Isolating the inter-personal mechanisms of absorptive capacity

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Preliminary and still doing robustness checks – please consume skeptically (and all feedback gratefully received).

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Abstract: We return to the cognitive foundations of absorptive capacity and test the idea that personal experience in a field makes it easier for an inventor to recognize and build upon local knowledge spillovers across firms in that field. Using inventor deaths and differential citations between regions with a deceased and still-living co-inventor of the same patent, we first provide causal evidence for the localization of knowledge spillovers across firms. We then establish that inventors with experience in a field are more likely to take advantage of local sources of knowledge, but that the value of absorptive capacity is greatest when they link the old knowledge to new fields of technology. Finally, inter-personal knowledge flows within firms do not appear to localize. We discuss implications for innovation strategy, location choice as a form of dynamic capabilities, and interpreting the results as evidence for Jacobs' spillovers.

JEL-Classification: O31, O33
Keywords: Absorptive Capacity, Knowledge spillovers, Patents, Inventor death, Agglomeration

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1. Introduction

The importance of knowledge spillovers across firm boundaries has remained central to economics for over a century, and arguably contributed to at least three Nobel prizes (Marshall 1890; Arrow 1962; Romer 1986; Krugman 1991). The implications of knowledge spillovers for firms quickly emerged as a central theme in the early strategy literature as well (Cohen and Levinthal, 1990; Teece et. al. 1997). Absorptive capacity (ABS) argued that firms must first invest in the capacity to understand outside knowledge before they can recognize, use, and benefit from spillovers (Cohen and Levinthal 1990). It has proven to be one of the most influential theories in strategy and has inspired work in economics and other fields (Aghion and Jaravel, 2015).

Despite its already widespread impact, ABS has remained vulnerable to theoretical and empirical critiques, "In its most reduced form, the theory holds that a firm's benefit from external knowledge increases with the level of its own R&D…the phenomenon currently ascribed to absorptive capacity is instead an artifact of prior empirical constraints." (Knott 2008, pg. 2054-5) While an undeniably influential idea, subsequent theoretical and empirical research has often struggled to find sharp and causal tests of hypotheses, arguably due to a lack of specific mechanisms and the difficulty of randomizing the availability of knowledge outside a firm's boundaries.

While the theory of absorptive capacity implicitly acknowledges the importance of the individual – indeed, its first pages (Cohen and Levinthal 1990) explicitly built upon cognitive and psychological models of learning and creativity – the strategy field has typically focused on the firm as the level of analysis. Lack of attention to individuals shouldn't surprise, however, given that the strategy field by definition seeks to understand organizational level advantage. Furthermore, ABS theory was formulated before widespread availability of data on individuals. In addition to their paradigmatic focus, strategy researchers lacked motivation to ponder the micro-foundations of ABS, because by and large, such foundations could not be observed, let alone rigorously tested.

Despite the firm level focus, knowledge spillovers ultimately flow between individual employees of different firms. Fortunately, and since the initial formulation of these theories, individual level data has become widely available; for example, it is now possible to observe all the patenting inventors inside a firm, and if one accepts the convention that a citation is at least correlated with some kind of knowledge flow (Jaffe et.al., 1993; Roach and Cohen 2013), one can trace the flow of knowledge from one inventor to another – both within and across firm boundaries. Combining these data with advances in methods, and in particular, quasi-experimental and arguably causal research designs, opens up the opportunity to better test the observable implications of absorptive capacity.

We argue that ABS can be usefully decomposed into 1) distinct mechanisms of absorption and 2) externally available knowledge that might be absorbed through that distinct mechanism. This enables theoretical elaboration of specific mechanisms, measurement of a firm's capabilities of those specific mechanisms, and empirical identification of exogenous changes in externally available knowledge that might be absorbed though specific mechanisms. This decomposition remains consistent with the original formulation, "A key assumption in the model is that exploitation of competitors' research findings is realized through the interaction of the firm's absorptive capacity with competitors' spillovers." (Cohen and Levinthal, 1990, pg. 141)

Acknowledging a range of plausible pathways for absorptive capacity, we focus on the mechanism of inter-personal knowledge spillovers. Confirming a great deal of prior work, and identifying both the personal source and destination of individual spillovers, we first establish that such spillovers localize. We identify such inter-personal spillovers by extending a causal method of estimation that compares local citations to the same collaborative patent, in regions with a recently deceased inventor, relative to regions where her co-author remains alive. Returning to the original definition (Cohen and Levinthal 1990), we measure a firm's absorptive capacity by its inventors' experiences in specific fields. This enables us to establish that an inventor's experience in a field increases their ability to make use of inter-personal knowledge spillovers, and that this effect is geographically localized. Again, consistent with the original formulation, absorptive capacity appears to matter most when inventors apply prior knowledge to create linkages into new fields. Finally, and in contrast to spillovers across boundaries, we illustrate in the discussion that knowledge flow within firms does not appear to localize.

2. Theory

All firms have the potential to absorb knowledge from other firms, through a variety of mechanisms. Firms vary greatly, however, in how effectively they can exploit different mechanisms of absorptive capacity, for example, can they reverse engineer a competitor's product, read and understand a competitor's science publications, or take advantage of local knowledge spillovers? They also vary in their potential exposure or opportunity to exploit the different mechanisms, for example, are their competitor's products physically accessible, do their competitors publish in the science literature, and are their competitors located nearby. Here we focus on local knowledge spillovers across firms as the source of external knowledge and measure a firm's absorptive capacity as the pertinent experience and "personal absorptive capacity" of their inventors. We exogenously vary the availability of the source of spillovers through a natural experiment, namely the death of an inventor at another local firm. This experiment can isolate and provide insights into one micro-mechanism of ABS.

There are many sources of new and external information for firms, for example, hiring, consulting, science papers, media, or product information. Each of these sources operates with different mechanisms and provides a different external and potential "conduit" by and through which knowledge can be recognized, assimilated, and applied. The conduit of inter-personal knowledge spillovers from other firms is localized (Balsmeier et. al. 2023), and this has not been highlighted to date in the ABS literature – that one possible and possibly very important conduit of ABS relies on the local and geographic context which firms operate in. A firm which operates near another firm makes itself vulnerable (in both positive and negative ways) to potential knowledge spillovers (Alcacer and Chung, 2007), through inter-personal knowledge spillover mechanisms.

Understanding the inter-personal mechanisms of localized knowledge spillovers and absorptive capacity requires consideration of both the original source and destination of the knowledge spillover. Foreshadowing our identification strategy, we will define an inventor who dies during patent pendency as the "source inventor." Restricting our analysis to co-authored patents whose inventors live in different regions, we will consider all inventors on all realized patents at other firms within a particular distance radius and a given time period around the deceased and still-living inventors as "destination inventors." We will measure the ABS of the realized destination inventors with their prior patenting record – if they have invented in the same field as the source patent, we consider them as possessing ABS in that field. Identification will come from observing local citations in regions around still-living co-authors (where the external source of inter-personal spillovers remains available), relative to local citations in regions around the deceased inventor (where the source of inter-personal spillovers becomes unavailable).

Hypotheses:

Knowledge can flow across firm boundaries in many ways, for example, in the hiring of competitors' employees, reading of published literature, reverse engineering of products, and the focus here, through the inter-personal interactions of employees that work at different organizations. Some of these interactions are intended, for example, engineers can be reluctant to seek help within their own firm, due to the fear of embarrassment and negative assessments by management. As a result, they often ask friends they can trust in outside firms (Allen 1977). Other interactions may not be intended, such as eavesdropping in the local coffee shop.

While some firms pursue strict norms that proscribe such knowledge flow and regularly warn their employees that they will be prosecuted, most often following publicized leaks (Mickle, 2023), such norms vary greatly, in their intent and effectiveness. Regional norms also vary, for example, Silicon Valley engineers from competing firms have been described as particularly collaborative, in bars and other public places, and the region's success has been partly attributed to this generous knowledge flow across firm boundaries (Saxenian 1994). Densely agglomerated clusters of firms, such as occur in Silicon Valley, increase the chance of random encounters and both intended and unintended sharing.

While inter-personal knowledge flow can certainly occur at a distance – the time period we study includes the transition from the rotary dial telephone to smart phones and Zoom – they are much more likely as geographic distances shrink; longer geographic distances impose higher costs for interacting in person. Inter-personal mechanisms of spillovers usually rely upon physical presence of the source and destination and are much more likely to occur when people are physically proximal. Despite advances in communications and transportation technology, people are far more likely to interact if they are geographically proximate, for example, if they work together, socialize after working, attend a professional (or any physical) event together, pass each other on the street, sit next to one another in a restaurant, or see one another at a shopping mall, Little League game, or school event.

As the physical distance between the source and destination inventors increases, inter-personal knowledge flows will decrease. This will be particularly important for more recent, complex, and tacit knowledge that can be more effectively transmitted through personal contact. Old information, such as that published in textbooks, will be less localized, as it is already more widely known and available in the absence of the author.

The argument that knowledge spillovers localize is old (Marshall, 1890; JTH 1993; Thompson and Fox-Kean, 2005; Roche 2020), however, here we focus on inter-personal mechanisms and establish that particular mechanism in the first hypothesis, before elaborating on the strategic implications of localized knowledge spillovers in later hypotheses.

H1: Inter-personal knowledge spillovers localize.

We now elaborate upon the theory of ABS by clearly specifying both the particular mechanism of absorption and the specific source of external knowledge. Building on H1, localized inter-personal knowledge spillovers provide one example of knowledge that is externally available to a local firm. Firms with appropriate ABS – in this case, an ability to learn from and absorb inter-personal knowledge spillovers - should be better able to take advantage of localized knowledge through this ABS mechanism. This implies first establishing the ABS of a firm's inventors, and then observing the likelihood of application, when a source of knowledge is - or is not – locally available.

Closely following the original arguments of ABS, we propose that inventors with experience in the field of the available knowledge source will have greater absorptive capacity in that field. An inventor with extant cognitive structures in a field will have a much easier time understanding, recognizing, and applying knowledge in that specific field. For example, if a firm's inventor has a background in semiconductors or biotech, then s/he will be better able to absorb and take advantage of locally available knowledge in semiconductors or biotech, respectively. Empirically, this implies that an inventor that has invented in semiconductors previously is more likely to take advantage of a locally available source of inter-personal knowledge spillovers, relative to a local inventor without semiconductor experience.

H2: Absorptive capacity enables a firm's inventors to take greater advantage of localized inter-personal knowledge spillovers.

Hypothesis 2 proposes that ABS makes the absorption and application of external knowledge easier. This argument might be incomplete, however – the advantage of experience could also vary with the difficulty of creative recombination. Building upon cognitive arguments, the original authors of absorptive capacity propose that, "…prior knowledge facilitates the learning of new related knowledge…prior possession of relevant knowledge and skill is what gives rise to creativity, permitting the sorts of associations and linkages that may have never been considered before." (Cohen and Levinthal 1990, pg. 129 and 130, respectively).

These arguments imply that an inventor with experience in the field of the source technology will be better able to absorb, apply, and link the knowledge in new and creative ways. If the recombination is easier, or "close", incremental, and an exploitation within a field, the value of experience should be smaller. If the recombination is more difficult, or "distant" and explores a combination across fields, the value of pertinent experience - of absorptive capacity in the relevant field - should be greater.

The argument can be re-stated from the perspective of and in the language of the regional economics literature, and in particular, by characterizing a spillover as a MAR, or within industry spillover (Glaeser et. al. 2012), and a Jacobs, or across industry spillover (Jacobs, 1969). A MAR spillover should be easier and less dependent upon the pertinent experience of the receiving node, because the cognitive demands of working within a field will be less. Empirically, invention within and application of externally available knowledge to the same technology field will depend less on ABS. A Jacobs spillover, however, will be more cognitively difficult and more dependent upon the pertinent experience of the receiving node. Empirically, invention outside the source field and recombination with a new field will depend more on ABS. Note that this hypothesis does not argue that MAR spillovers are more and Jacobs spillovers less common, rather, that the importance of absorptive capacity will be greater for Jacobs spillovers.

H3: The advantage of absorptive capacity will be greater for the creation of knowledge that links the prior knowledge to a new field.

3. Identification strategy

How might we estimate the causal impact of absorptive capacity? As argued above, there exist many conduits for ABS; here we focus upon an inventor's experience in a field, and vary the availability of external knowledge. The problem can be reconceptualized as estimating the causal impact of an inventor's presence on the geographic flow of knowledge to another inventor. Consider first an idealized experiment where: 1) two people hold the exact same knowledge, 2) one person becomes randomly unavailable, and 3) the risk set and characteristics of every potential recipient of the knowledge (for both the unavailable and available person) can be observed. We propose that patent data can provide something close to this stylized experimental setup, when two co-inventors of the same patent live far away from one another, one of them dies after application but before the patent grant, and the location and characteristics of all future inventors who might use the knowledge can be observed.

Figure 1 illustrates an idealized experiment with stylized patent data for explanation (the empirical reality is more complex, for example, multiple co-inventors and overlapping radii, and detailed at length in the appendices). Figures 2a to 2c show a corresponding example from real data. The approach makes three empirical assumptions. First, we assume that two co-inventors of the same patent hold the exact same piece of knowledge. Second, we assume that death makes a person unavailable to aid in the transmission of knowledge. Third, we assume that the different locations of the deceased and still living co-inventor allows us to separate future inventors into those who are close to the deceased inventor (and can be thought of as the treated group) from inventors who are close to the still living co-inventor (and can be thought of as the control group). Both groups of future inventors should be exposed to the exact same knowledge, i.e., the deceased patent, but the control group resides close enough to have easier in-person access to a living inventor of the patent.

The goal is to estimate the average propensity of all inventors living within circle A to cite patent *p*, relative to all inventors living within circle B. Note that under the null hypothesis that citations do not represent knowledge spillovers, we would not expect to find any significant difference in these propensities to cite. Furthermore, since we compare differentials *within* a patent, our approach should be immune to potential bias from unobserved reasons to cite patent *p* - other than being close to the still-living co-inventor. In other words, estimating effects within patents effectively rules out any observable or unobservable patent characteristic that influences the propensity to cite. Not needing to rely on matching two different inventions or similar but differently codified, prosecuted, or assigned versions of an invention is the key strength of this approach.

Figure 1: idealized empirical situation for testing the impact of personal presence on knowledge diffusion.

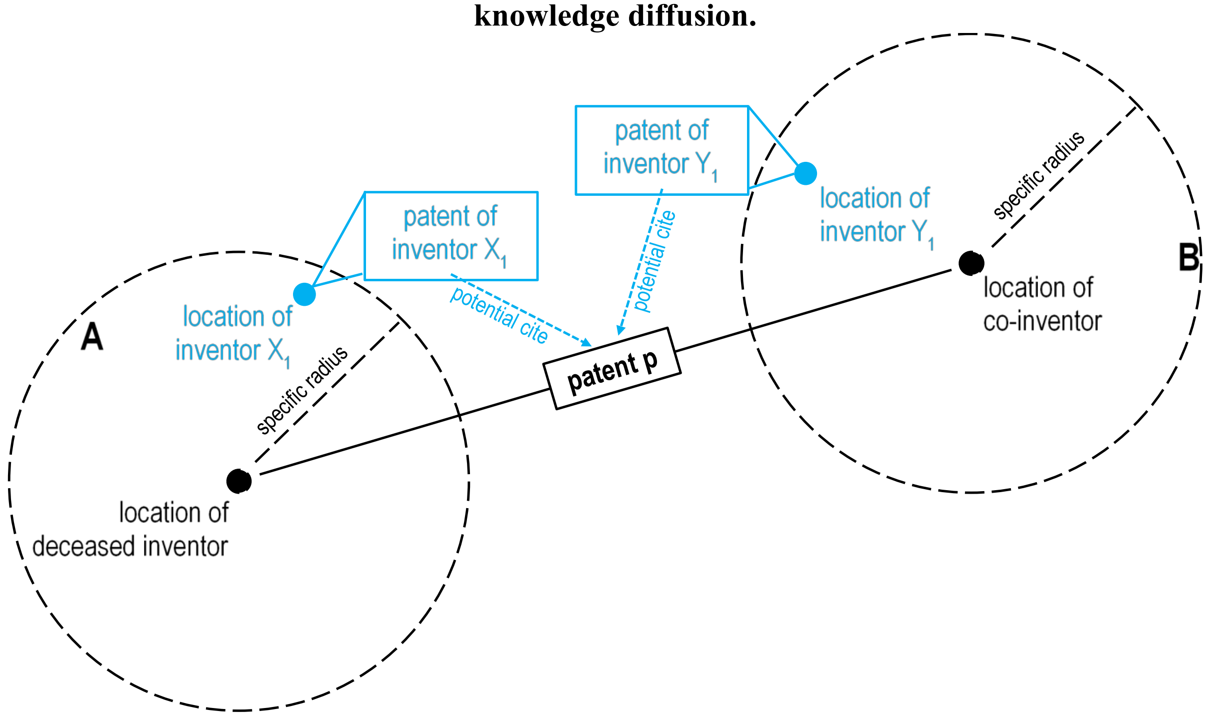
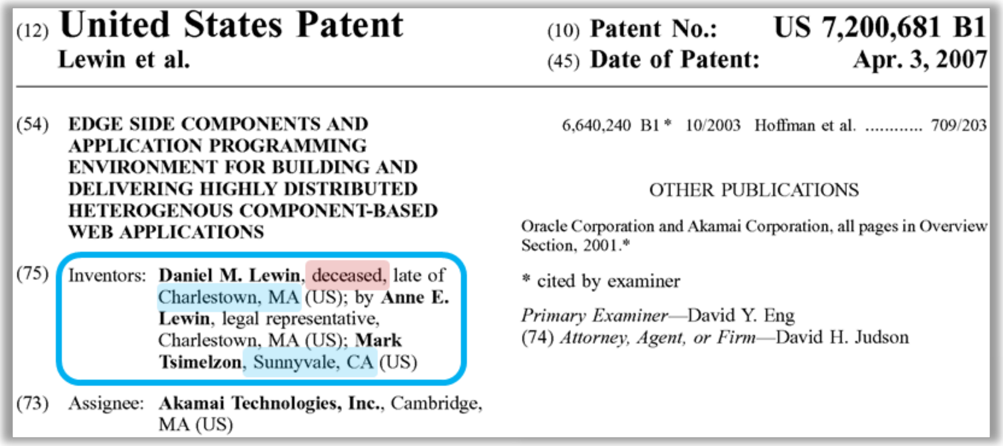


Figure 2a: Excerpt of original US patent (7,200,681) front page with information on deceased and still living co-inventor resembling the stylized experiment above (Figure 1)



(12) **United States Patent**
Lewin et al.

(10) **Patent No.: US 7,200,681 B1**
(45) **Date of Patent: Apr. 3, 2007**

(54) **EDGE SIDE COMPONENTS AND APPLICATION PROGRAMMING ENVIRONMENT FOR BUILDING AND DELIVERING HIGHLY DISTRIBUTED HETEROGENOUS COMPONENT-BASED WEB APPLICATIONS**

(75) Inventors: **Daniel M. Lewin**, deceased, late of Charlestown, MA (US); by **Anne E. Lewin**, legal representative, Charlestown, MA (US); **Mark Tsimelzon**, Sunnyvale, CA (US)

(73) Assignee: **Akamai Technologies, Inc.**, Cambridge, MA (US)

6,640,240 B1 * 10/2003 Hoffman et al. 709/203

OTHER PUBLICATIONS

Oracle Corporation and Akamai Corporation, all pages in Overview Section, 2001.*

* cited by examiner

Primary Examiner—David Y. Eng
(74) *Attorney, Agent, or Firm*—David H. Judson

Figure 2b: Mapping of deceased and living co-inventor of patent 7,200,681

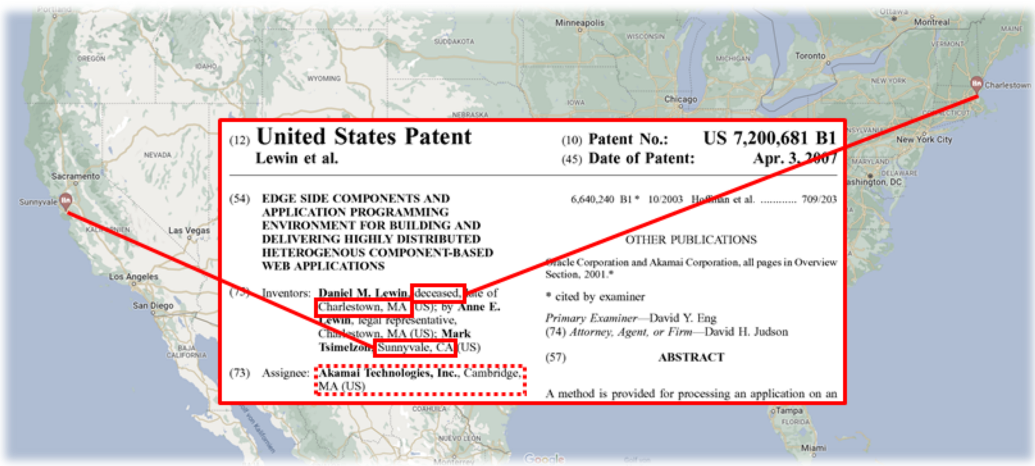
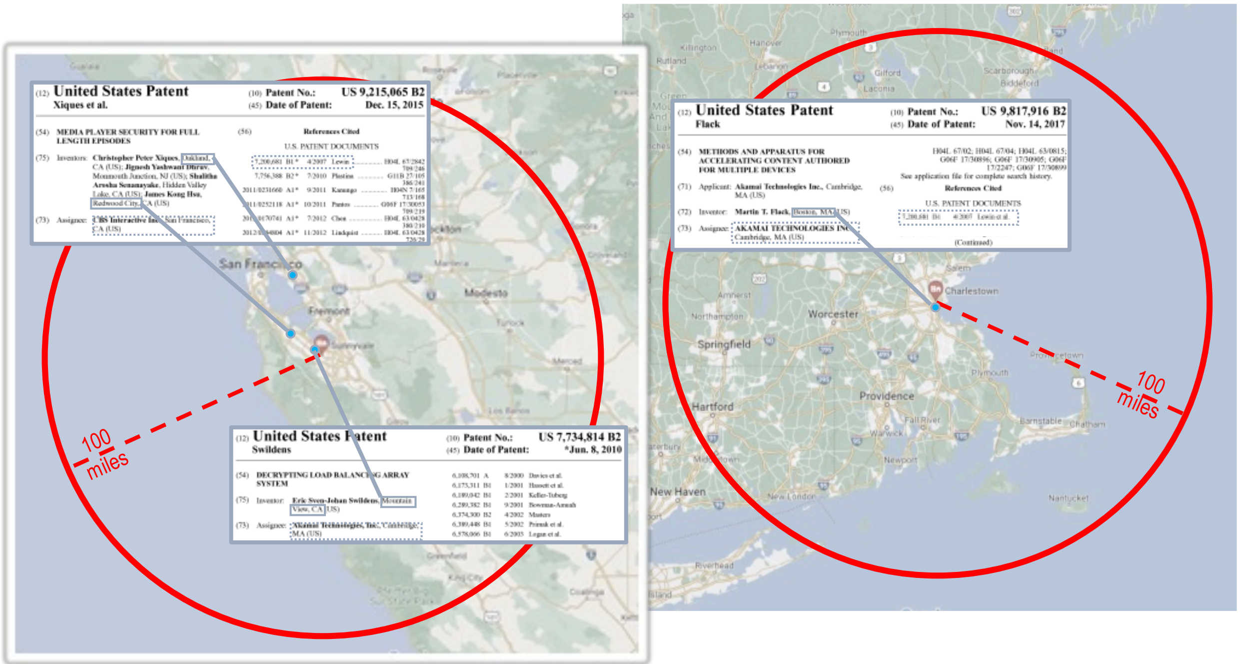


Figure 2c: Zoom into deceased and living co-inventor locations of patent 7,200,681



The approach makes two identifying assumptions. First, from the perspective of the inventors in circles A and B, it is equally likely to be exposed to the deceased inventor. This implies that where inventors die is quasi random and that death remains orthogonal to any location characteristic. In other words, inventors are not more or less likely to die where companies of the same industry co-locate, local labor market conditions are not particularly good or bad, or universities are in close proximity. The second assumption is that inventor death has no direct effect on the co-inventors' likelihood of being cited from within a certain radius, as might arise, for example, if inventor death had a negative impact on the future productivity of co-inventors (Javarel et al. 2018; Azoulay et al. 2010).[1] To minimize any such confounding influence in the first place we remove all follow-on work by co-inventors, as well as citations where any of the deceased patent's inventors appear as a citing inventor on a future patent.

[1] We check the first assumption by considering deaths by younger inventors. "self-cite" means that at least one inventor of the cited patent is identical to an inventor of the death patent. To the extent that third parties are indirectly negatively affected by the still living co-author, we note that this would work against us finding a significant effect.

The identification strategy goes beyond Balsmeier et al. (2023) by explicitly shifting the focus from only the source of knowledge spillovers to both the source and the destination. At the cost of much more computation and data analysis, it takes all potential spillover destinations within a given radius into account, as opposed to focusing only on the actually realized spillovers. It enables more accurate estimation of the differences amongst citing inventors, e.g. whether they work at the same company. In this particular instance, the likelihood of internal knowledge diffusion, as opposed to external knowledge spillover, is probably sensitive to how many inventors live locally and how many inventors work for the same firm. For example, we would expect significant differences, for rural and possibly one company towns, where most potentially citing inventors work for the same firm, as opposed to the center of Silicon Valley, where tens of thousands of inventors work for different firms and still reside within close vicinities.

Econometrics

Now we translate our identification strategy into an equation and data structure that enables us to estimate how an inventor influences the local diffusion of knowledge about a given patent. Resembling the perspective of the potential recipients of a knowledge transfer, we aim to estimate the relative difference in the propensity to cite a given patent *p* by an inventor within a certain radius *r* to the deceased inventor as compared to the propensity to cite the same patent *p* by an inventor who resides within the same sized radius to the still-living co-inventor of the same patent *p*. As the dependent variable is a dichotomous variable taking value one in case of an observed citation of patent *p* and zero otherwise, we estimate assumedly independent Probit models (results remain robust to alternatively estimating LPMs, please see Appendix):

$$\Pr(Cite_{ijrpt} = 1|X) = \Phi(\alpha_0 + \beta_1 Deceased_{jp} + \pi_p + \varepsilon_{ijrpt}) \quad (1)$$

where $Cite_{ijrpt}$ indicates a cite that comes from an inventor i within radius *r* of the location of inventor j for the same multi-author patent p within a time window of *t* since grant of *p*. $Deceased_{jp}$ indicates the inventor who died after application but before the grant of patent *p*. $\Phi(\cdot)$ is the cumulative standard normal distribution function, π_p is an indicator for patent fixed effects, and ε_{ijrpt} is the error term.

We present results for differing radii ranging from *r=10* miles to *r=100* miles. This implies 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. Since we hold the cited (deceased) patent constant, any measurable difference in the propensity to cite should only come from differences in the local exposure to the deceased vs. still-living inventors -- and not from any characteristic of the deceased patent. In other words, we identify the effect from the difference in the citation propensity from the immediate vicinities of the deceased inventor, relative to the citation propensity from the immediate vicinities of the still living co-inventors.

Data

The data structure follows our econometric specification. The unit of observation is a potentially citing inventor from within a certain radius around the deceased or still living co-inventors. We consider each observed patent with a deceased inventor and at least one differently located co-inventor(s) a quasi-natural experiment and combine them in one analysis sample to isolate and estimate the average local impact of an inventor. That implies that a potentially citing inventor may appear multiple times in the analysis sample if that specific inventor was at risk of citing different deceased patents at a given time.

Building the analysis sample starts with the population of all US patent inventors that appear on at least one patent issued by the U.S. Patent and Trademark Office (USPTO), from 1976 through 2005, during which time inventor deaths appear on the front page of the patent grant document. US inventors that died after application but before grant are often missing in many secondary patent data sources but appear as originally published on the USPTO html files (example in Figure 2a). We scraped all html data as described in Balsmeier et al. (2018) and kept only patents with at least two US inventors, with exactly one deceased inventor, and co-inventors who resided in a different city than the deceased. This leaves us with a total of 1,621 patents with exactly one deceased inventor that we consider quasi natural experiments. The total number of inventors on these deceased patents is 5,491. The distribution of inventors per patent (including the deceased) is skewed with most patents having two (41%), three (26%) or four inventors (14%), and the maximum of one patent with 18 inventors. Co-inventors tend to live relatively close to the deceased inventor at a median distance of 25 miles and an average of 284 miles, though some inventors

(13.2%) live more than 500 miles apart from the deceased. The number of patents applied for and granted per year ranges between 1 and 100, with higher numbers in the 1990s.

The U.S. city and state for each inventor comes from the front page of the original patent document. As the original location data suffers from inconsistencies in location names and misspellings, we disambiguated all city-state combinations, and used the Google maps algorithm to identify remaining cases (for example, some inventors list a neighborhood or unincorporated township). Latitude and longitude data come from SimpleMaps. [2]

We then identified all *potentially* citing inventors from future US patents (within a 10 year citation window as a baseline) that reside within a certain radius around each inventor of a deceased patent, i.e. deceased and alive co-inventor. Citation data comes from the USPTO Patentsview database.[3] Locations of all potentially citing inventors were again disambiguated and longitude/latitude information added from SimpleMaps, enabling calculation of the geographic distance between each potentially citing inventor to each inventor of a deceased patent. Resembling an experimental setup as close as possible we exclude all potentially citing inventors that live in overlapping regions of the radii around the deceased and living co-inventors. Locations of all inventors on the potentially citing patents were again disambiguated and longitude/latitude information added from SimpleMaps. As the discussion of ABS mechanisms centers around across firm spillovers, we restrict our analysis sample further towards potentially citing inventors from different firms as the deceased patent. Data on each patent's assignees comes from the Patentsview database.

Since inventor deaths are spread out over many years and the entire country (see map in the Appendix), many US inventors were at some point at risk of citing a deceased patent. We observe a total of 1,669,992 million potentially citing inventors (within 100 mile radii). In fact, over their entire patenting career and considering a ten-year potential citation window, most of them were residing within 100 miles of multiple death events. Recall that our identification strategy relies on considering each deceased inventor as an independent quasi-natural experiment such that all inventors that were exposed to the treatment (death) will enter the risk set each time someone died

[2] https://simplemaps.com, accessed Nov. 26, 2020.
[3] https://patentsview.org/download/data-download-tables

within a given radii. This results in between 12,488,242 (10 mile radius) to 38,047,431 (100 mile radius) data points in the analysis sample. For detailed descriptive statistics see Table 1. To ease interpretation, consider 10 deceased inventors in Silicon Valley. Our approach implies that each time an inventor died in Silicon Valley, *all* Silicon Valley inventors that ever patented within ten years after death will enter the risk set each time an inventor deceased. The same applies to all still living co-inventors of the same patent of the deceased inventor, who will typically also reside in a technological hub. Further, most deceased inventors had more than one co-inventor, each of which generates a control group of its own. Hence, the number of observations around the still living inventors is significantly larger than around the deceased inventors. Noteworthy, our estimates will not be biased by the higher number of observations around the living inventors because we will estimate the average propensity to cite a given patent at the potentially citing inventor level. In this case we will only find a significant higher citation propensity around the living if the total amount of observed citations relative to the total amount of inventors at risk of citation is higher in the regions around the living as compared to the regions around the deceased inventor of the same patent. As a final remark on the descriptive statistics, each sample (10 to 100 miles radii) include a different number of cited patents because we can empirically identify effects only from inventors at risk of citation residing outside the overlapping regions of the radii we draw around the deceased and living co-authors. In some case, we find inventors at risk only inside overlapping regions, leading to the exclusion of those patents from the sample. For the same reason, we can neither include patents without any citation occurring from non-overlapping regions.

Regarding the deceased patents only, the average number of cites that occur within 10 miles of a sampled inventor is 2.17, and increases to 5.55 within 150 miles. The number of cites is right skewed, with a median of zero or one, a maximum of 273 cites, and a high share of zeros ranging between 43% and 72% for the full analysis sample, over the entire available citation data. 31% of citations arise within 5 years, 59% within 10 years, and 80% within 15 years since patent grant. Since the last observed year of patent grant of the deceased patents is 2008 we observe at least a ten-year citation window for every patent which will thus also be our baseline citation window (while the last application date in the deceased sample is 2005, there is typically a delay or "pendency" for applications to be granted as patents by the USPTO, hence the last observed patent in the analysis sample was granted in 2008). We observe 15% of potentially citing inventors residing within 10 miles, 19% within 20 miles, and 28% of citations within 150 miles of the inventors on the deceased patents. Deceased and still-living co-inventors do not appear to live in different areas, in particular, the U.S. geographic centroid is only 18 miles apart for the two groups (please see Appendix for a graphical illustration of the geographic dispersion of deceased and living co-inventors across the US).

Table 1: Descriptive statistics of analysis sample

Radii	Obs.	Obs. near deceased	Obs. near living	No. of cited patents	No. of citing patents	No. of citing inventors	No. of cites	No. of cites to deceased	No. of cites to living
10	12,488,242	4,134,101	8,354,141	253	1,128,803	902,075	2,320	360	1,960
20	17,984,090	5,246,404	12,737,686	271	1,411,206	1,197,947	2,795	248	2,547
30	22,658,814	7,440,182	15,218,632	257	1,502,296	1,306,227	2,323	250	2,073
40	25,366,876	9,607,843	15,759,033	233	1,553,180	1,369,432	2,039	291	1,748
50	26,701,337	10,618,879	16,082,458	208	1,606,011	1,426,226	1,904	270	1,634
60	29,753,253	11,618,978	18,134,275	210	1,661,925	1,479,314	1,922	285	1,637
70	31,638,921	12,418,315	19,220,606	214	1,722,612	1,537,432	1,934	287	1,647
80	34,016,324	13,292,606	20,723,718	220	1,774,725	1,588,713	2,053	368	1,685
90	36,143,949	14,222,011	21,921,938	214	1,821,190	1,628,172	2,296	568	1,728
100	38,047,431	14,945,859	23,101,572	211	1,865,232	1,669,992	2,308	597	1,711

Note: This table presents descriptive statistics on the analysis sample. Each observation refers to a potentially citing inventor from future US patents (within a 10 year citation window as a baseline) that reside within a certain radius around each inventor of a deceased patent, i.e. deceased and alive co-inventors. Observations near living are larger than observations near deceased inventor because most deceased inventors had more than one co-inventor. Citation and assignee data come from the USPTO Patentsview database. Geographic distances were calculated based on longitude/latitude information from SimpleMaps. Inventors at risk of citation are restricted to those with different assignees as compared to the deceased patent and not living in overlapping regions of circles drawn around the deceased and still living co-inventors of the same patent.

4. Results

Table 2 shows the results based on the analysis sample for each separate estimation of equation (1), where the dependent dichotomous variable indicates a cite from an inventor within the specified radii around a deceased patent's inventor home city-center. Figures 3 illustrates the results graphically by plotting the estimated marginal citation propensities for at risk inventors residing around the deceased (grey dots) versus still living co-inventor of the deceased (green dots). Inventors who live within 10 miles of the deceased inventor are significantly more likely to cite a given patent relative to inventors living within 10 miles around the still living co-inventor. From there, the difference in the margins narrows with increasing distance, illustrating the localization of knowledge spillovers that can be attributed to physical collocation of inventors. Albeit being small in absolute terms, which is to be expected given the low unconditional citation probability, the relative difference in the marginal citation propensities appears sizable.

To calculate and interpret the marginal impact of deceased inventor, it is important to recall that the unconditional baseline probability of citing a specific patent is very small from a potentially citing inventor's perspective. In the 10 miles analysis sample this likelihood is 0.0186%. Our model predicts that the likelihood of citing a given patent by an inventor close to the deceased inventor is on average 0.02 percentage points smaller than the unconditional probability, and 0.01 percentage points larger than the estimated probability for an inventor that lives close to a still living co-inventor of the deceased. Putting this into perspective, we calculate that inventors who live within 10 miles of the living inventor are about 8 times more likely to cite a given patent than inventors who live within 10 miles of the deceased inventor.

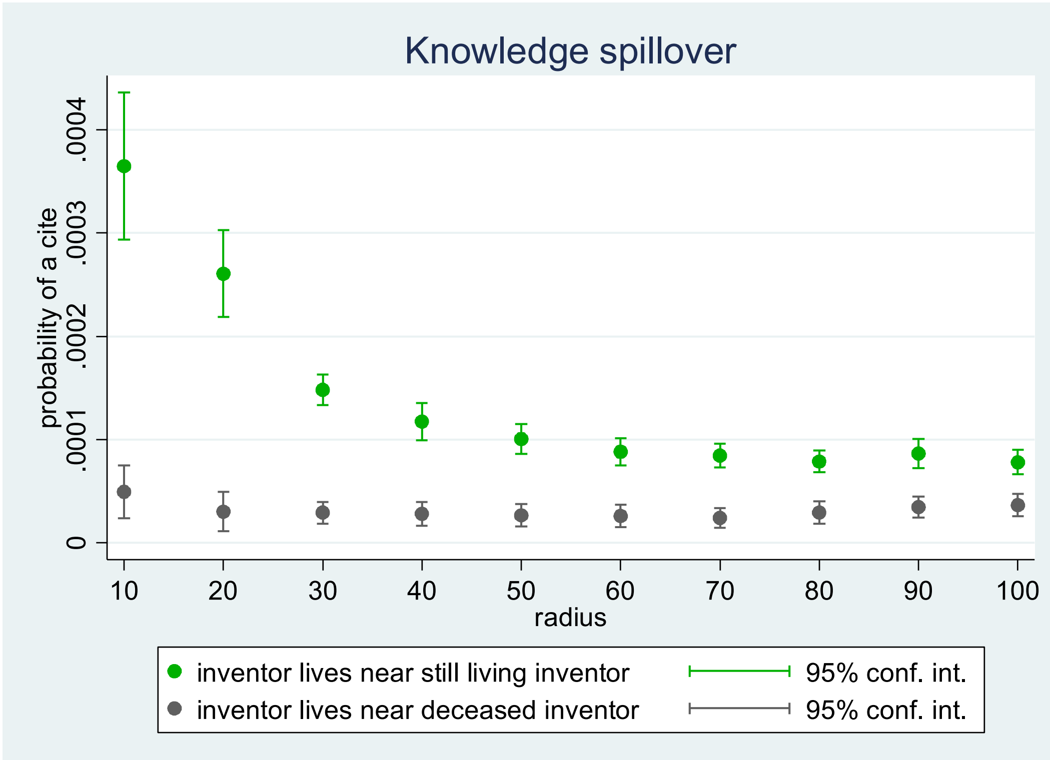
Table 2 confirms the baseline Hypothesis 1; inter-personal knowledge spillovers across firm boundaries localize. Figure 3 illustrates the point estimates and confidence intervals from 10 to 100 miles at 10-mile increments. The upper green estimates indicate how knowledge spillovers localize near the still-living inventor; the lower black estimates of the region around the deceased inventor are not significantly different from one another (indeed, one could draw a straight line between the confidence intervals of all ten point estimates). Note that the coefficients displayed in Table 2 can be interpreted as an estimation of the differences in the marginal effects

Table 2: Localization of inter-personal knowledge spillovers across firms

	10	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**
Dist. deceased	-0.559***	-0.585***	-0.427***	-0.372***	-0.341***	-0.312***	-0.317***	-0.252***	-0.237***	-0.197***
	(0.102)	(0.107)	(0.060)	(0.074)	(0.071)	(0.072)	(0.068)	(0.064)	(0.061)	(0.059)
Pseudo R^2	0.125	0.129	0.111	0.106	0.098	0.098	0.093	0.092	0.094	0.093
N	12,488,242	17,984,090	22,658,814	25,366,876	26,701,337	29,753,253	31,638,921	34,016,324	36,143,949	38,047,431
Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents coefficient estimates (for marginal effects see Figure 3 below) of the Probit model specified in equation (1), where the dependent variable is a dummy variable indicating a cite that occur within a radius *r* of the location of inventor *j* for the same multi-author patent *p* within 10 years since grant of *p*. Unit of observation is a 'cited patent inventor'-'at risk of citing patent inventor' pair. Dist. deceased = 1 indicates that the potentially citing inventor lives within radius *r* of the deceased inventor. Standard errors clustered at patent *p* reported in parentheses. Significant at the * 10% level; ** 5% level; *** 1% level.

Figure 3: Estimated citation propensities around deceased versus still living co-inventor as a function of geographic distance



Note: This graph plots the marginal citation propensities around deceased versus still living co-inventors as coming from the Probit models presented in Table 2, where the dependent variable is a dummy variable indicating a cite that occurs within a radius r of the location of inventor j for the same multi-author patent p within 10 years since grant of p. Unit of observation is a 'cited patent inventor'-'at risk of citing patent inventor' pair.

We now turn to the individual absorptive capacity as a function of inventor experience in the same technological area as the knowledge source. We measure experience based on the technological classification of each patent at the CPC subclass level. To determine whether an a potentially citing inventor has experience in the technology of the deceased patent we consider all CPC subclasses mentioned on any prior patents of inventors at risk of citation, i.e. we do not consider the cite generating patent itself as that tech classification might already be the result of the knowledge spillover and not the reason. For simplicity and ease of interpretation we differentiate between inventors with experience in the same CPC subclass from prior patenting and those that have no experience (see Appendix for robustness checks and models that control for prior patenting activity). We estimate differences across both groups by re-estimating our Probit model as introduced above with an additional dummy indicating citing inventor experience and the corresponding interaction of the experience dummy with the deceased dummy. Table 3 shows tabular results and Figure 4 plots the corresponding marginal effects for inventors with experience (the upper red line) and without experience (the lower blue line) residing around the deceased (left panel) versus the still living inventor (right panel).

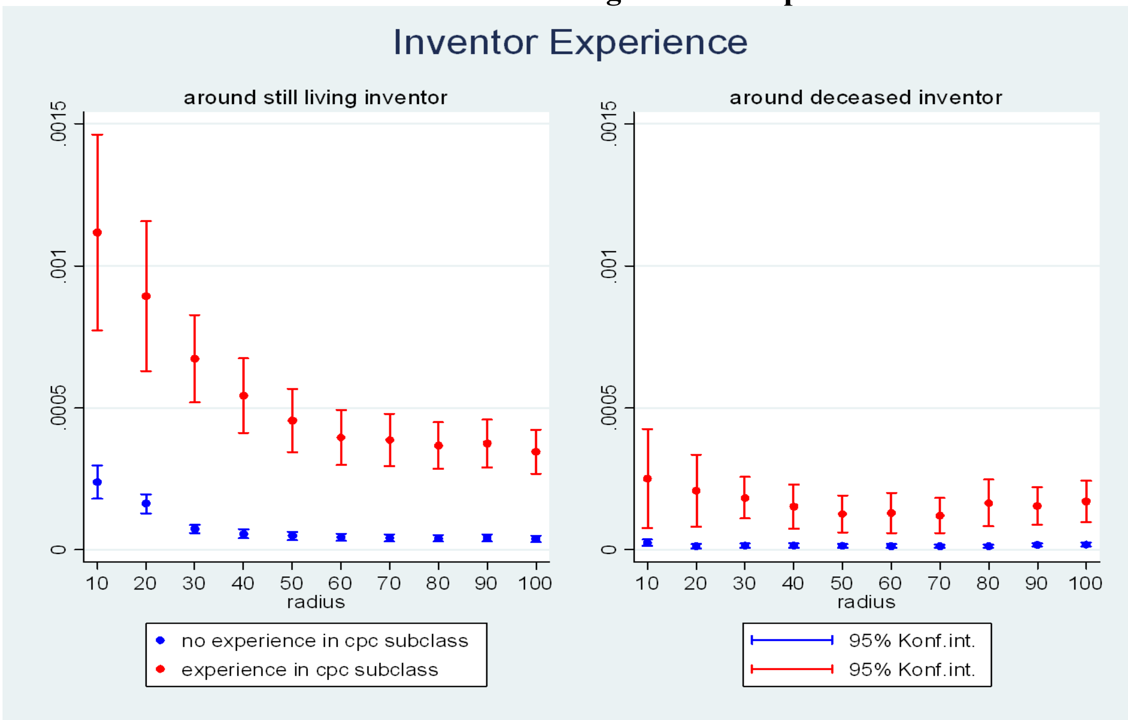
Inventor experience has always a positive effect on absorbing knowledge (compare red versus blue estimates) but the positive effect is larger when destination node is in close geographic proximity to the knowledge source (compare red estimates on the left versus red estimates on the right). The experience effect appears to localize as well as the difference increases with lower distance.

Table 3: Localization of inter-personal knowledge spillovers across firms with and without absorbing inventor experience

	10	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**
Dist. deceased	-0.621***	-0.672***	-0.410***	-0.341***	-0.311***	-0.297***	-0.300***	-0.274***	-0.225***	-0.189***
	(0.088)	(0.108)	(0.072)	(0.088)	(0.086)	(0.084)	(0.081)	(0.077)	(0.072)	(0.071)
Exp. in cpc (yes/no)	0.479***	0.512***	0.638***	0.642***	0.613***	0.602***	0.605***	0.606***	0.596***	0.594***
	(0.066)	(0.063)	(0.060)	(0.067)	(0.068)	(0.067)	(0.066)	(0.063)	(0.061)	(0.061)
Interaction	0.157	0.229***	0.024	-0.029	-0.053	-0.019	-0.028	0.045	-0.028	-0.012
	(0.103)	(0.086)	(0.068)	(0.073)	(0.068)	(0.067)	(0.063)	(0.067)	(0.070)	(0.069)
Pseudo R^2	0.157	0.165	0.162	0.156	0.144	0.143	0.138	0.140	0.138	0.137
N	12.453.692	17.929.947	22.586.211	25.285.238	26.613.402	29.653.779	31.531.949	33.899.595	36.018.652	37.914.572
Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents coefficient estimates (for marginal effects see Figure 4 below) of the Probit model specified in equation (1), where the dependent variable is a dummy variable indicating a cite that occur within a radius *r* of the location of inventor *j* for the same multi-author patent *p* within 10 years since grant of *p*. Unit of observation is a 'cited patent inventor'-'at risk of citing patent inventor' pair. Dist. deceased = 1 indicates that the potentially citing inventor lives within radius r of the deceased inventor. Exp. in cpc = 1 indicates that the potentially citing inventor has experience from prior patenting in the first mentioned CPC subclass of the cited patent *p*. Interaction represents the interaction term of dist. deceased and exp. in CPC. Standard errors clustered at patent p reported in parentheses. Significant at the * 10% level; ** 5% level; *** 1% level.

Figure 4: Estimated citation propensities around deceased versus still living co-inventor with and without absorbing inventor experience



Note: This graph plots the marginal citation propensities around deceased versus still living co-inventors as coming from the Probit models presented in Table 3, where the dependent variable is a dummy variable indicating a cite that occurs within a radius *r* of the location of inventor *j* for the same multi-author patent *p* within 10 years since grant of *p*. Unit of observation is a 'cited patent inventor'-'at risk of citing patent inventor' pair. Inventors with experience (red) and without experience (blue) residing around deceased (left) versus still living inventor (right). Potentially citing inventor has experience from prior patenting in the first mentioned CPC subclass of the cited patent *p*.

Elaborating on the basic argument of ABS in Hypothesis 2, the third hypothesis argued that the value of physical presence and personal ABS is greater, when inventors create linkages from their old knowledge into other fields. From the regional economics literature, this more difficult recombination can be described as Jacobs (1969) spillover, as opposed to a within-field MAR spillover (Glaeser et. al. 1992). For expositional simplicity we will refer to the linkage of knowledge within fields as a MAR spillover and a linkage from the prior ABS knowledge to a new field as a Jacobs spillover.

We analyze Jacobs and MAR spillovers by re-estimating our previous model with inventor experience separately for 1) citing inventors where the citing patent's CPC subclasses is different than the deceased patent's ('Jacobs') and 2) citing inventors where the citing patent's CPC subclasses is the same as the deceased patent's ('MAR'). Note that we keep the same inventor experience definition as above, i.e. we differentiate whether the citing inventor has prior experience in the deceased patent's technology, irrespective of whether that technology is applied to a new area ('Jacobs') or the same ('MAR'). Table 4 shows the estimated coefficients of our Probit models and Figure 5 plots the marginal citation propensities for each sample (Jacobs on the upper part, MAR on the lower part), for inventors with prior experience (red dots) or without (blue dots), and citing inventors residing around the deceased (right side) or living inventors (left side).

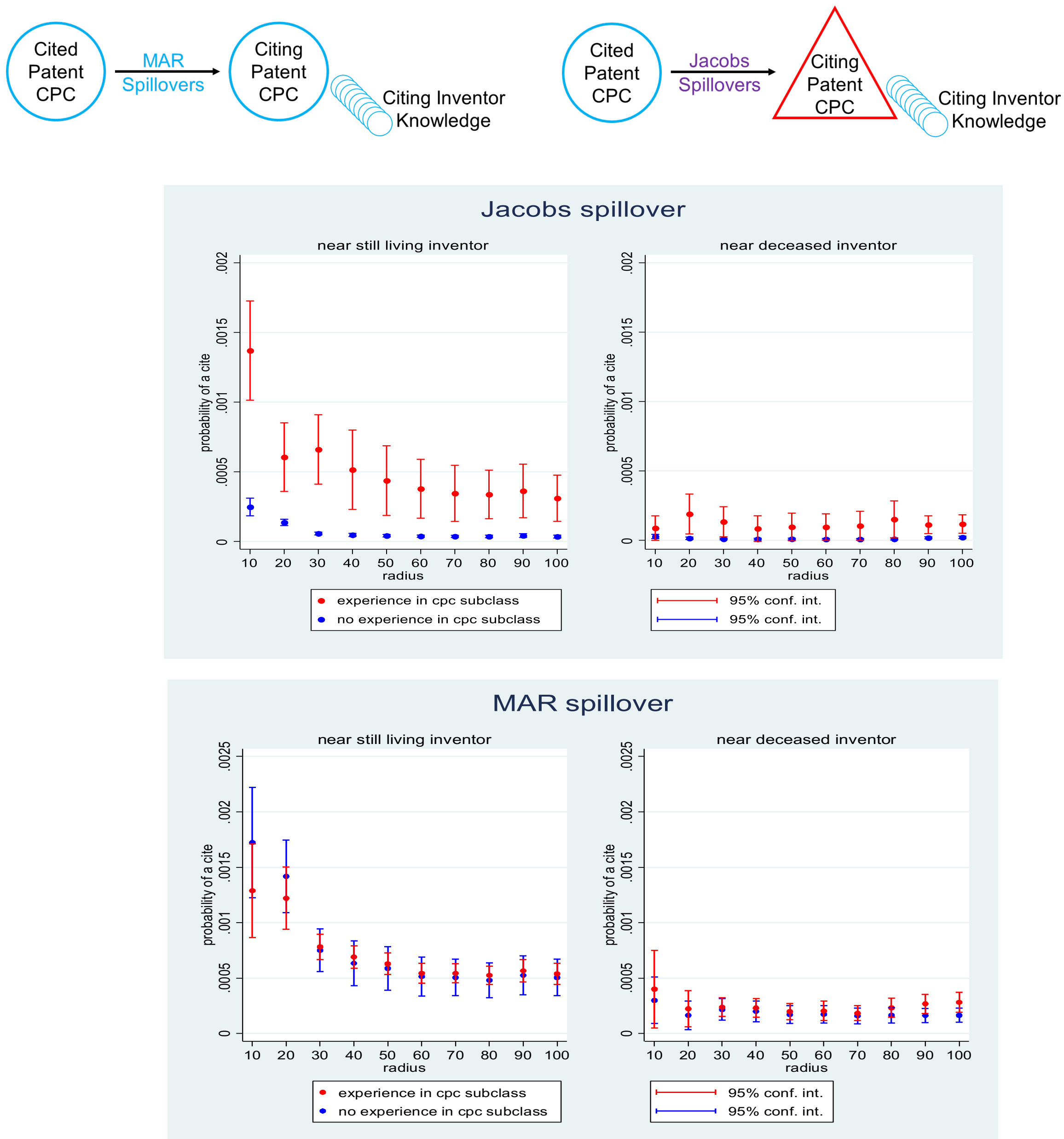
The graph illustrates three take aways: 1) knowledge flows localize irrespective of whether knowledge is applied to new or known fields (compare narrowing margins on left part (living) and right part (deceased), 2) individual absorptive capacity as measured by prior experience is a differentiating factor only when it comes to applying knowledge to new fields (compare differences between red and blue estimates in the upper (Jacobs) and lower (MAR) parts), 3) ABS is most valuable if the source of knowledge is collocated in person (compare red estimates left and right in the upper part), confirming our prior result.

Table 4: Jacobs and MAR spillovers across firms

	10	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**
Panel A: Jacobs										
Dist. deceased	-0.598***	-0.598***	-0.447***	-0.412***	-0.360***	-0.385***	-0.381***	-0.330***	-0.217**	-0.126
	(0.108)	(0.092)	(0.084)	(0.101)	(0.090)	(0.093)	(0.094)	(0.112)	(0.089)	(0.085)
Exp. in cpc (yes/no)	0.534***	0.446***	0.695***	0.671***	0.649***	0.628***	0.610***	0.610***	0.593***	0.595***
	(0.068)	(0.087)	(0.078)	(0.108)	(0.110)	(0.109)	(0.112)	(0.108)	(0.110)	(0.108)
Interaction	-0.228**	0.246**	-0.018	-0.103	-0.066	-0.001	0.048	0.103	-0.116	-0.148
	(0.101)	(0.120)	(0.138)	(0.181)	(0.181)	(0.186)	(0.190)	(0.193)	(0.136)	(0.133)
Pseudo R^2	0.166	0.188	0.159	0.151	0.143	0.142	0.137	0.137	0.134	0.134
N	5,564,551	7,286,262	8,344,126	8,567,680	9,130,419	9,807,156	10,349,107	10,872,674	11,793,732	12,765,042
Panel B: MAR										
Dist. deceased	-0.587***	-0.694***	-0.399***	-0.368***	-0.379***	-0.334***	-0.348***	-0.322***	-0.351***	-0.336***
	(0.151)	(0.151)	(0.099)	(0.113)	(0.111)	(0.110)	(0.103)	(0.100)	(0.097)	(0.095)
Exp. in cpc (yes/no)	-0.103	-0.052	0.013	0.028	0.022	0.017	0.023	0.028	0.023	0.020
	(0.065)	(0.051)	(0.059)	(0.063)	(0.065)	(0.064)	(0.063)	(0.062)	(0.061)	(0.060)
Interaction	0.196	0.144	0.016	0.018	0.022	0.033	0.019	0.073	0.124	0.138*
	(0.135)	(0.103)	(0.083)	(0.090)	(0.089)	(0.084)	(0.082)	(0.078)	(0.076)	(0.073)
Pseudo R^2	0.167	0.164	0.171	0.175	0.156	0.155	0.145	0.142	0.133	0.131
N	1,400,470	2,083,250	2,746,686	3,120,775	3,228,361	3,598,717	3,776,784	3,978,929	4,197,971	4,268,055
Patent FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents coefficient estimates (for marginal effects see Figure 5 below) of the Probit model specified in equation (1), where the dependent variable is a dummy variable indicating a cite that occur within a radius *r* of the location of inventor *j* for the same multi-author patent *p* within 10 years since grant of *p*. Unit of observation is a 'cited patent inventor'-'at risk of citing patent inventor' pair. Dist. deceased = 1 indicates that the potentially citing inventor lives within radius *r* of the deceased inventor. Exp. in cpc = 1 indicates that the potentially citing inventor has experience from prior patenting in the first mentioned CPC subclass of the cited patent *p*. Interaction represents the interaction term of dist. deceased and exp. in CPC. The 'Jacobs' panel is restricted to citing inventor patents with the same CPC as the cited (deceased) patent. The 'MAR' panel is restricted to citing inventor patents with a different CPC as the cited (deceased) patent. Standard errors clustered at patent p reported in parentheses. Significant at the * 10% level; ** 5% level; *** 1% level.

Figure 5: Estimated citation propensities around deceased versus still living co-inventor with and without absorbing inventor experience and differentiating between Jacobs and MAR spillovers



Note: This graph plots the marginal citation propensities around deceased versus still living co-inventors as coming from the Probit models presented in Table 3, where the dependent variable is a dummy variable indicating a cite that occurs within a radius *r* of the location of inventor *j* for the same multi-author patent *p* within 10 years since grant of *p*. Unit of observation is a 'cited patent inventor'-'at risk of citing patent inventor' pair. Inventors with experience (red) and without experience (blue) residing around deceased (left) versus still living inventor (right). Potentially citing inventor has experience from prior patenting in the first mentioned CPC subclass of the cited patent *p*. The 'Jacobs' panel is restricted to citing inventor patents with the same CPC as the cited (deceased) patent. The 'MAR' panel is restricted to citing inventor patents with a different CPC as the cited (deceased) patent.

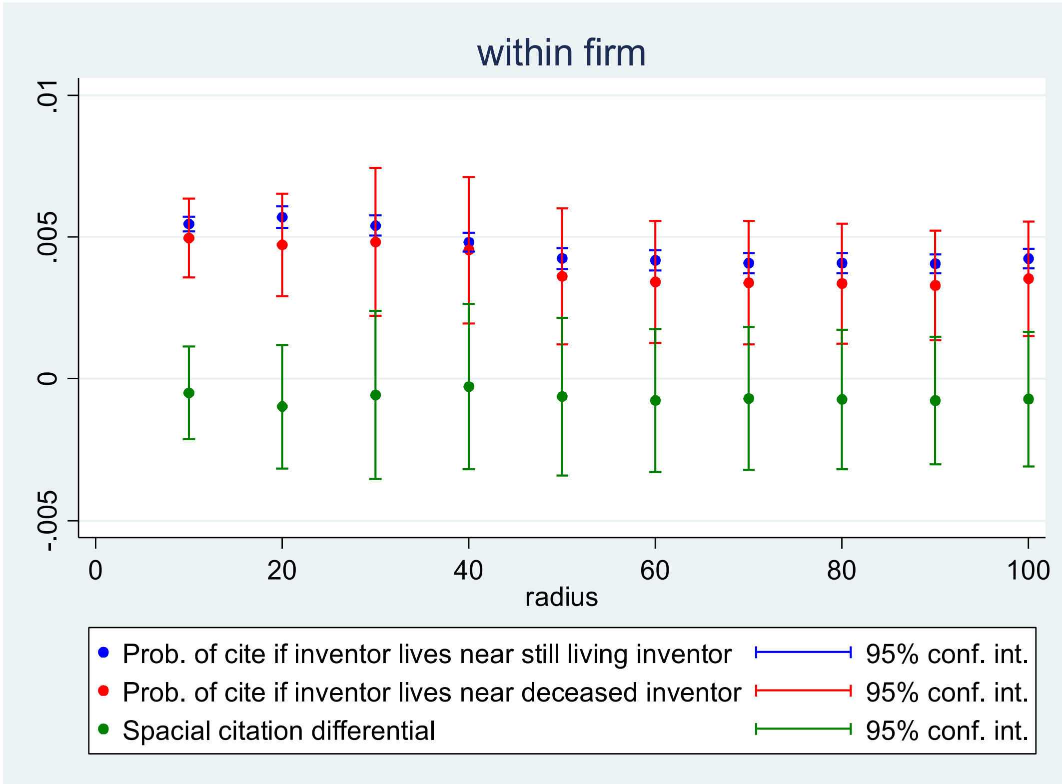
6. Discussion

The work has a number of shortcomings. First, not all spillovers are technical and can be measured with patents. For example, business and science knowledge probably spills locally as well. Second, patents do not even cover all technical knowledge, for example, algorithms and trade secrets cannot be observed. Finally, the method is empirically very demanding, and our (still significant) results depend on relatively few observations.

These shortcomings notwithstanding, the method opens a causal window into the impact of personal presence on knowledge flow between a particular source and particular destination. This work focused on the impact of organizational boundaries between the source and destination, and whether the destination inventor had prior experience in the field of the source inventor's inventions. Other characteristics can also be studied, for example, what is the impact of personal presence upon intra-firm knowledge spillovers? What if the source and destination both lie within the same organization – do knowledge flows within firms also localize, and fall off locally when an inventor dies? Figure 6 illustrates how the method enables exploration of this possibility.

Figure 6 illustrates, perhaps surprisingly, no localization of knowledge spillovers within firm boundaries, based on physical presence. The figure is essentially flat (no impact of geographic distance) and the difference in citations within the firm are not significantly different, for the region around the deceased, vs. the region around the still-living inventors. Following the death of an inventor, it appears that firms are quite capable of relying on other sources of information about the invention. Assumedly, technologies, notebooks, co-workers, and internal documentation provide enough contextual depth and detail to overcome the loss of one particular inventor.

Figure 6: Within firm knowledge spillovers do not localize.



While it was the strategy literature that motivated the current work, the results provide some of the first causal evidence for the juxtaposition of physical presence and diverse expertise, in the realization of Jacobs' spillovers (Jacobs 1969; Atkin et. al. 2022), namely, the knowledge flows across field and industry boundaries that create new industries and greater diversity. The current results imply that is not so much the (random) juxtaposition of diversity that results in new associations and linkages across fields, rather it is the physical colocation of people who have similar expertise and personal ABS. Ironically, it may be that similar backgrounds – be they technical, social, or geographical - facilitate risk taking and recombination into new fields. Future work should look for the sources of the inspiration that triggered the particular linkage to a new field – for example, perhaps the inventors became aware of and motivated to explore a new market or technological opportunity, or gained exposure to a new field through the inventors' social networks.

Recent research on the effectiveness of working from home confirms that physical collocation of employees is beneficial to their individual productivity, despite the widespread availability of more advanced technology to collaborate and share information online (Carmody et. al. 2022). While this research has not yet isolated the impact of inter-personal knowledge spillovers, it points out that new collaboration technologies remain an imperfect substitute for collaboration in person. It is consistent with the finding of no significant differences in the localization of inter-personal spillover effects over our sampling period (please see the Appendix) despite covering an area of substantial technological advances in online communication, most prominently email and the early internet.

The results have implications for other strategic frameworks besides ABS. For example, if personal knowledge spillovers exist across firm boundaries, and if such spillovers localize, then decisions on where to locate become decisions which can build – or lose - dynamic capabilities, defined as the ability to recognize and move into a strategically important area (Teece et. al. 1997). Firms should explicitly search out geographical locations that support their knowledge capability and innovation strategies. For example, if a firm needs to catch up in a field, they should locate next to the leader (or universities, see Balsmeier et. al. 2023), or if they are the leader, they should seek to locate where followers cannot set up shop next door (Alcacer and Chung, 2007). On the other hand, if a firm has prior experience in a technology, and no interest in applying that technology to new fields, then there is less need to locate near others (though that certainly appears be a short-sighted decision).

7. Conclusion

While the theory of absorptive capacity has been hugely influential in strategy research (Cohen and Levinthal 1990), empirical efforts to corroborate the theory with causal evidence have not followed easily (Knott 2008). By focusing on one possible type of absorptive capacity, namely the experience of a firm's inventors, and taking advantage of an exogenous change in the availability of outside knowledge, namely the death of a local inventor, this work offers causal evidence for absorptive capacity. The method can apply to other tests of absorptive capacity and to other investigations on the personal presence of localized spillovers. Confirming conjectures from the original theory (Cohen and Levinthal, 1990), as well as Jacobs' (1969) argument for the importance of physical presence for the creation of new industries, this work established that personal absorptive capacity matters most when inventors apply old knowledge to new fields. Perhaps surprisingly, this work also illustrated that firms do not rely upon physical presence for internal knowledge transfer and that their within-firm knowledge transfers do not localize.

While prior studies in the strategy literature were mostly agnostic about the geographic distance between the source and the recipient of a knowledge flow (Cohen and Levinthal, 1990; Teece et. al. 1997), and classic studies in the regional economics and knowledge flow literature (e.g. Glaeser et. al. 1992, Jaffe et. al. 1993) were mostly agnostic about organizational boundaries, this study brings both worlds together, confirming a strong localization of inter-personal knowledge flows across firms, and highlighting the important role of geographic distance and physical collocation of inventors for firm strategy. Ideally this knowledge flow across the field boundaries of strategy and regional economics will prove fruitful on both sides.

8. References

Aghion, P. and X. Jaravel. 2015. "Knowledge spillovers, innovation, and growth." The Economic Journal, 125 (March), 533–573.

Alcacer, J. and W. Chung (2007). "Location Strategies and Knowledge Spillovers." *Management Science* 53:5:760–776.

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

Arora, Ashish, Sharon Belenzon, and Honggi Lee. 2018. "Reversed Citations and the Localization of Knowledge Spillovers." *Journal of Economic Geography* 18 (3): 495–521.

Atkin, D. and K. Chen, A. Popov 2022. "The Returns to Face-to-Face Interactions: Knowledge Spillovers in Silicon Valley." NBER Working paper 30147.

Azoulay, Pierre, Christian Fons-Rosen, and Joshua S. Graff Zivin. 2019. "Does Science Advance One Funeral at a Time?" *American Economic Review* 109 (8): 2889-2920.

Azoulay, Pierre, Joshua G. Zivin, and Jialan Wang. 2010. "Superstar Extinction." *The Quarterly Journal of Economics* 125 (2): 549-589.

Balsmeier, Benjamin, Mohamad Assaf, Tyler Chesebro, Gabe Fierro, Kevin Johnson, Scott Johnson, Guan-Cheng Li, Sonja Lück, Doug O'Reagan, Bill Yeh, Guangzheng Zang, and Lee Fleming. 2018. "Machine Learning and Natural Language Processing on the Patent Corpus: Data, Tools, and New Measures." *Journal of Economics and Management Strategy,* 27 (3): 535–553.

Balsmeier, B., Fleming, L., & Lück, S. (2023). Isolating Personal Knowledge Spillovers: Co-inventor Deaths and Spatial Citation Differentials. *American Economic Review: Insights 5(1): 21–34.*

Balsmeier, B., Fleming, L., & Lück, S. (2023). "Scientists cluster: one reason it matters**."** Working paper, UC Berkeley Haas School of Business.

Carmody, D. and M. Mazzarello, P. Santi, T. Harris, S. Lehmann, T. Abbisaov, R. Dunbar, C. Ratti 2022. "The effect of co-location on human communication networks." *Nature Computational Science* volume 2, pages 494–503.

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

Ellison, Glenn, Edward L. Glaeser, and William R. Kerr. 2010. "What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns." *American Economic Review* 100 (3): 1195-1213.

Ganguli, Ina, Jeffrey Lin, and Nicholas Reynolds. 2020. "The Paper Trail of Knowledge Spillovers: Evidence from Patent Interferences." *American Economic Journal: Applied Economics* 12 (2): 278-302.

Iacus, Stefano M., Gary King, and Giuseppe Porro. 2012. "Causal Inference Without Balance Checking: Coarsened Exact Matching." *Political Analysis* 20 (1): 1–24.

Jacobs J. (1969). *The economy of cities*. New York, NY: Vintage.

Jaffe, A. 1986. “Technological opportunity and spillovers of R&D.” Amer. Econ. Rev. 76 984-1001.

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

Jaravel, Xavier, Neviana Petkova, and Alex Bell. 2018. “Team-Specific Capital and Innovation.” *American Economic Review* 108 (4-5): 1034-73.

Kaltenberg, Mary, Adam Jaffe, and Margie E. Lachman. 2021. "Matched Inventor Ages from Patents, Based on Web Scraped Sources." Harvard Dataverse https://doi.org/10.7910/DVN/YRLSKU (accessed July 20, 2021)

Knott, A. 2008. “R&D/Returns Causality: Absorptive Capacity or Organizational IQ.” *Management Science* Vol. 54, No. 12, pp. 2054-2067.

Krugman, Paul. 1991. *Geography and Trade.* Cambridge: MIT Press.

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

Mickle, T. 2023. “Regulators Find Apple’s Secrecy Violates Workers’ Rights.” NYT Jan. 31, 2023.

Murata, Yasusada, Ryo Nakajima, Ryosuke Okamoto, and Ryuichi Tamura. 2014. “Localized Knowledge Spillovers and Patent Citations: A Distance-based Approach.” *Review of Economics and Statistics* 96 (5): 967–985.

Roche, M. 2020. “Taking innovation to the streets: Micro-geography, physical structure, and innovation.” *The Review of Economics and Statistics*, December 2020, 102(5): 912–928.

Teece, D. and G. Pisano, A. Shuen 1997. “Dynamic Capabilities and Strategic Management,” *Strategic Management Journal*, Vol. 18, No. 7. (Aug., 1997), pp. 509-533.

Thompson, Peter, and Melanie Fox-Kean. 2005. “Patent Citations and the Geography of Knowledge Spillovers: A Reassessment.” *American Economic Review* 95 (1): 450-460.

Williams, Heidi L.. 2017. “How Do Patents Affect Research Investments?“ *Annual Review of Economics*, 9: 441-469.