Isolating geographic agglomeration mechanisms: inventor deaths and knowledge spillovers

Sonja Lück [a], Benjamin Balsmeier [b], and Lee Fleming [c]

a) University of Paderborn: sonja.lueck@uni-paderborn.de
b) University of Luxembourg: benjamin.balsmeier@uni.lu
c) University of California, Berkeley: lfleming@berkeley.edu

March 2021

Abstract
Estimates of the localization of knowledge spillovers have typically relied upon controversial case matching methods. We bypass matching entirely by using the after application but pre-grant deaths of differently located co-inventors of the same patent. Knowledge spillovers are largely absent in less densely populated areas. We estimate that the regional impact of an inventor diminishes at a greater than linear rate with increasing distance; an inventor has a 3 to 4 times larger impact within a 25 mile radius than within a 100 mile radius, and little influence beyond 100 miles, supporting the relevance of dense populations of knowledge workers, and strategic advantages of being physically close to the source of knowledge production. Knowledge flows across technology classes rely more heavily on local inventor density than flows within technology classes, supporting Jacobs' arguments for the importance of cities for invention of novelty.

Super preliminary results written down only for seminar presentations, please excuse errors!

JEL-Classification: O31, O33
Keywords: Knowledge diffusion, Localization, Patents, Inventor death

---

* The authors thank Guan Cheng Li for invaluable research assistance and feedback from seminar participants at Duke University, UC Berkeley, ETH, and INSEAD. We gratefully acknowledge financial support from The Coleman Fung Institute for Engineering Leadership and the National Science Foundation (1360228). Errors and omissions remain the authors'.

Marshall (1890) offered three (now canonical) explanations for the geographical agglomeration of economic activity: thicker labor markets, scale economies from collocation of production, and localized knowledge spillovers. These theories unfortunately imply similar observable outcomes (Ellison, Glaeser, and Kerr 2010) and empirical work has struggled to disentangle the mechanisms. Krugman (1991) made the classic argument that the last mechanism in particular cannot be estimated as, "…knowledge flows…are invisible; they leave no paper trail by which they may be measured and tracked." In response, Jaffe, Trajtenberg and Henderson (1993, hereafter JTH) offered a case matching method, the metric of patent citations as the paper trail, and the result that knowledge flows indeed appear to be localized. Since then perhaps hundreds of papers have applied, criticized, and argued over the validity of using case matching and patent citations as an empirical trail of knowledge flows. "Indeed, patent citations are the most widely employed measure of knowledge flows in the economics, management, and policy literatures… though a number of studies provide grounds for skepticism…" (Roach and Cohen 2013)

The critiques of JTH (clearly acknowledged in the original paper) mainly focus on whether citations indicate a real knowledge spillover, or simply one correlate of the colocation of industrial and technological activity. To address this, JTH matched each patent with a similar patent in technology and time. Most subsequent studies have followed the matching approach, for example, Almeida and Kogut (1999) show differences in localization spillovers within different regions, Alcacer and Gittleman (2006) confirm localization yet show inconsistencies between inventor and examiner citations, Belonzon and Shankerman (2013) demonstrate localization and border effects for university patents and weaker effects for science papers, and Marx and Singh (2013) use a choice-based sampling method to illustrate strong state border effects. A recent study exploited interference cases (simultaneous inventions) that until 2013 were identified by the United States Patent and Trademark Office (Ganguli, Lin, and Reynolds 2019), also matched to similar patents, found that interfering patents were 1.4 to 4 times more likely to be local, and argued that cites are likely to be a lower bound estimate of knowledge spillovers. These papers constitute a very limited sample, for a review of the extensive literature, see Jaffe and de Rassenfosse (2017).

The main concern with the matching approach, laid out most sharply in Thompson and Fox-Kean (2005), and further elaborated in Arora, Belenzon and Lee (2018), is that the matching can never be precise enough. A variety of analyses have demonstrated weaker (though often still significant) effects as matching becomes more precise. Thompson and Fox-Kean (2005) match at finer levels of technology classification and find localization only within international borders. Adopting a survey approach, Roach and Cohen (2013) find that patent citations to science papers are more representative of knowledge flow, and argue that patent citations underestimate knowledge flow. Using kernel density methods within technology classes, Murata and co-authors (2014) find localized spillovers even with finer-grained controls. Arora, Belenzon and Lee (2018) find that citations made to a patent with a priority filing that predates the focal patent are also localized – thus calling into question whether patent citations actually represent knowledge flows. Using neural network methods and lexical similarity, Blit and Packalen (2019) illustrate improved precision, bias in case matching methods, and still significant localization, even with improved precision. Feng (2019) uses similar methods and illustrates how common patent lawyers may be responsible for part of the observed localization effect.

Here we bypass matching altogether and instead use the death of a collaborative inventor to identify localized knowledge spillovers. Rather than attempting to match similar patents, and worry about the precision of the match, our approach uses the same patent and identifies the difference in citations between the different regions that host the deceased vs. still living co-authors of the same patent. Though we still use patent citations as a measure, our approach should avoid many of the criticisms of the case matching method, and avoid confounding effects of agglomeration (Duranton and Puga 2020). The approach builds upon recent literature that relies on death to identify the mechanisms of invention and science (Azoulay et al. 2010; Jaravel et al. 2018).

This approach provides a valuable complement to prior work because identifying the impact of physical inventor presence remains challenging, for a number of reasons. Most approaches miss a direct link to the specific inventor who is responsible for the invention and assumed to be the actual source of knowledge diffusion. This makes inference particularly difficult, as the physical presence of inventors is typically correlated with many unobservable regional characteristics that are surely conducive to knowledge flows (Almeida and Kogut 1999). Inventor emigration has been used (Agrawal, Cockburn, and McHale 2006), however, inventors move away from certain regions for unknown personal reasons and with unknown expectations, which might be correlated with patterns of regional knowledge diffusion. Inventor immigration is also problematic, as other inventors that cite a given inventor may have moved to the same region for unobserved but similar reasons (e.g. same employer) without any physical interaction, i.e. no actual knowledge flowed through interpersonal mechanisms. Common attorneys might conflate the observation of localized knowledge flow (Feng 2019). Finally, there is no easily identified and precisely comparable inventor who can serve as a counterfactual. Comparing two or more inventors on the same patent, one of which has died, addresses many of these issues. Assuming that the inventor death remains exogenous to local factors of production, and locally pooled labor, it enables cleaner estimation of the third Marshallian mechanism of knowledge flows, and in particular, it establishes the importance of physical presence for knowledge flows, both locally and at a further distance.

We also apply the method to investigate how the inventive context of the deceased inventor's location influences the subsequent diffusion of the idea. We demonstrate that local geographic inventor density provides the "ether" through which inter-personal knowledge spillovers flow. Other plausible factors, such as population density, wealth, and education do not demonstrate significant impacts (measures of professional STEM density show similar though smaller effects than inventor density). The deceased inventor's local inventor density influences not only her local spillovers, but also those at greater distances, e.g., 100 miles or greater. Confirming Jacobs' arguments, citations across technology classes are more reliant upon local inventor density than citations within technology classes. If technology class proxies for industry, then Marshall or within industry spillovers are less reliant upon inventor density than Jacobs or across industry spillovers.

Applying inventor death as an instrument, this work establishes the importance of physical presence on knowledge spillovers from other influences on agglomeration such as colocation of production and richer labor markets. Furthermore, by estimating the change in local citations between the deceased and still living inventors, on the same patent but at different distances, this work enables illustration of distance elasticity curves of personal presence and knowledge diffusion. This novel identification confirms the severe localization of spillovers (Jaffe et al. 1993), illustrates how the transmission of even codified knowledge (contained in patents) still depends on physical inventor presence, and illustrates that spillovers occur almost entirely in regions where other inventors also locate, particularly for knowledge flows across technology classes. Knowledge flows across technologies appear to be more reliant upon inventor density than those within technologies, thus supporting Jacobs' arguments regarding the importance of dense urban collections of inventors to the creation of novel technologies and industries.

Data

The U.S. Patent and Trademark Office (USPTO) provides front page patent data; we used data curated by PatentsView and Balsmeier et. al. (2018). The identification strategy relies on a specific set of U.S. patents, such that we can compare citations to still living and deceased inventors on the same patent. This requires the following data cuts, keeping patents only with:

- exclusively US inventors and data
- at least two inventors
- exactly one deceased inventor
- all inventors living in a different city than the deceased inventor
- latitude and longitude data (hometown) for all inventors
- an application date between 1976 and 2000 (the earliest grant year is 1976, and to avoid changes in disclosure laws, which influenced citation patterns (Lueck et al. 2020) only patents prior to the American Inventors Protection Act (AIPA) passed on 29.Nov.2000)
- inventor-id for all inventors (as determined by the USPTO Patentsview: https://api.patentsview.org/doc.html)

This subset of US patents results in 4,509 observations, comprised of:

- 1,415 patents
- 3,283 unique inventors
- 994 deceased inventors (number of lifetime patents ranged from 1-13)

The dependent variable in all cases is the number of citations in a specific region around a specific inventor, for the same multi-author patent, and for the elasticity curves, independent and increasing concentric rings of the distance centered on the home towns of the inventors (deceased and still living) and home towns of citing inventors. In other words, we look at the change in citations in the immediate vicinities of deceased inventor, relative to the citations in the immediate vicinities of the still living inventors. We estimated the results at 10, 25, 50, 75, 100, 150, and 250 or more miles (results were robust to other breakpoints).

We also integrate data on cities, including overall population, land mass, and education, aggregated from census and other government sources, as aggregated by data provided by simplemaps.com. We measure inventor density by the number of inventors in a city, as identified by the front-page patent data of inventor home town.

We estimate three different models for robustness, including an 1) OLS of ln (1 + citations), 2) a linear probability model, and 3) a Poisson model with robust standard errors. While OLS models are widely used for count data, they can suffer from bias, inefficiency, and inconsistency (King, 1988). A linear probability model reduces the influence of outliers. While a Poisson count model assumes an equal mean and variance, robust standard errors ensure consistent estimations (Wooldridge 2002 pg. 649). All models were estimated in STATA and returned consistent results, though the effect sizes and levels of significance varied.

$$\ln\left(1 + Cites_{pri}\right) = \alpha_0 + \beta_1 Deceased_{ip} + \pi_i + \varepsilon_{pri} \quad (1)$$

$$\Pr\left(Cites_{pri} > 0\right) = \alpha_0 + \beta_1 Deceased_{ip} + \pi_i + \varepsilon_{pri} \quad (2)$$

$$E\left[Cites_{pri} | X_{pri}\right] = e^{\left(\alpha_0 + \beta_1 Deceased_{ip} + \pi_i + \varepsilon_{pri}\right)} \quad (3)$$

Distance diffusion elasticity curves

Results are presented graphically in the body of the paper; tabular results are available in the appendix. Figure 1 illustrates the distance diffusion elasticity for the baseline model. As can be seen, and confirming a large number of results around agglomeration economies (Duranton and Puga 2020), the impact of personal communication attenuates quickly; results are clearly negative in the concentric rings closer to the deceased inventor, and grow progressively weaker further out. Figure 2 illustrates how this localized effect attenuates slowly with time.

One threat to identification is the possibility that local inventors change their citing behavior in response to the local inventor's death. For example, the surviving co-inventors might feel that they should cite their deceased colleague more, out of deference to the deceases, or less, because they need not credit the deceased. As illustrated in Figure 3, citations from patent examiners (Alcacer and Gittleman 2006) illustrate that the effect remains even without local inventors (removal of self-cites by co-inventors also has minimal effects on results). Although not shown, splitting the data sample by pendency also indicates no significant differences – within the same patent, the decrease in citations near the deceased is not influenced by how long the patent took to get through the patent office.

If these mechanisms are inter-personal, that is, through private communication and interaction, then the effects should be greater, to the extent that co-inventors are further apart. More distant co-inventors should be less able to substitute for the deceased, and this should be observable in greater effects for more spatially dispersed co-inventors. Figure 4 breaks out co-inventors by their distance to the deceased (either above or below the given threshold) and illustrates distant co-inventors drive almost all of the effect. We would also expect the impact of death to be less within firms, because organizations probably generate and share more documentation between inventors and other organization members. Although not shown, this indeed the case.

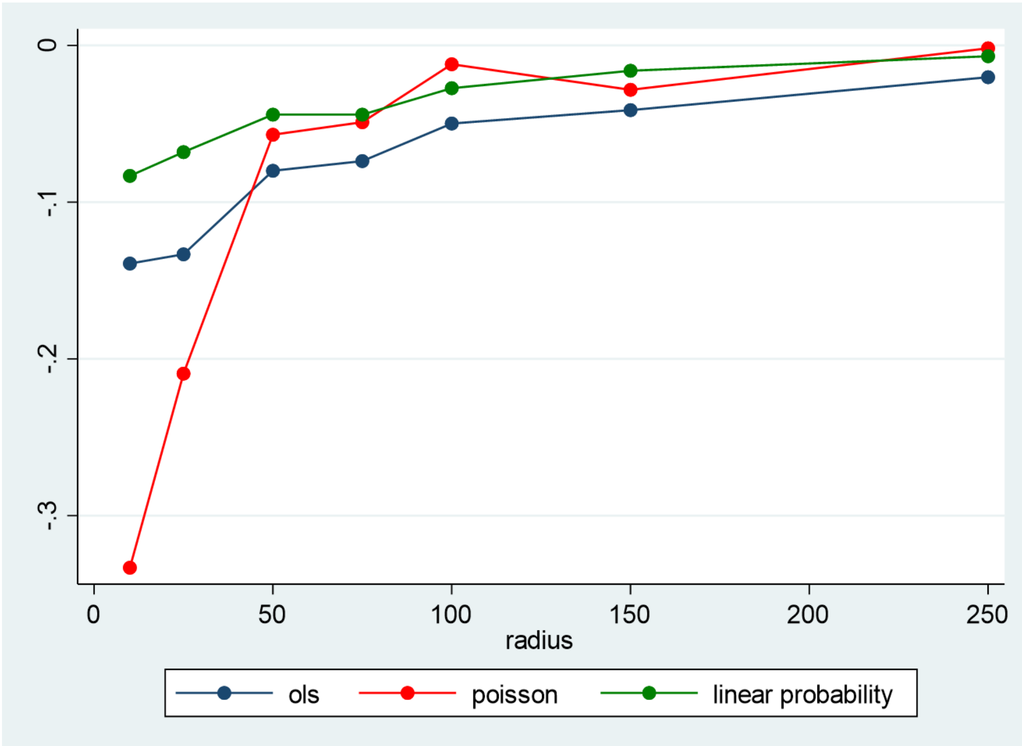

Figure 1: distance diffusion elasticity for baseline model.

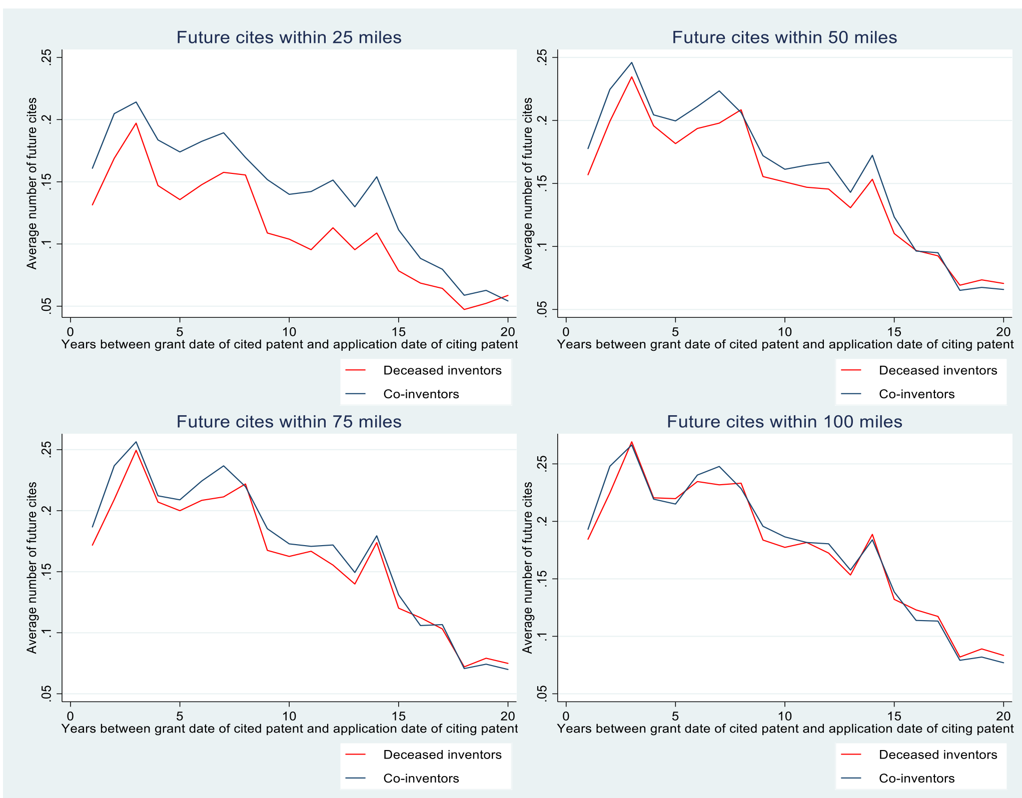

Figure 2: Temporal effects for baseline model.

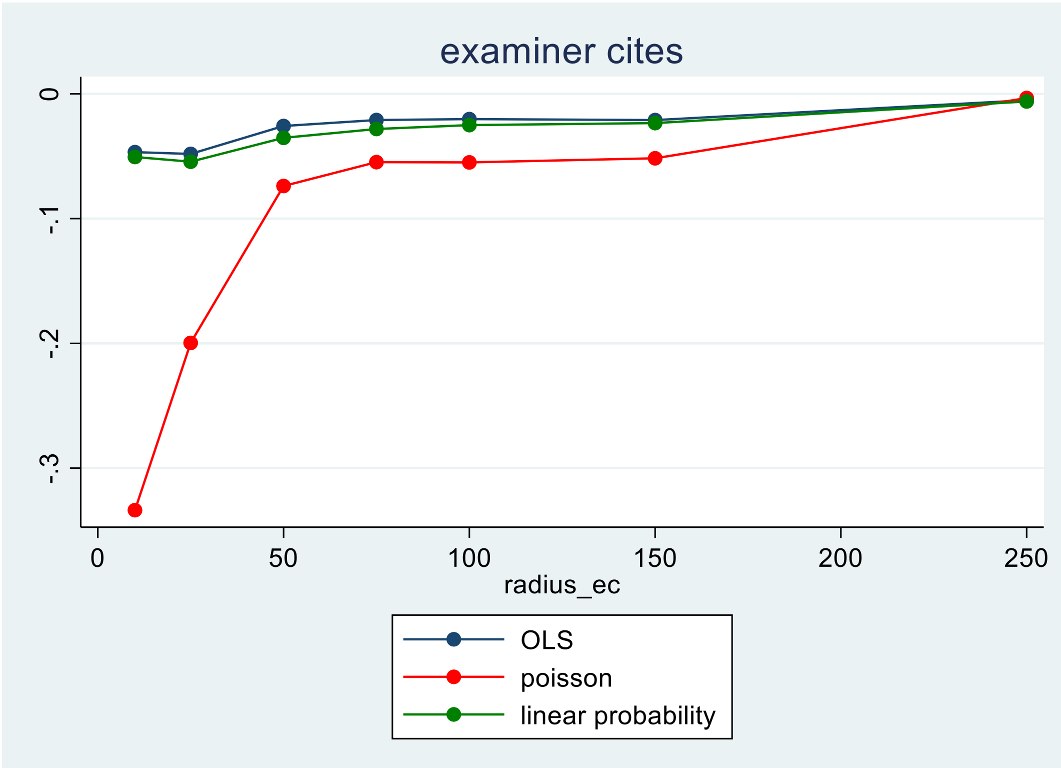

Figure 3: distance diffusion elasticity for examiner citation model.

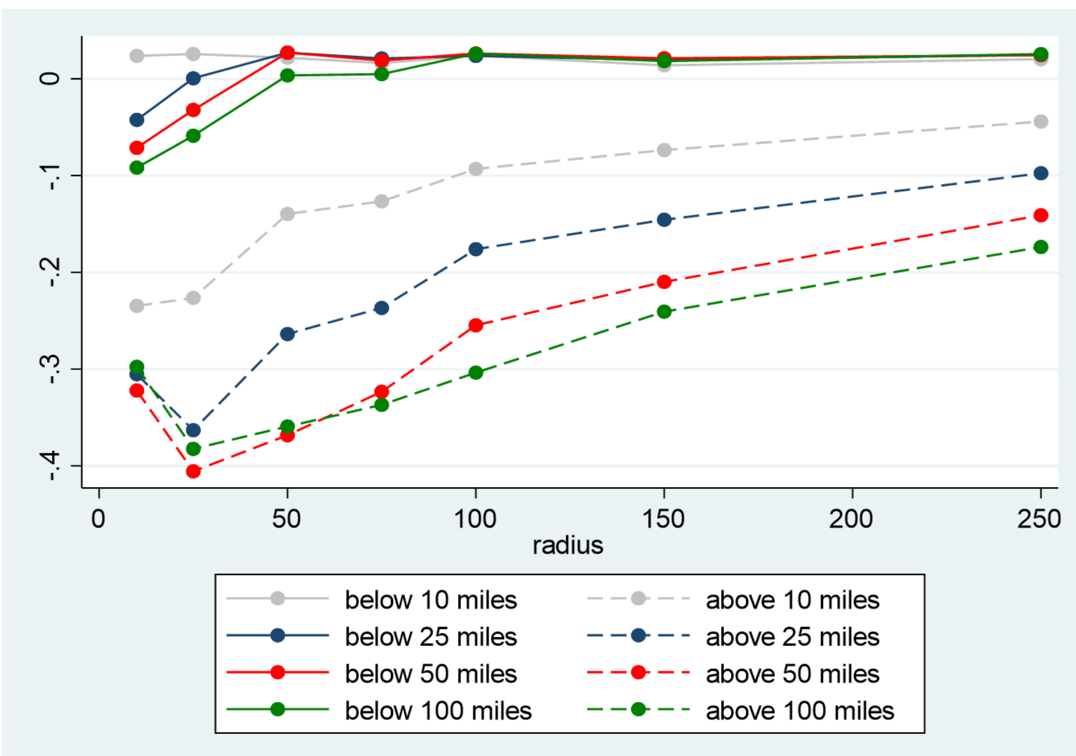

Figure 4: distance diffusion elasticity, for close vs. distant co-inventors.

Density and spillovers

A vibrant literature has demonstrated the importance of physical interaction and knowledge flow for invention (for example, the importance of alcohol and bars, as identified by their closure during prohibition, see Andrews 2020, and the importance of neighborhoods, see Roche 2020). Here we exploit inventor death to better understand where different types of knowledge flow more or less easily. According to Duranton and Puga (2020), “The [JTH matching] strategy cannot show whether density increases interactions nor whether those interactions affect innovation more broadly…social networks in dense urban environments are less characterized by clustering into relatively isolated groups, likely facilitating more widespread information flows.” While we cannot directly assess interactions, we here illustrate the importance of inventor density to knowledge flows, and in particular, to Jacobs spillovers.

Marshall-Arrow-Romer (MAR) spillovers have been defined to occur between firms in the same industry (Glaeser et al. 1992); here we model them as citations between similar technology patents, as measured by similar CPC classes. In contrast, Jacobs (1970) argues for the importance of spillovers from outside a core industry; here we model them as citations between dissimilar technology patents. Prior work has argued over the importance for these two types of spillovers in city formation and growth; here we focus on where these two types of spillovers are most likely to occur, as indicated by the magnitude of their decrease, following the death of an inventor. In particular, we propose, consistent with Jacobs’ arguments, that the unplanned interactions that occur in dense populations are more important for across technology knowledge spillovers. While density should aid all types of spillovers, it should be more important for spillovers between inventors from different fields.

The explanation is quite simple and intuitive; inventors in the same fields need less private communication to transfer or understand knowledge. Hence Jacobs spillovers are more reliant on personal interaction and communication than MAR spillovers, because inventors in the same field need less private communication and explanation to understand (especially codified) knowledge. It’s harder to transfer knowledge, explain a more distant concept, or understand an idea in a different field, such that it’s very helpful to have an expert in that field who can essentially teach. If this argument holds, then the density of inventors in the deceased inventor’s city should have a bigger positive on the transfer of Jacob's (across technology) spillovers, relative to MAR (within technology) spillovers.

Table 1 first splits cities above and below the median of inventor density (calculated as the log of number of inventors/(1,000,000*miles^2)), and then estimates a continuous model in the third column, for citations within 10 miles. In the top panel, the impact of death is greater in above median cities and the interaction of death and continuous density is also negative and significant. Both models thus indicate that the decrease in local citations following death is greater in regions with higher inventor density. The second and third panels of Table 1 split out the citations by within and across technology class cites. From the median models, within class cites are greater for below median density cities, and across class cites are greater for above median density cities. The continuous models demonstrate consistent results.

dependent var log(cites within 10 miles)

	(1) <= median density	(2) > median density	(3) Interaction model
Inventor density			0.020
			(0.014)
deceased_x_density			-0.064**
			(0.028)
deceased	-0.225***	-0.356***	-0.228***
	(0.057)	(0.071)	(0.032)
r2	0.830	0.807	0.780
N	659	730	1874

Note: Inventor Density = log(inventor/miles^2 *1,000,000)

dependent var log(cites from same tech class within 10 miles)

	(1) <= median density	(2) > median density	(3) Interaction model
Inventor density			0.002
			(0.011)
deceased_x_density			0.004
			(0.018)
deceased	-0.195***	-0.074*	-0.112***
	(0.048)	(0.039)	(0.025)
r2	0.894	0.916	0.882
N	659	730	1874

Note: Inventor Density = log(inventor/miles^2 *1,000,000)

dependent var log(cites from diff tech class within 10 miles)

	(1) <= median density	(2) > median density	(3) Interaction model
Inventor density			0.014
			(0.010)
deceased_x_density			-0.009
			(0.014)
deceased	-0.079*	-0.132***	-0.118***
	(0.046)	(0.048)	(0.026)
r2	0.808	0.789	0.750
N	515	513	1409

Note: Inventor Density = log(inventor/miles^2 *1,000,000)

Table 1: OLS regressions, of inventor density on differential in citations, to deceased vs surviving inventors on same patent.

Discussion

These results are consistent with both recent results and classical arguments. More urban locations appear to encourage spillovers across firms, as evidenced by greater citations across classes, arguably from chance meetings (Atkin, Chen, and Popov 2019). Jacobs also suggested that cities facilitate unplanned meetings that result in unintended spillovers (Jacobs 1961). More effective spillover mechanisms also probably contribute to the concentration and productivity of innovative activity (Audretsch and Feldman 1996, Carlino and Kerr 2015, Moretti 2019).

While the results imply that Jacob's spillovers are more reliant upon dense inventor co-location, one could investigate the mechanisms further. For example, Marshallian spillovers may rely upon very similar inventors and Jacobs spillovers might rely upon inventors upon somewhat similar inventors. It would be interesting if spillovers still occur between very dissimilar inventors, that is, those with little or no common basis for communicating. One could define 3 types (or a continuous distribution) of density in a city, all relative to deceased inventor, at varying degrees of granularity, but conceptually based upon the Jaffe correlation measure (1986):

1) inventors with closely similar profile (in exact same set of classes)
2) inventors with overlapping profile (with some sharing of classes)
3) inventors with zero overlap, completely dissimilar profile (without any overlapping classes)

All of these densities might operate completely independently, and hence remain difficult to tease out, since most major urban areas probably have all three.

Results not presented here indicated that the level of a city's STEM workforce demonstrated similar though weaker effects on the decrease in citations following the focal inventor's death. It might be possible that the local density of scientists would also influence the diffusion of knowledge spillovers. Further work should be done to elucidate the social substrate of technical professional networks, through which spillovers appear to flow.

One could also ask what sorts of cities facilitate spillovers, possibly those that encourage chance meetings, job hopping facilitated by local culture and labor law (Marx et al. 2009), and/or those with shorter commute times? These mechanisms would highlight the importance of rich inventor networks, socializing, mobility, and transportation infrastructure. There may also be differences in how the knowledge itself influences its flow, such that different types of technologies and industries need more localized spillovers. Some industries might need to be more localized, and this might change over time as technologies and industries matured. Process knowledge spillovers might rely more on inter-personal interactions than product knowledge spillovers, if process knowledge is more tacit and difficult to codify. Though the data are unfortunately thin, this work could also be extended, using direct and indirect citations, to provide empirical elaboration on the Kerr and Kominers (2015) agglomeration model.

Conclusion

The work makes two main contributions. First, it adds to the aggregation of evidence that spillovers are indeed local (JTH 1989, etc.), and a growing number of empirical innovations (Thompson Fox-Kean, etc.) that strengthen that inference. We used inventor death between the application and grant of a patent to estimate the personal impact of an inventor upon the diffusion of his or her invention from only their geographic location, providing an arguably causal method to isolate knowledge spillovers due to only one inventor him/herself. Most importantly, it avoided a matching of time and technology method that can rarely if ever be perfect. To investigate mechanisms, we established that the effect was stronger for more distant co-inventors, that the local density of inventors is of greater importance than urban population density, and that the density of inventors in a city is more important for Jacobs spillovers, than MAR spillovers.

Prior empirical research has struggled with these differing explanations of agglomeration because they all lead to the same prediction of a local concentration of cites to patents. Hence, while it seems clear that patenting activity and cites are regionally concentrated it remains unclear why this is the case (Arora, Belenzon, and Lee, 2018) and it has proven to be difficult to discriminate between the countervailing explanations (for details see the long ongoing discussion since Jaffee, Henderson and Trajtenberg's (1993) seminal paper and follow up papers by Thompson and Fox-Kean (2005), Murata (2014) and Blit and Packalan (2019)). Evidence of local knowledge diffusion remains indirect in general as it typically originates from the observation of a local concentration of cites to patents but misses a direct link to the specific inventor who is responsible for the invention and assumed to be the actual source of knowledge diffusion.

This work could be interpreted as one possible explanation for the causes of regional inequality between rural and urban locales. Independent of whether rural regions invent less popular or poorer quality patents, or suffer from a lack of human capital, entrepreneurs, or funding, the work of their inventors is simply less known and appreciated. If this lack of awareness translates into poorer valuation, entrepreneurship, and commercial success for the region, then weaker knowledge spillovers in rural regions might contribute to regional inequality.

References

Alcácer, J,. and M. Gittelman 2006. "Patent Citations as a Measure of Knowledge Flows: The Influence of Examiner Citations." *Review of Economics and Statistics* 88:4:774-779.

Almeida, P. and B. Kogut (1999). "The Mobility of Engineers in Regional Networks." *Management Science*, 45: 7: 905-917.

Agrawal, A., and I. Cockburn, J. McHale (2006). "Gone but not forgotten: knowledge flows, labor mobility, and enduring social relationships." *Journal of Economic Geography*, Volume 6, Issue 5, pp. 571–591.

Andrews, M. (2020). "Bar Talk: Informal Social Interactions, Alcohol Prohibition, and Invention," Working paper, University of Maryland.

Anton, J. And D. Yao, (1994). "Expropriation and Inventions: Appropriable Rents in the Absence of Property Rights." *The American Economic Review*, 84(1), 190-209.

Arora, A., Ceccagnoli, M., & Cohen, W.M. (2008). "R&D and the patent premium." *International Journal of Industrial Organization,* 26(5), 1153-1179.

Arora, A. and S. Belenzon, H. Lee, 2018. "Reversed citations and the localization of knowledge spillovers." Journal of Economic Geography 18 (2018) pp. 495–521.

Atkin, David, Keith Chen, and Anton Popov. 2019. "The Returns to Face-to-Face Interactions: Knowledge Spillovers in Silicon Valley." Unpublished.

Audretsch, D. and M. Feldman 1996. "R&D Spillovers and the Geography of Innovation and Production." American Economic Review 86(3):630-640.

Azoulay, P. and J. Zivin, J. Wang (2010). Superstar Extinction. *The Quarterly Journal of Economics* 125:2:549-589.

Balsmeier, B., Assaf, M., Chesebro, T., Fierro, G., Johnson, K., Johnson, S., Li, G., W.S. Lueck, O'Reagan, D., Yeh, W., Zang, G., Fleming, L. (2018) "Machine learning and natural language processing applied to the patent corpus." *Journal of Economics and Management Strategy,* 27:535–553.

Baruffaldi., S. & Simeth, M. (2018). "Patents and Knowledge Diffusion: The Effect of Early Disclosure." Available at SSRN: https://ssrn.com/abstract=3160533.

Belonzon, S. and M. Shankerman (2013). Spreading the word: geography, policy, and knowledge spillovers. *The Review of Economics and Statistics*, Vol. 95, No. 3, pp. 884-903.

Carlino, Gerald, and William R. Kerr. 2015. "Agglomeration and Innovation." In Handbook of Regional and Urban Economics, volume 5A, edited by Gilles Duranton, J. Vernon Henderson, and William Strange, 349–404. Amsterdam: Elsevier.

Duranton, and Puga (2020). "The Economics of Urban Density." *Journal of Economic Perspectives*, 34:3:3–26.

Glenn E., E. Glaeser; W. Kerr (2010). What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns *The American Economic Review*. 100(3):1195-1213.

Feng, S. (2019). The Proximity of Ideas: "An Analysis of Patent Text Using Machine Learning," Working Paper, NYU Stern School of Business.

Ganguli, I., and J. Lin, N. Reynolds 2019. "The Paper Trail of Knowledge Spillovers: Evidence from Patent Interferences," Federal Reserve Bank of Philadelphia WP 17-44.

Glaeser, Edward, Heidi D. Kallal, José A. Scheinkman, and Andrew Shleifer. 1992. "Growth in Cities." Journal of Political Economy 100 (6): 1126–52.

Jacobs, J. 1961. The Death and Life of Great American Cities New York: Random House.

Jacobs, J. 1970. The Economy of Cities. New York: Vintage Books.

Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. American Economic Review, 76 (5), 984–1001.

Jaffe, A. and G. Rassenfosse (2017). "Patent citation data in social science research: Overview and best practices." *Journal of the Association for Information Science and Technology.* 68:6:1360-1374.

Jaffe, A. M. Trajtenberg and R. Henderson (1993). Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations**.** *The Quarterly Journal of Economics* Vol. 108, No. 3, pp. 577-598.

Jaravel, X. and N. Petkova, A. Bell 2018. "Team-Specific Capital and Innovation. American Economic Review VOL. 108, NO. 4-5, APRIL 2018 (pp. 1034-73).

King, Gary. 1988. Statistical models for political science event counts: Bias in conventional procedures and evidence for the exponential Poisson Regression model. American Journal of Political Science 32(3): 838-863.

Kerr, William, and Scott Duke Kominers. 2015. "Agglomerative Forces and Cluster Shapes." Review of Economics and Statistics 97 (4): 877–99.

Krugman, P. (1991). Geography and Trade, MIT Press, Cambridge, MA.

Lueck, S., Balsmeier, B. , Seliger, F., Fleming, L. (2020). "Early disclosure of patents and reduced duplication; an empirical test." *Management Science*, articles in advance, March 13 2020.

Marshall, Alfred. 1890. Principles of Economics London: MacMillan.

Marx, M. and D. Strumsky, L. Fleming "Mobility, Skills, and the Michigan Non-compete Experiment," *Management Science*, 55 (2009): 875-889.

Marx, M. and J. Singh 2013. "Geographic Constraints on Knowledge Spillovers: Political Borders vs. Spatial Proximity." *Management Science*, 59:9:2056–2078.

Moretti, E. 2019. "The Effect of High-Tech Clusters on the Productivity of Top Inventors." NBER Working Paper 26270.

Roach, M. and W. Cohen 2013. "Lens or Prism? Patent Citations as a Measure of Knowledge Flows from Public Research." *Management Science* Vol. 59, No. 2, pp. 504–525.

Roche, M. 2020. "Taking Innovation to the Streets: Microgeography, Physical Structure, and Innovation." Review of Economics and Statistics 102:5: 912-928.

Thompson, P. and M. Fox-Kean (2005). "Patent citations and the Geography of Knowledge Spillovers: A Reassessment." American Economic Review, 95: 1: 450-460.

Wooldridge, J. 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge, MA.

Appendix

Cites within x miles	Obs	P25	P50	P75	Mean	SD	Min	Max
10	4509	0	0	1	2.48	8.89	0	172
25	4509	0	0	3	3.85	11.86	0	198
50	4509	0	1	3	4.58	13.55	0	200
75	4509	0	1	4	4.86	13.81	0	200
100	4509	0	1	4	5.17	14.42	0	200
150	4509	0	1	5	5.68	15.33	0	200
250	4509	0	2	6	6.70	16.84	0	208

Table A1: citations within given radii. Distance is defined as the minimal distance between the city center of the deceased/still living inventor of the cited patent and the city center of any inventor of the citing patent.