PRELIMINARY DRAFT

Measuring the Diffusion of Innovation: A Reassessment of Knowledge Spillovers Using Machine Learning

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Abstract

The ideas of new invention are encapsulated in the text of a patent. Empirical measures of knowledge flows have previously relied on citations, which reflect the influence of other patents on an invention but not external sources of knowledge. I use unsupervised machine learning methods to convert patent abstracts (which are descriptions of the invention) to vectors and analyse the similarity across patent text. Unlike most of the citations-based spillovers literature, I find that geographic localization effects are insignificant to modest: prior to controlling technological proximity, within technology field patents from the same city are about 0-0.08 standard deviations more similar than patents from different cities. Including further technology controls reduces estimates to -0.02 to 0.04. By contrast, citations based measures find that local patents have 0.24-0.30 standard deviations more citations from the same city compared to a non-local control. These findings suggest that geographic localization of knowledge spillovers may not be a strong driver of local innovation and agglomeration.

Contents

1. Introduction

Knowledge spillovers are considered a key driving force of endogenous growth. A prominent literature of measuring knowledge spillovers has emerged from Jaffe et al. (1993) (henceforth JTH) that uses patent citations to study the "paper trail" left by the diffusion of innovative knowledge. The widely held consensus is that knowledge spillovers are geographically localized, meaning that local inventors and firms benefit more from the positive externalities generated by the R&D of other local firms, compared to inventors and firms located in different cities.

This paper utilizes methodology made available by advances in unsupervised machine learning to analyze the ideas within inventions as represented by the patent abstract, which summarizes the invention. I make three key contributions: first, I derive vector representations of innovative ideas using the Document Vectors (DocVec) algorithm, developed by Google. Second, I extend the original research of JTH as a benchmark measure, and find that the citations based measures of geographic localization are large, significant, and growing over time. Third, I use cross-patent similarity within technology fields to measure if patents from the same city are more similar than those from differing cities.

I find that the evidence for localization is mixed. The citations-based benchmark finds that (i) localization estimates are large and significant: local patents receiving 0.24-0.30 SD more local citations compared to non-local patents; (ii) localization is increasing over the time frame 1975-2005. Similarity measures finds that (i) localization estimates are much smaller: local patents are -0.02 to 0.08 SD "more" similar to other local patents, after controlling for technological proximity; (ii) localization has declined 1995-2015.

After controlling for MSA-specific technological proximity, I find that local patents are on average 0.02 SD less similar to other local patents. This effect is particularly pronounced for patent pairs from highly similar sub-fields, that is, patents from local rivals. This implies that *local differentiation* may also play a role in the innovative process, where inventors distance themselves from other local inventors so as to broaden the scope of their patents. Such differentiation in innovation may also be related to product market rivalry (Bloom et al. (2013)). This dynamic would not be captured using citations.

The differences in the findings using citations and similarity knowledge spillover measures may be due to the influence of external knowledge sources, as inventors do not only learn from other inventors and their patents. This may include workplace training, technical journals, websites, magazines, textbooks and other publications. Focusing exclusively on citations will miss knowledge flows from outside sources, while patent text will capture the influence of *all* knowledge flows relevant for the innovation process. I examine the

influence of external knowledge flows by looking at the first patents to use new technological terms. I find that while similarity captures the overlap in the ideas expressed by inventions appropriating the same new technology, these patents have almost no backward citations in common. Citations would find that these patents arose from completely unrelated knowledge sources. This suggests that patents with no common citation link may still produce similar innovations through the influence of external knowledge flows.

There are also well-documented concerns that citations themselves may not be good proxies for the relevant patent-based knowledge flows. Cotropia et al. (2013) and Alcacer et al. (2009) detail the extent to which patent examiners add their own citations they consider to be relevant prior art for the applicant's invention. Lampe (2012) and Roach and Cohen (2013) find evidence that citations are made strategically in ways that do not reveal knowledge flows, at least to other firms' privately held patents. I find evidence that support the previous literature. First, I examine the inventors' self-citation rates before and after they change firms. I find that inventors consistently cite their own prior inventions less after shifting firms, particular for relatively highly similar previous patents. This may be explained by the strategic incentive for firms to protect the scope of their inventions and thus leave out related citations that they may be "reasonably ignorant" of. Second, I examine the change in patents cited by the inventor after they change firms. I find that inventors work on fairly similar inventions after changing firms (average similarity from 0.29 to 0.25), their list of cited patents changes drastically (from 25 average common backward citations to 2). This further suggests that citations may be determined by the firm's (or firm's lawyers') prior knowledge of other patents, rather than the indicating the relevant patents required by the inventor for the innovation.

These findings imply that current methods of measuring knowledge spillovers may overestimate localization by focusing only on citation networks. While citation networks may be localized, external knowledge sources also play a role in the innovation process: if such knowledge flows are non-local in nature, then this leads to less localization across patents.

The paper proceeds as follows. Section 2 discusses the previous literature, data sources, and outlines the NLP methodology. Section 3 and 4 assesses citation patterns when examined in conjunction with cross-patent similarity. Section 5 presents the estimation models and results for localization regressions. Section 6 examines the influence of external sources of knowledge through new technology terms appearing in the patent corpus.

2. Previous Literature and Data Construction

2.1. Previous Literature

Knowledge spillovers are widely believed to be one of the key contributors to the phenomena of agglomeration. In October 2017, Amazon lead a widely covered search for a location for their second headquarters. Motivating all 238 cities vying for such an opportunity was the promise of agglomeration, the benefits accruing from the proximity of workers and firms clustering in the same location. Krugman (1991) and Marshall and Marshall (1920) cite knowledge spillovers as a source of positive externality, but not necessarily confined to cities themselves. The localized nature of knowledge spillovers (i.e. the spread of knowledge is bounded within a geographic region) has been argued by Jacobs (1969), Manski (2000) and Glaeser et al. (1992), who observe that "intellectual breakthroughs must cross hallways and streets more easily than oceans and continents." Feldman (1994) motivates this by suggesting that firms in the same location reduce the uncertainty of innovation by sharing knowledge.

This is further complicated by the fact that location is also a strategic choice for firms. As Alcacer and Chung (2007) point out, firms may favor locations rich with knowledge sources. Thus, location is an endogenous choice. Bloom et al. (2013) also note that product market rivalry exists across firms, which may serve to dampen spillover effects. However, they find that the importance of technology spillovers outweigh rivalry effects.

The empirical knowledge spillovers literature began with Jaffe et al. (1993). JTH examines whether or not inventors are more likely to cite patents closer to them, compared with a control patent. *To* separate localization effects from the existing distribution of patenting activity across locations, JTH select a control patent from the same technology distribution using PTO classes. They argue that since patents from the same PTO class come from the same technology distribution, then if there were no localization effects, there would not be significant differences in their citations' distribution across locations. Their study finds highly significant localization effects using the control/treatment methodology.

There are three main concerns with their methodology: first, whether or not their control selection method (using PTO primary class) is appropriate. Thompson and Fox-Kean (2005) use PTO primary subclass and find less significant localization effects; Murata et al. (2014) draw counterfactuals from a distribution, and alongside Buzard et al. (2016), use a continuous distance measure. Both papers find substantial evidence supporting localization. Instead of drawing counterfactual patents from PTO classes, another strand of literature uses the geographic mobility of inventors and authors to identify local spillover

effects. Almeida and Kogut (1999), Agrawal et al. (2006), and Azoulay et al. (2011) all find that citations located in the inventor's or author's previous location is much higher than the control's citation rate. (These studies do still use the control/treatment method, just with stayers/movers) However, this does not address the second concern: that location choice cannot be taken as exogenous. As highlighted by Alcacer and Chung (2007), firms are strategic in their choice of location and may choose location based on where local spillover effects may be strong. Greenstone et al. (2010) directly address this by using "Million Dollar Plants" data to compare the agglomeration spillover effects in "winner" counties that were chosen as well as "runner-up" counties who narrowly lost, who serve as counterfactuals. They find evidence in favor of local TFP spillovers, though not directly addressing shared knowledge. Spatial econometrics have also been applied in addressing geographic localization. Following Bloom et al. (2013), Lychagin et al. (2016) find significant positive localization effects of technological proximity using vectorizations of PTO classes.

2.2. Data Sources

Patent data is taken from PatentsView on all utility patents granted 1976-2016, containing data both on inventors (including unique identifiers and location) and patents (assignee, application date, grant date, primary class and subclass). Bibliographic text data is taken from the USPTO Bulk Data Products, which has all patent bibliographic text from 1976 to end of 2015. Patent abstracts are taken to be representative of the knowledge contained in patents, as they are a summary of the invention.

Patent technology fields

Each patent is assigned three technological *fields*, with each field being nested in the previous. At the broadest level, an NAICS-based industry classification is given using the USPC to NAICS concordance crosswalk, which delegates each patent to a NAICS category according to its USPTO 3-digit primary classification. Additionally, many patents are also assigned a primary *sub*class.[1] Primary subclasses are nested in primary classes, which are in turn nested in a NAICS industry label. There are over 150,000 subclass labels; 450 class labels, and 33 NAICS industry labels.

[1]Patents may also include other discretionary classifications, which are not used in my data.

2.3. Patent Abstracts to Vector Space Representations

Using patent abstract texts, I use procedures standard in the NLP literature to clean and convert text to vector representations. I select two unsupervised algorithms (Latent Dirichlet Allocation and Document Vectors) for the conversion process that are most appropriate for the task at hand: to convert a large quantity of texts into meaningful vectors that allow for sensible cross-comparisons of the represented knowledge. LDA has received considerable attention in a wide variety of literatures, and has been applied to patents by Kaplan and Vakili (2015). Document Vectors is a relatively more recent technique that has performed very well in providing sensible results as deemed by human judgment. (TODO cite) For a survey of the literature, see (TODO cite).

2.3.1. Unsupervised Machine Learning Methods: Topic Models

Latent Dirichlet Allocation, first introduced by Blei et al. (2003), is a method of Topic Modelling that assumes that a document can be represented as a linear distribution hidden variables called *topics*. It is a Hierarchical Bayesian hidden variables model. The Data Generating Process assumes that each topic is a linear distribution over terms in the corpus. For each document, which is a distribution over topics, each term is assumed to be generated by first drawing a topic, then drawing a term from that topic. Because this is an unsueprvised method, the algorithm then jointly determines the topics distribution over terms and each document's distribution over topics. See A.1.2 for more details on the assumptions of the LDA model.

The number of topics K is a parameter that is determined ex-ante; as per Hoffman et al. (2010), the recommendation is that the model with the lowest log perplexity be selected, although there is not a universally agreed upon procedure. I fit a LDA model on a training subset of the same document-term matrix representing all patent abstracts with $20, 30, ..., 120$ topics. Then, the model was fit on the test set and the log-perplexity calculated. I selected $K = 60$ as it had the lowest log perplexity across the models.

A snippet from the resulting topics is shown in 2.1, alongside the six highest probability terms in teach topic. The output I am interested in is the probability across each of the 60 topics of each patent document. I take this as the Topic Model vector representation of each patent.

Topic	Distribution over terms	Description
0	0.040*"network" + 0.039*"inform" + 0.033*"comput" + 0.031*"communic" + 0.028*"user" + 0.027*"memori"	Networks & Coding
2	0.066*"time" + 0.057*"sensor" + 0.040*"detect" + 0.032*"event" + 0.031*"paramet" + 0.027*"level"	Monitoring & Coding
11	0.116*"power" + 0.068*"voltag" + 0.049*"output" + 0.045*"circuit" + 0.026*"suppli" + 0.026*"transistor"	Electronics
36	'0.071*"composit" + 0.059*"polym" + 0.049*"weight" + 0.041*"coat" + 0.018*"resin" + 0.016*"c"	Polymers, Chemicals
53	'0.065*"metal" + 0.065*"solut" + 0.037*"ion" + 0.036*"carbon" + 0.032*"concentr" + 0.023*"reaction"	Metals, Chemicals

Table 2.1: Selected Topics as outputted by LDA. Description added post hoc.

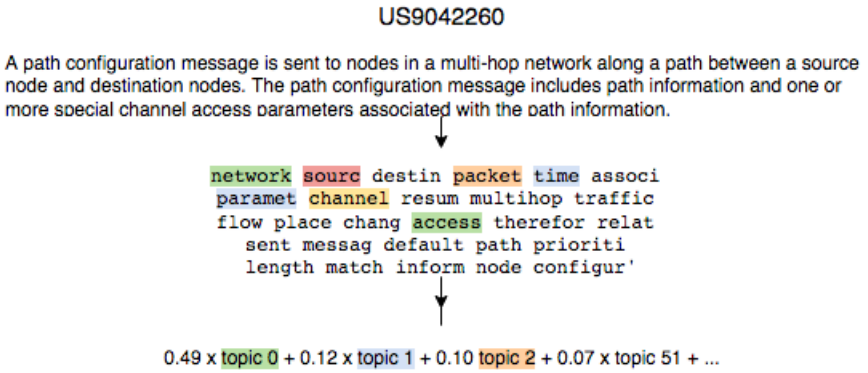


Figure 2.1: Example of a patent converted into a distribution over topics.

2.3.2. Unsupervised Machine Learning Methods: Document Vectors

Document Vectors was introduced by Le and Mikolov (2014), and is a straightforward extension of the word2vec model of Mikolov et al. (2013b,a). Word2vec was developed in order to address issues with the bag-of-words procedure, primarily the loss of information provided by word ordering, and its inability to identify similar terms. To address this, word2vec uses the "context" around each term in the document in order to represent a term in vector space. For example, for the sentence "Provides for unattended file transfers", the word "unattended" has the context ["Provides", "for", "file", "transfers"]. Every word and document is assigned a vector of dimension $N = 100$.[2] The resulting vector places words that arise in similar contexts close to each other. Since documents are treated more or less just like words, the algorithm places documents that contain similar terms close to each other in the vector space. See A.1.1 for more details on the algorithm.

The main difference between Document Vectors and other representations is that the columns of the vectors do not represent anything meaningful; its purpose is solely to find a way to place documents in a vector space such that distances across the vectors represent similarity across patents as detected by the algorithm.

[2]This is a rule-of-thumb in the literature, according to Lin et al. (2015)

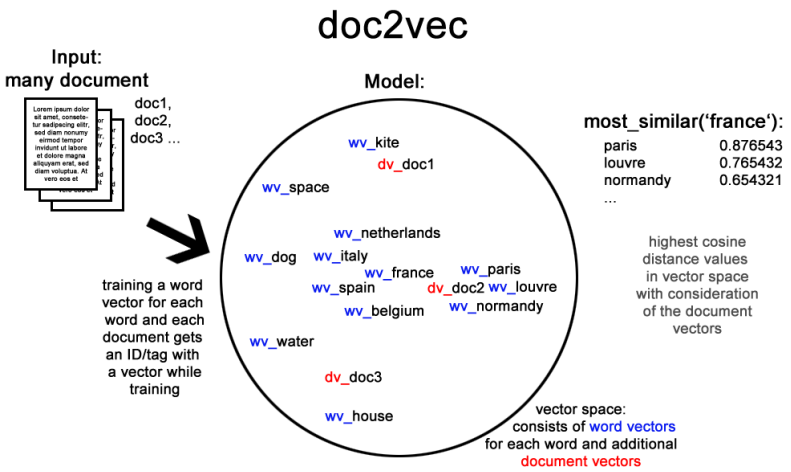


Figure 2.2: Illustration of Document Vectors. (Will redo with specific reference to my work)

2.4. Measuring Knowledge Spillovers: Cross Patent Similarity

Cosine similarity [3] has been used to measure technological proximity in Jaffe (1989) and Bloom et al. (2013), as well as being standard in the NLP literature (Mihalcea et al. (2006)). The primary advantage of NLP patent vector outputs is that they are *jointly* determined, and position each patent vector *relative* to all other patents within the corpus. Thus, cross-patent comparisons using NLP vector outputs are much more internally consistent.

For two patents, i and j, the cosine similarity between them is:

$$sim(i,j) = \frac{PV_i \cdot PV_j}{\|PV_i\| \, \|PV_j\|} \tag{2.1}$$

Where PV_i is the patent vector representation of i. This is preferred to Euclidean distance as it is factors in the "size" of the vector; a Euclidean distance measure would assign positive distance to two vectors that contained the exact same words, but of different quantities. Cosine similarity normalises all measures to be in the range $[-1, 1]$.

[3] Other measures, such as Hellinger distance, were also used but found to be very highly correlated with cosine similarity.

2.4.1. Technology Controls: Cross Field Similarity

Since each patent is assigned technology field labels, the vector representation of a technology field f at t can be the *median*[4] of all patents within the field granted from year $t-5$ to t:

$$FV_{f,t} = median(PV_i | i \in f)_{t-5,t} \tag{2.2}$$

Further, I can treat the fields at each location as a "sub"-field, and define a location field vector at some MSA l as:

$$LFV_{f,l,t} = median(PV_i | i \in f, i \in l)_{t-5,t} \tag{2.3}$$

For LDA, this represents the distribution of all patents in the field across each of the 60 topics. For Document Vectors, this represents the centroid of the set of all patents within the field. For any patent i in field f_i, cross-field similarity and cross-location-field similarity to patent j is analogously:

$$sim(f_i, f_j) = \frac{FV_{f_i} \cdot FV_{f_j}}{\|FV_{f_i}\| \left\|FV_{f_j}\right\|} \tag{2.4}$$

Intuitively, this is the *expected* similarity between two patents if only their technology field was known. Cross field similarity are analogous to the technological proximity measures of Jaffe (1986); Bloom et al. (2013). Both papers, alongside other citations-based methods of measuring technological proximity, rely on the vectorization of PTO classes. These methods may lead to inconsistent results as each patent may have any number of non-primary classifications. The standard procedure has been to normalize or weight each of the classes listed, which discretizes the vector space and leads to discontinuities in the proximity measures.[5]

2.4.2. Comparing LDAVecs and DocVecs in Measuring Document Similarity

TODO - will be examples, looking at where they differ, what they do well and not so well

[4] The median is chosen as a better representation of the field as it is less sensitive to outlier values.

[5] A patent with one class would be represented by a vector with 1 in the class column and 0 elsewhere; two classes 0.5 in each class column and elsewhere; and so on.

2.5. General Trends in Innovation

U.S. patents granted 1976-2015 are primary dominated by five main industries: Machinery (15.8%), Computer and Peripheral Equipment (11.4%), Semiconductors (9.3%), Navigational and other Instruments (9.1%), Communications Equipment (7.7%). Following more general trends in U.S. manufacturing, the pattern as time progresses has been the shift from Machinery related innovations to Computer related innovations. The cities dominating innovation have also shifted from the east coast to the west, particularly San Jose and San Francisco.

In terms of agglomeration, we may also be be interested in the concentration of innovation across various cities over time. Following Moser (2011), I use the Herfindahl index (HHI), which is commonly used to calculate market power, to examine the city-concentration of innovation within industries. I find that, in general, HHI declined from 1975-1995 before rising again 1995-2015 (figure D.1). In 2015, there was a sharp upward trend in city-concentration across a range of industries. In the Semiconductors industry, which I examine more closely in section §**??**, there is a noticeable incline in HHI 1990-2000. This may be due to the entry of new innovation in the field which is initially concentrated, then diffuses more widely through the economy. This U-shaped trend is also mirrored when looking at the HHI of *industry*-concentration over time (figure D.2): the decline in concentration of innovation within few industries is reversed around 1995, and has been rising steadily ever since.

This pattern also emerges in the within-industry similarity trend (figure D.3). However in the case of similarity, there is not a pronounced initial downward trend. The turning point here is around 1990, meaning that after 1990, patents within industries began to look more similar to one another. While this fact alone is not necessarily a cause of concern, combined with the growing city-concentration, these trends may indicate a decline in the diversity of innovation: as inventions in smaller cities decline, the new inventions from already concentrated centers dominate and industry patents look more alike. Additionally, note that the turning point for similarity occurs a few years prior to the turning point for city-concentration HHI. We may speculate that the rise in overall similarity, meaning a fall in overall difference, may be a preceding symptom of declines in innovativeness across smaller locations.

3. Comparing citations and similarity as measures of spillovers

The validity of citations as a measure of knowledge spillovers are challenged by the existing literature. It has been widely used in practice because, until now, another such measure has not been available. I argue that patent vector similarity is able to bypass the more damaging criticisms of citations, insofar as it does *not* reflect strategic considerations on the part of the applicant. Because patent abstracts must be accurate summaries of the invention at hand, this limits the ability of applicants to omit important technological terms in order to hide the relevance of previous knowledge. [6] Theoretically, it is difficult to imagine inventors internalizing the similarity of the text within their patent to all other patents in the corpus when choosing words to describe their invention.

The problems with using patent citations to proxy for knowledge flows have been well documented. The two dominant concerns are: (i) many citations added by external agents (either law firms or patent examiners), which obfuscates the relationship between the patent and citation as a direct knowledge "flow"; (ii) there are strategic reasons for withholding relevant citations. Namely, citing patents that are closely proximate to the invention limits the scope of the patent and thus reduces the value of the intellectual property. These effects can result in substantial measurement error: Alcacer and Gittelman (2006) find that on the average patent, two-thirds of citations are added by the examiner, while Cotropia et al. (2013) find that applicant citations are often ignored by examiners who conduct their own search of prior art. Citations are also strategic in that, according to Jaffe and De Rassenfosse (2017), "although applicants at the USPTO have a duty to disclose what they know, they have no duty to search for prior art and may be better off by remaining ignorant." Inventors seeking to maximise the value of their IP may be inclined to leave out the most relevant citations; Lampe (2012) finds that applicants withhold between 21% to 33% of relevant citations, as determined by the applicant firm's previous citations. Using a survey of lab managers, Roach and Cohen (2013) also find that patent citations are more reflective of a firm's appropriability strategies in ways that are not revealing of "true" knowledge flows.

A more nuanced challenge is in the assessment of which measure is a better proxy for knowledge spillovers. Similarity should not be taken as a replacement for citation measures. If we consider the innovation process, it requires a number of knowledge flow inputs:

1. Citations of other patents discovered through inventor networks. (observed)

2. Citations of non-commercial scientific publications discovered through scientific research (observed)

[6] Legal considerations could still affect the choice of words used in patents.

3. Outside sources of knowledge such as workplace training, non-academic technical and trade publications, professional conferences (unobserved)

The output of the innovation process is the invention, as described by the text of the patent. This invention would reflect all of the knowledge inputs, including what may be unobserved external sources of knowledge. These unobserved knowledge sources may then represent a "wedge" between the knowledge spillovers measured by citation patterns, compared to the similarity measure. For these reasons, unlike citations, $sim(p_i, p_j)$ should not be interpreted as a direct knowledge *flow* or an indication of such. While this means that similarity is suboptimal as a measure of *direct* knowledge flow, it may be a superior measure for knowledge spillovers, which is an *externality* from the exchange of knowledge flows. Since we have not had an alternative to measuring spillovers until this point, the theoretical case for which measure is better suited for the task remains to be determined and is beyond the scope of this paper.

3.1. Using similarity to determine trends in the relevance of citations

The incentives of the inventors in making citations are two-fold: firstly, to offset the likelihood of patent litigation (which rose sharply in 1990-2010); secondly, to maximise the scope of the patent by not making citations that may challenge the novelty of the invention.

In line with the first incentive, it has been well documented that the number of citations made by each new patent has been rising dramatically over time. I construct a sample comprised of all citation patent pairs (comprised of a *cited* patent and a forward *citing* patent granted within 10 years of the cited patent) with self-citations made by the same assignee removed. From 1985 to 2015, the average number of citations made by each patent rose from 2.3 to 6.0 (B.1). This trend is accompanied by evidence that this phenomena has reduced the relevance of the citations, and thus the quality of citations as measure of spillovers. I find that the proportion of citations made to patents within the same primary class has declined sharply, from 54.1% to 34.4%. While this fact alone is not decisive (as it may indicate greater inter-field influences) there has also been decline in the average DocVecs similarity of the citation to the cited patent, from 0.28 to 0.25 (B.4). This decline persists even for citations made within the same technological field (B.5). Taken together, these trends would indicate that the relevance of citations have been diluted by the addition of less related citations. However those made to patents within the same MSA has increased, although not consistently over the period: the share of local citations rose from 9.3% in 1985 to 12% in 2015. A possible explanation for this trend may be that other local inventors are more likely to discover

potential patent infringements, and thus the risk of patent litigation may be higher for local firms than non-local.

3.2. Evidence of general strategic citation using similarity

To explore this possibility, I construct a different sample of "potentially citable" patent pairs. (See C.1) I sample of set of target patents (*tp*) and find a complete list of their backward citations (patents cited by *tp*). For each backward citation, I find all their forward citations: each target patent is then matched with another such forward citation, granted *after tp.* Thus, each target is matched with a patent that has a backward citation in common, so that the target is "potentially citable" by the matched patent. I then calculate cross-patent similarity for each pair. To prevent noise from bins with few observations[7], the lowest bin includes all values below, and the highest bin includes all values above.

Hypothetically, we should have a number of expectations if there are weak incentives for omitting relevant citations:

1. The rate of direct citation should *monotonically increase* with the similarity between the two patents.
2. Rates of citation should be generally higher for patent pairs within the same location or technological field, as inventors are more likely to be familiar with other inventions close to them.
3. Rates of direct citation should be higher for primary class, as we should also expect inventors to be more familiar with patents in the same narrower band of technology field over the broader categorisation of NAICS.
4. If location does not bear any additional consideration on citations, then we should expect overall shape of the trends for local pairs vs non-local pairs to look like that of patent pairs in the same vs different technological fields.

I find evidence in support of (2) and (3), but against (1) and (4) (see figure 3.1). The rate of direct citation is *not* monotonically increasing with similarity, and in fact *declines* at the highest bracket of similarity. Overall, while 6.3% of tp patents are directly cited by op when their similarity ranges between 0.5-0.6, only 4.2% are cited for similarity 0.6-0.7+ (represented by the bin 0.7). This trend holds for patent pairs within the same technology field. Rates of citation were found to be higher for pairs from the same

[7] Below the 1st percentile and above the 99th

technological field over differing fields (supporting (2)) and from the same primary class over the same NAICS (supporting (3)), although that advantage faded as similarity grew.

Most interestingly, for pairs from the same location, there is an immense divergence in the citation rate for highly similar pairs (0.6-0.7+): 7.5% for 7163 local pairs and 2.2% for 11795 non-local pairs (see table B.1). In fact, patent pairs in the same location were the only group that behaved according to (1), implying that there are substantially weaker incentives to withhold highly relevant citations from the same location, compared to citations from different locations. Additionally, the rate of citation catches up for non-local to local patents when similarity is relatively high (0.4-0.6), [8] before sharply diverging. We would expect in the absence of strategic incentives that the rate of citation would meet at high levels of similarity and *not* diverge. The fact that these patterns look different to the patterns for technology fields (against (4)) further suggests that location *does* bear separate consideration when inventors make citation decisions, particularly for highly relevant patents.

Since local inventors are much less likely to withhold relevant citations to other local patents, these results support the notion that localization in citations may be driven by strategic behaviour on the part of inventors. To get a sense of the scale of the problem, as a counterfactual exercise, suppose inventors cited non-local patents at the same rate as they did local patents, conditional on similarity. This would imply a total of 53993 citations, compared to the actual figure of 41449. This implies that approximately 30% of non-local citations are "missing."

[8] This bin represents the 90-99th percentile of similarities in the sample.

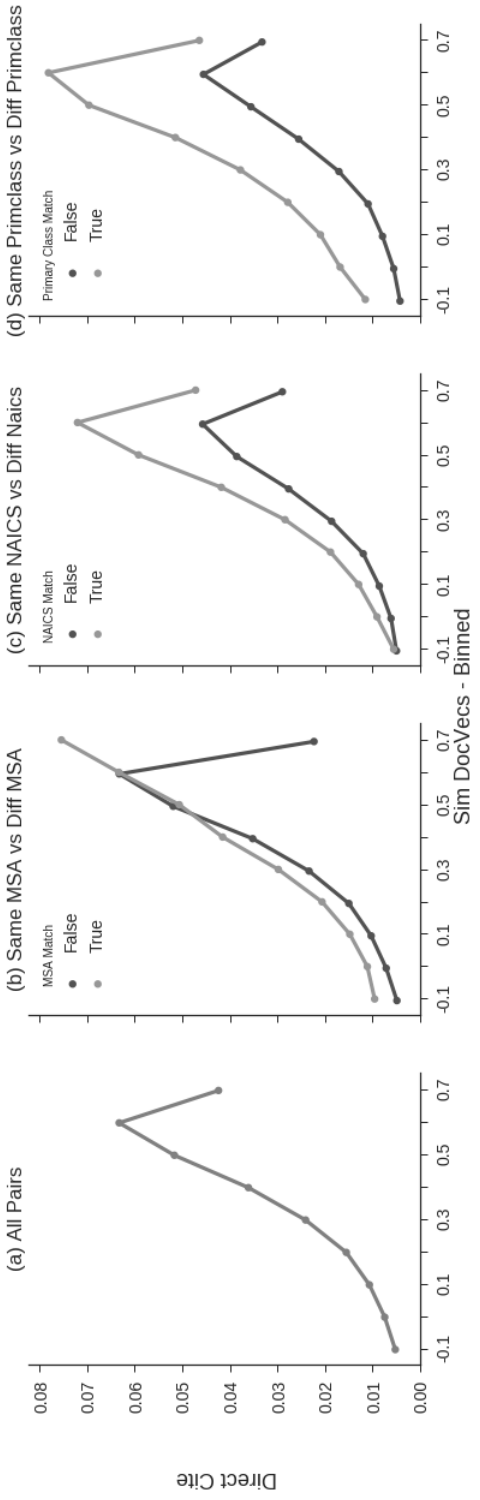


Figure 3.1: Rates of direct citation, conditional on Sim DocVecs

4. Differences in citations and similarity measures

I investigate the quality of citations as a signal of inventors' knowledge flows using citations and similarity across an inventor's own patents, before and after changing firms. In the first case, I explore the rate of citation for their own previous work, and find that strategic motives reduce the rate of self-citation for inventions at the first firm once inventors change firms. Then I discuss the shift in citations to other patents once the inventor changes firms, compared to the change in similarity. While the inventor's list of citations changes drastically once inventors moves, the change in similarity to their previous work is much smaller comparatively.

4.1. Inventor mobility and rate of self-citation

A clear example of where strategic non-citation might emerge is in the rate of citation for inventor's own patents, once they move to a different firm. Since inventors cannot reasonably claim to be ignorant of their own inventions, we can safely assume that any discrepancies in the rate of citation must be attributed to strategic withholding on the part of the new firm. I compare the rate of inventor self-citation when they are at their first firm, to the rate of self-citation of patents at their second firm to the patents at their first firm. Suppose inventor i has patents A, B, C at firm 1, and D, E at firm 2. Then I will compare the self-citation rates in the set AB, AC, BC before their firm change, and AD, AE, BD, BE, CD, CE after the change. Since inventors often work in slightly different areas at their new firm, it is also crucial to condition on pairwise similarity in order to ascertain the appropriate benchmark citation rate. I use all 12,377 inventors who have changed firms and their complete patents at their first and second firm to construct my sample. They account for 8.7% of the 141,583 total inventors in the data.

If, conditional on similarity, the rate of citation is lower for inventors after they change firms compared to before, then this indicates that the inventor or the new firm is more or less knowingly concealing relevant citations in order to enlarge the scope of the new invention. I find evidence to support this claim. There is a consistent and statistically significant gap in the rate of citation to the inventor's own previous inventions at almost every level of similarity. The difference does grow with similarity up to 0.6, after which the two measures converge. In the similarity range 0.5-0.6, inventors prior to their move across firms self-cited at a rate of 26.3%, while after the change it becomes 16.4%, a difference of close to 10%. Interestingly, the difference is not statistically significant at the highest level of similarity, largely due to the tapering off of *within* firm self-citation. One explanation is that there is no risk of patent infringement lawsuits from

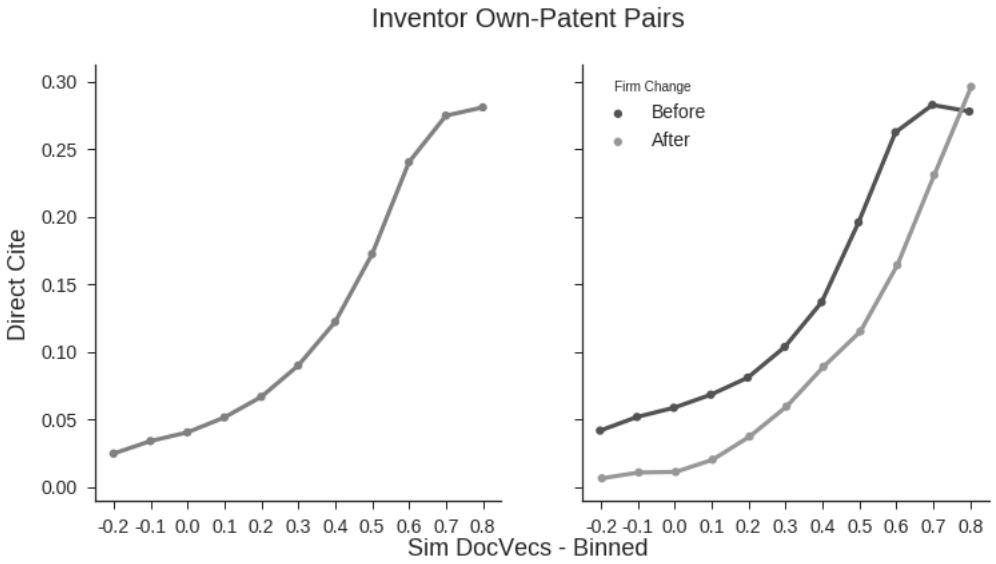


Figure 4.1: Rates of direct citation by DocVecs similarity

$sim\,DV$, binned	-0.2	-0.1	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8
Before Firm Change, N	671	3898	15868	38162	55625	54663	37899	20148	10389	5871	3553
Before Firm Change, Prop Cites	0.042	0.052	0.059	0.068	0.081	0.104	0.137	0.196	0.263	0.283	0.278
After Firm Change, N	624	2984	9869	20627	26876	24676	16732	8283	3008	1056	712
After Firm Change, Prop Cites	0.006	0.011	0.011	0.02	0.037	0.06	0.089	0.115	0.164	0.231	0.296
Diff, p-value	0	0	0	0	0	0	0	0	0	0.001	0.322

Table 4.1: Rate of self-citation before and after firm change

yourself, and so firms can expand the scope of their new patents by not listing their own highly similar previous inventions.

figure 4.2 shows an example of an inventor who produces two very similar inventions: first, US Patent 7204412 "Family store value card program" was assigned to CompuCredit Intellectual Property holdings, applied for December 27, 2004. US Patent 7325725 "Store value card account transfer system", assigned to Purpose Intellectual Property in February 5, 2005, and yet did *not* cite 7204412.

If inventors cited themselves at their new firms at the same rate as before their move, then the projected number of total citations would be 12112, compared to the actual number of 6422. The total number of "missing" self citations after changing firms represents 89% of the actual number of self-citations.

4.2. Inventor mobility and citation patterns

Examining only the citations that an inventor makes before and after they move firms, it would seem that they have altered their knowledge networks quite drastically. Prior to the move, the inventor has on average

United States Patent **7,204,412**
Foss, Jr. **April 17, 2007**

Family stored value card program

Abstract

A family stored value card program is provided. One embodiment is a method for implementing a stored value card program. One such method comprises: identifying an existing stored value card account; and enabling a first customer associated with the existing stored value card account to establish a new stored value card account associated with a second customer, the new stored value card account linked to the first stored value card account.

Inventors: **Foss, Jr.; Sheldon H.** (Suwanee, GA)
Assignee: **CompuCredit Intellectual Property Holdings Corp. III** (Las Vegas, NV)
Family ID: **39360819**
Appl. No.: **11/022,739**
Filed: **December 27, 2004**

Prior Publication Data

United States Patent **7,325,725**
Foss, Jr. **February 5, 2008**

Stored value card account transfer system

Abstract

Systems, methods, computer programs, merchant terminals, etc. for transferring finds between stored value card accounts are provided. One embodiment comprises a method for loading a stored value card. One such method comprises: identifying a first stored value card account associated with a first customer; receiving a selection from the first customer of a second stored value card account associated with a second customer and a load amount for transferring to the second stored value card account; and initiating a funds transfer of the load amount from the first stored value card account to the second stored value card account.

Inventors: **Foss, Jr.; Sheldon H.** (Suwanee, GA)
Assignee: **Purpose Intellectual Property Management II, Inc.** (Las Vegas, NV)
Family ID: **39304185**
Appl. No.: **11/050,301**
Filed: **February 3, 2005**

Figure 4.2: Example of an inventor moving firms and not self-citing. US Patent 7204412 was not cited by US Patent 7325725.

	Num Common Cited	Num Common Cited, Prev MSA	Sim DocVecs
Before Firm Change	25.01	1.74	0.29
After Firm Change	2.13	0.06	0.25
After Firm Change - Same MSA	2.37	0.07	0.26
After Firm Change - Diff MSA	1.67	0.02	0.22

Table 4.2: Patterns in common backward citations before and after firm change

25.0 common backward citations (with self-citations removed). After the move, the inventor averages 2.1 backward citations in common with their own previous patents, implying approximately a 91% decline in knowledge overlap. For citations within the same location as their previous firm, the number of common citations to the previous location falls drastically from 2.1 to 0.05. Even if the inventor moves to another firm in the same location, this decline is stark. However, the similarity of the inventor's new patents to their prior patents does not decline as sharply: from 0.29 to 0.25, this implies a 13.7% decline in knowledge overlap.

One potential explanation is that the list of citations made in patent applications are predominantly determined by firm-specific factors such as the firm's in-house prior knowledge of other patents and lawyer choice. This would imply that citations are weak indications of the inventor's own knowledge flows for what are relevant knowledge inputs into the invention. Citations overestimate the change knowledge spillover due to its determination by considerations external to relevant knowledge for the invention.

5. Measuring Local Knowledge Spillovers

5.1. Benchmark: Extension of JTH (1993)

I replicate and extend the work of JTH in order to have a baseline to compare the magnitude of localization effects. JTH sampled patents in their control (target) group in the following manner: from the years 1975 to 1980, they select a random sample of Top Corporate (top 200 by R&D total expenditure measured by Compustat) and Other Corporate patents, and all patents granted to Universities. Their sample size is 950 for 1975 and 1450 for 1980 respectively. Then, for each "target" patent in the sample find a control patent that is as close as possible to the target in *grant date* in the *same patent primary class.* JTH claim that this accounts for the "existing distribution of technological activity," and thus if citations are more likely to be from the same geographical area as the target patent over the control, then it is evidence for the existence of localized knowledge spillovers. Here, a citation is a patent that cites the target.

In my method, I use a larger sample of target patents granted 1976-2005,[9] and limit forward citations to be within 10 years of the target patent's grant date. Self-citations of patents granted to the same assignee are similarly excluded. The only point of departure is that due to lack of data, I do not use separate categories of patents by assignee "type", and pool all patents by grant year. Compared to the original JTH results (table III, p. 590), my results are fairly well aligned with their 1980 cohort figures for top corporate patents. [10]

I find that the measure of localization using citations based spillover measures is substantial and *rising* in size over time, concurring with Sonn and Storper (2008). The difference in the percentage of citations matching the target's MSA grows from 5.32% in 1975-85 to 6.46% two decades later. Relatively speaking, the effect is substantial: local patents are twice as likely to cite other local patents as non-local patents of the same primary class. The increase in both the target and the control's citations matching the target's MSA may indicate growing concentration in relevant inventions across locations.

To isolate the effect of localization, the above exercise can be represented as a regression model:

$$pct\,cites\,in\,MSA_T = \beta_0 + \beta_1 I(MSA_i = MSA_T) + Year\,FE + \epsilon \tag{5.1}$$

Primcary class fixed effects are also added:

[9] 2005 is the last year that 10 year forward citations are available for

[10] 8.8 for target match and 3.6 for control match; compared to 9.09 and 3.77 for my results. Slight discrepancies may arise due to sample selection and slight differences in removing self-citations.

Grant Year	Pct Targ Cites in MSA_T	Pct Control Cites in MSA_T	Diff	t-stat	p-value	N obs
1975-85	9.09	3.77	5.32	33.01	0.0	34489
1985-95	9.71	3.48	6.24	55.25	0.0	59102
1995-05	10.98	4.52	6.46	71.97	0.0	99248

Table 5.1: JTH Extension Results

$$pct\,cites\,in\,MSA_T = \beta_0 + \beta_1 I(MSA_i = MSA_T) + Year\,FE + \epsilon \tag{5.2}$$

Where $i \in \{T = target, C = control\}$. Here, $I(MSA_T = MSA_T) = 1$, $I(MSA_C = MSA_T) = 0$. Then, as in **??**, the estimated measure of localization is $\hat{\beta}_1$. In this case, $\hat{\beta}_1$ represents the (approximate) increase in the percentage of citations in a particular MSA for a patent in the same MSA vs from different MSAs.

5.2. Changing the spillover measure to similarity

With similarities, we do not necessarily require a control patent as a point of comparison. The use of the control patent has been scrutinized previously, notably by Thompson and Fox-Kean (2005), who argue that technological differences cannot be fully accounted for by selecting on primary class. In devising an analogous similarity measure of spillovers using the same sample above, I consider what approach is possible under similarities that was not using citations, that might better approximate local spillovers. Instead of using a control patent as baseline, I instead take the cross patent similarity of a target patent with citations from its own MSA, to citations in different MSAs. This approach has a straightforward interpretation: localization is present if a patent is more similar to its forward citations from the same MSA compared to those from different MSAs. This would mean that of the subsequent patents directly influenced by the target, on average, patents from the same location as the target share more in common.

I find that target patents *are* more similar to citations matching its own MSA, compared to citations from other MSAs. However, the relative magnitude of the effect is much smaller compared to the JTH citations measure. DocVecs measures find that local citations are about 15% more similar; for LDAVecs, same MSA citations are about 10% more similar than citations from different MSAs.

Grant Year	$\overline{sim_{DV}(T,j\|j\,in\,MSA_T)}$	$\overline{sim_{DV}(T,j\|j\,not\,in\,MSA_T)}$	Diff	t-stat	p-value
1975-85	0.35	0.29	0.05	25.53	0.0
1985-95	0.33	0.29	0.05	33.05	0.0
1995-05	0.32	0.28	0.04	42.39	0.0
2005-15	0.31	0.27	0.04	26.92	0.0

Grant Year	$\overline{sim_{LDA}(T,j\|j\,in\,MSA_T)}$	$\overline{sim_{LDA}(T,j\|j\,not\,in\,MSA_T)}$	Diff	t-stat	p-value
1975-85	0.58	0.53	0.05	17.81	0.0
1985-95	0.57	0.51	0.06	27.66	0.0
1995-05	0.54	0.49	0.05	33.25	0.0
2005-15	0.53	0.48	0.05	20.79	0.0

Table 5.2: JTH Replication Results with Similarity Measures.

Here, j is a patent that cites target T. $\overline{sim(T,j)}$ is the *average* of the pairwise similarities between the target and each of the forward citations j that are either located in the same MSA as T or not. In regression form, I estimate:

$$\overline{sim(T,j)} = \beta_0 + \beta_1 I(MSA_j = MSA_T) + Year\,FE + \epsilon \tag{5.3}$$

$$\overline{sim(T,j)} = \beta_0 + \beta_1 I(MSA_j = MSA_T) + Year\,FE + Primclass\,FE + \epsilon \tag{5.4}$$

$\hat{\beta}_1$ measures the proportional increase in the average similarity of a patent to citations in the same MSA compared to the similarity to citations in different MSAs, subject to controls.

5.3. Using random patent-pair similarity to measure spillovers and localization

As outlined in section 3, citations may omit many possible transmissions of knowledge. I change the measure of spillovers to similarity across random pairs of patents within a technology field, that is either (i) within primary class or (ii) within a NAICS field. [11]Including random pairs captures potential shared

[11]The caveat is that the interpretation of the localization measure is different to those using primary class patents, as in this case it measures the effect of being in the same location for two patents within the same *industry*, which is a much wider definition of technology. The mean cross-patent similarity is much lower in this sample, which leads to larger estimates for

knowledge for any pair of patents and not only those linked by citation relationships, which represent only a small fraction of possible patent pairs. The hypothesis becomes: *knowledge spillovers are localized if patent pairs within a field are more similar if they are from the same MSA compared to different MSAs*. Focusing on patent pairs also allows me to bypass issues related to composition with more aggregated measures, and make these results more directly comparable with the JTH-based exercises above. The use of both within-NAICS and within-primary class samples allows me to compare spillover effects at broader and narrower technology levels. If localization measure is different for NAICS and primary class, then this indicates that there are differences in the dynamics of knowledge diffusion at the industry level and at more specialized or granular definitions of technology. In addition, using the NAICS sample which is comprised of numerous primary classes allows me capture the possibility of knowledge spillovers occuring *across* narrower subfields of technology.

I begin by measuring localized knowledge spillovers in a comparable way to the JTH-based methodology described above. Since the sample used in this exercise is different to the sample in the previous section, I add a citations based "similarity" measure in order to have a more commensurate spillover measure to compare similarity with. One approach of measuring similarity using citations (cite TODO) is to find the number of common cited patents that appear as backward citations for both i and j.[12] Thus if $i$cites patents A, B, C, and j cites patents B, C, D, then the number of common cited patents is two. In this case, localization is significant if the number of common cited patents is higher between patent pairs from the same location.

5.3.1. Accounting for technological proximity and existing relationships between patents

There has been much discussion in the existing literature as to whether or not selecting within a technology field is an adequate control for technological proximity, even within JTH, who state: "... if a large fraction of citations to Stanford patents comes from the Silicon valley, we would like to attribute this to localization of spillovers. A slightly different interpretation is that a lot of Stanford patents relate to semiconductors, and a disproportionate fraction of the people interested in semiconductors happen to be in the Silicon valley, suggesting that we would observe localization of citations even if proximity offers no advantage in receiving spillovers." I accommodate this possibility in the second case: to better control for the existing technological proximity I also use cross-field similarity and cross-location-field similarity. Knowledge overlap may occur

coefficients on the log transform, even if the absolute magnitude of the change is roughly constant.

[12] After self-citations are removed.

just through being in the same or similar technological fields; that the inputs to creating innovation in class *396: Photography* might overlap significantly with class *398: Optical communications*. If these two fields are collocated (i.e. innovation in both classes occur in the same location), then we may over-attribute the effect of technological affinity to localization.

On the other hand, a well-known problem in the literature is that identification may be confounded as firms from similar technology fields also collocate in order to take advantage of potential spillovers, alongside other agglomeration benefits. Thus, controlling for the similarity across technology fields may be excessive. However, if we use the technology similarity control as a proxy for these other agglomeration effects, then any remaining knowledge localization effects is more reliably attributable to knowledge spillovers. This *strict* view may give us some sense of the lower bound for the size of localization.

I control for technological proximity using field similarity only within the NAICS sample, as subfield controls are not available for primary classes. Thompson and Fox-Kean (2005) have previously used primary sub-classes, but I find these measures to be extremely noisy: there are over 150,000 subclasses in the USPC system for approximately 2.3 million US patents, which on average implies just 15 patents per subclass.

Since each NAICS field encompasses only a number of primary classes, the number of outcomes for similarity across primary class may be limited. To increase variability, I also use MSA-specific field vectors as described in equation (2.3). This treats each field at each MSA as a separate subfield. The trade off, however, is that this measure can be much noisier, as many MSAs may only have a handful of prior patents in some patent classes.[13] These measures should also be a more "precise" approximation of the underlying patents, which further limits the remaining knowledge spillover to be explained by pure location effects. The expectation is that localization will be lowest when MSA-fields are controlled for.

Additionally, there are other potential prior connections between patents that may make the similarity between patent pairs higher for non-knowledge spillover related reasons. For example, if the patent pair share an inventor (after inventor has changed to a different firm), we would expect to see much higher similarity between patents without the presence of a "spillover." Additionally, if the patents are from different companies that share a lawyer, we may expect the lawyer to word inventions in a similar "style".

For the sampling procedure,[14] I sample a set of target patents, and pair these patents with both patents from the same field and MSA, and patents just within the same field. This is to ensure a sizable number

[13] I remove the MSA-fields with less than 10 patents
[14] See C for full outline

of patent pairs from the same MSA across a range of technological fields. Patent pairs are granted within 5 years of each other that are assigned to different firms. While some patent pairs may have the same target patent, the number of appearances made by multiples of the same patent is extremely small relative to the entire sample, thus curtailing the presence autocorrelation.[15]

5.3.2. Regression models for general localized knowledge spillovers

For general controls, I add year fixed effects and technology field fixed effects. The complete sample size for all years are approximately 1.5 million pairs for each sample. To allow for the effects to change over time, I group each sample into 10 year cross sections.

For both each measure, I begin by estimating the regression model without technology controls, where i, j are patent pairs within the same technology field:

$$sim(i,j) = \beta_0 + \beta_1 I(MSA_i = MSA_j) + Year\,FE + \epsilon \tag{5.5}$$

Then I add technology field fixed effects:

$$sim(i,j) = \beta_0 + \beta_1 I(MSA_i = MSA_j) + Year\,FE + Field\,FE + \epsilon \tag{5.6}$$

The first two equations are directly comparable to JTH regressions equation (5.1) andequation (5.3). The results from these regressions are reported in table E.3.

5.3.3. Regression models for strict localized knowledge spillovers

For the within NAICS sample,[16] pre-existing similarity across primary classes can be accounted for:

$$sim(i,j) = \beta_0 + \beta_1 I(MSA_i = MSA_j) + \beta_2 sim(pc_i, pc_j) + Year\,FE + Primclass\,FE + \epsilon \tag{5.7}$$

If patent i was granted in 2007 and had primary class *398: Optical communications*, the vector pc_i would represent the median of all patents with primary class *398* granted between 2001-2006.

[15] Heteroskedastic-robust standard errors are used in regression estimates

[16] These regressions can not be applied to the within-primary class sample, as similarity across primary class would be degenerate. Similarity across MSA-primary class pairs is also degenerate when $I(MSA_i = MSA_j) = True$, so it is not possible to separately identify β_1.

I also allow for the localization effect to affect the slope coefficient β_3, which would imply that the similarity between patents in the same location *grows more* with the similarity in their primary classes:

$$\begin{aligned} sim(i,j) &= \beta_0 + \beta_1 I(MSA_i = MSA_j) + \beta_2 sim(pc_i, pc_j) \\ &\quad + \beta_3 I(MSA_i = MSA_j) * sim(pc_i, pc_j) + Primclass\, FE \\ &\quad + Year\, FE + \epsilon \end{aligned} \tag{5.8}$$

MSA-primary class subfields may also be used:

$$\begin{aligned} sim(i,j) = \beta_0 + \beta_1 I(MSA_i = MSA_j) + \beta_2 sim(pc_{i,MSA_i}, pc_{j,MSA_j}) \\ + Year\, FE + Primclass\, FE + \epsilon \end{aligned} \tag{5.9}$$

$$\begin{aligned} sim(i,j) &= \beta_0 + \beta_1 I(MSA_i = MSA_j) + \beta_2 sim(pc_i, pc_j) \\ &\quad + \beta_3 I(MSA_i = MSA_j) * sim(pc_{i,MSA_i}, pc_{j,MSA_j}) + Primclass\, FE \\ &\quad + Year\, FE + \epsilon \end{aligned} \tag{5.10}$$

If patent i was granted in Los Angeles, pc_{i,MSA_i} represents the median of all patents granted in primary class 398 in the city of Los Angeles, from 2001-2006. The interpretation here would be that if $\hat{\beta}_1, \hat{\beta}_2$ or $\hat{\beta}_3$ are positive and significant, then innovations from the same location share more in common compared to other patent pairs from technology fields that are just as similar. For example, suppose $pc_i = 398$ and $MSA_i = Los\, Angeles$; $pc_j = 396$ and $MSA_j = Austin$; $pc_k = 396$ and $MSA_k = Los\, Angeles$. If the similarity of past patents from primary class 398 in Los Angeles to primary class 396 from both Austin and Los Angeles, and yet the patent pairs i, k from Los Angeles are more similar on average to the i, j Los Angeles-Austin patent pairs, then localization is significant.

5.4. Results: Estimating Localization From Regression

5.4.1. Localized knowledge spillovers: Baseline Comparison

To increases the comparability of localization from each method, I normalize all measures of spillovers. Then the estimate of $\hat{\beta}_1$, represents the standard deviation increase in knowledge spillovers when patents are local. For the baseline comparison, I include year and primary class fixed effects in each set of regression models.[17]The main finding is that the citations-based measure of the JTH extension exercise finds much larger relative effects for localization that for all other measures. Being in the same location increases the percentage of citations from that location by 0.24 standard deviations in 1975-85; this grows to 0.28 in 1995-2005. [18] By comparing same MSA citations to different MSA citations, a very different picture emerges. The normalized measure of average similarity does not find significantly higher similarity for in-MSA citations (although the difference is positive and significant in the raw data, table E.3) for the years 1985-2005.

For the within-NAICS sample, localization estimates using DocVecs similarity finds that being in the same and location increases similarity across patents by 0.03-0.06 standard deviations. This was lowest in 1975-85, rose 1985-2005, before declining slightly in 2005-15. For within-Primclass, the time trend is roughly similar: lowest at 0.05 in 1975-85, increasing to 0.08 1985-2005, and declining to 0.06 in 2005-15.

Localization estimates using the number of common cited patents are also much smaller in magnitude compared to JTH's citation measure. However, the time trend matches: both measures find overall increasing localization effects for the observed time period. Localization estimates rise from 0.002 to 0.05 over the period 1975-2015 for the within-NAICS sample; from 0.01 to 0.11 for within-Primclass. This agrees with DocVecs estimates that localization effects are higher for the Primclass sample. As patents are more similar to other local patents in narrower fields of technology. This indicates that local knowledge sharing may happen more in specialized areas of innovation, compared to knowledge sharing at the industry level.

The low estimates for localization is not due to noise in the similarity measures. If we replace $I(MSA\,Match)$ with another indicator which we expect to have a large effect on the similarity, the estimate of the coefficient aligns with expectations are is much larger than the estimate for localization. Using the within-NAICS sam-

[17]The same results with raw untransformed data is reported in table E.3, alongside results for LDAVecs (table E.4,table E.5). I will focus on the results from DocVecs which I consider a better approximation of document similarity, as discussed in section **??**; LDAVecs serve as a validation exercise for the results. In the vast majority of cases, the sign and significance of the the coefficient estimates align, while some magnitudes may differ.

[18]Results 2005-15 excluded as forward citations data only extend to 2015

KS =Pct Cites in Target's MSA, JTH Sample			
	1975-85	1985-95	1995-05
$I(MSA\,Match)$	0.2416***	0.2846***	0.2966***
	(0.0073)	(0.0051)	(0.0041)
N	58647	107358	185154
Adjusted R^2	0.03	0.05	0.05
Year FE	True	True	True
PC FE	True	True	True
KS =Similarity to Citations, JTH Sample			
	1975-85	1985-95	1995-05
$I(MSA\,Match)$	0.0444***	0.0158	0.0064
	(0.0145)	(0.0097)	(0.0066)
N	38541	69612	122217
Adjusted R^2	0.03	0.03	0.04
Year FE	True	True	True
PC FE	True	True	True

Table 5.3: Baseline regression results for JTH Sample.

ple, If the patent pair shares an inventor $(I(Inv\,Match) = 1)$, then this increases similarity by 1.27 to 1.52 standard deviations. Similarly, if patents are from the same primary class $(I(Primclass\,Match) = 1)$, then similarity increases by 0.4-0.44 standard deviations. (See full results in E.2) Thus, the similarity measure is able to capture significant effects.

5.4.2. Localized knowledge spillovers: technology proximity and other controls

I find that including prior similarity across primary classes as controls in the within NAICS sample reduces the estimate for localization further, so that local patent pairs are about 0.025-0.045 standard deviations higher than non-local pairs $(I(MSA\,Match) = False)$. For the same time range but without the similarity controls, [19] the localization estimate is 0.05-0.06. The time trend indicates that localization is diminishing over the period 1985-2015. The interaction term is also found to be slightly positive and significant for

[19] 1975-1985 sample drops out due to lack of data on past primary class patents.

1985-2015, stable at around 0.026; this means that local patent similarity grows at a slightly higher rate with primary class similarity. figure 5.1 depicts the conditional means plot. The raw data (table E.6) differs slightly in that the coefficient on the intercept dummy (i.e. $\hat{\beta}_1$ in equation (5.7)) is slightly negative and significant, versus positive and significant in the normalized regressions.

Interestingly, including MSA-specific primary class controls estimates localization to be significant and slightly *negative*. Local patent pairs are found to be between 0.017-0.023 standard deviations less similar than non-local patent pairs. The interaction term is found to be insignificant 1985-2005, and slightly positive and significant in 2005-2015. One thing that contributes to the negative estimate of the dummy intercept term is that $sim(pc_i, pc_j)$ is *not* highly correlated with $I(MSA\,Match)$ at 0.04; while the pairwise correlation with $sim(pc_{i,MSA_i}, pc_{j,MSA_j})$ is 0.19.[20] In other words, patent pairs from similar MSA-technology subfields are much more likely to be collocated than those from similar primary classes. Since the average difference between the local and non-local samples are already low, this slight collinearity may reduce the estimated effect of $I(MSA\,Match)$ even further. Another view could be that the collocation of patents from similar MSA subfields already indicates some presence of spillovers; while this certainly indicates the presence of clustering, whether or not clustering is equatable to local spillovers is open to interpretation.

The conditional mean plot (figure 5.2) also sheds light on this effect. The average similarity of non-local patent pairs is slightly higher than local pairs at *higher* levels of MSA-subfield similarity. What is interesting is that local similarity does not increase as subfield similarity rises from 2 s.d. above the mean to 2.5; while non-local similarity does substantially (the caveat being there are far fewer non-local patent pairs in the 2.5 bin). This may indicate the presence of *local differentiation* in technology space. One aspect of local knowledge spillovers may be that knowing more about neighbouring rivals' inventions may push inventors to distance themselves from one another. That is, inventors want their innovations to be novel from that of their peers, as patents are more valuable when they have a broader scope. These results show that learning from local rivals may not necessarily lead to greater technological affinity.

For patent pairs with subfield similarity above 2 s.d., approximately 19% are Pharmaceutical pairs and a further 14% are Other Chemical Product pairs. In the general sample, they comprise 3.3% and 4.9% respectively. In both industries, particularly pharmaceuticals, the patent to product progression is much more straight forward compared to most other industries. As patents in these industries behave more like products, the consideration of product market differentiation may induce greater distancing in technology

[20] The distributions of these two measures for local and non-local patent pairs are in figure E.1,figure E.2.

space by local firms.

While the sign of the results are different for MSA-specific primary class controls, in terms of absolute magnitude they do not differ substantially. The explanatory power of the primary class similarity measure is also slightly greater, as is its estimated effect on patent pair similarity. One standard deviation increase in $sim(pc_i, pc_j)$ increases $sim(i, j)$ by approximately 0.24-0.26 standard deviations; while for $sim(pc_{i,MSA_i}, pc_{j,MSA_j})$ the increase is between 0.17-0.19. Thus, while primary class similarity appear to be a slightly better fit for the data, the exercise using MSA-primary class similarity reveals potentially deeper dynamics of the knowledge spillovers process.

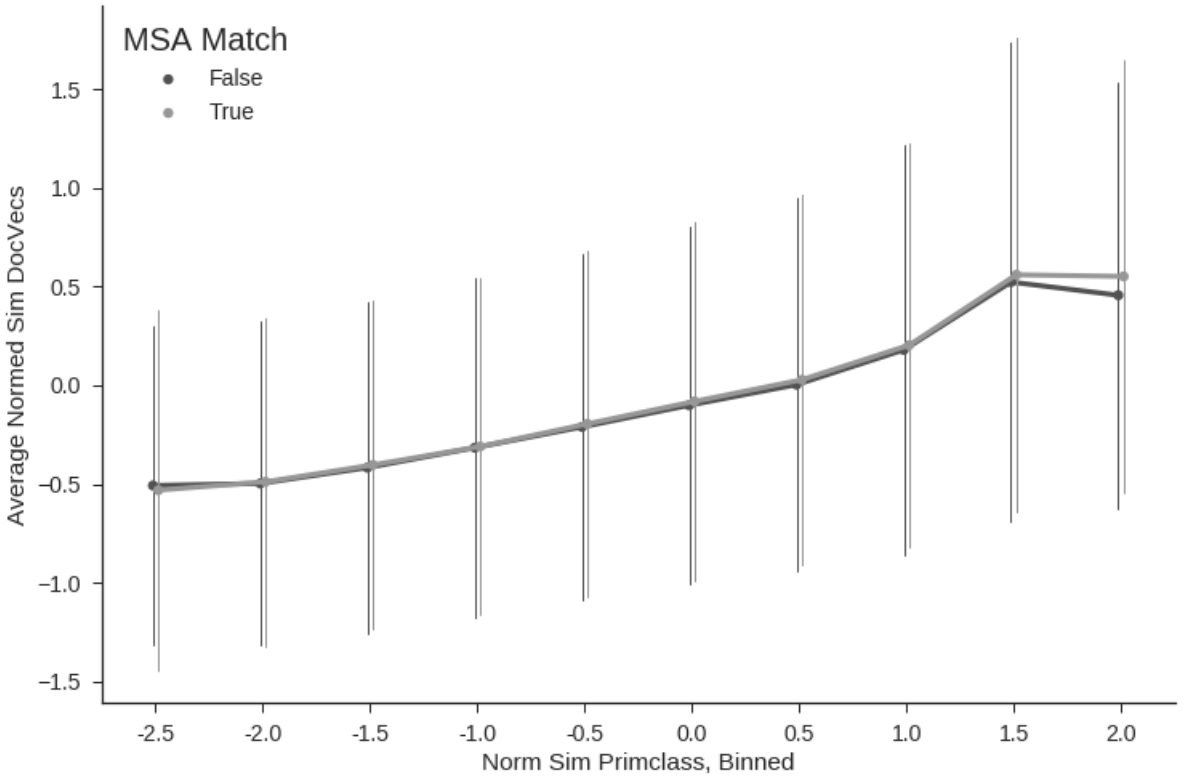


Figure 5.1: Conditional means of DocVec similarity by primary class similarity.

It has been documented by Moser (2011); Arora (1997) that industries such as Chemicals rely more heavily on secrecy to preserve intellectual property which leads to higher rates of localization. On the other hand, industries dominated by software patents which are known to have more diffuse knowledge networks, thus lowering the localization effect. I also drop Machinery pairs as they also constitute a large proportion of the total sample. I find that dropping each of these industries from the sample do not affect

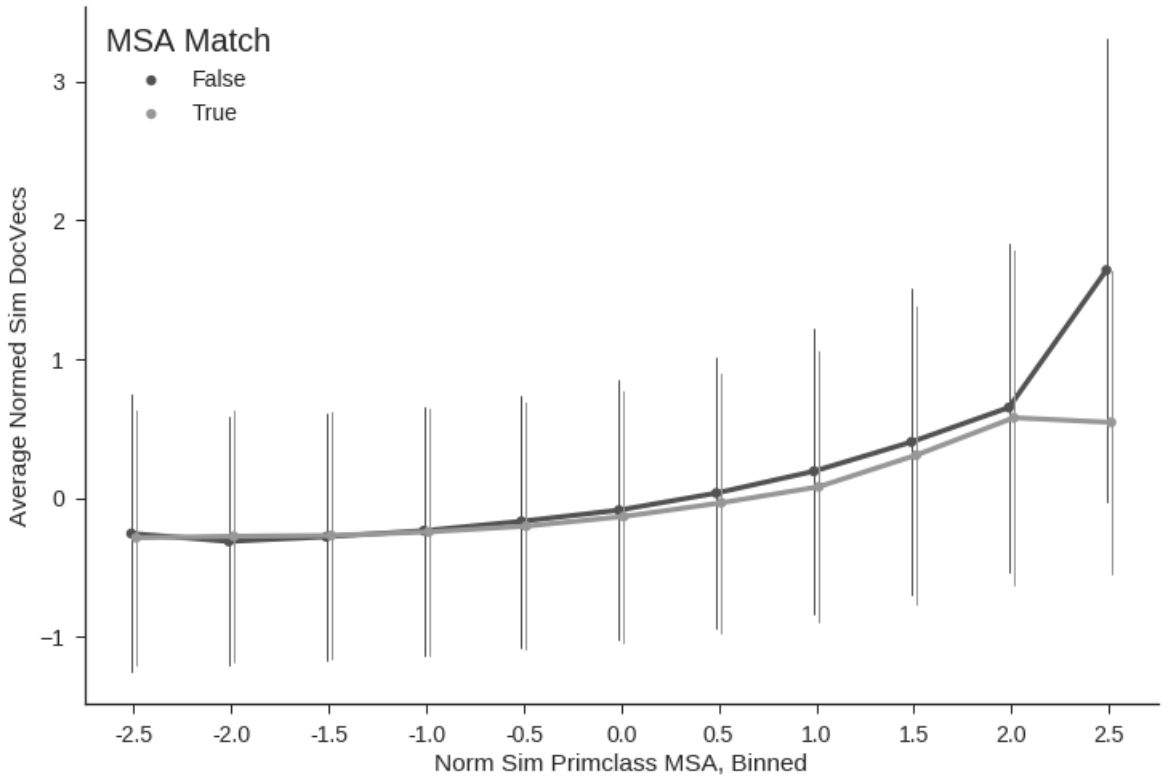


Figure 5.2: Conditional means of DocVec similarity by MSA-primary class similarity.

the estimation results in table 5.4 or table **??**. Using assignee level fixed effects such a firm size also have no effect. Using data at the patent pair level and including technology fixed effects has made the results fairly robust.

The overall findings on the presence and size of localized knoweldge spillovers is mixed using similarity measures. While citations finds large and significantly positive localization effects, the findings with similarity is comparatively muted. The difference in these findings, as discussed in 3, could possibly be attributed to the influence of external sources of knowledge which are less localized than citations networks.

KS =Sim DocVecs, Within-NAICS				
	1975-85	1985-95	1995-05	2005-15
$I(MSA Match)$	0.0323***	0.0605***	0.0610***	0.0571***
	(0.0053)	(0.0043)	(0.0034)	(0.0030)
N	192841	281222	437685	569252
Adjusted R^2	0.07	0.07	0.08	0.06
Year FE	True	True	True	True
PC FE	True	True	True	True
KS =Sim DocVecs, Within-Primclass				
	1975-85	1985-95	1995-05	2005-15
$I(MSA Match)$	0.0527***	0.0798***	0.0787***	0.0573***
	(0.0064)	(0.0050)	(0.0038)	(0.0032)
N	170882	252174	401623	529686
Adjusted R^2	0.07	0.07	0.08	0.07
Year FE	True	True	True	True
PC FE	True	True	True	True
KS =Num Common Cited, Within-NAICS				
	1975-85	1985-95	1995-05	2005-15
$I(MSA Match)$	0.0019***	0.0074***	0.0155***	0.0514***
	(0.0003)	(0.0014)	(0.0018)	(0.0084)
N	194131	282112	443885	578056
Adjusted R^2	0.00	0.03	0.00	0.00
Year FE	True	True	True	True
PC FE	True	True	True	True
KS =Num Common Cited, Within-Primclass				
	1975-85	1985-95	1995-05	2005-15
$I(MSA Match)$	0.0113***	0.0300***	0.0513***	0.1109***
	(0.0012)	(0.0029)	(0.0045)	(0.0084)
N	171893	252886	407176	537878
Adjusted R^2	0.01	0.05	0.00	0.01
Year FE	True	True	True	True
PC FE	True	True	True	True

Table 5.4: Baseline regression results for Number of Common Cited and Sim DocVecs.

6. External sources of knowledge: new technology terms

The introduction of new terms into the patent corpus provides an opportunity to examine the influence of unobserved external knowledge on patent text. As new technology are developed, references make their way into patents. Patents that are the first to contain the new term are assumed to share some external sources of knowledge about the new technology. In order to verify if citations or similarity are able to reveal evidence of shared knowledge for newly appearing technological terms, I create a sample of patent pairs that were applied for in the first year that a new term appears. As before, patent pairs from the same firm are removed as within-firm shared knowledge do not constitute spillovers.

Hypothetically, firms appropriating the same new technology should share some knowledge sources in common. However, looking at their list of shared cited patents, even very similar new patents using the new technology share very few backward citations. Above the 99th percentile of DocVecs similarity for this sample (around 0.40), the number of shared cited patents is 0.087, which represents about 0.8% of the first patent's total cited patents. While the shared knowledge measure using citations is rising with similarity, the overall magnitude is still modest. In G.2, the percentage of shared backward citations rises more if the patent pair is local, which is consistent with the expectation that citation networks are more localized. This comes into effect after the 95th percentile similarity of around 0.3.

In G.1, DocVecs similarity shows some indication of shared knowledge for patents using new technology. Citations based measures do not convey much relatedness between these patents. The distribution plots in G.3 for each measure of pairwise shared knowledge show that while DocVecs similarity is able to capture significant variation in the relatedness of new patents, citations measures do not.

Overall, there is little correlation between similarity and citations-based shared knowledge measures: the correlation coefficient is 0.05 in both cases.

6.1. Example: Adenovirus

7. Conclusion

This paper focuses on knowledge spillover dynamics of ideas embodied by innovation. By focusing on patent texts, the evidence for geographic localization is much weaker compared to results found by exclusively using patent citations. These findings reveal a potential difference between the the geographic dynamics of the inputs and influences to the innovative process and its knowledge outputs. This implies that studying the flows of knowledge using citations is not interchangeable with studying flows within knowledge content. This has profound impact for citations based research, which has relied on an assumption of equivalence between the two. I discussed reasons within the patent citations literature of what may be behind the discrepancies, largely due to the strategic manner in which citations are made in relation to the value of patents as intellectual property. However, I expect that this may be attenuated within the academic literature, where there are fewer incentives for strategic citations. More research should focus on when and why there are significant differences in the localization of knowledge inputs to knowledge outputs.

There are also implications for R&D policy: public investment in R&D has been advocated on the premise of the existence of large and significant local returns. These findings complicate the advantages that knowledge spillovers offers, in that they do not appear to benefit local firms and inventors significantly more so. Additionally, there is limited evidence that localization spurs further innovation within a city. If this is the goal, then R&D policy should be directed towards improving possibilities for novel and radical innovation, not necessarily the greater sharing of existing knowledge. Further research should be conducted to investigate the relationship between knowledge spillovers, innovation novelty, and innovation growth.

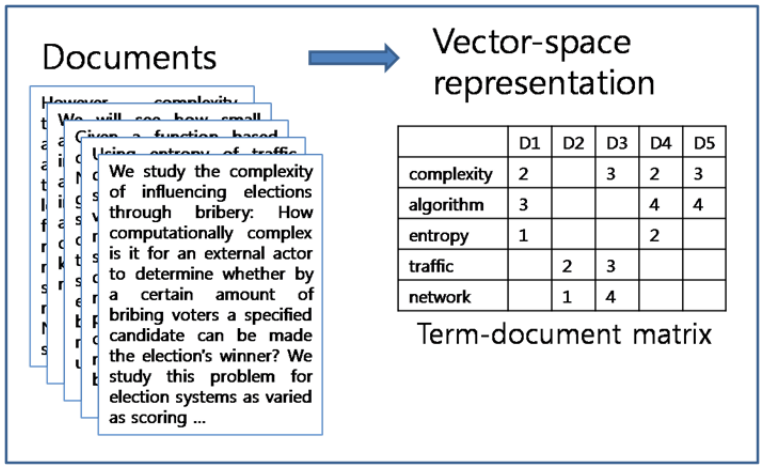
Appendix

A. Text to Data

A.1. Text cleaning

Each abstract is stemmed to the root word (for example, computer to comput), and stop words (such as "and", "the") are removed. The first step in converting text to data is to represent words and documents in their simplest vector forms. For all algorithms besides Document Vectors, input into the algorithms involve the construction of a document-term matrix from all patents; each row is indexed by the document ID and each column represents a word in the vocabulary. A document row vector represents the count of the number of times the term appears in the document. For the terms, I drop all terms that appear in more than 10% of all patents, and those that appear in fewer than 20.[21] Of the resulting terms, I keep the most common 40,000, in order to maintain a manageable matrix dimensionality. Once all 2,306,041 patents have been transformed into a document-term matrix of dimension 2306041×40000, I proceed to transforming patents into a smaller dimensional vector representation using the methods described below. This procedure is commonly called the *bag-of-words* representation of text data.

[21] Including very common and very infrequent terms may introduce noise and considerable increases in computation times.



	D1	D2	D3	D4	D5
complexity	2		3	2	3
algorithm	3			4	4
entropy	1			2	
traffic		2	3		
network		1	4		

Figure A.1: Example of Document Term Matrix

A.1.1. Paragraph Vectors (Doc2Vec)

One recent advance in NLP which utilises neural networks is Paragraph Vectors, introduced by Le and Mikolov (2014). This is a straightforward extension of the word2vec model of Mikolov et al. (2013b,a). The word2vec model attempts to rectify one of the well-known problems of NLP: the inability of "one-hot" word vectors to account for word similarity. Typically, word vectors are represented as sparse vectors. For example, in a complete vocabulary of ["good", "fair", "fine"], the word *good* would be represented as the vector $[1, 0, 0]$, *fair* as $[0, 1, 0]$ and *fine* as $[0, 0, 1]$. Clearly, each of these vectors are orthogonal to each other and have a similarity of 0. Instead of using this class of word vectors, word2vec tries to represent words as dense vectors that encode such similarities; a word2vec vector for each of the three words ["good", "fair", "fine"] will have a *high* similarity.

The way that this is done is through looking at the *context* of a word. For example, for the sentence "Provides for unattended file transfers", the word "unattended" has the context ["Provides", "for", "file", "transfers"]. We want to represent each of these words as a vector of arbitrary dimension n. One way to account for context is to predict the context words given the target (Skip-gram); while another way is to predict the target word given the context (Continuous Bag-of-Words). Under Skip-gram, the optimization problem is to maximise the probability of any context word given the current center word. So the objective function is given by:

$$J(\theta) = -\frac{1}{V}\sum_{t=1}^{V}\sum_{-m\leq j\leq m}\log p(w_{t+j}|w_t) \tag{A.1}$$

Where θ represents all parameters: input vector ("one-hot") representation of each word, and the output word2vec representation of each word. m represents the length of the context window; for example $m = 1$ gives the context for "unattended" as ["for", "file"]. The objective function is minimized using stochastic gradient descent.

Paragraph Vectors, or Doc2Vec, extends word2vec merely by adding an additional variable, which will be treated as an additional context vector: paragraph ID. For my data, this will be the patent number, which uniquely identifies every abstract document. Thus, including paragraph ID as an additional word for each context generated from that paragraph will also generate a unique vector associated with the paragraph, as well as the word vectors. Intuitively, the paragraph vector will represent what was learned in other context windows belonging to the paragraph, outside of the present context window: that is, it "acts as a memory that remembers what is missing from the current context." (Le and Mikolov (2014))

Such an approach has been shown to be extremely powerful in accurately capturing cross-word and cross-document similarity (papers?), which is why it is the main focus of my analysis. Other vector representations of patents that I use do not specifically optimize to capture such similarity using contexts.

A.1.2. Latent Dirichlet Allocation

Latent Dirichlet Allocation, introduced by Blei et al. (2003), is a method of topic modeling which seeks to uncover the underlying structure of a group of documents (corpus) using just the observed text. It is a probabilistic model based on hierarchical Bayesian analysis. With probabilistic models, treat observations as outcomes of a data generating model and infer the hidden parameters of that model using posterior inference. Define a "topic" as a discrete distribution over a fixed vocabulary. Assume each topic is generated by drawing a distribution over terms in the vocabulary represented by the vector: $\boldsymbol{\beta_k} = (\beta_{k,1}, ..., \beta_{k,V}) \sim Dir(\eta)$. Additionally, asssume that each document d is generated by the following process:

1. Draw a vector distribution over topics: $\boldsymbol{\theta}_d = (\theta_{d,1}, ..., \theta_{d,K}) \sim Dir(\boldsymbol{\alpha})$
2. For each word $w_{d,n}$:
    a) Draw a topic $k_{d,n} \sim Multinomial(\boldsymbol{\theta}_d)$
    b) Draw a word based on that topic's distribution over the vocabulary $w_{d,n} \sim Multinomial(\boldsymbol{\beta}_{z_d,n})$

Then the posterior of the hidden variables, conditional on the observed words in each document, is given by:

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D}|w_{1:D}) = \frac{p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D})}{p(w_{1:D})} \tag{A.2}$$

An inference algorithm is used to approximate the posterior. Thus, from the observed set of V vocabulary terms $w \in 1, ..., V$, the hidden topics $k \in 1, ..., K$ (a distribution over words in the vocabulary), and each document's distribution over topics $(\theta_{d,1}, ..., \theta_{d,K})$ are derived.

Example

Probably go through heuristic example with the highlighted text (borrow from any paper)

B. Citations and Patent Vector Similarity

C. Sampling Summary

C.1. Potentially Citable Patents

I sample a set of patents (target patents, tp), and find patents they cite from the sample *CPP*. I then find all other patents (op) granted *after* the target tp that also cite those patents, and pair them with the target patents. The idea is that if op cited the same patents as tp, then it is plausible that the two patents are related enough that op might also cite tp. I then calculate the similarity of all pairs in this sample, and find the conditional mean of the rates of direct citation between op and tp for each similarity bin. Over 2.4 million pairs of similarities are calculated.

D. Summary of Data

E. Regressions

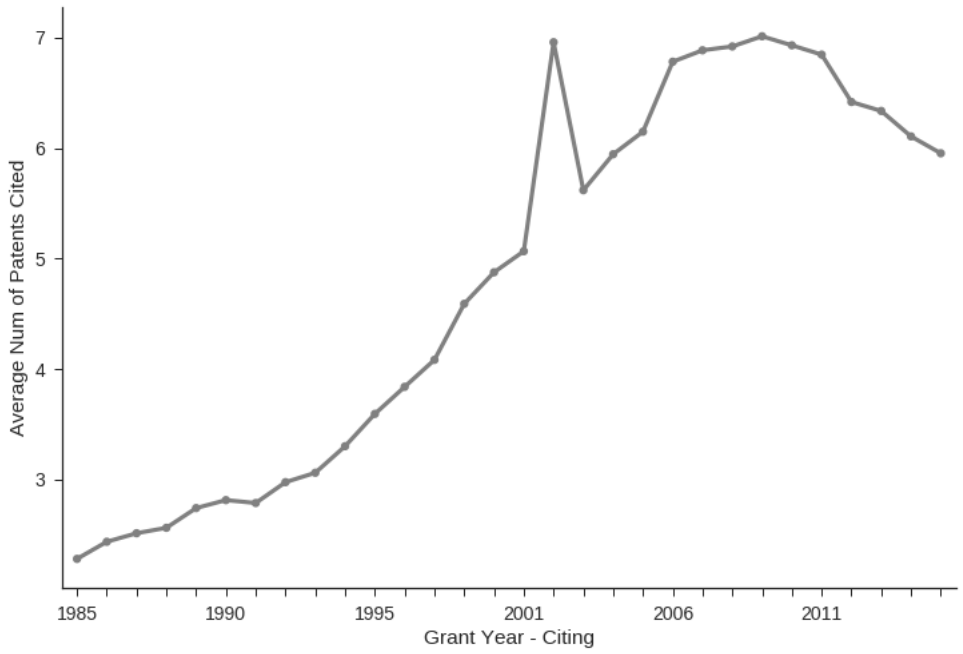


Figure B.1: Averate number of patents cited over time

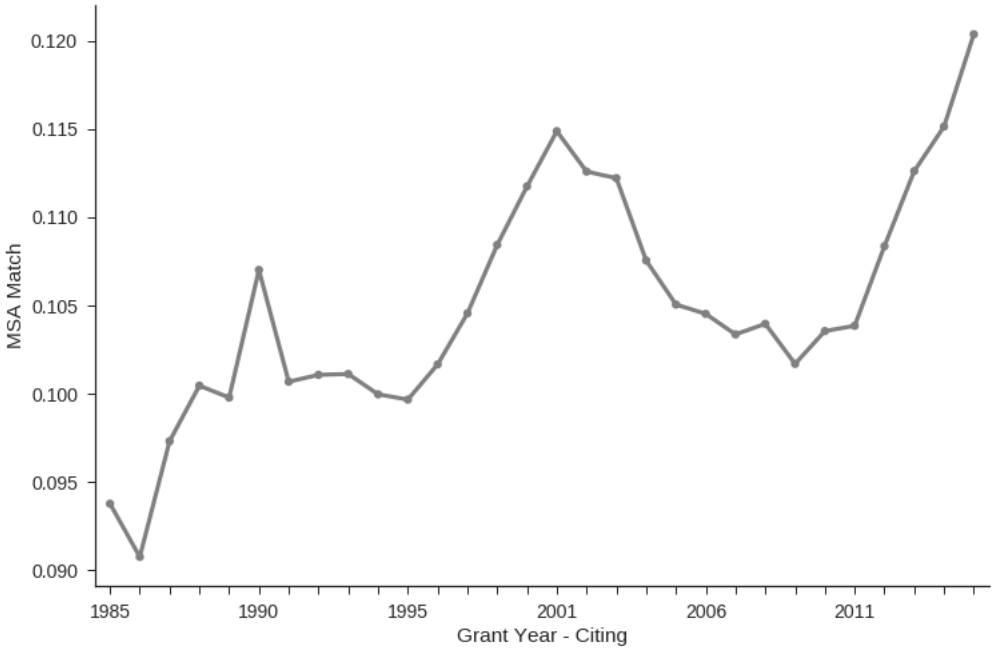


Figure B.2: Proportion of cited patents in the same MSA over time

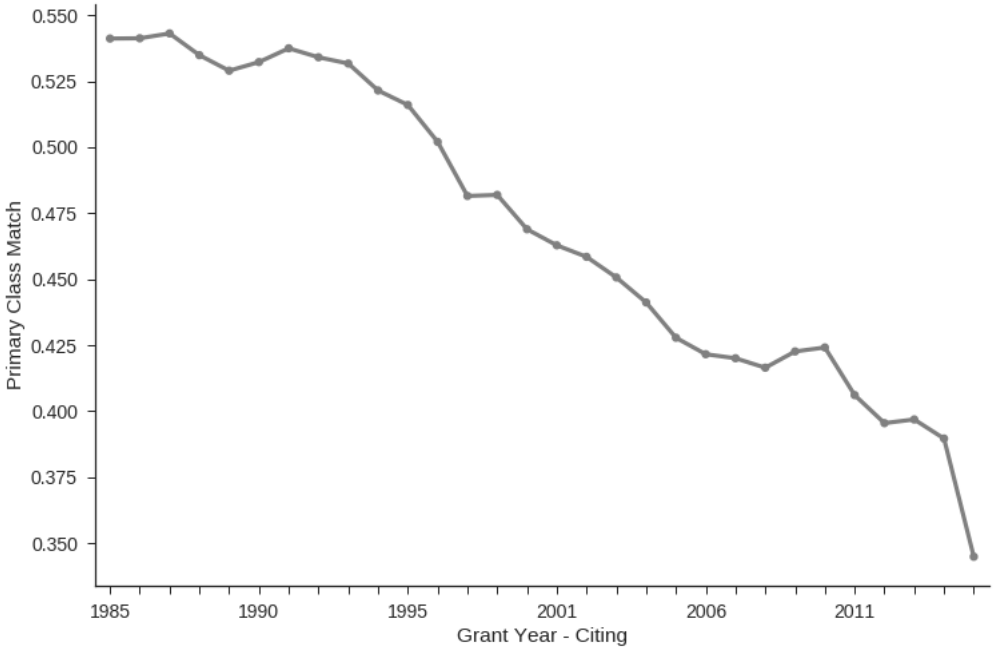


Figure B.3: Proportion of cited patents in the same primary class over time

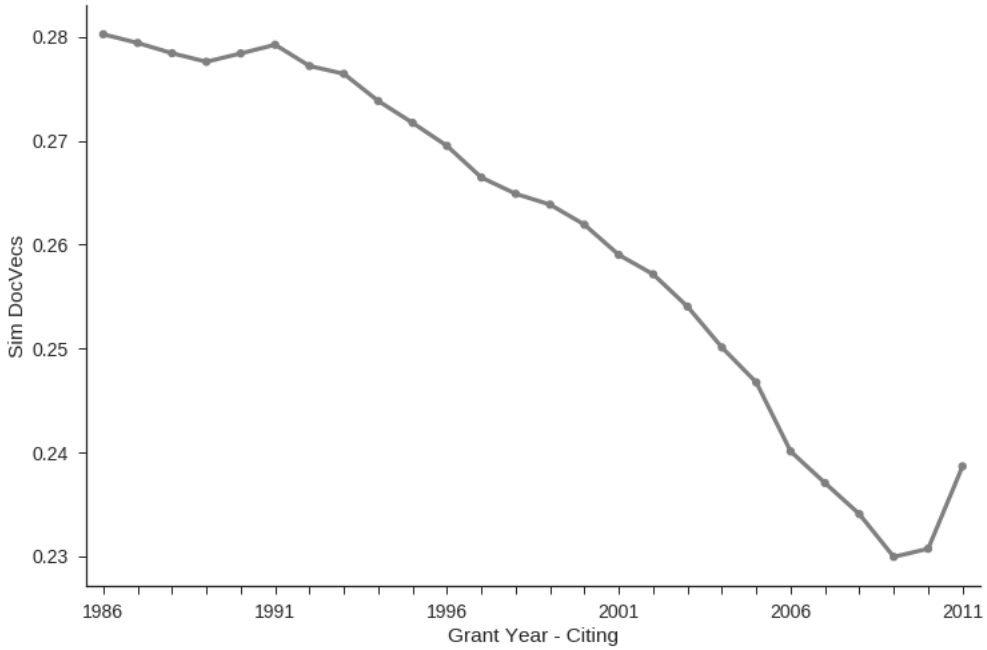


Figure B.4: Average DocVecs similarity to cited patents

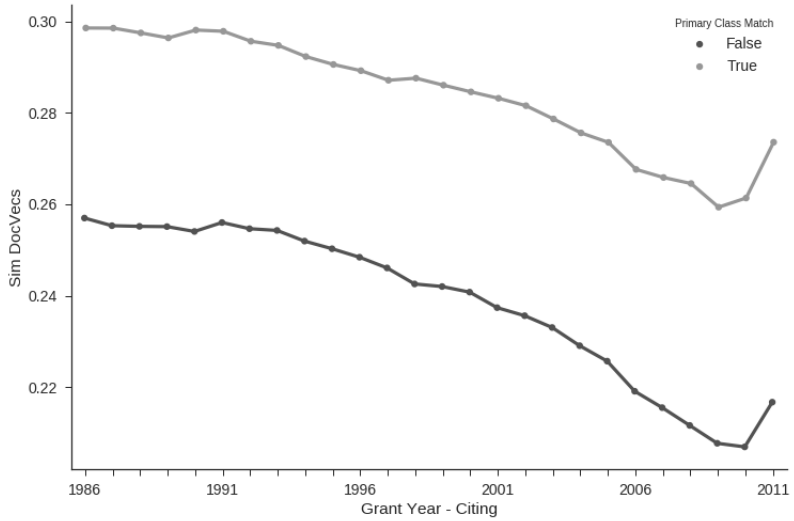


Figure B.5: Average DocVecs similarity to cited patents in the same primary class

$sim\ DV$, binned	-0.1	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7
All Pairs, N	51355	205500	498927	685041	562529	293309	102019	27531	18958
All Pairs, Prop Cited	0.005	0.007	0.011	0.016	0.024	0.036	0.052	0.063	0.042
Same MSA, N	3768	16056	42380	65643	63246	41573	19994	8327	7163
Same MSA, Prop Cited	0.01	0.011	0.015	0.021	0.03	0.041	0.051	0.063	0.075
Diff MSA, N	47587	189444	456547	619398	499283	251736	82025	19204	11795
Diff MSA, Prop Cited	0.005	0.007	0.01	0.015	0.023	0.035	0.052	0.063	0.022
Same NAICS, N	21756	92343	239948	354306	313789	175065	64802	18362	13949
Same NAICS, Prop Cited	0.006	0.009	0.013	0.019	0.028	0.042	0.059	0.072	0.047
Diff NAICS, N	29599	113157	258979	330735	248740	118244	37217	9169	5009
Diff NAICS, Prop Cited	0.005	0.006	0.009	0.012	0.019	0.028	0.039	0.046	0.029
Same Primclass, N	7035	34445	105794	185777	190332	119502	48211	14968	13148
Same Primclass, Prop Cited	0.012	0.017	0.021	0.028	0.038	0.051	0.07	0.078	0.046
Diff Primclass, N	44320	171055	393133	499264	372197	173807	53808	12563	5810
Diff Primclass, Prop Cited	0.004	0.006	0.008	0.011	0.017	0.026	0.036	0.046	0.033

Table B.1: Summary table of rates of direct citation in the PCPP sample by DocVecs similarity

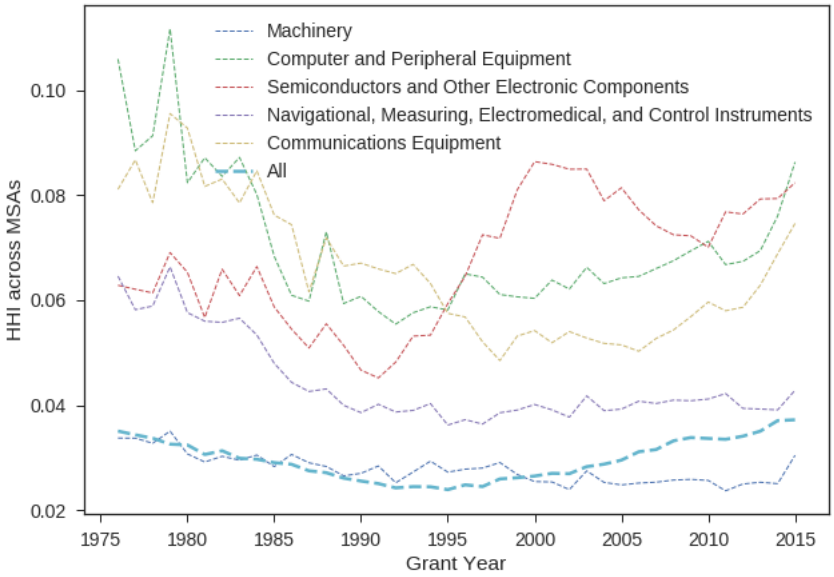


Figure D.1: HHI of concentration across cities for industry innovation

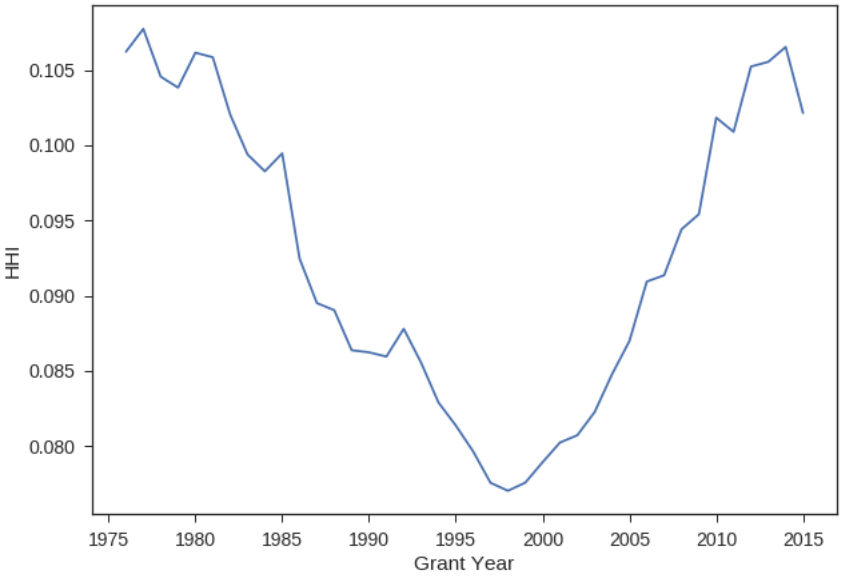


Figure D.2: HHI of concentration across cities for industry innovation

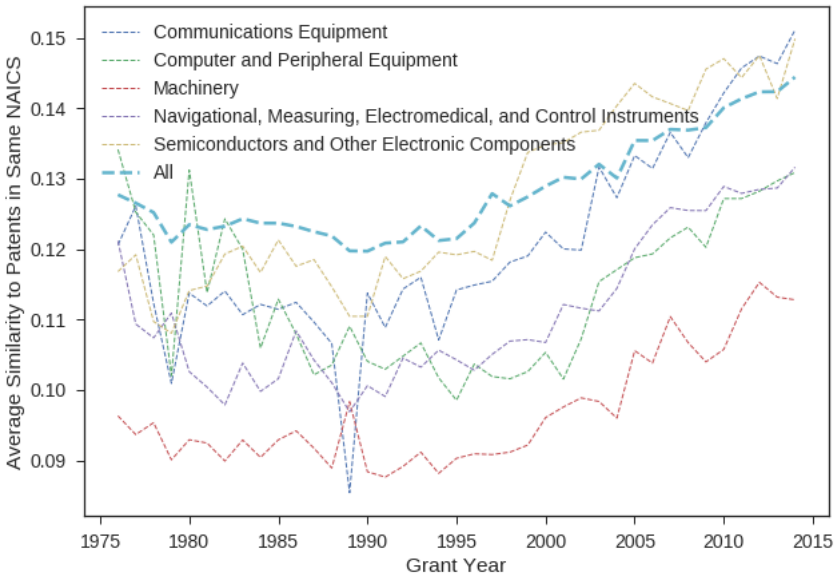


Figure D.3: DocVecs Similarity to other patents within the same industry over time

Sample	Subset	y, KS	N	Mean	Std Dev	Min	25%	50%	75%	Max
JTH Extension	All	$pct\,cites\,in\,MSA_T$	507870	0.082	0.217	0.000	0.000	0.000	0.000	1.000
	$MSA\,Match = T$	$pct\,cites\,in\,MSA_T$	282079	0.112	0.250	0.000	0.000	0.000	0.042	1.000
	$MSA\,Match = F$	$pct\,cites\,in\,MSA_T$	225791	0.045	0.159	0.000	0.000	0.000	0.000	1.000
JTH Cite Sim	All	$\overline{sim_{LDA}(T,j)}$	283080	0.510	0.201	0.002	0.369	0.509	0.654	1.000
	$MSA\,Match = T$	$\overline{sim_{LDA}(T,j)}$	57897	0.550	0.222	0.002	0.392	0.555	0.721	1.000
	$MSA\,Match = F$	$\overline{sim_{LDA}(T,j)}$	225183	0.500	0.194	0.002	0.365	0.499	0.638	1.000
JTH Cite Sim	All	$\overline{sim_{DV}(T,j)}$	283080	0.289	0.124	-0.552	0.211	0.285	0.362	0.936
	$MSA\,Match = T$	$\overline{sim_{DV}(T,j)}$	57897	0.323	0.151	-0.552	0.224	0.314	0.409	0.936
	$MSA\,Match = F$	$\overline{sim_{DV}(T,j)}$	225183	0.280	0.114	-0.518	0.209	0.279	0.351	0.890
NAICS	All	$sim_{LDA}(i,j)$	1483214	0.242	0.222	0.001	0.061	0.174	0.368	1.000
	$MSA\,Match = T$	$sim_{LDA}(i,j)$	363370	0.255	0.228	0.001	0.067	0.188	0.389	1.000
	$MSA\,Match = F$	$sim_{LDA}(i,j)$	1119844	0.237	0.220	0.001	0.059	0.169	0.361	1.000
NAICS	All	$sim_{DV}(i,j)$	1481000	0.131	0.135	-0.416	0.039	0.123	0.213	0.679
	$MSA\,Match = T$	$sim_{DV}(i,j)$	362662	0.136	0.136	-0.416	0.043	0.128	0.219	0.679
	$MSA\,Match = F$	$sim_{DV}(i,j)$	1118338	0.129	0.134	-0.416	0.037	0.121	0.211	0.679
Primclass	All	$sim_{LDA}(i,j)$	1355828	0.377	0.245	0.001	0.172	0.347	0.559	1.000
	$MSA\,Match = T$	$sim_{LDA}(i,j)$	285175	0.389	0.249	0.001	0.180	0.360	0.577	1.000
	$MSA\,Match = F$	$sim_{LDA}(i,j)$	1070653	0.374	0.244	0.001	0.170	0.343	0.554	1.000
Primclass	All	$sim_{DV}(i,j)$	1354365	0.188	0.139	-0.371	0.094	0.183	0.275	0.748
	$MSA\,Match = T$	$sim_{DV}(i,j)$	284609	0.196	0.142	-0.367	0.100	0.190	0.284	0.748
	$MSA\,Match = F$	$sim_{DV}(i,j)$	1069756	0.186	0.138	-0.371	0.093	0.181	0.273	0.748

Table E.1: Summary statistics of knowledge spillover measures.

	1975-85	1985-95	1995-05	2005-15
$I(Primclass\,Match)$	0.4413***	0.4449***	0.4291***	0.4045***
	(0.0085)	(0.0066)	(0.0050)	(0.0042)
N	192841	281222	437685	569252
Adjusted R^2	0.08	0.09	0.10	0.07
Year FE	True	True	True	True
PC FE	True	True	True	True

	1975-85	1985-95	1995-05	2005-15
$I(Inv\,Match)$	1.2789***	1.5206***	1.3817***	1.2664***
	(0.1042)	(0.0713)	(0.0559)	(0.0563)
N	192841	281222	437685	569252
Adjusted R^2	0.07	0.07	0.08	0.06
Year FE	True	True	True	True
PC FE	True	True	True	True

Table E.2: Regression results replacing MSA Match with Inventor Match and Primclass Match.

1975-85								
Sample	JTH Cite		JTH Cite Sim		NAICS		Primclass	
Spillover	$pct\ cites\ in\ MSA_T$		$\overline{sim_{DV}(T,j)}$		$sim_{DV}(i,j)$		$sim_{DV}(i,j)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I(MSA\ Match)$	0.0530***	0.0523***	0.0543***	0.0540***	0.0025***	0.0044***	0.0067***	0.0073***
	(0.0016)	(0.0016)	(0.0021)	(0.0021)	(0.0007)	(0.0007)	(0.0009)	(0.0009)
N	58647	58647	38541	38541	192841	192841	170882	170882
Adjusted R^2	0.02	0.03	0.02	0.05	0.00	0.07	0.00	0.07
Year FE	True	True	True	True	True	True	True	True
PC FE	False	True	False	True	False	True	False	True

1985-95								
Sample	JTH Cite		JTH Cite Sim		NAICS		Primclass	
Spillover	$pct\ cites\ in\ MSA_T$		$\overline{sim_{DV}(T,j)}$		$sim_{DV}(i,j)$		$sim_{DV}(i,j)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I(MSA\ Match)$	0.0624***	0.0616***	0.0468***	0.0469***	0.0070***	0.0082***	0.0108***	0.0111***
	(0.0011)	(0.0011)	(0.0014)	(0.0014)	(0.0006)	(0.0006)	(0.0007)	(0.0007)
N	107358	107358	69612	69612	281222	281222	252174	252174
Adjusted R^2	0.03	0.05	0.02	0.05	0.00	0.07	0.00	0.07
Year FE	True	True	True	True	True	True	True	True
PC FE	False	True	False	True	False	True	False	True

1995-05								
Sample	JTH Cite		JTH Cite Sim		NAICS		Primclass	
Spillover	$pct\ cites\ in\ MSA_T$		$\overline{sim_{DV}(T,j)}$		$sim_{DV}(i,j)$		$sim_{DV}(i,j)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I(MSA\ Match)$	0.0646***	0.0642***	0.0408***	0.0422***	0.0078***	0.0082***	0.0116***	0.0109***
	(0.0009)	(0.0009)	(0.0010)	(0.0010)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
N	185154	185154	122217	122217	437685	437685	401623	401623
Adjusted R^2	0.03	0.05	0.02	0.06	0.00	0.08	0.00	0.08
Year FE	True	True	True	True	True	True	True	True
PC FE	False	True	False	True	False	True	False	True

2005-15								
Sample	JTH Cite		JTH Cite Sim		NAICS		Primclass	
Spillover	$pct\ cites\ in\ MSA_T$		$\overline{sim_{DV}(T,j)}$		$sim_{DV}(i,j)$		$sim_{DV}(i,j)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I(MSA\ Match)$	0.0740***	0.0729***	0.0420***	0.0423***	0.0076***	0.0077***	0.0083***	0.0079***
	(0.0012)	(0.0012)	(0.0016)	(0.0015)	(0.0004)	(0.0004)	(0.0005)	(0.0004)
N	154619	154619	52710	52710	569252	569252	529686	529686
Adjusted R^2	0.02	0.05	0.02	0.05	0.00	0.06	0.00	0.07
Year FE	True	True	True	True	True	True	True	True
PC FE	False	True	False	True	False	True	False	True

Table E.3: Regression results for general spillovers with raw data for DocVec similarity.

1975-85								
Sample	JTH Cite		JTH Cite Sim		NAICS		Primclass	
Spillover	$pct\,cites\,in\,MSA_T$		$\overline{sim_{LDA}(T,j)}$		$sim_{LDA}(i,j)$		$sim_{LDA}(i,j)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I(MSA\,Match)$	0.2448***	0.2416***	0.0033	-0.0008	0.0465***	0.0313***	0.0566***	0.0423***
	(0.0074)	(0.0073)	(0.0139)	(0.0135)	(0.0050)	(0.0052)	(0.0057)	(0.0062)
N	58647	58647	38541	38541	193173	193173	171099	171099
Adjusted R^2	0.02	0.03	0.00	0.11	0.11	0.00	0.18	0.00
Year FE	True	True	True	True	True	True	True	True
PC FE	False	True	False	True	False	True	False	True
1985-95								
Sample	JTH Cite		JTH Cite Sim		NAICS		Primclass	
Spillover	$pct\,cites\,in\,MSA_T$		$\overline{sim_{LDA}(T,j)}$		$sim_{LDA}(i,j)$		$sim_{LDA}(i,j)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I(MSA\,Match)$	0.2881***	0.2846***	0.0280***	0.0057	0.0621***	0.0535***	0.0647***	0.0516***
	(0.0052)	(0.0051)	(0.0094)	(0.0091)	(0.0041)	(0.0043)	(0.0045)	(0.0050)
N	107358	107358	69612	69612	281625	281625	252478	252478
Adjusted R^2	0.03	0.05	0.00	0.10	0.10	0.00	0.18	0.00
Year FE	True	True	True	True	True	True	True	True
PC FE	False	True	False	True	False	True	False	True
1995-05								
Sample	JTH Cite		JTH Cite Sim		NAICS		Primclass	
Spillover	$pct\,cites\,in\,MSA_T$		$\overline{sim_{LDA}(T,j)}$		$sim_{LDA}(i,j)$		$sim_{LDA}(i,j)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I(MSA\,Match)$	0.2983***	0.2966***	0.0017	-0.0123*	0.0980***	0.0987***	0.0626***	0.0723***
	(0.0041)	(0.0041)	(0.0068)	(0.0065)	(0.0033)	(0.0035)	(0.0035)	(0.0039)
N	185154	185154	122217	122217	438317	438317	402006	402006
Adjusted R^2	0.03	0.05	0.00	0.11	0.12	0.00	0.20	0.00
Year FE	True	True	True	True	True	True	True	True
PC FE	False	True	False	True	False	True	False	True
2005-15								
Sample	JTH Cite		JTH Cite Sim		NAICS		Primclass	
Spillover	$pct\,cites\,in\,MSA_T$		$\overline{sim_{LDA}(T,j)}$		$sim_{LDA}(i,j)$		$sim_{LDA}(i,j)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I(MSA\,Match)$	0.3417***	0.3365***	0.0173	-0.0003	0.0804***	0.0921***	0.0433***	0.0629***
	(0.0054)	(0.0054)	(0.0111)	(0.0107)	(0.0030)	(0.0032)	(0.0031)	(0.0034)
N	154619	154619	52710	52710	570099	570099	530245	530245
Adjusted R^2	0.02	0.05	0.00	0.12	0.15	0.00	0.20	0.00
Year FE	True	True	True	True	True	True	True	True
PC FE	False	True	False	True	False	True	False	True

Table E.4: Regression results for general local spillovers with normed data for LDAVec similarity.

1975-85								
Sample	JTH Cite		JTH Cite Sim		NAICS		Primclass	
Spillover	$pct\ cites\ in\ MSA_T$		$\overline{sim_{LDA}(T,j)}$		$sim_{LDA}(i,j)$		$sim_{LDA}(i,j)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I(MSA\ Match)$	0.0530***	0.0523***	0.0542***	0.0534***	0.0069***	0.0103***	0.0104***	0.0139***
	(0.0016)	(0.0016)	(0.0030)	(0.0029)	(0.0012)	(0.0011)	(0.0015)	(0.0014)
N	58647	58647	38541	38541	193173	193173	171099	171099
Adjusted R^2	0.02	0.03	0.01	0.12	0.00	0.11	0.00	0.18
Year FE	True	True	True	True	True	True	True	True
PC FE	False	True	False	True	False	True	False	True
1985-95								
Sample	JTH Cite		JTH Cite Sim		NAICS		Primclass	
Spillover	$pct\ cites\ in\ MSA_T$		$\overline{sim_{LDA}(T,j)}$		$sim_{LDA}(i,j)$		$sim_{LDA}(i,j)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I(MSA\ Match)$	0.0624***	0.0616***	0.0570***	0.0526***	0.0119***	0.0138***	0.0126***	0.0158***
	(0.0011)	(0.0011)	(0.0020)	(0.0020)	(0.0009)	(0.0009)	(0.0012)	(0.0011)
N	107358	107358	69612	69612	281625	281625	252478	252478
Adjusted R^2	0.03	0.05	0.01	0.11	0.00	0.10	0.00	0.18
Year FE	True	True	True	True	True	True	True	True
PC FE	False	True	False	True	False	True	False	True
1995-05								
Sample	JTH Cite		JTH Cite Sim		NAICS		Primclass	
Spillover	$pct\ cites\ in\ MSA_T$		$\overline{sim_{LDA}(T,j)}$		$sim_{LDA}(i,j)$		$sim_{LDA}(i,j)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I(MSA\ Match)$	0.0646***	0.0642***	0.0486***	0.0459***	0.0219***	0.0217***	0.0177***	0.0153***
	(0.0009)	(0.0009)	(0.0015)	(0.0014)	(0.0008)	(0.0007)	(0.0010)	(0.0009)
N	185154	185154	122217	122217	438317	438317	402006	402006
Adjusted R^2	0.03	0.05	0.01	0.12	0.00	0.12	0.00	0.20
Year FE	True	True	True	True	True	True	True	True
PC FE	False	True	False	True	False	True	False	True
2005-15								
Sample	JTH Cite		JTH Cite Sim		NAICS		Primclass	
Spillover	$pct\ cites\ in\ MSA_T$		$\overline{sim_{LDA}(T,j)}$		$sim_{LDA}(i,j)$		$sim_{LDA}(i,j)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$I(MSA\ Match)$	0.0740***	0.0729***	0.0502***	0.0468***	0.0204***	0.0178***	0.0154***	0.0106***
	(0.0012)	(0.0012)	(0.0024)	(0.0023)	(0.0007)	(0.0007)	(0.0008)	(0.0007)
N	154619	154619	52710	52710	570099	570099	530245	530245
Adjusted R^2	0.02	0.05	0.01	0.13	0.00	0.15	0.00	0.20
Year FE	True	True	True	True	True	True	True	True
PC FE	False	True	False	True	False	True	False	True

Table E.5: Regression results for general local spillovers with normed data for LDAVec similarity.

	1985-95			
	(1)	(2)	(3)	(4)
$I(MSA\,Match)$	0.0054***	-0.0024***	-0.0064***	-0.0037***
	(0.0006)	(0.0006)	(0.0019)	(0.0012)
$sim_{DV}(pc_i, pc_j)$	0.1748***		0.1700***	
	(0.0017)		(0.0018)	
$sim_{DV}(pc_{i,MSA_i}, pc_{j,MSA_j})$		0.0933***		0.0922***
		(0.0014)		(0.0018)
$I_{MSA} * sim_{DV}(pc_i, pc_j)$			0.0179***	
			(0.0029)	
$I_{MSA} * sim_{DV}(pc_{i,MSA_i}, pc_{j,MSA_j})$				0.0028
				(0.0025)
N	281018	227029	281018	227029
Adjusted R^2	0.11	0.09	0.11	0.09
Year FE	True	True	True	True
PC FE	True	True	True	True
	1995-05			
	(1)	(2)	(3)	(4)
$I(MSA\,Match)$	0.0049***	-0.0031***	-0.0076***	-0.0040***
	(0.0004)	(0.0005)	(0.0015)	(0.0010)
$sim_{DV}(pc_i, pc_j)$	0.1728***		0.1678***	
	(0.0013)		(0.0015)	
$sim_{DV}(pc_{i,MSA_i}, pc_{j,MSA_j})$		0.1042***		0.1034***
		(0.0011)		(0.0013)
$I_{MSA} * sim_{DV}(pc_i, pc_j)$			0.0184***	
			(0.0023)	
$I_{MSA} * sim_{DV}(pc_{i,MSA_i}, pc_{j,MSA_j})$				0.0019
				(0.0019)
N	437485	382972	437485	382972
Adjusted R^2	0.12	0.11	0.12	0.11
Year FE	True	True	True	True
PC FE	True	True	True	True
	2005-15			
	(1)	(2)	(3)	(4)
$I(MSA\,Match)$	0.0044***	-0.0024***	-0.0091***	-0.0066***
	(0.0004)	(0.0004)	(0.0017)	(0.0011)
$sim_{DV}(pc_i, pc_j)$	0.1803***		0.1751***	
	(0.0013)		(0.0015)	
$sim_{DV}(pc_{i,MSA_i}, pc_{j,MSA_j})$		0.1040***		0.1015***
		(0.0010)		(0.0012)
$I_{MSA} * sim_{DV}(pc_i, pc_j)$			0.0186***	
			(0.0024)	
$I_{MSA} * sim_{DV}(pc_{i,MSA_i}, pc_{j,MSA_j})$				0.0071***
				(0.0017)
N	569100	516531	569100	516531
Adjusted R^2	0.09	0.08	0.09	0.08
Year FE	True	True	True	True
PC FE	True	True	True	True

Table E.6: Regression results for strict local spillovers with raw data for DocVec similarity.

	1985-95			
	(1)	(2)	(3)	(4)
$I(MSA\,Match)$	0.0274***	-0.0415***	0.0280***	-0.0412***
	(0.0038)	(0.0042)	(0.0039)	(0.0042)
$sim_{LDA}(pc_i, pc_j)$	0.4123***		0.4094***	
	(0.0023)		(0.0026)	
$sim_{LDA}(pc_{i,MSA_i}, pc_{j,MSA_j})$		0.3994***		0.4221***
		(0.0026)		(0.0031)
$I_{MSA} * sim_{LDA}(pc_i, pc_j)$			0.0114***	
			(0.0044)	
$I_{MSA} * sim_{LDA}(pc_{i,MSA_i}, pc_{j,MSA_j})$				-0.0619***
				(0.0047)
N	281421	227396	281421	227396
Adjusted R^2	0.21	0.21	0.21	0.21
Year FE	True	True	True	True
PC FE	True	True	True	True
	1995-05			
	(1)	(2)	(3)	(4)
$I(MSA\,Match)$	0.0535***	-0.0202***	0.0533***	-0.0174***
	(0.0031)	(0.0033)	(0.0031)	(0.0032)
$sim_{LDA}(pc_i, pc_j)$	0.4349***		0.4286***	
	(0.0019)		(0.0021)	
$sim_{LDA}(pc_{i,MSA_i}, pc_{j,MSA_j})$		0.4219***		0.4366***
		(0.0019)		(0.0023)
$I_{MSA} * sim_{LDA}(pc_i, pc_j)$			0.0234***	
			(0.0034)	
$I_{MSA} * sim_{LDA}(pc_{i,MSA_i}, pc_{j,MSA_j})$				-0.0417***
				(0.0035)
N	438117	383569	438117	383569
Adjusted R^2	0.24	0.24	0.24	0.25
Year FE	True	True	True	True
PC FE	True	True	True	True
	2005-15			
	(1)	(2)	(3)	(4)
$I(MSA\,Match)$	0.0356***	-0.0279***	0.0343***	-0.0215***
	(0.0028)	(0.0029)	(0.0027)	(0.0028)
$sim_{LDA}(pc_i, pc_j)$	0.4299***		0.4274***	
	(0.0016)		(0.0018)	
$sim_{LDA}(pc_{i,MSA_i}, pc_{j,MSA_j})$		0.4096***		0.4197***
		(0.0016)		(0.0019)
$I_{MSA} * sim_{LDA}(pc_i, pc_j)$			0.0090***	
			(0.0028)	
$I_{MSA} * sim_{LDA}(pc_{i,MSA_i}, pc_{j,MSA_j})$				-0.0304***
				(0.0028)
N	569947	517333	569947	517333
Adjusted R^2	0.26	0.27	0.26	0.27
Year FE	True	True	True	True
PC FE	True	True	True	True

Table E.7: Regression results for strict local spillovers with normed data for LDAVec similarity.

	1985-95			
	(1)	(2)	(3)	(4)
$I(MSA\,Match)$	0.0061***	-0.0092***	0.0038***	0.0044***
	(0.0008)	(0.0009)	(0.0010)	(0.0012)
$sim_{LDA}(pc_i, pc_j)$	0.2331***		0.2315***	
	(0.0013)		(0.0015)	
$sim_{LDA}(pc_{i,MSA_i}, pc_{j,MSA_j})$		0.2509***		0.2652***
		(0.0016)		(0.0020)
$I_{MSA} * sim_{LDA}(pc_i, pc_j)$			0.0064***	
			(0.0025)	
$I_{MSA} * sim_{LDA}(pc_{i,MSA_i}, pc_{j,MSA_j})$				-0.0389***
				(0.0030)
N	281421	227396	281421	227396
Adjusted R^2	0.21	0.21	0.21	0.21
Year FE	True	True	True	True
PC FE	True	True	True	True
	1995-05			
	(1)	(2)	(3)	(4)
$I(MSA\,Match)$	0.0119***	-0.0045***	0.0069***	0.0053***
	(0.0007)	(0.0007)	(0.0008)	(0.0009)
$sim_{LDA}(pc_i, pc_j)$	0.2459***		0.2423***	
	(0.0011)		(0.0012)	
$sim_{LDA}(pc_{i,MSA_i}, pc_{j,MSA_j})$		0.2651***		0.2743***
		(0.0012)		(0.0015)
$I_{MSA} * sim_{LDA}(pc_i, pc_j)$			0.0133***	
			(0.0019)	
$I_{MSA} * sim_{LDA}(pc_{i,MSA_i}, pc_{j,MSA_j})$				-0.0262***
				(0.0022)
N	438117	383569	438117	383569
Adjusted R^2	0.24	0.24	0.24	0.25
Year FE	True	True	True	True
PC FE	True	True	True	True
	2005-15			
	(1)	(2)	(3)	(4)
$I(MSA\,Match)$	0.0079***	-0.0062***	0.0057***	0.0019**
	(0.0006)	(0.0007)	(0.0007)	(0.0008)
$sim_{LDA}(pc_i, pc_j)$	0.2430***		0.2416***	
	(0.0009)		(0.0010)	
$sim_{LDA}(pc_{i,MSA_i}, pc_{j,MSA_j})$		0.2573***		0.2637***
		(0.0010)		(0.0012)
$I_{MSA} * sim_{LDA}(pc_i, pc_j)$			0.0051***	
			(0.0016)	
$I_{MSA} * sim_{LDA}(pc_{i,MSA_i}, pc_{j,MSA_j})$				-0.0191***
				(0.0017)
N	569947	517333	569947	517333
Adjusted R^2	0.26	0.27	0.26	0.27
Year FE	True	True	True	True
PC FE	True	True	True	True

Table E.8: Regression results for strict local spillovers with raw data for DocVec similarity.

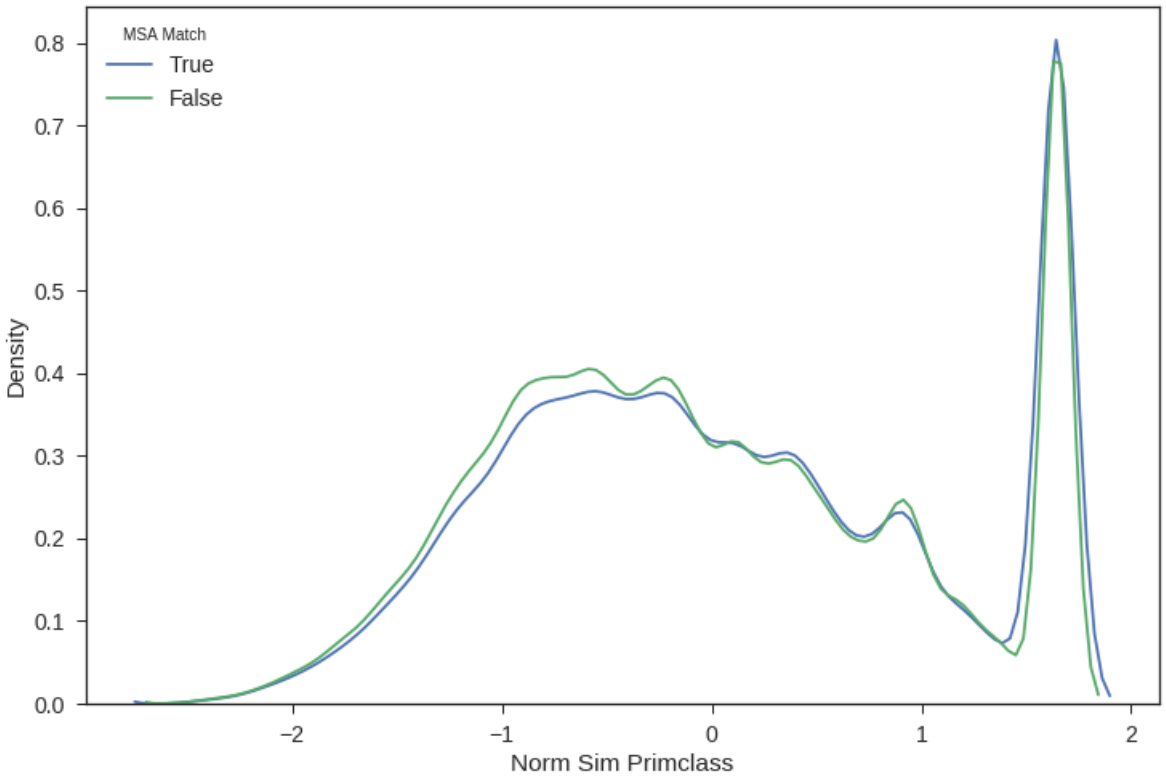


Figure E.1: Distribution of $sim(pc_i, pc_j)$ for local and non-local patent pairs.

F. Exogenous new knowledge

G. New Terms

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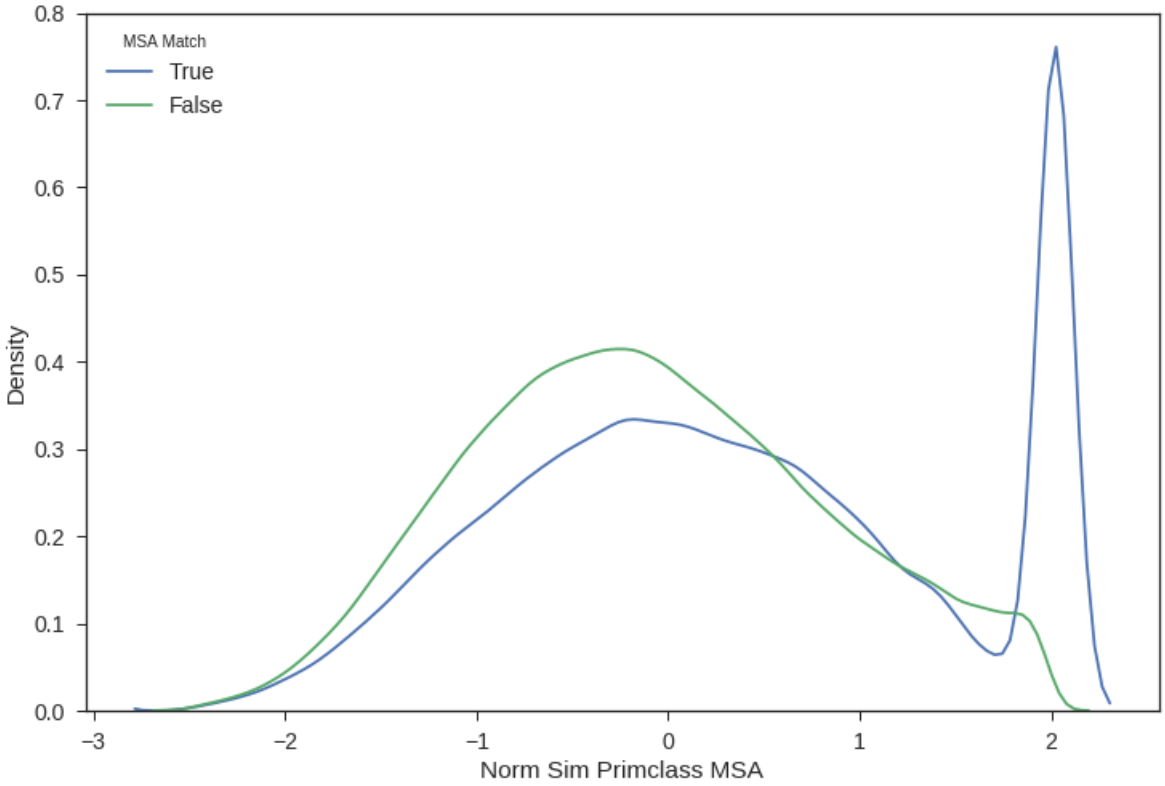


Figure E.2: Distribution of $sim(pc_i, pc_j)$ for local and non-local patent pairs.

Appl. Year	Mean Localization, Uni Patents	Std Dev, Uni Patents	Mean Localization, Other Patents	Std Dev, Other Patents	Diff	p-value
1975	0.004	0.027	0.005	0.037	-0.001	0.687
1976	0.001	0.046	0.005	0.040	-0.004	0.406
1977	-0.000	0.046	0.006	0.048	-0.006	0.175
1978	0.006	0.062	0.005	0.054	0.001	0.851
1979	-0.015	0.074	0.005	0.071	-0.020	0.022
1980	-0.003	0.039	0.005	0.039	-0.008	0.007
1981	0.004	0.036	0.005	0.044	-0.001	0.688
1982	0.003	0.050	0.004	0.048	-0.001	0.737
1983	-0.002	0.068	0.005	0.057	-0.007	0.185
1984	0.002	0.076	0.005	0.074	-0.002	0.704
1985	0.001	0.042	0.006	0.040	-0.004	0.095
1986	0.002	0.039	0.005	0.043	-0.003	0.160
1987	0.002	0.046	0.005	0.044	-0.003	0.210
1988	0.002	0.058	0.004	0.052	-0.002	0.595
1989	0.003	0.069	0.005	0.066	-0.002	0.676

Table F.1: Comparison of mean and standard deviation of localization effect for university vs non-university patents within the same industry by application year

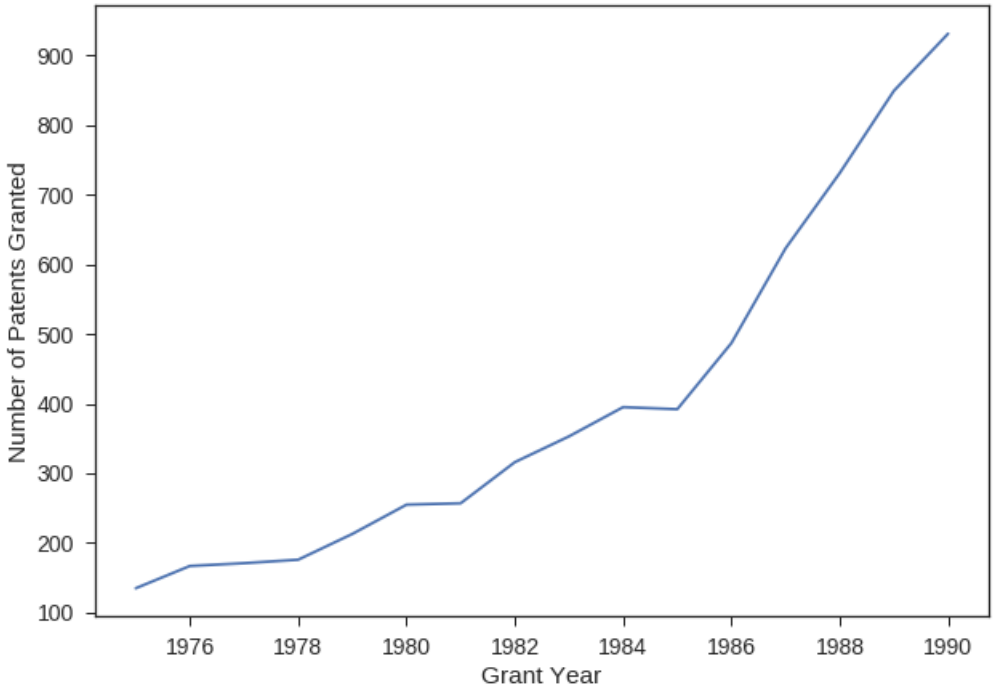


Figure F.1: Number of university patents by application year

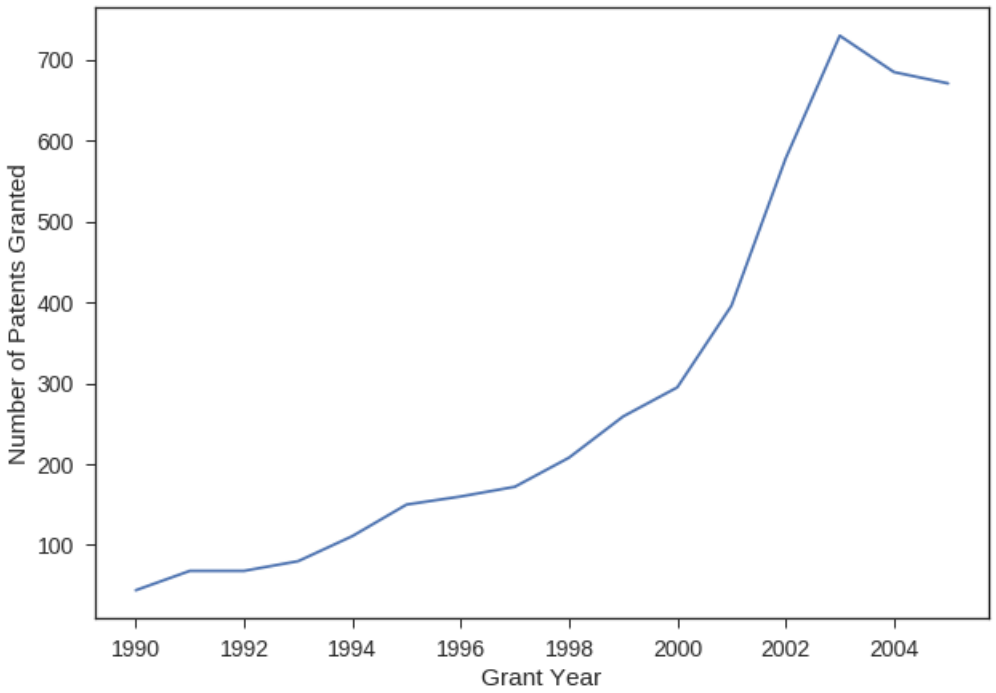


Figure F.2: Number of nanotechnology patents by application year

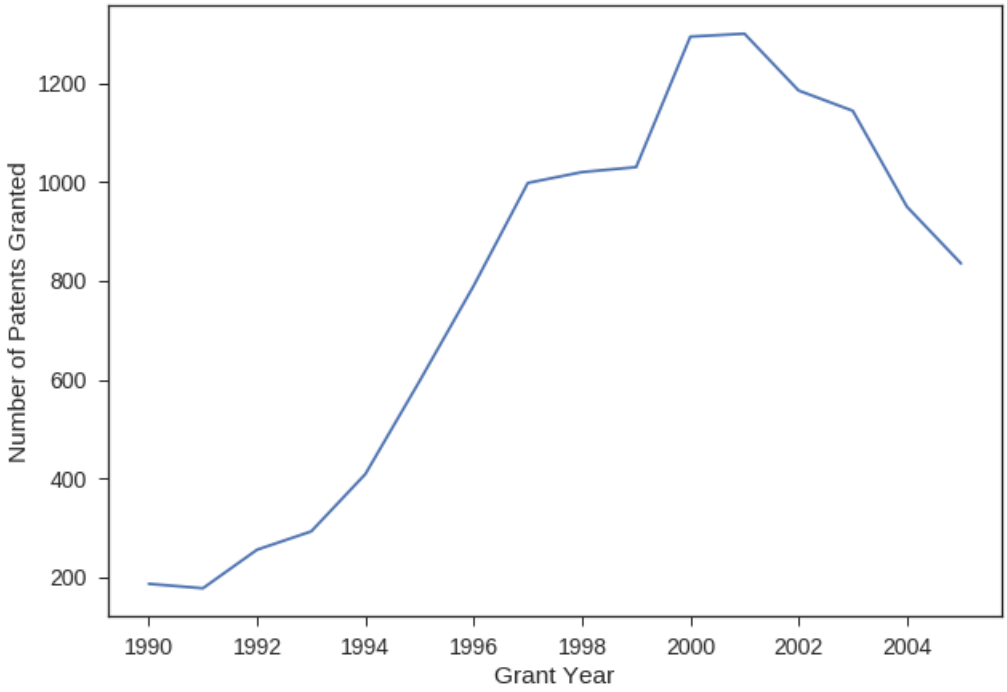


Figure F.3: Number of software patents by application year

Appl. Year	Mean Localization, Nano Patents	Std Dev, Nano Patents	Mean Localization, Other Patents	Std Dev, Other Patents	Diff	p-value
1990	-0.013	0.034	0.022	0.065	-0.034	0.005
1991	0.024	0.039	0.028	0.069	-0.004	0.674
1992	0.009	0.026	0.027	0.078	-0.018	0.114
1993	0.067	0.074	0.024	0.086	0.043	0.071
1994	0.020	0.086	0.024	0.106	-0.004	0.856
1995	0.007	0.058	0.022	0.062	-0.015	0.290
1996	0.008	0.041	0.019	0.065	-0.011	0.210
1997	0.016	0.048	0.023	0.073	-0.006	0.540
1998	0.017	0.060	0.022	0.086	-0.005	0.591
1999	0.012	0.086	0.023	0.111	-0.011	0.402
2000	-0.001	0.053	0.017	0.058	-0.019	0.010
2001	0.010	0.059	0.016	0.063	-0.006	0.368
2002	0.015	0.068	0.017	0.073	-0.003	0.684
2003	0.007	0.079	0.018	0.085	-0.011	0.128
2004	0.009	0.104	0.019	0.107	-0.010	0.238
2005	0.009	0.071	0.018	0.085	-0.009	0.083

Table F.2: Comparison of mean and standard deviation of localization effect for nanotechnology vs non-nanotechnology patents within the same industry by application year

Appl. Year	Mean Localization, Software Patents	Std Dev, Software Patents	Mean Localization, Other Patents	Std Dev, Other Patents	Diff	p-value
1990	0.007	0.029	0.006	0.034	0.000	0.938
1991	0.001	0.032	0.007	0.036	-0.006	0.098
1992	0.008	0.043	0.005	0.039	0.002	0.566
1993	0.001	0.044	0.003	0.043	-0.002	0.613
1994	0.006	0.051	0.006	0.056	-0.000	0.984
1995	0.004	0.027	0.006	0.032	-0.002	0.281
1996	0.006	0.029	0.005	0.033	0.002	0.271
1997	0.003	0.033	0.004	0.040	-0.001	0.355
1998	0.001	0.037	0.004	0.047	-0.003	0.092
1999	0.000	0.049	0.004	0.060	-0.003	0.194
2000	0.003	0.029	0.003	0.036	-0.001	0.613
2001	0.001	0.036	0.005	0.038	-0.004	0.004
2002	-0.002	0.038	0.003	0.043	-0.006	0.001
2003	-0.001	0.042	0.004	0.051	-0.005	0.008
2004	0.007	0.054	0.004	0.056	0.003	0.285
2005	0.006	0.043	0.002	0.046	0.003	0.140

Table F.3: Comparison of mean and standard deviation of localization effect for software vs non-software patents within the same industry by application year

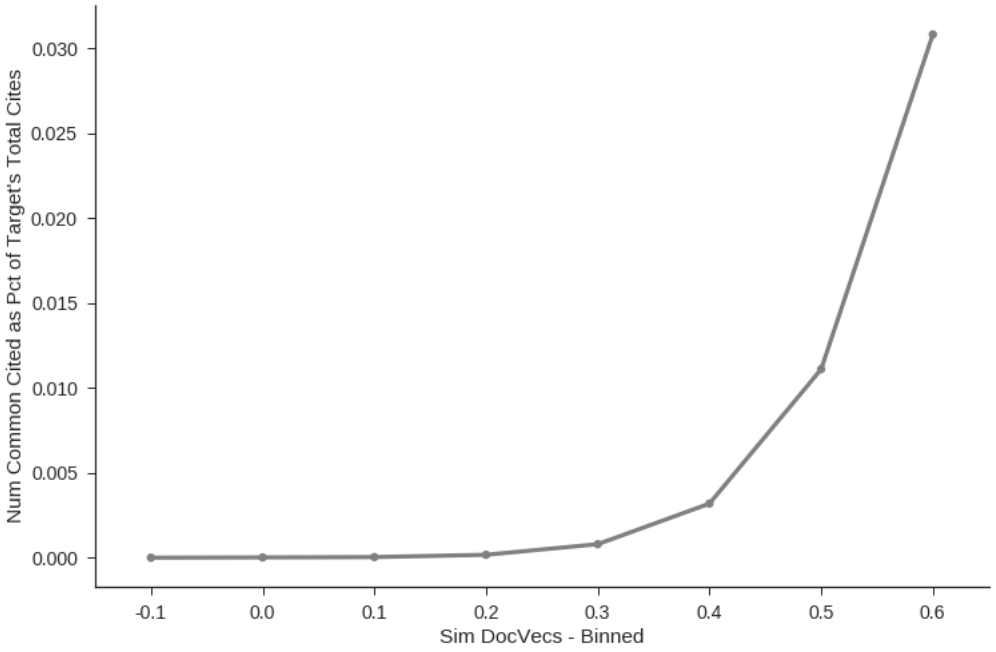


Figure G.1: Number of common cited patents as a percentage of target's total citations, by DocVecs similarity

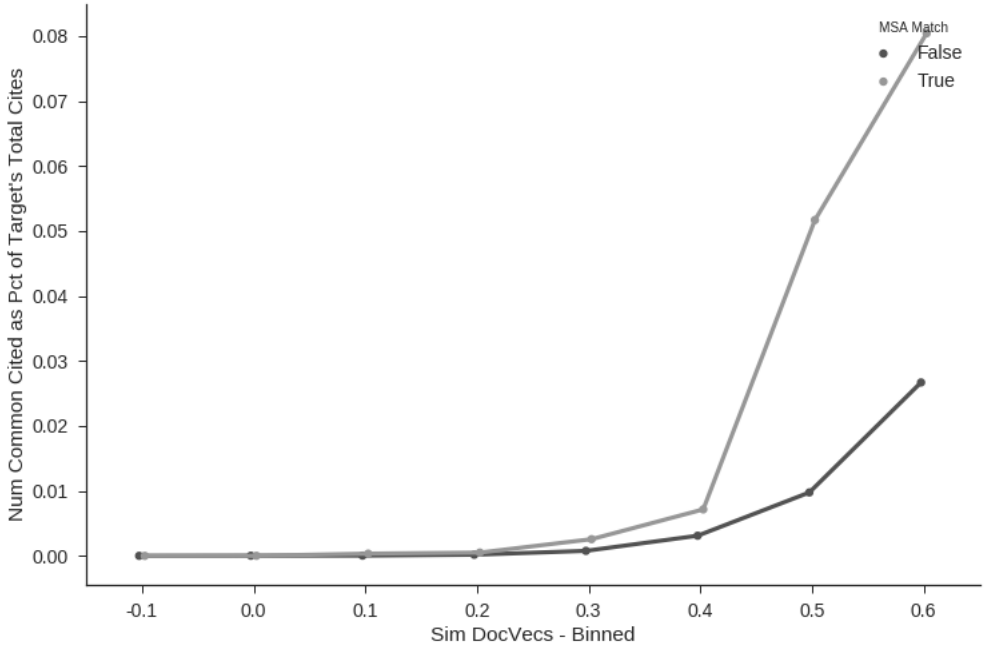
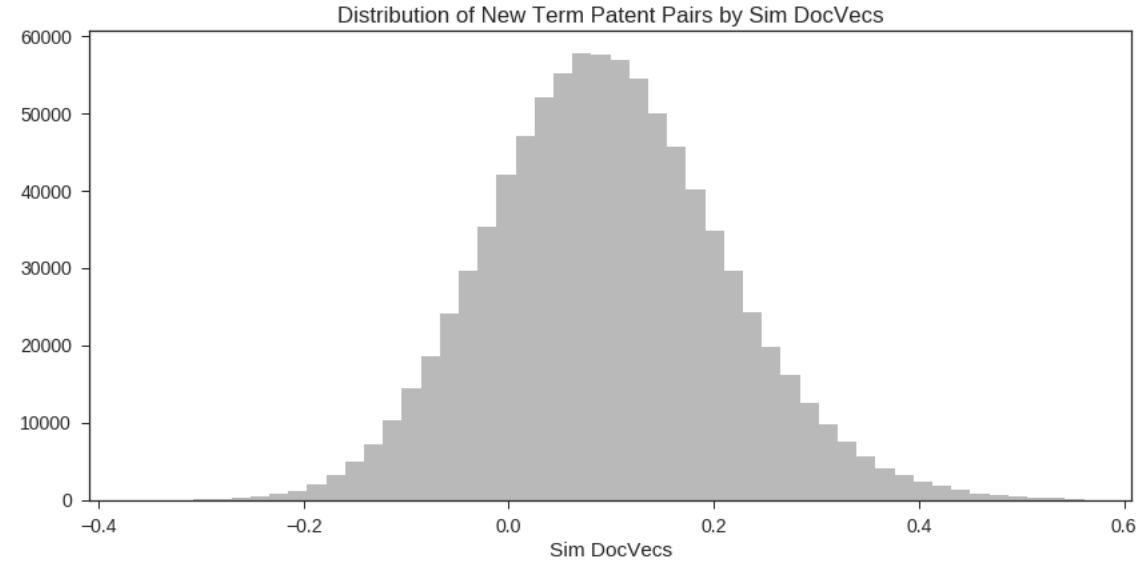


Figure G.2: Number of common cited patents as a percentage of target's total citations, by DocVecs similarity

	Sim DocVecs	Num Common Cited	**Pct Common Cited, Target's Citations**	First Year	First Year, Num Pats	First Year, Num Pairs
gui	0.09	0.00	0.00	1992	1348	796727
lun	0.12	0.00	0.00	1995	415	63044
asic	0.11	0.00	0.00	1987	198	16716
url	0.10	0.01	0.00	1995	111	4847
serd	0.12	0.02	0.00	1998	75	1929
chat	0.10	0.00	0.00	1992	9	1299
bist	0.12	0.00	0.00	1990	42	810
femto	0.15	0.04	0.00	2007	27	563
angst	0.16	0.00	0.00	1994	40	549
mcm	0.10	0.00	0.00	1991	32	440
www	0.15	0.01	0.01	1995	9	291
efus	0.12	0.02	0.00	2000	22	201
femtocel	0.22	0.09	0.00	2007	8	198
adenovir	0.26	0.03	0.00	1993	15	98
cyclin	0.18	0.00	0.00	1991	13	80
n 1	0.13	0.00	0.00	1998	13	63
dvd	0.16	0.00	0.00	1996	10	44
websit	0.18	0.00	0.00	1996	10	42
gpu	0.05	0.00	0.00	2001	9	36
pcie	0.21	0.00	0.00	2004	9	35

Table G.1: Comparison of similarity and backward citation overlap for new patents using new terms.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20000
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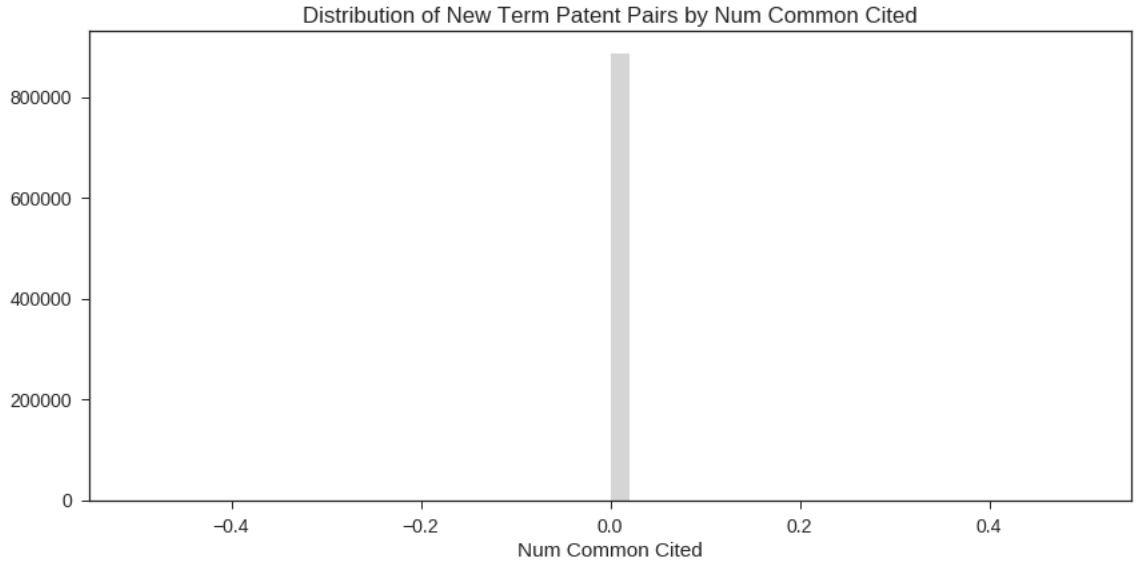
−0.2
0.0
0.2
0.4
0.6
Sim DocVecs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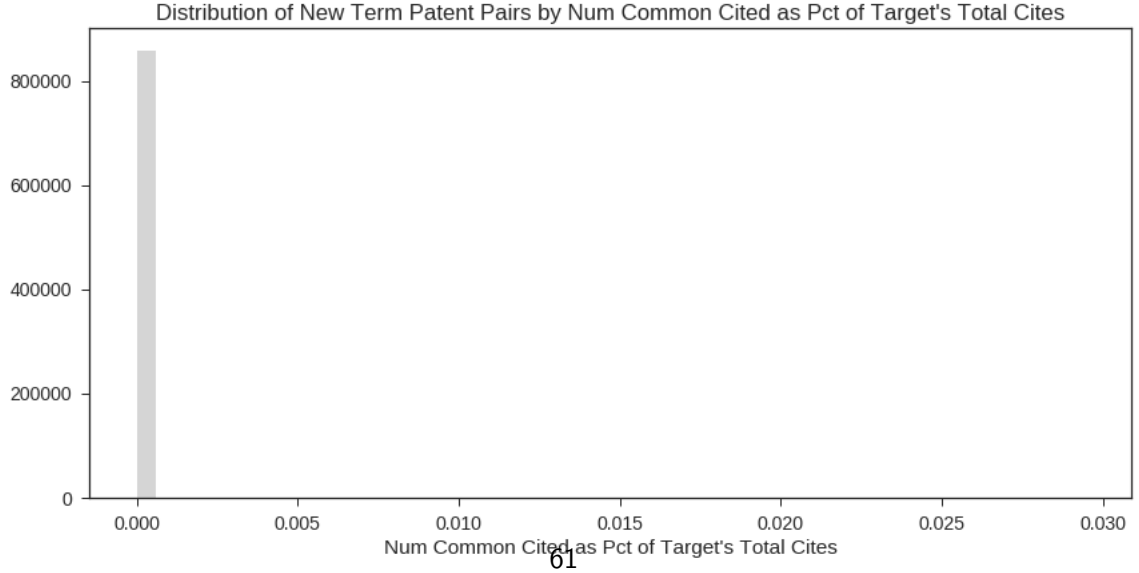
0.4
Num Common Cited


Distribution of New Term Patent Pairs by Num Common Cited as Pct of Target's Total Cites
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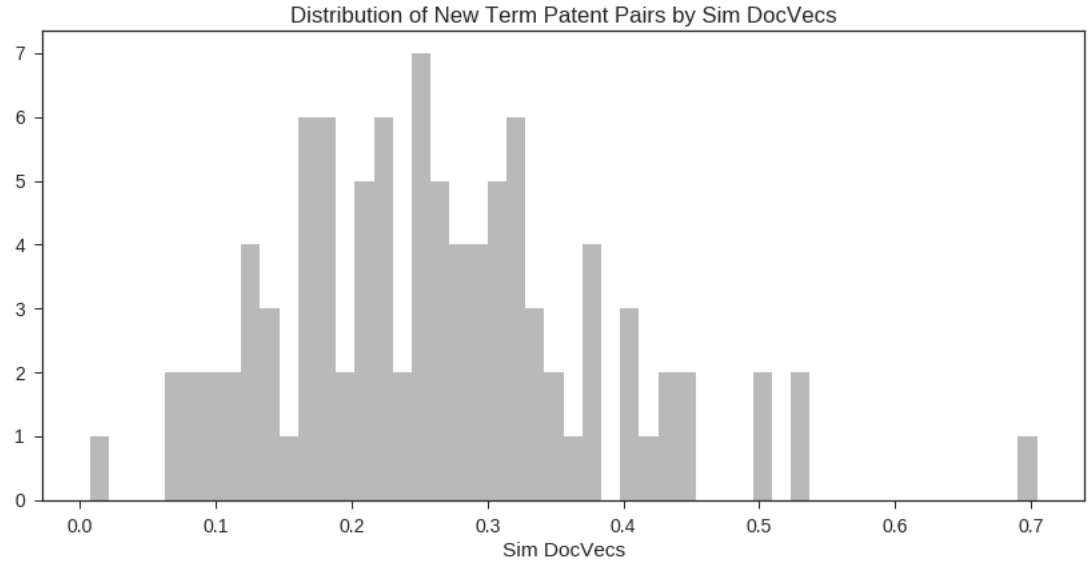
0.020
0.025
0.030
Num Common Cited as Pct of Target's Total Cites


Distribution of New Term Patent Pairs by Sim DocVecs
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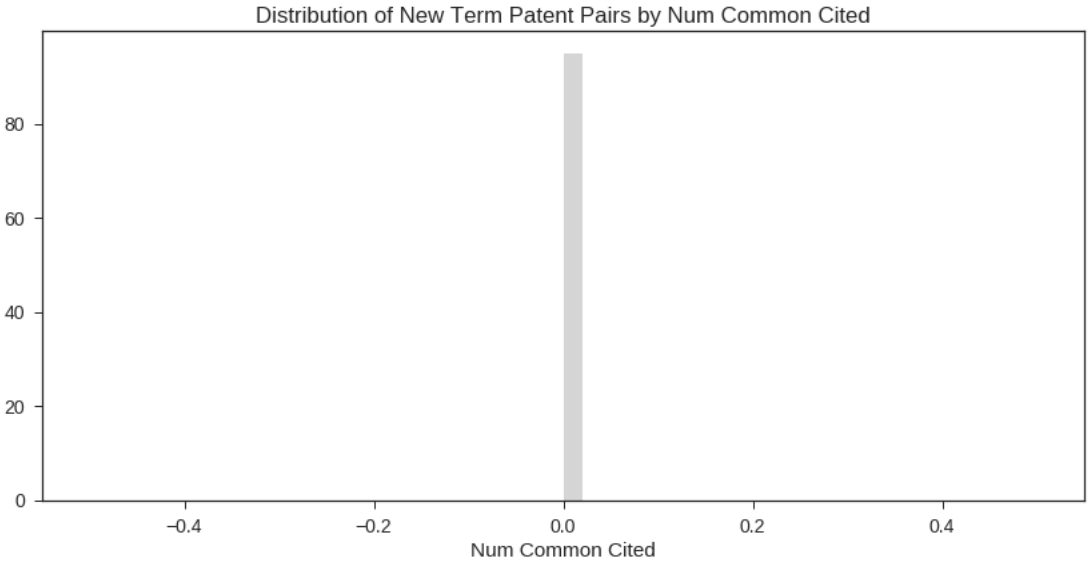
0.4
0.5
0.6
0.7
Sim DocVecs


Distribution of New Term Patent Pairs by Num Common Cited
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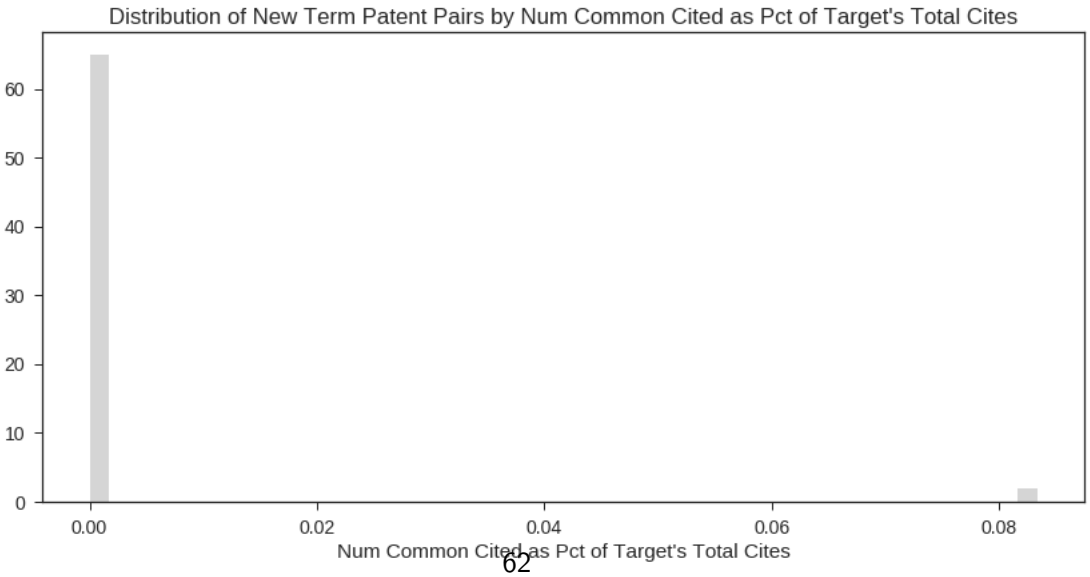
−0.2
0.0
0.2
0.4
Num Common Cited


Distribution of New Term Patent Pairs by Num Common Cited as Pct of Target's Total Cites
0
10
20
30
40
50
60
0.00
0.02
0.04
0.06
0.08
Num Common Cited as Pct of Target's Total Cites

References

Ajay Agrawal, Iain Cockburn, and John McHale. Gone but not forgotten: knowledge flows, labor mobility, and enduring social relationships. *Journal of Economic Geography*, 6(5):571–591, 2006.

Juan Alcacer and Wilbur Chung. Location strategies and knowledge spillovers. *Management science*, 53 (5):760–776, 2007.

Juan Alcacer and Michelle Gittelman. Patent citations as a measure of knowledge flows: The influence of examiner citations. *The Review of Economics and Statistics*, 88(4):774–779, 2006.

Juan Alcacer, Michelle Gittelman, and Bhaven Sampat. Applicant and examiner citations in us patents: An overview and analysis. *Research Policy*, 38(2):415–427, 2009.

Paul Almeida and Bruce Kogut. Localization of knowledge and the mobility of engineers in regional networks. *Management science*, 45(7):905–917, 1999.

Ashish Arora. Patents, licensing, and market structure in the chemical industry. *Research policy*, 26(4-5): 391–403, 1997.

Pierre Azoulay, Joshua S Graff Zivin, and Bhaven N Sampat. The diffusion of scientific knowledge across time and space: Evidence from professional transitions for the superstars of medicine. Technical report, National Bureau of Economic Research, 2011.

David M Blei, Andrew Y Ng, and Michael I Jordan. Latent dirichlet allocation. *Journal of machine Learning research*, 3(Jan):993–1022, 2003.

Nicholas Bloom, Mark Schankerman, and John Van Reenen. Identifying technology spillovers and product market rivalry. *Econometrica*, 81(4):1347–1393, 2013.

Kristy Buzard, Gerald A Carlino, Robert M Hunt, Jake K Carr, and Tony E Smith. Localized knowledge spillovers: Evidence from the agglomeration of american r&d labs and patent data. 2016.

Christopher A Cotropia, Mark A Lemley, and Bhaven Sampat. Do applicant patent citations matter? *Research Policy*, 42(4):844–854, 2013.

Maryann P Feldman. Knowledge complementarity and innovation. *Small business economics*, 6(5):363–372, 1994.

Edward L Glaeser, Hedi D Kallal, Jose A Scheinkman, and Andrei Shleifer. Growth in cities. *Journal of political economy*, 100(6):1126–1152, 1992.

Michael Greenstone, Richard Hornbeck, and Enrico Moretti. Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings. *Journal of Political Economy*, 118(3):536–598, 2010.

Matthew Hoffman, Francis R Bach, and David M Blei. Online learning for latent dirichlet allocation. In *advances in neural information processing systems*, pages 856–864, 2010.

Jane Jacobs. *The economy of cities*. Vintage Books, 1969.

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

Adam B Jaffe. Real effects of academic research. *The American economic review*, pages 957–970, 1989.

Adam B Jaffe and Gaétan De Rassenfosse. Patent citation data in social science research: Overview and best practices. *Journal of the Association for Information Science and Technology*, 68(6):1360–1374, 2017.

Adam B Jaffe, Manuel Trajtenberg, and Rebecca Henderson. Geographic localization of knowledge spillovers as evidenced by patent citations. *the Quarterly journal of Economics*, 108(3):577–598, 1993.

Sarah Kaplan and Keyvan Vakili. The double-edged sword of recombination in breakthrough innovation. *Strategic Management Journal*, 36(10):1435–1457, 2015.

Paul R Krugman. *Geography and trade*. MIT press, 1991.

Ryan Lampe. Strategic citation. *Review of Economics and Statistics*, 94(1):320–333, 2012.

Quoc Le and Tomas Mikolov. Distributed representations of sentences and documents. In *Proceedings of the 31st International Conference on Machine Learning (ICML-14)*, pages 1188–1196, 2014.

Chu-Cheng Lin, Waleed Ammar, Chris Dyer, and Lori Levin. Unsupervised pos induction with word embeddings. *arXiv preprint arXiv:1503.06760*, 2015.

Sergey Lychagin, Joris Pinkse, Margaret E Slade, and John Van Reenen. Spillovers in space: does geography matter? *The Journal of Industrial Economics*, 64(2):295–335, 2016.

Charles F Manski. Economic analysis of social interactions. Technical report, National bureau of economic research, 2000.

Alfred Marshall and Mary Paley Marshall. *The economics of industry*. Macmillan and Company, 1920.

Rada Mihalcea, Courtney Corley, Carlo Strapparava, et al. Corpus-based and knowledge-based measures of text semantic similarity. In *AAAI*, volume 6, pages 775–780, 2006.

Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013a.

Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119, 2013b.

Petra Moser. Do patents weaken the localization of innovations? evidence from world's fairs. *The Journal of Economic History*, 71(2):363–382, 2011.

Yasusada Murata, Ryo Nakajima, Ryosuke Okamoto, and Ryuichi Tamura. Localized knowledge spillovers and patent citations: A distance-based approach. *Review of Economics and Statistics*, 96(5):967–985, 2014.

Michael Roach and Wesley M Cohen. Lens or prism? patent citations as a measure of knowledge flows from public research. *Management Science*, 59(2):504–525, 2013.

Jung Won Sonn and Michael Storper. The increasing importance of geographical proximity in knowledge production: an analysis of us patent citations, 1975–1997. *Environment and Planning A*, 40(5):1020–1039, 2008.

Peter Thompson and Melanie Fox-Kean. Patent citations and the geography of knowledge spillovers: A reassessment. *American Economic Review*, pages 450–460, 2005.