# 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).

*Keywords*: Knowledge Spillovers, Knowledge Diffusion, Product and Process Innovation, Patents, Corporate R&D

# 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 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.

Product and process innovations have different information properties, which may cause them to generate different amounts and types of knowledge spillovers (Kraft 1990; Kotabe and Murray 1990). Uncovering differences in the knowledge spillovers generated by product and process innovations would have a wide range of implications for optimal innovation policy and firm strategy. Despite the importance of the topic, we have relatively sparse evidence on the nature of the knowledge spillovers that products and processes create.

This paper addresses this gap in the literature and provides novel evidence that product innovations generate more knowledge spillovers than process innovations. I use data from Davison 2023; Davison 2025, which distinguishes patents as product or process innovations for all patents granted to U.S. manufacturing firms from 1980-2015. My primary measure of knowledge flows is patent-to-patent citations (Jaffe, Trajtenberg, and Henderson 1993). I find that patents with a higher product innovation intensity generate more citations relative to patents which are more process oriented, indicating that product patents create more knowledge spillovers. My results are robust to a wide variety of tests including limiting to citations which are more likely to represent knowledge flows and using a text-based measure of knowledge flows. Given that product innovations have been hypothesized to be more externally focused, I test whether product patents are more likely to diffuse to a broader set of external firms. Although the effects are small in magnitude, I find that product patents are less intensively reused internally and diffuse to a broader set of firms. The results suggest that product patents do not simply create more knowledge spillovers, but the knowledge they create diffuses to a broader set of external firms.

Next, I show that product and process patenting not only impact the quantity of follow-on innovation, but they also alter the nature of cumulative innovation. Given that product innovations more often diffuse to rivals, leading to imitation, I hypothesize that innovations which build upon a product innovation are less novel. In support of this, I find that the patents which build upon product patents are more textually similar to the patent corpus from the preceding five years. The finding suggests that product innovation generates more follow-on innovations which are imitations or incremental improvements to products. This helps provide additional context to the result that product innovations generate more knowledge spillovers. While the quantity of knowledge spillovers from product patents is greater, the spillovers generate less novel follow-on innovation.

Finally, I examine how a firm's product life cycle interacts with these effects. I find evidence which supports my hypothesis that at the beginning of the product life cycle during the "product development" stage, product innovations generate a moderate amount of knowledge spillovers, while the amount of knowledge spillovers a given product innovation generates reaches its nadir in the "process optimization" and "product decline" stages and hits its zenith in the "mature product" stage. These results highlight that it is not universally true that product innovations generate more knowledge spillovers than process innovations. The finding is dependent on factors such as the location of the originating firm in their product life cycle.

This work builds on the literature concerned with empirically measuring the impact of knowledge spillovers (Griliches 1992; Bloom et al. 2013; Zacchia 2020; Myers and Lanahan 2022). 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 (Nelson 1959). My research deepens our understanding of knowledge spillovers by examining how different types of innovation generate alter the quantity and quality of knowledge spillovers.

More specifically, my results contribute to the literature which has examined the difference in knowledge spillovers between product and process innovation. Ornaghi 2006 uses data from Spanish manufacturing firms and finds that generic knowledge spillovers (not split into product and process spillover pools) have a larger positive effect on demand for the firm's products than on increasing the efficiency of production. While Ornaghi 2006 measures the effect of overall knowledge spillovers on proxies for product and process innovation[1], this study examines the differences in spillovers generated by product and process innovations. I enrich our understanding of the spillovers that products and processes create by showing that product innovations tend to produce cumulative innovations that are much more similar to the innovation being built upon. 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. I contribute to the findings of Mansfield 1985 by showing that product innovations not only diffuse faster but they more often built upon by external firms as opposed to internal self-building and they diffuse to a broader set of external firms.

## 2 Conceptual Framework

One way to think about the difference between a product and process patent is the orientation of the patent. Product patents are oriented externally, that is, towards the customer, as the ultimate goal of the firm is to sell the product for a profit (Scherer 1984). On the other hand, process patents are oriented inward, as the goal of the firm is to improve their own process of production (Scherer 1984).

Since product innovations can be purchased, they are subject to the possibility that they will be reverse-engineered. While not all products equally lend themselves to being reverse-engineered, reverse-engineering is a common practice, especially for firms in developing economies who are catching up to the technological frontier (Malik and Kotabe 2009; McMahon and Thorsteinsdóttir 2013; Zhang, Zhu, et al. 2023; Miao et al. 2018; Chadha

[1] Ornaghi 2006 measures how knowledge spillovers impact production efficiency and demand which are respectively assumed to be impacted by product and process innovation. Process innovation is assumed to drive efficiency while product innovation is assumed to increase demand.

2009). Reverse-engineering not only allows firms to imitate one another, but it also creates a knowledge base which can be drawn upon to produce novel innovations (Zhang and Zhou 2016; Zhang, Zhu, et al. 2023).

It is possible that product imitation and reverse-engineering would become so common in an industry that firms have little incentive to engage in internal R&D because the firm is unable to effectively enforce property rights over their innovation (Arrow 1962; Audretsch and Belitski 2022). Further, if knowledge spillovers are high within an industry, a firm may find it more cost-efficient to source their knowledge from spillovers rather than internal R&D (Denicolai et al. 2016; Audretsch and Belitski 2023). At the limit, this may suggest that high levels of knowledge spillovers in an industry would lead to less follow-on innovation even though knowledge is freely available to build upon. Thus, if either product or process innovations had higher external knowledge flows, this might not necessarily translate into increased cumulative innovation.

While this chilling effect of knowledge spillovers on the incentive to innovate exists, the literature has identified mechanisms that counteract this effect and shown the necessity of firms relying on both internal and external knowledge (Antonelli and Colombelli 2015). First, there are transaction costs associated with the use of external knowledge as firms need to coordinate different pieces of knowledge embedded across their organization (Camacho 1991; Audretsch and Belitski 2023; Saura et al. 2023). Second, firms need to be actively engaged in R&D to be able to absorb external knowledge (Cohen and Levinthal 1990; Zahra and George 2002; Grimpe and Kaiser 2010). Third, firms who rely too much on knowledge spillovers which are available to rivals risk losing their uniqueness in the market as the capacity of the firm to create novel products and processes is "diluted" (Grimpe and Kaiser 2010). These forces increase the cost of absorbing knowledge spillovers and ensure that firms stay actively engaged in R&D, even if the risk of unwanted knowledge spillovers is high. Finally, firms can benefit from knowledge spillovers as recipient firms (those who build on the spilled knowledge) provide information to the originating firm about what types of knowledge can be combined with the original knowledge to create something novel (Belenzon 2012; Yang and Steensma 2014). This positive effect of knowledge spillovers for the firm originating the knowledge also helps to ensure that even with weak property rights over their knowledge, firms see benefit from internal R&D.

While new products themselves are more visible, by virtue of being for sale, the patent system is based on the idea of disclosure. The exchange offered by patent offices is that inventors publicly disclose the details of their invention in exchange for exclusive rights to their invention for a set period of time. To the extent that the disclosure function of patents is functioning as intended, the technological content of either a product or process patent should be available to external parties through what is disclosed in the patent. While there is evidence that the patent system does promote disclosure (Furman et al. 2021), there is also evidence suggesting that the disclosure effect of patents is small (Hall et al. 2010) and imperfect ("The Disclosure Function of the Patent System (Or Lack Thereof)" 2005). This suggests that while the disclosure function of patents exists, it is not likely enough to eliminate any visibility gap between product and process patents. The increased visibility of product patents, the frequency with which they are reverse-engineered, and the imperfect disclosure of patents, leads me to my first hypothesis:

**Hypothesis 1:** *Product patents generate more knowledge spillovers than process patents.*

While Hypothesis 1 posits that product and process patents generate differing quantities of knowledge spillovers, these two types of patents may also lead to qualitative differences in the types of innovations created. (Mansfield et al. 1981) shows that the imitation of competitor products is a common practice with Cappelli et al. 2014 showing that spillovers from rivals lead to more imitation. The source of knowledge spillovers also affects whether a firm engages in product or process innovation, with Antonelli and Fassio 2016 showing that knowledge from rivals pushes a firm to product innovation while knowledge from vertically upstream sources leads to process innovation. Taken together, these studies suggest that, relative to process innovations, product innovations more often originate from the technologies of competitors, resulting in innovations that disproportionately tend to mimic those of the competition. This leads me to Hypothesis 2:

**Hypothesis 2:** *On average, innovations which build upon a product innovation are less novel relative to the innovations that build on a process innovation.*

The firm's life cycle is known to directly affect the incentive for the firm to engage in product and process innovation. Utterback and Abernathy 1975 theorize that product innovation will be high at the beginning of the product life cycle when the product is nonstandard and its technical functionality is being refined. As the product becomes standardized and more competition takes place, there is increasing focus on cost minimization and product innovation gives way to process innovation. On the other hand, there is little process innovation at the beginning of the life cycle as the product has not been refined and is being produced in small quantities. As competition increases and the product becomes standardized, firms increasingly focus on process innovation as they seek to lower their costs and take advantage of their growing scale. The focus on process innovation is only justifiable at later stages in the product life cycle when uncertainty about the product is low enough that the risk of creating dedicated processes around a product's design are profitable in expectation (Vernon 1966). Once the product is mature, both the product and the production process are highly developed and integrated, making any alterations to the production process costly. In this stage, process innovation falls from its peak but remains above the low levels seen at the beginning of the life cycle (Utterback and Abernathy 1975).

The life cycle of a firm may also impact how the knowledge a firm creates diffuses to others. Most models of the product life cycle start with a new product category that is made available through technology or some other exogenous change (Klepper 1996). At this product development stage, there is uncertainty regarding consumer preferences about the product (Clark 1985). The combination of a new opportunity and uncertainty about which product design will "win" leads to significant entry in the market as firms look to find the dominant product design (Klepper 1997). The strong incentive firms have to find the dominant design suggests that when a firm generates a new product innovation in the early stages of the product life cycle there will be a significant amount of innovation built on top of it. On the other hand, the uncertainty around the dominant design may chill follow-on innovation as others may be fearful of building upon an innovation that ultimately may not become the dominant design. Taken together, this suggests that there will be a moderate amount of follow-on product innovation in the early stages of the product life cycle.

During the next stage of process optimization, uncertainty about the dominant design is rapidly reduced and the firms with the dominant design(s) are focused on achieving economies of scale and process innovation. During this period, the winning firms are focused less on product innovation, and the firms who missed the dominant design quickly become unable to catch up as they cannot achieve a large enough scale to have competitive costs. As a result, a given product innovation should have less follow-on product innovation in this stage as other firms are more interested in building on the process innovations of others.

In the next phase when the product enters maturity, firms are focused on incremental and steady product innovations that help them maintain their market leadership position without generating too much risk to their current business. During this phase, the product converges to its dominant design and firms place a priority on learning from and reverse-engineering the products of rivals. Given that this stage is characterized by incremental innovation, consolidation, and a dominant design, firms are highly incentivized, in this stage, to build upon the product innovations of others to stay one step ahead of their competition without incurring too much risk. Finally, in the last stage of the life cycle, firms are relatively uninterested in building on products which are in decline, leading to low levels of follow-on innovation for every given product innovation. I summarize my hypotheses about how the firm's product life cycle will impact the follow-on innovation differences between product and process innovation in Hypothesis 3:

**Hypothesis 3:** *A firm's life cycle moderates the effect of product share on knowledge spillovers, with the gap between product and process patent spillovers widening for patents created in the new and mature product stages and narrowing for patents in the process innovation and product decline life cycle stages.*

# 3 Data

The data supporting this article is based on the Economically Based Product Process Dataset (EPP) (Davison 2023; Davison 2025). The EPP classifies the claims of patents assigned to publicly traded U.S. manufacturing firms as product or process claims. These claims are then aggregated to the patent level to get the share of claims which are product claims. It is important to point out that the EPP classifies individual claims as product or process claims, so that patents are often not wholly product or process patents as it is a common occurrence that patents will introduce an innovative method of manufacturing, along with a new product that can be created with the manufacturing process[2]. As the claims of the patent are the individual components of the innovation that are legally protected, the share of claims which are product or process claims naturally measures to what extent a patent is a product or process patent.

I take the measure of the product claim share for each patent provided by the EPP, and I merge it with the DISCERN database to get information on the firm assigned to the patent (Arora et al. 2020; Arora et al. 2021). Combining this with the USPTO PatentViews database provides forward citations (patents which provide backward citations to EPP patents) and backwards citations (the patents which EPP patents cited). Data from Kogan et al. 2017 provide information on the market value of each patent based on abnormal stock market returns around the time of the patent. Arts et al. 2021 provides a text-based measure of novelty which I use to construct an alternative measure of knowledge flows relative to patent citations. I also use the text-based measure of novelty to test Hypothesis 2. Hoberg and Maksimovic 2022 provide data on the location of firms in the life cycle through a text analysis of public financial documents which I use to test Hypothesis 3.

# 4 Empirical Strategy

My primary approach to testing whether product patents generate more knowledge spillovers than process patents uses patent-to-patent citations as a measurement of knowledge flows (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. Thus, if product patents garner more citations on average, then this suggests that they generate more knowledge flows and cumulative innovation.

Since Jaffe, Trajtenberg, and Henderson 1993 introduced patent citations as a measure of knowledge flows, there have been many studies examining whether patent-to-patent citations

[2] See U.S. Patent 7271654 as an example.

can be properly interpreted as knowledge flows. Jaffe, Trajtenberg, and Fogarty 2000 relied on a survey of inventors to show that ≈40% of backward citations were to inventions the inventor knew about before or during the development of their invention. While this is a sizeable amount, the other 60% of citations did not represent knowledge flows as the inventor either was unaware of the cited work or became aware of the cited work after the invention had been created. Since Jaffe, Trajtenberg, and Fogarty 2000, the literature has made progress in understanding which types of citation are more likely to represent knowledge flows, and I rely on this literature to restrict to various sets of citations that are more likely to represent genuine knowledge flows. For example, Kuhn et al. 2020 show that increasingly it is the case that a small number of patents generate a large number of citations that are unlikely to represent knowledge flows. I follow the recommendation of Kuhn et al. 2020 and test the robustness of my findings to removing all citations coming from patents which make more than 20 backward citations.

Another concern is that of strategic citation withholding, where firms would intentionally fail to cite relevant work in the hopes that it would make their own patent application look more novel. The existence of strategic citation withholding would be problematic if the likelihood of withholding a citation depended on whether the patent that was to potentially be cited was a product or process patent. Although earlier literature argued for the existence of strategic citation withholding (Lampe 2012; Roach and Cohen 2013), Kuhn et al. 2023 show that there is no evidence of strategic citation withholding for USPTO patents, likely due to the "duty of candor" principle in U.S. patent law which results in revocation of the patent if the applicant fails to report known and relevant prior art (Jaffe and Rassenfosse 2017).

Another form of strategic patenting is defensive patenting where firms patent many inventions of dubious quality in order to be able either defend their future innovations in the technological area (Hegde, Mowery, et al. 2009) or use the patents as leverage in licensing negotiations (Shapiro 2000). Hegde, Mowery, et al. 2009 identifies the use of continuing and divisional applications as commonly associated with defensive patenting strategies. Intuitively this is because a continuing application can be thought of as re-applying for the patent, introducing a delay into the system which can create uncertainty for other innovators. To mitigate the effect of defensive strategies, I check the robustness of my results to removing all citations from patents which ever had a continuing or divisional application originate from them.

The literature has also documented that, for USPTO patents, about two-thirds of citations are added by examiners (Alcácer, Gittelman, and Sampat 2009). Although the number of citations made by examiners is correlated with patent renewal (a measure of private value) (Hegde and Sampat 2009), the literature has questioned the extent to which examiner citations could reflect knowledge flows as it is unlikely the inventor had explicit knowledge of the patents the examiner cites when the inventor was creating their innovation (Jaffe and Rassenfosse 2017; Corsino et al. 2019). Further, there is heterogeneity in how examiners cite prior art which has the potential to bias results (Cockburn et al. 2002; Alcácer and Gittelman 2006; Cotropia et al. 2013). Given the concerns with examiner citations measuring knowledge flows, I test the robustness of my findings to excluding examiner citations.

To test Hypothesis 1, I estimate Equation (1) where $Y_{pfnt}$ is the count of the number of citations that patent $p$, assigned to firm $f$, belong to NBER category[3] $n$, and applied for in year $t$ receives. Product $\text{Share}_p$ ranges between zero and one and measures the share of independent publication claims that are product claims as classified in (Davison 2023; Davison 2025). $X_p$ is a vector of controls which includes the log market value of the patent (Kogan et al. 2017) and the number of claims the patent makes which controls for the scope of the patent (Marco et al. 2019). Firm fixed effects are included and allow for a within firm interpretation and remove any time-invariant heterogeneity in the number of citations a firm would receive and their propensity to patent innovations with high product or process shares. This set of fixed effects also helps to ameliorate concerns about bias from examiner citations and strategic patenting by firms as Alcácer, Gittelman, and Sampat 2009 show that firm-specific variables explain most of the variation in examiner citation shares and Corsino et al. 2019 find that in relation to strategic patenting the measurement error of patent citations in measuring knowledge flows is firm-specific. I include various forms of fixed effects which account for the time the patent was applied for and the NBER category

[3] There are six NBER categories: chemical, computers and communication, electrical and electronics, drugs and medical, mechanical, and other.

of the patent (Lerner and Seru 2022; Jaffe and Rassenfosse 2017). These fixed effects are important for several reasons. First, citations accumulate over time, meaning that older patents will have had more time to accumulate citations leading to strong "cohort effects" (Jaffe and Rassenfosse 2017). Further, citation practices change over time, specifically the number of backward citations made per patent has been increasing over time (Kuhn et al. 2020). By controlling for year of application fixed effects, I remove these cohort effects. But citation activity does not simply vary by year of application but it interacts with the technological domain of the invention as fields have varying citation practices which change over time (Jaffe and Rassenfosse 2017; Lerner and Seru 2022). For example, it could be the case that process patents are predominantly found in an NBER category that tends to receive few citations. Without NBER category fixed effects included, we may wrongly conclude that process patents receive fewer citations as a result of being process patents, when in reality they receive fewer citations simply because they are more likely to be found in an NBER category where all patents, regardless of their product or process status, receive fewer citations. As a result, my preferred specification uses year of application × NBER category fixed effects to account for changing citation behavior by technological area. I use Poisson regression as the number of citations is a count variable and estimate robust standard errors.

$$\mathbb{E}[Y_{pfnt}|X_{pfnt}] = \exp\left(\beta_0 + \beta_1 \times \text{Product}_p + X_p + \gamma_f + \delta_{f(n,t)}\right) \tag{1}$$

# 5 Results

## 5.1 Quantity of Knowledge Spillovers

Table 1 displays the results, with column (1) estimating the relationship between the product share of claims on a patent and the number of citations the patent receives when only year of application fixed effects are included as controls. The results indicate that a pure product patent receives ≈ 30% more citations relative to a pure process patent. Column (2) includes year × NBER category fixed effects, which effectively limit comparisons to be within broad technological categories and years of application. While the coefficient declines, the results still indicate a strong and economically significant relationship between the product share of a patent and the number of citations it receives, with a pure product patent estimated to receive $\approx 20\%$ more citations than a pure process patent. One potential explanation of the result in column (2) 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, in column (3) 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 the product orientation of a patent generates 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. The results are materially unchanged by the introduction of these two control variables despite the strong positive relationship between each of these variables and the number of citations received.

### 5.1.1 Robustness

While the results in Table 1 provide suggestive evidence that product patents generate more knowledge spillovers relative to process patents, I have not addressed the concerns laid out earlier about the integrity of using citations to measure knowledge flows. Column (1) of Table 2 addresses the concern that examiner citations may be biasing the results by excluding all citations made by examiners. The results show an even stronger relationship than previously estimated, a pure product patent receives $\approx 40\%$ more applicant citations than a pure process patent. Column (2) eliminates citations coming from patents that make more than 20 backward citations. While this reduces the size of the estimated coefficient the result remains highly significant and economically meaningful. Finally, in column (3) I exclude citations coming from patents which are more likely to be strategic patents by

Table 1: Product Share and Citation Quantity

| | Forward Citations | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Product Share | 0.286*** | 0.219*** | 0.206*** |
| | (0.008) | (0.009) | (0.009) |
| ln(Market Value) | | | 0.046*** |
| | | | (0.004) |
| ln(Claims) | | | 0.218*** |
| | | | (0.006) |
| Year FE | ✓ | | |
| NBER Category × Year FE | | ✓ | ✓ |
| Observations | 833,117 | 833,117 | 833,117 |

*Notes*: This table presents results from estimating Equation (1) via Poisson Regression. The dependent variable is the count of the number of citations a patent receives. The independent variable of interest is the share of the patent's publication claims which are product claims as classified by Davison 2023; Davison 2025. The market value of the patent is taken from Kogan et al. 2017 and measures the abnormal stock returns generated by the patent around the time of the patent's publication. Standard errors are robust and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

Table 2: Product Share and Restricted Citation Quantity

| | Forward Citations | | |
|---|---|---|---|
| | (1) App Cites | (2) Ex. >20 Bcites | (3) Ex. Cont./Div. |
| Product Share | 0.391*** | 0.075*** | 0.188*** |
| | (0.017) | (0.005) | (0.009) |
| ln(Market Value) | 0.023*** | 0.045*** | 0.040*** |
| | (0.006) | (0.002) | (0.003) |
| ln(Claims) | 0.249*** | 0.177*** | 0.191*** |
| | (0.009) | (0.003) | (0.005) |
| NBER Category × Year FE | ✓ | ✓ | ✓ |
| Observations | 832,997 | 833,095 | 736,706 |

*Notes*: This table presents results from estimating Equation (1) via Poisson Regression. In column (1) the dependent variable is number of forward citations a patent receives, only including citations made by the applicant. In column (2) the dependent variable is number of forward citations a patent receives, excluding all citations coming from patents who have more than 20 backward citations. In column (3) the dependent variable is number of forward citations a patent receives, excluding all citations coming from continuation or divisonal patents. Standard errors are robust and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

removing all citations coming from continuation or divisional patents. In this case, the results are similar to what was found in Table 1. Overall, the results in Table 2 show that when restricting to the subset of citations that are more likely to represent knowledge flows, the positive relationship between the product share of the patent and the number of citations it receives holds firm.

The results in Table 2 still rely on citations to capture knowledge flows. To test the robustness of my results to using alternative measures of knowledge flows, I turn to a text-based measurement of knowledge flows which does not rely on citations. Specifically, I use the dataset provided by Arts et al. 2021 with all unique keywords of each USPTO patent filed between 1980 and February 2018. Additionally, Arts et al. 2021 provide a list of all novel 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.[4] I then trace out the diffusion of these novel keyword combinations by identifying the patents 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.

For each patent, I then sum the number of novel keyword combinations. 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. This allows me to reuse specification Equation (1), making the results directly comparable to the patent-to-patent citation results found in Table 1.

Table 3 presents the results from estimating Equation (1) but with the total number of novel keyword combination reuses by subsequent patents, scaled by the number of novel keyword combinations in the patent, as the dependent variable. In my most preferred specification in column (3), a pure product patent has $\approx 5\%$ more reuse of their novel keyword combinations relative to a pure process patent. These results support the citation-based evidence presented earlier and provide further evidence that product patents generate more knowledge spillovers than process patents.

If product patents do generate more knowledge spillovers relative to process patents, we may expect there to be differences in who is using the knowledge. For example, product patents may have a smaller proportion of their knowledge flows taking place internally within the firm as the knowledge is disseminating to a wider group of firms. This fits with the notion that process patents are more internally oriented and thus should have more self citations. Likewise, 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 as the knowledge would more easily leak out to a broad set of rivals.

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

Table 3: Product Share and Novel Text Reuse

| | Reuse Per Novel Combo | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Product Share | 0.115*** | 0.052*** | 0.053*** |
| | (0.006) | (0.006) | (0.006) |
| ln(Mkt. Value) | | | 0.019*** |
| | | | (0.002) |
| ln(Claims) | | | -0.030*** |
| | | | (0.003) |
| Year FE | ✓ | | |
| NBER Category × Year FE | | ✓ | ✓ |
| Observations | 692,984 | 692,984 | 692,984 |

*Notes*: This table presents results from estimating **??** via Poisson Regression. Standard errors are robust and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

To test whether the follow-on innovation from product patents is done more by external firms, I use the internal citation share, which is calculated as the share of citations made to the patent which are made by the firm who originated the patent. I use this as the dependent variable in my preferred specification of Equation (1) but with the additional control of the log of the number of citations the patent receives. This control variable accounts for the fact that patents which receive varying amounts of citations may have different patterns regarding who generates citations. In addition, I estimate Equation (1) using OLS instead of Poisson regression as the dependent variable is a proportion.

Column (1) of Table 4 presents the result. As expected, the coefficient on the product share of the patent is negative, indicating that patents with a higher share of product claims have a lower proportion of their citations which originate internally. This indicates that the knowledge in product patents is more commonly reused by other economic agents outside the firm who created the product patent. While the estimate is statistically significant and negative, the magnitude of the estimate is small, with a coefficient of $-0.002$, indicating that off of mean levels, a pure product patent has a $\frac{0.002}{0.12} \approx 1.67\%$ lower international citation share relative to a pure process patent.

Next, I provide an empirical test of whether firms have less control over the reuse of

Table 4: Internal and External Citation Activity

| | (1)<br>Internal Cite Share | (2)<br>External Concentration |
|---|---|---|
| Product Share | -0.002** | -0.019*** |
| | (0.001) | (0.001) |
| ln(Market Value) | 0.007*** | 0.000 |
| | (0.000) | (0.000) |
| ln(Claims) | 0.003*** | -0.009*** |
| | (0.000) | (0.000) |
| ln(Cites) | -0.013*** | -0.079*** |
| | (0.000) | (0.000) |
| $\overline{\text{Y}}$ | 0.12 | 0.49 |
| NBER Category × Year FE | ✓ | ✓ |
| Observations | 758,004 | 753,394 |

*Notes*: This table presents results from estimating Equation (1) via OLS. In column (1) the dependent variable is the internal citation share, which is calculated as the share of citations made to the patent which are made by the firm who originated the patent. In column (2) the dependent variable is the share of citations coming from the most citing external firm. Standard errors are robust and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

their product patents relative to their process patents. To conduct this test, I rely on the work of Fadeev 2024 who show that the concentration of citations among a handful of firms indicates that the firm is intentionally sharing knowledge with the citing firms. On the contrary, if citations are spread out among many different firms, this indicates the presence of unintentional knowledge leakage. Using a measure pioneered by Fadeev 2024, I estimate the external concentration of knowledge spillovers from a patent using the share of citations coming from the most citing external firm. Column (2) of Table 4 shows the results when this measure of external concentration is the dependent variable. As hypothesized, the results show that a higher product share leads to decreased external concentration, consistent with the information in product patents diffusing to a wider group of firms and having more knowledge leakages. Quantifying the size of this effect, the results indicate that a pure product patent has $\frac{0.019}{0.49} \approx 3.88\%$ lower external concentration relative to a pure process patent. Overall, the results in Table 4 further support the notion that more product oriented patents generate more knowledge spillovers than process oriented patents by showing that product patents proportionally generate less internal usage and that their external reuse tends to concentrate less within a single firm, indicating less of an ability to intentionally control who uses the knowledge.

## 5.2 Novelty of Building Patents

Next, I move on to testing Hypothesis 2 which hypothesizes that, on average, innovations which build upon a product innovation are less novel relative to the innovations that build on a process innovation. To test this, I use data from Arts et al. 2021 which measures the textual novelty of patents. For each patent, Arts et al. 2021 measures the mean cosine similarity between the focal patent and all patents filed in the five years before the filing of the focal patent. Patents which have a low average backward cosine similarity have text that is dissimilar to the text of patents in the preceding five years, indicating that the patent is a relatively novel contribution. I calculate the mean backward cosine similarity across all patents which cite the focal patent make a log transformation and then negate the value to get a measure that can be interpreted as the novelty of the text. I estimate Equation (1) using OLS instead of Poisson regression as the dependent variable is no longer a count variable.

Column (1) of Table 5 shows the results when the dependent variable is the log of average textual novelty of citing patents. In support of Hypothesis 2, the coefficient on the product share of claims is negative, revealing that the patents which build upon a pure product patent are less novel by about 3%. The results suggest that product innovation evolves more incrementally, with more technological similarity between technological generations.

Columns (2)-(3) use statistics other than the mean to summarize citing patents. Column (2) show that of all patents citing a focal patent, the least novel patent is still less novel if it is citing a product patent. Likewise, column (3) shows that the most textually novel patent of the citing patents is also less novel if the focal patent being cited is a product patent. These findings suggest that the decline in textual novelty of building patents occurs across the range of similarity to the focal patent. To see the importance of looking across the range of similarity, consider the finding in column (1) which could be explained by a few citing patents which are less novel while all other citing patents are just as novel. Columns (2) and (3) suggest that across the distribution, the novelty of citing patents is lower for

Table 5: Product Share and the Novelty of Citing Patents

| | ln(Novelty) | | |
|---|---|---|---|
| | (1) Mean | (2) Min | (3) Max |
| Product Share | -0.028*** | -0.026*** | -0.030*** |
| | (0.001) | (0.001) | (0.002) |
| ln(Market Value) | 0.004*** | 0.003*** | 0.006*** |
| | (0.000) | (0.000) | (0.001) |
| ln(Claims) | -0.000 | -0.002*** | 0.003*** |
| | (0.001) | (0.000) | (0.001) |
| ln(Cites) | -0.013*** | -0.108*** | 0.176*** |
| | (0.000) | (0.000) | (0.000) |
| NBER Category × Year FE | ✓ | ✓ | ✓ |
| Observations | 713,109 | 634,855 | 634,855 |

*Notes*: This table presents results from estimating Equation (1) via OLS instead of Poisson Regression. Backward cosine similarity is taken from Arts et al. 2021 and, for a given patent making a citation is calculated as the average cosine similarity between the text of the citing patent and all patents filed in the prior five years. To get a score for novelty, I negate the backward cosine similarity score. In column (1) the dependent variable is the average novelty of the text of patents who cite the focal patent. In columns (2) - (4) only patents who receive more than one citation are included. In column (2) the dependent variable is the maximum (in absolute value) novelty of the text of patents who cite the focal patent. In column (3) the dependent variable is the minimum (in absolute value) novelty of the text of patents who cite the focal patent. Standard errors are robust and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

patents citing product patents relative to those citing process patents. Overall, the results support Hypothesis 2 and provide evidence suggesting that the innovations generated by the spillovers of product patents are more incremental and less novel in nature than those that come as a result of process patent spillovers.

### 5.3 Moderating Effect of Firm Life Cycle

To test whether the location of a firm in their life cycle moderates how the product share of an innovation relates to knowledge spillovers, I use the Hoberg and Maksimovic 2022 data which measures where firms are in the product life cycle. Specifically, the Hoberg and

Maksimovic 2022 data probabilistically places firm $\times$ year observations into the four stages of the Utterback and Abernathy 1978 model: product development, process optimization, mature product, and product decline. Hoberg and Maksimovic 2022 use the 10-K filings of firms along with text analysis techniques in order to determine the intensity with which firms refer to words and phrases which are associated with the four life cycle stages. Recognizing that firms are not exclusively located in one of the four stages, Hoberg and Maksimovic 2022 instead measure each firm's location in the product life cycle using a four-element vector, $\{\text{Product Development}, \text{Process Optimization}, \text{Mature Product}, \text{Product Decline}\}$, where each element in the vector corresponds to the share of relevant paragraphs in the firm's 10-K which are associated with the life cycle stage. The vector sums to unity and is populated by non-negative elements which are bounded between zero and one inclusively. The measure is only available for firms from 1997-2017, and I match it to patents based on the patent's year of application. I then estimate Equation (1) but interact the Hoberg and Maksimovic 2022 product life cycle measure with the product share measure. Since the life cycle vector sums to unity, I choose the product development stage to serve as the omitted category.

Table 6 display the results showing that relative to the product development phase, the process optimization and product decline phases have a smaller citation gap between product and process patents. In other words, any given product patent in these two stages will generate fewer knowledge spillovers, as measured by citations, compared to product patents which were created in the product development or mature product phase. In fact, individually summing the main effect of product share and the interactions with process optimization and product decline highlight that a pure product patent filed in these stages generates fewer citations than a pure process patent. In short, Hypothesis 1 is flipped on its head during the process optimization and product decline stages, consistent with rival firms being more concerned with the processes of other firms during these stages. In contrast, the interaction of the product share with the mature product phase is positive, large, and highly significant indicating that product patents generate the most knowledge spillovers when they occur in the mature product phase. Specifically, the results indicate that a given product innovation generates nearly twice as many citations when filed in the mature product phase, relative to when it is filed in the product development phase.

Table 6: The Moderating Effect of Firm Life Cycle

| | Forward Citations | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Product Share | 0.324*** | 0.263*** | 0.238*** |
| | (0.064) | (0.065) | (0.065) |
| Product Share × Process Optimization | -0.460*** | -0.352*** | -0.344*** |
| | (0.090) | (0.092) | (0.093) |
| Product Share × Mature Product | 0.660*** | 0.612*** | 0.607*** |
| | (0.113) | (0.114) | (0.115) |
| Product Share × Product Decline | -0.614*** | -0.662*** | -0.644*** |
| | (0.167) | (0.167) | (0.169) |
| ln(Market Value) | | | 0.048*** |
| | | | (0.005) |
| ln(Claims) | | | 0.221*** |
| | | | (0.008) |
| Year FE | ✓ | | |
| NBER Category × Year FE | | ✓ | ✓ |
| Observations | 523,192 | 523,192 | 523,192 |

*Notes*: This table presents results from estimating **??** via Poisson Regression. The firm's position in the life cycle is taken from Hoberg and Maksimovic 2022. Standard errors are robust and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

Table 7: Horizontal and Vertical Relatedness

| | | Vertical Relatedness Score | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | Competitor Share | Upstream | Downstream |
| Product Share | 0.028*** | 0.014*** | 0.034*** |
| | (0.001) | (0.002) | (0.002) |
| ln(Market Value) | 0.002*** | -0.001 | 0.002** |
| | (0.001) | (0.001) | (0.001) |
| ln(Claims) | 0.004*** | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) |
| ln(Cites) | -0.001*** | -0.010*** | -0.014*** |
| | (0.000) | (0.001) | (0.001) |
| $\overline{\text{Y}}$ | 0.23 | 0.36 | 0.35 |
| NBER Category × Year FE | ✓ | ✓ | ✓ |
| Observations | 449,201 | 449,201 | 449,201 |

*Notes*: This table presents results from estimating **??** via OLS. In column (1) the dependent variable is the share of citing patents where the assignee is a competitor of the focal firm. Competitors are assigned using TNIC3 industries as created by Hoberg and Phillips 2016. In columns (2) and (3) the dependent variable is the average vertical relatedness score between the citing firm and the focal firm with column (2) orienting the citing firm as upstream of the focal firm and column (3) orienting the citing firm as downstream of the focal firm. Vertical relatedness scores are multiplied by 100 and taken from Frésard et al. 2020. Standard errors are robust and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

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# A Appendix

Table A.1: Predicting Product and Process R&D with Tax Credits

| | (1)<br>ln(1 + Product R&D) | (2)<br>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

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

Table A.2: Product Innovation and Product/Process Technological Spillovers

| | ihs(CW Pdt Patents) | | | | | |
|---|---|---|---|---|---|---|
| | (1) OLS | (2) OLS | (3) IV | (4) OLS | (5) OLS | (6) IV |
| $\ln(\text{Spilltech}_{t-1})$ | 0.944* | 0.584 | 0.526 | | | |
| | (0.524) | (0.355) | (0.398) | | | |
| $\ln(\text{Spilltech Pdt}_{t-1})$ | | | | 0.844 | 0.464 | 2.299** |
| | | | | (1.059) | (0.734) | (1.154) |
| $\ln(\text{Spilltech Prs}_{t-1})$ | | | | 0.150 | 0.154 | -1.436 |
| | | | | (0.847) | (0.601) | (0.895) |
| $\ln(\text{Spillsic}_{t-1})$ | 0.105 | 0.076 | 0.089 | 0.104 | 0.075 | 0.096 |
| | (0.103) | (0.071) | (0.073) | (0.103) | (0.071) | (0.073) |
| $\ln(\text{Pdt Cites}_{t-1})$ | | 0.304*** | 0.304*** | | 0.304*** | 0.303*** |
| | | (0.015) | (0.015) | | (0.015) | (0.015) |
| $\ln(\text{Prs Cites}_{t-1})$ | | 0.173*** | 0.173*** | | 0.173*** | 0.173*** |
| | | (0.013) | (0.013) | | (0.013) | (0.013) |
| $\mathbb{1}\{\text{No Patent}_{t-1}\}$ | | -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 (**??**) and (**??**). 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 A.3: Process Innovation and Product/Process Technological Spillovers

| | ihs(CW Prs Patents) | | | | | |
|---|---|---|---|---|---|---|
| | (1) OLS | (2) OLS | (3) IV | (4) OLS | (5) OLS | (6) IV |
| $\ln(\text{Spilltech}_{t-1})$ | 1.360*** | 1.065*** | 1.473*** | | | |
| | (0.413) | (0.296) | (0.341) | | | |
| $\ln(\text{Spilltech Pdt}_{t-1})$ | | | | 0.614 | 0.360 | 1.024 |
| | | | | (0.818) | (0.585) | (0.979) |
| $\ln(\text{Spilltech Prs}_{t-1})$ | | | | 0.711 | 0.666 | 0.461 |
| | | | | (0.653) | (0.476) | (0.791) |
| $\ln(\text{Spillsic}_{t-1})$ | -0.025 | -0.036 | -0.012 | -0.027 | -0.038 | -0.013 |
| | (0.094) | (0.069) | (0.071) | (0.094) | (0.070) | (0.071) |
| $\ln(\text{Pdt Cites}_{t-1})$ | | 0.141*** | 0.141*** | | 0.142*** | 0.141*** |
| | | (0.010) | (0.010) | | (0.010) | (0.010) |
| $\ln(\text{Prs Cites}_{t-1})$ | | 0.242*** | 0.242*** | | 0.242*** | 0.242*** |
| | | (0.016) | (0.016) | | (0.016) | (0.016) |
| $\mathbb{1}\{\text{No Patent}_{t-1}\}$ | | 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 (**??**) and (**??**). 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).