists in Kansas City would be 3.18% higher than the observed productivity in 2007. The corresponding figures for Omaha, NE, Portland ME, Memphis, TN and New Orleans are 13.23%, 17.50%, 23.02% and 34.85%.

Table 12 reports the estimated effect of size equalization on inventor productivity for all fields in 2007 by initial cluster size. Unsurprisingly, large clusters experience declines in per-inventor productivity, while small clusters experience gains in per-inventor productivity. Clusters in the bottom quartile of the size distribution gain on average 27.22% in per inventor productivity. Clusters with sizes between the 25th percentile and the median gain 18.22%. Since the mean is above the median in most fields, clusters with size between the median percentile and the 75th percentile also gain, although only 9.29% By contrast, clusters above the mean lose productivity. The changes in per inventor productivity for clusters with size between 75th and 90th percentile, 90th and 95th percetile, and 96th and 100th percetile are, -0.50%, -8.09% and -14.56%, respectively.

Overall, Tables 11 and 12 indicate that small clusters gain productivity and large cluster lose. The question is what happens in the aggregate. Using equation 5, I estimate the the aggregate effect of equalizing cluster size in each research field on the total number of patents produced in the US in that field. Table 13 shows estimates for 2007, by field. The total number of patents created in the US in Computer Science would be 13.18% lower in 2007 if computer scientists were uniformly distributed across cities. The losses in biology and chemistry, semiconductors, other engineering and other science would be -9.92%, -14.68%, -7.62%, and -9.64%, respectively.

The last row shows the total effect across all fields. The change in the total number of patents produced in the US in 2007 is -11.07%. This estimate suggests that the aggregate productivity gains from agglomeration are large in the US.

6 Conclusions

One of the most remarkable and consequential aspects of the economic geography of the US is the strong degree of geographical clustering of the high-tech sector. High-tech firms and workers appear to concentrate in a small number of expensive labor markets, such as San Francisco, New York, Boston and Seattle, and not in less expensive locations. The top ten clusters in the computer science, semiconductors, and biology and chemistry fields account, respectively, for 70%, 79% and 59% of all inventors in their field in 2007. These shares were significantly larger in 2007 than in 1971, pointing to increasing geographical agglomeration of inventors.

I find an economically important effect of cluster size on an inventor's productivity. An inventor moving from a small cluster to a large cluster enjoys an increase in annual productivity, as measured by the number of patents produced in a year or number of citations. The estimated elasticity of number of patents produced in a year with respect to cluster size is 0.0662 (0.0138). This estimate reflects the intensive margin of the effect of cluster size on productivity but misses the extensive margin. Therefore it is likely to be a lower bound of overall effect. I also find aggregate gains for the US as a whole from agglomeration of inventors. My estimates suggest that the overall number of patents created in the US in a given year is 11.07% larger relative to a counterfactual scenario where all clusters are equalized.

Clustering of the high-tech sector may exacerbate inequality in earnings and income across communities. At the same time it appears to be important for overall production of innovation in the US.[26] Policies designed to spread innovation across communities, such as place based subsidies that favor areas with little high-tech presence, need to take into account both benefits and costs.

[26]Kline and Moretti (2014b) provide a formal discussion of the equity-efficiency trade off in placed-based policies.

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Table 1: Largest Patent Assignees by Total Number of Patents 1971-2007

	Number of Patents
INT BUSINESS MACHINES	155708
GEN ELECT	69019
MICROSOFT	43550
INTEL	42087
EASTMAN KODAK	41553
MOTOROLA	40977
XEROX	35042
MICRON TECHNOLOGY	32010
TEXAS INSTRUMENTS	27886
E I DU PONT DE NEMOURS	25291
HEWLETT-PACKARD DEV LP	25022
AT&T	24891
ADV MICRO DEVICES	21280
DOW CHEM	19866
GEN MOTORS	19756
US OF AMER AS REPRESENTED BY SECR. OF NAVY	19698
LUCENT TECHNOLOGIES	18863
EXXON RES ENGN	18562
HONEYWELL INT	18195
PROCTER GAMBLE	17746
REGENTS OF UNIV OF CALIFORNIA	16800
APPL MATERIALS	16441
HEWLETT-PACKARD	15980
SUN MICROSYSTEMS	15357
BOEING	14698

Table 2: Largest Clusters in “Computer Science" - 2007

	Size
San Jose-San Francisco-Oakland, CA	.2617478
New York-Newark-Bridgeport, NY-NJ-CT-PA	.091019
Seattle-Tacoma-Olympia, WA	.0839432
Austin-Round Rock, TX	.0596916
Boston-Worcester-Manchester, MA-NH	.0478379
Los Angeles-Long Beach-Riverside, CA	.0399758
Minneapolis-St. Paul-St. Cloud, MN-WI	.0338676
Raleigh-Durham-Cary, NC	.0287269
Denver-Aurora-Boulder, CO	.0237678
San Diego-Carlsbad-San Marcos, CA	.0227396
Portland-Vancouver-Beaverton, OR-WA	.0221953
Washington-Baltimore-Northern Virginia, DC-MD-VA-WV	.0194134
Dallas-Fort Worth, TX	.0155428
Chicago-Naperville-Michigan City, IL-IN-WI	.0153614
Burlington-South Burlington, VT	.0145751
Atlanta-Sandy Springs-Gainesville, GA-AL	.0124584

Notes: Cluster size is defined as number of inventors in a city$x$field$x$year, excluding the focal inventor, as a share of all inventors in field$x$year.

Table 3: Largest Clusters in “Biology and Chemistry" and “Semiconductors" - 2007

	Size
Biology and Chemistry	
New York-Newark-Bridgeport, NY-NJ-CT-PA	.113863
San Jose-San Francisco-Oakland, CA	.111812
Boston-Worcester-Manchester, MA-NH	.0697689
Philadelphia-Camden-Vineland, PA-NJ-DE-MD	.0632221
Los Angeles-Long Beach-Riverside, CA	.0593068
San Diego-Carlsbad-San Marcos, CA	.0443517
Minneapolis-St. Paul-St. Cloud, MN-WI	.0376765
Houston-Baytown-Huntsville, TX	.0314506
Chicago-Naperville-Michigan City, IL-IN-WI	.0309371
Washington-Baltimore-Northern Virginia, DC-MD-VA-WV	.028113
Raleigh-Durham-Cary, NC	.0200899
Seattle-Tacoma-Olympia, WA	.0195764
Cincinnati-Middletown-Wilmington, OH-KY-IN	.0162388
Indianapolis-Anderson-Columbus, IN	.0156611
Pittsburgh-New Castle, PA	.0136714
Detroit-Warren-Flint, MI	.0132863
Semiconductors	
San Jose-San Francisco-Oakland, CA	.255391
New York-Newark-Bridgeport, NY-NJ-CT-PA	.149261
Los Angeles-Long Beach-Riverside, CA	.061945
Dallas-Fort Worth, TX	.0503171
Phoenix-Mesa-Scottsdale, AZ	.0498943
Boise City-Nampa, ID	.0469345
Portland-Vancouver-Beaverton, OR-WA	.0463002
Austin-Round Rock, TX	.0399577
Burlington-South Burlington, VT	.0361522
Boston-Worcester-Manchester, MA-NH	.035518
Albany-Schenectady-Amsterdam, NY	.0215645
Minneapolis-St. Paul-St. Cloud, MN-WI	.0158562
Raleigh-Durham-Cary, NC	.0145877
San Diego-Carlsbad-San Marcos, CA	.0133192
Rochester-Batavia-Seneca Falls, NY	.0114165
Washington-Baltimore-Northern Virginia, DC-MD-VA-WV	.010148

Notes: Cluster size is defined as number of inventors in a city$x$field$x$year, excluding the focal inventor, as a share of all inventors in field$x$year.

Table 4: Difference in Difference Estimates: 1996-2007 Productivity Change of Non-Kodak Inventors in Rochester Compared to Other Cities

	(1)	(2)	(3)	(4)	(5)
Rochester × 2007	-0.0658***	-0.0696***	-0.0835***	-0.0984***	-0.0760***
	(0.00759)	(0.00678)	(0.00630)	(0.00640)	(0.00591)
Rochester	-0.0132	-0.0346***	-0.0296***	-	-
	(0.0105)	(0.0101)	(0.00982)		
2007	-0.190***	-0.189***	-	-	-
	(0.00759)	(0.00707)			
N	194110	194110	194110	194110	193194
Field		Y	Y	Y	Y
Field × Year			Y	Y	Y
Field × City				Y	Y
Drop Xerox					Y

Notes: Each column is a separate regression. The level of observation in the regressions is inventor-year. The dependent variable is log of number of patents filed in a year. The sample includes non Kodak inventors in years 1996 and 2007. Inventors with patents in the “Photography" or "Electrophotography” technology classes are excluded. Standard errors clustered by city in parenthesis.

Table 5: Within-Inventor Difference in Difference Estimates: 1996-2007 Productivity Change of Non-Kodak Inventors in Rochester Compared to Other Cities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel (A): Rochester =1 if inventor in Rochester in 1996								
Rochester × 2007	-0.206***	-0.220***	-0.256***	-0.321***				
	(0.0771)	(0.0766)	(0.0800)	(0.0744)				
2007	-0.206***	-0.206***	-	-				
	(0.0190)	(0.0193)						
Rochester	-	-	-	-				
Panel (B): Rochester =1 if inventor in Rochester in 1996 and 2007								
Rochester × 2007					-0.313***	-0.325***	-0.366***	-0.399***
					(0.0189)	(0.0192)	(0.0178)	(0.0233)
2007					-0.205***	-0.206***	-	-
					(0.0189)	(0.0192)		
Rochester					-	-	-	-
N	16426	16426	16426	16426	16426	16426	16426	16426
Inventor	Y	Y	Y	Y	Y	Y	Y	Y
Field		Y	Y	Y		Y	Y	Y
Field × Year			Y	Y			Y	Y
Field × City				Y				Y

Notes: Each column is a separate regression. The level of observation in the regressions is inventor-year. The dependent variable is log of number of patents filed in a year. The sample includes non-Kodak inventors who are observed both in 1996 and 2007. Inventors with patents in the "Photography" or "Electrophotography" technology classes are excluded. In Panel A, for a given inventor the Rochester dummy is set equal to 1 if the inventor is in Rochester in 1996, irrespective of 2007 location. In Panel B, for a given inventor the Rochester dummy is set equal to 1 if the inventor is in Rochester both in 1996 and 2007. Standard errors clustered by city in parenthesis.

Table 6: Effect of Cluster Size on Inventor Productivity – Baseline Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Size	0.0514***	0.0751***	0.0870***	0.0897***	0.0668***	0.0910***	0.0514***	0.0662***
	(0.00812)	(0.0166)	(0.0186)	(0.00924)	(0.00861)	(0.00980)	(0.0116)	(0.0138)
N	932008	932008	932008	932008	932008	932008	932008	823359
Year	y	y	y	y	y	y	y	y
City	y	y	y	y	y	y	y	y
Field	y	y	y	y	y	y	y	y
Class	y	y	y	y	y	y	y	y
City × Field		y	y	y	y	y	y	y
City × Class			y	y	y	y	y	y
Field × Year				y	y	y	y	y
Class × Year					y	y	y	y
Inventor						y	y	y
City × Year							y	y
Firm								y

Notes: Each column is a separate regression. The level of observation in the regressions is inventor-year. The dependent variable is log of number of patents filed in a year. The model estimated is equation 1. Standard errors are clustered by city × research field.

Table 7: Effect of Cluster Size on Inventor Productivity – Patent Citations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(A) Dependent Variable: Number of Citations							
Log Size	0.119***	0.168**	0.192**	0.202***	0.226***	0.205***	0.154***	0.156***
	(0.0335)	(0.0782)	(0.0937)	(0.0449)	(0.0391)	(0.0306)	(0.0422)	(0.0435)
	(B) Dependent Variable: Number of Citations Per Patent							
Log Size	0.0676**	0.0928	0.105	0.113***	0.160***	0.114***	0.102***	0.0894**
	(0.0303)	(0.0672)	(0.0812)	(0.0435)	(0.0370)	(0.0279)	(0.0394)	(0.0400)
N	932008	932008	932008	932008	932008	932008	932008	823359
Year	y	y	y	y	y	y	y	y
City	y	y	y	y	y	y	y	y
Field	y	y	y	y	y	y	y	y
Class	y	y	y	y	y	y	y	y
City × Field		y	y	y	y	y	y	y
City × Class			y	y	y	y	y	y
Field × Year				y	y	y	y	y
Class × Year					y	y	y	y
Inventor						y	y	y
City × Year							y	y
Firm								y

Notes: The dependent variable is log of patent citations (Panel A) or log of citations per patent (Panel B). In particular, Panel A shows estimates where the dependent variable is the log number of patents that cite any patent filed by inventor i in year t, where the citing patent may be filed in any year between t and the end of the sample. Panel B shows estimates where the dependent variable is the log of number of subsequent patents that cite patents filed by inventor i in year t divided by the number of patents filed by inventor i in year t. The model estimated is equation 1. Standard errors are clustered by city × research field.

Table 8: Effect of Cluster Size on Inventor Productivity – Stayers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(A) Inventors Who Do Not Change City								
Log Size	0.0551***	0.0927***	0.113***	0.117***	0.0879***	0.124***	0.0912***	0.110***
	(0.00978)	(0.0181)	(0.0207)	(0.0112)	(0.0108)	(0.0143)	(0.0157)	(0.0193)
N	529023	529023	529023	529023	529023	529023	529023	465171
(B) Inventors Who Do Not Change Field								
Log Size	0.0332***	0.0926***	0.116***	0.107***	0.0880***	0.125***	0.188***	0.219***
	(0.0120)	(0.0210)	(0.0259)	(0.0141)	(0.0114)	(0.0148)	(0.0286)	(0.0354)
N	375405	375405	375405	375405	375405	375405	375405	321446
(C) Inventors Who Do Not Change City or Field								
Log Size	0.0259*	0.100***	0.131***	0.123***	0.105***	0.146***	0.217***	0.246***
	(0.0136)	(0.0237)	(0.0297)	(0.0181)	(0.0150)	(0.0185)	(0.0354)	(0.0421)
N	251722	251722	251722	251722	251722	251722	251722	213999
Year	y	y	y	y	y	y	y	y
City	y	y	y	y	y	y	y	y
Field	y	y	y	y	y	y	y	y
Class	y	y	y	y	y	y	y	y
City × Field		y	y	y	y	y	y	y
City × Class			y	y	y	y	y	y
Field × Year				y	y	y	y	y
Class × Year					y	y	y	y
Inventor						y	y	y
City × Year							y	y
Firm								y

Notes: Each entry is a separate regression. Dependent variable is log number of patents in a year. Models in Panel A include inventors who do not change city during the sample period. Models in In Panel B include inventors who do not change field during the sample period. Models in Panel C include inventors who do not change city or field during the sample period. The model estimated is equation 1. Standard errors are clustered by city × research field.

Table 9: Models in Differences: Effect of Changes in Cluster Size on Changes in Inventor Productivity – OLS and IV Estimates

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)	2SLS (7)	2SLS (8)	2SLS (9)	2SLS (10)	2SLS (11)	2SLS (12)
Panel (A): All												
Δ log Size	0.0144***	0.0148***	0.0156***	0.0169***	0.0167***	0.0162***	0.0291**	0.0475***	0.0345**	0.0315***	0.0310**	0.0307**
	(0.00255)	(0.00256)	(0.00258)	(0.00280)	(0.00276)	(0.00277)	(0.0120)	(0.0144)	(0.0141)	(0.0120)	(0.0121)	(0.0122)
First Stage							0.983***	0.948***	0.965***	1.238***	1.272***	1.278***
							(0.0345)	(0.0495)	(0.0500)	(0.0653)	(0.0644)	(0.0650)
F stat.							811.90	366.14	372.73	358.91	390.60	386.49
N	419599	419599	419568	405095	405095	403942	419599	419599	419568	405095	405095	403942
Panel (B): Stayers – Same City and Field												
Δ log Size	0.0340***	0.0336***	0.0348***	0.0448***	0.0438***	0.0415***	0.110*	0.131*	0.0897	0.128**	0.107*	0.124*
	(0.00769)	(0.00768)	(0.00769)	(0.00926)	(0.00914)	(0.00944)	(0.0598)	(0.0696)	(0.0714)	(0.0631)	(0.0648)	(0.0683)
First Stage							0.283***	0.266***	0.273***	0.368***	0.380***	0.380***
							(0.0157)	(0.0212)	(0.0206)	(0.0268)	(0.0265)	(0.0274)
F stat.							326.81	157.67	175.18	188.58	205.17	192.51
N	176263	176263	176245	166253	166251	164454	176263	176263	176245	166253	166251	164454
Year	y	y	y	y	y	y	y	y	y	y	y	y
Field		y	y	y	y	y		y	y	y	y	y
Class			y	y	y	y			y	y	y	y
Firm				y	y	y				y	y	y
Field $\times$ Year					y	y					y	y
Class $\times$ Year						y						y

Notes: Each entry is a separate regression. Dependent variable is the change in the log number of patents in a year. The sample in Panel A includes inventors observed in consecutive years. The sample in Panel B includes inventors observed in consecutive years who do not change city or field in the sample period. The model estimated is equation 3. The instrumental variable for workers in firm j in cluster fct is defined as $IV_{jfct} = \sum_{s \neq j} D_{sfc(t-1)} \frac{\Delta N_{sf(-c)t}}{\Delta N_{ft}}$ where $D_{jcf(t-1)}$ is an indicator equal to 1 if firm j has at least 1 inventor in city c in field f in year $t-1$. $N_{jf(-c)t}$ is the number of inventors that firm j has in field f, year t in all the cities excluding city c; and $\Delta N_{jf(-c)t} = N_{jf(-c)t} - N_{jf(-c)(t-1)}$ is the change in $N_{jf(-c)t}$ between time $(t-1)$ and t. Standard errors are clustered by city $\times$ firm.

Table 10: Some Examples of Firm-Specific Productivity Spillovers – 2007

Firm	City	Estimated Productivity Spillover
(A) Computer Science		
MICROSOFT	Seattle-Tacoma-Olympia, WA	.0806
INT BUSINESS MACHINES	Minneapolis-St. Paul-St. Cloud, MN-WI	.0415
CISCO TECHNOLOGY	San Jose-San Francisco-Oakland, CA	.0020
DELL PROD	Austin-Round Rock, TX	.0061
TEXAS INSTRUMENTS	Dallas-Fort Worth, TX	.0184
CATERPILLAR	Peoria-Canton, IL	.1047
MOTOROLA	Chicago-Naperville-Michigan City, IL-IN-WI	.0088
HEWLETT-PACKARD	San Jose-San Francisco-Oakland, CA	.0007
Average Firm	**Average City**	.0032
(B) Biology and Chemistry		
E I DU PONT DE NEMOURS	Philadelphia-Camden-Vineland, PA-NJ-DE-MD	.0117
BRISTOL-MYERS SQUIBB	New York-Newark-Bridgeport, NY-NJ-CT-PA	.0054
PROCTER GAMBLE	Cincinnati-Middletown-Wilmington, OH-KY-IN	.0347
AMGEN	Los Angeles-Long Beach-Riverside, CA	.0065
CHEVRON RES	San Jose-San Francisco-Oakland, CA	.0014
3M	Duluth, MN-WI	.0899
PFIZER	Hartford-West Hartford-Willimantic, CT	.0124
EXXON RES ENGN	Washington-Baltimore-Northern Virginia, DC-MD-VA-WV	.0043
Average Firm	**Average City**	.0024

Notes: Entries reflect the impact that a specific firm is estimated to have on the productivity of scientists in other firms in the same cluster in 2007. For a given firm j, field f and city c, entries are obtained as $\hat{\alpha}\Delta S_{-jfct}$ where $\hat{\alpha} = 0.066$ is the estimated elasticity in Table 6, column 8 and $\Delta \ln S_{-jfct}$ is the difference in log cluster size with and without a given firm. In particular, $\Delta \ln S_{-jfct} = [\ln(N_{fct}/N_{ft}) - \ln(N_{jfct}/N_{ft})]$, where N_{fct} in the number of scientists in cluster fct; N_{ft} is number of scientists in field f and year t; N_{jfct} is number of scientists in firm j in cluster fct; and $t = 2007$.

Table 11: Some Examples of the Effect of Cluster Size Equalization on Inventor Productivity – Computer Science in 2007

	Percent Change
Examples of Losers	
San Jose-San Francisco-Oakland, CA	-22.52%
New York-Newark-Bridgeport, NY-NJ-CT-PA	-16.91%
Seattle-Tacoma-Olympia, WA	-16.47%
Austin-Round Rock, TX	-14.56%
Boston-Worcester-Manchester, MA-NH	-13.30%
Minneapolis-St. Paul-St. Cloud, MN-WI	-11.29%
Raleigh-Durham-Cary, NC	-10.32%
San Diego-Carlsbad-San Marcos, CA	-8.92%
Portland-Vancouver-Beaverton, OR-WA	-8.78%
Pittsburgh-New Castle, PA	-2.63%
Boise City-Nampa, ID	-2.53%
Examples of Winners	
Miami-Fort Lauderdale-Miami Beach, FL	1.50%
Kansas City-Overland Park-Kansas City, MO-KS	3.18%
Buffalo-Niagara-Cattaraugus, NY	6.37%
Omaha-Council Bluffs-Fremont, NE-IA	13.23%
Des Moines-Newton-Pella, IA	14.39%
Portland-Lewiston-South Portland, ME	17.50%
Scranton-Wilkes-Barre, PA	21.22%
Toledo-Fremont, OH	23.02%
Memphis, TN-MS-AR	23.02%
Oklahoma City-Shawnee, OK	25.39%
New Orleans-Metairie-Bogalusa, LA	34.85%

Notes: Entries are estimates of the percent difference between mean inventor productivity in the counterfactual scenario and observed productivity.

Table 12: Effect of Cluster Size Equalization on Inventor Productivity - All Fields, 2007

	Percent Change
0-25th Percentile	27.22%
25th-50th Percentile	18.22%
50th-75th Percentile	9.29%
75th-90th Percentile	-0.50%
90th-95th Percentile	-8.09%
95th-100th Percentile	-14.56%

Notes: Entries are the estimated percent difference between inventor productivity in the counterfactual scenario and observed productivity, by initial size of cluster.

Table 13: Aggregate Effects of Cluster Size Equalization – 2007

	Percent Change
"Computer Science"	-13.18%
"Biology and Chemistry"	-9.92%
"Semiconductors"	-14.68%
"Other Engineering"	-7.62%
"Other Science"	-9.64%
All Fields	-11.07%

Notes: Entries are the estimated percent difference between total number of patents created in the US in the counterfactual scenario and observed number of patents created in the US.

Figure 1: Share of Top Ten Cities Over Time

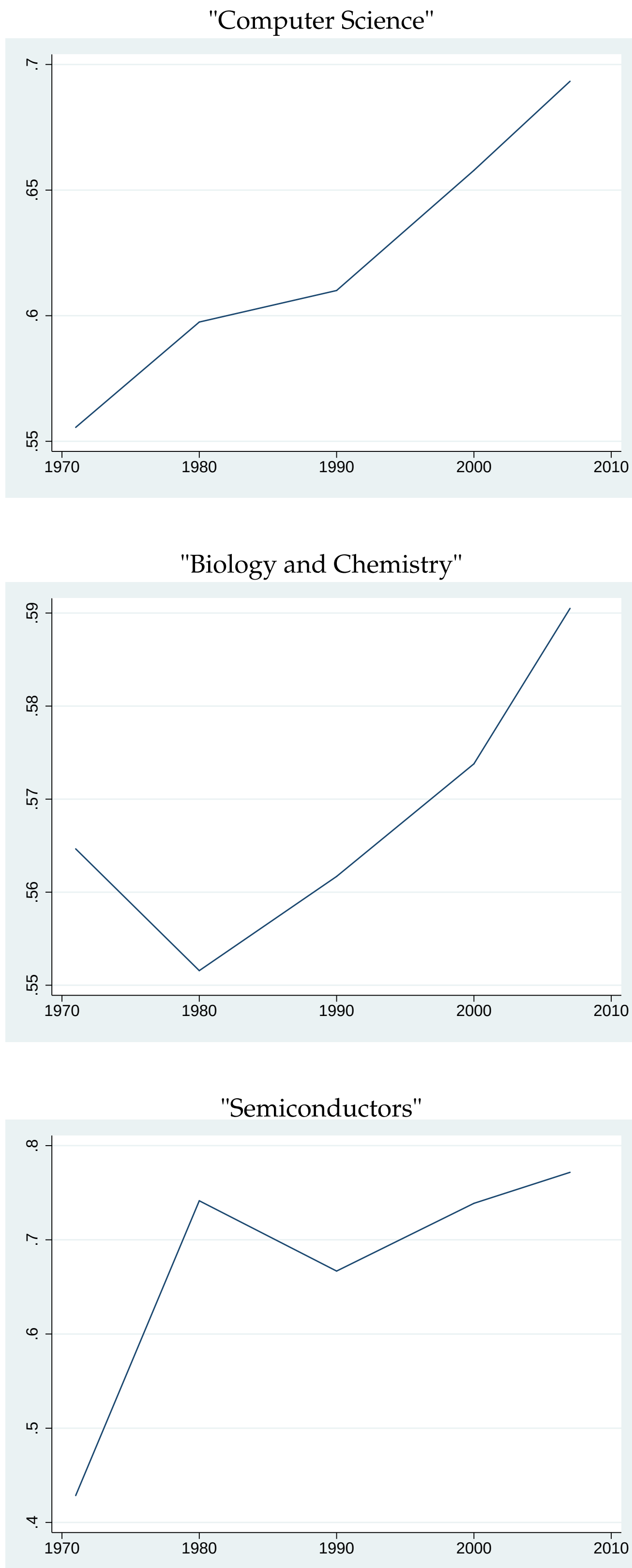
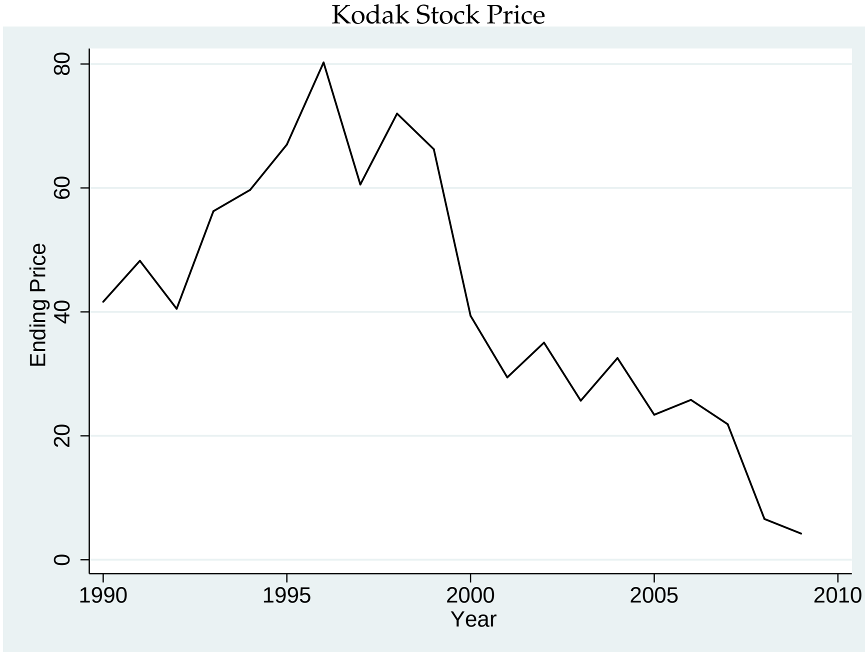


Figure 2: Kodak Decline

Kodak Stock Price



Kodak Inventors in Rochester

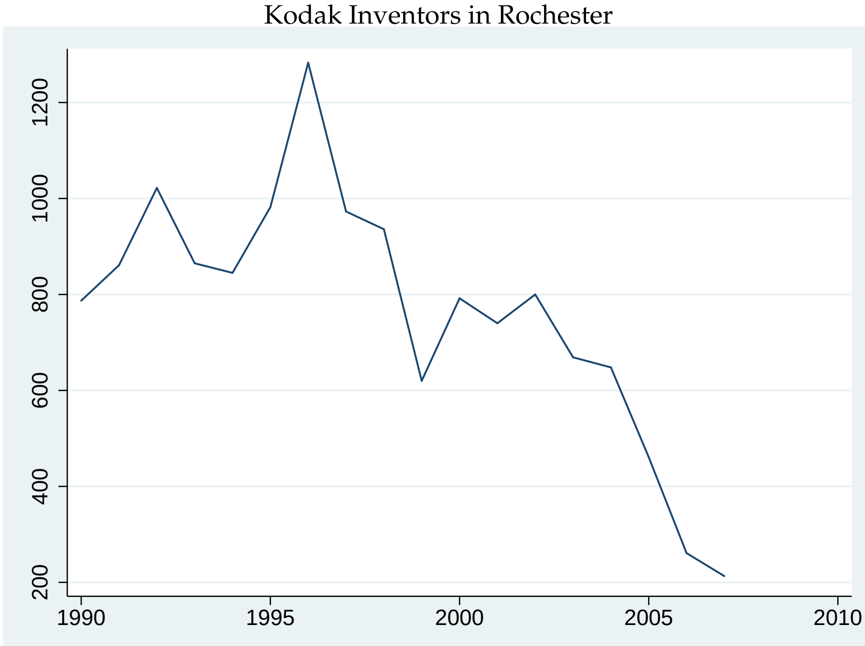
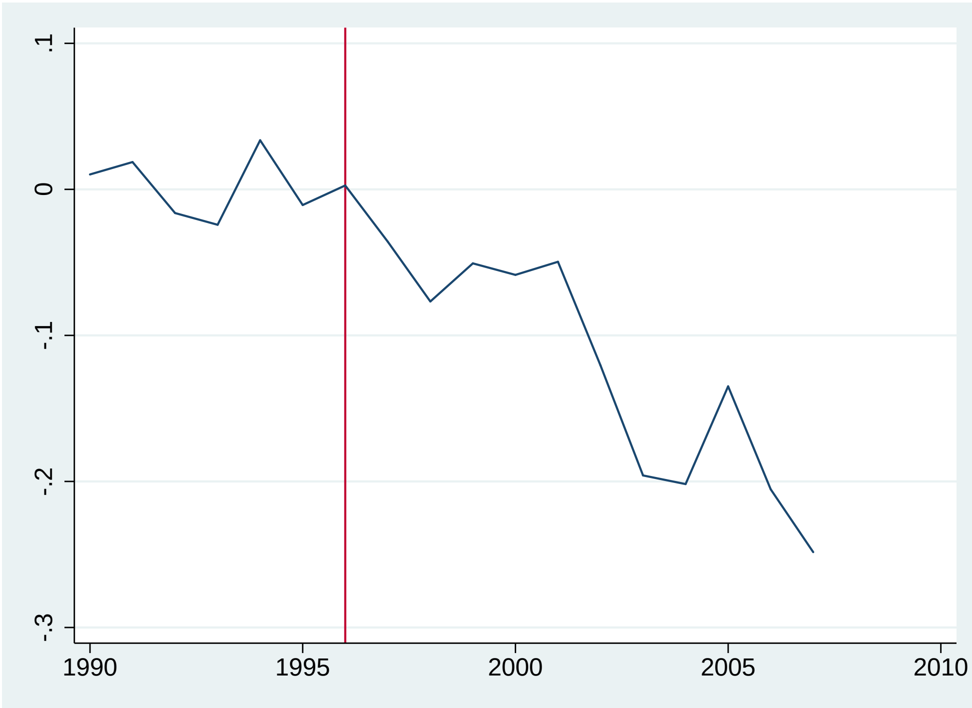
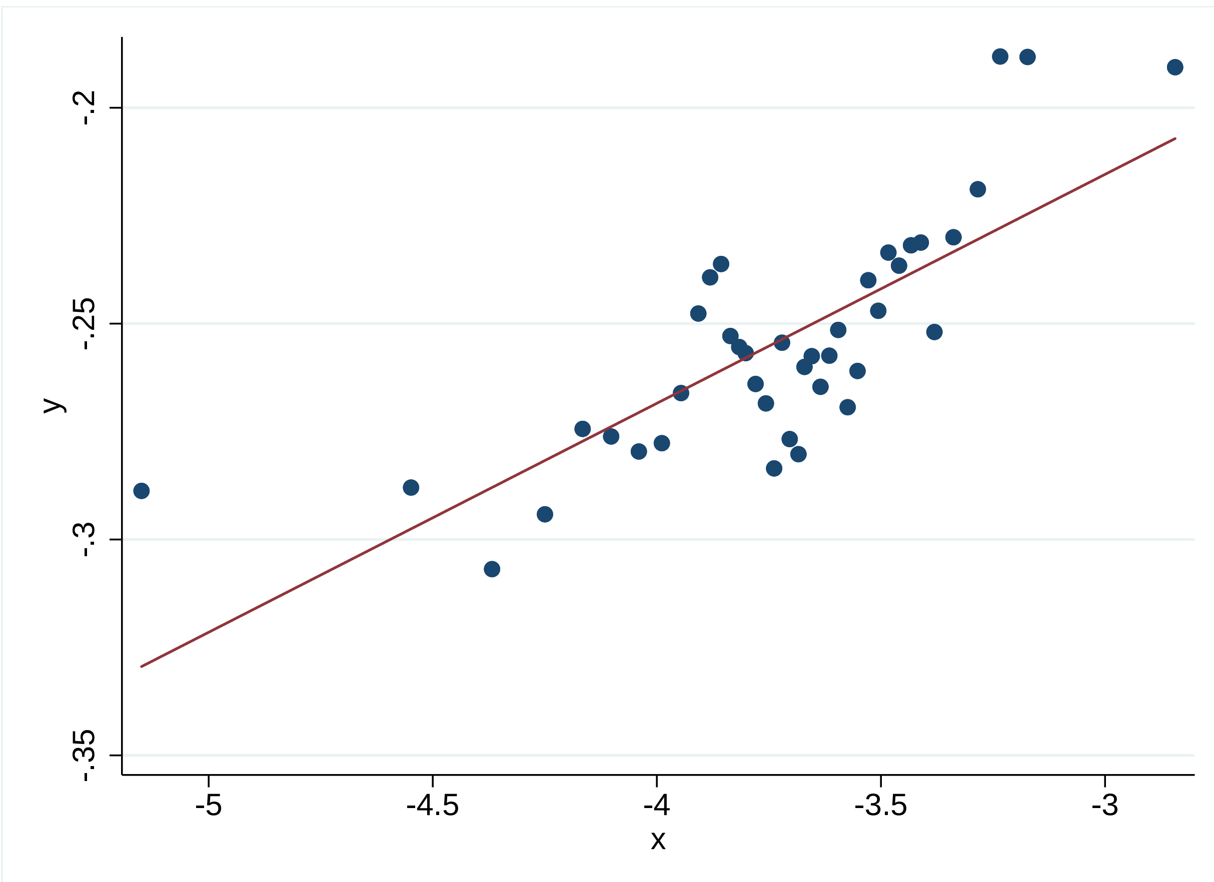


Figure 3: Average Inventor Productivity in Rochester Outside Kodak



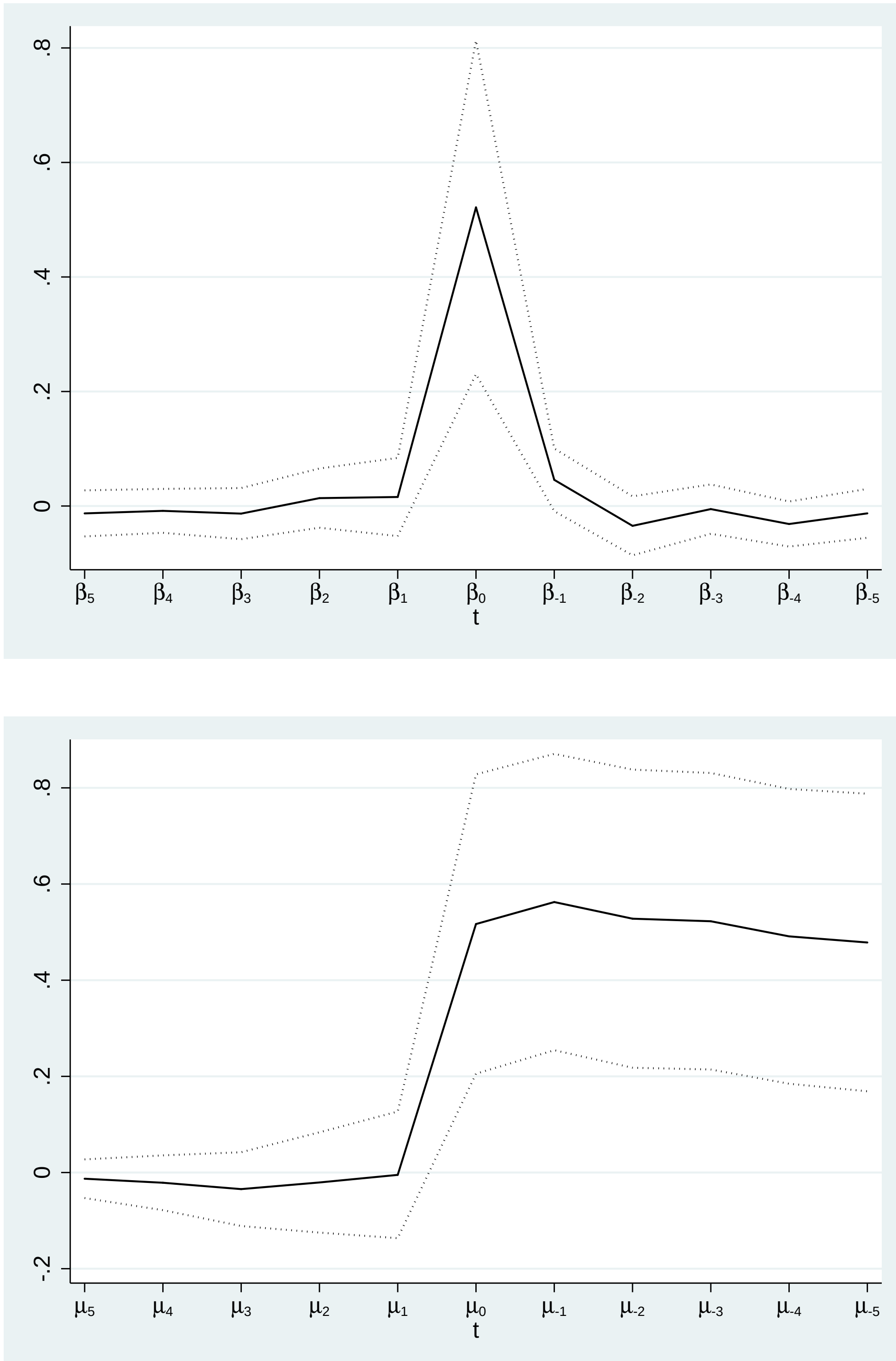
Notes: Controls include research field dummies.

Figure 4: Average Log Number of Patents Per Inventor Per Year and Log Cluster Size — All Years and Fields



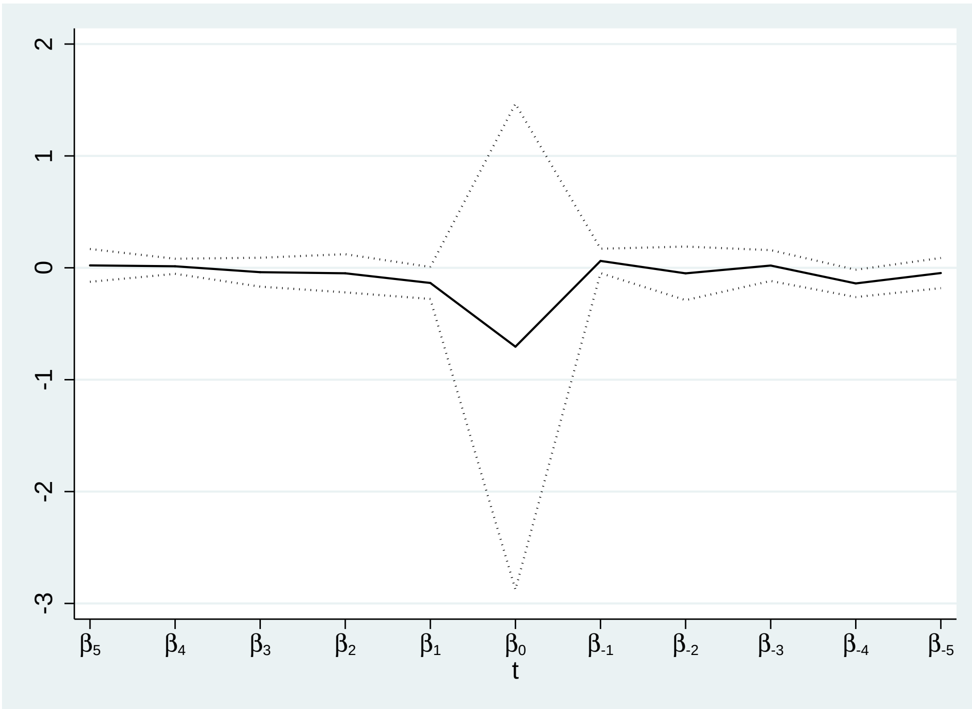
Notes: The slope is 0.053 (0.008). Controls include dummies for year, field and city.

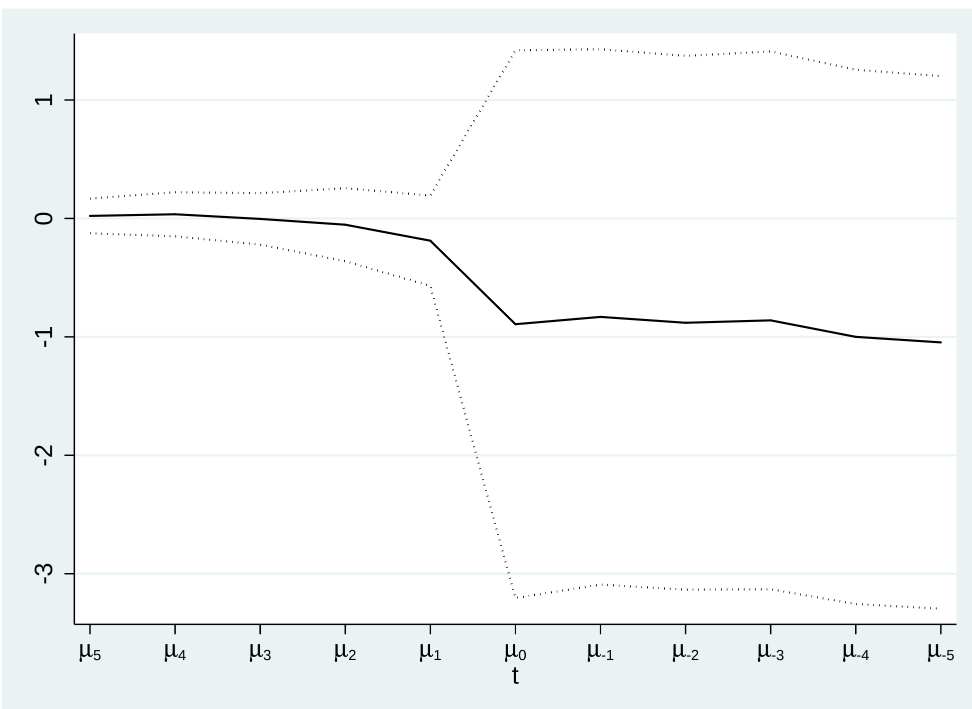
Figure 5: Dynamic Response Following a Change in Cluster Size



Notes: This figure is based on equation 2 in the text. In the top panel I plot the estimated β coefficients in equation 2 on the lag and lead terms. For example, β_5 is the coefficient on the fifth lead term. In the bottom panel, I plot the cumulative response, where the μ's are defined as: $\mu_n = \beta_5 + \beta_4 + ... + \beta_n$ for $n = -5$ through 5. Standard errors are clustered by city $\times$ research field.

Figure 6: Dynamic Response Following a Change in Cluster Size – Pharmaceutical Only





Notes: This figure is based on equation 2 in the text. In the top panel I plot the estimated β coefficients in equation 2 on the lag and lead terms. For example, β_5 is the coefficient on the fifth lead term. In the bottom panel, I plot the cumulative response, where the μ's are defined as: $\mu_n = \beta_5 + \beta_4 + ... + \beta_n$ for $n = -5$ through 5. Standard errors are clustered by city $\times$ research field.

Appendix

Appendix Table A.1: Effect of Cluster Size on Inventor Productivity When Custer Size is Measured by Number of Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Size	0.0726***	0.0879***	0.0955***	0.0853***	0.0597***	0.0620***	0.0203**	0.0238**
	(0.0103)	(0.0181)	(0.0200)	(0.0102)	(0.00916)	(0.01000)	(0.00989)	(0.0119)
N	930867	930867	930867	930867	930867	930867	930867	822410
Year	y	y	y	y	y	y	y	y
City	y	y	y	y	y	y	y	y
Field	y	y	y	y	y	y	y	y
Class	y	y	y	y	y	y	y	y
City × Field		y	y	y	y	y	y	y
City × Class			y	y	y	y	y	y
Field × Year				y	y	y	y	y
Class × Year					y	y	y	y
Inventor						y	y	y
City × Year							y	y
Firm								y

Notes: Dependent variable is log number of patents in a year. Standard errors are clustered by city×research field.

Appendix Table A.2: Interpolation

		Interpolation	
	Baseline	1 Year	2 Years
	(1)	(2)	(3)
Log Size	0.0662***	0.186***	0.218***
	(0.0138)	(0.0196)	(0.0212)
N	823359	860753	873311
Year	y	y	y
City	y	y	y
Field	y	y	y
Class	y	y	y
City × Field	y	y	y
City × Class	y	y	y
Field × Year	y	y	y
Class × Year	y	y	y
Inventor	y	y	y
City × Year	y	y	y
Firm	y	y	y

Notes: Dependent variable is log number of patents in a year. Baseline is the entry in Col 8 of Table 6. Standard errors are clustered by city × research field.

Appendix Table A.3: Alternative Units of Time

	1 Month	2 Months	3 Months	6 Months	1 Year (Baseline)	2 Years	3 Years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log Size	-0.0249***	-0.0114	0.000793	0.0302***	0.0662***	0.130***	0.164***
	(0.00852)	(0.00933)	(0.00985)	(0.0107)	(0.0138)	(0.0147)	(0.0192)
N	1321679	1234595	1165614	1013440	823359	610122	500797
Year	y	y	y	y	y	y	y
City	y	y	y	y	y	y	y
Field	y	y	y	y	y	y	y
Class	y	y	y	y	y	y	y
City × Field	y	y	y	y	y	y	y
City × Class	y	y	y	y	y	y	y
Field × Year	y	y	y	y	y	y	y
Class × Year	y	y	y	y	y	y	y
Inventor	y	y	y	y	y	y	y
City × Year	y	y	y	y	y	y	y
Firm	y	y	y	y	y	y	y

Notes: Dependent variable is log number of patents in unit of time. Baseline is the entry in Col 8 of Table 6. Standard errors are clustered by city × research field.

Appendix Table A.4: Alternative Definitions of Star Inventors

	All	Top 25%	Top 10% (Baseline)	Top 5%	Top 1%	Top 0.5%
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Years in Sample	2.14	4.58	7.01	8.94	13.20	13.60
log Size	0.0189	0.0380***	0.0662***	0.104***	0.247***	0.269***
	(0.0117)	(0.0115)	(0.0138)	(0.0179)	(0.0406)	(0.0419)
N	2355529	1344991	823359	526344	155210	131805
Year	y	y	y	y	y	y
City	y	y	y	y	y	y
Field	y	y	y	y	y	y
Class	y	y	y	y	y	y
City $\times$ Field	y	y	y	y	y	y
City $\times$ Class	y	y	y	y	y	y
Field $\times$ Year	y	y	y	y	y	y
Class $\times$ Year	y	y	y	y	y	y
Inventor	y	y	y	y	y	y
City $\times$ Year	y	y	y	y	y	y
Firm	y	y	y	y	y	y

Notes: Dependent variable is log number of patents in a year. Baseline is the entry in Col 8 of Table 6. Standard errors are clustered by city$\times$research field.

Appendix Table A.5: Alternative Measures of Cluster Size

	(1)	(2)	(3)	(4)	(5)	(6)
(a) Baseline	0.0662***					
	(0.0138)					
(b) 1 Year Ago		0.0799***				
		(0.0103)				
(c) 2 Years Ago			0.0531***			
			(0.0106)			
(d) Mean Over 3 Years				0.100***		
				(0.0150)		
(e) Min Over 3 Years					0.0637***	
					(0.0114)	
(f) Max Over 3 Years						0.105***
						(0.0150)
N	823359	821644	820155	823572	823572	823572
Year	y	y	y	y	y	y
City	y	y	y	y	y	y
Field	y	y	y	y	y	y
Class	y	y	y	y	y	y
City $\times$ Field	y	y	y	y	y	y
City $\times$ Class	y	y	y	y	y	y
Field $\times$ Year	y	y	y	y	y	y
Class $\times$ Year	y	y	y	y	y	y
Inventor	y	y	y	y	y	y
City $\times$ Year	y	y	y	y	y	y
Firm	y	y	y	y	y	y

Notes: Dependent variable is log number of patents in a year. Baseline is the entry in Col 8 of Table 6. Standard errors are clustered by city$\times$research field.

Appendix Table A.6: First Stage and 2SLS Estimates: Non-Kodak Inventors in Rochester Compared to Other Cities

	(1)	(2)	(3)	(4)
(A) First Stage				
Rochester$\times$ 2007	-0.492***	-0.464***	-0.451***	-0.396***
	(0.128)	(0.113)	(0.115)	(0.0455)
F stat.	14.68	16.84	15.31	75.71
(B) Second Stage				
Cluster Size	0.134***	0.150***	0.185***	0.249***
	(0.0380)	(0.0379)	(0.0499)	(0.0398)
Rochester	Y	Y	Y	Y
2007	Y	Y	Y	Y
Field		Y	Y	Y
Field $\times$ Year			Y	Y
Field $\times$ City				Y

Notes: Each entry is a separate regression. The dependent variable in Panel A is log cluster size. The dependent variable in Panel B is log number of patents in a year. Entries in Panel B are the ratio of reduced form estimates in the first row of Table 4 divided by the corresponding first stage estimates in Panel A of this Table. The level of observation in the regressions is inventor-year. The sample includes all non Kodak inventors in years 1996 and 2007, excluding those employed in the Photography sector. Standard errors clustered by city in parenthesis.

Appendix Table A.7: Heterogeneity in Elasticity By Cluster Size

	(1)	(2)
First Quartile (Smallest)	0.0523***	0.0685***
	(0.0113)	(0.0136)
Second Quartile	0.0563***	0.0743***
	(0.0118)	(0.0140)
Third Quartile	0.0537***	0.0720***
	(0.0121)	(0.0144)
Fourth Quartile (Largest)	0.0571***	0.0776***
	(0.0137)	(0.0162)
N	932008	823359
p-value equal elasticities	0.224	0.094
Year	y	y
City	y	y
Field	y	y
Class	y	y
City $\times$ Field	y	y
City $\times$ Class	y	y
Field $\times$ Year	y	y
Class $\times$ Year	y	y
Inventor	y	y
City $\times$ Year	y	y
Firm		y

Notes: Dependent variable is log number of patents in a year. Each column is a separate regression. Standard errors are clustered by city$\times$research field.