

Strategic geography: isolating the inter-personal mechanisms of absorptive capacity

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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 firms' inventors 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(s) 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 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 its observable implications, arguably due to a lack of articulation 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) built explicitly 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 within firms. In addition to their paradigmatic focus, strategy researchers lacked motivation to ponder the micro-foundational mechanisms of ABS, because by and large, such foundations could not be observed, let alone rigorously tested.

Despite the understandable focus of strategy scholars on firms, knowledge spillovers ultimately flow across firm boundaries and 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 often their home town. Furthermore, if one accepts the convention that a citation between patents at least sometimes corresponds to some type 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 ideally causal research designs, opens up the opportunity to formalize and better test the predictions and observable implications of absorptive capacity.

Taking advantage of these innovations in data, measures, and methods, we argue that the operationalization of 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 through those specific mechanisms, and empirical identification of exogenous changes in externally available knowledge that might be absorbed through the same 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)

Fully acknowledging a wide range of plausible pathways for absorptive capacity, we focus on the mechanism of inter-personal knowledge spillovers. Confirming a great deal of prior work (Jaffe et. al. 1993; Thompson 2006, for a literature review, please see Jaffe and de Rassenfosse, 2017), and identifying both the personal source and destination of individual spillovers, we first establish that such spillovers localize geographically. 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 (Balsmeier et. al. 2023a). 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 across firms -- and that this effect localizes geographically. Again consistent with the original formulation, absorptive capacity appears to matter most when inventors

apply prior knowledge in a field to create linkages into new fields. Finally, and in contrast to spillovers across boundaries, we illustrate in the discussion that knowledge flows within firms do 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 hire a competitor's employees, 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, do their region's labor laws allow them to hire competitor's employees, are their competitor's products accessible, do their competitors publish in the science literature, or 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, reverse engineering, consulting, science papers, media, or product information. Each of these sources operates through 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 localizes (Balsmeier et. al. 2023a), and this has not been highlighted to date in the ABS literature – that one plausible and possibly very important conduit of ABS relies on the local and geographic context within which firms operate. A firm which operates near another firm exposes itself (in both positive and negative ways) to potential knowledge spillovers (Alcacer and Chung, 2007), through inter-personal knowledge spillover mechanisms. Indeed, Apple Computer has been accused of setting up a physical presence near a competitor, to hire the competing firm's employees, gain knowledge, and ultimately, infringe on patents (Coy, 2023).

Unpacking 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 – after the application but before the grant - as the “source inventor.” Restricting our analysis to co-authored patents whose co-inventors live in different towns, we will consider all inventors on all realized patents at other firms within the radius of a similar distance around the deceased and still-living inventors as “destination inventors.” We will measure the ABS of the potentially 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, reverse engineering of products, reading of published literature, 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 professional embarrassment and negative assessments by co-workers and management. As a result, they often ask friends they can trust in outside firms (Allen 1977). Inventors also maintain professional networks outside their current employer, based on prior employment, school, or postdocs. Given a problem that their friends might be able to help with, and permission from their employers, they might seek advice and even collaborate to solve the problem (Fleming et. al. 2007). Other interactions may not be intended, such as eavesdropping in the local coffee shop, or hearing second-hand about a new approach.

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 historical success has been partly attributed to this generous knowledge flow across firm boundaries (Saxenian 1994). Independent of where they occur, densely agglomerated clusters of firms probably 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 proximal co-presence of the source and destination and are much more likely to occur when people are physically collocated. Despite advances in communications and transportation technology, people are still 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.

The argument that knowledge spillovers localize is old (Marshall, 1890; JTH 1993; Thompson and Fox-Kean, 2005; Thompson, 2006; Roche 2020), however, here we focus on an inter-personal mechanism and establish that particular mechanism in the first hypothesis, before elaborating on the strategic implications of localized knowledge spillovers in later hypotheses. In summary, if these arguments are correct, then as the physical distance between the source and destination inventors increases, inter-personal knowledge flows should decrease.

H1: Inter-personal knowledge spillovers localize.

We now elaborate upon the theory of ABS by focusing on the mechanism and conduit of inter-personal spillovers. Localized inter-personal knowledge spillovers provide one example of an external knowledge conduit that is available to a firm. Firms with pertinent ABS – in this case, those who employ inventors who can learn from and absorb inter-personal knowledge spillovers - should be better able to take advantage of localized knowledge, if and when such spillovers exist. This implies first establishing the ABS of the absorbing firm's inventors, and then observing their

likelihood of using locally available knowledge spillovers, when a source of spillover knowledge is - or is not – locally available. In other words, given that a potential conduit for ABS has been observed, does a knowledge spillover actually occur, when an external source of knowledge is available?

Because this strategic mechanism operates through individuals (while we talk about spillovers between firms, they are actually knowledge transfers between employees of those firms), we identify a potential and specific source of external knowledge and how that source varies exogenously, namely, whether a (local) inventor of the same collaborative patent remains alive or has recently died. We also consider the potential destination for the knowledge as all subsequent (local) patents, any of which might potentially cite the collaborative source patent. We measure the potential destination's personal ABS as prior experience in the same field as the source patent.

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 greater advantage of locally available knowledge spillovers in semiconductors or biotech, respectively.

These arguments imply 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 about semiconductors, relative to a local inventor without semiconductor experience. Empirically, they imply that citations from a destination inventor with experience in semiconductors are more likely to occur, relative to citations from a biotech inventor, and in the region of the still-living co-author, relative to the region of the deceased co-author.

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 theory might be incomplete, however – the advantage of experience could also vary with the difficulty of the new application. If the new application is easier, or “close”, incremental, and an exploitation within a field, the value of experience should be smaller. If the application 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 original authors of absorptive capacity recognized this and built upon cognitive arguments to 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). An inventor with experience in the field of the source technology will be better able to absorb, apply, recombine, and link the knowledge in new and creative ways.

The argument is consistent with evidence that a decrease in the costs of airline travel between scientists – and an assumed increase in physical interaction - increased the rate and success of collaborations, and in particular, more complex, inter-disciplinary, and exploratory collaborations (Catalini et. al. 2020). Though we study knowledge flow between inventions and not collaborations within science discoveries, a similar dynamic should hold; more complex, inter-disciplinary, and exploratory inventions should benefit more from personal and proximal availability of knowledge.

The argument can also be motivated from the regional economics literature, by differentiating a spillover as a MAR, or within industry spillover (Glaeser et. al. 2012), vs. 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 entirely within a field will be less. Empirically, invention within and application of externally available knowledge to the same technology field should depend less on ABS. A Jacobs spillover, however, will be more cognitively challenging and more dependent upon the pertinent experience of the receiving node, as well as the local availability of an inter-personal spillover in the original field. Empirically, invention outside the source field and recombination into a new field will depend more on ABS; it will be observed by a citation from a patent in a new technology field (by an inventor with experience in the original field). Note that this hypothesis does not argue that MAR

spillovers are more and Jacobs spillovers less common (though that is true in our data), rather, that the importance of the combination of personal ABS and locally available knowledge spillovers 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 prior experience in a field and take advantage of exogenous changes in the availability of external knowledge to that inventor. The problem can be reconceptualized as estimating the causal impact of one inventor's presence on the geographic flow of knowledge to another inventor. The latter inventor may or may not have prior experience (personal ABS in our parlance) in that field of knowledge.

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 cite the prior knowledge can be observed and compared, for the respective regions around the deceased and still-living inventor. 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, that death makes a person unavailable to aid in the interpersonal transmission of knowledge. Third, 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 but published patent, but the control group resides close enough to have easier in-person access to a still-living inventor of the patent.

The goal is to estimate the average propensity of all inventors living within circle A of Figure 1 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 geographical 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 ideally 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 (or similar but slightly different inventions) is the key strength of this approach.

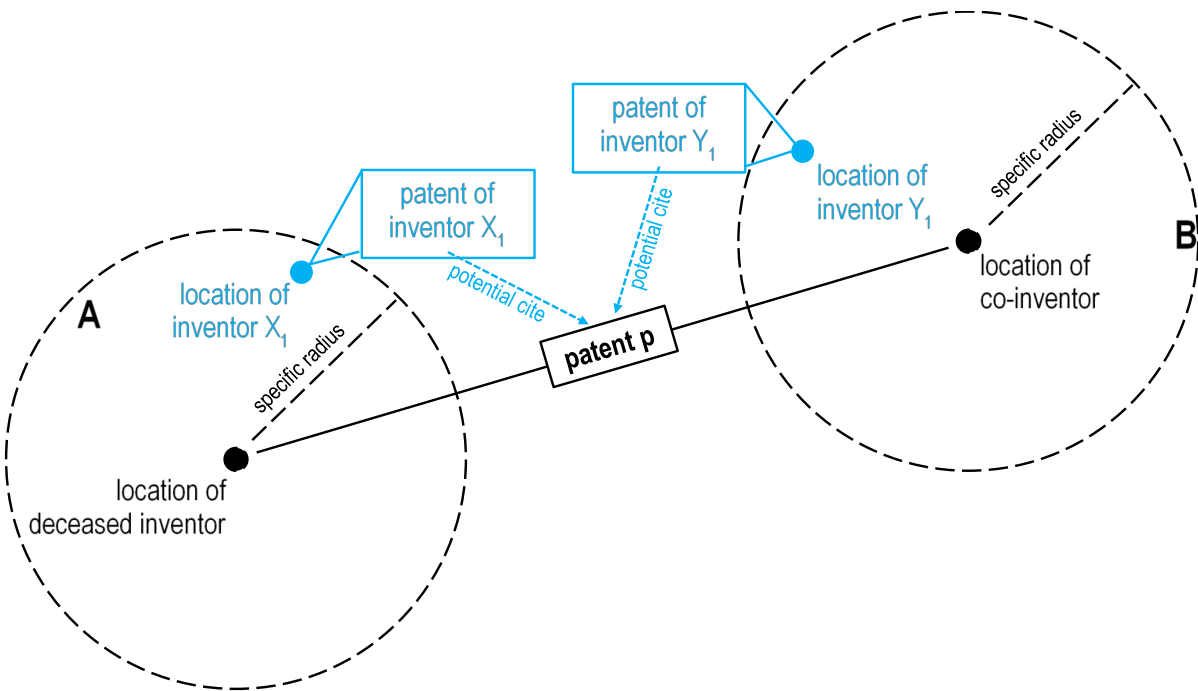


Figure 1: idealized empirical situation for testing the impact of personal presence on knowledge diffusion.

(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	6,640,240 B1 * 10/2003 Hoffman et al. 709/203
(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)	OTHER PUBLICATIONS Oracle Corporation and Akamai Corporation, all pages in Overview Section, 2001.* * cited by examiner <i>Primary Examiner</i> —David Y. Eng (74) <i>Attorney, Agent, or Firm</i> —David H. Judson
(73) Assignee: Akamai Technologies, Inc., Cambridge, MA (US)	

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	6,640,240 B1 * 10/2003 Hoffman et al. 709/203
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(73) Assignee: Akamai Technologies, Inc., Cambridge, MA (US)	(57) ABSTRACT A method is provided for processing an application on an

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

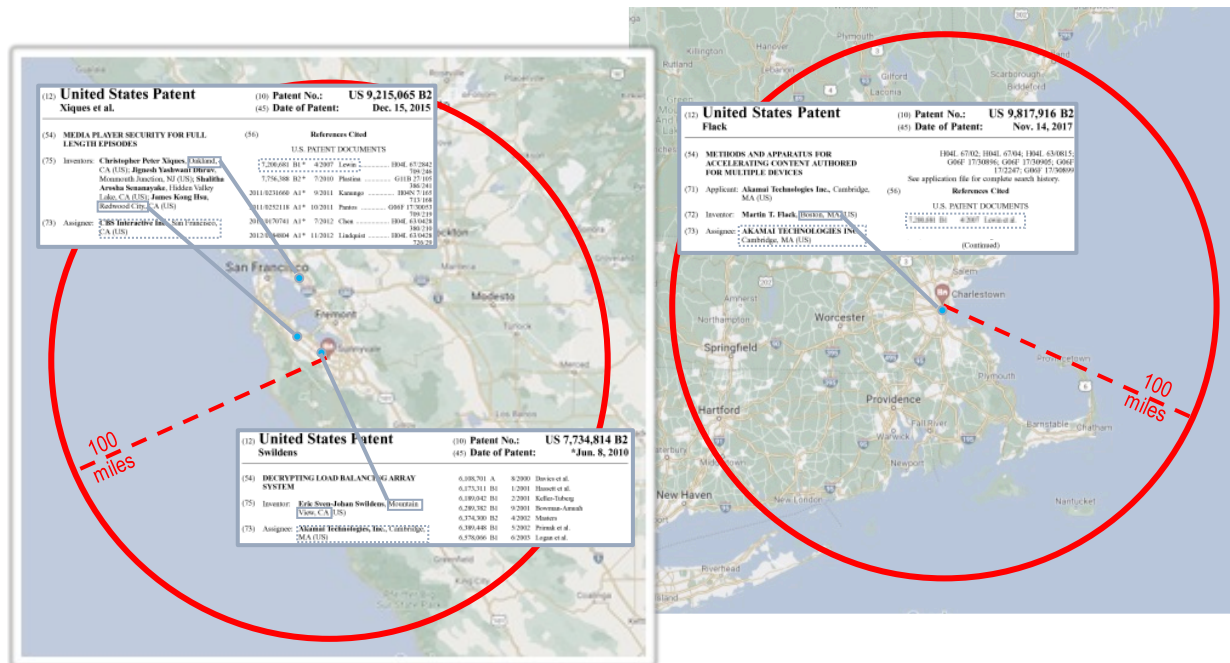


Figure 2c: Zoom into deceased and living co-inventor locations of patent 7,200,681

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 or different industry co-locate, local labor market conditions are not particularly good or bad, or coffee shops proliferate. 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 (Jaravel 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.

The identification strategy goes beyond Balsmeier et al. (2023a) by explicitly shifting the focus from only the source of knowledge spillovers to both the source and the destination. At the cost of

¹ We check the first assumption by considering deaths by younger inventors. We define "self-cite" as at least one inventor of the cited patent is also 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.

much more computation and data analysis, it takes all potentially realized spillover destinations within a given radius into account, as opposed to counting only the realized spillovers. It enables more accurate estimation of the differences amongst citing inventors, e.g., whether they work at the same company, or whether they have prior experience in the technological field. For example, 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 yet still reside within close proximity.

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. Taking 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 the 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 pare the analysis sample further to only include potentially citing inventors from different firms as the deceased patent (we will use these pared data in the discussion and consider knowledge diffusion within the firm). 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 patents that might potentially cite the deceased patent (within a 100 mile radii and within 10 years). 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-

² <https://simplemaps.com>, accessed Nov. 26, 2020.

³ <https://patentsview.org/download/data-download-tables>

natural experiment such that all inventors that were exposed to the treatment (death) will enter the risk set each time someone died 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 each death will enter the risk set each time an inventor deceased. The same applies to *all* inventors that patented in the regions around the still living co-inventors of the same patent of the deceased inventor, who will by construction reside in a different location. Further, most deceased inventors had more than one co-inventor, each of which generates a control group of his or her own. Hence, the number of observations around the still living inventors is often larger than around the deceased inventors.

Of note, 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) includes a different number of cited patents because we can empirically identify effects only from inventors at risk of citation residing outside any overlapping regions of the radii we draw around the deceased and living co-authors. In some cases, we find inventors at risk only inside overlapping regions, leading to the exclusion of those patents from the sample (because there are 0 citations and hence no identification). For the same lack of identification, we can also not 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 can 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 the center of a deceased patent inventor's home city. Figure 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 less 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 an inventor. Although 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.

Table 2 confirms the baseline Hypothesis 1; inter-personal knowledge spillovers across firm boundaries localize. The plotted figures illustrate the point estimates and confidence intervals from 10 to 100 miles at 10-mile increments, using STATA's margins command, essentially the average of the predicted probabilities of citation for each data point at each distance (Greene 2000, pg. 816), with the deceased indicator set at 0 or 1, and other variables at their observed value (not at the mean to avoid an overly strong or weak impact on marginal effects due the non-linear nature of the Probit function). The upper green estimates of Figure 3 indicate how knowledge spillovers localize near the still-living inventor (they are higher at shorter distances and decrease significantly with longer distances); the lower black estimates of the region around the deceased inventor are not significantly different from one another at different distances (indeed, one could draw a straight line between the confidence intervals of all the lower black point estimates). Note that the coefficients displayed in Table 2 can be interpreted as an estimation of the differences in the plotted citation propensities.

To interpret the marginal impact of a still-living inventor, it is important to recall that from the perspective of an inventor who might possibly cite the deceased patent, that the unconditional baseline probability of citation is very small. Within the ten-mile radius this likelihood is 0.0186% (which reassuringly falls in between the still-living upper and deceased lower point estimates at the distance of 10 miles in Figure 3). Our model predicts that the likelihood of citing a given patent by an inventor close to the deceased inventor is ~0.01 percentage points smaller than the baseline unconditional probability (the lower and gray point estimate in Figure 3 at a distance of 10 miles).

For regions around still-living inventors, the estimate is ~ 0.02 percentage points larger (the higher and green point estimate in Figure 3 at a distance of 10 miles). Combining the upper and lower estimates together implies a back of the envelope interpretation that inventors who live within 10 miles of the living inventor are about 7 or 8 times more likely to cite a given patent, relative to inventors who live within 10 miles of the deceased inventor (essentially, dividing the upper point estimate by the lower point estimate for the data and model within a 10-mile radius).

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

	10	20	30	40	50	60	70	80	90	100
<i>Dist. deceased</i>	-0.559*** (0.102)	-0.585*** (0.107)	-0.427*** (0.060)	-0.372*** (0.074)	-0.341*** (0.071)	-0.312*** (0.072)	-0.317*** (0.068)	-0.252*** (0.064)	-0.237*** (0.061)	-0.197*** (0.059)
<i>Pseudo R²</i>	0.125	0.129	0.111	0.106	0.098	0.098	0.093	0.092	0.094	0.093
<i>N</i>	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.

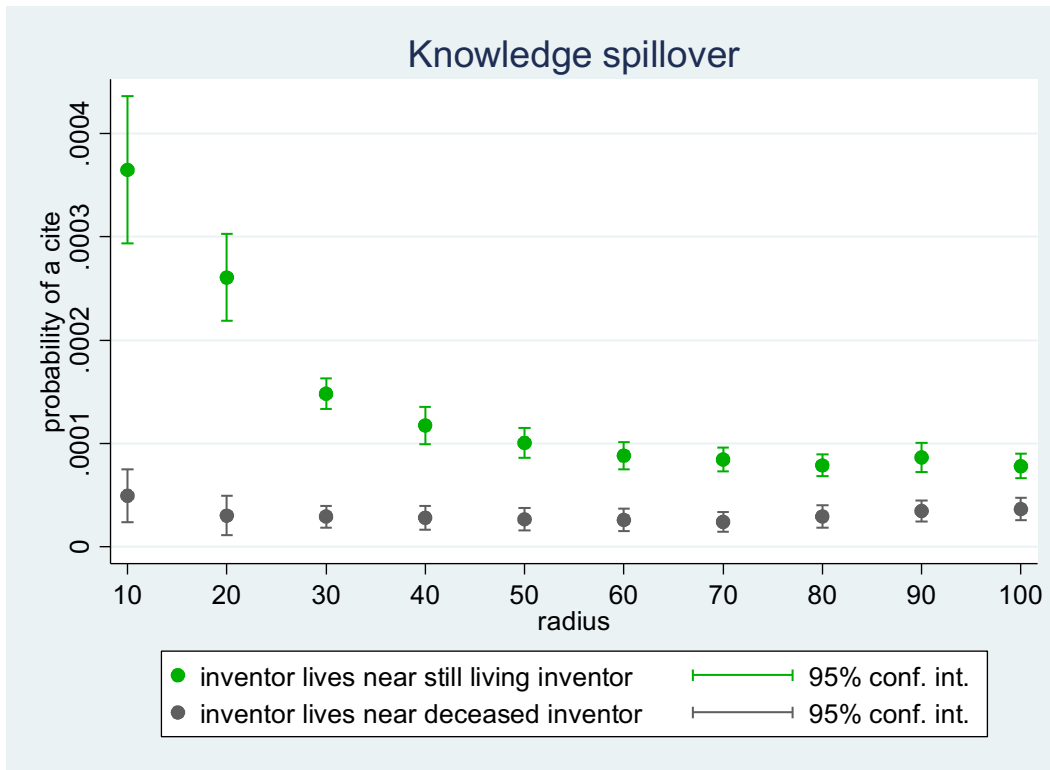


Figure 3: Estimated citation propensities around deceased versus still living co-inventor as a function of geographic distance. *Note:* This graph plots the marginal citation propensities around deceased versus still living co-inventors as coming from the Probit models presented in Table 2, where the 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. The graph plots the average predicted probability of a living versus deceased inventor getting cited by another inventor from within X miles around her/him. STATA first calculates for each observation the predicted likelihood of getting cited, based on the Probit with all variables in the model, i.e. including patent fixed effects. Then it takes the average across all observations.

We now turn to the effect of an individual’s absorptive capacity as a function of inventor experience in the same technological area as the deceased or still-living knowledge source patent. We measure experience based on the technological classification of each patent at the CPC subclass level. To determine whether a potentially citing inventor has experience in the technology of the deceased patent, we consider all CPC subclasses on any prior patents of each inventor that is 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. 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 overall 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 (right panel) versus the still living inventor (left panel).

Inventor experience always has a positive effect on absorbing knowledge (compare red versus blue estimates) but the positive effect is larger when the destination node is in close geographic proximity to the knowledge source (compare red estimates on the left versus red estimates on the right). The advantage of ABS experience appears to localize and the advantage decreases with greater distance. This speaks to the research design; we find evidence for the value of absorptive capacity when the exogenous source of spillovers is turned “on” (that is, the individual with ABS lives closer to the still-living inventor).

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
<i>Dist. deceased</i>	-0.621*** (0.088)	-0.672*** (0.108)	-0.410*** (0.072)	-0.341*** (0.088)	-0.311*** (0.086)	-0.297*** (0.084)	-0.300*** (0.081)	-0.274*** (0.077)	-0.225*** (0.072)	-0.189*** (0.071)
<i>Exp. in cpc (yes/no)</i>	0.479*** (0.066)	0.512*** (0.063)	0.638*** (0.060)	0.642*** (0.067)	0.613*** (0.068)	0.602*** (0.067)	0.605*** (0.066)	0.606*** (0.063)	0.596*** (0.061)	0.594*** (0.061)
<i>Interaction</i>	0.157 (0.103)	0.229*** (0.086)	0.024 (0.068)	-0.029 (0.073)	-0.053 (0.068)	-0.019 (0.067)	-0.028 (0.063)	0.045 (0.067)	-0.028 (0.070)	-0.012 (0.069)
<i>Pseudo R²</i>	0.157	0.165	0.162	0.156	0.144	0.143	0.138	0.140	0.138	0.137
<i>N</i>	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.

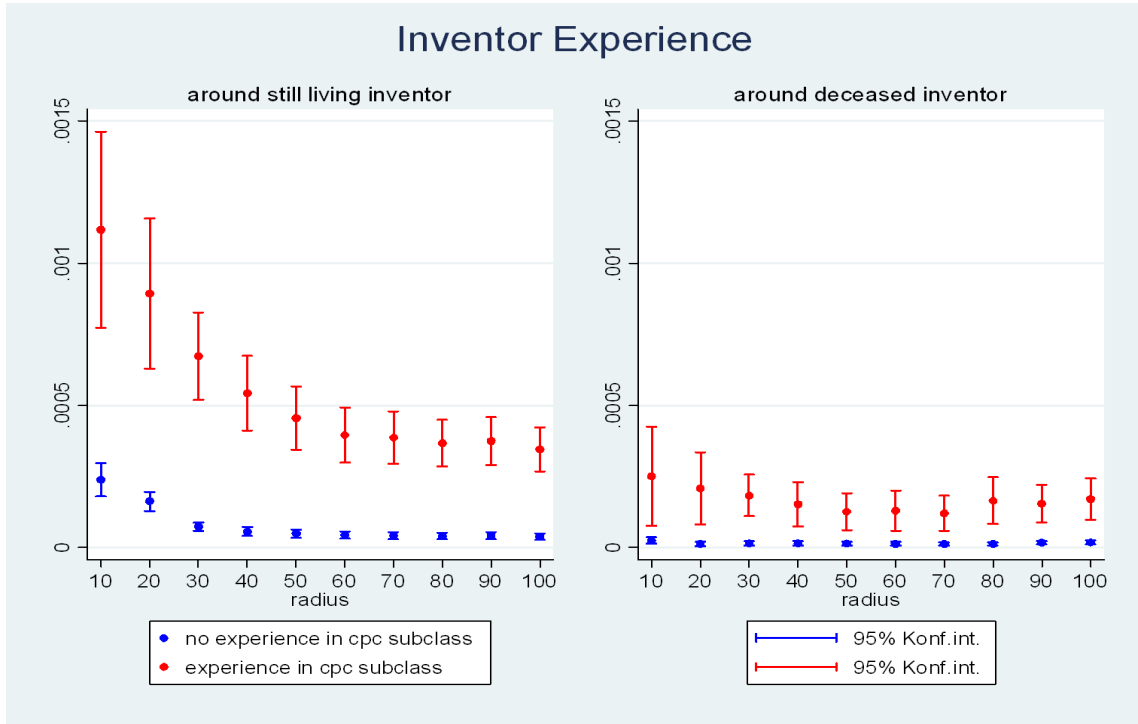


Figure 4: Estimated citation propensities around deceased versus still living co-inventor with and without absorbing inventor experience. *Note:* This graph plots the marginal citation propensities around

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 proposed that the value of physical presence and personal ABS is greater, when inventors create linkages from their old and common knowledge into other fields. From the regional economics literature, this more difficult innovation might be described as building on a Jacobs (1969) spillover, as opposed to a within-field MAR spillover (Glaeser et. al. 1992). For expositional simplicity we will henceforth 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) the citing patent’s CPC subclasses are different than the deceased patent’s (“Jacobs”) and 2) the citing patent’s CPC subclasses are the same as the deceased patent’s (“MAR”). Note that we keep the same citing 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 area

(“MAR”). Table 4 shows the estimated coefficients of our Probit models and Figure 5 plots the marginal citation probabilities for each sample (Jacobs in the upper panels, MAR in the lower panels), for inventors with prior experience (red dots) or without (blue dots), and citing inventors residing around living inventors (left side sub-panels) or the deceased (right side sub-panels).

Table 4: Jacobs and MAR spillovers across firms

	10	20	30	40	50	60	70	80	90	100
Panel A: Jacobs										
<i>Dist. deceased</i>	-0.598*** (0.108)	-0.598*** (0.092)	-0.447*** (0.084)	-0.412*** (0.101)	-0.360*** (0.090)	-0.385*** (0.093)	-0.381*** (0.094)	-0.330*** (0.112)	-0.217** (0.089)	-0.126 (0.085)
<i>Exp. in cpc (yes/no)</i>	0.534*** (0.068)	0.446*** (0.087)	0.695*** (0.078)	0.671*** (0.108)	0.649*** (0.110)	0.628*** (0.109)	0.610*** (0.112)	0.610*** (0.108)	0.593*** (0.110)	0.595*** (0.108)
<i>Interaction</i>	-0.228** (0.101)	0.246** (0.120)	-0.018 (0.138)	-0.103 (0.181)	-0.066 (0.181)	-0.001 (0.186)	0.048 (0.190)	0.103 (0.193)	-0.116 (0.136)	-0.148 (0.133)
<i>Pseudo R²</i>	0.166	0.188	0.159	0.151	0.143	0.142	0.137	0.137	0.134	0.134
<i>N</i>	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										
<i>Dist. deceased</i>	-0.587*** (0.151)	-0.694*** (0.151)	-0.399*** (0.099)	-0.368*** (0.113)	-0.379*** (0.111)	-0.334*** (0.110)	-0.348*** (0.103)	-0.322*** (0.100)	-0.351*** (0.097)	-0.336*** (0.095)
<i>Exp. in cpc (yes/no)</i>	-0.103 (0.065)	-0.052 (0.051)	0.013 (0.059)	0.028 (0.063)	0.022 (0.065)	0.017 (0.064)	0.023 (0.063)	0.028 (0.062)	0.023 (0.061)	0.020 (0.060)
<i>Interaction</i>	0.196 (0.135)	0.144 (0.103)	0.016 (0.083)	0.018 (0.090)	0.022 (0.089)	0.033 (0.084)	0.019 (0.082)	0.073 (0.078)	0.124 (0.076)	0.138* (0.073)
<i>Pseudo R²</i>	0.167	0.164	0.171	0.175	0.156	0.155	0.145	0.142	0.133	0.131
<i>N</i>	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
<i>Patent FE</i>	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.

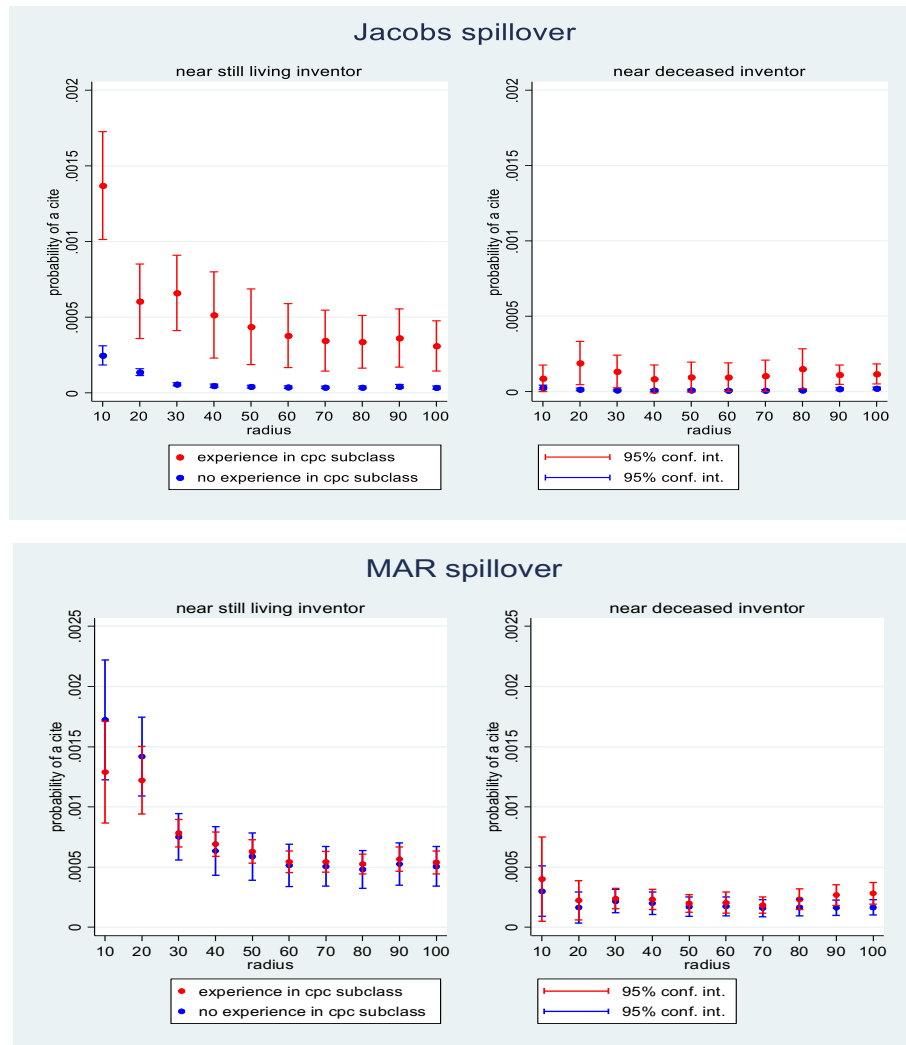
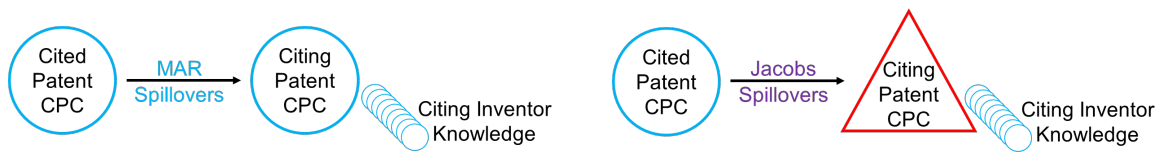


Figure 5: Estimated citation propensities around deceased versus still living co-inventor with and without absorbing inventor experience and differentiating between Jacobs and MAR spillovers.

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.

Figure 5 illustrates three take-aways. First, inter-personal knowledge flows localize irrespective of whether knowledge is applied to new or known fields (compare decreasing effects with distance

on both the left-hand graphs (living) as opposed to no change with distance on both the right-hand graphs (deceased) – there is a decreasing probability of citation on the left graphs with distance, yet no significant difference with distance on the right graphs. This provides evidence that both Jacobs and MAR spillovers localize.

Second, individual absorptive capacity as measured by prior experience is a differentiating factor only when it comes to applying prior knowledge to new fields - compare significant differences between red and blue estimates in the upper-left (Jacobs) against insignificant differences in the lower-left (MAR) graphs. This provides evidence that prior experience appears to matter for Jacobs spillovers and be less or unimportant for MAR spillovers.

Third, the conduit of inter-personal ABS is most valuable if the source of knowledge is physically proximate and collocated in person (compare red and blue estimates in the upper-left and upper-right) – there is a wide and decreasing-with-distance gap on the upper-left graph, and narrow, flat, and often insignificant differences, in the deceased region). This provides evidence that inter-personal ABS is most effective when the source of local spillovers is turned on.

We estimated additional models in order to assess the robustness of results. First, to ameliorate concerns that deceased inventors are different, and in addition to a similar national centroid of deceased vs. still-living inventor location, Balsmeier et. al. (2023) split inventors by age at death (with the assumption that younger inventors' deaths were less likely to be anticipated) as well as Fixed Effects models by deceased inventor. Second, to control for idiosyncratic and constant citation practices within a firm, we estimated Fixed Effects models by citing firm. Third, we estimated different models, including a linear, linear probability model, and as presented, Probit. Results remained robust to all these analyses.

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 (Balsmeier et. al. 2023b). Second, patents do not even cover all technical knowledge, for example, algorithms and trade secrets cannot be observed. Third, the estimates do not differentiate between firms that compete vs. those that cooperate (Fadeev, 2023). Fourth, the method is empirically very demanding (many patents are not cited much in aggregate and cannot contribute to the estimation

if there are no citations within the smaller radii), and our (still significant) results depend on relatively few observations. Fifth, interpreting non-linear models for rare events remains challenging and complex. Finally, the possibility of unobserved covariates between death and personal absorptive capacity weakens the causal inference for the second and third hypotheses.

These shortcomings notwithstanding, the method opens an arguably causal window into the impact of personal presence on localized knowledge spillovers between a particular source and particular destination inventor. Motivated by classic predictions in the strategy literature (Cohen and Levinthal, 1990), 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.

Keeping in mind that unobserved correlates with a mechanism will always threaten causal inference, other characteristics can also be studied, for example, the availability of inter-personal spillovers is probably particularly important for more recent, complex, and tacit knowledge that is more effectively transmitted through personal contact (Catalini et. al. 2020).⁴ Old information, such as that published in textbooks, will probably be less localized, as it is already more widely known and available from other sources and in the absence of the author. Just as it did with firm boundaries and Jacobs vs. MAR spillovers, bibliographic patent data could observe and estimate the age and the degree to which newer or more complex knowledge remains tacit and reliant upon inter-personal interaction. Other mechanisms could be investigated, for example, the social networks of inventors (through which knowledge surely flows, see Singh, 2005 and Fleming et. al. 2007), and a probable correlate, regional job mobility (Alameida and Kogut, 1999). Scientific networks, experience, and understanding may also influence the diffusion of technologies and ideas.

To illustrate one application of the approach, we now estimate the localization of within-firm knowledge transfer (we use the word transfer rather than spillover as spillover typically implies an across firm knowledge externality). While the main results here provide evidence that inter-firm knowledge spillovers are more likely when the inter-personal source is local and the destination

⁴ We would like to thank Wes Cohen for suggesting this idea.

has personal ABS in the same field, it is also possible to estimate whether the same localization holds within firms. To state the question more narrowly, if the source and destination both lie within the same organization, do knowledge flows within firms also localize, and fall off with distance when an inventor dies? Figure 6 explores this question.

As might be expected, the baseline citation propensity differs significantly between within firm versus across firm cites. This would appear plausible for several reasons. First, firms have a natural interest to try and maximize within firm knowledge flows and minimize knowledge leakage to other firms. Second, the amount of same firm inventors at risk of citation is largely limited due to the relatively small number of inventors inside a firm as compared to all inventors outside the firm, which can be large, particularly in technological hubs. Inside firm citations are also limited by our research design because there is only a limited set of firms that experienced an inventor death with differently located co-inventors and at least a few potentially citing inventors within the vicinities of each of the inventors on the deceased patent.

Figure 6 illustrates much less and insignificant localization of knowledge spillovers within firm boundaries, based on physical presence (independent of ABS). While there appears to be some localization around still-living inventors, the confidence intervals overlap for the regions around the deceased, vs. the regions around the still-living inventors. Even ignoring the large errors, the difference in point estimates would not create the almost monotonic decrease in citations that the across firm spillover models display. It appears that firms do not rely as much on geographical colocation within their boundaries, and that firms are capable of building on other sources of information about the invention, following the loss of an inventor. Assumedly, technologies, notebooks, co-workers, and internal documentation provide enough contextual depth and detail to overcome the loss of one particular inventor. Figure 6 does not include IBM, which demonstrates even less localization of knowledge diffusion within its boundaries (in other words, Figure 6 illustrates a conservative estimate).

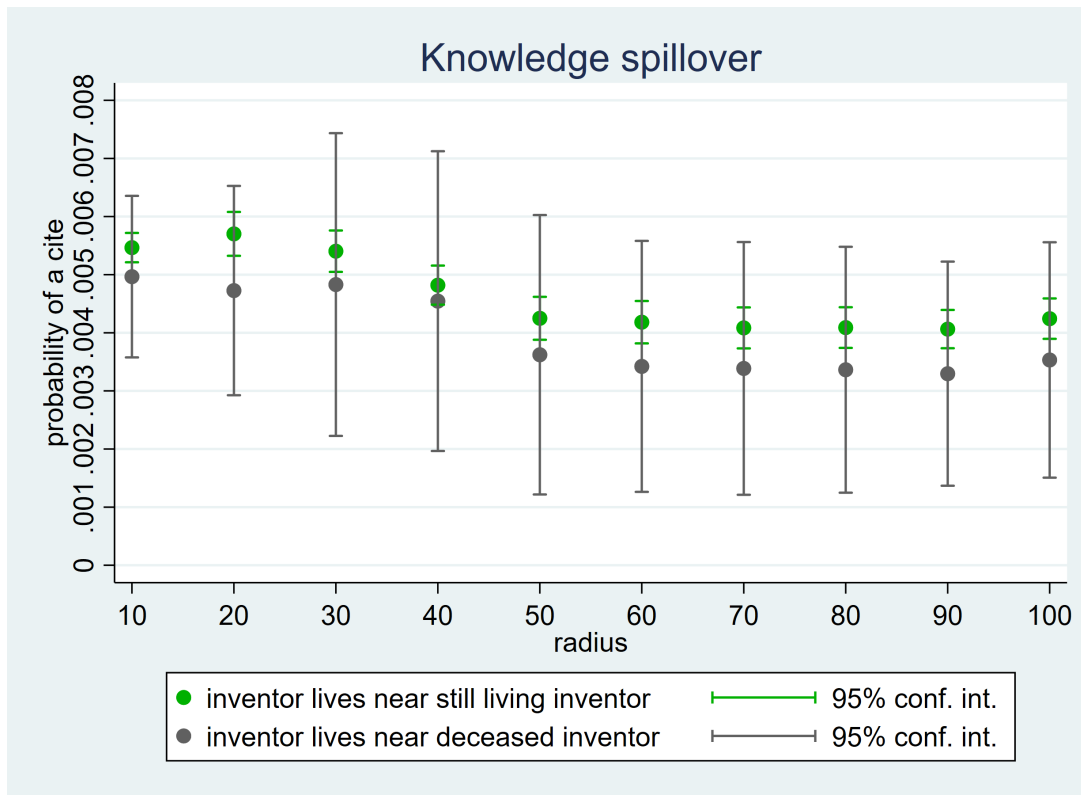


Figure 6: Within firm knowledge spillovers localize less. *Note:* This graph plots the marginal citation propensities around deceased versus still living co-inventors as coming from the Probit models, where the dependent variable is a dummy variable indicating a cite that occurs within a radius r of 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. These data only include within firm citations and do not include IBM (which indicate even less significant differences).

While it was the strategy literature that motivated the current work, the results provide some of the first causal evidence for the benefits of the juxtaposition of physical location and expertise, for the realization of Jacobs’ spillovers (Jacobs 1969; Atkin et. al. 2022), namely, the knowledge flows across field and industry boundaries that are thought to generate more creative combinations and new industries. Interestingly, the current results imply that is not so much the juxtaposition of diversity that results in new associations and linkages across fields, rather it is the physical collocation of people who have similar expertise and (unobserved in this study) interest in applying that expertise in new areas. Having a shared and similar technical background might facilitate risk taking and recombination into new fields – which implies that Jacobs inventions could actually arise from regions with relatively homogenous technical work forces.

Future work could look for the sources of the inspiration that triggers a “Jacob’s” spillover, i.e., the linkage to a new field within industrially homogenous regions – for example, possible exposure to academic science (Shin et. al. 2023). It could also seek to understand why some regions with homogenous work forces do not invent new and diverse technologies - or, if they do invent them, why the firms in the regions do not pursue and benefit commercially from them. Along with the potential mechanisms described above, the current methodology could also be used to investigate the impact of human capital and regional knowledge spillovers on regional innovation. For example, what is the impact of the loss of an inventor to future patent productivity in a region - particularly in the field of the deceased inventor? Or, following the implications of Bloom et. al. (2013), are knowledge spillovers less likely between market competitors, conditional on their the firms’ proximity in technological space?

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 our finding of no significant differences in the localization of inter-personal spillover effects over our sampling period (please see the Appendix) despite covering a time period of substantial technological advances in online communication, most prominently email and the early internet.

The results also have implications for other strategic questions besides ABS. For example, Teece et. al. (1997) defined dynamic capabilities as a firm’s ability to recognize and move into a strategically important new technology. 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 - such capabilities. 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. 2023a), or if they are the leader, they should seek to locate where followers cannot easily locate nearby (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 might turn out to be a short-sighted decision).

The results also highlight the importance of people and physical location for regional and national competitive advantage, for example, they imply that the geographical location of invention of emerging technologies such as AI are important, and that countries should attract the best and brightest (students) to work and innovate within their borders, despite concerns about such inventors' original home countries.

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 of the influence of personal presence on the types and mechanisms of localized spillovers and knowledge diffusion. 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. The work also illustrated that firms do not rely as heavily upon physical presence for internal knowledge transfer and that their within-firm knowledge transfers do not localize significantly.

While prior studies in the strategy literature were mostly agnostic about the local 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

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