Knowledge Spillovers of Products and Processes

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Abstract

This paper provides evidence that product innovations generate more knowledge spillovers than process innovations. I measure the existence of knowledge spillovers using patent-to-patent citations, the text of patents, and by measuring the stock of product and process R&D available to a firm. I find that product patents generate more citations and that the novel text in product patents is more likely to be reused relative to process patents. The result is robust a rich set of controls and heterogeneity analysis reveals that the gap in product and process knowledge spillovers widens for innovations that are novel or occurring in rapidly evolving areas of technology. I also find that when the stock of product (process) R&D available to a firm increases, patenting at the firm increases (decreases).

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1 Introduction

Knowledge is a cumulative process. The knowledge produced in the present is built upon, resulting in future innovation. Due to imperfections in the market for ideas, firms often use the knowledge of other firms without compensating the firm who created the knowledge. These knowledge spillovers cause the social value of R&D effort to exceed the private value, leading to under-investment in the creation of knowledge (Nelson 1959). This has been used as one of the primary justifications for government intervention in the market for ideas. Yet there are many different types of innovative knowledge. Firms engage in product innovation by introducing new product varieties, and they also introduce process innovations by altering the assembly of their products.

These different types of knowledge may have different information properties, causing them to generate different amounts of knowledge spillovers (Kraft 1990; Kotabe and Murray 1990). A long standing hypothesis has been that product innovations generate more knowledge spillovers since they are available for purchase and can be reverse-engineered. On the other hand, process innovations are supposed to be more internally focused and less visible, resulting in fewer knowledge spillovers. Despite the importance of knowledge spillovers for creating optimal innovation policy, we have very little evidence on whether product or process innovations generate more knowledge spillovers. The evidence on this topic has remained sparse largely for two reasons. First, is the lack of large-scale, high quality data distinguishing product and process innovation. Second, is finding the right empirical strategy to address the question.

This paper addresses both gaps in the literature and provides novel evidence that product innovations generate more knowledge spillovers than process innovations. I use data from Davison 2022, which distinguishes patents as product or process innovations for all patents granted to U.S. manufacturing firms from 1980-2015. With this data, I measure knowledge spillovers in several ways. First, I rely on patent-to-patent citations as a measure of knowledge flows (Jaffe, Trajtenberg, and Henderson 1993). Next, I utilize the novel keyword combinations of patents to characterize the unique components that make up the invention (Arts, Cassiman, et al. 2018). For example, the patent associated with the discovery of

HIV has the novel keyword combination “virus hiv-2” which was reused in 403 subsequent patents. When a novel keyword combination of a patent is reused in another patent, I take this as evidence that a knowledge flow took place. I find that product patents generate more citations and have higher average reuse of their novel content. The finding holds when I control for firm and year fixed effects, the patent’s market value, and its intellectual scope, indicating that the result is not an artifact of product patents being more valuable, having broader intellectual scope, or being concentrated in a particular firm or year.

In addition to measuring the quantity of knowledge flows that a patent creates, I also explore whether other aspects a patent’s knowledge flows are consistent with product patents generating more knowledge spillovers. For each patent, I measure the number of days it takes for the first firm besides the firm who originated the knowledge to either cite or use the novel content of the patent. If product patents generated more knowledge spillovers, we would expect them to diffuse faster to rivals outside the firm (Mansfield 1985). Using patent citations, I find evidence that it takes less time for another patent to cite a product patent, but I find smaller and less precisely estimated effects using the text-based measure of knowledge flows.

Process innovations have also been hypothesized to be more internally focused, being designed around methods of production the firm has previously developed. Internally focused innovations are less likely to generate knowledge flows since they are not as useful outside the firm. To test this, I measure the share of citations or reuse of novel keyword combinations that come from the firm who originated the knowledge. Using patent citations, I find evidence that product innovations are less internally focused with a lower share of citations being made by the firm who created the patent. The text-based methods show no sign that product patents have different levels of internal focus.

Finally, if product innovations generate more knowledge spillovers, we would expect that the firms who create the knowledge would have less control over who uses the knowledge. Fadeev 2021 provides evidence that firms intentionally share their knowledge when citations are concentrated among a single citing firm. If citations are spread out among many different firms, this indicates unintentional knowledge flows. I measure the external concentration of a patent using the share of citations coming from the most citing external firm. Using both citation and text-based measures, I find evidence that product innovations diffuse to a broader set of external firms, relative to process innovations. Overall, the evidence suggests that product innovations do not simply create more knowledge flows, but the knowledge they create diffuses to a broader set of external firms.

My final way of measuring knowledge spillovers involves creating a measure of the total pool of spillovers available to a firm in a given year. To measure the amount of knowledge available to a firm, I use the method of Bloom et al. 2013 who rely on the patent portfolios of firms to construct distance between firms in technological space. Using these distance metrics and the R&D spending firms, I am able to construct proxies for the product and process knowledge pools that are available to a firm in a given year. I find that when the pool of product knowledge available to a firm increases, it increases the firm's patenting activity. In contrast, I find that firms decreases their patenting activity when the stock of process knowledge available to the firm increases. One issue with identifying the effect of product and process spillovers is that the innovative activity of firms is endogenous. Using federal and state tax credits to instrument for the R&D activity of firms, I arrive at the same result that product spillovers lead to increased innovative activity while process spillovers do not.

My result that product innovations generate more knowledge spillovers contribute to the literature concerned with empirically measuring knowledge spillovers (Griliches 1991; Bloom et al. 2013; Zacchia 2020; Myers and Lanahan 2021). This literature has used a variety of empirical strategies to document that the positive externalities from knowledge spillovers outweigh the negative externalities from business stealing which occur when the innovation of one firm simply shifts revenue from one firm to another. This evidence supports the view that the market will generate under-investment in innovation relative to the socially optimal level. My research deepens our understanding of knowledge spillovers by examining how different types of innovation generate different amounts of knowledge spillovers. The findings highlight that product innovations generate a disproportionate amount of the knowledge spillovers that come from innovation.

There are a few papers examining the question of whether product or process innovations generate more knowledge spillovers. Mansfield 1985 use survey data to find that at the median it takes 12-18 months for the nature and operation of a process innovation to diffuse to rivals, but only 6-12 months for the diffusion of a product innovation. Ornaghi 2006 uses data from Spanish manufacturing firms and finds that knowledge spillovers have a larger positive effect on demand for the firm's products than on increasing the efficiency of production. Ornaghi 2006 take this as evidence that knowledge spillovers have a greater impact on product innovation and that product innovation drives more knowledge spillovers. My work brings new data and fresh empirical strategies to examine the question, confirming the previously found result that product innovations generate more knowledge spillovers than process innovations.

2 Patent Data

The underlying data on product and process innovation comes from other work of mine where I classify over one million patents as product or process innovations (Davison 2022). I define a product innovation as an innovation that describes a physical object that the firm sells in the output market with no discussion about how the object is created. All other innovations are defined to be process innovations. The data includes all patents granted to U.S. publicly traded manufacturing firms from 1980-2015. To classify patents as product or process innovations, I hand classified a sample of 14,000 patents as product or process innovations.

To more concretely see how this works in practice, I have taken three patents granted to Micron Technology, a firm operating in the semiconductor industry and specializing in the production of computer memory. The semiconductor industry is highly innovative, having the most patents of any industry in my data. As an example of a product patent, consider US patent number 6952359, which is titled: "Static content addressable memory cell" and pictured in Panel (a) of Figure 1.

[Figure 1 about here.]

This patent is for a content addressable memory cell, a product that Micron sells in the output market. The motivation for the patent is described in the text of the patent which says: "There is a...need for an alternative CAM cell design that is relatively small and yet has acceptably low soft-error rates." There is no discussion of how the product is created, making this patent a product innovation that is meant to address shortcomings in currently available product offerings.

Now consider Panel (b) of Figure 1 which shows a different patent assigned to Micron Technology that has the title: "Thermal conditioning apparatus." The description of the patent's CPC classification reads: "Apparatus specially adapted for handling semiconductor or electric solid state devices during manufacture or treatment thereof..." Further the patent goes on to state: "A problem that arises with the prior art...is that when the heating or cooling assemblies must be repaired or replaced, extensive and costly amounts of downtime occur." From the CPC description and the text of the patent, it is clear that this machine is used to more effectively produce semiconductors. According to my definition this invention is a process innovation since it describes a physical object that Micron does not sell but is used to produce physical objects that Micron will sell.

But not all inventions are strictly product or process innovations. Consider, US patent number 7271654, which has the title: "Low voltage CMOS differential amplifier" and is shown in Panel (c) of Figure 1. From the title, it would appear that the patent is for an object that Micron Technology will sell, yet the second sentence of the abstract states that: "there is provided a method of manufacturing a device..." This indicates that the patent contains information about how this object is constructed. In this sense, the patent has both a product component since it describes features of a physical object that Micron will sell, but it also has a process component since it describes how to manufacture the product. Fortunately, the publication claims of a patent enumerate all the individual innovations that make up the invention in the patent. Specifically, the publication claims of a patent legally define what is protected by the patent, with each independent publication claim standing on its own. Because dependent publication claims rely on independent publication claims, I restrict my attention to independent publication claims. The current patent of consideration, US patent number 7271654, has four independent publication claims, which will henceforth be referred to as claims for brevity:

1. A method of manufacturing a device comprising...

2. A device comprising...
3. A method of operating a set of differential pairs comprising...
4. An input buffer comprising...

The first claim refers to a process innovation since it discusses a process used to create an object that the firm will sell. The next three claims pertain to descriptions of the CMOS differential amplifier, along with descriptions about how to use it. To capture the fact that this patent contains both product and process innovations, I assign this patent a product share of 0.75 where the product share is the proportion of a patent's claims that are product innovations. In the previous two examples, all the claims were either product innovations, as in the case of the memory cell in US6952359, or process innovations as in the case of the thermal conditioning apparatus in US6051074. I apply this method of individually classifying patent claims as product or process innovations and then calculate a product share for each patent. This method ensures that I capture the fact that patents can contain both product and process innovations.

These patents also foreshadow how product and process innovations have different information properties. Process innovations such as Micron's thermal conditioning apparatus tend to be more internally focused, making it less likely that their knowledge leaks out to rivals. On the other hand, product innovations, such as Micron's memory cell, are more easily reverse-engineered since the product is available for purchase.

After hand classifying the claims of over 14,000 patents, I use machine learning methods combined with the text of the claims to predict the product/process status of all patent claims that I did not hand classify.[1] This gives me a product share for all 1,023,854 patents in my original sample.

[1]For more details on this procedure and the quality of the classification, see Davison 2022

3 Empirical Strategies & Results

3.1 Citation-Based Spillovers

My first approach to measuring knowledge spillovers uses patent-to-patent citations (Jaffe, Trajtenberg, and Henderson 1993). The idea is intuitive, if a patent cites another patent then the citation should signal that the focal patent is building upon knowledge found in the cited patent, indicating that a knowledge flow took place. While the simplicity of measurement is appealing, a small body of evidence shows that not all patent-to-patent citations reflect genuine knowledge flows. In a survey of inventors conducted by Jaffe, Trajtenberg, and Fogarty 2000, 38% of inventors indicated that they had learned about the cited invention either before or during the development of their own invention. Another third learned about the patent they cited after the development of their invention, and the remaining third were completely unaware of the patent citation before the arrival of the survey. This suggests that the majority of patent citations do not represent knowledge flows that are actively used in the creation of an invention.[2] Despite the issues with patent-to-patent citations, Younge and Kuhn 2016 shows that patents which share a citation link have high levels of textual similarity. Overall, while using patent citations is not without problems, the evidence suggests that cited patents are textually similar to the focal patent and some sizeable share of the citations represent knowledge flows that were used in the inventive process.

When a patent makes a backward citation to another patent, I take this as evidence that the technological content of the cited patent was influential in the creation of the citing patent. If product patents generate more knowledge spillovers, then I hypothesize that we should see several facts emerge in the data. First, product patents should be cited more often. Next, if it is easier for rivals to use the new knowledge generated by product innovations, then we should see that it takes a shorter amount of time for the first external firm to cite a

[2] There are also concerns that patent citations are influenced by bureaucratic and strategic considerations on the part of patent examiners, attorneys, and firms. Using granted USPTO patents from 2001-2003, Alcácer et al. 2009 find that 40% of citations were added by patent examiners. Primae facie, it seems that citations added by patent examiners are unlikely to represent genuine knowledge flows. While this may be the case for many examiner citations, Lampe 2012 estimates that 20% of his sample's citations were strategically withheld and then added by the examiner. This suggests many patent examiner citations may indeed reflect knowledge flows.

product innovation where an external firm is simply any firm besides the one who created the patent. To measure time to diffusion, I use the inverse hyperbolic sine (IHS) of the number of days that it takes for another firm (not the firm who introduced the cited patent) to first cite the patent. The IHS transformation approximates a natural logarithm transformation, but allows me to retain zero values. I use the IHS transformation across specifications for consistency of interpretation. These tests are reminiscent of Mansfield 1985 who found that it takes a shorter amount of time for rivals to obtain information about the product innovations of their competitors relative to process innovations. In addition, we should see that a smaller share of the citations are made by the firm that created the cited patent. Smaller self citation shares indicate that the innovation is relatively less useful internally. This fits with the hypothesis that process innovations are more useful internally since they are created around the specific manufacturing processes of a firm and may not be applicable to other competing firms who developed a different technology for production.

My final hypothesis relates to the concentration of citations amongst external firms. Fadeev 2021 documents the stunning fact that the majority of forward citations to highly cited patents come from only one external firm. This concentration of citations exceeds any reasonable expectation if citations were randomly distributed across relevant firms. He goes on to propose that this excess concentration of forward citations indicates greater focal firm control over who uses their knowledge. The argument is that when forward citations are heavily concentrated with one firm, this indicates that the focal firm intentionally shared their knowledge with that firm, theoretically due to complementarities between the firms. As a result, I hypothesize that if firms have less control over who uses their product innovations, then external citations should be less concentrated amongst outside firms. To measure the external concentration of knowledge, I use the share of external citations coming from the most citing external firm.[3] This is similar to the metric used in Fadeev 2021.

I restrict my sample to only include patents that have a non-missing market value as given by Kogan et al. 2017 because that will be a crucial control variable I use in my analysis. This reduces my sample from 1,023,854 patents to 875,364 patents. Table 1 displays summary statistics for the variables used in my analysis. 92% of patents in my sample receive at

[3] An external firm is defined as a firm that is not the firm who is assigned the cited patent.

least one citation. The distribution of citations received is skewed with the average number of citations received being at 18, which is approximately the value at the 75th percentile. Around half of patents are never cited by an external firm and those that are diffuse slowly. On average, it takes patents five years to diffuse to external firms as captured by the first citation from an external firm. On average, 13% of citations are self citations and consistent with the findings in Fadeev 2021, on average half of the external citations made to a patent are made by the most citing external firm. The patents in my sample are valuable with the average market value being approximately $15 million 1982 dollars, as given by the measure in Kogan et al. 2017 which relies on abnormal stock returns of firms around the issuance of a patent.

[Table 1 about here.]

For each of my four hypotheses, I use the outcome variables described above and estimate equations of the following form via OLS:

$$\mathrm{Y}_{pft} = \beta \mathrm{Product}_p + \phi_f + \delta_t + \mathrm{X}_p + \varepsilon_{pft} \tag{1}$$

I observe outcomes Y_{pft}, of patent p, where the patent is assigned to firm f, and applied for in year t. $\mathrm{Product}_p$ is the share of claims that are product innovations for patent p. Firm fixed effects (ϕ_f) make comparisons within firm, removing time-invariant firm heterogeneity. These fixed effects are important to include because firms may have significant heterogeneity in the average number of citations they recieve per patent. If this was systematically correlated with a firm's product/process composition then that would bias estimates of β. Year of application fixed effects (δ_t) remove annual shocks which are particularly important to remove for several reasons. First, recent patents have less time to accumulate citations; year fixed effects address this issue. Second, the product share of innovation has been on a secular upward trend. Without year fixed effects, the combination of these two factors would lead me to compare recent patents (that have higher product shares and lower time for citations to accumulate) with older patents. This has the potential to produce a spurious negative correlation between the product share and the number of citations. X_p is a vector of patent level controls that I include in some specifications. The coefficient β is my coefficient of interest. It captures the average change in outcome Y_{pft} for a patent with a product share of one relative to a patent that has a product share of zero. I cluster standard errors at the firm level to account for correlation in the error term by firm.

Table 2 displays the results. I find evidence in support of all four hypotheses. In column (1) with firm and year fixed effects only, the estimates indicate that product patents are cited approximately 19% more than process patents. One potential explanation of this result is that product patents may inherently have higher value to the firms who create them. If this were true, then the reason that product patents are cited more than process patents could simply be because they are more valuable, not because they generate more knowledge spillovers. To control for the value of the cited patent, I use the natural log of the estimated market value of the patent from Kogan et al. 2017. In addition, the novel content of patents with narrower scope is less likely to be reused since the patent's claims don't span a broad domain of knowledge. If product patents systematically had broader or narrower scope, then this would bias my estimate of whether product patents generate more knowledge spillovers. To measure patent scope, I use the number of independent claims that the patent makes (Marco et al. 2019). Patents with more independent claims have broader scope as their claims cover more intellectual territory. Column (2) reveals that the main result that product patents generate more citations is not driven by systematic differences in patent value or scope. After controlling for the log market value and the number of independent claims the patent makes, the coefficient on the product share decreases slightly but remains large and precisely estimated.

Columns (3) and (4) examine how long it takes for the innovation to diffuse to external firms. Conditional on the patent ever being cited by an external firm, product innovations take approximately 3% less time to be cited by an external firm.[4] Relative to the mean amount of time to the first external citation, this suggests that product innovations diffuse to external firms approximately 2 months faster than process innovations. This is consistent with the findings in Mansfield 1985 that at the median it takes six extra months for the nature and operation of a process innovation to diffuse to rivals, relative to a product inno-

[4]The sample size is halved relative to the main specification since the dependent variable can only be calculated for patents that are cited by an external firm.

vation. Columns (5) and (6) test the hypothesis that a smaller share of the knowledge flows that are created by product innovations are knowledge flows that are internal to the firm. With and without controls, the share of internal citations made to product patents are 1.4 percentage points lower than those of process patents. This constitutes approximately a 10% decline off the mean level of 13%. This indicates that relatively more of the knowledge generated by product patents is used outside the firm who created the patent. Finally, columns (7) and (8) examine the hypothesis that for product innovations external citations are less concentrated amongst external firms. In column (8), with controls, the most citing external firm makes 3.6 percentage points less of the external citations when the cited patent is a product patent. Again, this represents a meaningful effect, a 7% decrease off the mean level of 50%. Since a higher concentration indicates more intentional knowledge sharing (Fadeev 2021), the evidence suggests that fewer of the product innovation knowledge transmissions are intentional. Firms appear to be less able to control who reuses their product innovations.

[Table 2 about here.]

3.2 Text-Based Spillovers

Patent-to-patent citations are not the only way of measuring knowledge flows. Recent advancements in computing power and the proliferation text analysis methods have allowed researchers to use textual clues in patents to infer knowledge flows (Arts, Cassiman, et al. 2018; Pezzoni et al. 2022). This is similar in spirit to the approach of using citations. When a patent has text that is very similar to a previous patent's text, then the probability of a direct or indirect knowledge flow is thought to be higher. In contrast with the citation approach, the patent text approach is more flexible as it allows for both continuous and discrete measures of knowledge flow potential between patents.

My starting point for measuring the dissemination of knowledge using the text of patents is a dataset provided by Arts, Hou, et al. 2021 with all unique keywords[5] of each USPTO patent filed between 1980 and Feburary 2018. Additionally, they provide a list of all novel

[5]"Keywords are taken from the patent's title, abstract, and claims of the patent. Keywords are selected by removing all numbers, one-character words, stop words from the Natural Language Toolkit (NLTK) in the Python library, and words appearing in only one patent. In addition to natural stop words, we remove a manually compiled list of 32,255 very common keywords." (Arts, Hou, et al. 2021).

keyword combinations along with the patents that introduce them. To arrive at this list, they calculate every pairwise combination of keywords for each USPTO patent. Note that the arrangement of keywords in the patent's text does not matter. Novel keywords combinations of a patent are keyword combinations of the patent that have not been used before the patent is filed.[6] I then trace out the diffusion of these novel keyword combinations by identifying the patents in my product/process sample that reuse previously discovered novel keyword combinations. When a patent reuses a novel keyword combination that was previously introduced, I take this as evidence that a knowledge flow took place.

Since my variation between product and process innovations is at the patent level and not the novel keyword combination level, I collapse my analysis down to the patent level. This allows me to reuse specification (1), making the results directly comparable to the patent-to-patent citation results found in Table 2. Summary statistics for the text-based analysis are presented in Table 3. Since some patents have more novel keyword combinations than others, then this will mechanically induce a positive relationship between the novelty of a patent and the number of reuses it obtains. This was similar to the concern that valuable patents will mechanically be cited more, even if they are not generating more knowledge flows. To address this, I scale the total number of reuses of all the patent's novel keyword combinations by the number of novel keyword combinations that the patent has. On average, each novel keyword combination in a patent is reused one time. To measure time to diffusion I calculate the number of days to the first reuse of one of the patent's novel keyword combinations. On average, it takes about 2.5 years for a novel keyword combination of patent to be reused by an external firm, about half of the five years it takes for an external firm to cite a patent. On average, each novel keyword combination of a patent has 36% of its reuses coming from patents within the firm. The concentration of external reuse across firms is quite high, with the average novel keyword combination of a patent having 85% of its external reuses coming from the most reusing external firm.

[Table 3 about here.]

Table 4 displays the results from estimating equation (1) via OLS with the text-based

[6] The keyword combinations of patents filed before 1980 are used to establish a baseline list of keyword combinations.

measures of knowledge spillovers as the dependent variables. In column (1) the dependent variable is the IHS of the average number of reuses per novel keyword combination on a patent. Using the IHS allows me to loosely interpret results as being percentage changes in the dependent variable while still allowing me to account for patents whose novel keyword combination(s) are never reused. Column (1) shows that the novel keyword combinations of product innovations are reused approximately 5% less than those of process innovations. These results are not driven by differences in market value or patent scope, with the point estimate remaining unchanged even with the introduction of those controls. Columns (3)-(6) show that I do not find evidence in support of the hypothesis that the novel keyword combinations of product innovations diffuse faster or are less likely to be reused by the introducing firm. In columns (7) and (8), I find evidence that the concentration of reuse among external firms is lower for product patents than process patents. Similar to the interpretation of Table 2, the results in columns (7) and (8) suggest that firms have less control over which external firms use their product innovations. Although the text-based analysis does not confirm all the results I found using the citation based approach, I view the results as generally supportive of the conclusion that product innovations generate more knowledge spillovers relative to process innovations.

[Table 4 about here.]

3.3 Spillovers Based on Technological Proximity

Citation and text based methods of measuring knowledge spillovers rely on observing direct links between patents that indicate the presence of a knowledge spillover. The next approach to measuring knowledge spillovers does not look for direct evidence of spillovers, but instead measures the potential pool of spillovers available to a firm based on the technological proximity of firms. To implement this approach, I follow the framework of Bloom et al. 2013 (BSV) to test whether product innovations generate more knowledge spillovers than process innovations.

To calculate the potential pool of knowledge spillovers available to a firm, I rely on the intuitive idea that when a firm conducts R&D in an area of technology, that knowledge becomes part of the spillover pool of knowledge that is available to other firms working on the same or similar technologies. As BSV point out, knowledge spillovers are not the only kind of spillovers, the R&D of one firm generates a negative externality through the output market rivalry effect. When a firm conducts R&D, this can steal business from their rivals which inflates the private return to R&D relative to the social return. Correlation between R&D which is available as knowledge spillovers and R&D that generates output market rivalry could bias estimates on the effect of knowledge spillovers. I measure the pool of output market spillovers using the idea that when a firm, who sells their output in a given industry, conducts R&D, firms operating in that same industry experience an output market rivalry effect.

To make this more concrete, consider the case of Apple Inc. and Micron Technology. Apple mainly designs consumer computing devices while Micron designs and produces computer memory. Over the whole time period of my sample (1980-2015) Apple took out 39% of its patents in CPC subclass G06F: "Electric Digital Data Processing." Over this same time period Micron Technology took out 6.5% of its patents in the same subclass (G06F). Given this overlap in patenting activity, it is reasonable to suspect that Apple and Micron are close enough in technological space that if one firm was able to gain access to the other's knowledge they would be able to profitably use that knowledge. Despite this technological overlap, Apple and Micron compete very little in the output market. From 1980-2015, 95% of Micron's sales were in four digit SIC code 3674 (Semiconductors and Related Devices) while Apple did none of its sales in this industry.

I measure how technologically close two firms are by using the distribution of a firm's patents across the 627 CPC subclasses which define broad areas of knowledge that the firm is working in. For each firm, I calculate the vector $T_f = [T_{f1}, T_{f2}, ..., T_{f627}]$ where each element T_{fc} is the share of firm f's patents which fall into CPC subclass c over the 1980-2015 time period. With each firm's location in technological space being defined by this vector of patenting activity, I now need to define a distance metric to capture how close firms are to one another in technological space.

Consider two firms, i and j. One way to measure how similar the two firms' innovation portfolios are would be to simply take the uncentered correlation coefficient between T_i and

T_j, as in Jaffe 1986. While this method is appealing for its ease of computation and simplicity, it does not allow for cross CPC subclass similarities. To illustrate the point consider CPC subclass H01G (Capacitors, rectifiers, detectors, switching devices or light-sensitive devices of the electrolytic type) and H01H (electric switches, relays, selectors, emergency protective devices). These two groups are clearly related to one another but the correlation coefficient would not capture this relationship.

To incorporate these cross group relationships I use the Mahalanobis distance metric (Mahalanobis 1936). The calculation first starts by creating $TECH^J = \tilde{T}'\tilde{T}$ where $TECH^J$ is an N $\times$ N (N is the number of firms in my sample) matrix containing the uncentered correlation between firm's technology share vectors in each element.[7] Next is construction of Ω, which is a 627 $\times$ 627 matrix where each element provides the uncentered correlation between CPC subclass i and CPC subclass j. To create the Ω matrix, I start with matrix $\tilde{X} = [\frac{T_{(:,1)}'}{(T_{(:,1)}T_{(:,1)}')^{1/2}}, \frac{T_{(:,2)}'}{(T_{(:,2)}T_{(:,2)}')^{1/2}}, ..., \frac{T_{(:,627)}'}{(T_{(:,627)}T_{(:,627)}')^{1/2}}]$ where $T_{(:,1)}$ is (1, N) and lists out the patent shares of the first CPC subclass for all firms in the sample. Intuitively, $\tilde{X}$ is the normalized CPC subclass shares across firms. With $\tilde{X}$ in hand, Ω is calculated as $\Omega = \tilde{X}'\tilde{X}$, yielding the uncentered correlation coefficients between CPC subclasses. If CPC subclass i and j frequently coincide within the same firm, then Ω_{ij} will be close to one. The Mahalanobis distance matrix, $TECH^M$, is calculated as $\tilde{T}'\Omega\tilde{T}$. Note that when $\Omega = \mathbb{I}$ we have $TECH^J = TECH^M$. In this case, regardless of whether I use the Mahalanobis distance metric or the uncentered correlation metric, the technological proximity between firms is equal to the uncentered correlation coefficient between their CPC subclass share vector. Each element of $TECH^M$ serves as my measure of how close two firms are to one another in technological space. To capture the fact that two firms may be close in product innovation space but not in process innovation, I calculate $TECH^M$ using only the product (process) patents of each firm, yielding $TECH^{M,PRODUCT}$ ($TECH^{M,PROCESS}$).

While firms may be close in technological space, they may or may not be product market competitors. It is precisely this variation that is useful in distinguishing the output market rivalry effect from knowledge spillovers. To measure the output market proximity of two firms, I use the Compustat Segment database which decomposes firm sales in a given year

[7] $\tilde{T} = [\frac{T_1'}{(T_1 T_1')^{1/2}}, \frac{T_2'}{(T_2 T_2')^{1/2}}, ..., \frac{T_N'}{(T_N T_N')^{1/2}}]$

across four-digit industries. For each firm-year observation in my sample, I compute the vector S_{ft} for firm f in year t where each element is the share of the firm's total sales in year t through year $t-4$ which fall into four-digit SIC industry z. By using five years worth of sales data, this creates a rolling distribution of a firm's sales across industries which allows firms to change in output market space through the 1980-2015 period. I follow Lucking et al. 2019 in using this dynamic measure of a firm's location in output market space as firms can change their output market over time.[8] For each year, I create SIC_t^M which is the Mahalanobis distance matrix where each element captures how close two firms are in output market space in year t. SIC_t^M is constructed in analagous fashion as $TECH^M$, except using rolling industry sales instead of CPC subclass patent counts to allocate shares.

These metrics give me time-invariant measures of how close each firm is to one another in both technological and output market space. I will now describe how I use these time-invariant measures to create time-varying and firm-specific estimates of the pools of knowledge spillovers and output market rivalry R&D. First, for each firm f, I create a stock of both product and process R&D expenditure. To do this, I take the product share of patents for firm f and applied for in year t as a way to allocate R&D spending to product and process spending. While it is true that the fraction of innovative output (patents) may not directly correspond to the inputs (R&D expenditure), I follow BSV in using R&D expenditure as a proxy for a firm's innovative scale. In years where a firm applies for no patents but has positive R&D spending, the mean product share for the firm across all years is imputed in order to allocate their R&D spending. Given these flows of product and process R&D spending, I create stocks of product and process R&D using the perpetual inventory method with the depreciation rate $(\delta) = 0.15$ and the real growth rate $(g) = 0.05$ (Hall et al. 2010).[9]

I measure the stock of product knowledge spillovers available to firm i in year t according to equation (2) which calculates the weighted sum of all other firms' product R&D stocks where the weights are the product technological proximity between firm i and j. These

[8] For example, IBM started out as an IT manufacturer and now mainly sells software services. While it is true that firms can change their location in technological space, I follow Lucking et al. 2019 in using a static measure of a firm's location in technological space since firms are slower to change their technological specialities and patents are sparse for many firms.

[9] These parameters are most commonly used to create R&D stocks. The initial R&D stock is calibrated to be set at the steady state level of $\text{Stock}_0 = \frac{\text{R\&D}_0}{\delta+g}$. After the initial year the stock is calculated as $\text{Stock}_t = \text{R\&D}_t + (1-\delta)\text{Stock}_{t-1}$

weights capture the fact that the R&D spending of firms patenting in similar areas to firm i should be given more weight in measuring the effective pool of technology available to the focal firm. I similarly measure process technology spillovers. Equation (3) displays the corresponding calculation which captures the output market rivalry effect that R&D has on a firm's output market competitors.

$$\text{Spilltech Pdt}_{it} = \sum_{j \neq i} TECH_{ij}^{M,PRODUCT} * \text{Product R\&D Stock}_{jt} \tag{2}$$

$$\text{Spillsic}_{it} = \sum_{j \neq i} SIC_{ijt}^{M} * \text{R\&D Stock}_{jt} \tag{3}$$

Notice that the stock of process and product spillover stocks available to a firm are firm and time specific for two reasons. The time specific nature is due to the fact that both the composition of product and process innovation being done at other firms, j, is changing over time and the level of R&D expenditures is changing (Product R&D Stock$_{jt}$). This time variation is interacted with the firm specific Mahalanobis technological distance between firm j and the focal firm, allowing the knowledge spillover pool to vary at the firm-year level.

With these spillover stocks in hand I would like to estimate how product and process innovation differentially flow to technological peers and impact the innovation decision of a firm. To examine this, I estimate regressions of the following form where ln(Y$_{fzt}$) is the natural log of outcome Y$_{fzt}$, for firm f, in four-digit SIC industry z, and year t:

$$\ln(\text{Y}_{fzt}) = \beta_1 \ln(\text{Spilltech Prs}_{f,t-1}) + \beta_2 \ln(\text{Spilltech Pdt}_{f,t-1}) + \tag{4}$$
$$\beta_3 \ln(\text{Spillsic}_{f,t-1}) + \text{X}_{f,t-1} + \phi_f + \delta_{zt} + \varepsilon_{fzt}$$

ln(Spillsic$_{f,t-1}$) controls for the pool of output market rivalry spillovers that the firm faces. X$_{f,t-1}$ is a vector of controls that includes variables which measure lagged innovative activity of the firm. These variables control for any differential trajectory that firms may be on in their innovative activity. Firm fixed effects remove time-invariant firm heterogeneity across firms and industry by year fixed effects controls for any industry-time varying shocks such as industry-level demand shocks As my main dependent variable, I am interested in measuring how the innovation of a firm responds to the amount of product and process knowledge spillovers available to the firm. The coefficients β_1 and β_2 estimate the elasticity of a firm's innovative activity with respect to changes in the process and product knowledge spillover pool. In the case where product innovations are more effective at creating knowledge spillovers we should observe $\beta_1 < \beta_2$. Estimating equation (4) via OLS will result in biased estimates of β_1 and β_2 due to the endogeneity of other firm's R&D. As firms respond to positive demand shocks, innovative activity and output will increase for the focal firm and for other firms operating in similar technological and output market areas (Acemoglu and Linn 2004). The inclusion of industry (four-digit SIC) by year fixed effects controls for any industry-time varying shocks such as industry-level demand shocks. While this set of fixed effects is quite restrictive, it cannot remove all sources of endogeneity which is likely to bias estimates of β_1 and β_2 upwards.

To address these issues I use an instrumental variables strategy which relies on federal and state R&D tax credits to generate exogenous changes in the user cost of undertaking innovation efforts (Wilson 2009; Lucking et al. 2019). Crucially, changes in the availability of R&D tax credits are assumed to impact the cost of R&D while not changing the benefit. I take data from Lucking et al. 2019 on both the federal and state components of the user-cost of R&D that a firm faces. The federal component is based the interaction between a firm's observable balance sheet characteristics and federal tax treatment of R&D expenditures, while the state level component is based on the lagged ten year moving average of the distribution of a firm's inventors across states.[10] As states change their R&D tax credit policies, firms will vary in their ability to use these credits given their previous distribution of R&D activity across states. To implement this instrumental variables strategy, I regress one plus the log of product or process R&D on the federal and state user costs of R&D, firm fixed effects, and industry-by-year fixed effects. Table A1 presents the results of this, documenting that lower federal or state tax credits (higher user cost) lead to lower product and process R&D spending.

I then predict the value of product or process R&D for each firm-year observation and aggregate these measures into stocks for each firm. Next, I substitute in the predicted value

[10]For a detailed discussion of the construction of these measures see Lucking et al. 2019

of the product or process R&D stock, Product $\widehat{\text{R\&D}}$ Stock$_{jt}$ for Product R&D Stock$_{jt}$ in equation (2) to generate the predicted pool of spillovers available to each firm. The predicted pools of spillovers are then used to instrument for the endogenous pools of spillovers in equation (4).

Table 5 displays the results where I use the empirical strategy outlined in equation (4) and the outcome variable is the IHS of citation weighted patents. Column (1) examines the effect of total technological spillovers on the patenting activity of the firm. The point estimate on the log total knowledge spillover stock is quite large, implying an elasticity of 0.58, but the estimate is imprecisely estimated. The coefficient on the log output market rivalry stock (Spillsic$_{f,t-1}$) is significantly smaller, and also imprecisely estimated. In column (2), I control for lags of the firm's patenting activity, cutting the coefficients in half. In column (3), I instrument for the endogeneous spillover stocks using the strategy outlined previously. I find a very strong first stage relationship and similar estimates as was found in column (2).

In columns (4)-(6) I differentiate between product and process spillovers. Across all three specifications, the coefficient on product spillovers is large, positive and remains statistically significant at conventional levels. This indicates that increasing the size of the available product knowledge spillover pool leads to more innovative output for firms. The point estimates on the pool of process innovation is the opposite, with negative and statistically significant coefficients, even when instrumenting for the spillover pools. The Kleibergen-Paap F-statistic, testing the joint significance of the instruments when the endogenous variables are regressed on the instruments, eliminates concerns for weak instruments. In addition, I can reject the equality of the coefficient on product and process spillovers across all specifications, indicating that the effect of product knowledge spillovers on firm innovative activity is larger than that of process knowledge spillovers.

[Table 5 about here.]

In Table 6 and Table 7, I examine whether this finding differs when product or process citation weighted patenting is the dependent variable. When citation weighted product patenting is the dependent variable, I find similar results using my preferred specification in column (6). When process innovation is the dependent variable, the results are noisier and I am not able to distinguish between the effects of product and process spillovers with precision. Although the approach to measuring knowledge spillovers is quite different from using citations or patent text, the findings in this section suggest that product innovations are much more likely to flow to technological peers and spark the creation of new innovations.

[Table 6 about here.]

[Table 7 about here.]

4 Heterogeneity

4.1 Novelty

Now that I have laid out the evidence that product patents generate more knowledge spillovers than process patents, I turn to examining what characteristics strengthen or weaken this effect. To do this, I return to the citation and text based empirical strategy which will allow me to use patent-level heterogeneity in the analysis. I first examine whether the gap in knowledge spillover generation between product and process innovation changes as patents become more novel. Since product innovations are more easily reverse-engineered, we may expect that the gap between product and process spillovers widens as patents become more novel. This would be consistent with a story where novel product patents could be reverse-engineered, albeit with slightly more difficulty than incremental product innovations. On the other hand, a novel process innovation would be very difficult to obtain information about, whereas an incremental process innovation would be much easier to learn about, either through the patent text or the inventors themselves.

To test if this is the case, I augment equation (1) by fully interacting a measure of novelty with the product share of the patent. The coefficient on the interaction term between the product share and novelty measure reveals whether the gap in knowledge spillovers between product and process innovations differs as the novelty measure changes. My first proxy is a text-based measure of novelty taken from Arts, Hou, et al. 2021. The measure is constructed by starting with the average cosine similarity of the focal patent's text with all other patents filed in the five years before the focal patent. To calculate cosine similarity, each patent is represented as a vector of 1,362,971 dimensions where each dimension corresponds to one keyword from the entire patent corpus and its value captures the frequency of this keyword in the particular patent document. Since novel patents will have text that is very dissimilar to previous patents, I use one minus this measure of backward similarity as my metric of textual novelty.

My second measure of novelty captures a different dimension of novelty. I use the "Rapidly Evolving Technology" (RETech) metric from Bowen III et al. 2022 which measures whether the patent pertains to a technological area that is rapidly evolving or stable. To capture this, they measure the intensity with which a patent's vocabulary is growing in use across all recent and contemporary patents. The RETech measure is high if a patent uses vocabulary that is growing rapidly in the patent corpus overall. This measure says less about the novelty of the particular patent, but instead relates more to whether the patent is in a novel and growing area of technology.

Table 8 displays the results from estimating equation (1) with the IHS of patent citations and the IHS of the average number of reuses per novel combination being the dependent variables. These two outcomes are used since they provide the most direct measures of the number of knowledge spillovers a patent creates. In columns (1) and (3), I fully interact the product share with the measure of textual novelty described above. In column (1) when the citation based measure of knowledge flows is the dependent variable, I find that the gap between the number of citations a product and process innovation create increases by approximately five percentage points for every standard deviation increase in textual novelty. In column (3) when I used the text-based measure of knowledge flows, I obtain a similarly sized and positive point estimate. The results suggest that relative to process patents, product patents generate even more knowledge spillovers when they are more novel. This is consistent with firms being able to reverse-engineer product innovations, regardless of their novelty, while process innovations become even more difficult to gain information about as they become more novel.

In columns (2) and (4), I test whether the gap between product and process spillovers is different for patents that are in rapidly evolving technological areas. As new domains of technology form, we may expect that firms focus on product innovations at the expense of process innovations. This is because firms would be hesitant to invest in process innovation when the technological area may quickly change and render their process innovation obsolete. Utterback and Abernathy 1975 and Klepper 1996 find evidence in favor of this view, showing that firms begin their life with product innovation but gradually increase their process innovation over the life cycle. Using the citation and text-based measures of knowledge spillovers, I find that the gap between the number of knowledge flows a product and process innovation creates increases by approximately three to four percentage points for every standard deviation increase in the RETech measure. This is consistent with the view that firms place emphasis on process innovation in stable and established technologies.

[Table 8 about here.]

4.2 Firm Size

Firm size plays an important role in the product/process innovation decision of a firm (Cohen and Klepper 1996). Ornaghi 2006 also find evidence that size plays a role in knowledge diffusion, arguing that knowledge flows primarily from small firms to large firms. To test if firm size plays a role in magnifying or weakening the gap between product and process spillovers, I follow a similar approach as the one used in Section 4.1, but I fully interact the product share with measures of firm size instead of novelty. My measures of firm size are the log number of employees and the log of assets at the firm in the year the patent was applied for. As before, I standardize these measures to have mean zero and standard deviation of one for ease of interpretation and comparability. Columns (1) and (2) of Table 9 display results when a citation-based measure of knowledge spillovers is the dependent variable. Whether using employment or assets to measure firm size, I find precisely estimated null effects on the interaction between the product share and firm size measure. This indicates that relative to process patents, product patents do not generate different amounts of citations for large firms. Using text-based measures of knowledge flows in columns (3) and (4) yields similar results. The results suggest that firm size plays no direct role in explaining that product innovations generate more knowledge spillovers than process innovations.

[Table 9 about here.]

5 Conclusion

This paper addresses the question of whether product or process innovations generate more knowledge spillovers. Using three distinct empirical approaches, I find evidence that product innovations generate more knowledge spillovers than process innovations. This gap in product and process spillovers widens for innovations that are novel or occurring in rapidly evolving areas of technology. Preferential policy towards innovation, such as R&D tax credits, is justified on the grounds that knowledge spillovers cause the social benefits from innovation exceed the private benefits, a classic example of a market failure. My results indicate that this market failure is worse for product innovations where the gap between the social and private value is wider than the gap for process innovations. This suggest that broad based R&D tax credits which do not account for product and process heterogeneity are likely sub-optimal.

While my findings suggest that product innovations generate more knowledge spillovers than process innovations, a richer understanding of the topic would include research on whether product or process innovation are substitutes or complements. If product and process innovations were complementary, then it would be difficult for policy to change the product/process composition without having a detrimental effect on the total amount of innovation occurring in the economy. On the other hand, if the two types of innovation are substitutes, then it would be easier to effectively change the product/process composition. An answer to the question of whether the two forms of innovation are complements or substitutes would give us more insight into whether it is optimal to provide more generous support for product R&D as opposed to treating product and process R&D equally. It would also give us valuable information on how changes to the product/process composition would alter the innovative ecosystem.

Embedding the insights from this paper and any subsequent empirical work on the topic into a model that could assess optimal tax policy would be a valuable contribution as it would allow us to properly assess the welfare implications of favoring product R&D over process R&D. This project makes an important step forward in providing answers to these questions by documenting that product innovations generate more knowledge spillovers than process innovations.

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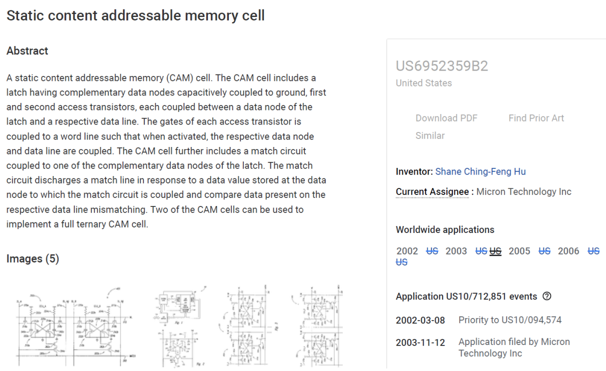
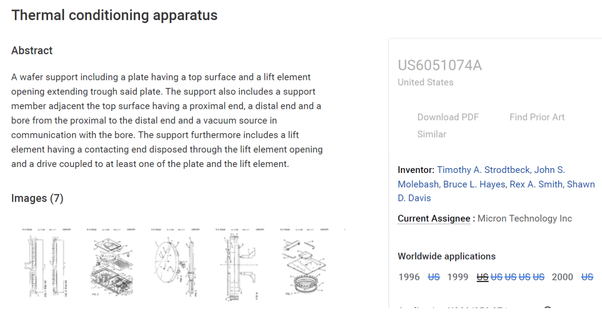
Figure 1: Three "Micron Technology" Patents

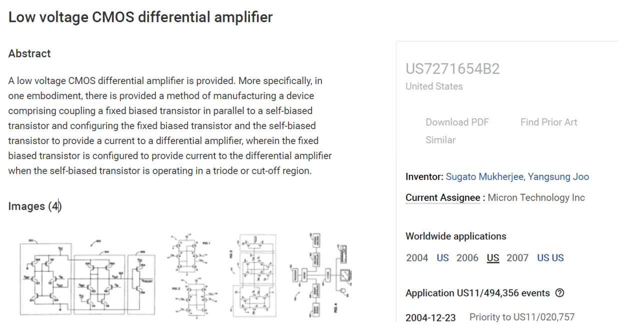
(a) Product



(b) Process



(c) Product & Process



Notes: This figure depicts the Google Patents webpages for three Micron Technology patents. Panel (a) depicts a product patent, US6952359. Panel (b) depicts a process patent, US6051074. Panel (c) depicts a patent that contains both product and process innovations, US7271654.

Table 1: Summary Statistics for Citation Analysis

	Mean	St. Dev.	25%	75%	Obs
$\mathbb{1}\{\text{Cites} > 0\}$	0.92	0.27	1.00	1.00	875,082
Cites	18.25	37.02	3.00	20.00	875,082
Years to First Citation	5.34	4.89	2.07	6.92	426,622
Share Citations Own Firm	0.13	0.23	0.00	0.17	782,769
External Concentration	0.50	0.28	0.28	0.67	748,082
Market Value, 1982 (million)	15.11	37.62	2.78	13.61	875,082
# Independent Claims	2.88	2.15	2.00	3.00	875,082

Notes: is table presents summary statitistics for variables relevant to the citation analysis. $\mathbb{1}\{\text{Cites} > 0\}$ is an indicator for whether the patent is ever cited by any patents, the citing patent does not need to be a part of the product/process sample. Cites is the number of citations the patent receives from all patents (the patents do not need to be in the product/process sample). "Years to First Citation" measures the number of years it takes for the first external firm (a firm besides the firm originating the patent) to make a citation. Only citations made by firms in the product/process sample are considered. "Share Citations Own Firm" is defined as the share of citations coming from the firm assigned to the patent (all citations are considered). "Competitor Concentration" is defined as the share of citations coming from the most citing external firm (only citations in the product/process sample are considered). Market Value 1982 (million) $ is the real market value of a patent in millions of 1982 dollars, taken from Kogan et al. 2017. # Independent Claims is the number of independent publication claims that the patent has.

Table 2: Citation Based Process Innovation Spillovers

	ihs(Cites)		ihs(Days to First Citation)		Share Citations Own Firm		External Concentration	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Product	0.192***	0.168***	-0.029**	-0.027**	-0.014***	-0.014***	-0.039***	-0.036***
	(0.017)	(0.017)	(0.013)	(0.013)	(0.005)	(0.005)	(0.002)	(0.002)
ln(MV)		0.062***		-0.020**		0.006***		-0.006***
		(0.009)		(0.009)		(0.002)		(0.001)
ln(Claims)		0.206***		-0.022***		-0.001		-0.026***
		(0.009)		(0.004)		(0.002)		(0.001)
Obs	875,082	875,082	426,300	426,300	782,769	782,769	748,082	748,082
$\overline{\text{Y}}$					0.13	0.13	0.50	0.50

Notes: The sample includes all patents in my product/process sample with non-missing control variables. "Product" is the share of independent claims that are categorized as product innovations. ihs(Cites) is the inverse hyperbolic sine of the number of citations the patent has received. ihs(Days to First Citation) is the IHS of the number of days it took for the patent to receive its first external citation. External citations are made by firms other than the firm granted the patent. "Share Citations Own Firm" is the share of citations where the cited and citing patent are assigned to the same firm. "External Concentration" is defined as the share of external citations going to the most citing external firm. Across the reuse measure, only patents in the product/process sample are considered except in the case of ihs(Cites), for this variable all citations received are used. $\overline{\text{Y}}$ is the dependent variable mean. Firm and year fixed effects of the introducing assignee are included in all regressions. Standard errors are clustered by the at the firm level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table 3: Summary Statistics for Text-Based Analysis

	Mean	St. Dev.	25%	75%	Obs
# Novel Combos	153.03	2,814.42	2.00	74.00	864,619
# Reuses per Novel Combo	1.00	5.36	0.03	1.00	694,971
Years to First External Reuse	2.59	3.46	0.39	3.38	487,032
Share Reuses Own Firm	0.36	0.39	0.00	0.75	544,487
External Concentration	0.85	0.16	0.75	1.00	486,711

Notes: This table presents summary statistics for variables relevant to the text-based analysis. # Novel Combos is the number of novel keyword combinations the patent introduces. # Reuses per Novel Combo is the average number of reuses each novel keyword combination on the patent has (only defined for those patents that have novel keyword combinations). "Years to First Reuse" measures the number of years it takes for the novel keyword combination to be reused by a firm other than the firm assigned to the introducing patent. "Share Reuses Own Firm" is defined as the share of patents reusing the novel keyword combination that were granted to the introducing patent firm. "External Concentration" is defined as the share of external reusing patents of the most reusing external firm where. An external firm is any firm in the product/process sample and not the same firm as the firm assigned to the introducing patent. Across the reuse measures, only patents in the product/process sample are considered.

Table 4: Text Based Spillovers

	ihs(Reuse per Novel Combo)		ihs(Days to First Reuse)		Share Reuses Own Firm		Competitor Concentration	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Product	0.050***	0.050***	-0.025	0.001	0.002	0.004	-0.013***	-0.013***
	(0.010)	(0.010)	(0.031)	(0.031)	(0.007)	(0.007)	(0.001)	(0.001)
ln(MV)		0.019***		-0.022*		0.004		-0.002**
		(0.005)		(0.012)		(0.003)		(0.001)
ln(Claims)		-0.002		-0.241***		-0.019***		-0.003***
		(0.004)		(0.011)		(0.003)		(0.001)
Observations	694,971	694,971	486,711	486,711	544,487	544,487	486,711	486,711
$\overline{\mathrm{Y}}$					0.36	0.36	0.85	0.85

Notes: ihs(Reuse per Novel Combo) is the inverse hyperbolic sine of the number of average number of reuses per novel keyword combination on the patent. ihs(Days to First Reuse) is the inverse hyperbolic sine of the number of days it takes for the first novel keyword combination of a patent to be reused by a firm other than the firm assigned to the introducing patent. "Share Reuses Own Firm" is defined as the average share of patents reusing the novel keyword combination that were granted to the introducing patent firm across a patent's novel keyword combinations. "Competitor Concentration" is defined as the average share of external reusing patents of the most reusing external firm across novel keyword combinations. An external firm is any firm in the product/process sample and not the same firm as the firm assigned to the introducing patent. Across the reuse measures, only patents in the product/process sample are considered. Firm and year fixed effects of the introducing assignee are included in all regressions. Standard errors are clustered by firm shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table 5: Innovation and Product/Process Technological Spillovers

	ihs(CW Patents)					
	(1) OLS	(2) OLS	(3) IV	(4) OLS	(5) OLS	(6) IV
$\ln(\text{Spilltech}_{t-1})$	0.584	0.274	0.241			
	(0.548)	(0.364)	(0.408)			
$\ln(\text{Spilltech Pdt}_{t-1})$				1.969***	1.219**	1.637***
				(0.721)	(0.473)	(0.572)
$\ln(\text{Spilltech Prs}_{t-1})$				-1.106**	-0.782**	-1.093**
				(0.520)	(0.355)	(0.448)
$\ln(\text{Spillsic}_{t-1})$	0.074	0.036	0.049	0.025	0.007	0.009
	(0.098)	(0.066)	(0.066)	(0.099)	(0.066)	(0.066)
$\ln(\text{Pdt Cites}_{t-1})$		0.309***	0.308***		0.308***	0.307***
		(0.014)	(0.014)		(0.014)	(0.014)
$\ln(\text{Prs Cites}_{t-1})$		0.180***	0.180***		0.180***	0.180***
		(0.013)	(0.013)		(0.013)	(0.013)
$\mathbb{1}\{\text{No Patent}_{t-1}\}$		-0.015	-0.012		-0.018	-0.018
		(0.048)	(0.048)		(0.048)	(0.048)
p-value ($H_0 : \beta_1 = \beta_2$)				.004	.005	.002
F-Stat			1,500.9			282.2
Observations	20,673	20,673	20,673	20,673	20,673	20,673

Notes: The dependent variable is the inverse hyperbolic sine of the number of citation weighted patents firm f applies for in year t. The spillover measures are constructed according to equation (2) and (3). The spillover measures are instrumented with the instrumental variables constructed according to the description in the text. Standard errors are clustered by the at the firm level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table 6: Product Innovation and Product/Process Technological Spillovers

	ihs(CW Pdt Patents)					
	(1) OLS	(2) OLS	(3) IV	(4) OLS	(5) OLS	(6) IV
ln(Spilltech$_{t-1}$)	0.944*	0.584	0.526			
	(0.524)	(0.355)	(0.398)			
ln(Spilltech Pdt$_{t-1}$)				0.844	0.464	2.299**
				(1.059)	(0.734)	(1.154)
ln(Spilltech Prs$_{t-1}$)				0.150	0.154	-1.436
				(0.847)	(0.601)	(0.895)
ln(Spillsic$_{t-1}$)	0.105	0.076	0.089	0.104	0.075	0.096
	(0.103)	(0.071)	(0.073)	(0.103)	(0.071)	(0.073)
ln(Pdt Cites$_{t-1}$)		0.304***	0.304***		0.304***	0.303***
		(0.015)	(0.015)		(0.015)	(0.015)
ln(Prs Cites$_{t-1}$)		0.173***	0.173***		0.173***	0.173***
		(0.013)	(0.013)		(0.013)	(0.013)
$\mathbb{1}\{$No Patent$_{t-1}\}$		-0.022	-0.020		-0.021	-0.028
		(0.047)	(0.047)		(0.047)	(0.048)
p-value ($H_0 : \beta_1 = \beta_2$)				.706	.81	.064
F-Stat			1,204.2			168.9
Observations	20,685	20,685	20,685	20,685	20,685	20,685

Notes: The dependent variable is the inverse hyperbolic sine of the number of citation weighted patents firm f applies for in year t. The spillover measures are constructed according to equation (2) and (3). The spillover measures are instrumented with the instrumental variables constructed according to the description in the text. Standard errors are clustered by the at the firm level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table 7: Process Innovation and Product/Process Technological Spillovers

	ihs(CW Prs Patents)					
	(1) OLS	(2) OLS	(3) IV	(4) OLS	(5) OLS	(6) IV
ln(Spilltech$_{t-1}$)	1.360***	1.065***	1.473***			
	(0.413)	(0.296)	(0.341)			
ln(Spilltech Pdt$_{t-1}$)				0.614	0.360	1.024
				(0.818)	(0.585)	(0.979)
ln(Spilltech Prs$_{t-1}$)				0.711	0.666	0.461
				(0.653)	(0.476)	(0.791)
ln(Spillsic$_{t-1}$)	-0.025	-0.036	-0.012	-0.027	-0.038	-0.013
	(0.094)	(0.069)	(0.071)	(0.094)	(0.070)	(0.071)
ln(Pdt Cites$_{t-1}$)		0.141***	0.141***		0.142***	0.141***
		(0.010)	(0.010)		(0.010)	(0.010)
ln(Prs Cites$_{t-1}$)		0.242***	0.242***		0.242***	0.242***
		(0.016)	(0.016)		(0.016)	(0.016)
$\mathbb{1}\{$No Patent$_{t-1}\}$		0.031	0.036		0.034	0.038
		(0.033)	(0.033)		(0.033)	(0.033)
p-value ($H_0 : \beta_1 = \beta_2$)				.95	.764	.746
F-Stat			1,204.2			168.9
Observations	20,685	20,685	20,685	20,685	20,685	20,685

Notes: The dependent variable is the inverse hyperbolic sine of the number of citation weighted patents firm f applies for in year t. The spillover measures are constructed according to equation (2) and (3). The spillover measures are instrumented with the instrumental variables constructed according to the description in the text. Standard errors are clustered by the at the firm level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table 8: Heterogeneity by Novelty

	ihs(Cites)		ihs(Reuse Per Novel Combo)	
	(1)	(2)	(3)	(4)
Product	0.170***	0.170***	0.047***	0.039***
	(0.018)	(0.019)	(0.008)	(0.010)
Text Novelty	-0.067***		0.019***	
	(0.011)		(0.006)	
Product × Text Novelty	0.051***		0.041***	
	(0.014)		(0.006)	
RETech		0.011		0.039***
		(0.009)		(0.006)
Product × RETech		0.034**		0.038***
		(0.014)		(0.006)
ln(MV)	0.063***	0.062***	0.018***	0.019***
	(0.009)	(0.009)	(0.005)	(0.005)
ln(Claims)	0.201***	0.201***	0.002	-0.006
	(0.009)	(0.010)	(0.004)	(0.004)
Observations	694,965	694,965	694,965	694,965

Notes: ihs(Cites) is the inverse hyperbolic sine of the number of citations the patent has received. ihs(Reuse per Novel Combo) is the inverse hyperbolic sine of the number of average number of reuses per novel keyword combination on the patent. RETech is taken from Bowen III et al. 2022 and measures whether the patent pertains to a technological area that is rapidly evolving (i.e., following breakthroughs) or stable. Text novelty is taken from Arts, Hou, et al. 2021 and measures one minus the average cosine similarity between the focal patent and all other patents filed in the five years before the focal patent. Both measures are winsorized at the 1st and 99th percentiles and standardized to have mean zero and standard deviation one. Firm and year fixed effects of the introducing assignee are included in all regressions. Standard errors are clustered by firm and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table 9: Heterogeneity by Firm Size

	ihs(Cites)		ihs(Reuse Per Novel Combo)	
	(1)	(2)	(3)	(4)
Product	0.177***	0.177***	0.051***	0.050***
	(0.018)	(0.017)	(0.010)	(0.010)
ln(Emp)	-0.195***		-0.135***	
	(0.052)		(0.036)	
Product × ln(Emp)	0.001		-0.010	
	(0.016)		(0.008)	
ln(Assets)		-0.161***		-0.141***
		(0.049)		(0.027)
Product × ln(Assets)		-0.003		-0.003
		(0.023)		(0.008)
ln(MV)	0.063***	0.066***	0.019***	0.022***
	(0.009)	(0.009)	(0.004)	(0.004)
ln(Claims)	0.203***	0.204***	-0.003	-0.003
	(0.010)	(0.010)	(0.004)	(0.004)
Observations	674,604	674,604	674,604	674,604

Notes: ihs(Cites) is the inverse hyperbolic sine of the number of citations the patent has received. ihs(Reuse per Novel Combo) is the inverse hyperbolic sine of the number of average number of reuses per novel keyword combination on the patent. Firm and year fixed effects of the introducing assignee are included in all regressions. Standard errors are clustered by firm and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

A Appendix

[Table A1 about here.]

Table A1: Predicting Product and Process R&D with Tax Credits

	(1) ln(1 + Product R&D)	(2) ln(1 + Process R&D)
ln(Federal Tax User Cost)	-3.798***	-1.742***
	(0.512)	(0.666)
ln(State Tax User Cost)	-0.506***	-0.610***
	(0.151)	(0.177)
Joint F-test of the tax credits	33.03	9.51
Observations	23,357	23,357

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$