Creative Construction: Knowledge Sharing and Cooperation Between Firms*

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Abstract

Involuntary knowledge spillovers are often assumed to diffuse across a diverse range of firms. A common measure of such spillovers is patent citations. I show that citations are highly concentrated and primarily come from business partners. I provide empirical evidence suggesting that, instead of involuntary spillovers, concentrated citations reflect intentional knowledge transfers between collaborating firms. The concentration of citations has increased since 2000, indicating more selective knowledge sharing among partners. I develop a theory that shows how market forces affect knowledge flows. Firms control knowledge flows to competitors through incomplete information disclosure in patents and to partners through licensing and selective trade secret sharing. In line with the model's predictions, I provide evidence that secrecy and competition lead to more concentrated knowledge flows. The increased reliance on secrecy can explain the decline in knowledge sharing among partners.

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1 Introduction

Knowledge flows among firms are often assumed to take a form of involuntary spillovers "in the air" (Marshall 1920) rather than intentional knowledge sharing.[1] This paper shows evidence suggesting that knowledge does not flow through ether but through pipes of business relations. I argue that firms have significant control over the knowledge they generate, selectively sharing it with a limited set of business partners, such as input suppliers and customers. Intentional knowledge sharing has substantially declined over time due to changes in incentives for collaboration between partners.

Table 1: Example of a patent with a high concentration of citations

Patent Number	Assignee	Total Number of Citations	% of Citations from Amkor Technology Inc
5877043	IBM	218 top 0.005%	94%

A prevailing measure of knowledge spillovers is patent citations.[2] The existence of patents is often justified by the claim that they promote knowledge diffusion through the disclosure of inventions.[3] I show that the distribution of citations across firms is highly concentrated, raising a question about the role of patents in the diffusion of knowledge. For example, IBM's patent in Table 1 is heavily cited, but almost all of its citations come from IBM's *input supplier*, Amkor Technology Inc. Figure 1 shows that citations are highly concentrated in general: the most cited patents granted in the U.S. between 1980 and 2000 received around 50% of citations from one firm only, and this concentration increased to 77% in 2014.

The high concentration of citations is puzzling because valuable technologies disclosed in public patent files would be expected to generate spillovers across a broader set of firms (Romer 1990). Thus, interpreting patent citations as a measure of knowledge spillovers might be incorrect. Instead, I provide evidence supporting the view that citations reflect cooperation and intentional knowledge transfers between business partners.

I collect data on various inter-firm relations between publicly listed U.S. companies. I show that business partners — such as suppliers, customers, or firms with research collaboration —

[1]The existence of knowledge spillovers is key in models of economic growth (Romer 1990; Grossman & Helpman 1991; Aghion & Howitt 1992) and a common justification for R&D subsidies (Bloom et al. 2019).

[2]For example, patent citations are used to estimate growth models (Caballero & Jaffe 1993; Eeckhout & Jovanovic 2002; Akcigit & Kerr 2018), evaluate the localization of spillovers in space (Jaffe et al. 1993; Thompson & Fox-Kean 2005; Singh & Marx 2013), provide policy recommendations (Liu & Ma 2023), and identify high-quality technologies (Aghion et al. 2023; Akcigit et al. 2021; Moretti 2021).

[3]"[T]he patent system represents a carefully crafted bargain that encourages both the creation and the public disclosure of new and useful advances in technology, in return for an exclusive monopoly for a limited period of time" (*Pfaff v. Wells Elecs., Inc.*, 525 U.S. 55, 63, 1998). See also Mazzoleni & Nelson (1998).

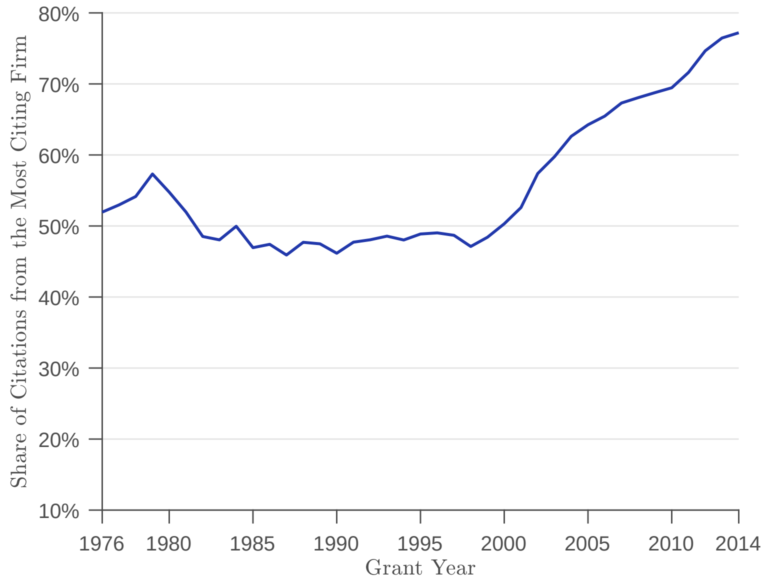


Figure 1: Concentration of Citations

This figure shows the average concentration of citations for the most cited patents between 1976 and 2014. In each grant year and technology class for the period of 1976–2014, I track citations within a five-year window for the top 1% of the most cited patents. For each cited patent, the concentration is defined as the share of citations coming from the most citing firm. The technological classes are defined at the group level in the cooperative patent classification system. To construct the aggregate measure, I take the average concentration across patents within each class and then the average across classes weighted by the number of patents.

account for approximately 76% of inter-firm citations. Changes in citation patterns among partners explain around 84% of the rise in the concentration since 2000. In particular, the average number of partners citing a typical firm declined by 42%, even though the overall number of partners for a firm increased. These changes are explained by increasing differences across firms in their citation probabilities rather than shifts in the distribution of patent counts or the composition of partners. For example, a rise of superstar firms with large patent portfolios cannot explain the increasing concentration.

In addition, citations are specific to firms citing each other rather than individual inventors. I show that an inventor who heavily cites a particular patent in one company significantly decreases her citations to this patent once she moves to another firm. This evidence suggests that citations should be explained based on firm relationships rather than human capital factors. I also show that the results are not driven by citations from patent examiners or attorneys and are robust to various specifications.

I argue that firms might control the diffusion of their knowledge, at least as measured by citations. They selectively share knowledge with a few partners, thereby providing them an advantage in creating follow-on innovations. According to U.S. patent law, these partners are required to cite the original patent when they file for patents on the follow-on innovations. As a result, citations are concentrated because only a few partners of a patent owner gain access to the knowledge embodied in the patent.

I develop a theory that explains how firms might control knowledge diffusion. Firms have incentives to share knowledge with business partners and conceal it from competitors. Sharing knowledge with partners exposes the firm to potential misappropriation because they can use it without compensating the firm. For example, a supplier can use the knowledge to serve other customers. Patenting can solve this problem by providing knowledge protection and allowing the writing of licensing contracts on knowledge transfers. However, it discloses the information to competitors who can improve upon that knowledge and replace the firm.

A potential solution to this dilemma is combining patenting with secrecy. Consider knowledge with two complementary components, such as labor and capital productivity in a production function. By patenting one component and keeping another secret, the firm can create a dependency barrier: partners cannot fully benefit from the secret without access to the patented knowledge, and competitors face significant difficulties in improving the technology without observing the secret knowledge. Thus, this strategy can minimize the misappropriation while concealing much of the knowledge from the competitors. Legal scholars argue that firms often combine patenting with secrecy despite the disclosure requirements of the patent system (e.g., Roin 2005). For instance, patents on biological products do not disclose manufacturing details, which was a significant barrier to scaling the production of mRNA-based COVID-19 vaccines (Price & Rai 2016; Price et al. 2020).

In the model, the firm chooses between full patenting, a patent-secrecy combination, and complete secrecy. Greater reliance on secrecy decreases the risk of being replaced by a competitor but impedes contractible knowledge sharing with partners, resulting in less knowledge flows. The increasing bundling of patents with secrets can explain the decline in knowledge flows among firms despite the increase in the number of partners.

I test two predictions from the model. First, the model predicts that bundling patents with trade secrets leads to more concentrated knowledge flows. Testing this connection is challenging because trade secrets are not observable. I use trade secret litigation data to find patents that were likely to be bundled with trade secrets. For example, the legal case *Waymo v. Uber* was about misappropriation of trade secrets related to the light detection and ranging (LiDAR) technology for self-driving cars.[4] However, the same lawsuit also had claims regarding patent infringement, and in the legal complaint, Waymo described the complementarity between their patents and secrets. I show that patents which were involved in both patent and trade secret litigation have more concentrated citations relative to similar patents within the same firm that were involved in patent litigation only. This evidence suggests that the complementarity

[4] *Waymo LLC v. Uber Technologies, Inc.*, No. 17-2235 (Fed. Cir. 2017).

between a patent and trade secrets might lead to a higher concentration of citations.

Second, the model predicts that higher Schumpeterian competition leads to more concentrated knowledge flows. By Schumpeterian competition, I mean the competition that reduces incentives to innovate due to lower profit rents after R&D investments (Schumpeter 1942; Shapiro 2012).[5] Autor et al. (2020) show that import competition from China reduced profitability, patenting, and R&D investments of U.S. companies. Using the same empirical strategy, I show that technologies more exposed to import competition from China experienced higher growth in the concentration of citations.

This paper is related to the literature on innovation and knowledge diffusion. Involuntary knowledge spillovers are fundamental in models of economic growth (Jones 2005; Aghion et al. 2014), provide a rationale for R&D subsidies (Bloom et al. 2019), and can explain the agglomeration of economic activity (Marshall 1920; Carlino & Kerr 2015).

The U.S. Supreme Court has emphasized that disseminating knowledge is one of the primary functions of the patent system (see references in Roin 2005). Theories of economic growth also assume that patents facilitate knowledge spillovers: "[I]nventors are free to spend time studying the patent application for the widget and learn knowledge that helps in the design of a wodget. The inventor of the widget has no ability to stop the inventor of a wodget from learning from the design of a widget" (Romer 1990, p. 84).

Patent citations have been the prevailing measure of knowledge spillovers since the seminal work by Jaffe et al. (1993). Several surveys of inventors and firms confirm that citations are correlated with knowledge flows (e.g., Jaffe et al. 2000; Duguet & MacGarvie 2005). While these flows might represent intentional knowledge sharing, patent citations are commonly interpreted as unintended knowledge spillovers, for example, in the growth literature (e.g., Caballero & Jaffe 1993; Akcigit & Kerr 2018) and urban studies (e.g., Ellison et al. 2010; Singh & Marx 2013).

I provide evidence suggesting that citations measure intentional knowledge transfers rather than involuntary spillovers. The importance of intentional knowledge sharing is highlighted in the literature on patent licensing (e.g., Gans & Stern 2000; Arora et al. 2001; Galasso & Schankerman 2015; Arqué-Castells & Spulber 2022). In my model, the benefits of patent protection and licensing are weighed against the cost of information disclosure to competitors. Therefore, firms control knowledge diffusion not only through licensing contracts but also through incomplete disclosure and selective trade secret sharing.

The theoretical literature on intellectual property protection traditionally views patenting and secrecy as substitutes (see a review in Hall et al. 2014). I argue that the combination of patents and trade secrets might be used to protect the same technology. This idea is supported

[5] Schumpeterian competition contrasts with ex-ante competition occurring before investments in R&D (Arrow 1962). Ex-ante competition positively affects innovation incentives (Shapiro 2012; Whinston 2012).

by firm surveys (Cohen et al. 2000; Mezzanotti & Simcoe 2023), management studies (Amara et al. 2008), patent policy discussions (Anton et al. 2006), legal research (Jorda 2008), and case studies in the chemical and pharmaceutical sectors (Arora 1997; Price et al. 2020).

The paper is also related to the literature on competition and innovation (e.g., Aghion et al. 2005; Shapiro 2012). The standard growth models assume knowledge flows in the form of involuntary spillovers (e.g., Aghion et al. 2014). In these models, the distribution of knowledge spillovers across firms is not affected by changes in market conditions. I show that import competition from China changed the distribution of patent citations. I rationalize this finding through increased reliance on secrecy and more selective knowledge sharing among partners.

Akcigit & Ates (2022) argue that a decline in knowledge flows among competitors might be responsible for the recent macro trends in the U.S. economy, such as the rising market concentration and declining business dynamism. The evidence in this paper is consistent with the decline in knowledge diffusion, especially among business partners. I show how increasing reliance on secrecy can explain the decline in knowledge flows to competitors and partners.

I show that firms identified as suppliers and customers account for most citations among partners. The importance of vertical knowledge flows is highlighted in the literature on R&D cooperation (e.g., Cassiman & Veughelers 2002) and foreign direct investment (e.g., Alfaro-Ureña et al. 2022; Bai et al. 2022).

Finally, the evidence in this paper gives a new interpretation to the spatial localization of patent citations (Jaffe et al. 1993). This finding is commonly interpreted as evidence of the importance of proximity and serendipitous face-to-face interactions in knowledge diffusion (Carlino & Kerr 2015). However, the results in this paper suggest that such diffusion is either not serendipitous or that the localization of citations is a consequence of the co-location of business partners for reasons unrelated to spillovers (Ellison et al. 2010).

This paper is organized as follows. Section 2 documents that patent citations are highly concentrated. Section 3 shows that citations primarily come from business partners. Section 4 develops and tests a model of optimal information disclosure and knowledge sharing among partners. Section 5 concludes.

2 Concentration of Patent Citations

This section documents that patent citations are highly concentrated. Section 2.1 provides background on the U.S. patent system and describes the data. Section 2.2 shows that, even for the most cited patents, the majority of citations come from one firm only, and this concentration has significantly increased since 2000. Section 2.3 shows that the concentration of citations should be explained based on the difference across firms in their citation behavior rather than differences in the number of patents. In Section 2.4, I use the movement of inventors across firms to show that the concentration is primarily driven by firms rather than inventors. Section 2.5 documents multiple additional facts and robustness checks. Finally, Section 2.6 extends the concentration measure to the firm level.

For statistics on the concentration of citations, I also report the counterfactual statistics that would be observed if citations were random. Since I observe the universe of all patents and citations in the USPTO, there is no sampling uncertainty (Abadie et al. 2020). Instead, I assume that the randomness of citations provides a basis for inference. The details are given in Section 2.3.

2.1 Data and Background

Patents consist of two parts: a written description of an invention, including citations to prior art (patents, publications, etc.), and claims defining the boundaries of intellectual property rights. To be patentable, an invention must be patent-eligible, useful, novel, and non-obvious. Additionally, the text of the application should satisfy the disclosure requirements.[6] Patent examiners use references to prior art to check whether the invention is novel and non-obvious. In the U.S., applicants have a "duty of candor" to disclose relevant prior art that they are aware of, and failure to do so can lead to patent invalidation. Prior art is generally used to strengthen, narrow, or reject certain claims. Therefore, citations serve the legal function of delimiting intellectual property rights on an invention.

I use the data on utility patents granted by the U.S. Patent and Trademark Office (USPTO) for the period from 1976 to 2019. Most granted patents contain information about assignees (patent owners). I clean assignee names to group patents by firms, individual inventors, universities, and other organizations. Autor et al. (2020) provide a matching of patent assignees to names of publicly traded firms in the Compustat data set. I extend their matching for the additional years of 2015–2019 and for private firms. Details are given in Appendix A.1.

2.2 High Concentration of Patent Citations

For each year and technological class from 1976 to 2014, I track citations within a five-year window for the top 1% of the most cited granted patents. The sample includes patents assigned to publicly traded companies, private firms, and non-corporate entities. In Section 2.5, I show that the results are robust to other thresholds, time frames, and sample selections.

[6] These requirements are governed by the U.S. Code, Title 35, sections 101, 102, 103, and 112. For a review, see Scotchmer (2004), ch. 3.

There are two reasons to focus on the set of the most cited patents. First, the value of patents is highly skewed, with many being of no value to the firm, so the empirical literature on innovation is often focused on the most cited patents (e.g., Aghion et al. 2023). This focus is justified by the positive correlation between the number of patent citations and the firm's stock market valuation (Hall et al. 2005; Kogan et al. 2017). Second, by construction these patents are expected to generate most follow-on innovations and knowledge flows, providing a lower bound on the concentration measure. Taking a five-year window controls for the truncation bias that older patents have more time to accumulate citations. Comparing patents within each technological class controls for differences across classes in citation patterns (Lerner & Seru 2022). To classify technologies, I use the group level of the Cooperative Patent Classification (CPC) system, which has 672 groups.

For each patent among the most cited ones, I compute the distribution of citations across different organizations. The variable $n_{k,i}$ denotes the number of citations from organization i to patent k. Organizations are mostly firms but also include non-corporate entities, such as government agencies and universities. I exclude citations from individual inventors and patents with missing assignee information. The concentration measure for patent k is the share of citations coming from the most citing organization:[7]

$$\mathcal{C}_k = \max_i \left\{ \frac{n_{k,i}}{n_k} \right\} \tag{2.1}$$

where n_k is the total number of citations patent k receives. The most citing organizations are predominantly corporations, so I will use the terms "firms" and "organizations" interchangeably. To construct an aggregate measure, for each year I take the average of patents' concentration measures within each technological class and then the average across technological classes weighted by the number of patents in a class. Appendix A.2 provides more details.

Figure 1 on page 2 shows the resulting aggregate concentration measure. On average, a patent (among the most cited ones) granted between 1976 and 2000 received around 50% of citations from one firm only. This concentration has significantly increased since 2000: a patent granted in 2014 received around 77% of citations from one firm only.

2.3 Control for Specialization and Number of Patents

The concentration of citations could be explained by technological specialization. Suppose all firms have equal access to the knowledge disclosed in a patent. However, this knowledge is

[7]In Section 2.6, I also consider the Herfindahl-Hirschman Index (HHI) for the distribution of citations across citing firms.

valuable only within a narrow technological space, and only a few firms specialize (patent) in this space. According to this explanation, Amkor is responsible for 94% of citations to IBM's patent in Table 1 because Amkor has more patents than other companies in a technology that benefits from IBM's patent.

I show that the concentration of citations is observed even within narrow technological classes. For instance, contrary to the "specialization" hypothesis, Amkor has fewer patents in its technological space than other companies. Citations are concentrated because a large share of Amkor's patents cite IBM's patent, while other companies do not.

Consider patent k that can receive citations from M firms. Firm i has $N_i > 0$ patents and makes $n_{k,i} \geqslant 0$ citations. The number of citations can be decomposed into intensive and extensive margins

$$n_{k,i} = p_{k,i} \cdot N_i \tag{2.2}$$

where $p_{k,i} = {}^{n_{k,i}}/_{N_i}$ is the share of patents in firm i that make citations to patent k. The concentration measure for patent k is defined as

$$\mathcal{C}_k = \max_i \left\{ \frac{n_{k,i}}{\sum_{j=1}^{M} n_{k,j}} \right\} = \max_i \left\{ \frac{p_{k,i} \cdot N_i}{\sum_{j=1}^{M} p_{k,j} \cdot N_j} \right\}$$

The "specialization" explanation assumes that firms do not differ in their citation behavior ($p_{k,i} = p_{k,j}$ for $i \neq j$), but one firm dominates others in terms of the number of patents ($N_i \gg N_j$ for $j \neq i$).

To evaluate this theory, one needs to find all patents that could have potentially made citations to patent k. I divide all granted patents into disjoint groups based on common characteristics. Then, I find all patents that share similar characteristics with patents that *actually* make citations to patent k. For characteristics of patents, I choose an application year and a detailed technological class (main subgroup level in CPC). Below I also describe a robustness check based on textual similarity of patents using BERT model.[8]

For example, patents making citations to IBM's patent in Table 1 ($k = 5877043$) are divided in 68 disjoint groups based on the application year and technological class. Most citations (16 out of 218, all from Amkor) come from patents in technological class $H01L23$ and with application year 2003. Overall, there are 1465 patents with such characteristics, and only 20 of them are assigned to Amkor. Many companies have more patents than Amkor in this class and year, for instance, Intel and Micron Technology have 122 and 101 patents, respectively.

To evaluate the role of "specialization" theory in the concentration of citations, for each

[8] Bidirectional Encoder Representations from Transformers (BERT) is a family of language models developed by Google in 2018 (Devlin et al. 2019).

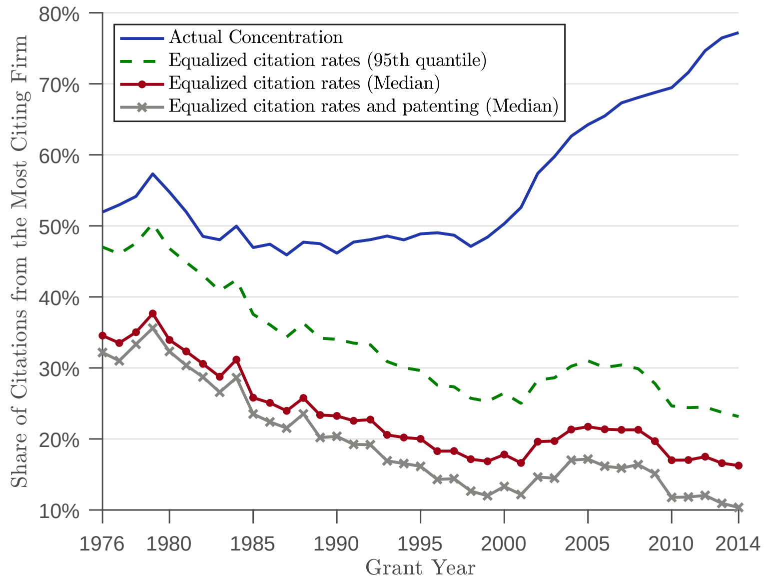


Figure 2: Decomposition of the Concentration of Citations

This figure compares the actual concentration of citations (the upper solid line) with the counterfactual ones in which citation rates are equalized across firms (the dashed and the dotted lines in the middle), and in which both citation rates and the number of patents are equalized across firms (the crossed line at the bottom). These counterfactual concentration measures are constructed using Monte-Carlo simulations in which citations are allocated randomly across observationally similar patents (equalized citation rates) and across firms with observationally similar patents (equalized citation rates and patenting). The details are given in Appendix A.4.

patent I do the decomposition from (2.2) within all possible groups of citing patents:

$$n_{k,i}(g) = p_{k,i}(g) \cdot N_i(g)$$

where $n_{k,i}(g)$ is the number of citations from firm i to patent k from patents within group g. For example, for IBM's patent the number of citations from patents in technological class $H01L23$, with application year 2003, and assigned to Amkor is $n_{k,i}(g) = 16$, where $k = 5877043$, $i =$ Amkor, and $g = \{H01L23, 2003\}$. In this example, $N_i(g) = 20$ and $p_{k,i}(g) = {}^{16}\!/_{20}$ for $i =$ Amkor, and $p_{k,j}(g) = 0$ for $j \neq$ Amkor.

Next, I do two types of Monte-Carlo simulations. First, I randomize $n_{k,i}(g)$ citations across all patents with the same characteristics g. This exercise equates citation rates across firms that have patents with characteristics g ($p_{k,i}(g) = p_{k,j}(g)$ for $i \neq j$). Second, I allocate $n_{k,i}(g)$ citations randomly across firms assuming that all firms with patents in g have the same number of patents. This exercise equates both the citation rates and the number of patents across firms ($p_{k,i}(g) = p_{k,j}(g)$ and $N_i(g) = N_j(g)$ for $i \neq j$). I do these Monte-Carlo simulations for the most cited patents, and then I recompute the aggregate concentration measure from Section 2.

Figure 2 shows the results of Monte-Carlo simulations. The upper solid line shows the actual aggregate concentration ($\mathcal{AC}_t$). The dashed and the dotted lines in the middle show the 95th quantile and the median of the concentration in which citation probabilities are equalized across firms (denote by $\mathcal{RC}_t$ the median). Finally, the crossed line at the bottom shows the median concentration with equalized citation rates and equalized patenting across firms ($\mathcal{PC}_t$).

The variable $\mathcal{PC}_t$ shows a part of the concentration that is driven by the number of firms. For example, with M firms the concentration cannot be lower than $1/M$. The measure $\mathcal{PC}_t$ has declined over time, indicating an increase in the number of firms filing patents within the same technological class over the same time period.

The difference $\mathcal{RC}_t - \mathcal{PC}_t$ quantifies the impact of variations in the number of patents among firms, conditional that each firm has at least one patent in a given (application year, technological class) pair. These variations in patenting rates account for only a minor portion of the overall concentration in citations.

Finally, the difference $\mathcal{AC}_t - \mathcal{RC}_t$ shows the role of variations in citation intensities across firms. This difference has significantly increased over time, indicating growing disparities in citation behavior among firms. The difference in citation intensities across firms explains around 38% of the concentration in 1980, 50% in 1990, and 79% in 2014.[9] Although the "specialization" theory provides a reasonable approximation to citations until the 1990s, it is inconsistent with the observed changes in citation patterns.

The decomposition in Figure 2 might underestimate the role of specialization in patenting if technological classes are not granular enough to capture this specialization. I use the technological classification which is more granular than the one commonly used in the literature.[10]

As a robustness check, I also use a natural language processing model called BERT to find textual similarity between patents, in addition to considering application years and technological classes. For each cited patent, I measure a similarity between patents citing it. I then select all patents that exhibit at least as much similarity to the citing patents as the citing ones do among themselves. The details are given in Appendix A.4. Figure B1 in Appendix B shows that the results are robust with this more restrictive specification.

Another important patent characteristic that might affect citations is a location of inventors. In Section 2.4, I show that the concentration is high even within the same inventor who is located in the same geographical area and works across multiple companies.

The decomposition in Figure 2 might also overestimate the role of specialization in patenting because it excludes citations from never-citing technologies. For example, IBM's patent in

[9] The difference in citation intensities explains x% of the concentration where $x = 100 \cdot \frac{\mathcal{AC}_t - \mathcal{RC}_t}{\mathcal{AC}_t - \mathcal{PC}_t}$.

[10] The main subgroup level in CPC has 7137 detailed categories while the literature (e.g., Jaffe et al. 1993 and Bell et al. 2019) often considers technologies to be similar if they come from the same 3-digit USPC or NBER sub-class classifications, which have 876 and 445 categories, respectively.

Table 1 receives most citations from IBM's supplier, Amkor Technology. Therefore, the citations are allocated randomly across the patents that are similar to Amkor's patents and are likely to represent non-competing technologies to IBM. This randomization exercise does not take into account many patents from IBM's competitors that could have made citations to it.

2.4 Movement of Inventors: Concentration is Explained by Firm Relationships

One of the theories for the agglomeration of economic activity is based on serendipitous face-to-face interactions between inventors (Marshall 1920; Saxenian 1996). According to this theory, patents are surrounded by tacit knowledge, and interactions between inventors facilitate the diffusion of this knowledge (Carlino & Kerr 2015). Patent citations are used to measure knowledge spillovers from these interactions and to evaluate their geographical localization (e.g., Jaffe et al. 1993; Atkin et al. 2022).

If citations measure spillovers from inventors' interactions, then the concentration of citations can be explained by limited communication between inventors from different firms. For instance, Amkor might be responsible for 94% of citations to IBM's patent in Table 1 because inventors from IBM exclusively communicate with inventors at Amkor. The central question is whether firms control this communication or if it occurs independently of firm relationships.

I separate the roles of firms and inventors by tracing citations of inventors who filed similar patents in multiple companies. I define patents to be similar if they have close application years, the same narrow technological class, and the same geographical location of an inventor-mover. I show that inventors significantly change their citation probabilities to a particular patent once they move to another company and that the concentration of citations is primarily explained by firm-specific factors. This evidence suggests that firms might have significant control over knowledge diffusion, at least for knowledge flows measured by patent citations.

Formally, consider the following statistical framework. Suppose inventor ℓ worked in two companies, i and j, and created $N_i^\ell(g)$ and $N_j^\ell(g)$ patents with characteristics g, respectively. Assume that each patent in firm i (j) makes an independent citation to patent k with probability $p_{k,i}^\ell(g)$ ($p_{k,j}^\ell(g)$). Then the expected number of citations from inventor ℓ in firm i to patent k is

$$n_{k,i}^\ell(g) = p_{k,i}^\ell(g) \cdot N_i^\ell(g),$$

and the goal is to test whether $p_{k,i}^\ell(g) = p_{k,j}^\ell(g)$. To do this, I compare the actual concentration of citations within an inventor with the counterfactual one where citation probabilities are equalized across companies ($p_{k,i}^\ell(g) = p_{k,j}^\ell(g)$).

For example, during 2008 to 2017 inventor Stefan G. Schreck from California created 16

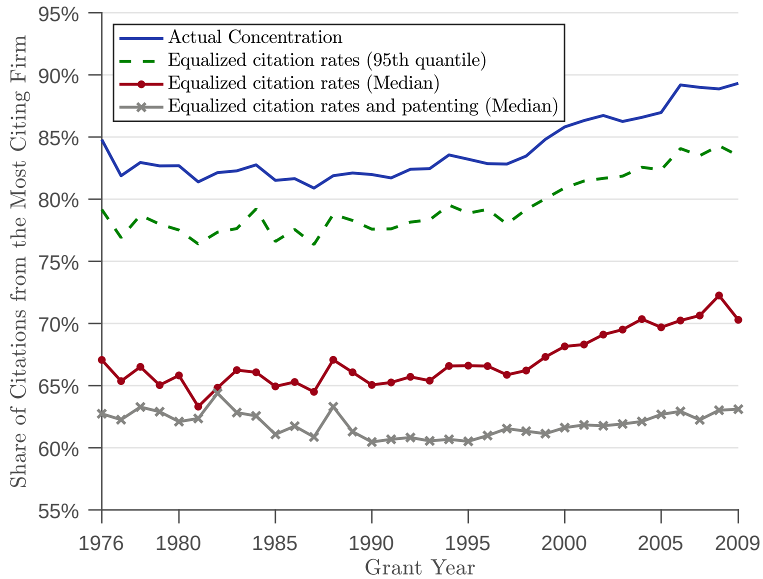


Figure 3: Decomposition of the Concentration Within Inventors Who Moved Across Firms

This figure shows the same decomposition from Figure 2 for the concentration of citations across firms within inventors who patented in multiple companies. The solid line shows the actual aggregate within-inventor concentration of citations across firms. The dashed and the dotted lines show the 95th quantile and the median of the same measure in the Monte-Carlo simulations where citations rate are equalized across firms within an inventor. The crossed line at the bottom shows the concentration (median) where both the citation rates and the number of patents are equalized across firms within an inventor. The averages are almost the same as the medians. To increase the sample size I consider citations from all years, not only 5-year window. The graph is taken until 2009 to ensure that patents have enough time to accumulate citations from inventors-movers. More details are given in Appendix A.5.

patents in the technological class $A61F2$ while working in Endologix Inc. In 15 out of 16 patents, he made a citation to patent 5690642 assigned to Cook Incorporated. He also applied for 9 patents with similar characteristics in another company, Edwards Lifesciences Corporation, but made zero citations to patent 5690642. If 15 citations were allocated randomly across $16 + 9 = 25$ patents, the expected share of citations from Endologix Inc. would be $^{9.5}/_{15} = 0.63$ and the 95th quantile would be $^{12}/_{15} = 0.8$. However, the actual share ($^{15}/_{15} = 1$) is significantly higher. Notice that for an inventor who worked in two companies the concentration (the share of citations from the most citing firm) cannot be less than 50%.

I compute the average concentration of citations across firms within all inventors who moved between companies, and do the decomposition from Section 2.3. The details are given in Appendix A.5. Figure 3 shows the actual average concentration within an inventor ($\mathcal{AC}_t^w$), the 95th quantile and the median of the concentration with equalized citation rates across firms ($\mathcal{RC}_t^w(q95)$ and $\mathcal{RC}_t^w$), and the median concentration in which both citation rates and patenting are equalized across firms ($\mathcal{PC}_t^w$).[11] The actual average concentration within an

[11]The variable $\mathcal{PC}_t^w$ is greater than 50% because the majority of inventor-movers worked in two firms only.

inventor is significantly higher relative to the what we would expect if citation probabilities were equalized across firms ($\mathcal{AC}_t^w > \mathcal{RC}_t^w(q95)$). The average decomposition over all years

$$\underbrace{\overline{\mathcal{AC}}^w - \overline{\mathcal{PC}}^w}_{22.1\%} = \underbrace{\overline{\mathcal{AC}}^w - \overline{\mathcal{RC}}^w}_{17.0\%} + \underbrace{\overline{\mathcal{RC}}^w - \overline{\mathcal{PC}}^w}_{5.1\%}$$

shows that the concentration is primarily explained by the differences across firms in citation probabilities rather than by the variance in the number of patents. The difference $\mathcal{AC}_t^w - \mathcal{RC}_t^w$ is stable over time, and there was a slight increase in the difference $\mathcal{RC}_t^w - \mathcal{PC}_t^w$, meaning that the dispersion in the number of patents across firms within an inventor has slightly increased by the end of the period.

This evidence should be interpreted with caution because inventors-movers might differ in their citation rates from inventors who always work in one company. My conjecture is that non-movers would have higher concentration of citations across firms if they were randomly moved to another company. Below I argue that citations are correlated with access to trade secrets. Based on this interpretation, the conjecture is that inventors who do move between companies are less bound by contractual obligations, such as confidentiality agreements and non-compete clauses, resulting in a less concentrated distribution of citations. An interesting area for future research is to study the movement of inventors caused by exogenous shocks to firms, for example, natural disasters (Barrot & Sauvagnat 2016) or financial constraints (Chodorow-Reich 2014).

2.5 Robustness and Additional Results

Figures B2 and B3 in Appendix B provide additional results on the concentration. Figure B2 shows that the increase in the concentration is primarily driven by changes within technological classes rather than the rise of technologies with high concentrations of citations. An increase in the concentration after 2000 is observed in 87% of classes. Panel (a) of Figure B3 shows that the average number of citations has significantly increased over time: the most cited patents granted in 2014 received 11 times more citations within five years from the grant day than patents granted in 1976. Panel (b) shows that more cited patents have a higher concentration of citations, and that this relationship is driven by patents granted after 2000.[12] Therefore, the increase in the concentration of citations is not driven by the decline in the number of citations.

For example, with two citations randomly allocated across two firms the expected concentration measure is

$$\frac{1}{4} \cdot 1 + \frac{1}{4} \cdot 0.5 + \frac{1}{4} \cdot 0.5 + \frac{1}{4} \cdot 1 = 0.75$$

[12]The relationship holds for patents with more than seven citations. For patents with fewer than seven citations, the concentration is high due to a low number of citations. See Section 2.3 for more details.

Figures B4 – B6 provide multiple robustness checks. In particular, the results are robust to different thresholds for the most cited patents (top 5% and 10%). The concentration is not driven by superstar firms in patenting, and it is robust to the exclusion of firms' self-citations to themselves. The concentration is also robust when I group citations of patents from the same within-country family (continuations, continuations-in-part, and divisionals) as a single citation, indicating that its rise is not driven by increasing patent families. Citation patterns might be affected by patent examiners (Alcácer et al. 2009). I show that the concentration of citations from patent examiners is around two times lower than the concentration based on citations from non-examiners. Citations might also be affected by patent lawyers. In Section 2.4, I use the movement of inventors across companies to show that the concentration of citations is driven by firms rather than inventors. Using the same technique, I show that the concentration of citations is not driven by patent lawyers either. Appendix A.3 describes more robustness checks, including controls for outliers, different samples, and weighting schemes.

2.6 Concentration at the Firm Level

In Section 2.2, the concentration of citations for the most cited patents is defined as a share of citations coming from the most citing firm. This definition is easy to interpret and allows for detailed controls at the patent level. However, it omits citations to patents that are not among the most cited ones and citations from firms other than the top citing entity.

This section extends the concentration measure in two directions. First, I consider citations to all patents of a given firm, for example, all citations to IBM's patents granted in a particular year rather than to each individual patent. Defining the concentration measure at the firm level will be helpful in Section 3 because the data on relationships between firms are not available at the patent level. Second, I compute the concentration using the Herfindahl-Hirschman Index (HHI) rather the share of citations from the most citing firm.

For each firm in a year, I define the concentration measure as the Herfindahl-Hirschman Index (HHI) of all citations to the firm's patents granted in this year within a five-year period. The aggregate concentration in year t is defined as

$$\mathcal{H}_t = \sum_k s_{k,t} \mathcal{H}_{k,t} \tag{2.3}$$

where the summation goes across all firms receiving citations to their patents granted in year t, $s_{k,t}$ is the share of citations firm k receives in year t in the total number of citations firms receive in this year, and $\mathcal{H}_{k,t}$ is the HHI concentration of citations for firm k.

Figure B7 in Appendix B shows that the firm-level concentration follows the same pattern as in Figure 1: a stable or slightly declining concentration of citations until 2000 and a significant rise after. This result is robust to different sample selections: I consider citations among all corporate patents, excluding self-citations, and between U.S. publicly listed companies only. The results are also robust if the concentration is defined as the share of citations from the most citing firm, as in Section 2.2. The additive structure of the HHI measure will be useful for evaluating the role of partners in the concentration in Section 3.

In Section 3, I evaluate the role of business partners in the sample of inter-firm citations among publicly traded companies after 2001. Figures B8 and B9 in Appendix B provide more details on the rise in the concentration of citations in this sample. Figure B8 decomposes the increase in the concentration from 2001 to 2014 based on the methodology of Melitz & Polanec (2015). The rise in the concentration is primarily explained by the increasing concentration of citations within firms rather than the re-allocation of citations across firms or the exit and entry of new firms out of and into patenting. Figure B9 shows the decomposition of the concentration from Section 2.3. Similarly to the patent-level concentration, the firm-level concentration has increased due to changes in citation probabilities across firms rather than shifts in patent counts.

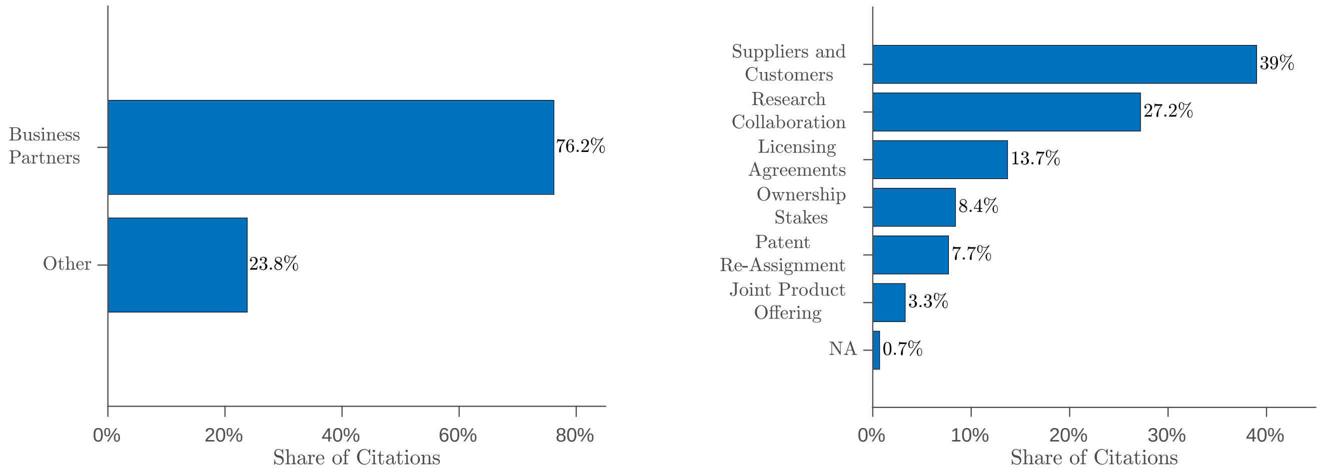
3 The Role of Business Partners

This section evaluates the role of business partners in the concentration of citations. Section 3.1 describes the data. Section 3.2 shows that business partners account for most citations between firms. The concentration of citations has increased due to changes within firms in how they receive citations from partners. Section 3.3 analyzes the increasing concentration of citations among partners. Section 3.4 discusses the results and provides some robustness checks.

3.1 Data

I use three data sets to find the types of relationships between cited and citing firms. First, I use the FactSet Revere Supply Chain Relationships data set, which is based on public sources such as filings with the U.S. Securities and Exchange Commission (SEC), investor presentations, and press releases to collect data on business relations between firms. The data list partners such as suppliers and customers, firms with licensing agreements, research collaborations, joint product offerings, and firms with ownership stakes (e.g., joint ventures). Second, I use the Compustat Segments to collect data on supplier-customer relationships between firms. Finally, I use the USPTO data on patent re-assignment to find firms that are trading patents with each other. The data sets cover the period from 2003 to 2022.[13] I match all data sets with patents using company names. Details are given in Appendix A.1.

[13]FactSet covers most relationships between firms, though its coverage starts only from 2003. In general, Compustat Segments and USPTO re-assignment data provide coverage since 1976 and 1968, respectively.



(a) Citations by Relationship Between Firms

(b) Citations Within Partners

Figure 4: Distribution of Citations Based on Relationship Between Firms

This figure shows the distribution of patent citations across different types of relationships between cited and citing firms. Panel (a) shows the share of citations coming from business partners. Panel (b) shows the distribution of citations coming from business partners across different types of partners.

3.2 Business Partners in Patent Citations

To document the role of partners in patent citations, I focus on inter-firm citations between U.S. publicly listed firms for patents granted after 2001. The sample selection is driven by data limitations.[14] I discuss how these limitations might affect the results at the end of this section. I consider patents granted until 2014 and trace citations within a five-year window from a grant date. The large role of partners is robust to alternative time windows.

I compute the distribution of citations across firms based on their relationship with a cited firm. I define firms to be business partners if they had at least one of the following relationships between 2003 and 2022:[15] suppliers or customers, research collaborations, licensing agreements, joint product offering, patent re-assignment, joint ownership stakes (e.g., a joint venture), and partners with an uncertain relationship.[16]

Panel (a) of Figure 4 shows that 76% of citations occur between business partners. This share is 72% if I consider citations within a 10-year window. Panel (b) shows the distribution

[14] The data on relationships cover the period from 2003 to 2022. I include the years 2001 and 2002 to analyze the rise in the concentration since 2001, but the results are similar without these years. The coverage of relationships is limited for private and foreign firms.

[15] Around 75% of citations between partners occur during the period of a reported relationship. The data are based on information disclosed by firms in public sources, but the disclosed dates often do not correspond to the actual dates of a contractual relationship between companies. Firms might delay the disclosure of a relationship relative to its actual start and might stop reporting it before it actually ends. Therefore, 75% provides a lower bound on the share of citations occurring during a business relationship.

[16] Table B1 in Appendix B provides the full list of all business relationships. FactSet defines some partners without clarifying the nature of the relationship. These account for only 0.7% of citations between partners.

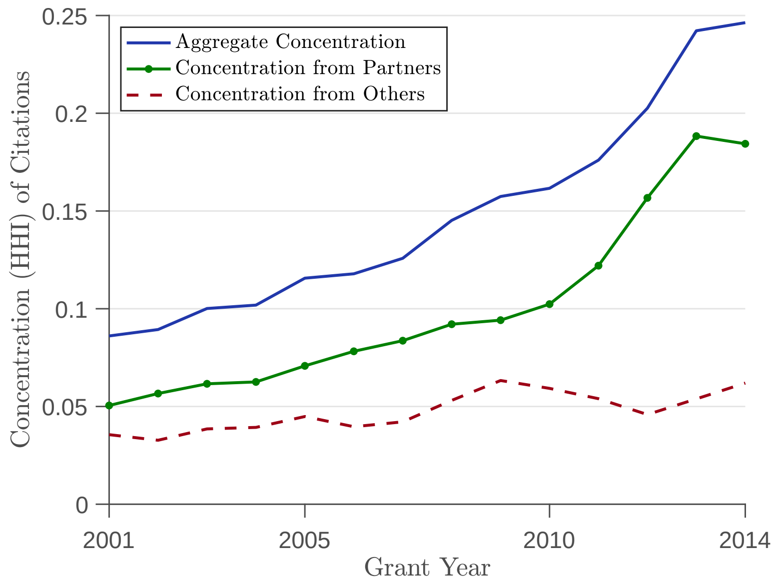


Figure 5: Decomposition of the Concentration Based on Relationship Between Firms

This figure decomposes the concentration into the roles of partners and other firms, see equation (3.1).

of citations among partners based on a relationship between firms. If two firms have multiple relationships, I divide citations evenly across them. Firms with a supplier-customer relation and research collaboration account for the majority of citations: 39% and 27%, respectively. Other types of partners account for 34% of citations and include firms that signed licensing agreements, re-assigned patents, had joint ownership stakes, and had joint product offerings.

As I discuss in Section 3.4, the distribution of citations across partnerships might be biased because types of relationships are self-reported. The correct interpretation of panel (b) is that partners responsible for most citations had *at least* a supplier-customer relationship or research collaboration. It is reasonable to assume that they also had licensing agreements.

To evaluate the importance of partners in the concentration of citations, I decompose the HHI concentration within a firm (2.3) into citations from partners and other firms:

$$\mathcal{H}_{k,t} = \sum_i \left(\frac{n_{k,i,t}}{n_{k,t}}\right)^2 = \mathcal{H}^{\mathcal{P}}_{k,t} + \mathcal{H}^{\mathcal{O}}_{k,t} = \underbrace{\sum_{i \in \mathcal{P}_k} \left(\frac{n_{k,i,t}}{n_{k,t}}\right)^2}_{\text{Partners },\mathcal{H}^{\mathcal{P}}_{k,t}} + \underbrace{\sum_{i \in \mathcal{O}_k} \left(\frac{n_{k,i,t}}{n_{k,t}}\right)^2}_{\text{Other },\mathcal{H}^{\mathcal{O}}_{k,t}} \tag{3.1}$$

where $n_{k,i,t}$ is the number of citations from firm i to firm k for patents granted in year t, $n_{k,t}$ is the total number of citations firm k receives to patents granted in year t, $i \in \mathcal{P}_k$ means that firm i was a business partner to firm k, and $i \in \mathcal{O}_k$ means that firm i was not a (revealed) business partner to firm k.

Figure 5 shows the decomposition into partners and other firms from equation (3.1). On

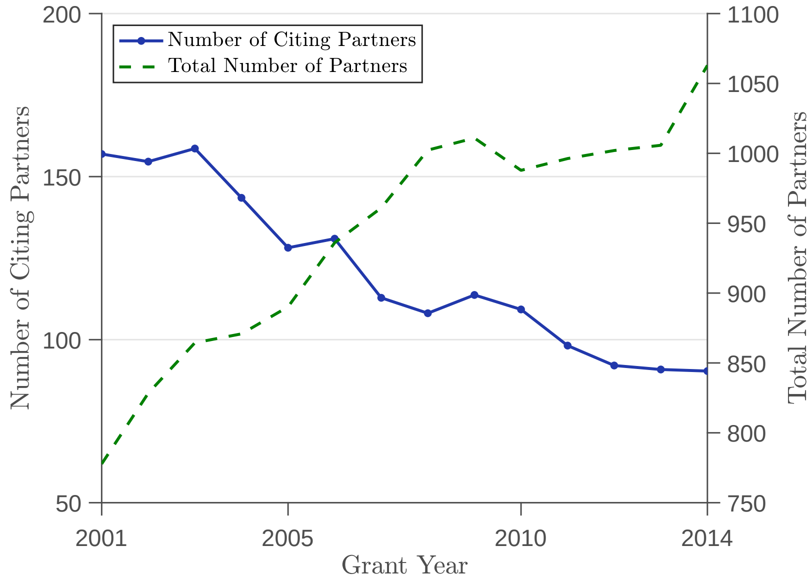


Figure 6: Decline in Citations Among Partners

This figure shows the average number of citing partners relative to the total number of partners for a typical firm. For each firm, the number of partners is weighted by the number of citations this firm receives. The total number of partners of a firm in a given year is defined using partners reported within five years of this year. The graph is constructed using a sample of patents with a unique assignee. Patents with more than one assignee account for less than 1% of citations.

average, partners explain around 66% of the concentration in citations: 59% in 2001 and 75% in 2014. Changes in citations among partners account for 84% of the rise in the concentration. Suppliers, customers, and firms with research collaboration account for 60% of the rise in the concentration. Figure B10 in Appendix B offers more details.

To provide further evidence, I also analyze citations by industries of the cited and citing firms. Figure B11 in Appendix B shows that firms within the same industry account for only 8% of the increase in the concentration of citations. Therefore, the rise in the concentration is largely driven by changes in citations among firms that are unlikely to be direct competitors.[17]

3.3 Rise in the Concentration of Citations Among Partners

The concentration of citations among partners is determined by the number of citing partners (an extensive margin) and the distribution of citations within them (an intensive margin).

Figure 6 shows changes at the extensive margin: from 2001 to 2014, the average number of citing partners for a typical firm declined by 42%, even though the number of (reported)

[17] In general, defining competitors requires a definition of the market, and industry affiliation might be an imperfect proxy for competitors. Nevertheless, firms from the same industry are more likely to compete with each other than with firms from different industries. Industries are defined at the four-digit level in Standard Industry Classification.

partners increased over time.

Figure B12 in Appendix B shows the rise in the concentration due to changes in the intensive margins. Specifically, I compare the actual concentration of citations to the counterfactual one in which citations are allocated uniformly across citing partners, subject to the integer constraint on the number of citations. For example, consider a firm receiving 10 citations from three partners with a citation distribution of $(8, 1, 1)$; the HHI is $\left(\frac{8}{10}\right)^2 + 2 \cdot \left(\frac{1}{10}\right)^2 = 0.66$. The uniform distribution would be $(4, 3, 3)$ with $\text{HHI}_u = \left(\frac{4}{10}\right)^2 + 2 \cdot \left(\frac{3}{10}\right)^2 = 0.34$. Figure X shows that the average difference between HHI and HHI_u has significantly increased over time, meaning that citations became more skewed within partners.

3.4 Discussion

Previous subsections show that most inter-firm citations among U.S. publicly traded companies occur between business partners. Moreover, the rise in the concentration of citations is primarily explained by the decline in citations among partners. Below, I discuss data limitations and whether strategic withholding of citations can explain the high share of partners in citations. In Section 4, I develop and test a theory that can rationalize the evidence on patent citations.

Data Limitations

The data on inter-firm relations have some limitations because they are primarily based on the disclosure of relationships by publicly traded companies. Therefore, the data do not cover relations between all firms. As a robustness check, I focus on a sample of citations in which at least one of the firms is a U.S. publicly traded company, but not necessarily both. Figure B13 in Appendix B shows that partners explain 51% of citations, and the distribution within partners is similar to Panel (b) in Figure 4. The share of partners is lower in this sample, but it might reflect the incompleteness of the data for private or foreign firms, rather than the absence of a relationship. Moreover, Figure B7 in Appendix B shows that the concentration dynamics are consistent whether considering all firms or just U.S. publicly traded companies. Therefore, I expect a minimal bias regarding the role of partners in the rise of the concentration when focusing on the sample of U.S. publicly traded companies.

Another limitation of the data is related to firms' incentives to disclose relationships with other firms. Although regulation SFAS No. 131 requires publicly traded companies to report the identity of any customer representing more than 10% of their total sales, smaller customers or other types of relationships are self-reported. Firms' incentives to disclose a relationship with another firm might differ across types of relationships. For example, firms might have stronger incentives to conceal the identity of research collaborators relative to established input suppliers. In addition, the data lack details of contracting between firms, and certain types of relationships are not mutually exclusive. For instance, firms with a research collaboration might not report that they also have licensing agreements as part of the collaboration. Therefore, the comparison of citation patterns based on the type of partnership should be interpreted with caution.

Strategic Citations

The large share of partners in patent citations could be explained by strategic withholding of citations. The U.S. patent applicants must disclose all relevant prior art they are aware of. However, firms might potentially withhold citations to make patent claims broader (Lampe 2012). If firms follow this strategy, then partners are less likely to withhold citations because it is harder for them to prove they were unaware of the prior art.

There are several arguments why strategic withholding of citations is unlikely to explain the citation patterns. First, withholding of citations can make the whole patent uneforceable, not just specific claims (Ouellette & Masur 2023). Therefore, this practice bears considerable risks, especially for patent attorneys. Second, Kuhn et al. (2023) provide empirical evidence and legal arguments that firms are unlikely to practice the strategic withholding of citations.

Finally, I test this hypothesis using the movement of patent attorneys across business partners of a given firm. Similarly to the exercise on the movement of inventors, I find attorneys who filed similar patents in multiple companies. In addition, I restrict the sample to citations among partners and attorneys moving from one partner of a given firm to another. If citations were strategic, such attorneys would be expected to cite a patent from all partners of the patent owner. In contrast, Figure B14 shows that even in this sample, citations are highly firm-specific: an attorney who heavily cites a particular patent in one firm does not continue citing it in another firm, where both firms are partners to the patent owner.

4 Patenting, Secrecy, and Knowledge Sharing

Sections 2 and 3 show that patent citations are highly concentrated and primarily come from partners. The concentration cannot be explained by technological specialization; it is driven by firm relationships rather than inventors; it cannot be explained by patent examiners, attorneys, or strategic withholding of citations. I provide multiple other robustness checks. Overall, the evidence suggests that citations among partners measure intentional knowledge transfers.

In this section, I develop and test a theory of how firms might control knowledge diffusion. Firms conceal knowledge from competitors through incomplete information disclosure in patent applications. They manage knowledge flows among partners through licensing and trade secret sharing. Section 4.1 provides institutional background on patent disclosure, and Section 4.2 describes the formal model.

The model predicts that bundling patents with secrets leads to more concentrated knowledge flows relative to full information disclosure in patents. I test this prediction using trade secret litigation data in Section 4.3. The model also predicts that higher Schumpeterian competition leads to more concentrated knowledge flows. By Schumpeterian competition, I mean the competition that reduces profit rents and incentives to innovate (Schumpeter 1942; Shapiro 2012). Autor et al. (2020) show that import competition from China reduced profitability, patenting, and R&D investments of U.S. companies. In Section 4.4, I use trade with China to test the relationship between competition and knowledge flows. Section 4.5 discusses how the endogeneity of knowledge flows can bring new insights into the growth and innovation literature.

In Section 4.3, I use Lex Machina data on patent litigation. Lex Machina complements the USPTO data on patent litigation with information on whether the patents were involved in trade secret litigation. In Section 4.4, I use the data on trade with China from Autor et al. (2020). Details are given in Appendix A.1.

4.1 Institutional Background and Examples

Patents are supposed to facilitate knowledge diffusion through the disclosure of information in the award. The U.S. Supreme Court has stated that patent disclosures "will stimulate ideas and the eventual development of further significant advances in the art" and that these "additions to the general store of knowledge are of such importance" that they are worth "the high price of . . . exclusive use."[18]

Despite the disclosure requirements of the patent system, firms often do not reveal all information in patent applications (Roin 2005; Fromer 2008). For example, patents on biological products, including mRNA-based COVID-19 vaccines, do not disclose manufacturing details (Price & Rai 2016; Price et al. 2020). The undisclosed knowledge is not necessarily tacit: the manufacturing details are codified and submitted to the Food and Drug Administration but not disclosed to the public.

Arora (1997) describes how dyestuff producers in the 20$^{\text{th}}$ century patented individual chemical compounds but kept the knowledge of how to combine them secret. Similarly, "[the] Haber-Bosch process for ammonia, a truly significant process innovation, was protected by more than 200 patents that covered the apparatus, temperatures, and pressures, but avoided particulars about the catalysts employed or their preparation. The catalyst was critical to the

[18] *Kewanee Oil Co. v. Bicron Corp.*, 416 U.S. 470, 481 (1974) and Ouellette (2012).

successful operation of the process, and keeping it secret significantly increased the expense and time for firms trying to circumvent the Haber-Bosch patent" (Arora 1997, p. 394).

Semiconductor firms rely more heavily on secrecy than patents to protect their intellectual property (Levin et al. 1987; Cohen et al. 2000). Yet, their patenting activity has significantly increased over time. Hall & Ziedonis (2001) show that large semiconductor manufacturers accumulate patent portfolios for licensing negotiations. The model in Section 4.2 clarifies that a firm can license its technology without disclosing all of its knowledge to the public and sharing secrets with a licensee.

There are at least two reasons for the failure of the patent system's disclosure function. First, patent applications are filed at a very early stage in technology development. At this stage, many details about the technology are unknown, and firms are not required to disclose them later. Ouellette (2016) describes "prophetic" patents that seem "more like a grant application than a technical contribution."

Second, the disclosure requirements are hard to enforce. Patent examiners are time-constrained and lack the necessary skills and experience. On average, a patent examiner spends around 20 hours per patent application (Frakes & Wasserman 2017). Less than 4% of them have a PhD (Mann 2014), and most have less than four years of experience (Lemley & Sampat 2012). Examiners mostly spend time on prior art and reject applications based on obviousness and lack of novelty.[19]

The disclosure requirement is also hard to enforce in courts. For instance, applicants are required to disclose their preferred method for carrying out the invention ("best mode"). However, proving the failure to disclose the best mode requires proof that the applicant was aware of this knowledge at the time of the application filing (Jorda 2008). The difficulty of enforcing this rule led to changes in U.S. patent law. According to the America Invents Act of 2011, applicants are still required to disclose the best mode practice in patent applications. However, failing to do so can no longer invalidate a patent once it has been granted.[20]

4.2 Model of Information Disclosure and Knowledge Sharing

A product can be produced using a constant returns to scale production function $F(z_1x_1, z_2x_2)$, where x_1 and x_2 are two inputs, z_1 and z_2 are input productivity levels (knowledge components). A marginal cost of producing one unit of the product is denoted by $c(z_1, z_2)$:

$$c(z_1, z_2) = \min_{x_1, x_2} \{w_1x_1 + w_2x_2\}$$
$$\text{s.t. } F(z_1x_1, z_2x_2) = 1$$

[19]See https://blog.juristat.com/most-common-rejections.
[20]See https://www.uspto.gov/web/offices/pac/mpep/s2165.html.

where w_i is a price of input $i \in \{1,2\}$.

An incumbent firm has access to the technology with $z_1 = z_2 = \overline{z}$. The incumbent's profits come from two sources. The first source does not require the firm to share its knowledge with others. For instance, it might manufacture and sell the product directly to final consumers in a particular market. Denote these profits under monopoly pricing by π. The second source requires knowledge transfers to business partners. There are n_p contract manufactures who can produce and sell the product in separate markets. Denote by $v_j(z_{1,j}, z_{2,j})$ the profit partner j can generate as a function of its access to the incumbent's technology. If the partner has access to productivity of input $i \in \{1,2\}$, then $z_{i,j} = \overline{z}$; otherwise, $z_{i,j} = \underline{z}$ for some generic technology, $\underline{z} < \overline{z}$. Profits $v_j(z_{1,j}, z_{2,j})$ are increasing in $z_{1,j}$ and $z_{2,j}$.

The knowledge for each component $i \in \{1,2\}$ of the technology can be patented or kept secret. If it is patented, the incumbent and the partners can write a contract (licensing agreement) on a knowledge transfer. If it is kept secret, once the incumbent shares it with partners, they can use it without compensating the incumbent. I assume that if both components are kept secret, the incumbent does not share them with partners.

Patenting also makes knowledge publicly available. There are n_e entrants who can improve productivity. Entrant j can discover a new pair (z_1^e, z_2^e):

$$z_{i,j}^e = \psi_j \cdot Z_i, \;\; i \in \{1,2\}$$

where $Z_i = \overline{z}$ if component i is patented, $Z_i = \underline{z} < \overline{z}$ if it is kept secret, and ψ_j is a random draw from a continuous distribution $\Psi(\cdot)$ with the support on $[0,\infty)$. The random variables ψ_j are independent across entrants.

The competition consists of three stages. First, upon receiving ψ_j, entrant j can observe whether $c(z_{1,j}^e, z_{2,j}^e) < c(\overline{z}, \overline{z})$. It decides whether to patent $z_{1,j}^e$ and $z_{2,j}^e$ or not. Assume that patenting involves a small fixed cost $\delta > 0$. Second, all firms can observe $c(z_{1,j}^e, z_{2,j}^e)$ for $j \in \{1, 2, \ldots, n_e\}$. To participate in the market, a firm has to pay a small fixed cost $\varepsilon > 0$. Third, firms that paid ε compete in prices to final consumers in the incumbent's market and in licensing fees to partners in other markets. Each partner needs only one technology from one firm, and knowledge components from different technologies (firms) are incompatible.

I assume that fixed costs δ and ε are very small and ignore them in profit equations. The fixed cost of patenting (δ) ensures that inefficient firms do not patent. The fixed cost of entry into the market (ε) simplifies the equilibrium. Since firms compete in prices, only the most efficient firm will pay $\varepsilon > 0$ and set monopoly prices.

The timing of this game is the following:

1. For each component $i \in \{1,2\}$, the incumbent decides whether to patent the knowledge

about its productivity or keep it secret;

2. The entrants receive independent draws $\psi_j \sim \Psi(\cdot)$ for $j \in \{1, 2, \ldots, n_e\}$;

3. The incumbent and entrants compete.

To simplify the equilibrium, I make the following assumptions on partners' profit functions:

Assumption 1. *Profit function of partner $j \in \{1, 2, \ldots, n_p\}$ satisfies the following conditions:*

1. *Symmetry: $v_j(z_1, z_2) = v_j(z_2, z_1)$;*

2. *Gains from licensing: $v_j(\overline{z}, \overline{z}) - v_j(\underline{z}, \underline{z}) \geqslant \max\{v_j(\overline{z}, \overline{z}) - v_j(\underline{z}, \overline{z}), v_j(\overline{z}, \underline{z}) - v_j(\underline{z}, \underline{z})\}$*

3. *Imperfect Substitution: $v_j(\overline{z}, \overline{z}) - v_j(\underline{z}, \overline{z}) > 0$*

The first condition reduces the number of patent-secrecy combinations that need to be considered. The second condition specifies that the incumbent prefers licensing both knowledge components rather than just one. Suppose both components are patented, and the incumbent makes a take-it-or-leave-it offer to partner j. In that case, it will set the licensing fee to $v_j(\overline{z}, \overline{z}) - v_j(\underline{z}, \underline{z})$. The third condition states that knowledge components are not perfect substitutes. It is still valuable to license one component even if partner j already has access to another.

Equilibrium

Consider the last stage. Since there is only one period of entry, entrants have no incentives to conceal their knowledge. For entrants with $c(z^e_{1,j}, z^e_{2,j}) < c(\overline{z}, \overline{z})$, the probability of having the most efficient technology is positive. Since the cost of patenting δ is sufficiently small, these entrants patent both components of their knowledge. Once firms observe all technologies of each other, only the most efficient firm will pay the fixed cost of participating in the market.

The incumbent exits if at least one of the entrants has a more productive technology:

$$\min_j \left\{c(z^e_{1,j}, z^e_{2,j})\right\} < c(\overline{z}, \overline{z})$$

In the first stage, the incumbent faces the following trade-off. On the one hand, complete secrecy eliminates licensing opportunities: once the incumbent shares its private knowledge to a partner, the partner can use the technology without paying for it. On the other hand, patenting both knowledge components discloses too much information to the entrants. The incumbent can also use partial disclosure by patenting one component and keeping another secret. If these pieces of knowledge are complementary to each other, such strategy reduces the misappropriation from the partners, while minimizing the disclosure of the technology to the entrants.

If the incumbent survives the competition, it gets π from direct sales to the final consumers. The optimal patenting-secrecy choice depends on the trade-off between licensing revenue and higher risks of competition. Under complete secrecy, the firm cannot profit from licensing, but the probability of being replaced is minimal. The incumbent's expected profits are

$$\Pi_{secrecy} = \pi \cdot \mathbb{P}\left(\min_j \left\{\psi_j^{-1} \cdot c(\underline{z}, \underline{z})\right\} \geqslant c(\overline{z}, \overline{z})\right) = \pi \cdot \left[\mathbb{P}\left(\psi \leqslant \overline{z}/\underline{z}\right)\right]^{n_e}$$

where the last equality follows from the assumption on the constant returns to scale in the production function and independence of ψ_j across entrants.

Under partial disclosure, one of the knowledge components is secret. The incumbent decides whether to share this secret with each partner. If it does not share the secret, a partner's benefits are limited to what can be derived from licensing one technological component. If the incumbent shares its secret with the partner, the partner can use it without compensating the incumbent. The following lemma shows that the incumbent shares trade secrets with the partner if the patented and the secret knowledge are complementary in the partner's profits:

Lemma 1. *The incumbent firm relying on partial disclosure shares its trade secrets with partner j if and only if $v_j(\overline{z}, \overline{z}) - v_j(\underline{z}, \overline{z}) \geqslant v_j(\overline{z}, \underline{z}) - v_j(\underline{z}, \underline{z})$.*

Proof. If the incumbent does not share its secrets with partner j, it can charge $v_j(\overline{z}, \underline{z}) - v_j(\underline{z}, \underline{z})$ for its patented knowledge. If it shares the secrets, it can charge $v_j(\overline{z}, \overline{z}) - v_j(\underline{z}, \overline{z})$. Therefore, the incumbent shares its secrets with partner j if $v_j(\overline{z}, \overline{z}) - v_j(\underline{z}, \overline{z}) \geqslant v_j(\overline{z}, \underline{z}) - v_j(\underline{z}, \underline{z})$. □

A sufficient condition for knowledge sharing with partner j is if $v_j(z_1, z_2)$ has increasing differences in (z_1, z_2). The substitution or complementarity between different parts of knowledge depends on their technological complementarity and on market conditions partner j faces. Below, I provide an example of how properties of product demand can make knowledge components substitutable despite their technological complementarity.

Denote by $\mathcal{N}_c$ the set of partners for whom z_1 and z_2 are complements, and by $\mathcal{N}_s$ the set of partners for whom they are substitutes. I assume that these two sets are non-empty.

Assumption 2. *There is at least one partner for whom the incumbent's knowledge components are complements ($\mathcal{N}_c \neq \varnothing$), and at least one partner for whom they are substitutes ($\mathcal{N}_s \neq \varnothing$).*

The incumbent's profits under partial disclosure are

$$\Pi_{\text{partial}} = \left(\pi + \overbrace{\sum_{j \in \mathcal{N}_s} \left[v_j(\overline{z}, \underline{z}) - v_j(\underline{z}, \underline{z})\right]}^{\text{substitutes}} + \overbrace{\sum_{j \in \mathcal{N}_c} \left[v_j(\overline{z}, \overline{z}) - v_j(\underline{z}, \overline{z})\right]}^{\text{complements}}\right) \cdot \left[\mathbb{P}\left(\psi \leqslant \frac{c(\overline{z}, \underline{z})}{c(\overline{z}, \overline{z})}\right)\right]^{n_e}$$

Finally, if the incumbent patents both knowledge components, it can maximize the extracted surplus from partners. However, such strategy also increases the probability of being replaced. The profits are

$$\Pi_{\text{full disclosure}} = \left(\pi + \sum_{j \in \mathcal{N}_s \cup \mathcal{N}_c} \left[v_j(\overline{z}, \overline{z}) - v_j(\underline{z}, \underline{z})\right]\right) \cdot \left[\mathbb{P}\left(\psi \leqslant 1\right)\right]^{n_e}$$

where I simplified $\mathbb{P}\left(\min_j \left\{\psi_j^{-1} c(\overline{z}, \overline{z})\right\} \geqslant c(\overline{z}, \overline{z})\right)$ to $\left[\mathbb{P}\left(\psi \leqslant 1\right)\right]^{n_e}$.

Higher reliance on secrecy decreases knowledge flows to partners and competitors. However, while the effect on competing entrants is uniform, it is not for partners. With full patenting, all partners gain access to both knowledge components. Under partial disclosure, a subset $\mathcal{N}_c$ still gains access to both components. However, other firms only get a licensing agreement on the patented knowledge without access to the secret knowledge. Under complete secrecy, none of the partners get access to the knowledge. Therefore, the shift from full patenting (disclosure) to patent-secrecy combination makes knowledge flows more concentrated.

Proposition 1. *Bundling patents with secrets leads to more concentrated knowledge flows relative to full patenting.*

Proof. Follows from Lemma 1. □

The next proposition summarizes the relationship between competition and knowledge flows. By competition, I mean the number of entrants n_e who can replace the incumbent.

Proposition 2. *There is a value $n_e^\star$ such that for $n_e < n_e^\star$, the incumbent patents both knowledge components; for $n \geqslant n_e^\star$, the incumbent keeps at least one component secret. As a result, higher competition (n_e) leads to more concentrated knowledge flows.*

Proof. If $n_e = 0$, then $\Pi_{\text{full disclosure}} \geqslant \Pi_{\text{partial}}$. If $n_e \to \infty$, $\Pi_{\text{full disclosure}}/\Pi_{\text{partial}} \to 0$ for the non-degenerate cumulative distribution function $\Psi(\cdot)$. Since $\Pi_{\text{full disclosure}}/\Pi_{\text{partial}}$ is continuous and monotonically decreasing in n_e, there is $n_e^\star$ such that for $n_e \geqslant n_e^\star$ partial disclosure dominates full patenting. Then, the result follows from Proposition 1. □

Mapping Theory To Patent Citations

In the model, all entrants with $c(z^e_{1,j}, z^e_{2,j}) < c(\overline{z}, \overline{z})$ patent their knowledge. Since they rely on the incumbent's knowledge, I assume that they cite its patent. I also assume that whenever partners get access to the incumbent's technology, they might adapt it to their market, patent this adaptation, and cite the incumbent's patent. Suppose that a partner patents and cites the incumbent with probability $\underline{q}$ if it gets access to one knowledge component and with probability $\overline{q} > \underline{q}$ if it gets access to both components.

Suppose that with n_e entrants the incumbent relies on full patenting. The expected number of citations is

$$n_p \cdot \overline{q} + n_e \cdot \mathbb{P}\left(\psi \leqslant 1\right)$$

Assume with $n'_e > n_e$ entrants the incumbent relies on patent-secrecy bundling. The expected number of citations is

$$n_s \cdot \underline{q} + n_c \cdot \overline{q} + n'_e \cdot \mathbb{P}\left(\psi \leqslant \frac{c(\overline{z}, \underline{z})}{c(\overline{z}, \overline{z})}\right)$$

where n_s is the number of partners for whom z_1 and z_2 are substitutes ($|\mathcal{N}_s|$) and n_c is the number of partners for whom the knowledge components are complements ($|\mathcal{N}_c|$). The increase in the number of competitors leads to more concentrated citations among partners. The effect on citations from competitors is ambiguous because $n'_e > n_e$ but $\mathbb{P}\left(\psi \leqslant \frac{c(\overline{z},\underline{z})}{c(\overline{z},\overline{z})}\right) < \mathbb{P}\left(\psi \leqslant 1\right)$.

In Sections 4.3 and 4.4, I use patent citations to test Propositions 1 and 2.

Example: Market Conditions and Substitution Between Knowledge Components

Suppose the production function is Cobb-Douglas, $F(z_1x_1, z_2x_2) = (z_1x_1)^{\frac{1}{2}}(z_2x_2)^{\frac{1}{2}}$, and input prices are one, $w_1 = w_2 = 1$. Suppose partner j faces the following demand in its market:

$$Q(p) = A - p$$

where p is a product price, and A is some constant. Monopoly profits are

$$v_j(z_1, z_2) = \left(\frac{A - (z_1^{\frac{1}{2}} z_2^{\frac{1}{2}})^{-1}}{2}\right)^2$$

Components z_1 and z_2 are complementary to each other in the cost function: $\frac{\partial^2 c(z_1,z_2)}{\partial z_1 \partial z_2} > 0$. However, they might be substitutes in the partner's profits if

$$\frac{\partial^2 v_j(z_1, z_2)}{\partial z_1 \partial z_2} \leqslant 0 \Leftrightarrow A(z_1z_2)^{\frac{1}{2}} \geqslant 2$$

4.3 Evidence: Secrecy and Knowledge Flows

This section tests Proposition 1, which states that bundling patents with secrets leads to more concentrated knowledge flows. Testing the connection between secrecy and patent citations is challenging at least for two reasons. First, trade secrets are not observable. I suggest using trade secret litigation to make progress in this measurement problem. Specifically, I find patents involved in federal trade secret litigation.[21] These patents are likely to be a part of a broader technology that also involves trade secrets. For example, the legal case *Waymo LLC v. Uber Technologies, Inc.* was about misappropriation of the trade secrets related to the LiDAR technology for self-driving cars.[22] However, the same lawsuit also had claims regarding patent infringement for three patents.[23] In the complaint, Waymo describes how these patents and trade secrets are complementary to each other:

> "The Replicated Board reflects Waymo's highly confidential proprietary LiDAR technology and Waymo trade secrets. Moreover, the Replicated Board is specifically designed to be used in conjunction with many other Waymo trade secrets and in the context of overall LiDAR systems covered by Waymo patents."

This example highlights that many technologies consist of multiple pieces of knowledge, some of which are kept secret. To replicate and build on a technology, a firm needs access not only to patents, but also to trade secrets.

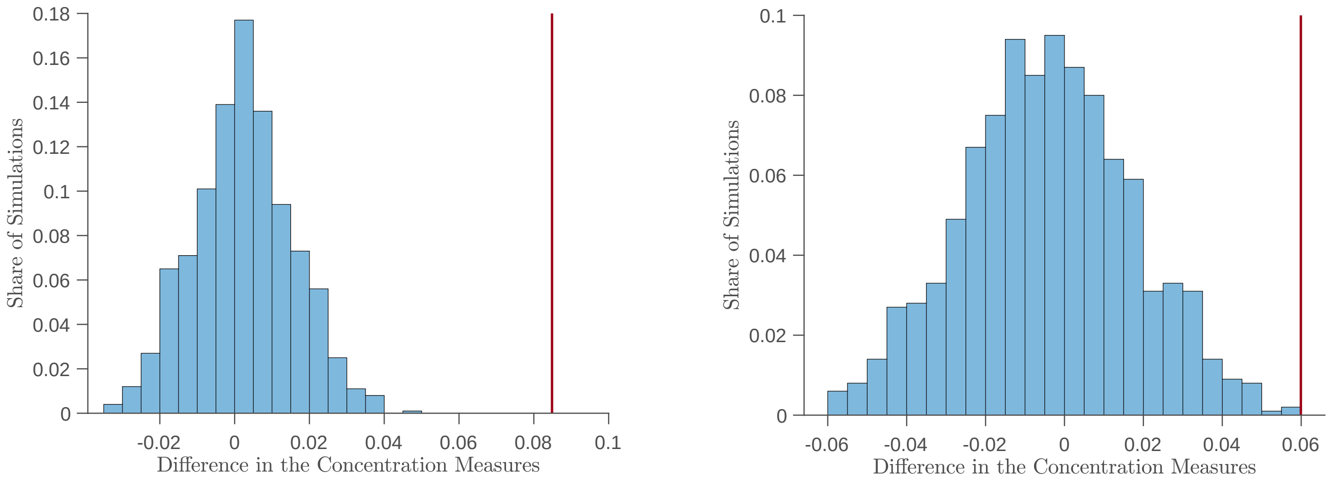
The second challenge in testing the connection between secrecy and patent citations is identification. Patents bundled with secrets and involved in trade secret litigation are not random. For instance, citations to these patents might differ from citations to other patents due to a publicity effect of litigation. Furthermore, the intellectual property strategies of firms engaged in litigation could differ from those of other companies. To partially address this concern, I find control patents involved in patent infringement litigation but *without* trade secret claims, and I require both treatment and control patents to be from the same firm. In various specifications, I also require patents to share similar characteristics, such as grant years, technological classes, and a number of citations. Nevertheless, the comparison of citation patterns to these patents should be interpreted with caution.

For each patent involved in trade secret litigation, I find control patents which were involved in patent infringement litigation but without trade secret claims. I compute the difference in the concentration of citations between treatment and control patents using two measures: Herfindahl-Hirschman Index and the share of citations from the most citing firm ("Top Share"). Then, I take the average of this difference across patents. I test whether the average difference in the concentration between patents with and without trade secret claims significantly deviates from the difference we would expect if citations were random, controlling for application years, locations of inventors, and technological classes of patents (see Section 2.3). The details are given in Appendix A.6.

[21] The misappropriation of trade secrets can be litigated in both state and federal courts. However, the infringement of patents is litigated in federal courts. Therefore, there is no loss of generality in a focus on federal litigation.

[22] *Waymo LLC v. Uber Technologies, Inc.*, No. 17-2235 (Fed. Cir. 2017).

[23] The patent numbers are 8836922, 9368936, and 9086273.



(a) Herfindahl-Hirschman Index (HHI)

(b) Share From the Most Citing Firm

Figure 7: The Difference in the Concentration of Citations Between Patents With and Without Trade Secrets

These figures show the average difference in the concentration of citations between patents involved in litigation with and without trade secret claims. The vertical lines show the actual difference in the concentration. The histograms show the distribution of the difference when citations are random within (time, location, technology) triple (see Section 2.3 for the details). Panel (a) shows the results when the concentration is measured as the Herfindahl-Hirschman Index, and Panel (b) shows the results when the concentration is measured as the share of citations from the most citing firm.

Figure 7 gives a visual test against the null hypothesis. The vertical line shows the actual difference in the concentration, and the histogram shows the distribution of this difference if citations were random within the same application years, locations of inventors, and technological classes. For the HHI measure, the difference in concentration is 0.085 which corresponds to approximately 16% higher concentration of citations for patents bundled with trade secrets. For the "Top Share" measure, the difference in concentration is 0.06 which corresponds to approximately 9.2% higher concentration of citations. Table B2 in Appendix B shows the results based on different criteria for selecting control patents, that is whether treatment and control patents have the same grant year, receive a similar number of citations, belong to the same technological class, or are assigned to plaintiffs rather than defendants.[24] Figure 7 shows the results for the most restrictive set of controls (columns 4 and 8 in Table B2). All specifications show a positive and significant difference in concentration

[24]Controls for grant years and technological classes ensure that patents represent similar technologies. A control for the number of citations ensures that there are no mechanical differences in the concentration. Requiring patents to be assigned to a plaintiff increases a probability that patents are bundled with trade secrets involved in litigation. For example, if firm A shares secrets with firm B under some contractual arrangement (e.g., an acquisition), and firm B patents these secrets, then firm A might sue firm B for misappropriation of the trade secrets. However, in this situation, patents are not bundled with secrets. Requiring patents to be assigned to a plaintiff eliminates such cases.

between patents involved in litigation with and without trade secret claims.

4.4 Evidence: Competition and Knowledge Flows

This section tests Proposition 2, which states that higher Schumpeterian competition leads to more concentrated knowledge flows. Autor et al. (2020) show that import competition from China reduced profitability, patenting, and R&D investments of U.S. companies, suggesting that it increased Schumpeterian competition in the U.S. Moreover, the rise of China occurred around 2000 which coincides with the increase in the concentration of patent citations. Using the empirical strategy from Autor et al. (2020), I study the relationship between import competition from China and citations patterns between firms.

Following Autor et al. (2020), I define the measure of trade exposure at the four-digit Standard Industry Classification (SIC) over the two subperiods, 1991 to 1999 and 1999 to 2007,

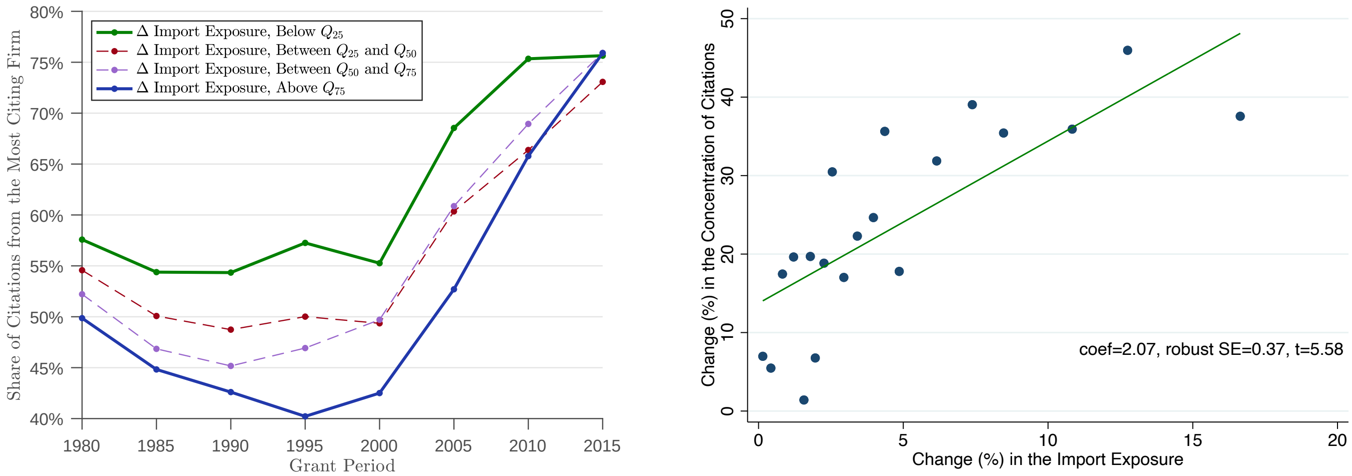
$$\Delta IP_{i1} = \frac{M_{i,1999} - M_{i,1991}}{Y_{i,91} + M_{i,91} - E_{i,91}} \text{ and } \Delta IP_{i2} = \frac{M_{i,2007} - M_{i,1999}}{Y_{i,91} + M_{i,91} - E_{i,91}} \tag{4.1}$$

where $M_{i,t}$ is the U.S. imports from China for industry i and year $t \in \{1991, 1999, 2007\}$, and $Y_{i,91} + M_{i,91} - E_{i,91}$ is the absorption at the start of the period (industry shipments plus imports minus exports). For each patent, I calculate the import penetration for its technological class using the mapping of four-digit SIC industries to technological classes implied from patents owned by publicly traded firms as in Autor et al. (2020).

Panel (a) of Figure 8 shows the concentration measure from Figure 1 for different technological classes based on their exposure to import competition from China, ΔIP_{i2}. All classes experienced an increase in the concentration of citations after 2000. However, the dynamics are different based on the exposure to import competition. For classes with the least exposure (below first quartile Q_{25}), the concentration of citations was initially high (around 55%) and stable prior to 2000, and then it increased up to 75%. For classes with the most exposure (above the third quartile Q_{75}), the concentration was initially lower (around 50%), decreased to around 40% near 2000, and then it also increased up to 75%. Thus, technological classes with the most exposure to China shock experienced faster growth in the concentration.

I study the change in the concentration of citations around 2000 in the regression specifications. For each technological class, I define the average concentration measure among patents granted in the following seven-year periods: 1977–1983, 1984–1990, 1991–1997, 1998–2004, 2005–2011.[25] Appendix A.7 provides more details. The concentration measure for technological class j and for the period starting from t is denoted by $\mathcal{C}_{j,t}$. I define the following

[25] The periods are chosen to map the data from Autor et al. (2020).



(a) The concentration for technological classes with different exposure to import competition.

(b) Changes in the concentration and in the import penetration from China.

Figure 8: Trade with China and Concentration of Citations

These figures show the relationship between the concentration of citations and the exposure to import competition from China. Panel (a) shows the concentration measure from Section 2 (Figure 1) for different technological classes divided into quartiles based on their exposure to import competition from China, ΔIP_{i2} in (4.1). The concentration measure for year t shows the average concentration in years $[t-4, t]$. Panel (b) shows the binned scatter plot of the change in the concentration of citations and the change in the import exposure from China. The specification is weighted by the number of Compustat-matched U.S.-inventor patents in a technology class.

growth measures

$$\Delta y_{j1} = 100 \cdot \ln\left(\mathcal{C}_{j,1998}/\mathcal{C}_{j,1991}\right) \text{ and } \Delta y_{j2} = 100 \cdot \ln\left(\mathcal{C}_{j,2005}/\mathcal{C}_{j,1998}\right)$$

Panel (b) of Figure 8 shows that technological classes more exposed to trade with China ($\Delta IP_{j\tau}$) experienced a higher growth in the concentration of citations ($y_{j\tau}$).

I estimate the following specification

$$\Delta y_{j\tau} = \beta \Delta IP_{j\tau} + \gamma X_{j0} + \varepsilon_{j\tau} \tag{4.2}$$

where $\tau \in \{1, 2\}$ and X_{j0} is the set of controls. To control for the aggregate trend in the concentration of citations, I include time fixed effects. Since the concentration measure depends on the total number of citations, I also include the change in the average number of citations for each technological class. Moreover, I include two lags of the outcome variable to control for technology-specific trends prior to China shock. I also include fixed effects for 11 manufacturing sectors and for 6 main NBER technological categories. Finally, I control for the rising importance of software inventions (Chattergoon & Kerr 2021). Specifically, for each technological class I

Table 2: Trade with China and Increase in the Concentration of Citations

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: OLS			
Δ Tech Class Exposure	2.06	1.52	1.51	1.77	1.41	1.41
to Chinese Imports	(0.44)	(0.42)	(0.42)	(0.37)	(0.42)	(0.42)
			Panel B: 2SLS			
Δ Tech Class Exposure	2.31	1.57	1.55	1.92	1.71	1.70
to Chinese Imports	(0.49)	(0.50)	(0.50)	(0.44)	(0.61)	(0.62)
Time FE		Yes	Yes	Yes	Yes	Yes
Δ Citations			Yes	Yes	Yes	Yes
2 Lags of outcomes				Yes	Yes	Yes
11 sectors, 6 Tech					Yes	Yes
Software Patents						Yes

Notes: This table shows the estimated coefficient β for the specification in (4.2). Panel A shows the results for simple OLS regressions. Panel B shows the results for the specification in which the import penetration from China is instrumented with Chinese exports to non-U.S. high-income markets (Autor et al. 2020). Regressions consider the effect of higher growth in import penetration from China on the increase in the concentration of citations at the technology class level. Industry exposure to Chinese competition is mapped to technology class exposure using the mapping implied by the U.S. publicly traded firms in Compustat as in Autor et al. (2020). Controls include time fixed effects, a change in the average number of citations for a technology class, 2 lags of the outcome variable, fixed effects for 11 manufacturing sectors and for 6 main NBER technology categories, and a dummy for software technological classes. I define the software classes as classes where more than 50% of software subclaclasses according to Graham & Vishnubhakat (2013). All specifications are weighted by the number of Compustat-matched U.S.-inventor patents in a technology class. Standard errors are clustered at the technology class level.

include a dummy variable indicating whether it has more than 50% of software subclasses (Graham & Vishnubhakat 2013).

Panel A in Table 2 shows the results of simple OLS regressions, and Panel B shows the results for the specification in which changes in US import exposure ($\Delta IP_{j\tau}$) are instrumented by changes in Chinese exports to non-U.S. high-income countries (Autor et al. 2013; Autor et al. 2020). All specifications show a positive and significant relationship between the changes in the import competition from China and the growth in the concentration of citations.

Discussion and Robustness Checks

Trade with China has had a profound effect on various aspects of the U.S. economy, from innovation (Autor et al. 2020; Hoberg et al. 2021) and labor markets (Autor et al. 2013) to the structure of supply chains (Antràs et al. 2017). The evidence in this section suggests that it might have also affected incentives for knowledge sharing among business partners. I provide additional discussion and robustness checks for this result below.

The instrument from Autor et al. (2013) is designed to isolate changes in the trade with China unrelated to U.S. demand and technological shocks. Table B3 in Appendix B shows the results from two additional placebo exercises. First, I show that the relationship between China shock and the rise in the concentration is insignificant for patents assigned to non-corporate entities (e.g., universities and government agencies). Therefore, the effect of trade competition with China is specific to the corporate sector, and the results are unlikely to be driven by the correlation between general technological changes and globalization. Second, I regress lag outcome variables (pre 1991) on future changes in imports from China. The coefficients are insignificant, so the main results are unlikely to be driven by contemporaneous changes in the technological opportunities and trade.

Using the methodology outlined in Section 2.3, I also study whether China shock influenced the rise in the concentration of citations through changes in firm patenting behavior (N) or in firm citation rates (p).[26] Figure B15 in Appendix B shows that 84% of the rise in the concentration of citations in the technologies most exposed to trade with China is attributed to changes in the citation rates. In contrast, for the least exposed technologies this share is 45%. Overall, China shock changed the way firms cite each other. This effect is distinct from the decline in patenting documented in Autor et al. (2020). For instance, firms' exit from patenting cannot fully explain the rise in the concentration of citations.

4.5 Implications for the Innovation Literature

In Section 4.2, I develop a model of endogenous knowledge flows among firms. Knowledge flows to competitors are controlled through incomplete information disclosure in patent applications; knowledge sharing among partners is managed through licensing and trade secret sharing. In this section, I discuss the model's implications for the innovation literature.

The assumption on the accumulation of knowledge lies at the heart of most growth models. The endogenous growth literature (Romer (1990), Grossman & Helpman (1991), Aghion & Howitt (1992)) assumes that the productivity growth is independent of the current productivity. The semi-endogenous growth models (Jones (1995), Kortum (1997), Segerstrom (1998)) assume that the higher the productivity, the harder it is to improve upon it. Bloom et al. (2020) provide empirical evidence supporting the latter assumption.

One way to model the productivity dynamics is to assume that $z^e = \psi \cdot (\overline{z})^{\beta}$, where $\overline{z}$ is the

[26]In addition to application years and technological classes, I also control for the location of inventors to take into account the geographical specialization of firms (see Appendix A.4).

current productivity level, z^e is the productivity of an entrant who replace the incumbent firm, and ψ is an independent draw from a continuous distribution on $\mathbb{R}_+$ (Buera & Oberfield 2020). In this specification, β measures the degree of knowledge diffusion and is usually exogenously assumed. If $\beta = 1$, then the probability of positive productivity growth $\mathbb{P}\left[z^e > z\right]$ is independent of the current productivity level; if $\beta < 1$, then this probability negatively depends on the current productivity level (ideas are harder to find).

The choice of information disclosure can endogenize β. Consider the model from Section 4.2 with Cobb-Douglas function, $y = (z_1 x_1)^{\frac{1}{2}} (z_2 x_2)^{\frac{1}{2}}$, and input prices equal to 1, $p_1 = p_2 = 1$. Suppose that $\overline{z} > \underline{z} = 1$ and there is one entrant ($n_e = 1$) with total productivity $z^e = (z_1^e)^{\frac{1}{2}} (z_2^e)^{\frac{1}{2}}$. Under full patenting, the productivity dynamics is $z^e = \psi \cdot \overline{z}$, and the probability of positive productivity growth $\mathbb{P}\left(z^e/\overline{z} = \psi > 1\right)$ is independent of the current productivity. Under partial disclosure, the productivity dynamics is $z^e = \psi \cdot \overline{z}^{1/2}$, and the probability of positive productivity growth $\mathbb{P}\left(z^e/\overline{z} = \psi/\overline{z}^{1/2} > 1\right)$ negatively depends on the current productivity level. Under complete secrecy, this probability is even lower, $\mathbb{P}\left(z^e/\overline{z} = \psi/\overline{z} > 1\right)$. In other words, ideas are harder to find if less information is disclosed to the public.

In the previous example, β can take only values in $\left\{0, \frac{1}{2}, 1\right\}$ depending on the information disclosure. The model can be extended to make $\beta \in [0, 1]$. Suppose the production function is $y = \exp\left(\int_0^1 z_i x_i \mathrm{d}i\right)$ with continuum of inputs in $[0, 1]$. The technology corresponds to continuum of productivity levels $\{z_i\}_{i \in [0,1]}$. As in Section 4.2, each component can be patented or kept secret. Suppose share β of components is patented and revealed to the public while share $1 - \beta$ is kept secret. Then, the productivity dynamics is $z^e = \psi \cdot (\overline{z})^{\beta}$. The parameter β can be determined by exogenous factors: for instance, some knowledge components can be reverse-engineered while others are tacit and unpatentable. However, as long as there are knowledge components for which a firm can choose between patenting and secrecy, β is endogenously determined.

One implication of firms' ability to control knowledge flows is that the degree of ideas getting harder to find might respond to changes in market conditions. For example, Proposition 2 shows that higher Schumpeterian competition can lead to greater reliance on secrecy. Despite a higher number of competing firms, the business dynamism can decrease once firms rely more on secrecy. Formally, suppose if there are n_e entrants, the firm fully discloses information in patents. The probability of the incumbent's replacement is $1 - \left[\mathbb{P}\left(\psi \leqslant 1\right)\right]^{n_e}$. Suppose the firm shifts to partial disclosure if there are $n_e' > n_e$ entrants. The probability of the incumbent's replacement is $1 - \left[\mathbb{P}\left(\psi \leqslant \overline{z}^{1/2}\right)\right]^{n_e'}$. Although there are more entrants, $n_e' > n_e$, partial disclosure makes it harder for each to improve upon the incumbent's technology, $\mathbb{P}\left(\psi > \overline{z}^{1/2}\right) < \mathbb{P}\left(\psi > 1\right)$.

Akcigit & Ates (2022) argue that a decline in knowledge flows among competitors can explain several trends in the U.S. economy, including the decline in business dynamism. They model this decline through a decrease in the exogenous knowledge diffusion parameter responsible for the probability of a lagging competitor catching up with a frontier firm. Their quantitative results "stress the importance of future research to understand the underlying reasons for slower knowledge diffusion" (Akcigit & Ates (2022), p. 2064). I show how a competitive threat from entrants can lead to a decrease in knowledge flows to competitors if the frontier firm can choose the degree of information disclosure to the public.

The citations patterns documented in Sections 2 and 3 show that business partners, especially vertical ones, account for a significant share of knowledge flows. These partners are likely to develop complementary technologies. The importance of complementary innovations is highlighted in the literature on general purpose technologies (Helpman 1998; Bresnahan 2010) economic history (e.g., Rosenberg 1963; Rosenberg 1979): "The growing productivity of industrial economies is the complex outcome of large numbers of interlocking, mutually reinforcing technologies, the individual components of which are of very limited economic consequence by themselves. The smallest relevant unit of observation is seldom a single innovation but, more typically, an interrelated clustering of innovations" (Rosenberg 1979, p. 28–29). In this paper, I show how competition can affect knowledge sharing among partners, linking creative destruction and construction forces.

5 Conclusion

This paper provides evidence that firms have significant control over the diffusion of knowledge they generate. They combine patents and trade secrets, sharing secrets with selected partners. Knowledge flows are shaped by the firm's incentives for cooperation with other companies and the risks associated with disclosing knowledge to rivals. As a result, knowledge flows depend on the details of the economic environment, such as the degree of competition. Further research on how firms manage their intellectual property and share knowledge with partners might provide deeper insights into the process of economic growth.

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Appendix. For Online Publication

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A Data Appendix

A.1 Data Details

Patents. The main source of patent data is PatentsView. Autor et al. (2020) provide a matching of patent assignees to Compustat firm names for publicly traded firms. I use their existing matching of assignee names to Computstat firms for the period 1976–2014 to extend it for years up to 2019. For the rest of the patents, I follow the procedure outline in Autor et al. (2020) for cleaning and standardizing firm names (e.g., replace "Incorporated" with "INC"). Finally, I matched around 100 thousand patents manually for the largest assignees.

FactSet Revere. I use two data sets from FactSet. FactSet Revere Company provides basic information on companies, including their names. FactSet Revere Supply Chain Relationships provides information on business relationships between firms. I discuss the types of relationships below. The following quote from FactSet's manual describes how they collect data on business relationships:

> "FactSet analysts systematically collect companies' relationship information exclusively from primary public sources such as SEC 10-K annual filings, investor presentations, and press releases, and classify them through normalized relationship types. Company information is fully reviewed annually, and changes based on corporate actions are monitored daily. The result is a comprehensive, detailed and up-to-date dataset of material intercompany relationships."

FactSet also provides information on the names of subsidiaries in some business relationships. I match all these names, including subsidiaries, with the names of assignees listed in patents, using the same matching procedure as I did for patents.

FactSet records licensing and supplier-customer relationships in a duplicate manner. Specifically, a firm receiving a licensing is also recorder as a customer, and a firm providing the intellectual property is also listed as a supplier. For all firm pairs involved in licensing agreements, I exclude the recordings on supplier-customer connections.

Compustat Segment. I take the supplier-customer data from Compustat Segments data set. For publicly traded firms, the data list names of the main customers, which are mostly other firms but can also be government agencies. Regulation SFAS No. 131 requires publicly traded firms to report the identity of any customer representing more than 10% of their total sales. Using Compustat Segments, Barrot & Sauvagnat (2016) constructed a data set of suppliers and customers for the U.S. publicly traded firms for the period 1976–2013. I extend their data up to 2022 using name matching and manual inspection.

USPTO Patent Re-Assignment. The data on patent re-assignment is described in Graham et al. (2018). I leave only re-assignment of patents between companies. Formally, I leave only transactions with 'convey_ty' equal to 'assignment'. I clean firm names in the same way as for patents. Then I match these data to patent assignees.

All three data sets — FactSet, Segments, and Re-Assignment — provide information on the date of a transaction or a relationship. These dates are self-reported, so they might not correspond to the dates of actual relationships. For each firm-pair, I find the minimum and the maximum of years in which the relationship between firms was active. I leave only relationships active between 2003 (the first year in FactSet) and 2022.

I group certain relationships into more aggregated groups. Table B1 in Appendix B provides a summary of all relationships.

Lex Machina. Lex Machina offers comprehensive data on federal litigation involving patents and trade secrets. Each case entry in the database includes details such as the names of plaintiffs, defendants, and any third parties involved. In cases related to patent litigation, the database also lists the patents at issue. Additionally, the data indicate whether a given case has overlapping claims with trade secret litigation.

In my analysis, I identified $1,092$ cases that featured a total of $2,541$ patents and were involved in both patent and trade secret litigation. These cases were filed from 2001 to 2021.

China Shock. Autor et al. (2020) provides a measure of the exposure to import competition from China at the main group level in the US Patent Classification (USPC). I use these data in Section 4.4.

A.2 Details to Section 2: Concentration of Patent Citations

The concentration measure from Figure 1 is constructed in the following way. First, I identify the top 1% of the most cited patents within each grant year and technological class. Second, for these patents I compute the share of citations coming from the most citing firm. Finally, I aggregate these measures within and across technological classes.

The first step is to identify the top 1% of the most cited patents. Denote $y_{km} = 1$ if patent $m \in \mathcal{P}$ makes a citation to patent $k \in \mathcal{P}$ and $y_{km} = 0$ otherwise, where $\mathcal{P}$ is the set of all granted patents. Each patent has an assignee (owner) or, in rare cases (around 3%), multiple assignees. For the majority of patents, the assignee is a corporate firm but it can also include universities, government agencies, and individual inventors. In the second step, I compute the distribution of citations across different organizations, so I exclude citations from individual inventors and patents with missing assignee information.[27] Each patent $k \in \mathcal{P}$ has a grant year

[27]Formally, I set $y_{km} = 0$ where patent m belongs to an individual inventor and does not have have an assignee information.

t_k^g and a primary technological class c_k. I define the technological classes at the group level in the Cooperative Patent Classification (primary class is a class listed first in the patent file). Denote the set of all groups in Cooperative Patent Classification (CPC) system by $\mathcal{CPC}$. For each patent $k \in \mathcal{P}$, I compute the number of citations within a 5-year window from a grant day

$$n_k = \sum_{m \in \mathcal{T}_k} y_{km} \text{ where } \mathcal{T}_k = \{m \in \mathcal{P} : \text{Grant Date}_m - \text{Grant Date}_k \leqslant 5 \cdot 365 \text{ Days}\} \tag{A.1}$$

For each grant year t and technological class c, I define the set of all granted patents receiving at least one citation

$$\Omega_{t,c} = \{k \in \mathcal{P} : t_k^g = t \text{ and } c_k = c \text{ and } n_k > 0\}$$

and take the top 1% of patents in terms of the number of citations within this set. Denote it by $\Omega_{t,c}^{top}$, and define the *"Main"* sample as top patents for all years and technology classes:

$$Main = \left\{\Omega_{t,c}^{top}\right\}_{c \in \mathcal{CPC} \text{ and } t=1976...2014} \tag{A.2}$$

In the second step, for each patent in the *Main* sample I compute the share of citations coming from the most citing organization. To account for patents with multiple assignees, I define a weighted citation as $y_{km}^w = y_{km}/F_m$ where F_m is the number of assignees for patent m. Define the number of citations to patent $k \in \mathcal{P}$ from organization i as

$$n_{k,i} = \sum_{m \in i, m \in \mathcal{T}_k} y_{km}^w$$

where $m \in i$ means that organization i is an assignee for patent $m \in \mathcal{P}$. Then, the concentration measure for patent $k \in \mathcal{P}$ is

$$\mathcal{C}_k = \max_i \left\{\frac{n_{k,i}}{n_k}\right\}$$

In the third step, I aggregate these measures. Specifically, within each grant year (t) and technological class (c) I compute a simple average across patents[28]

$$\mathcal{C}(t,c) = \frac{1}{|\Omega_{t,c}^{top}|} \sum_{k \in \Omega_{t,c}^{top}} \mathcal{C}_k \tag{A.3}$$

where $|\Omega_{t,c}^{top}|$ is the number of patents in $\Omega_{t,c}^{top}$. Then I aggregate across technological classes using the weighted average of $\mathcal{C}(t,c)$ where weights are defined by the number of patents in each

[28]The results are robust if instead of a simple average I use a citation-weighted average, or median instead of an average.

$\Omega_{t,c}^{top} \neq \varnothing$

$$\mathcal{C}(t) = \sum_{c \in \mathcal{CPC}} \frac{|\Omega_{t,c}^{top}|}{\sum_{c \in \mathcal{CPC}} |\Omega_{t,c}^{top}|} \mathcal{C}(t,c) \tag{A.4}$$

The variable $\mathcal{C}(t)$ for $t = 1976 \ldots 2014$ is shown in Figure 1.

A.3 Robustness to Section 2: Concentration of Citations

Panel (a) in Figure B4 shows that the concentration of citations is similar if we restrict the sample to corporate patents only. I also consider different thresholds for the most cited patents: top 5% and 10%. Finally, I exclude the sample of citing patents that are assigned to superstar firms. Specifically, in each year and group level in Cooperative Patent Classification I find top 1% of firms in terms of the number of patents, and exclude their patents from the sample of citing patents. Panel (b) shows that the results are robust if one uses the citation-weighted average or the median instead of the average to aggregate concentration measures within technological classes. Panel (c) shows that the results are the same when I exclude self-citations of firms to itself, so the concentration is driven by citations between firms rather than self-citations. Kuhn et al. (2020) argue that the quality of citations as a measure of knowledge flows has declined over time due to a small number of patents responsible for a large share of backward citations. Panel (c) shows that the results on the concentration are robust when I exclude top 1% of patents in terms of the number of backward citations. Finally, I exclude citations between patents sharing a common law firm to ensure that the concentration is not driven by lawyers citing themselves. I also group citations from patents from the same within-country family (continuations, continuations-in-part, divisionals) as a single citation. This ensures that the rise in concentration is not driven by increasing patent families. Finally, for the period after 2001 I separate citations made by patent examiners and non-examiners. Figure B5 shows the concentration based on citations from patent examiners is around two times lower than the concentration based on citations from non-examiners.[29]

I also check whether citations are not driven by lawyers. Specifically, I track citations of lawyers who worked in multiple firms similar to the movement of inventors in Section A.5. The only difference is that there is no data for the location of lawyers, so I consider patents which are filed by the same lawyer in at least two companies, have a similar application period, and are classified to the same main subgroup in Cooperative Patent Classification system. Figure B6 shows that the actual concentration of citations across firms is around 95% within lawyers who represented similar companies. It is significantly higher relative to the 95th quantile of the concentration measure where citation rates are equated across companies within a lawyer.

[29]The USPTO started to separate examiner and non-examiner citations only around 2001.

A.4 Details on Monte-Carlo Simulations

The details on the Monte-Carlo simulations are the following. First, I divide all granted patents into disjoint groups based on common observational characteristics. Then, for each cited patent I find all patents sharing the same observational characteristics as the citing patents. Second, for each patent I randomize citations across similar patents to equalize citation rates across firms. Third, I randomize citations to equalize both citation rates and patenting across firms. For each patent, I compute the concentration measure on the simulated sample. I repeat this procedure 300 times to construct the distribution of concentration measures. Finally, I aggregate different moments of this distribution in a way similar to the actual concentration measure.

A.4.1 Step 1: Find Patents with Similar Characteristics

In Section 2.3, I use application years and technological classes for patent characteristics. For technological classes, I use the main subgroup level in CPC. Denote by t_k^a and $\tilde{c}_k$ an application year and a technological class of patent k. For each patent, I divide its citing patents based on their characteristics $g = (t^a, \tilde{c})$. Then, I find all patents, citing and non-citing, with the same characteristics.

As a robustness, in Section 2.3 I also group patents based on their textual similarity of abstracts. Specifically, as in the main analysis, for each cited patent I find all patents with the same characteristics $g = (t^a, \tilde{c})$ as the citing ones. Then, for all these patents, citing and non-citing, I compute the vector embedding of their abstracts using BERT model developed by Google. I use the version of BERT model called "all-MiniLM-L6-v2". The embedding is a vector that provides a mapping from text to a numerical representation. Then, I compute pairwise cosine similarities between patents that actually make citations. I find the minimum of this similarity. Next, for each non-citing patent I compute all pairwise cosine similarities with all citing patents. I leave a non-citing patent in the sample only if its similarity with at least one citing patent is greater or equal to the minimum similarity among citing patents. In this exercise, patent characteristics are specific to a cited patent. Denote

In Sections 2.4 – **??**, I also use a geographical location of the majority of inventors for patent characteristics. Denote the location for patent k by ℓ_k. I define the geographical location at the state level if an inventor is located in the U.S., and at the country level if an inventor is located outside the U.S. For example, the location for an inventor living in Cambridge, MA, USA is (USA, MA), and for an inventor living in Berlin, Germany is $Germany$. If a patent has several inventors in different locations, I define the location for a patent based on the location of the majority of inventors. In the case of a tie, I take the location based on the alphabetical order. In this case, the set of patent characteristics is $g = (t^a, \tilde{c}, \ell)$.

A.4.2 Step 2: Equalize Citation Rates

Denote the number of citations to patent k from patents with characteristics g by $n_k(g)$. For each g, I equate citation rates across firms. Formally, for each patent characteristic g I randomize $n_k(g)$ citations across all patents that have characteristics g and satisfy sample selection constraints from Section A.2.[30] As a result of this randomization, every patent can make a citation with the same probability. Denote the total number of such patents, citing and non-citing, by $N_k(g)$. Then every patent makes a citation with probability

$$p_k(g) = \frac{n_k(g)}{N_k(g)}$$

A.4.3 Step 3: Equalize Citation Rates and Patenting

This Monte-Carlo exercise is similar to the previous one except the details on the randomization of citations. To equate citation rates and patenting, I assume that $n_k(h)$ citations are allocated randomly to firms with the same probability. In other words, I assume that all firms have the same number of patents. Formally, denote by $\mathcal{F}_k(g)$ the set of firms that have at least one patent with characteristic g. Each citation out of $n_k(g)$ is randomly allocated to firm $j \in \mathcal{F}_k(g)$ with probability

$$\frac{1}{|\mathcal{F}_k(g)|}$$

where $|\mathcal{F}_k(g)|$ is the number of firms in $\mathcal{F}_k(g)$.

A.4.4 Step 4: Aggregation

I repeat the randomization procedures 300 times, and each time I compute the counterfactual concentration of citations for patent k. For an exercise with equal citation rates, denote the concentration measure for patent k in round s by $\mathcal{RC}_{k,s}$. For an exercise with both equal citation rates and the number of patents, denote the concentration measure for patent k in round s by $\mathcal{PC}_{k,s}$. I compute the median and the 95th quantile based on the distribution $\{\mathcal{RC}_{k,s}\}_{s=1}^{300}$ and $\{\mathcal{PC}_{k,s}\}_{s=1}^{300}$. These moments are denoted by $\mathcal{RC}_k(q)$ and $\mathcal{PC}_k(q)$, where q denotes quantile. Then I aggregate these measures across patents in the same way as with the actual concentration, see equations (A.3) and (A.4).

[30] Citations should be within a 5-year window from a grant day of a cited patent. I also exclude citations from patents assigned to individual inventors or with missing assignee information

A.5 Movement of Inventors and Citation Patterns

To distinguish whether the concentration of citations is driven by firms or inventors, I track citations of inventors who worked for multiple companies. I compute the concentration measure similar to the one in Section 2 but within inventors-movers, and then I do the decomposition of the concentration measure similar to the one in Section 2.3. This exercise follows the same procedure as the Monte-Carlo exercise in Section A.4 except that the sample is restricted to inventors who worked in multiple companies, and citations are randomized within an inventor.

To increase the sample size, I consider all citations rather than the ones within a five year window. As a result, I consider the trend in citation patterns for cited granted patents until 2009, so that they have 10 years to accumulate citations. I also focus on the sample of patents granted to publicly listed firms in Compustat.[31] Moreover, I exclude patents assigned to multiple companies because it is impossible to distinguish which company an inventor represents.

For each patent, I compute the distribution of citations across inventors. I leave only patents that received at least 20 citations from one inventor. The results are robust to other thresholds. This is done in order to ensure greater variability in the concentration measure. For example, if an inventor cited a patent only one time, then this patent would always receive a citation from one firm only, and the within-inventor concentration measure would always be 100%. For each citing patent, I find all patents that were filed by the same inventor in the same U.S state or foreign country and the same main subgroup category in Cooperative Patent Classification system.[32] Patents should also be applied in the same time period: I find all patents applied in the period $[t_j^a, t_j^a + 2]$ where t_j^a is the application year of the citing patent. Then, I equate citation rates across firms by randomizing citations within each inventor across all these patents with similar characteristics: citing ones and control patents that are observationally similar to the citing ones. I remove citing patents where no inventor worked in at least two companies and filed for similar patents. To equate citation rates and patenting, I randomize citations across firms that had observationally similar patents filed by the same inventor. The procedures are the same as in Section A.4.

The final data set is the following. Each cited patent has at least one citing inventor who filed similar patents in multiple firms. I compute the actual concentration of citations within each of these citing inventors (if there are many). Next, I compute the same concentration in Monte-Carlo simulations where citations are allocated randomly. For each cited patent, I take

[31] Matching of patents to Compustat firms is cleaner in a sense that I use the data from Autor et al. (2020) to control for potential subsidiary-parent relationship. If a patent is granted to a subsidiary of a certain firm, I match it to the parent company. Therefore, when the same inventor has patents in two firms in Compustat, these firms are more likely to represent different organizations relative to cases where the same inventor has patents in two private firms or foreign firms not listed in the U.S.

[32] If there are several inventors in the citing patent, I do this procedure for each of them.

the average of the concentration measures across all citing inventors-movers. This gives within-inventor actual and counterfactual average concentrations of citations for each cited patent. Then, I aggregate within and across technological classes in a way similar to Section 2. Figure 3 shows the results. The average within-inventor concentration measure is significantly higher relative to the 95th quantile of the same measure in Monte-Carlo simulations. This means that citations are driven by firms rather than inventors: inventors tend to cite different patents in various companies despite doing similar technologies.

A.6 Details to Section 3.5: Trade Secret Litigation and Concentration of Citations

Using Lex Machina data, I identify 2541 patents that were involved in both patent and trade secret litigation (for cases filed between 2001 and 2021). I exclude patents granted after 2014 to leave 5 years for accumulation of citations.

For each patent involved in trade secret litigation ("treated" patents), I find control patents that have only been involved in patent litigation, without any trade secret claims. I use four criteria, each with progressively stricter conditions, to select control and "treated" patents. First, control patents should be assigned to the same firm and have the same grant year as the "treated" patent. Second, in addition to the first condition, control patents should have approximately the same number of citations as the "treated" patent: between 0.8 and 1.2 of the number of citations that the "treated" patent receives. Third, control patents should come the same CPC group as the "treated" patent. Finally, I focus on "treated" patents assigned to plaintiffs only.

To increase the sample size, I trace citations from all years, rather than limiting citations to a 5-year window. The reason for this approach is to ensure that patents accumulate enough citations for the computation of the concentration measure. Notice that patents involved in in trade secret litigation are not necessarily the most cited ones. Since both "treated" and control patents have the same grant years, the results are not biased due to truncation of the citation data. I compute the concentration of citations using two measures: Herfindahl-Hirschman Index (HHI) and the share of citations coming from the most citing firm ("Top Share"). For each "treated" patent, I compute the difference between its concentration and the average concentration of citations for its control patents. Then I take the average of these differences across all "treated" patents.

Next, I compute the counterfactual distribution of the difference in the concentration if citations were random. Specifically, for both "treated" and control patents I find all patents sharing the same application year, technological class (main subgroup CPC), and location of inventors. Then, I randomize citations to equalize citation rates across patents. The details are given in A.4.

To explain the importance of such randomization, consider the following example. Suppose a patent involved in trade secret litigation (the "treated" patent) receives all of its citations from one firm. Therefore, the concentration is equal to 1. All patents of this firm come from the same application year, technological class, and location of inventors. This firm is the only one who has patents with such characteristics. Therefore, even under randomization of citations the concentration for the "treated" patent would be equal to 1.

Suppose the "treated" patent has one control patent. The control patent receives an equal number of citations from two firms. Therefore, the concentration is equal to 0.5. Suppose that, as with the "treated" patent, these two citing firms specialize in their respective technologies: one firm is a patent monopolist in technology A and another firm is a patent monopolist in technology B. There are no other firms who have patents in these technologies. Therefore, even under randomization of citations the concentration for the control patent would be equal to 0.5.

The actual difference in the concentration is $1 - 0.5 = 0.5$. However, this difference is driven by specialization of citing firms and would be observed even under random citations. I show that the actual difference in the concentration of citations between patents with and without trade secret claims is significantly higher relative to the difference explained by observable patent characteristics.

A.7 Details to Section 4.2: Import Competition from China

Section 4.4 estimates how import competition from China affected citations patterns. For this exercise, I follow the methodology in Autor et al. (2020) (Appendix B.3) for the analysis at the technological class level. Specifically, I do the following steps.

First, I take the set of the top 1% of the most cited patents ($Main$ sample defined in appendix A.2). For the specification with corporate patents, I leave only patents assigned to corporate firms (both public and private). Denote by f_k the assignee of patent k and by t_k^g the grant year of patent k. I group patents into five 7-year periods based on the grant year. Formally, I define the following sets

$$S_{1977} = \{k \in Main : f_k \in \text{Corporate}, t^g_k \in [1977, 1983]\}$$
$$S_{1984} = \{k \in Main : f_k \in \text{Corporate}, t^g_k \in [1984, 1990]\}$$
$$S_{1991} = \{k \in Main : f_k \in \text{Corporate}, t^g_k \in [1991, 1997]\}$$
$$S_{1998} = \{k \in Main : f_k \in \text{Corporate}, t^g_k \in [1998, 2004]\}$$
$$S_{2005} = \{k \in Main : f_k \in \text{Corporate}, t^g_k \in [2005, 2011]\}$$

where the sample $Main$ is defined in Section A.2.

Second, for each set S_t and each technology class I compute the aggregated concentration measure. I take the simple average across concentration measures. Autor et al. (2020) provides a mapping between USPC technological classes and SIC industries. Moreover, there exists a matching from USPC to NBER technology categories that will be used as controls. Therefore, for technology classes I use the USPC system. Denote the aggregate concentration measure for technology class j and set S_t by $\mathcal{C}_{j,t}$.

Third, given the constructed $\mathcal{C}_{j,t}$ the analysis proceeds as described in Section 4.4. Data construction with non-corporate patents is the same except that in the first step I leave only non-corporate patents from the $Main$ sample.

B Figures and Tables

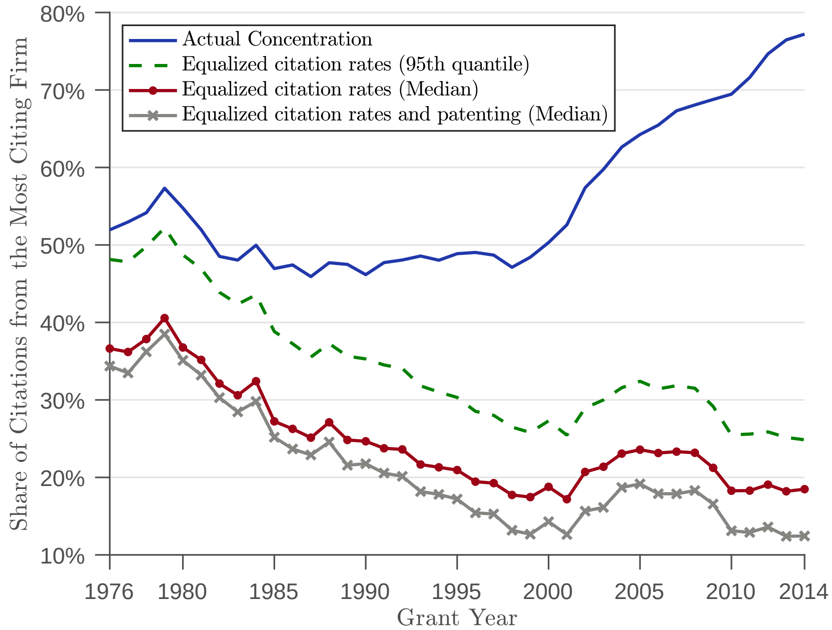
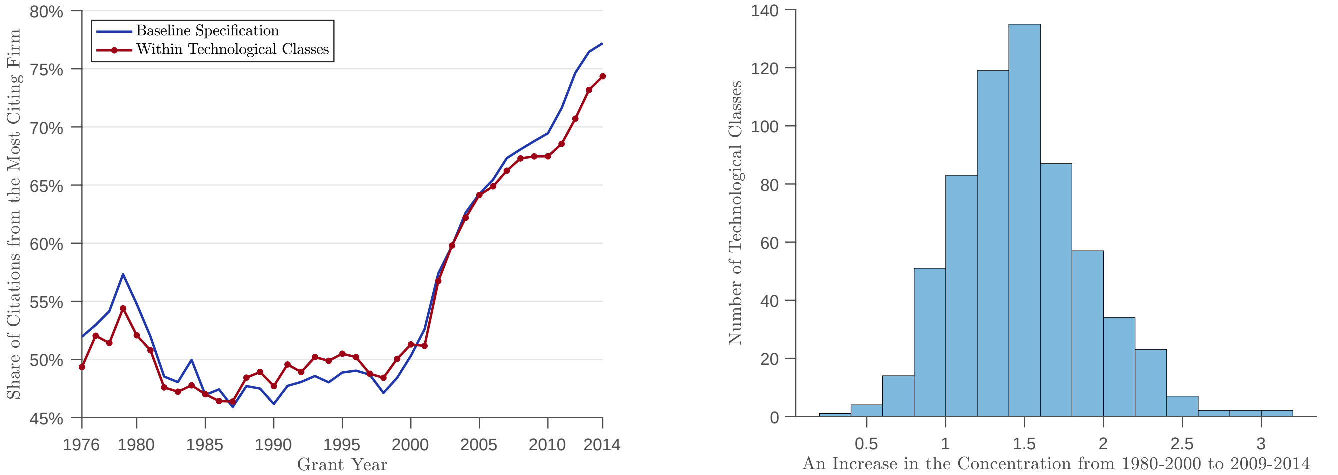


Figure B1: Decomposition of the Concentration of Citations Based on the Textual Similarity Between Patents

This figure does a decomposition similar to Figure 2 using textual similarity of patents. Specifically, in addition to application years and technological classes, I also control textual similarity of abstracts between non-citing patents and citing patents. I use BERT model to measure textual similarity. The details are given in Appendix A.4.

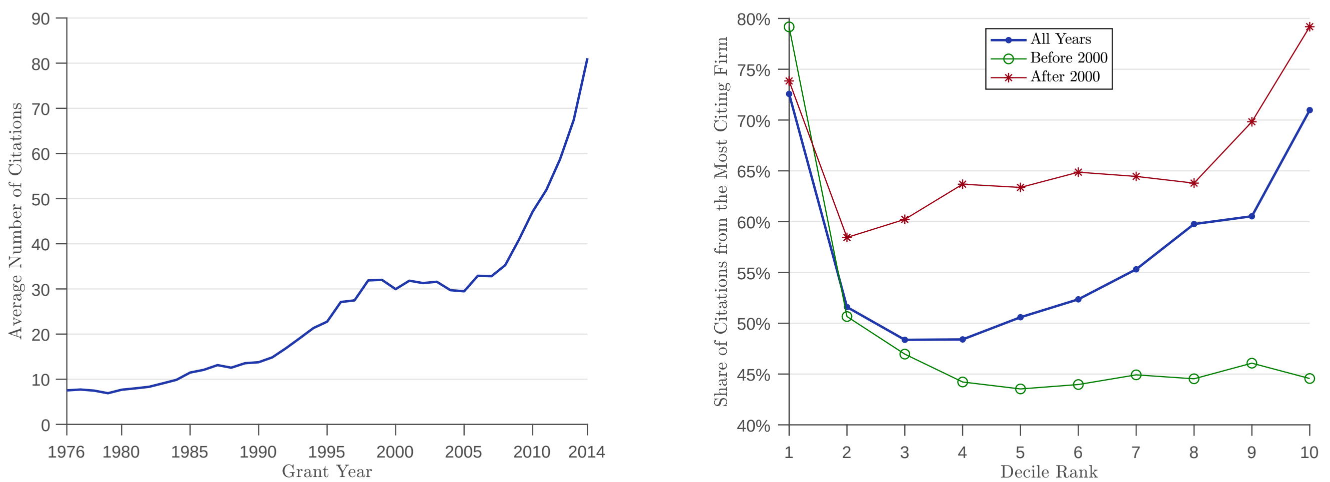


(a) Baseline vs. Within Technological Classes

(b) Distribution of the Increase Across Classes

Figure B2: Concentration of Citations Within Technological Classes

Panel (a) shows the aggregate concentration of citations that is driven by changes within technological classes. In the baseline specification, I aggregate concentration measures across classes by taking an average weighted by the number of patents in a class. The dotted red line shows the concentration in which the average across classes is unweighted. In Panel (b), for each technological class (a group category in CPC) I compute the ratio of the average concentration between 2009 and 2014 to the average concentration between 1976 and 2000. Panel (b) shows the distribution of the increase in the concentration measure across classes.

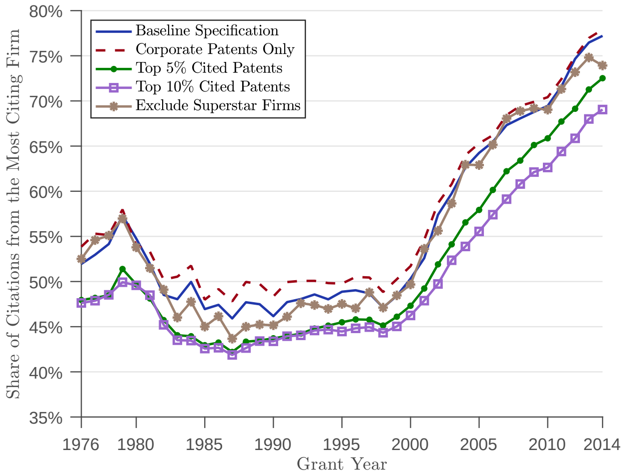


(a) Number of Citations by Years

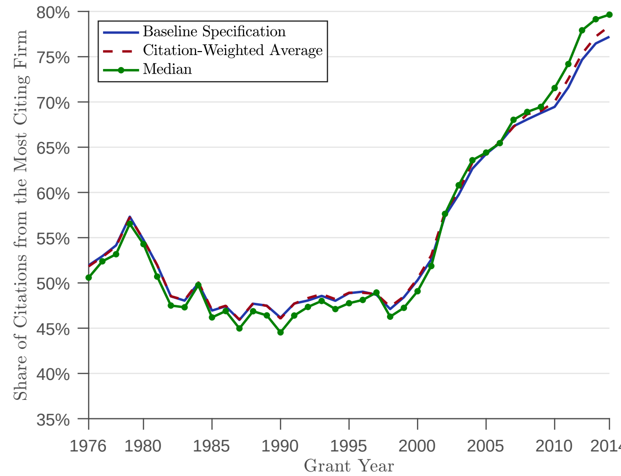
(b) Number of Citations and Concentration

Figure B3: Number of Citations and Concentration

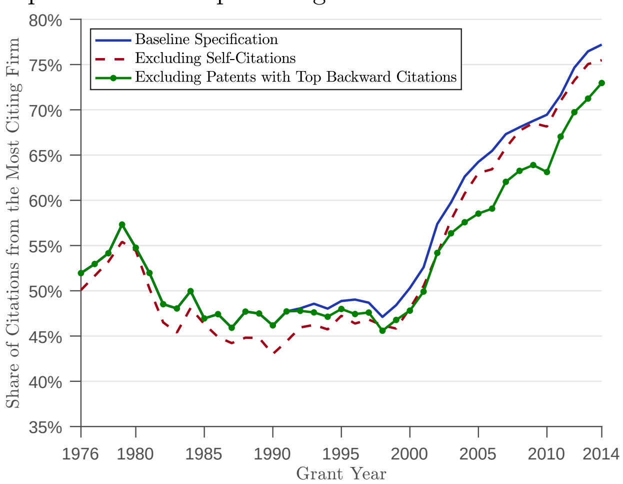
Panel (a) shows the average number of citations by years. Panel (b) shows the relationship between the average number of citations and the concentration. The dotted line shows the relationship based on patents granted in all years. The lines with circles and asterisks show the results for patents granted before and after 2000, respectively.



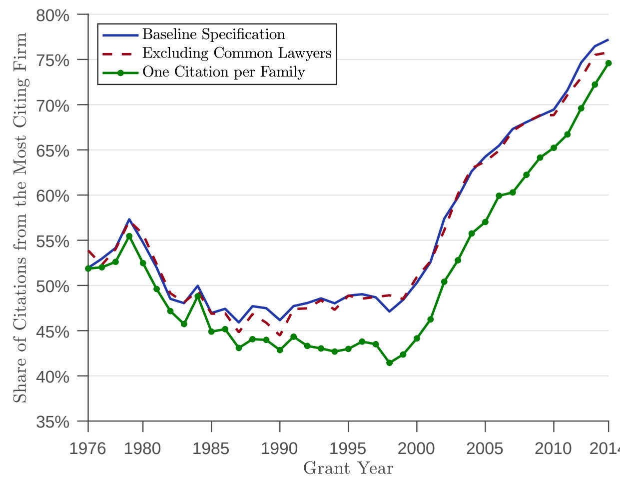
(a) Corporate patents, top 1%, top 10%, exclude superstar firms in patenting



(b) Alternative aggregation: citation-weighted average and median within classes.



(c) Exclude Self-Citations and top patents in terms of backward citations.



(d) Exclude Citations from common lawyers and group patents from one family.

Figure B4: Robustness for the Concentration of Patent Citations

These figures show robustness exercises for the concentration measure in Figure 1. Panel (a) shows that the concentration of citations in the sample of corporate patents only. I also consider different thresholds for the most cited patents: top 5% and 10%. Finally, I exclude citations from superstar firms in terms of the number of patents. Specifically, in each year and group level in Cooperative Patent Classification I find top 1% of firms in terms of the number of patents, and exclude their patents from the sample of citing patents. Panel (b) shows the results if one uses the citation-weighted average or the median instead of the average to aggregate concentration measures within technological classes. Panel (c) shows the concentration in the sample without self-citations of firms to themselves. It also shows the concentration in the sample without top 1% of patents in terms of the number of backward citations. Figure (d) shows the results in the sample without citations between patents sharing a common law firm. I also group citations from patents from the same within-country family (continuations, continuations-in-part, divisionals) as a single citation.

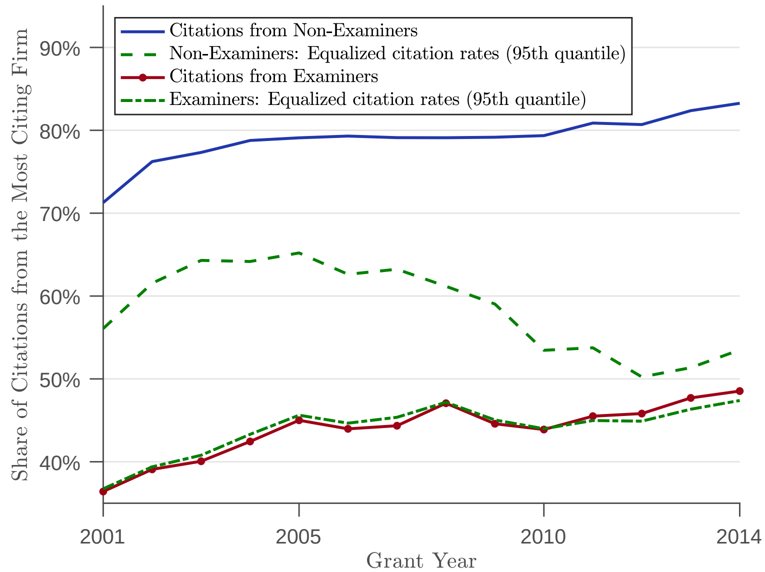


Figure B5: Concentration of Citations: Examiners vs. Non-examiners

This figure shows the concentration of citations across firms in which I separate citations from examiners and non-examiners. The USPTO started to distinguish citations from examiners in 2001. The dashed lines show 95th quantiles of the same measures in Monte-Carlo simulations in which citation probabilities are equalized across firms within the same (application year, technological class, location of inventors), see details in Appendix A.4.

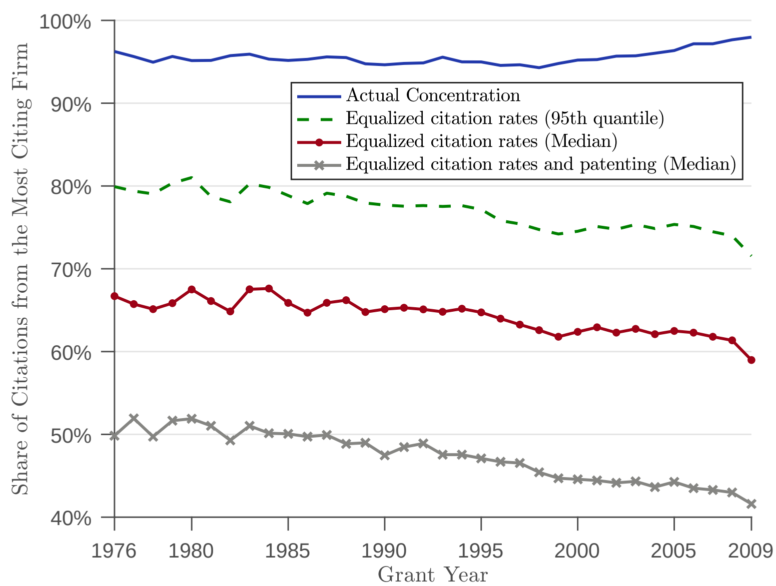
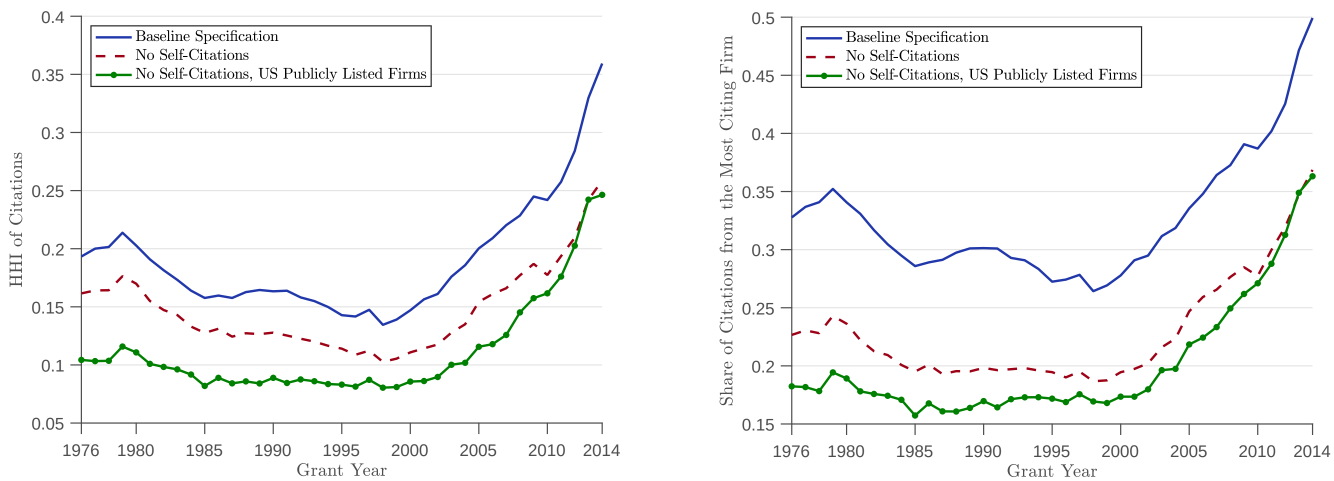


Figure B6: Concentration of Citations for Lawyers Who Represented Several Firms

This figure shows the concentration of citations across firms within lawyers who represented multiple companies. I compare patents with similar characteristics: the same main subgroup level in Cooperative Patent Classification and application time (within 2 years from the citing application year). The solid line shows the actual aggregate within-lawyer concentration of citations across firms measured by the share of citations coming from one firm only. The dashed line shows the 95th quantile of the same measure in Monte-Carlo simulations where citations are allocated randomly within a law firm.



(a) Herfindahl-Hirschman Index

(b) Share from the Most Citing Firm

Figure B7: Concentration of Citations at the Firm Level

Panel (a) shows the results for the concentration defined by the Herfindahl-Hirschman Index of citations across firms, see equation (2.3) on page 14. The solid line shows the baseline concentration using all citations. The dashed line shows the concentration without self-citations. The dotted line shows the concentration based on citations between US publicly listed firms. Panel (b) provides a robustness check for the firm-level concentration defined as the share of citations from the most citing firm. For each firm in a year, I define the concentration based on citations within five years to the firm's patents granted in this year. The aggregate measure is defined as the average concentration across firms weighted by the number of citations.

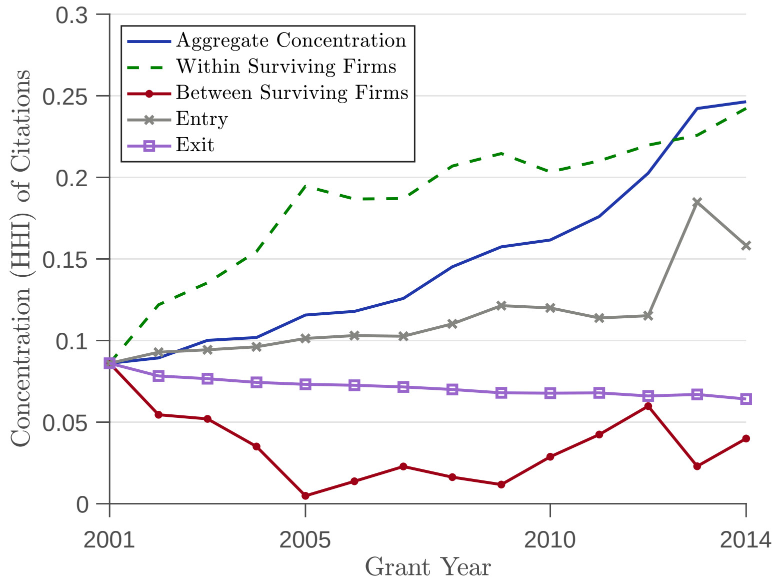


Figure B8: Concentration Over Time: Within-Firm, Between-Firm, Entry, and Exit

This figure decomposes the rise in the concentration of citations, defined in equation (2.3) on page 14, from 2001 to 2014 into within-firm, between-firm, and entry/exit components (Melitz & Polanec 2015). For each component, I plot how the average concentration would evolve if it were driven by this component only. For years t and $t + s$, the decomposition considers changes within and between firms that received citations both in t and $t + s$ ("surviving firm"). Additionally, it accounts for the impact of firms that stopped receiving citations by $t + s$ ("exiting firm") and those that began receiving them in $t + s$ ("entering firms"). Around 97.5% of the rise in the concentration from 2001 to 2014 is explained by changes in the concentration within surviving firms. If the concentration within these firms stayed constant, the average concentration among surviving firms would decline by 28.8% due to re-allocation of citations from firms with high concentration to firms with low concentration of citations. On average, entrants have higher concentration relative to surviving firms, and they explain 45% of the rise in the aggregate concentration. Exiting firms also have higher concentration relative to surviving ones, and their exit contributes to a decline in the average concentration (13.7%).

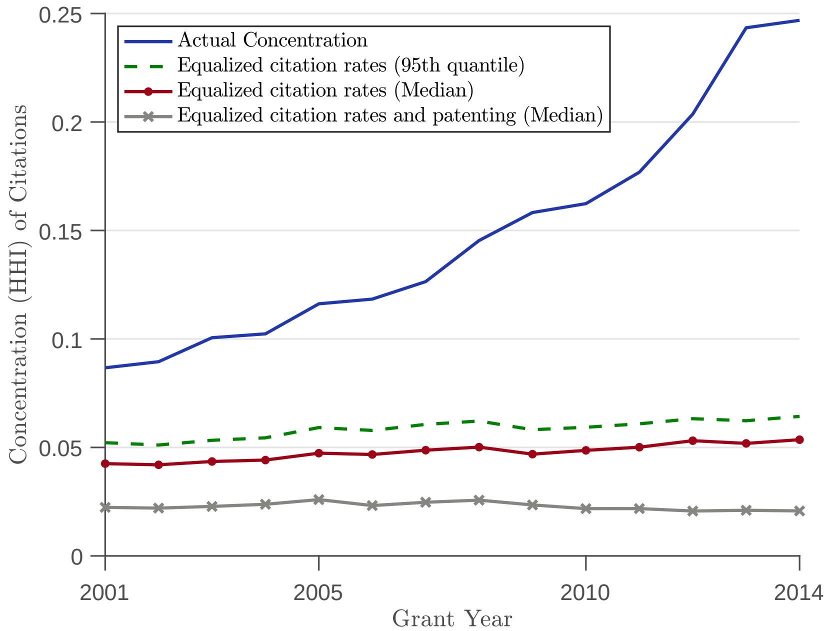
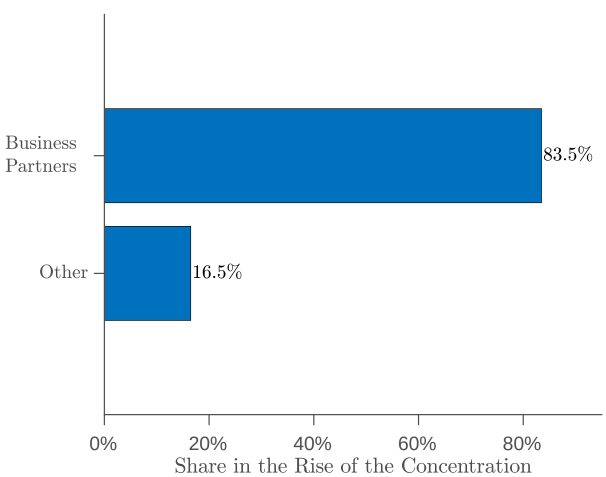
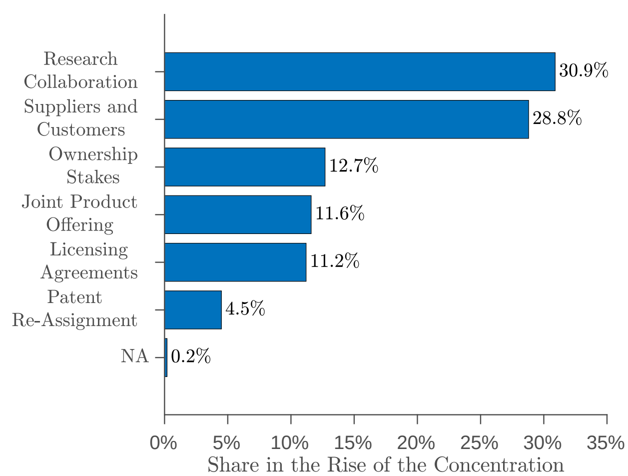


Figure B9: Decomposition of the Firm-Level Concentration of Citations

This figure does a decomposition similar to Figure 2 for the firm-level concentration of citations. There are two main differences from the computation in Figure 2. First, I allocate citations randomly within the set of publicly traded companies, rather than across all firms. The random allocation of citations follows the procedure described in Appendix A.4. Second, I aggregate citations at the firm level, as defined in Section 3.



(a) Citations by Relationship Between Firms



(b) Citations Within Partners

Figure B10: Role of Partners in the Rise of the Concentration

This figure shows the share of the rise in the concentration of citations that can be explained by business partners. Panel (a) shows the aggregate role of partners. Formally, $\frac{\mathcal{H}^{\mathcal{P}}_{2014}-\mathcal{H}^{\mathcal{P}}_{2001}}{\mathcal{H}_{2014}-\mathcal{H}_{2001}} \approx 0.835$, where $\mathcal{H}_t$ is the aggregate concentration from equation (2.3), and $\mathcal{H}^{\mathcal{P}}_t$ is the aggregate concentration from partners based on equation (3.1). Panel (b) shows a similar decomposition within partners across different types of relationships.

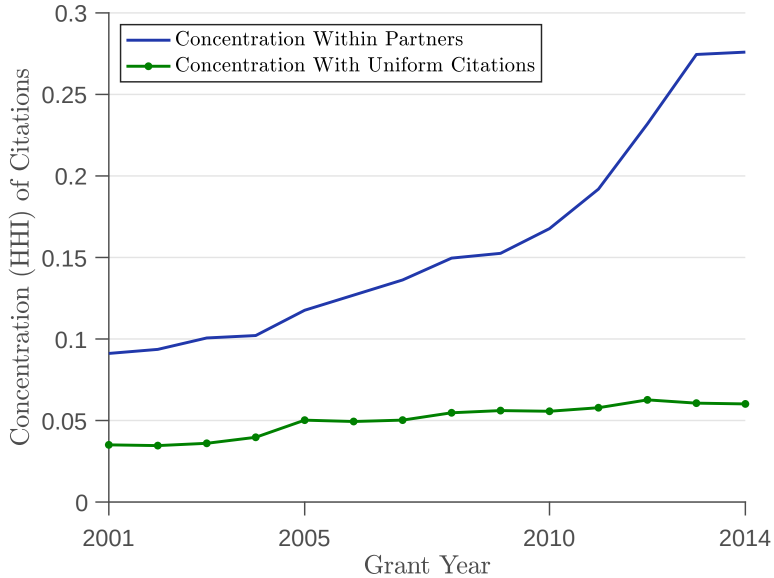


Figure B12: The Skewness of Citations Among Partners

This figure shows the average concentration of citations (HHI) from business partners. The dotted line shows the counterfactual concentration, in which citations are distributed across firms as uniformly as possible to minimize the HHI, given the existing number of citing firms. The graph is constructed using a sample of patents with a unique assignee. Patents with more than one assignee account for less than 1% of citations.

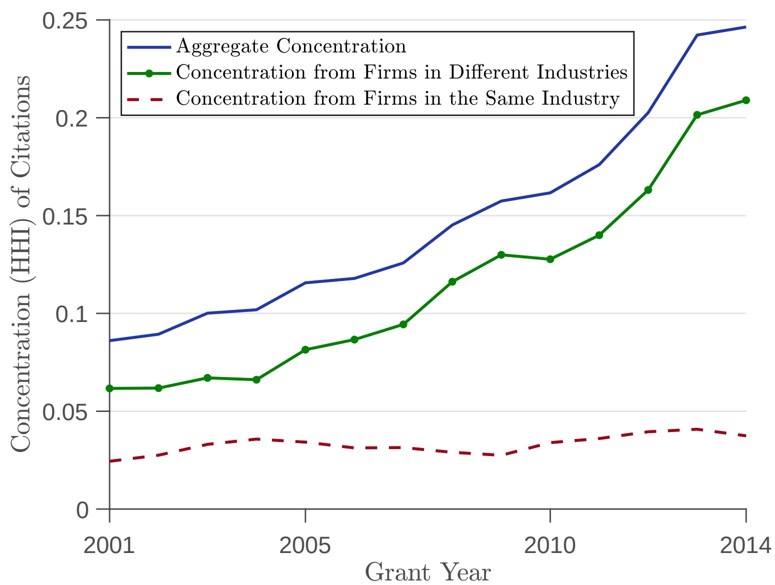
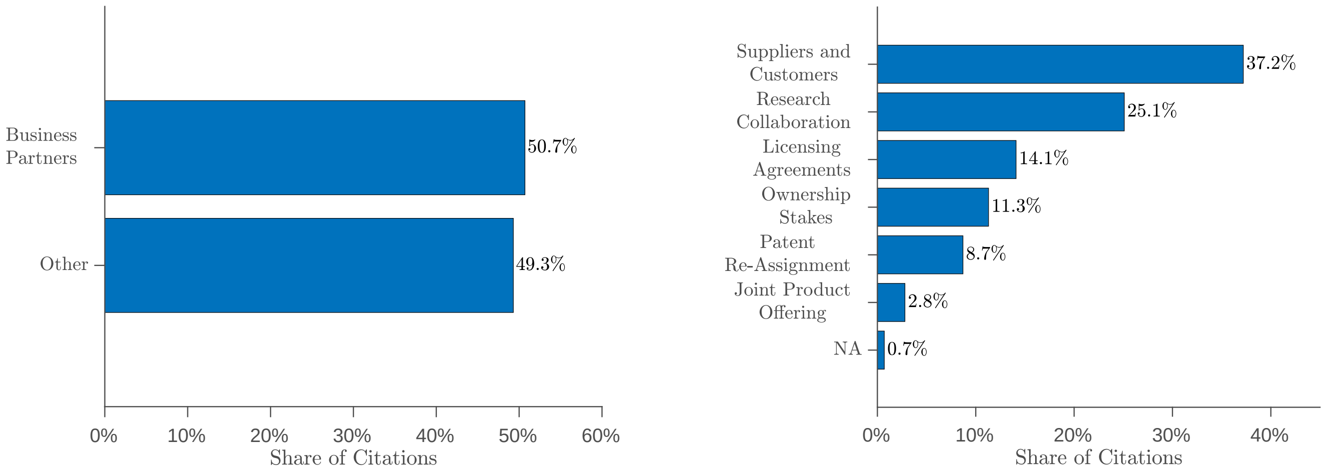


Figure B11: Decomposition of the Concentration Based on Industries

This figure decomposes the concentration into the roles of firms from the same industry as a cited firm and firms from other industries. The decomposition is similar to the one in equation (3.1): instead of partners and other firms I define cited-citing firm pairs as coming from the same 4-digit Standard Industry Classification Industry or from different industries.



(a) Citations by a Relationship Between Firms

(b) Citations Within Partners

Figure B13: Distribution of Citations, Robustness to Figure 4 With a Broader Sample

This figure shows the distribution of patent citations across different types of relationships between cited and citing firms. In Figure 4, I consider citations between publicly traded US companies. In the sample of firms for this figure, only one firm is required to be a publicly traded US company. Panel (a) shows the share of citations coming from business partners. Panel (b) shows the distribution of citations coming from business partners across different types of partners.

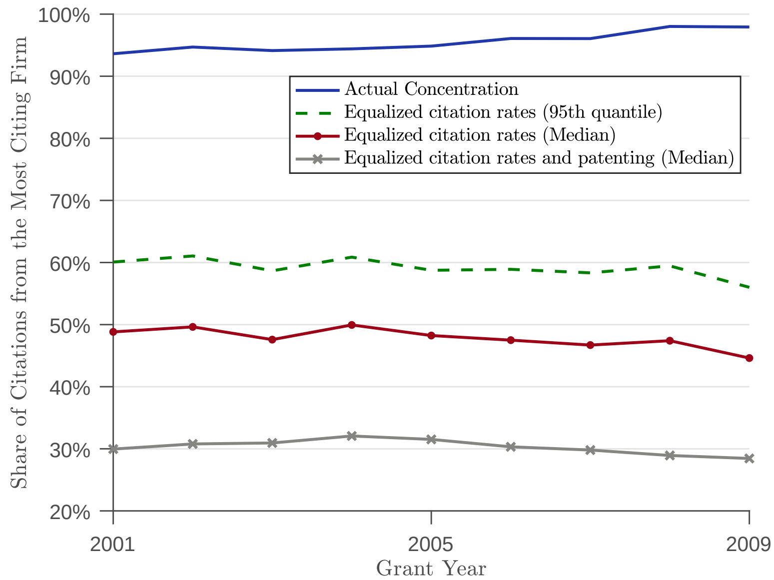


Figure B14: Test for Strategic Citations Using Movement of Patent Attorneys

This figure shows the results of a test for the role of strategic citations. I compute the concentration of citations within attorneys who filed similar patents at different business partners of a given firm. The difference from Figure B6 is that I focus on the sample of citations among partners rather than all firms. I compare patents with similar characteristics: the same main subgroup level in Cooperative Patent Classification and application time (within 2 years from the citing application year). The solid line shows the actual aggregate within-lawyer concentration of citations across firms measured by the share of citations coming from one firm only. The dashed line shows the 95th quantile of the same measure in Monte-Carlo simulations where citations are allocated randomly within an attorney.

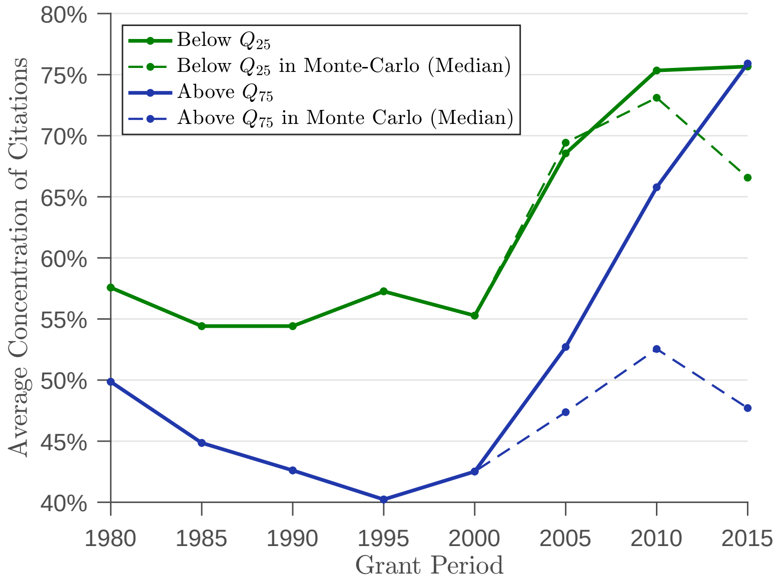


Figure B15: Trade with China. Actual Concentration vs. Counterfactual One with Equalized Citation Rates

This figure shows the concentration measure from Section 2 (Figure 1) for different technological classes divided into quartiles based on their exposure to import competition from China, ΔIP_{i2} in (4.1). The solid lines show the concentration measures over time for the technologies most (the blue line) and least (the green line) exposed to the competition from China. The dashed lines show the counterfactual concentration measures that are evolved due to changes in patenting across firms holding firms' citation rates fixed at the level of 2000. Formally, for patents granted after 2000 I compute the median concentration measures in the in the Monte-Carlo simulations where citations are allocated randomly across patents sharing the same application years, technological classes, and locations of inventors (see Appendix A.4). I add the difference between the actual and the counterfactual concentration measures in 2000.

Table B1: Types of Business Partnerships Between Firms

Type	Data	Description from FactSet	Group
Customer	FactSet Segments	Entities to which the source company sells products/services.	Suppliers and Customers
Supplier	FactSet Segments	Entities from which the source company purchases goods or services.	Suppliers and Customers
Manufacturing	FactSet	Entities who provide paid manufacturing services to the source company.	Suppliers and Customers
Marketing	FactSet	Entities who provide paid marketing and/or branding/advertising services to the source company.	Suppliers and Customers

Continued on next page

Table B1 – continued from previous page

Type	Data	Description	Group
Distribution	FactSet	Entities whom the source company pays to distribute this company's products/services.	Suppliers and Customers
In-Licensing	FactSet	Entities from whom the source company license products, patents, intellectual property, or technology	Licensing
Out-Licensing	FactSet	Entities to whom the source company licenses products, patents, intellectual property, and technology; also entities where the source company is paid by the target entity, commonly upfront and in periodic future payments.	Licensing
Research Collaboration	FactSet	Entities collaborating with the source company for research and development, generally for new product development, common between science companies and between technology companies. This designation is applicable for products in development, not marketed.	Research Collaboration
Equity Investment	FactSet	Entities in which the source company owns an equity stake. This designation applies only when the source company owns equity in another company - i.e. working interests, royalties, property, or well claims do not qualify for the Equity Investment designation.	Ownership Stakes
Investor	FactSet	Entities which own equity in the source company.	Ownership Stakes
Joint Venture	FactSet	Entities where the source company jointly owns a separate company with one or more companies.	Ownership Stakes

Continued on next page

Table B1 – continued from previous page

Type	Data	Description	Group
Integrated Product Offering	FactSet	Entities with whom the source company agrees to bundle standalone products/services of each company and are then marketed together as one offering. No money is exchanged upfront, and costs, risks, and profits are shared.	Integrated Product Offering
NA	FactSet	Partners with an unknown relationship. They are responsible for only 0.7% of citations among partners.	NA
Patent Re-Assignor	USPTO	Entity who transfers its right, title, and interest in a patent or patent application to an assignee.	Patent Re-Assignment
Patent Re-Assignee	USPTO	Entity who receives the right, title, and interest in a patent or patent application from an assignor.	Patent Re-Assignment

Note: This table describes all business partnerships used in Section 3. The description for all relationships except NA and Patent Re-Assignment comes from FactSet's Data and Methodology Guide. In the analysis of citations between partners, I use the grouping of relationships from the last column.

Table B2: Trade Secret Litigation and Concentration of Citations

Concentration Measure	HHI				Top Share			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Concentration	2.11	4.78	6.19	8.49	2.53	5.07	4.53	5.99
	(0.44)	(0.59)	(1.25)	(1.33)	(0.62)	(0.82)	(1.57)	(2.14)
Controls:								
Same Firm and Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Same N of Citations		Yes	Yes	Yes		Yes	Yes	Yes
Same Tech Class			Yes	Yes			Yes	Yes
Plaintiffs Only				Yes				Yes

Notes: This table shows the average difference in the concentration of citations between patents involved in litigation with and without trade secret claims. Columns 1–4 measure the concentration as the Herfindahl-Hirschman Index (HHI), and columns 5–8 — as the share of citations coming from the most citing firm. All measures are multiplied by 100. The numbers in brackets show standard errors of the difference in the concentration of citations when citations are allocated randomly within the same application years, technological classes, and locations of inventors (see Appendix A.4). I use four sets of controls. First, I require control patents (patents involved in patent infringement litigation but without trade secret claims) to be from the same firm and grant year. Second, I require control patents to have approximately the same number of citations as the treatment patents (patents involved in litigation with trade secret claims): between 0.8 and 1.2 of citations. Third, I require patents to be from the same CPC group. Finally, I focus on patents assigned to plaintiffs only.

Table B3: Placebo Tests: Trade with China and Increase in the Concentration of Citations

	Non-Corporate Patents					Lag Outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ Tech Class Exposure to Chinese Imports	−1.68	−1.58	0.90	4.33	5.04	−0.46	−0.47	−1.31	−1.42
	(1.85)	(1.81)	(1.21)	(5.33)	(5.67)	(0.64)	(0.65)	(1.10)	(1.11)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Δ Citations		Yes	Yes	Yes	Yes		Yes	Yes	Yes
2 Lags of outcomes			Yes	Yes	Yes				
11 sectors, 6 Tech				Yes	Yes			Yes	Yes
Software Patents					Yes				Yes

Notes: This table shows the results for the falsification tests in specification (4.2) and Table 2. Changes in US import exposure are instrumented with Chinese exports to non-U.S. high-income markets (Autor et al. (2020)). In columns (1)–(4), I regress the change in the concentration of citations for non-corporate patents on the changes in import competition from China. In columns (5)–(7), I regress the change in the concentration measure pre-period (pre 1991) on future changes in import exposure. Standard errors are clustered at the technology class level. All specifications are weighted by the number of Compustat-matched U.S.-inventor patents in a technology class.