Journal of Financial Economics 180 (2026) 104276

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/finec

Foundational processes and growth[☆,☆☆]

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ARTICLE INFO

Dataset link: Foundational Processes and Growth (Reference data)

Keywords:
Foundational process innovation
Process innovation
Product innovation
Process-driven products
Firm growth
Technological possibility frontier

ABSTRACT

This paper studies the interaction between process and product innovations and their distinct role in firm growth dynamics. We differentiate empirically and theoretically two types of process innovations: foundational processes that advance production technology and cost-reducing processes that enhance existing production efficiency. We develop an innovation model of product varieties with quality heterogeneity to illustrate how these innovations impact firm growth differently and highlight how process innovation induces product innovation. By analyzing millions of patent texts from 1900 to 2020, we classify innovations into product, cost-reducing process, and foundational process innovations. We find that foundational processes lead to sustained firm growth, especially through their effect on subsequent product creation. R&D-intensive firms focused on “deep-tech” innovations have an advantage in creating foundational processes, resulting in superior product quality. Using patents linked to FDA-approved drugs, we show that firms with a comparative advantage in creating foundational processes, due to greater knowledge and technological stock, tend to produce higher-value products.

1. Introduction

Technological progress is the result of complex innovation activities, which economists commonly categorize as product and process innovations (e.g., Cohen and Klepper, 1996). Although product innovation (the creation of new or improved products) and process innovation (invention of new methods, processes, and techniques in the production or delivery of products) are fundamentally different, standard models of economic growth (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992) and empirical studies of innovation often do not differentiate between these different types of innovation. As a result, the interaction between process and product innovations and how they distinctly determine firm growth dynamics are not well understood.

Process innovation can be heterogeneous as some processes improve production efficiency while others lay the foundation for the subsequent development of entirely new products. For example, the development of the photolithography method in semiconductor manufacturing enabled the miniaturization of circuitry on silicon chips, catalyzing significant growth within the electronics sector and beyond. Similarly, the Polymerase Chain Reaction (PCR) method facilitated the rapid duplication of DNA sequences, underpinning breakthroughs in developing new genetic tests, vaccines, and treatments, and biomedical

☆ Dimitris Papanikolaou was the editor for this article. This paper supersedes the previously circulated paper “Advanced Manufacturing, Product Innovations, Productivity and Growth”. We are very grateful to Dimitris Papanikolaou and an anonymous referee for extremely insightful comments that have been instrumental to the development of the final paper. We thank Jan Bena, Laurent Cavenaile (discussant), Vicente Cunat, Thierry Foucault, Murray Frank, Simon Fuchs, Johan Hombert, Po-Hsuan Hsu (discussant), Felipe Saffie, Gordon Phillips, Justin Pierce (discussant), Elena Simintzi, Scott Stern, John Walsh, Alminas Zaldokas, and participants at the AEA, ABFER, AIEA-NBER Conference, CEPR Rising Asia Workshop, Virtual Corporate Finance seminar, FIRN Corporate Finance meeting, Taiwan Symposium on Innovation Economics and Entrepreneurship, AFBC, FMA Asia, EARIE, SETA, Macro Research Group Workshop, University of Sydney Business Financing and Banking Research Group Annual Workshop, Emory University, HEC Paris, Monash University, Swinburne University of Technology, UTS, Macquarie University, and University of Sydney for very helpful comments. We thank Angela Chen for excellent research assistance and Alt Data Tech for providing data support. We are very indebted to Michael I Montembeau, Suja C, Ganesh Venkatraman and their team at Maxval Group Inc., as well as Catriona Bruce and Tom Millist and their team at IP Australia for their input with the patent classification measures. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Atlanta, the Federal Reserve System, or its staff.
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https://doi.org/10.1016/j.jfineco.2026.104276
Received 16 January 2025; Received in revised form 3 March 2026; Accepted 6 March 2026

innovation. We label such process innovations that unlock novel technological possibilities for new product introductions as *foundational process innovations*. *Cost-reducing process* innovations, such as production, supply chain, and inventory management systems, have also been vital. For instance, Tesla's unboxed system streamlines assembly through modular subcomponents, similar to building with Lego blocks, while Raytheon Technologies uses 3D printing to reduce material waste, reduce costs, and accelerate production.

In this paper, we study theoretically and empirically the role of process innovation in creating the technological foundation for future product development and its implications for growth. We introduce the key difference between product innovation and foundational and cost-reducing process innovations in a simple growth framework and analyze predictions of this model of heterogeneous innovations using the U.S. Patent and Trademark Office (USPTO) patent and Food and Drug Administration (FDA) "Orange Book" data. We extend the empirical methodology of Kelly et al. (2021) to identify foundational and cost-reducing processes at the firm level over a long time series, allowing us to study their role in firm growth. We show that process innovations, and especially foundational processes, drive product innovations, and this interaction between different types of innovations is important for firm growth.

We frame our analysis using a simple innovation model that formalizes the distinction between product and process innovations, helping us to understand how they relate to firm growth and guiding our empirical analysis. In the model, consumers value products based on how well products match their preferences. Consumer preferences are distributed on a familiar Salop circle (Salop, 1979), and firms are engaged in product innovation – introducing different product varieties on an interior ring of the Salop circle – defined as the firm's technological possibility frontier (TPF). The TPF determines (vertical) the product quality that the firm can offer with the existing production technology. Process innovation manifests in two ways, reflecting the earlier examples. First, firms engage in foundational process innovation, which introduces fundamentally new processes that alter the firms' production technology and *expand* the technological frontier, TPF. Second, firms can also engage in cost-reducing process innovation and increase production efficiency for the *existing* technological frontier. Given its TPF and production efficiency, the firm decides on product innovation (creating new product varieties) that ultimately determines the match (distance) between consumer preferences and the firm's products. Despite being widely observed in practice, these heterogeneous innovations have not been extensively integrated into extant innovation-driven growth models. In this paper, we take the first step in this direction.

Our model predicts two reduced-form relations for foundational, cost-reducing, and product innovations and firm growth, which we confirm with our proposed innovation measures. Most notably, the model predicts that process innovation leads to more product innovation, with more foundational process discovery resulting in more and higher-quality product creation. Essentially, foundational processes create the technological groundwork that allows firms to subsequently develop higher-quality products using completely new processes; and improved quality further incentivizes a wider product offering (e.g., advancements in photolithography that enabled chip miniaturization led firms to introduce smartphones, wearables, smaller and more powerful laptops, etc.). As a result, the model predicts that process and product innovations drive firm growth, and foundational process discoveries largely induce product introductions.

To empirically examine these predictions, we construct new measures of heterogeneous innovations building on Kelly et al. (2021) and Bena and Simintzi (2025). We apply textual analysis on the high-dimensional patent document data to first categorize patents into process and product innovation, before further separating them into cost-reducing, foundational, and product innovation. We categorize patents using a "bag-of-words" approach by utilizing an expanding corpus of terms based on the hypernyms of "*activities*" and "*physical entities*" for classification, which does not depend on specific words or predefined word lists. The preamble of claims and titles referring to an *activity* (e.g., process, method) are classified as process patents, whereas those referring to a *physical entity* (e.g., product, device) are classified as product patents. We construct patent document similarity of each patent pair in the spirit of Kelly et al. (2021) and identify foundational process patents as those whose content is distinct from prior product patents but is similar to future product patents within firms. Consistent with our model, the measure captures novel processes (foundational ones) that have a significant impact on future firm product innovations. Over 58% of U.S. patents granted between 1900 and 2020 are product patents. Within process patents, 69% are classified as cost-reducing, with the rest classified as foundational patents. We find that foundational process patents cite substantially more non-patent literature (NPL), e.g., academic publications, indicating that foundational processes may represent deep-tech corporate innovations that leverage spillovers from basic scientific research, aligning with the microfoundations of our model. On the other hand, cost-reducing processes are highly correlated with lower labor costs and the frequent use of terms related to efficiency gains and cost-reduction in firm annual reports (10K/Q).

Using our measures, we first study the relation of these innovations with firm growth and productivity. We use Local Projection Regressions to directly estimate impulse responses over 1–10 year horizons (Jordà, 2005). We find that both product and process innovations are associated with significantly higher firm growth (profits, sales, labor, capital, and TFP) in subsequent years. Process innovation has an especially large impact in the short term (one to five years), and both types of innovations have equally sizable cumulative effects in the long run (up to a 10-year horizon).

We further unpack the growth effects associated with process innovations by exploring two types of process innovations: cost-reducing and foundational innovations. Cost-reducing process innovations, like additive manufacturing and 3D printing, are linked to higher future sales and profits in the short run (up to three years), highlighting the direct and immediate effects of such innovations on improving production efficiency. This efficiency allows firms to potentially offer products at more competitive prices, thus enhancing sales and profit margins.

Foundational process innovations operate differently from cost-reducing processes. They are associated with higher impact and sustained growth over the short and medium term (up to seven years). Consistent with the model predictions, we also find evidence that foundational processes indirectly enhance firm performance through products. Specifically, we show that sustained firm growth attributed to product innovations largely comes from products that build on foundational processes — those with a high similarity to or citing foundational process patents. These findings underscore the transformational impact and long-term benefits of foundational processes.

Next, we investigate the relation between the two types of process innovation (foundational and cost-reducing) and subsequent product innovation. As the model predicts, we find that foundational processes are associated with higher vertical product quality and more product variety. Specifically, we observe that product patents citing foundational process innovations have higher market valuations and demonstrate superior quality compared to those not based on foundational processes. We find a positive and significant association between firms with more foundational processes and the number and quality of future product innovations.

To explore how foundational processes translate into commercially successful products beyond patent inventions, we utilize the newly digitized NBER FDA "Orange Book" dataset, which links approved small-molecule drugs to their associated patents. Our analysis reveals that drugs built on foundational patents have higher market value and more sales, aligning with our firm-level findings. Overall, our findings support the prediction that process innovations, particularly foundational processes, create the groundwork for subsequent product development and significantly affect future product introductions.

Our paper makes three key contributions. This is the first paper to present new evidence on the critical role of foundational process innovation in firm growth, extending beyond the impact of cost-reducing processes (Cohen and Klepper, 1996; Klepper, 1996; Dhingra, 2013). Prior empirical work exploring the role of process innovations studies their distinct effect on labor-saving technologies and the direction of technological progress (Kogan et al., 2020; Bena et al., 2022). Instead, here, we demonstrate the key role of process innovations in the development of subsequent new products. The tight interaction between process and product innovations also underscores the importance of considering these innovation choices jointly and the need for richer theoretical foundations for understanding the interaction between product and process-based innovations.

The inability to measure the real quantitative effects of process innovation over a long time series has constrained the empirical testing of many economic models related to cost-reduction processes. Our proposed measures not only enable the examination of the significance of process innovation over a long time series but also provide novel empirical insights, which are tied into a growth model that emphasizes the crucial role of foundational process innovation in driving firm expansion through enhanced product variety and quality. Also, foundational process patents cite substantially more non-patent literature, showing that they leverage spillovers from basic scientific research. Our findings provide firm-level empirical support for the importance of basic science in fostering growth through knowledge spillovers to applied science, consistent with the findings of Akcigit et al. (2020).

Second, this paper demonstrates how data on patenting activities can be integrated with information from patent titles and textual content to classify patent types for the USPTO and international patents. We advance the current literature by (1) proposing a novel methodology for measuring foundational and cost-reducing process innovations using patent text, leveraging detailed information in patent data; (2) providing a long time series measure of U.S. process innovation from 1900 to 2020; and (3) introducing a new title-based measure for USPTO and international patents. We validate our measure against intellectual property expert classifications from Maxval Group Inc. and patent examiner classifications from IP Australia.

Bena and Simintzi (2025) and Bena et al. (2022) use process claims information from 1976 to 2012 to classify process patents and examine the relation among U.S. firms' labor, capital, and innovation investment decisions. Building on this foundation, we introduce new hypernym-based and title-based methods to create new classifications and study firm growth dynamics. Notably, our methodological approach focusing on patent titles (instead of claims) allows us to extend the observational timeline to include data prior to 1976 and broaden the geographical scope to over 60 countries, enhancing the robustness of our analyses. A significant advantage of our categorizations is their use in examining the dynamics of heterogeneous processes and product innovations and their relation to growth at both the firm and economy levels over extended periods and across multiple countries. These categorizations provide opportunities to explore previously unexamined questions on the innovation dynamics of multi-product firms within the fields of industrial organization, international trade, innovation economics, and finance.

Finally, we contribute to the innovation-based endogenous growth literature, rooted in the seminal contributions of Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992). Process and product innovations are not meaningfully differentiated in these and subsequent growth models and are largely isomorphic. Our model highlights the distinct contributions of various types of innovation to firm growth and microfounds how process innovation induces product innovation in a basic setting with analytical expressions. Foundational process discoveries in our framework unlock a range of product innovations, triggering bursts of product introductions — consistent with evidence in Berlingieri et al. (2025). While our approaches differ, both papers highlight how certain innovations can catalyze product dynamism. Another strand of the literature analyzing industry lifecycles models product and process innovation as separate activities over the firm or industry life cycle (Utterback and Abernathy, 1975; Klepper, 1996; Cavenaile et al., 2024). However, these studies consider only the cost-reducing nature of process innovations with no effect of these processes on product innovation — the emphasis of our model and the key empirical regularity we document. In addition, by integrating modeling tools from recent innovation models with vertical and horizontal differentiations (Bar-Isaac et al., 2023; Baslandze et al., 2023), we provide a useful foundation for developing richer quantitative models that capture joint dynamics of different types of innovation, including foundational process discoveries, cost-reducing innovations, and product variety creation.

2. A simple model of product and process innovation

We introduce a simple motivating model of innovation that formalizes the distinction between product and process innovations and derives how they distinctly affect firm growth. The model guides our empirical analysis. In the model, *product innovation* captures the creation of product varieties to better tailor to consumer preferences either through a higher vertical quality or a better taste match (horizontal differentiation).[1] We distinguish between two types of process innovation: cost-reducing and foundational process innovations. *Cost-reducing process innovation* allows firms to cut the marginal costs of their existing production. *Foundational process innovation*, in turn, introduces fundamentally new processes that alter the firm's production technology. The defining feature of foundational process innovation that we want to capture is that it lays the technological foundation that allows firms to subsequently develop new products using completely new processes. To this end, we introduce the concept of the *technological possibility frontier* (TPF) that the discovery of new foundational processes can advance. Product varieties offered by firms are determined by the technological frontier that the firms own (e.g., if the firm has a method to create touch screens it can use this method to integrate new features in the products it introduces to the market). The model highlights the distinct roles played by different types of innovation for firm growth and shows how process innovation induces product innovation.

The model draws insights from the endogenous growth literature (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992) but jointly models product and process innovations and considers their interaction. To zoom into the distinct roles played by heterogeneous innovations, we microfound the product quality in innovation models via the product-consumer quality match. For that, we build on insights from Bar-Isaac et al. (2023) who adapt the Salop (1979) model of horizontal differentiation to add a vertical dimension of product heterogeneity, allowing us to conveniently model foundational process innovations as expanding the technological possibility frontier (vertical quality); and we follow Baslandze et al. (2023) to model variety expansion (product innovation) in the Salop setting.[2] Here, we present a concise version of the model and refer readers to Appendix A for derivations and more details.

[1] We use the terms: products, varieties, and product varieties interchangeably.

[2] One can think of foundational process innovations in our model as microfounding how new innovation waves/clusters appear in Akcigit and Kerr (2018).

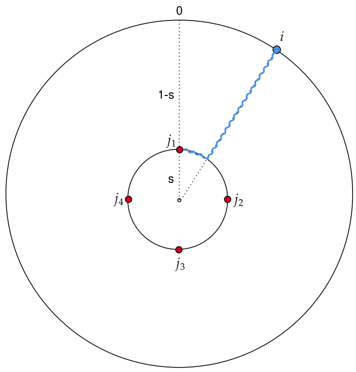


Fig. 1. Consumer preferences and product-consumer match.

Setup. Consider a partial equilibrium economy with monopolistic competition across a continuum of product lines. Each product line is represented by a familiar (Salop, 1979) unit-radius circle with 2π consumers uniformly distributed on its circumference. Within the product line, a monopolist offers n product varieties located on a ring of radius $s < 1$ within the unit-radius circle, which we label as the *technological possibility frontier (TPF)*. In Fig. 1, the outer circle corresponds to the consumers' preferences, while the inner ring depicts the *TPF* of the producer. A consumer/product is indexed by the angle of its location relative to zero. That is, consumer i in the figure spans an angle i relative to the vertical dashed line, while varieties n are located at $0,\ 2\pi s\frac{1}{n},\ 2\pi s\frac{2}{n},\ \ldots,\ 2\pi s\frac{n}{n}$, with $n = 4$ as an example.

All varieties are sold at a price p. If consumer i chooses a specific product variety j, then the demand is:

$$c = q(i,j)p^{-\varepsilon}, \tag{1}$$

where $q(i,j)$ is the product quality from the consumer's perspective, or the product-consumer preference match; and $\varepsilon > 1$ is the elasticity of substitution between different product lines.[3] As Eq. (1) shows, demand for a higher-quality product is higher.[4]

The quality $q(i,j)$ depends on how close the variety is to the consumer's location (her preference), so it depends negatively on the distance "traveled" from consumer i to the product j. The consumer first "travels" the vertical distance from i to the production ring and then the shortest arc distance to the product location j (in the figure in blue). Specifically,

$$q(i,j) = \chi - \lambda(1-s) - \mu s|i-j|,$$

where χ is the maximum quality level enjoyed by the consumer, and λ and μ are disutilities from the mismatch. If $j = i$, so a product is located at the same angle as the consumer, $q(i,i) = \chi - \lambda(1-s)$; this is the best product available to the consumer given the current technology. Unlike the classic Salop circle, where quality differentiation is only horizontal, this two-dimensional travel cost brings in the vertical quality differentiation (Bar-Isaac et al., 2023). For example, a vertical dimension may represent some features that improve the overall functionality of a product (e.g., touch screen, speed), while the horizontal dimension may represent features of the product (e.g., size, number of buttons) that are differentially valued based on consumer preferences.

A consumer chooses the variety closest to her preference. This way, for a product located at 0, there will be $2\pi/n$ measure of consumers in $[-\pi/n, \pi/n]$ who will buy it. As a result, the aggregate demand for a firm's products is (see Appendix A for details):

$$c = [2\pi(\chi - \lambda(1-s)) - \mu s\frac{\pi^2}{n}]p^{-\varepsilon}. \tag{2}$$

Two important margins affect firm demand: vertical quality $(1-s)$ and horizontal match. To see the first, assume $n \to \infty$, that is, all consumers' horizontally differentiated tastes are satisfied. Then, demand is $2\pi(\chi - \lambda(1-s))p^{-\varepsilon}$, and it increases in s. So, if the technological possibility frontier is closer to the consumer's preference circle (higher vertical quality), consumers demand more. On the other hand, vertical quality and horizontal match reinforce each other: when a product has a high vertical quality s, it is even more valuable if it also closely matches consumers' tastes. Consider a few illustrative examples. Once integrated circuit (IC) chips became smaller and more powerful due to the discovery of photolithography (higher s), the differentiated products that emerged – such as smartphones and smartwatches – offered much higher value. In contrast, under lower-quality technologies, these same product varieties would have been bulky and unattractive (e.g., a huge smartphone or smartwatch), making horizontal differentiation far less relevant.[5] Consumers, thus, value intrinsic product quality and taste match jointly. The idea that vertical quality improvements increase the marginal value of product variety is consistent with studies in trade and industrial organization, where high-quality products tend to perform better when they also align better with consumer preferences.[6]

Product innovation. Now, consider the problem of a monopolist that chooses how many product varieties to produce on the existing technological possibility ring $s < 1$ and what price to set at $t = 1$. Assume the firm has a certain production technology with marginal cost k^{-1}. *Product innovation* — the creation of product varieties, is costly. To create n varieties on the existing ring s, the firm needs to spend $\gamma n^{1/\gamma}$ $(0 < \gamma < 1)$. As a result, the firm's problem is:

$$\max_{p,n}\left\{\underbrace{p^{1-\varepsilon}[2\pi(\chi - \lambda(1-s)) - \mu s\frac{\pi^2}{n}]}_{Revenue} - \underbrace{k^{-1}p^{-\varepsilon}[2\pi(\chi - \lambda(1-s)) - \mu s\frac{\pi^2}{n}]}_{Production\,cost} - \underbrace{\gamma n^{1/\gamma}}_{Innovation\,cost}\right\}. \tag{3}$$

The resulting solution for prices and product variety is:

$$p^* = \frac{\varepsilon}{\varepsilon - 1}k^{-1}, \tag{4}$$

$$n^* = \left(\frac{1}{\varepsilon}(\frac{\varepsilon}{\varepsilon-1}k^{-1})^{1-\varepsilon}\mu s\pi^2\right)^{\gamma/(1+\gamma)}. \tag{5}$$

Price is a familiar markup over marginal cost, while optimal product variety choice depends both on TPF and firm efficiency. The resulting revenue and profits as functions of k and s are:

$$Rev(k,s) = (\frac{\varepsilon}{\varepsilon-1}k^{-1})^{1-\varepsilon}[2\pi(\chi - \lambda(1-s)) - \mu s\frac{\pi^2}{n^*(k,s)}], \tag{6}$$

$$\Pi(k,s) = \frac{Rev}{\varepsilon} - \gamma n^{*1/\gamma}. \tag{7}$$

[3] See Appendix A for the derivation of this standard demand function in the model with CES consumption aggregation.

[4] Note that while we explicitly refer to "consumer preferences" and "consumer demand", these phrases can be easily substituted for "(final) producer's needs" and "(final) producer's demand", respectively, and the model can be interpreted as an innovation model of intermediate-good producers instead of final variety producers.

[5] Likewise, the invention of zero-calorie sweeteners enabled Coca-Cola to introduce a wider range of differentiated products that appealed to health-conscious consumers, varieties that would not have been valued when low-calorie options tasted worse.

[6] See, for example, Goldberg (1995), Crozet et al. (2011), and Di Comite et al. (2014).

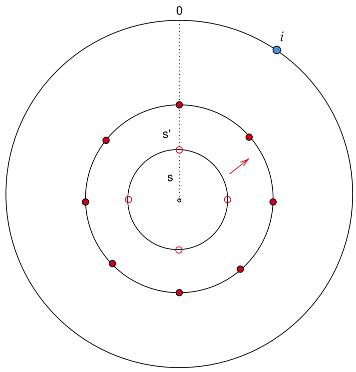


Fig. 2. Consumer preferences and product-consumer match.

Process innovation. So far, we have considered the optimal product innovation and price setting for the firm with a given TPF s and efficiency k. In the prior period ($t = 0$), firms can invest in process innovation to upgrade s and k. As standard, *cost-reducing process innovation* increases production efficiency k; that is, it reduces marginal cost, given the production possibility frontier s. Motivated by the introductory examples, we also consider a different type of process innovation that helps the firm discover completely new technologies and processes that open new technological possibilities. In particular, we consider *foundational process innovation* that advances the TPF. If a new foundational process is discovered, it widens the TPF radius s to s' (see Fig. 2). Varieties produced on a new ring have higher vertical quality and can potentially cater better to each consumer's preference. In other words, foundational process discovery lays out the technological groundwork that allows for the subsequent development of new and better products.

Assume innovations are stochastic and follow a Poisson process. The arrival rate of foundational innovation is ξ_k and that of cost-reducing innovation is ξ_s, with respective costs of $\eta\xi_k^{1/\eta}$ and $\eta\xi_s^{1/\eta}$, where $0 < \eta < 1$. If innovations are successful, k and s are growing by Δk and Δs, respectively.[7] The firm with given k and s solves the following one-shot problem of choosing foundational and cost-reducing innovation rates:

$$\max_{\xi_k,\xi_s}\left\{\xi_k\Pi(k+\Delta k,s)+\xi_s\Pi(k,s+\Delta s)+(1-\xi_k-\xi_s)\Pi(k,s)-\eta\xi_k^{1/\eta}-\eta\xi_s^{1/\eta}\right\}.$$

The optimality conditions stipulate that the incremental gain from a higher s should equal the marginal cost (the condition for k is analogous):

$$\xi_s=[\Pi(k,s+\Delta s)-\Pi(k,s)]^{\frac{\eta}{1-\eta}}.$$

This completes the exposition of the model and leads us to analyze the firm's product introduction and growth dynamics. For simplicity, in what follows, we assume $\lambda = \mu$.[8]

Let us start with an analysis of the firm's product introduction dynamics. When the firm makes a foundational process discovery, it leads to sizable new product introductions for two reasons. First, the firm upgrades its existing product varieties, which now become of higher quality s' (varieties move up to the new TPF ring). Second, and more interestingly, the new TPF also incentivizes the creation of more varieties — as seen from (5), $\frac{\delta n^*}{\delta s} > 0$.[9] As discussed earlier, vertical product quality s and the number of varieties are complements in the consumer's demand function (1). As a result, when product quality and, hence, demand is higher, the return on each variety creation is higher. To summarize:

Proposition 1 (*Product Introduction*). *Foundational process innovation leads to more and higher-quality product introduction.*

Cost-reducing process innovation incentivizes variety creation, too, but through a different mechanism and to a smaller extent. As seen from (4), higher efficiency leads to lower prices. This, in turn, increases demand and revenue for each variety, implying higher returns to variety creation. However, unlike with foundational process innovation, new product varieties have the same vertical quality s and hence are not novel, as well as the amount of new product introductions is significantly lower.[10]

Next, we analyze firm growth dynamics.[11] How does revenue change after the introduction of additional products? With more varieties, products now match consumers' preferences better, leading to higher sales, as demonstrated by the positive derivative of the revenue function below. This growth in sales is higher if varieties are less substitutable (higher μ) and declines in n, i.e., if more products are already on the market:

$$\frac{\partial Rev}{\partial n}=\left(\frac{\varepsilon}{\varepsilon-1}k^{-1}\right)^{1-\varepsilon}\mu s\frac{\pi^2}{n^2}. \tag{8}$$

The firm also grows as a result of successful process innovations but through very different channels. Consider foundational and cost-reducing process innovations, in turn:

$$\frac{\partial Rev}{\partial s}=\underbrace{\left(\frac{\varepsilon}{\varepsilon-1}k^{-1}\right)^{1-\varepsilon}\pi\mu\left(2-\frac{\pi}{n}\right)}_{Higher\ quality\ (given\ n)}+\underbrace{\frac{\partial Rev}{\partial n}\frac{\partial n^*(k,s)}{\partial s}}_{More\ varieties}. \tag{9}$$

Firm growth after foundational innovation is driven by two components. The first component comes from a change in sales because of higher vertical product quality s, conditional on n. This term is positive as long as $n > 1$. The second component comes from more varieties induced by foundational processes (Proposition 1) and the resulting revenue growth, as discussed above. This component is positive, too.

Consider next a change in revenue as a result of the change in efficiency k. The firm grows from two margins. First, production costs are now lower; hence, prices decline, resulting in higher sales. At the same time, given the price and vertical quality, the number of varieties increases (although, unlike with foundational processes, new varieties are not of higher quality), as discussed earlier, and this also contributes to growing sales:

$$\frac{\partial Rev}{\partial k}=\underbrace{\left(\frac{\varepsilon}{\varepsilon-1}\right)^{1-\varepsilon}(\varepsilon-1)k^{\varepsilon}\left[2\pi(\chi-\mu(1-s))-\mu s\frac{\pi^2}{n}\right]}_{Lower\ price}+\underbrace{\frac{\partial Rev}{\partial n}\frac{\partial n^*(k,s)}{\partial k}}_{More\ varieties}. \tag{10}$$

Using the derivations above, we summarize the implications of the product and process innovations for firm revenue growth from $t = 0$ to $t = 1$. It is convenient to show the following decomposition using the

[7] Recall that the probability of two Poisson events occurring at the same time is zero.

[8] Appendix A provides more details about alternative cases.

[9] It is worth noting that the expansion (widening) of the TPF resulting from the new foundational processes serves as a modeling device but is not essential to the results. What is essential, however, is that the new TPF enables the production of higher-quality products, and that this intrinsic quality is more highly valued by consumers when the product is a closer match to their tastes. This point is clearly laid out in the Internet Appendix IA.1.

[10] It is easy to show that the number of new varieties introduced after foundational process innovation, $n^*(s+\Delta s)$, is much higher than those introduced after cost-reducing process innovation, $n^*(k+\Delta k)-n^*(k)$, see Appendix A. Also note that in the model, cost-reducing process innovation applies to the firm's entire technological frontier, which we think is a plausible assumption. If, instead, cost-reduction applied to only the existing varieties produced by the firm, cost-reducing innovations would not incentivize variety creation.

[11] We focus on revenue as a measure of firm size, but the same logic applies to profits, capital, and labor.

first-order approximation:

$$\Delta Rev \approx \Delta k \xi_k \frac{\partial Rev}{\partial k} + \Delta s \xi_s \frac{\partial Rev}{\partial s}$$

$$= \underbrace{\Delta k \xi_k \Delta^{price} Rev}_{Cost-reducing\ process} + \underbrace{\underbrace{\Delta s \xi_s [\Delta_s^{variety} Rev + \Delta^{quality} Rev]}_{...due\ to\ foundational\ process} + \underbrace{\Delta k \xi_k \Delta_k^{variety} Rev}_{...due\ to\ cost-reducing\ process}}_{Product\ innovation...},$$

where $\Delta^{price} Rev$ denotes revenue change due to lower price p (see (10)); $\Delta_s^{variety} Rev$ and $\Delta_k^{variety} Rev$ denote the revenue changes due to more varieties n induced by change in s and k, respectively (see (9) and (10)); and $\Delta^{quality} Rev$ denotes revenue change due to higher quality s (see (9)). The decomposition implies that the firm's revenue grows both from product and process innovation. The revenue growth from product innovation is induced by process innovation, especially the foundational process discoveries. We summarize this discussion with the following propositions[12]:

Proposition 2 (*Firm Growth*). *Product, foundational process, and cost-reducing process innovations positively affect firm growth.*

Proposition 2a (*Firm Growth*). *The revenue growth from product introductions is largely induced by process innovation, especially the foundational process discoveries that lead to higher-quality product introductions.*

Although the model does not explicitly feature the gradual rollout of varieties to the market and other dynamic interdependencies, we could expect that sales growth following product innovation would be gradual, as new varieties need to build on each other. In contrast, we expect cost-reducing process innovations to have a more immediate and shorter-term (level-shift) effect. Foundational innovations are expected to have an immediate and also more sustained effect resulting in more and higher-quality new product introductions in the future.

3. Classification and data

To measure the importance of different types of innovations and their interaction, one needs comprehensive measures of heterogeneous innovations that are objectively verifiable over a long time series covering a broad range of firms and industries across countries. The long time series is important for studying the relation between innovation and growth (firm and aggregate economic) over several (slow-moving) business cycles, and providing more statistical testing power. We investigate heterogeneous innovations using patents, as patent data covers two centuries of innovation across a broad range of firms and countries. Patent documents contain detailed information on inventors, assignees, application and grant dates, legal claims, citations, and the technical nature of the invention. This information allows for the classification of patents into different types of innovation, and the measurement of technology diffusion and patent complementarity.

In this section, we briefly describe how we classify patents into process and product innovations using patent titles and claims, with more detail in Appendix B, which includes the external classification validation from IP experts and examiners. Motivated by the model, we further classify process patents into foundational and cost-reducing process innovations and validate these measures. Foundational innovation in the model and in our anecdotal examples is related to future product innovation and is distinct from prior products of the firm. Cost-reducing innovation tends to align more closely with prior products and less with future ones. We build on this differentiation to define foundational patents as a subset of process patents. Finally, we describe the patent and other (non-patent) data used in the paper.

3.1. Patent data and classification of process and product patents

We use two datasets for patent data: U.S. patent information from Google Patents and international patent data from the EPO-OECD-PATSTAT data (PATSTAT hereafter), which aggregates national patent offices, European Patent Office (EPO), and World Intellectual Property Office (WIPO) data in the largest international patent database. Table E.1 describes the patent-related variables in the Google Patents dataset. We parse the texts (structured and unstructured) for the entire history of granted U.S. utility patents for the sample period 1836 to 2020. PATSTAT has over 20 tables with bibliographic data, citations, and patent family links for applications from over 200 countries. We use the Autumn 2020 edition of the data, which contains 79,208,374 individual records for the period 1782 to 2020.

To construct our process and product innovation measures, we exploit patent office requirements and guidelines for patentees and their IP lawyers to carefully choose the wording of patent titles and claims to describe the main subject of the invention. In a patent (application), the claims define, in technical terms, the extent of the protection conferred (sought) by a patent. The title of the invention should reflect the invention to which the claims are directed. Claims are informative about the scope and detailed content of the patented invention, while the title provides a high-level description of the invention claimed. Therefore, patents can be classified using titles and/or claims, and they should generally provide consistent classifications.

Patent titles are available for all patents in standard patent datasets, while claims require the availability of the full patent text. There has been considerable effort in digitizing U.S. patents; however, such information is much sparser for international patents.[13] The USPTO has digitized all patents from 1976, while pre-1976 patent information has been parsed by Google Patents from USPTO patent images in an unstructured format. Non-USPTO patent office information in PATSTAT contains systematically digitized information on titles, abstracts, and citations, but does not include patent text and claims. An important advantage of using titles for patent classification is that we can analyze international patent data. Our patent classification enables us to investigate cross-country variations in process and product innovation that otherwise would not be possible because of the lack of claim information in non-U.S. patent data.

Therefore, we primarily focus on the textual analysis of patent titles to categorize patents into process or product patents. Invention titles are important, and all patent offices require the title of the invention to be meaningful, clear, and concise in reflecting the invention to which the claims are directed. WIPO guidelines impose strict requirements for patent titles for all patent offices. Under the "Guidelines for the Wording of Titles of Invention", WIPO requires: "The patent title should clearly, concisely and as specifically as possible indicate the ***main subject*** to which the invention relates. If the patent document contains claims in different categories (product, process, apparatus, use), this should be evident from the title". Patent applicants with titles that are not descriptive and reflective of the invention claimed will be requested

[12] For tractability, we analyze a setting with a single firm per product line. However, our qualitative results would hold if we allowed for multiple firms competing within a product line. The revenue function in (6) would adjust accordingly, with similar modifications to Eqs. (8), (9), and (10) but the main propositions would remain unaffected.

[13] Other than the USPTO, the EPO provides English claims information on their website, which can be web scrapped.

by the patent examiner to supply new titles.[14] In other words, patented inventions must use titles that describe the main claim of an invention.

At the nexus of our classification method is the heuristic separation between activities and physical entities, where titles referring to an activity (e.g., process, method, or use) are classified as process patents, whereas titles referring to a physical entity (e.g., product or apparatus) are classified as product patents. First, we create an expanding set of activity and physical entity hypernyms from patent titles, which we use to classify the patents into process and product patents. Fig. E.1 presents the word cloud of the relevant words in all the patents classified as process patents in Panel A and product patents in Panel B.

Next, we classify each patent into product and process using the following hypernym rule-based procedure, described in detail in Appendix B.2. First, patent titles are split into multiple partitions using the conjunction "and". If the words before the coordinating conjunctions (e.g., "for", "of", etc.) across all partitions belong to the activities set but not to the physical entity set, we classify the patent as a process patent. If the title contains words that are physical entities but not activities across all partitions, we classify the patent as a product patent.[15]

An alternative way to classify patents is to use patent claims. Bena and Simintzi (2025) is the first paper to classify process claims for the period 1976–2020. They classify process claims as "*those that begin with "A method for" or "A process for" (or minor variations of these two strings) followed by a verb (typically in gerund form)*". We use a larger word net to capture what is a process, as pertaining to an activity. For comparison, we classify every claim for the period 1976–2020 using the hypernym rule-based procedure. The correlation between the number of process claims in Bena and Simintzi (2025) and our classification is 87.1%. Unsurprisingly, our classification produces more process claims/patents because we use a more extensive set of process-related words; see Panel B in Fig. E.1.

To validate our classification method, we cooperated with patent experts from Maxval Group Inc. (vendor for Google Patents, referred to us by Tech Lead at Google Patents) and patent examiners in IP Australia, detailed in Appendix B.3. There is a 93.3% overlap between our classification and the validation set classified by IP experts and patent examiners. The external validation shows that the hypernym rules-based classification is reliable and highly correlated with expert classifications. Our main analysis is based on the title classification for two reasons. First, it allows for the consistent and comparable classification of every patent (U.S. or non-U.S., from the beginning of patent records). Second, it does not depend on specific words or pre-defined word lists, which may not be exhaustive. We provide comparison and robustness analysis using claims-based (rule and machine learning) classifications in Appendix B.

We systematically classify the sample of all U.S. patent data and all PATSTAT patents with English titles. 93.0% of PATSTAT patents from 90 IP offices (with at least one English patent title) in our sample have English titles. Our final sample consists of over 50 million classified patents.

3.2. Foundational process patents

We use the process patents as classified above to further separate processes into foundational and cost-reducing innovations. Conceptually, foundational processes advance the *technological possibilities frontier* by allowing the production of new product varieties. As such, a foundational process innovation is one that gives rise to more products in the future, but it is not correlated with the current products of the firm. Here, we provide a quick overview of our classification methodology and then continue with the definition of foundational process patents and its validation.

3.2.1. Patent similarity measure

At the core of our classification of foundational patents is the patent similarity work of Kelly et al. (2021), which uses Term Frequency-Inverse Document Frequency (TFIDF) to measure similarity; see details in Appendix C. We use the same notation, q for patent p similarity ratio, defined as:

$$q^{\tau}_{p,t} = \frac{FS^{\tau}_{p,t}}{BS^{-\tau}_{p,t}},$$

where FS is forward similarity, and BS is backward similarity using TFIDF. *FS* is the sum of similarities between the focal process patent p and product patents filed after the focal patent within a time window τ, and *BS* is the sum of similarities between the focal process patent p and product patents filed prior to the focal patent within the same time window τ. We set $\tau = 10$ for the main analysis; however, our findings are robust to using alternative time windows, e.g., 3, 5, or 7 years.

Foundational process innovation in the model and our anecdotal examples is related to future products and is distinct from prior products of the firm. Foundational processes open a new product frontier and are different from the firm's current product offerings. Hence, foundational process patents should be more similar to future firm products and have high FS and low BS (hence a higher q-ratio). In contrast, cost-reducing patents tend to align more closely with prior products of the firm and less with future ones. A firm invests in cost-reducing processes to improve the production processes of its current products. Hence, there should be a high similarity between the firm's current and past products and cost-reducing processes, high BS and low q. As a result, we restrict our attention to patents originating from the same firm and calculate FS and BS for process and product patents within the firm. To do so, we need to know entity structures and have disambiguated patent owner information, which is available for publicly listed firms only (Kogan et al., 2017).

We define foundational patents as those with a q-ratio exceeding the yearly 80th percentile among all process patents granted to publicly listed firms, while the remainder is categorized as cost-reducing. Different percentile cut-offs (70th and 90th percentile) do not affect the results quantitatively. We also conduct additional analysis using similarities of process and product patents across firms, cross-firm q. Results of additional analyses are presented in Appendix E and are referred to in the relevant sections.

Validation of Cost-reducing Innovation Measure

To validate our cost-reducing process innovation measure and, by implication, the foundational innovation measure, we use firm accounting information and firms' annual report filings (10K/Q). Cost-reducing innovations increase production efficiency, allowing firms to produce more output with the same or fewer inputs (capital efficiency) or substitute and replace labor with machines. This implies that a higher stock of cost-reducing innovation should be correlated with lower capital expenditure and capital stock (at least in the short run), as well as a lower employee-to-capital ratio (Karabarbounis and Neiman, 2013). We exploit the relation between cost-reducing innovation and firm capital investments, expenditures, and employee-to-capital ratio to validate the process innovation classification.

[14] For example, there are strict guidelines by the USPTO on the structure, technical accuracy, and descriptive details of patent titles; see https://www.uspto.gov/web/offices/pac/mpep/s606.html on the requirements for an appropriate title. If the applicant provides no satisfactory title, the examiner may change the title by an examiner's amendment; see MPEP 1302.04(a) and MPEP 606.01 in https://mpep.uspto.gov/RDMS/MPEP/e8r9#/e8r9/d0e131704.html.

[15] There is also a category of patents that have both process and product-related titles, around 17% of our sample. In the main analysis, we focus on process and product-only innovation. In robustness analysis, we include the mixed patents in two ways, allocating them proportionally to the two groups and analyzing them separately. The results remain qualitatively similar and are available from the authors upon request.

Table 1
Validation of cost-reducing patents.
Panel A. Accounting information

	EMP/PPE	CAPX/AT	PPE/AT
	(1)	(2)	(3)
Ln(Foundational Stock)	0.001	0.086***	0.051
	(1.11)	(3.78)	(0.79)
Ln(Cost-reducing Stock)	−0.009***	−0.059***	−0.122**
	(−5.42)	(−3.03)	(−2.29)
Ln(Product Stock)$_t$	−0.002	−0.014	0.236**
	(−0.90)	(−0.39)	(2.34)
Controls	✓	✓	✓
Year FE	✓	✓	✓
Firm FE	✓	✓	✓
Obs.	148,220	151,774	153,370
Adj. R^2	0.84	0.55	0.87

Panel B. Company filings

	10K/Q
	(1)
Ln(Foundational)	−0.004
	(−0.70)
Ln(Cost-reducing)	0.016***
	(2.99)
Ln(Product)	−0.015***
	(−3.12)
Controls	✓
Year FE	✓
Firm FE	✓
Obs.	127,519
Adj. R^2	0.45

This table presents validation analysis for the classification of cost-reducing patents. In Panel A, the dependent variables are the number of employees per million of property, plant, and equipment (PPE), capital expenditures (CAPX), and PPE both expressed as shares of total assets. In Panel B, the dependent variable is an indicator variable equal to one when cost-reduction terms are mentioned in firms 10-K/Q filings, and zero otherwise. The search terms include the following and their variants: cost-reducing, reduce cost, operational efficiency, efficiency gain, increase productivity, improve productivity, productivity improvement, process efficiency, cost cutting, reduced labor, operational improvement, overhead reduction, efficiency improvement, cost containment, expense control, workflow optimization, cost control, cost minimization, increase efficiency, improve efficiency, efficiency enhancement, and resource optimization. Foundational and cost-reducing patents are defined using the within-firm q-ratio at the 80th percentile. The included control variables are: Ln(Total assets), Tobin's Q, cash flow, R&D expenditure, and a missing R&D indicator. Standard errors are clustered at the firm level. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. All variable definitions are provided in Table E.2 in the Appendix. The sample period for Panel A is 1976 to 2020, and 1993 to 2020 for Panel B, when 10-K/Q electronic filings are available.

In Panel A of Table 1, we present panel regression analysis of the relation between the stock of the different types of innovation and the employee-to-capital (PPE) ratio, firm capital expenditures (CAPX), and property plant and equipment (PPE), a proxy for capital stock, for publicly listed U.S. firms. We create the patent stock as the sum of unexpired patents of firm i in year t. The analysis includes control variables for Ln(Total assets), Tobin's Q, cash flow, R&D expenditure, a missing R&D indicator, as well as firm and year fixed effect. All variable definitions are provided in Table E.2 in the Appendix. Firm fixed effects absorb any variation that is time-invariant at the firm level, and time fixed effects absorb firm-invariant unobservable confounding effects. In line with the idea that cost-reducing innovation can be labor-saving, we see that the labor-to-PPE ratio declines when the firm accumulates more cost-reducing patents in column (1), which is not the case for other types of patents. In addition, cost-reducing patents are correlated with a lower share of capital expenditures (column 2) and PPE (column 3) relative to the firm's total assets, consistent with increased capital efficiency. These results align with the labor cost-reducing role of process innovation in Bena et al. (2022). Interestingly, different from cost-reducing processes, foundational process patents are associated with increased capital expenditures (columns 2 and 3), indicating that foundational changes to production technology are accompanied by investment in new capital goods.

Another way to validate the cost-reducing classification is to use the information firms provide for their shareholders in annual reports. If firms introduce cost-reducing technology, they are likely to refer to it in their filings to inform shareholders of such measures at the time of their introduction. We search firms' 10K/Q filings with the Securities and Exchange Commission (SEC) for the use of cost reduction terminology in any given year.[16] The use of this terminology should be contemporaneously positively correlated with cost-reducing innovation. Panel B of Table 1 provides the regression results. Cost-reducing patents in year t are positively correlated with cost-reduction terminology in firms' annual reports in the same year. The opposite results hold for product patents, indicating that firms do not simultaneously increase product variety and reduce costs.

We also analyze the relation of the same outcomes with foundational and cost-reducing patents defined at different thresholds, 70th and 90th percentile. Results in Table E.3 show that as we increase the threshold for foundational patents from the 70th to 90th percentile, the relation between cost-reducing patent stock and capital investments weakens, becoming largely insignificant. The positive relation with 10K reporting also weakens with the increase of the threshold. These results imply that as we increase the threshold, more non-cost-reducing patents are added to this category and are potentially misclassified. The 80th percentile separation seems to be a reasonable cut-off.

[16] Specifically, we search for the following bi-grams and their variants: cost-reducing, reduce cost, operational efficiency, efficiency gain, increase productivity, improve productivity, productivity improvement, process efficiency, cost cutting, reduced labor, operational improvement, overhead reduction, efficiency improvement, cost containment, expense control, workflow optimization, cost control, cost minimization, increase efficiency, improve efficiency, efficiency enhancement, and resource optimization.

Table 2
Industry distribution and firm characteristics by patents type.

Panel A. Industry Distribution

Industry	Foundational	Cost-reducing	Process	Product	Total
Oil, Gas, and Coal Extraction and Products	8%	35%	50%	50%	159,484
Finance	15%	24%	50%	50%	31,234
Wholesale, Retail, and Some Services	16%	26%	48%	52%	27,978
Business Equipment	9%	31%	45%	55%	1,198,126
Utilities	2%	6%	40%	60%	3771
Chemicals and Allied Products	6%	26%	38%	62%	201,738
Telephone and Television Transmission	7%	23%	37%	63%	125,909
Other	4%	25%	34%	66%	211,414
Healthcare, Medical Equipment, and Drugs	5%	21%	32%	68%	230,184
Manufacturing	4%	20%	28%	72%	533,659
Consumer Durables	4%	18%	26%	74%	248,519
Consumer NonDurables	4%	12%	26%	74%	37,061

Panel B. Firm Characteristics

	Foundational			Cost-reducing			Product			Non-Foundational		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ln(Total Asset)	6.93	6.87	2.20	6.55	6.46	2.27	5.98	5.78	2.31	4.88	4.67	2.10
Ln(Market Cap)	6.91	6.86	2.29	6.53	6.45	2.35	5.98	5.83	2.39	4.85	4.68	2.19
Tobin's Q	2.00	1.49	1.50	1.99	1.47	1.53	2.03	1.47	1.65	2.11	1.43	1.97
Cash Holdings	0.19	0.11	0.21	0.19	0.11	0.22	0.20	0.11	0.23	0.21	0.11	0.24
ROA	−0.00	0.05	0.19	−0.02	0.04	0.22	−0.03	0.04	0.24	−0.08	0.03	0.32
CAPX	0.05	0.04	0.04	0.05	0.04	0.04	0.05	0.04	0.04	0.05	0.04	0.05
PPE	0.25	0.23	0.17	0.25	0.21	0.17	0.24	0.21	0.17	0.24	0.19	0.19
Sales Growth	0.11	0.07	0.33	0.11	0.07	0.36	0.13	0.08	0.42	0.16	0.07	0.57
R&D	0.07	0.04	0.11	0.08	0.03	0.12	0.08	0.03	0.12	0.08	0.02	0.15
Missing R&D	0.09	0.00	0.29	0.12	0.00	0.33	0.16	0.00	0.37	0.30	0.00	0.46
Profit ($mil)	2419.47	335.99	6140.44	1,956.54	221.08	5367.93	1,395.31	113.37	4291.96	344.55	37.25	1041.00
Output ($mil)	6855.19	953.47	17,772.53	5,569.20	634.85	15,347.96	3,928.44	324.48	11,734.45	1,105.51	109.25	3358.43
Capital ($mil)	45.49	3.80	145.04	37.12	2.34	123.28	25.58	1.11	89.81	7.87	0.31	33.07
TFP	−0.11	−0.13	0.57	−0.18	−0.18	0.58	−0.24	−0.23	0.57	−0.30	−0.17	0.50
N	29,963			38,967			58,818			56,002		

The table presents the industry distribution of foundational and cost-reducing process patents, product patents, and firm characteristics for patent-holding firms. Patents are classified based on their titles and the within-firm Q-ratio. Panel A presents the percentage distribution of foundational and cost-reducing process patents, as well as product patents, across each Fama–French twelve-industry classification (sourced from the Ken French Data Library). The sample period spans from 1930 to 2020. Panel B reports characteristics of firms with at least one foundational process patent, cost-reduction process patent, product patent and non-foundational patent. To be included, a firm–year must hold at least one patent in the patent portfolio. A patent is assumed to have a lifespan of twenty years. The dataset comprises a CRSP-Compustat firm–year panel from 1976 to 2020. All variable definitions are provided in Table E.2 in the Appendix.

3.3. Firm data

For firm-level and patent value analysis, we use data on publicly listed firms from the CRSP-Compustat merged (CCM) database. This is also the sample for which foundational patents are defined. We use the market value (ξ) of granted patents to U.S. publicly listed firms from Kogan et al. (2017) for the firm growth analysis. The CRSP sample period is 1926–2020, which includes 3,053,011 patents granted to U.S. publicly listed firms. The Compustat sample period starts in 1950 and includes 2,778,675 patents. For the firm-level analysis, we use the sample period from 1976 to 2020 because the coverage of small firms in Compustat in early periods is relatively incomplete (Fama and French, 1992). We present results for the full sample starting from 1950 in robustness analysis in the internet appendix.

We exclude firm–year observations with missing total assets and SIC classification codes. We also exclude the two heavily regulated industries of utilities (SIC code 4900–4949) and financial firms (SIC code 6000–6799) in the empirical analysis, although we include all firms in the industry descriptive statistics in Table 2. Table E.2 in the Appendix provides the definition of all the variables used in the analyses.

4. Characteristics of process and product patents

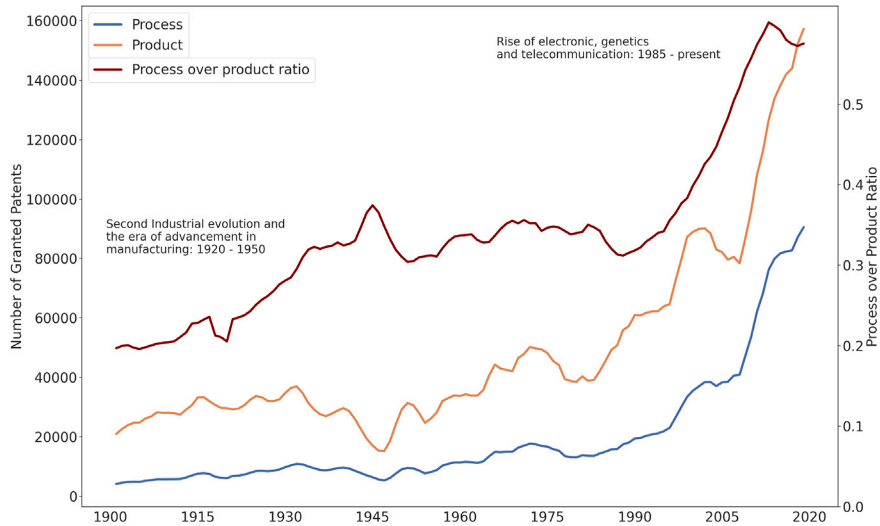
In this section, we present characteristics of different patent types classified as process and product, and foundational and cost-reducing process patents. We also present statistics on cross-industry and firm variation and explore the time series and cross-country dimension of our data.

4.1. Time-series variation

Fig. 3 presents the time-series variation in USPTO granted patents. Panel A highlights the trends in process and product patents and their ratio from 1900–2020. Patent grants correspond to significant innovation waves in U.S. history. In particular, the number of process patents increased steadily between 1920 and 1935 (post-second industrial revolution advancements in manufacturing) and from 1985 to the present (the recent boom in electronics, genetics, and telecommunication). The rapid rise in process patents started in 1910 and coincided with the sharp increase in the average capital productivity in American manufacturing in the following decades. The 1920s and 1930s marked an era of accelerated applications of scientific knowledge, leading to substantial enhancements in manufacturing plants, equipment, and processes consistent with the evidence in Field (2003). The acceleration in process patents post-1985 reflects transformative developments in computing, genetics, and telecommunications, consistent with the evidence in Kelly et al. (2021). By the turn of the century, one process patent is granted for every two product patents.

Panel B focuses on foundational process patents and their ratio to product patents using both a simple patent count and a market-value-weighted index (ξ_p). This sample only includes U.S. publicly listed

Panel A. Process and product innovation: all patents



Panel B. Foundational process innovation: publicly listed firms

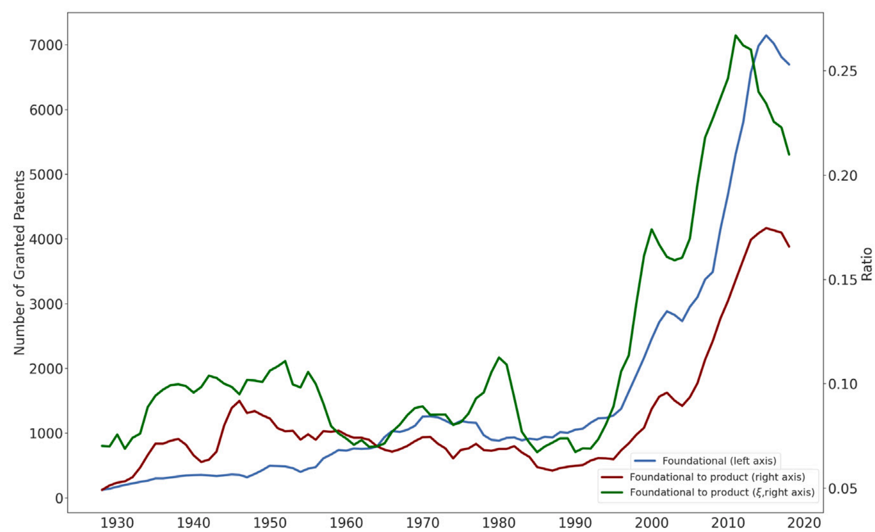


Fig. 3. Historical evolution of heterogeneous innovations.
The figure presents the time-series variation in the number of different types of innovations for U.S. patents granted from 1900 to 2020, as a three-year moving average. Panel A displays the number of process and product patents (left axis) and the process-to-product ratio (right axis) for all USPTO granted patents. Panel B shows the evolution of foundational process patents (left axis) and the foundational process-to-product ratio (right axis) by the number of patents and market value (ξ) weighted for the subset of U.S. publicly listed firms, available from 1929.

firms, and hence starts in 1929. The prevalence of foundational process innovation has steadily increased, especially from 1990, to about 17% of product patents, coinciding with the advent and maturation of the digital revolution, biotechnology, and microelectronics. While the patent-count ratio mirrors trends in Panel A (by construction, trends in all processes and foundational processes are linked), the market-value-weighted ratio reveals new insights. It peaks during major waves of technological change: the Second Industrial Revolution and the leap in advanced manufacturing between 1930 and 1950; the introduction of integrated circuits and computers in the 1980s; and the mid-1990s to the present, with breakthroughs in genetics and telecommunications.

4.2. Cross-industry and firm variation

To further understand the prevalence and distribution of heterogeneous innovations, we explore industry and firm-level variation. This analysis is based on publicly listed firms because of the need for industry classification and information on firm characteristics.

Panel A of Table 2 presents the industry distribution of process and product patents for the Fama and French 12 industries. The sample period is 1930 to 2020, as per industry classification information availability. The business equipment, manufacturing, consumer durables, and healthcare industries have the largest number of granted patents in the sample period. The share of process patents varies between 26%–50% across industries; thus, at a minimum, a quarter of the innovation in each industry represents process innovation. Most process patents are found in the business equipment and oil and gas industries. Generally, there is a higher percentage of product patents in the manufacturing, healthcare, and consumer (non)durable industries. Our findings are consistent with Cohen and Klepper (1996), who reports that the propensity to apply for product innovation is higher than for process innovation, using a survey of 1065 U.S. research laboratories

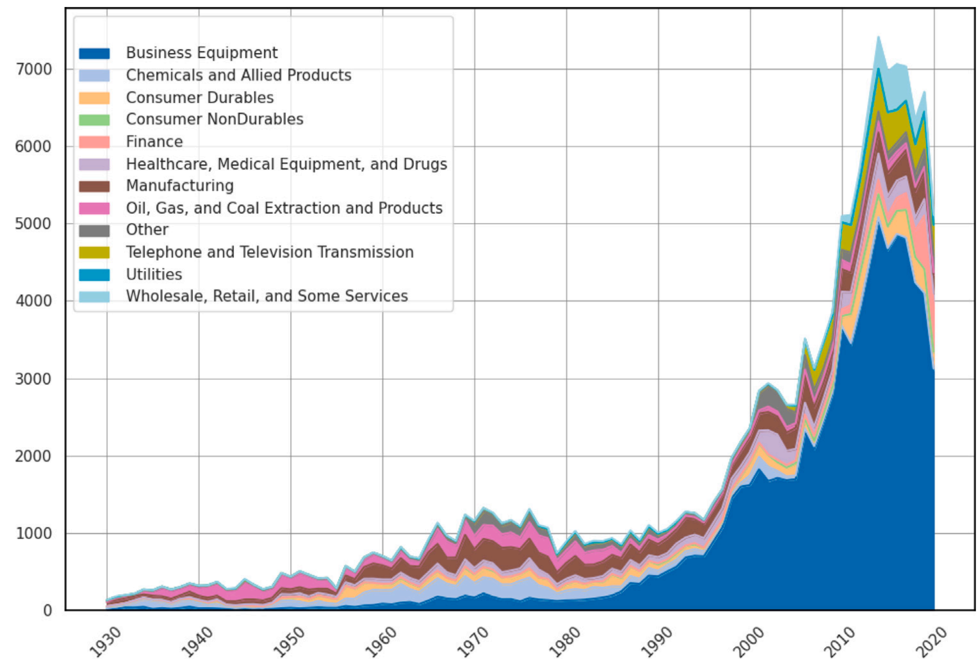


Fig. 4. Foundational process patents across industries.
The figure presents the time-series variation of the number of U.S. foundational patents granted to publicly listed firms by Fama–French 12 industries for the sample period from 1930 to 2020.

in manufacturing between 1991 and 1993. Fig. 4 presents the time-series variation of foundational processes by industry, highlighting the increasing significance of these processes in the Business Equipment sector after 1990, propelled by advancements in photolithography, thin film oxidation, and related technologies.

Panel B of Table 2 presents univariate differences in firm characteristics for foundational process firms, cost-reducing process firms, and product-oriented firms. We only include firms with at least one patent in their patent portfolio in a year, assuming a twenty-year life span per patent. Foundational firms (columns 1–3) are defined as having at least one foundational process patent in their portfolio, cost-reducing (columns 4–6) include firms that have at least one cost-reducing process patent, product firms (columns 7–9) are defined as those with a larger proportion of product relative to process patents in their patent portfolio in a year, and non-foundational (columns 10–12) are firms with no foundational patents in their portfolio. Congruent with Fig. 3, the sample has product-oriented firm–years.

We find that larger firms (total assets and market capitalization) with more sales growth and cash holdings are more likely to have foundational and cost-reducing processes. This is consistent with larger firms, which are in the latter part of firm and product life cycles, taking advantage of economies of scale in production cost reduction through process innovation (see, Cohen and Klepper, 1996; Fritsch and Meschede, 2001), or pushing the technology frontier.

4.3. Quality and value of process and product patents

Table 3 compares process and product patent characteristics within the same technology class and cohort using panel regression models with fixed effects. The dependent variables are ten patent quality measures, which are described in Appendix D: the number of claims, patent scope, backward citations, originality, forward citations, generality, private economic value ξ, the number of non-patent literature (NPL) citations, the number of reassignments, and the renewal rates of patents. We include technology class (IPC4) interacted with time fixed effects (IPC4 $\times$ year) to facilitate the comparison within each cohort (year)-technology class, which mitigates the truncation problem related to patent age and class (Hall et al., 2001). We use Poisson regressions for dependent variables involving count data (columns 1, 2, 3, 5, 8, 9) and standard OLS regressions for the rest of the estimations (columns 4, 6, 7, 10). For generality and originality measures, we only include patents with at least one forward or backward citation. For market values, the sample is restricted to publicly listed firms within the CRSP sub-sample. We cluster the standard errors at the technology class level (IPC4).

In Panels B and C, we focus on foundational process patents. *Foundational* is an indicator variable equal to one for foundational patents and zero otherwise. We add an outcome variable here, *Other Cites*, citations by non-focal firms, which captures the broader applicability of foundational patents. In Panel B, we compare foundational and cost-reducing patents within the subset of process patents. Foundational patents have more forward citations, especially from other firms, which indicates that they generate more social value through knowledge spillovers (Bloom et al., 2013). They also show substantially higher private economic value (30%) than cost-reducing patents. Furthermore, consistent with foundational process discoveries being the outcome of R&D that pushes the technological possibility frontier, we observe that foundational patents cite substantially more (16%) non-patent literature (NPL), i.e, scientific publications, indicating that they rely more on basic science. The results are similar when we compare foundational patents to all other patents of U.S. publicly-listed firms in Panel C. Here, it is clear that foundational patents build much more closely on basic science with 21% more NPL citations than other patents.

We further investigate the relation between the different innovations and basic science, through the link with academic publications. We evaluate the relation of the number of academic papers a firm publishes, using data from the Reliance on Science project, with the stock

Table 3
Process and foundational patent characteristics.

Panel A. Process and product patent

	Claims	Scope	Backward	Originality	Forward	Generality	ln(ξ)	NPL	Re-assignments	Renewal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Process	0.038***	−0.010	0.005	0.004**	−0.013	0.000	0.132***	0.202***	0.066***	0.017***
	(7.63)	(−0.95)	(0.14)	(2.16)	(−0.45)	(0.07)	(7.09)	(4.94)	(10.94)	(7.42)
IPC4 × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	5,919,347	5,919,347	5,919,324	5,548,336	5,917,759	4,259,515	2,103,202	5,249,028	5,824,053	3,443,614
Adj. R^2				0.14		0.14	0.18			0.22

Panel B. Foundational and cost-reducing patents

	Claims	Scope	Backward	Originality	Forward	Other cites	Generality	ln(ξ)	NPL	Re-assignments	Renewal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Foundational	0.080***	0.008	0.144***	0.006***	0.416***	0.324***	0.029***	0.302***	0.163***	0.002	0.029***
	(14.08)	(1.61)	(3.32)	(4.83)	(12.10)	(9.57)	(5.24)	(4.59)	(6.11)	(0.18)	(7.98)
IPC × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	716,870	716,870	716,836	671,448	715,830	715,448	524,080	716,870	636,592	689,628	716,870
Adj. R^2				0.12			0.17	0.15			0.42

Panel C. Foundational and all other patents

	Claims	Scope	Backward	Originality	Forward	Other cites	Generality	ln(ξ)	NPL	Re-assignments	Renewal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Foundational	0.081***	−0.005	0.082	0.005***	0.323***	0.244***	0.020***	0.427***	0.206***	−0.011	0.028***
	(13.27)	(−0.66)	(1.50)	(3.84)	(9.29)	(6.65)	(2.78)	(7.51)	(5.39)	(−0.81)	(8.98)
IPC × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	2,103,139	2,103,139	2,103,095	1,983,748	2,101,912	2,101,669	1,584,747	2,103,135	1,840,387	2,048,733	2,103,139
Adj. R^2				0.14			0.16	0.19			0.39

The table reports the differences in characteristics for different innovation types. All patent metrics in this table are described in detail in D. *Claims* is the number of claims by the patent; *Scope* is the unique number of IPC 4-digit classifications of a patent; *Backward* is backward citations measured as the number of U.S. patents the patent cites; *Originality* is the HHI index of IPC4 classes of the backward citations; *Forward* is forward citations measured as number of U.S. patents citing the patent; *Generality* is the HHI index of IPC4 classes of the forward citations; and ξ is the market value of patent as in Kogan et al. (2017). *NPL* is the number of non-patent literature citations. *Re-assignments* is the number of USPTO reported re-assignments of the patent. *Renewal* is an indicator variable equal to 1 when a patent is renewed after 12 years and zero otherwise. Coefficients in columns 1, 2, 3, 5, 8, 9 are estimated using Poisson regressions and OLS regressions for columns 4, 6, 7, and 10. Panel A presents regression coefficients for differences in patent quality metrics between process and product patents across all patents. *Process* is an indicator variable equal to one if the patent is a process patent using the title-based classification and zero otherwise. Panel B presents differences between foundational and cost-reduction processes. These are available for publicly listed firms only. *Foundational* is an indicator variable equal to 1 if the process is a foundational process and zero otherwise. Panel C presents differences between foundational patents and all other patents for publicly listed firms only. Standard errors are clustered at the IPC4 level. ***,** ,* indicates significance level at 1%, 5% and 10%. The sample period is 1900 to 2020 using populated patent information for each measure.

of different patents in its portfolio.[17] Results in Table E.4 show that firms with a larger stock of foundational patents publish more academic papers, which is not the case for cost-reducing and product patent stock. Specifically, using a Poisson regression model, we find that foundational patents are strongly linked to future scientific research output, with an elasticity of approximately 0.5. These results again show that foundational patents carry important scientific value and content and provide firm-level empirical support for the importance of basic science in fostering growth through knowledge spillovers to applied science.

4.4. Cross-country variation

Our patent classification method allows us to classify international patents. Table E.5 provides the process/product share of patents by patent office for the sample period with a minimum of ten overlapping years of GDP/TFP and patent data between 1954 and 2020 (which is a subset of our full classified sample), due to GDP/TFP information availability. From 1954 to 2020, China has granted the most patents, followed by the U.S. and Japan. This table shows that many countries start having GDP/TFP and/or patent information at different times during this sample. For ease of comparison, we focus on the common period from 1984 to 2020, which includes complete patent information for China, the largest patenting country in the sample. Fig. E.2 presents the share of process and product patents granted by the top 25 patent offices ranked by the number of patents per office. We find that product patents dominate the granted patents across all patent offices, i.e., all patent offices have less than 50% of process patents, similar to the U.S. However, there is considerable variation in the proportion of process patents across countries. The country with the lowest share of process patents is China (15%), while many patent offices grant a high share of process patents, e.g., Poland (42.47%), Finland (40.3%).

The international data allows us to understand differences across countries, particularly the relation between foundational innovation and growth. We investigate the relation between the foundational-process innovation ratio (foundational to non-foundational patents) and cross-country growth (GDP and TFP). We assess this relation in a panel regression in Table E.6, including control variables and time fixed effects, and present the estimated coefficients for the relation between foundational innovation ratio and growth in Fig. 5. We find a strong positive correlation between foundational patents and subsequent aggregate growth up to four years ahead.[18]

[17] The data is available from Matt Marx's website: https://relianceonscience.org/patent-paper-pairs. As noted in this dataset, in some cases, a patent *is* a paper, representing both the idea and its practical implementation. More information about the data construction is available in Marx and Scharfmann (2024).

[18] The foundational-process innovation ratio is by construction related to the process-to-product ratio: $\frac{\text{Foundational}_{c,t}}{\text{Product}_{c,t}+\text{Cost reducing}_{c,t}} = \frac{0.2\times\ \text{Process}_{c,t}}{\text{Product}_{c,t}+0.8\times\text{Process}_{c,t}}$, with a 50% correlation. Therefore, one may wonder whether the growth relation stems from the process-to-product ratio or from foundational processes. In unreported regression analysis conditioning on only the process-to-product ratio, we find that the relation between the process-to-product ratio and GDP/TFP is much weaker. These results indicate that the documented effects mainly stem from foundational processes. Results are available from the authors upon request.

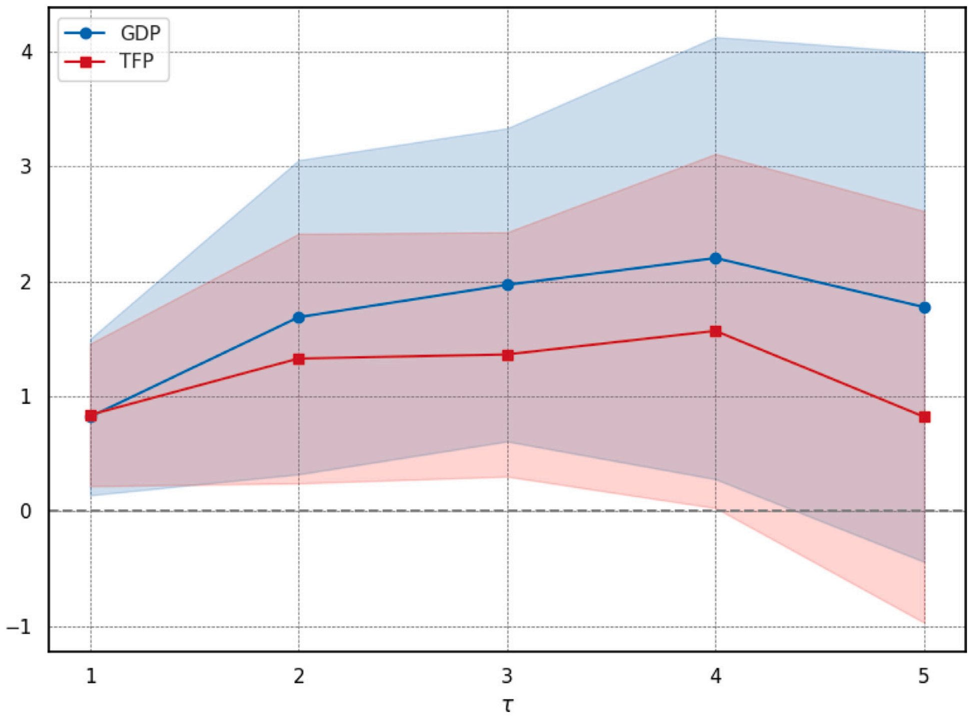


Fig. 5. Cross-country growth and foundational processes regression.
This figure presents the coefficients from cross-country growth regressions of the form:

$$\ln(Y_{c,t+\tau}) - \ln(Y_{c,t}) = \beta_0 + \beta_1 \frac{\text{Foundational}_{c,t}}{\text{Product}_{c,t} + \text{Cost-reducing}_{c,t}} + \gamma ln(Y_{c,t}) + \Lambda X'_{c,t} + \alpha_c + \delta_t + \epsilon_{c,t+\tau}$$

where Y represents the growth measures of real GDP per capita and TFP. *Foundational* is the number of foundational process patents, *Product* is the number of product patents, and "Cost-reducing" is the number of cost-reducing patents filed in country c in year t. X is a vector of control variables, including the labor share (labor compensation scaled by GDP) and capital share (capital stock scaled by GDP). We estimate for $\tau = 1$ to $\tau = 5$ (x-axis). Foundational and cost-reducing patents are identified using patent families with foundational/cost-reducing patents with the USPTO. The GDP and TFP data are from the Penn World Tables. The sample period is from 1954 to 2019. Shaded areas represent 90% confidence intervals. Full regression estimates are presented in Table E.6.

5. Empirical results

Our empirical analysis is motivated by the model's implications, which underscore the role of heterogeneous (process and product) innovations in driving firm growth and the role of process innovations in driving product innovations. In Section 5.1, we explore the role of heterogeneous innovations for firm growth. Specifically, Proposition 2 asserts that both types of innovation – product and process innovations – are key drivers of firm growth. We begin by delineating the respective contributions of product and process innovation to firm growth. We anticipate a positive association between firm growth and different types of innovation, but we expect to see distinct growth dynamics across the innovation types. Within our framework, process innovation influences firm growth through two primary channels: foundational process discovery, which extends a firm's technological possibility frontier, and cost-reducing process innovation, which enhances production efficiency. To explore these dynamics, we examine the differential contributions of product and process patents to firm growth. Further, building on Proposition 2, Proposition 2a attributes the growth contribution of product innovation largely to process innovations, especially the foundational ones which enable the production of more and higher-quality products. To empirically test this proposition, we distinguish between foundational process-based product innovation and other forms of product innovation and examine their contributions to growth. Hence, the results in this section speak to process innovations' direct and indirect (through product innovations) contributions to firm growth.

Next, in Section 5.2, we turn to the mechanism behind the observed growth contributions of different types of innovations. Proposition 1 posits that the mechanism through which process innovation, especially foundational processes, affects firm growth is by enabling the introduction of new and higher-quality products. We examine how foundational processes lead to subsequent products of higher value and impact than those not rooted in foundational processes using data on patents and drug introductions, using information from the FDA "Orange Book" data.

5.1. Heterogeneous innovations and firm growth

To study the role of heterogeneous innovations for firm growth, we estimate the relation between the different types of innovation and a firm's future growth and productivity using Local Projection Regression (LPR) or Jordà regressions (Jordà, 2005). LPR is a simple, flexible, and robust (to model misspecification and structural breaks) method with excellent statistical properties to estimate the same impulse responses in a population as VAR, which is particularly well-suited for analyzing dynamic effects over time while accommodating potential persistence in the data. The LPR framework is advantageous in addressing unobserved persistent shocks, particularly in time series data, by allowing the estimation of dynamic responses without imposing restrictive assumptions on the persistence structure of the variables, see Jordà (2005), Plagborg-Møller and Wolf (2021), and Stock and Watson (2018) for other advantages of using LPR. We estimate the impulse responses for one to ten-year horizons following specifications in Jordà (2005), Kogan et al. (2017), and Kelly et al. (2021).

We focus on the following five measures of firm growth: (a) profits, defined as sales minus cost of goods sold; (b) sales; (c) capital,

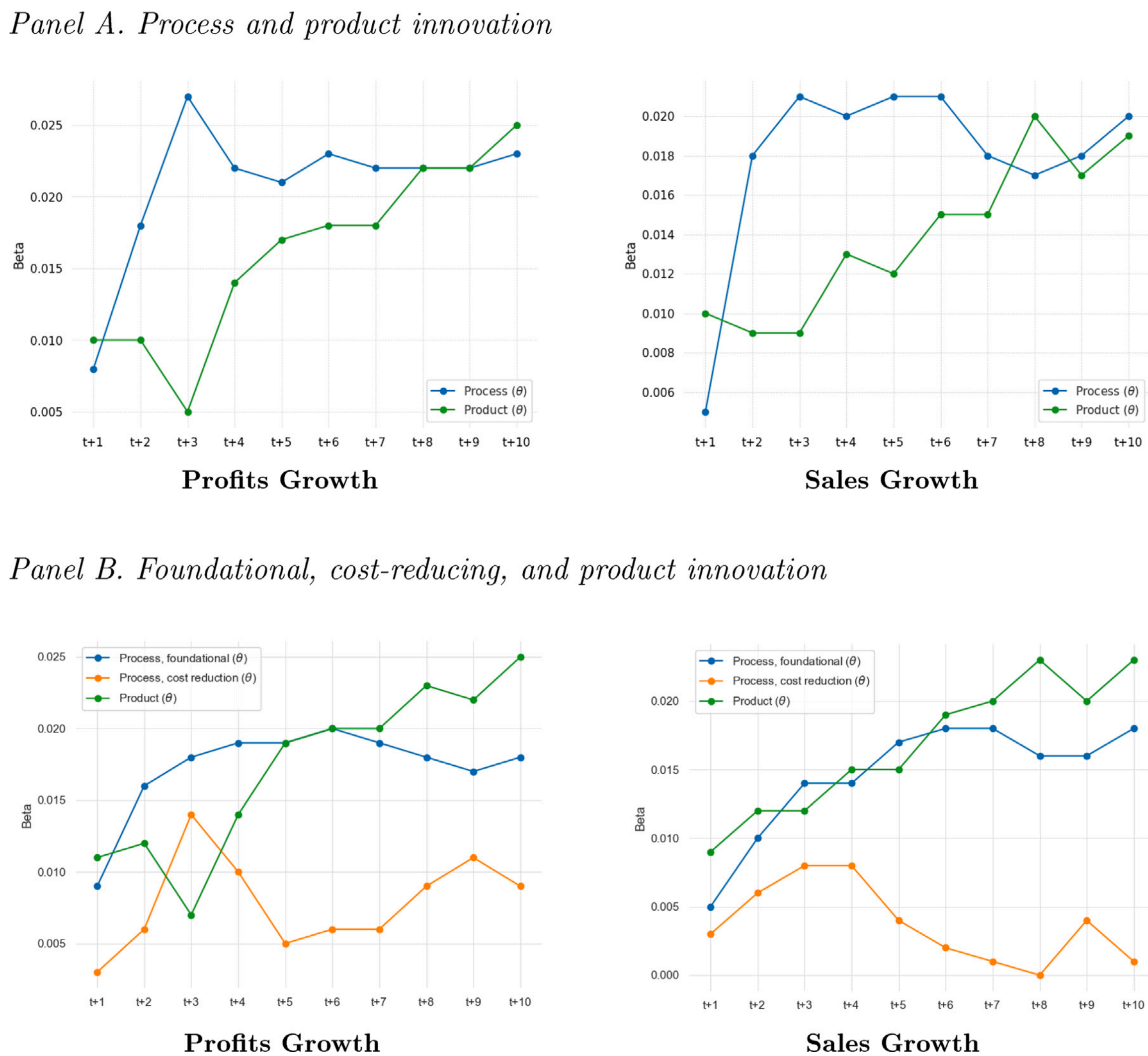


Fig. 6. Heterogeneous innovations and firm growth.
This figure presents the coefficients from firm growth regressions on various types of innovations of the form:

$$\ln(Y_{i,t+\tau}) - \ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_\tau^{Pats} \theta_{i,t}^{Pats} + \gamma_1 ln(i, Y_t) + \gamma_2 ln(i, Y_{t-1}) + \Gamma X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y represents firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different type of patents ($Pats$) granted in year t by firm i, scaled by total assets. $X_{i,t}$ is a vector of control variables, including log capital stock, log employment, log total assets, and idiosyncratic volatility, with $\tau \in \{1, \dots, 10\}$. α_{sic3} and δ_t are industry and year fixed effects, respectively. All right-hand-side variables are scaled to unit standard deviation, and standard errors are clustered at the firm level. Panel A reports the coefficients on process and product θ. Panel B reports the coefficients for foundational process patents, cost-reduction process patents, and product patents. The sample period is 1976 to 2020.

measured as deflated gross property, plant, and equipment; (d) employment; and (e) revenue-based productivity (TFP) constructed using the methodology of Olley and Pakes (1996) applied using the procedure in İmrohoroğlu and Tüzel (2014). All variable descriptions are detailed in Table E.2.

For the innovation variables, we construct a firm–year innovation index for each type of innovation: process, foundational, cost-reducing, product, and foundational process-based product innovation by summing up the market value of patents granted in each category to firm i at year t.[19] This value is then normalized by the total assets of firm i at year t to facilitate cross-sectional comparison among firms of different sizes.[20] Using market values (ξ) to weight patent counts helps to isolate the shock component of the patent grant, filtering out the market anticipation effects. In Kogan et al. (2017), π_j in the estimation of ξ_j in Eq. (1) and implemented in Equation (3) accounts for the market's ex ante probability assessment that the patent application is successful. In addition, the inclusion of contemporaneous and lagged values of the

[19] The results are qualitatively similar when using patent application rather than patent grant dates. The results are available from the authors upon request.

[20] Larger firms file for more patents (Kogan et al., 2017) and invest more in process innovation (Cohen and Klepper, 1996; Fritsch and Meschede, 2001), so the firm innovation index may inherently capture firm size.

outcome variables further absorbs anticipatory effects of patent grants on the outcomes of interest.[21]

We test the relation between innovation types and firm growth with regressions of the following form:

$$ln(Y_{i,t+\tau})-ln(Y_{i,t})=\alpha_0+\sum_{Pats}\beta_{\tau}^{Pats}\theta_{i,t}^{Pats}+\gamma_1 ln(Y_{i,t})+\gamma_2 ln(Y_{i,t-1})+\Lambda X_{i,t}'+\alpha_{sic3}+\delta_t+\epsilon_{i,t}, \tag{11}$$

where Y_{it} are profit, sales, capital, employment, and TFP of firm i in year t. $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different patent categories (*Pats*) granted to firm i in year t scaled by total assets, $X_{i,t}$ is a vector of control variables including log capital stock, log employment, log total asset, and idiosyncratic volatility, and $\tau \in \{1,\dots,10\}$. α_{sic3} are industry fixed effects, which account for unobserved time-invariant industry characteristics, and δ_t are year fixed effects, which account for unobserved time-specific heterogeneity. All right-hand-side variables are scaled to unit standard deviation to facilitate the comparison across different specifications. The estimated coefficients β_τ represent the impulse responses at each horizon τ. Our sample for the baseline estimations is for patents classified using patent titles for U.S. publicly listed firms over the sample period from 1976 to 2020. The relevant subsections and the Internet Appendix present and discuss various robustness exercises.

5.1.1. Process vs. Product innovation

The results from estimating Eq. (11) for process and product innovation are presented in Panel A of Fig. 6 and Table 4. We find that process innovation significantly contributes to firm growth and productivity in the short- to medium-term. Specifically, an increase in process patent value by one standard deviation is associated with 2.7%, 2.1%, 1.7%, 1.5%, and 1.5% increase in profits, sales, capital, employment, and TFP, respectively, in the first three years. The process innovation effects on growth are generally smaller over the longer term (e.g., five to ten years), with cumulative effects still being sizable. Our findings are consistent with process innovations that directly reduce production costs upon implementation, which increases firm profits and allows for more sales.

However, product innovation continuously contributes to firm growth over the long horizon, which can be observed through the timing of growth associated with product innovations. Product innovation is positively associated with an increase of 2.5%, 1.9%, 2.3%, 1.0% and 1.4% in profits, sales, capital, employment, and TFP, respectively, over ten years, with less than half of the effect observed up to three years. Our findings are consistent with the notion that product innovations generally open new markets and slowly build on each other, creating long-run revenue streams and strengthening competitive positioning. Moreover, product innovation requires time to be developed and gradually commercialized into products, while process innovation can be implemented more quickly to generate cost savings, higher profits, and higher productivity.[22]

These results support Proposition 2 with a strong correlation between process innovation and profit increase at the firm level, through higher sales and increased returns to scale. There is also considerable heterogeneity between process and product innovation.

5.1.2. Foundational and cost-reducing processes

We further decompose the effect of process innovations into foundational and cost-reducing ones. We study the impact of the three innovation types: foundational, cost-reducing, and product innovation by estimating regressions of the following form:

$$\begin{aligned}\ln(Y_{i,t+\tau})-\ln(Y_{i,t}) &= \alpha_0+\beta_{1\tau}\theta_{i,t}^{\text{foundational}}+\beta_{2\tau}\theta_{i,t}^{\text{cost-reducing}}+\beta_{3\tau}\theta_{i,t}^{\text{product}}\\ &\quad+\gamma_1\ln(Y_{i,t})+\gamma_2\ln(Y_{i,t-1})+\Lambda X_{i,t}'+\alpha_{\text{sic3}}+\delta_t+\epsilon_{i,t}.\end{aligned} \tag{12}$$

We present the results in Panel B of Fig. 6 and Table 5. Our findings indicate that foundational process innovations are important in driving firm growth and productivity, especially over the short to medium term. Specifically, one standard deviation increase in foundational process patent value is associated with 1.8%, 1.4%, 1.3%, 1.0%, and 0.8% increase in profits, sales, capital, employment, and TFP in three years, respectively. The separation of process innovation into foundational and cost-reducing marginally affects the product innovation coefficients. These results align with the model's prediction that foundational processes are the key process innovation contributor to growth.

In contrast, cost-reducing process innovations show a more immediate but limited effect on growth, with very low effect at longer horizons. While these innovations enhance efficiency by lowering production costs, they do not expand the technological frontier nor create new revenue streams as foundational innovations do. As a result, their impact on profits and other growth metrics is short-term and of a modest magnitude compared to the growth generated by foundational processes. This finding aligns with theoretical expectations, as cost-reducing innovations primarily boost production efficiency without fundamentally improving the quality of the firm's product offerings or expanding its technological capabilities.[23]

5.1.3. Growth from product innovations: The role of foundational processes

As previous results show, product innovations are associated with a sizable and gradual effect on firm growth. Proposition 2a ascribes growth from product innovation to process innovations, especially foundational processes, which lead to more and higher quality products. To rigorously establish that foundational processes underpin sustained growth from product innovation, we compare the growth impact of foundational process-based product patents, defined as product patents with high backward similarity, to foundational process patents with that of other product patents. The distinction of foundational process-based product innovation allows us to assess their contribution to firm growth, compared to other products, after controlling for other types of innovation. Specifically, we split the product patent market value ξ proportionally between the foundational and cost-reducing innovation index based on the backward similarity of the product patent

[21] In robustness analysis, we report results conditioning on lagged patent market values in Internet Appendix Tables IA.1–IA.3, which are discussed in the relevant subsections.

[22] We provide various robustness analyses to the above results. First, we categorize patents based on claims rather than titles, as described in B.1. Results in Table E.7 show that results remain qualitatively similar. Second, we include two lags of the patent market value index as conditioning information in Table IA.1 in the Internet Appendix. Third, we incorporate different dependent variable lag structures in the analysis in Internet Appendix Tables IA.4 (Y_t), IA.7 (Y_t, Y_{t-1}, Y_{t-2}), and IA.10 (no dependent variable controls). Finally, we analyze the longer sample available using title-based classifications for the period 1950 to 2020 in Internet Appendix Table IA.13. Overall, the results from the robustness analysis are qualitatively similar to the baseline results.

[23] Our results may be sensitive to using within firm-defined q. Table E.8 provides estimates of Eq. (12) using q built on product and process patent similarity across firms. Furthermore, the selected q threshold may affect the analysis and inference. In Tables E.9 and E.10, we introduce different cut-offs for foundational patents (70th and 90th percentile). Results remain qualitatively similar, albeit cost-reducing processes become more important with the increase in the q threshold. We also use claims to classify process and product patents as robustness, and continue to find similar results in Table E.11. Robustness analysis with two lags of the patent market value index (θ^{Pat}) in Table IA.2 and different dependent variable lag structures in Tables IA.5 (Y_t), IA.8 (Y_t, Y_{t-1}, Y_{t-2}), and IA.11 (no dependent variable controls) in the Internet Appendix, shows that foundational process effects remain strong, after controlling for unobserved dynamic effects of persistent shocks. We also find qualitatively similar results for the analysis of the longer sample, starting in 1950, as reported in Internet Appendix Table IA.14.

Table 4
Firm growth — process and product patents.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Process (θ)	0.008***	0.018***	0.027***	0.022***	0.021***	0.023***	0.022**	0.022**	0.022**	0.023**
	(3.25)	(4.68)	(4.31)	(3.01)	(2.94)	(2.83)	(2.35)	(2.25)	(1.97)	(2.29)
Product (θ)	0.010***	0.010**	0.005	0.014*	0.017**	0.018**	0.018*	0.022*	0.022*	0.025**
	(3.15)	(2.07)	(0.67)	(1.93)	(2.00)	(2.00)	(1.84)	(1.91)	(1.77)	(2.07)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel B. Sales										
Process (θ)	0.005*	0.018***	0.021***	0.020***	0.021***	0.021***	0.018**	0.017**	0.018**	0.020**
	(1.90)	(4.62)	(3.74)	(3.63)	(2.95)	(2.77)	(2.19)	(2.06)	(2.12)	(2.34)
Product (θ)	0.010***	0.009**	0.009*	0.013**	0.012	0.015*	0.015*	0.020**	0.017	0.019*
	(4.19)	(2.49)	(1.75)	(2.14)	(1.51)	(1.74)	(1.84)	(2.19)	(1.61)	(1.84)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel C. Capital										
Process (θ)	0.007***	0.013***	0.017***	0.019***	0.021***	0.022***	0.020***	0.019***	0.020***	0.022***
	(3.02)	(4.49)	(4.72)	(4.54)	(4.33)	(3.97)	(3.07)	(2.71)	(3.01)	(3.05)
Product (θ)	0.008***	0.016***	0.020***	0.023***	0.024***	0.024***	0.026***	0.027***	0.025***	0.023**
	(4.55)	(5.08)	(4.98)	(4.61)	(3.60)	(3.34)	(3.16)	(2.98)	(2.76)	(2.51)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel D. Employment										
Process (θ)	0.005***	0.011***	0.015***	0.016***	0.018***	0.019***	0.018***	0.016***	0.017***	0.017***
	(3.29)	(4.78)	(5.01)	(4.60)	(4.53)	(4.29)	(3.56)	(3.00)	(3.15)	(3.05)
Product (θ)	0.007***	0.011***	0.011***	0.012***	0.010**	0.008	0.009	0.011	0.011*	0.010
	(4.57)	(4.00)	(3.21)	(2.95)	(2.11)	(1.52)	(1.56)	(1.62)	(1.66)	(1.56)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel E. Total Factor Productivity										
Process (θ)	0.010***	0.011***	0.015***	0.015***	0.014***	0.014***	0.014***	0.016***	0.016***	0.017***
	(4.78)	(3.29)	(3.55)	(3.21)	(3.02)	(2.96)	(3.00)	(3.65)	(3.54)	(3.97)
Product (θ)	0.012***	0.017***	0.003	0.005	0.010	0.009	0.010	0.010	0.013*	0.014**
	(3.88)	(5.14)	(0.36)	(0.66)	(1.54)	(1.36)	(1.36)	(1.35)	(1.86)	(2.10)
Obs.	98,859	88,409	79,714	72,084	65,481	59,556	54,412	49,688	45,421	41,640

The table presents analysis of the relation between process and product innovation and firm-level outcomes. Patents are classified using titles. We present the coefficients (β_τ) from estimations of the following model:

$$ln(Y_{i,t+\tau}) - ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_\tau^{Pats} \theta_{i,t}^{Pats} + \gamma_1 ln(Y_{i,t}) + \gamma_2 ln(Y_{i,t-1}) + \Lambda X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y are the firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different types of patents ($Pats$) granted to firm i in year t scaled by total assets, $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in \{1, \dots, 10\}$. α_{sic3} and δ_t are industry and year fixed effects. Panel A presents results for gross profits, Panel B for sales, Panel C for capital stock, Panel D for employment, and Panel E for total factor productivity. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. All variable definitions are provided in Table E.2 in the Appendix. The sample period is 1976 to 2020.

with these two types of processes.[24] We then re-estimate Eq. (12) with only the two types of products, foundational and cost-reducing based, focusing on profits and sales, but results for other growth measures are qualitatively similar.

Results focusing only on the product split are depicted in Fig. 7 and presented in Table 6.[25] We find that firm future sales and growth are highly correlated with product innovations that have higher backward similarity to foundational patents but not to cost-reducing patents. This is in line with the model implication of foundational processes expanding the technological frontier and contributing to firm growth through product expansions.

We conduct multiple robustness checks on this analysis and find a qualitatively similar strong relation between foundational process-based products and firm growth.[26] Overall, our results provide robust evidence that process innovation affects firm growth directly and indirectly — through foundational processes and their effect on product innovation.

5.2. Foundational processes and new products

This section provides support for the notion that process innovations, particularly the foundational processes, create the groundwork for subsequent product development and significantly affect future

[24] For example: if a product patent has a market value of \$10 million, with a backward similarity score of 2000 to foundational process innovation index θ and 3000 to cost-reducing patents, 2/5 or \$4 million are attributed to foundational process patents and \$6 million to cost-reducing innovation θ.

[25] The first step of this analysis is the split between products based on processes as opposed to products based on other products. Results in Table E.12 show that process-based products are the only ones correlated with future growth and sales.

[26] First, we use spillovers defined using citations rather than backward similarity in Tables E.13 and E.14 and we use q defined using cross-firm forward and backward similarity in Table E.15. We continue to find a strong relation between foundational-process-based products and firm growth. Second, we use different independent variable lag structures in Table IA.3 and dependent variable lag structures in Tables IA.6 (Y_t); IA.9 (Y_t, Y_{t-1}, Y_{t-2}), and IA.12 (no dependent variable controls); and third we use the longer sample starting from 1950 in Table IA.15 presented in the Internet Appendix. We continue to find economically similar results for the role of foundational processes.

Table 5
Firm growth — foundational, cost-reducing process and product patents.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Process, foundational (θ)	0.009***	0.016***	0.018***	0.019***	0.019***	0.020***	0.019***	0.018**	0.017**	0.018**
	(3.80)	(3.82)	(3.51)	(3.32)	(3.20)	(2.97)	(2.76)	(2.51)	(2.22)	(2.28)
Process, cost-reducing (θ)	0.003	0.006	0.014**	0.010	0.005	0.006	0.006	0.009	0.011	0.009
	(1.00)	(1.37)	(2.26)	(1.57)	(0.75)	(0.84)	(0.69)	(0.96)	(1.09)	(1.09)
Product (θ)	0.011***	0.012**	0.007	0.014**	0.019**	0.020**	0.020**	0.023**	0.022*	0.025**
	(3.20)	(2.36)	(0.79)	(1.96)	(2.24)	(2.21)	(2.01)	(1.98)	(1.76)	(2.18)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel B. Sales										
Process, foundational (θ)	0.005***	0.010***	0.014***	0.014***	0.017***	0.018***	0.018***	0.016***	0.016***	0.018***
	(3.25)	(3.71)	(3.79)	(3.66)	(3.97)	(3.95)	(3.80)	(3.43)	(3.09)	(3.23)
Process, cost-reducing (θ)	0.003	0.006	0.008	0.008	0.004	0.002	−0.001	0.000	0.004	0.001
	(1.49)	(1.37)	(1.18)	(1.32)	(0.58)	(0.24)	(−0.14)	(0.02)	(0.46)	(0.07)
Product (θ)	0.009***	0.012***	0.012**	0.015**	0.015*	0.019**	0.020**	0.023**	0.020*	0.023**
	(3.85)	(3.16)	(2.04)	(2.32)	(1.83)	(2.16)	(2.28)	(2.53)	(1.83)	(2.24)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel C. Capital										
Process, foundational (θ)	0.004***	0.009***	0.013***	0.016***	0.020***	0.022***	0.024***	0.025***	0.025***	0.026***
	(2.64)	(3.15)	(3.38)	(3.52)	(3.60)	(3.70)	(3.77)	(3.84)	(3.91)	(3.99)
Process, cost-reducing (θ)	0.001	0.003	0.006*	0.007	0.005	0.003	−0.001	−0.002	−0.000	−0.000
	(0.94)	(1.47)	(1.66)	(1.54)	(1.04)	(0.59)	(−0.16)	(−0.29)	(−0.03)	(−0.03)
Product (θ)	0.010***	0.018***	0.022***	0.024***	0.026***	0.026***	0.029***	0.029***	0.027***	0.025***
	(5.81)	(5.61)	(5.19)	(4.95)	(4.00)	(3.75)	(3.60)	(3.38)	(3.12)	(2.89)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel D. Employment										
Process, foundational (θ)	0.003***	0.006***	0.010***	0.011***	0.012***	0.014***	0.014***	0.015***	0.016***	0.016***
	(2.66)	(3.13)	(3.43)	(3.47)	(3.50)	(3.68)	(3.71)	(3.83)	(3.87)	(3.89)
Process, cost-reducing (θ)	0.002	0.003	0.006*	0.006*	0.007*	0.006	0.004	0.002	0.003	0.003
	(1.46)	(1.47)	(1.78)	(1.76)	(1.75)	(1.28)	(0.72)	(0.35)	(0.60)	(0.53)
Product (θ)	0.008***	0.013***	0.013***	0.013***	0.012**	0.010*	0.012*	0.013*	0.013*	0.012*
	(4.79)	(4.54)	(3.53)	(3.28)	(2.42)	(1.89)	(1.92)	(1.94)	(1.91)	(1.82)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel E. Total Factor Productivity										
Process, foundational (θ)	0.004***	0.005**	0.008***	0.008***	0.007***	0.009***	0.009***	0.007***	0.007**	0.007***
	(2.83)	(2.36)	(2.81)	(2.92)	(2.92)	(3.35)	(3.42)	(2.82)	(2.51)	(2.79)
Process, cost-reducing (θ)	0.004*	0.005	0.006*	0.007*	0.006	0.003	0.005	0.009**	0.010**	0.011***
	(1.89)	(1.42)	(1.76)	(1.66)	(1.33)	(0.57)	(0.88)	(2.26)	(2.33)	(2.64)
Product (θ)	0.014***	0.019***	0.005	0.006	0.011*	0.011*	0.011*	0.010	0.013**	0.013**
	(4.53)	(5.27)	(0.55)	(0.87)	(1.80)	(1.83)	(1.70)	(1.47)	(2.03)	(2.17)
Obs.	98,859	88,409	79,714	72,084	65,481	59,556	54,412	49,688	45,421	41,640

The table presents relation between foundational, cost-reduction process and product innovation and firm-level outcomes. Patents are classified using titles and within-firm patent similarity. We present the coefficients (β_τ) from estimations of the following model:

$$ln(Y_{i,t+\tau}) - ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_\tau^{Pats} \theta_{i,t}^{Pats} + \gamma_1 ln(Y_{i,t}) + \gamma_2 ln(Y_{i,t-1}) + \Lambda X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y are the firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different types of patent ($Pats$, foundational, cost-reducing, product) granted to firm i in year t scaled by total assets, $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in \{1, \dots, 10\}$. α_{sic3} and δ_t are industry and year fixed effects. Panel A presents results for gross profits, Panel B for sales, Panel C for capital stock, Panel D for employment, and Panel E for total factor productivity. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. All variable definitions are provided in Table E.2 in the Appendix. The sample period is 1976 to 2020.

product introductions. We provide evidence in three steps. First, we proxy firm product introductions with product patents and show that product patents based on foundational processes have distinct quality. Then, we show that firms with more foundational processes grow their product space as measured by the set of technology classes the firm innovates in. Lastly, using external data source on drug introductions from the FDA "Orange Book" data, we conclude with additional evidence on the importance of foundational process innovation for product development. Overall, our results indicate that foundational process innovations are associated with the introduction of more and higher-quality products.

5.2.1. Foundational processes and product patents

We first proxy firm product introductions using product patents and analyze the link between foundational processes and future product patents. We start by analyzing differences in product patent quality for patents that cite foundational process and other patents. In this analysis, we include only product patents for the sample of publicly listed firms, which is a subset of those in Panel C of Table 3. We conduct cross-sectional analysis at the patent level, estimating regressions of the form:

$$Product\ Patent\ Quality_p = \beta_0 + \beta_1 I\{Foundational\}_p + \delta_{ipc \times t(p)} + \epsilon_p,$$

where *Foundational* is equal to one if a product patent (of any firm) cites a foundational process patent and zero otherwise. Note that foundational patents are defined based on within-firm patent similarity, not citations. The patent quality measures are described in Appendix D. We control for technology class-year (IPC4×year) interacted fixed effects to account for technology-specific cohort effects.

In Table 7, we find that product patents that rely (cite) more heavily on foundational process patents are of substantially higher quality with more claims, more forward citations, higher private economic value, and originality compared to product patents with no foundational process patent backward citations in the same tech class and year.

Table 6
Growth from product innovations: The role of foundational processes.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Product (θ, BS to Foundational)	0.013***	0.019***	0.017**	0.020***	0.021***	0.026***	0.027***	0.029***	0.030***	0.032***
	(4.81)	(3.95)	(2.50)	(3.04)	(2.92)	(3.24)	(3.02)	(2.98)	(2.89)	(3.07)
Product (θ, BS to Cost-reducing)	0.001	0.000	0.001	0.001	0.000	−0.002	−0.002	−0.003	−0.003	−0.003
	(0.59)	(0.13)	(0.22)	(0.16)	(0.03)	(−0.48)	(−0.54)	(−0.70)	(−0.69)	(−0.77)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel B. Sales										
Product (θ, BS to Foundational)	0.012***	0.017***	0.018***	0.020***	0.018***	0.020***	0.022***	0.025***	0.024***	0.025***
	(6.75)	(5.55)	(4.03)	(3.89)	(2.99)	(3.00)	(3.23)	(3.44)	(2.77)	(2.94)
Product (θ, BS to Cost-reducing)	−0.000	−0.001	0.000	−0.000	0.001	0.000	0.000	−0.000	−0.000	0.000
	(−0.30)	(−0.36)	(0.08)	(−0.09)	(0.25)	(0.14)	(0.05)	(−0.14)	(−0.04)	(0.02)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013

The table compares the growth effects of products based on foundational processes to those based on cost-reducing processes. Patents are categorized based on their titles, and market values of product patents are weighted according to their backward similarity to both foundational and cost-reducing process patents. For example, if a product patent has a market value of $10 million, with a backward similarity score of 2000 to foundational patents and 3000 to cost-reducing patents, 2/5 or $4 million would be attributed to foundational patents and $6 million to cost-reducing patents. We present the coefficients (β_τ) from estimations of the following regression model:

$$\ln(Y_{i,t+\tau}) - \ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_\tau^{Pats}\theta_{i,t}^{Pats} + \gamma_1 ln(Y_{i,t}) + \gamma_2 ln(Y_{i,t-1}) + \Gamma X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y represents firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different types of product patents ($Pats$) granted to firm i in year t, with the market value split between foundational (*BS to Foundational*) and cost-reducing patents (*BS to Cost-reducing*), scaled by total assets. $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in \{1,\dots,10\}$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. All variable definitions are provided in Table E.2 in the Appendix. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. The sample period is 1976 to 2020.

Table 7
Foundational process-based product patents.

	Claims	Scope	Backward	Originality	Forward	Generality	ln(ξ)	NPL	Re-assignments	Renewal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foundational	0.111***	0.030***	1.073***	0.070***	0.337***	0.025***	0.225***	1.246***	0.001	0.016***
	(16.42)	(2.75)	(41.64)	(25.86)	(10.31)	(3.48)	(12.81)	(26.56)	(0.06)	(9.72)
IPC4 × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	1,294,575	1,358,484	1,358,482	1,346,312	1,357,453	1,058,761	1,363,490	1,052,982	1,249,618	1,363,490
Adj. R^2				0.21		0.17	0.22			0.39

This table presents patent metrics comparing product patents that cite foundational patents with all other patents. We estimate regressions of the form:

$$Product\ Patent\ Quality_p = \beta_0 + \beta_1 I\{Foundational\}_p + \delta_{ipc\times t(p)} + \epsilon_p,$$

where *Product Patent Quality$_p$* are patent quality metrics, *Foundational* is an indicator variable equal to one for all product patents that cite foundational process patents (own or other firms) and zero otherwise, and $ipc \times t(p)$ are patent class interacted with year fixed effects. All patent metrics in this table are described in detail in D. *Claims* is the number of claims by the patent; *Scope* is the unique number of IPC 4-digit classifications of a patent; *Backward* is backward citations measured as the number of U.S. patents the patent cites; *Originality* is the HHI index of IPC4 classes of the backward citations; *Forward* is forward citations measured as number of U.S. patents citing the patent; *Generality* is the HHI index of IPC4 classes of the forward citations; and ξ is the market value of patent as in Kogan et al. (2017). *NPL* is the number of non-patent literature citations. *Re-assignments* is the number of USPTO reported re-assignments of the patent. *Renewal* is an indicator variable equal to 1 when a patent is renewed after 12 years and zero otherwise. Columns 1, 2, 3, 5, 8 and 9 are estimated using a Poisson specification, while columns 4, 6, 7 and 10 use OLS. T-statistics, adjusted for clustered standard errors at the IPC4 level, are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. All variable definitions are provided in Table E.2 in the Appendix. The sample period is 1930 to 2020, depending on variable information availability.

A product patent that cites ten percent more foundational process patents has, on average, 34% more forward citations and 22.5% higher private market value than patents in the same tech class and year. In addition, these product patents are much more likely to cite non-patent literature, i.e., scientific publications, which is congruent with these products being on a higher technology rung.

5.2.2. Foundational processes and product space

In the model, foundational processes allow for the expansion of the technological possibility frontier and the expansion of product lines. Short of having data on the firm's actual products, we focus on the IPC (technology) classes in which the firm patents as a proxy for the production space of a firm. We investigate this conjecture with Poisson panel regression analysis of the number of IPC classes at $t+1$ and the stock of foundational and other patents at t, controlling for firm size, R&D investments, and firm and year fixed effects. A patent is in a firm's patent stock for 20 years, the maximum protection time afforded by a patent.

In Panel A of Table 8, we present the results for different granularity of IPC classes, from 3 (coarser) to 7 (the finest). There is a strong economic and statistically significant relation between foundational patents' stock and future technology expansion at the firm level. A 10% increase in foundational patents increases IPC7 classes by 4.3% in the next period. The stock of product patents has a limited effect on broader IPC categories but is significant for the addition of new varieties at the more granular level, which is in line with more product variety. Interestingly, cost-reducing patents are negatively associated with future product variety, indicating that efficiency gains in producing existing products limit incentives to expand into new product categories to which old production processes may be less applicable.

We further map the expansion of the product space to the foundational process innovation stock more directly, at the patent level. Specifically, we classify each patent with an indicator equal to one

Table 8
Innovation and product differentiation.
Panel A. Foundational processes and product differentiation

	IPC 3_{t+1}	IPC 4_{t+1}	IPC 6_{t+1}	IPC 7_{t+1}
	(1)	(2)	(3)	(4)
Ln(Foundational Stock)$_t$	0.331***	0.346***	0.398***	0.426***
	(16.65)	(19.08)	(17.77)	(12.49)
Ln(Cost-reducing Stock)$_t$	−0.278***	−0.292***	−0.282***	−0.263***
	(−16.91)	(−18.50)	(−15.20)	(−11.57)
Ln(Product Stock)$_t$	−0.061***	0.010	0.058***	0.090***
	(−3.41)	(0.57)	(3.01)	(3.66)
R&D	0.840***	0.858***	0.996***	1.155***
	(4.81)	(5.09)	(5.25)	(4.68)
Ln(Total Asset)	0.344***	0.345***	0.347***	0.335***
	(15.78)	(14.70)	(12.75)	(9.15)
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Obs.	75,261	78,712	81,865	82,932

Panel B. Foundational process contribution to new IPC classes

	New IPC 3	New IPC 4	New IPC 6	New IPC 7
	(1)	(2)	(3)	(4)
BS to Foundational	0.002*	0.007***	0.016***	0.013**
	(1.88)	(3.07)	(3.84)	(2.36)
BS to Cost-reducing	−0.001	−0.004	−0.010	−0.011
	(−0.43)	(−0.84)	(−1.05)	(−1.05)
BS to Product	−0.009***	−0.022***	−0.050***	−0.069***
	(−3.40)	(−3.62)	(−3.94)	(−4.96)
R&D	−0.168***	−0.215***	−0.258**	−0.189*
	(−4.23)	(−3.08)	(−2.43)	(−1.71)
Ln(Total Asset)	−0.021***	−0.028***	−0.034***	−0.021***
	(−6.64)	(−6.43)	(−5.22)	(−2.65)
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Obs.	1,003,543	1,003,543	1,003,543	1,003,543
Adj. R^2	0.18	0.18	0.19	0.18

This table present results of the analysis of the role of foundational process in expanding the firm's product space. Panel A presents results of regressions of the number of new technology classes measured by 3-digit IPC main classes, 4-, 6-, and 7-digit IPC subclasses at $t+1$ and the stock of different types of patents at time t. The explanatory variables are the natural log of the stock of foundational process, cost-reducing, and product patents up to time t. The sample includes firms that have at least one patent in their portfolio, where a patent has a maximum life span of 20 years. Panel B presents analysis at the product patent level. The dependent variable is an indicator equal to one if a patent belongs to a technology class new to firm i, and zero otherwise. All BS variables measure the backward similarity of the focal patent p to prior foundational, cost-reducing, and other product patents; they are standardized to unit standard deviation. Standard errors are clustered at the firm level. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. All variable definitions are provided in Table E3 in the Appendix. The sample period is 1976 to 2020.

if it introduces a new IPC class for the firm, and zero otherwise. We then analyze the probability that a patent falls into a new IPC class as a function of its similarity to existing patents within the firm — focusing on foundational, cost-reducing, and product innovations. The results, presented in Panel B of Table 8, show that patents with higher similarity to foundational processes are significantly more likely to be in new IPC classes. This likelihood increases from 0.02% to 1.3% as IPC class granularity increases. By contrast, the coefficients for other innovation types are either insignificant or, in the case of product patents, negative.

These results further highlight a key distinction: innovations building on product patents tend to be incremental and focused on improving existing product lines, whereas those linked to foundational processes are more likely to expand the technological frontier by introducing entirely new classes. Taken together, results so far are in line with the relations posited in Proposition 1. Foundational processes produce higher value (citations and market value) products as well as expand the product opportunity set for the firm in terms of the number of products and product variety.

5.2.3. Foundational processes and new drug introductions

To better capture the link between foundational processes and product introduction, ideally, we want a mapping between patents and actual products introduced by the firms; however, this mapping is not available for all patents (Argente et al., 2020). In our final analysis, we focus on an industry where the product can be directly linked to patents to narrow down the effect of foundational patents on firm growth through better product offerings. We link foundational process patents to small molecular drugs in the pharmaceutical industry, where individual drugs (products) are mapped to patents. We use the FDA-based NBER "Orange Book" data, which allows us to compare the value and revenue of drugs based on foundational processes to those of other drugs, thus quantifying the commercial impact of foundational-process-based products.

Specifically, we analyze small molecular drugs approved by the FDA for which information has been collated in the NBER Orange Book and described meticulously in Durvasula et al. (2023). The data provides information on the link between drugs and the patents that protect the individual drug, covering 5511 unique patents associated with 2173 distinct New Drug Applications from 1985 to 2016. The data only provides information on approved drugs, thus we cannot estimate the probability of drug approval, i.e., the quantity effect. However, we can investigate the quality of the product introductions. We focus on three aspects of quality: (1) the market value of the drug introduction as in Krieger et al. (2021); (2) the priority review designation of a drug; and (3) drug sales through health insurance and Medicaid spending.

For the first quality measure, we construct the three-day cumulative abnormal market reaction to the FDA's drug approval, which closely

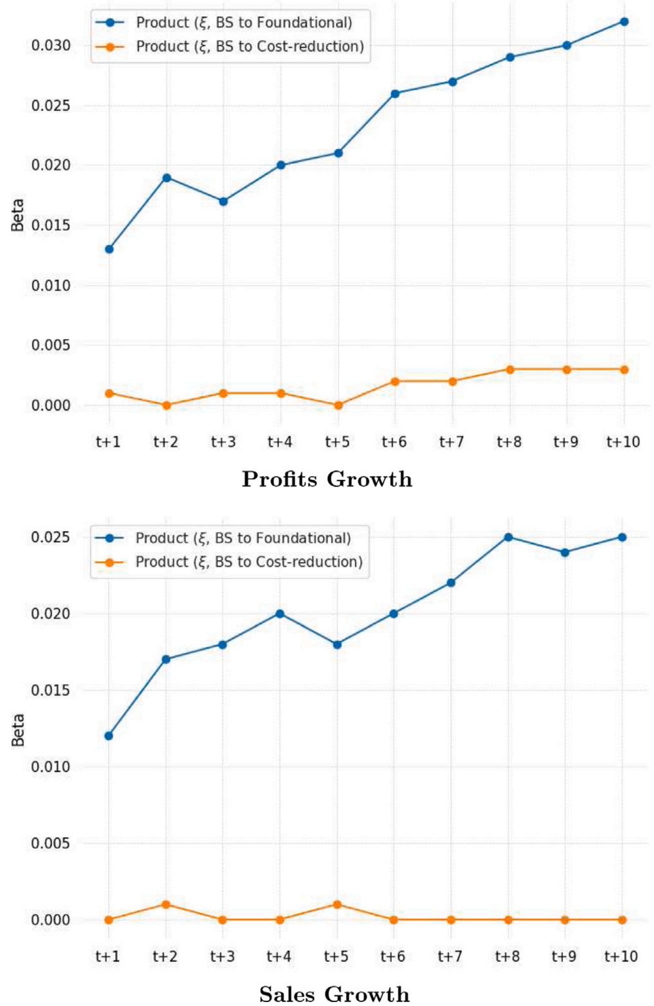


Fig. 7. Growth from product innovations: The role of foundational processes. This figure presents the coefficients from regressions of the relation between firm growth and product innovations that build on foundational vs. cost-reducing patents. We estimate regressions of the form:

$$\ln(Y_{i,t+\tau})-\ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_{\tau}^{Pats}\theta_{i,t}^{Pats} + \gamma_1 ln(Y_{i,t}) + \gamma_2 ln(Y_{i,t-1}) + \Gamma X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y represents firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different types of patents ($Pats$) granted to firm i in year t, with the market value split between foundational (*BS to Foundational*) and cost-reducing patents (*BS to Cost-reducing*), scaled by total assets. The values of product patents are weighted according to their backward similarity to foundational and cost-reducing process patents. For example, if a product patent has a market value of \$10 million, with a backward similarity score of 2000 to foundational patents and 3000 to cost-reducing patents, 2/5 or \$4 million would be attributed to foundational patents and \$6 million to cost-reducing patents. $X_{i,t}$ is a vector of control variables, including log capital stock, log employment, log total assets, and idiosyncratic volatility, log process patents, with $\tau \in \{1,\dots,10\}$. α_{sic3} and δ_t are industry and year fixed effects, respectively. The coefficients for product patents, with their ξ split into foundational process and cost reducing process categories based on the fraction of total backward similarity to these two groups, are plotted. The sample period is 1976 to 2020.

aligns with the market value estimations for patent introductions in Kogan et al. (2017). Arguably, the approval of a drug on a specific day is unknown to the market, and the market reaction captures the potential private benefits the drug-owning firm will derive from this drug. Our second quality measure is *Priority* — an indicator variable equal to one if a drug is designated for priority review by the FDA and zero otherwise. Priority-review-designated drugs are given shorter review times because they: (a) have the potential to provide significant improvements in the treatment, prevention, or diagnosis of a disease; (b) there are few or no alternative treatments for the conditions in question or distinct advantages over existing treatments; (c) can address public health emergencies or issues of national interest. Therefore, priority drugs could be more valuable and of higher quality. Last, we calculate drug spending in health insurance parts B, D, and Medicaid programs from 2017 to 2021 using the Center for Medicare and Medicaid Services (CMS) data. We exclude from the analysis drugs approved after 2013 to allow sufficient time for it to enter the Medicare system (the median time from FDA approval to Medicare coverage is five years, see Sexton et al., 2023).

We conduct a cross-sectional regression analysis at the approved drug level, examining drug quality and the share of foundational processes in the patents cited by each drug. Each drug is mapped to a firm using drug-patent information from the Orange Book and patent-firm mapping from Kogan et al. (2017). We match drugs in the Orange Book to CMS drugs using a Levenshtein-distance-based string-matching algorithm, retaining only drug names with at least 90% string similarity. This matching process is highly accurate, as drug names are quite standard. Firm × year fixed effects are included to control for unobserved time-varying firm confounders. Hence, our analysis exploits within-firm variation and compares drugs that more heavily build on foundational processes with others. Results in Table 9 show that a larger fraction of foundational process patents is correlated with more valuable FDA drugs — measured by market reaction at the announcement, priority designation, and sales. Instead, drugs that heavily build on other types of patents do not show robust positive quality differences.

Results presented in this section show the link between foundational processes and the quantity and quality of product offerings at the firm level. These results corroborate the model's implications that foundational processes enable firms to produce a greater volume of high-quality, profitable products by extending the technological frontier.

5.3. Robustness: Breakthrough product innovation

One may wonder if there are product patents that have a similar impact on firm growth as foundational process patents. Conceptually, these would be products that are the equivalent of foundational processes, i.e., products that allow for other products to be built. We refer to these products as breakthrough products. To investigate this conjecture, we calculate the q-ratio for each product patent relative to other product patents within the same firm, as with foundational process patents. We then define breakthrough product patents as those with a q-ratio exceeding the yearly 80th percentile among all product patents granted to publicly listed firms. We show that, by and large, conditioning on the group of breakthrough products does not qualitatively change the results compared to those in Tables 5–9 in relation to the role of foundational processes. The analysis highlights that it is the process-based nature of the patents we identify as foundational that drives the results.

Specifically, we first revisit heterogeneous innovations and firm growth Tables 5 and 6. We add all heterogeneous innovation types as control variables in Table F.1, where profits and sales are correlated with foundational and cost-reducing processes, and product innovation market value is separated into foundational, cost-reducing, breakthrough, and other product-based. In this setting, we assign each product patent's market value ξ proportionally to the backward similarity to foundational process, cost-reducing process, breakthrough product, or other product innovations. After accounting for other types of innovation, foundational processes and foundational-based products continue

Table 9
Foundational processes and FDA drug quality.

	ln(Abnormal Returns)	Priority	Ln(Patient Spending)
	(1)	(2)	(3)
Foundational (Fraction of Orange Book)	0.523***	0.497***	2.310***
	(2.64)	(3.60)	(12.66)
Cost-reducing (Fraction of Orange Book)	−0.084	0.162***	−0.387
	(−0.55)	(6.28)	(−0.60)
Product (Fraction of Orange Book)	−0.059	0.141**	0.111
	(−0.93)	(2.30)	(0.31)
Firm × Year FE	✓	✓	✓
Obs.	632	632	261
Adj. R^2	0.94	0.68	0.78

This table presents the results on the relation between drug product quality and foundational patents. The dataset consists of unique drug products approved and listed in the Orange Book. We examine three key variables: *Abnormal returns* calculated using the methodology of Kogan et al. (2017), which captures the 3-day market reaction to drug approvals; *Priority* an indicator variable equal to one if the drug is under Priority Review by the FDA and zero otherwise; and *Patient Spending* is drug spending in health insurance programs (Part B, Part D, and Medicaid) from 2017 to 2021. Priority Review is reserved for drugs that offer significant advancements in treatment, prevention, or diagnosis of diseases, lack alternative treatments, provide distinct advantages over existing treatments, or address public health emergencies or national health issues. The explanatory variables are the fraction of foundational, cost-reducing and product patents listed in the Orange Book. Standard errors are clustered at the firm level. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. All variable definitions are provided in Table E.2 in the Appendix. The sample period is 1982 to 2020.

to have large and significant correlations with future sales and profitability. In Panel A, a one standard deviation increase in foundational-based products is correlated with 2.4% higher profits in five years, while a similar increase in breakthrough product-based products is either negatively or not correlated with future profit growth. The difference between foundational process-based products and breakthrough product-based products (Diff. ($\hat{\beta}^{Foundational} - \hat{\beta}^{Breakthrough}$)) ranges between 2.4 and 4.1% for profits between one and seven years ahead. The Wald statistic for the difference in coefficients is significant in all these years.

Second, we include breakthrough products as a separate category in the analyses of the role of foundational processes in shaping future products (Section 5.2). We start with the analysis of product patents and the types of patents they cite — analogous to Table 7. In Panel A of Table F.2, we regress patent quality measures on indicator variables for both foundational processes and breakthrough products, where each indicator is equal to one if the focal patent cites a foundational process (breakthrough product) patent and zero otherwise. These categories are not mutually exclusive. In Panel B, we only focus on patents that cite either foundational processes or breakthrough products, and include a foundational process indicator variable. In both panels, product patents that cite foundational processes consistently exhibit higher quality across several dimensions — including forward citations, scientific basis, and private market value.

We next turn to the analysis of product differentiation in Table 8. In Table F.3, we control for the stock of breakthrough and other product patents. Including these additional controls does not qualitatively change the relation between a firm's product space and its foundational patents. Both the stock of foundational process and breakthrough product patents are important determinants of future product variety. However, foundational process patents have a substantially larger impact on product differentiation — a difference that is statistically significant based on the Wald test. Finally, we include breakthrough product patents in the FDA product analysis (Table 9). The results in Table F.4 continue to highlight foundational processes as the key driver of drug value.

6. Conclusion

Our work provides new insights into the distinct contributions of foundational and cost-reducing process innovations to firm growth and technological progress. Our analysis underscores how product and process innovations, particularly foundational processes, jointly shape firm growth. Foundational process innovations, which enable subsequent product development, demonstrate a significant and lasting influence on firms' capacity to produce higher-quality products and to diversify their product offerings. These innovations extend the technological frontier and foster long-term growth. In contrast, cost-reducing process innovations yield more immediate benefits by enhancing production efficiency and lowering costs, translating into short-term improvements in profits and productivity.

This distinction between heterogeneous forms of process innovation has important academic and policy implications. By integrating various types of process innovations into an innovation model, we gain a more comprehensive understanding of their joint impact on firm growth and competitiveness. From a policy perspective, our findings underscore the delicate balance between short-term efficiency gains and sustained innovation capacity. Investments in cost-reducing processes can boost firm growth in the near term but may not cultivate the deeper, broad-based technological capabilities essential for long-run product development. Policies that promote advanced manufacturing and nurture foundational process research, especially basic scientific discovery, are therefore critical for sustaining a robust innovation ecosystem. Since most of today's high-tech products are complex and have low modularity, where product design choices drive and are driven by manufacturing choices, outsourcing advanced manufacturing can limit process innovation and its role in driving new product innovations. Our findings on the interaction between the firm's process and product innovations indicate that policymakers should carefully evaluate the challenges posed by offshoring advanced manufacturing and the benefits of reshoring in promoting sustained domestic innovation. Patent classifications developed in this work should prove useful for future studies of these and other related questions as they enable researchers to measure firms' cost-saving process innovations.

Our work highlights the need to explore further (1) the mechanisms through which foundational process innovations diffuse, (2) the role of inter-firm knowledge spillovers and basic science linkages in shaping technological frontiers, and (3) how different innovation types interact across diverse industrial and international contexts in shaping economy-wide growth trajectories and bridging the growth gap. Another important avenue for future research is how competitive environments influence firms' choices between different types of innovation. While we do not model these dynamics explicitly, our framework and new patent classification provide a foundation for studying how competition shapes the trade-off between foundational processes, cost-cutting, and product innovations. Finally, our findings reveal that foundational process innovations not only provide substantial private value to firms but also generate significant social value through increased spillovers to other companies. This has implications for heterogeneous innovation subsidies (Bloom et al., 2013) that would be interesting to explore using richer quantitative growth models.

CRediT authorship contribution statement

Wing Wah Tham: Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Salomé Baslandze:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Elvira Sojli:** Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Leo Liu:** Writing – original draft, Visualization, Validation, Software, Investigation, Formal analysis, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Elvira Sojli reports financial support was provided by Australian Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Model appendix

A.1. Consumer demand

The economy has a 2π continuum of consumers with logarithmic utility over the composite consumption bundle C, which is a CES aggregate of consumption from the continuum of product lines:

$$C = \left(\int_0^1 q_k^{\frac{1}{\varepsilon}} c_k^{\frac{\varepsilon-1}{\varepsilon}} dk \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{B13}$$

where q_k is product quality and evolves endogenously as a result of firms' product innovation decisions that improve the product-to-consumer match, and c_k is the quantity consumed from product line k. As seen, each consumer consumes a specific (most preferred, as defined later) variety from each product line k. $\varepsilon > 1$ is the elasticity of substitution between product lines. The consumption bundle is a numeraire.

A consumer with total expenditure E who chooses the optimal expenditures across different product lines solves the following optimization problem:

$$\max_{c_k} \left(\log\left(\int_0^1 q_k^{\frac{1}{\varepsilon}} c_k^{\frac{\varepsilon-1}{\varepsilon}} dk \right)^{\frac{\varepsilon}{\varepsilon-1}} - \lambda\left(\int_0^1 p_k c_k - E\right) \right).$$

The first-order conditions with respect to c_k and c_j are:

$$\lambda p_k = \frac{c_k^{-\frac{1}{\varepsilon}} q_k^{\frac{1}{\varepsilon}}}{C^2}$$

and

$$\lambda p_j = \frac{c_j^{-\frac{1}{\varepsilon}} q_j^{\frac{1}{\varepsilon}}}{C^2}.$$

Dividing these two FOC's gives:

$$\left(\frac{p_k}{p_j}\right)^{\varepsilon} = \frac{c_j q_k}{c_k q_j},$$

which, after rearranging, gives:

$$p_k c_k = c_j \frac{q_k}{q_j} p_j^{\varepsilon} p_k^{1-\varepsilon}. \tag{B14}$$

The total expenditure should equal C since aggregate consumption is a numeraire. So, $E = \int_0^1 p_i c_i = C$. Integrating (B14), we obtain

$$C = \int_0^1 p_k c_k dk = \frac{c_j}{q_j} p_j^{\varepsilon} \int_0^1 q_k p_k^{1-\varepsilon} dk.$$

Therefore, $\frac{c_j}{q_j} p_j^{\varepsilon} = C / \int_0^1 q_k p_k^{1-\varepsilon} dk$, which we can now substitute into (B14):

$$p_k c_k = q_k p_k^{1-\varepsilon} C / \int_0^1 q_k p_k^{1-\varepsilon} dk.$$

And since the aggregate consumption basket is a numeraire, $\int_0^1 q_{kt} p_{kt}^{1-\varepsilon} dk = 1$.[27] Rewriting and normalizing $E = 1$ gives us:

$$c_k = q_k p_k^{-\varepsilon}, \tag{B15}$$

which is the demand function in (1). There are small notational differences with respect to the main text here. First, the main text omits the product line-specific subscript k since the problem in each product line is the same and, for brevity, we focus on the problem of one product line in the main text. Second, the main text indexes q accordingly to emphasize the consumer and product locations, but here, the generic notation is used instead.

A.2. Deriving aggregate demand

In this section, we derive aggregate demand expression in (2). Recall that the utility of consuming a variety depends on how well the variety j matches the consumer i taste:

$$q(i,j) = \chi - \lambda(1-s) - \mu s|i-j|.$$

A consumer will choose a variety closest to her preference. This way, for a product located at 0, there will be $2\pi/n$ measure of consumers in $[-\pi/n, \pi/n]$ who will buy it.

What is the average quality derived by all consumers to whom the variety j is sold, $\bar{q}_j$? Because of symmetry, this average quality is the same for all varieties j, so, for simplicity, we derive the expression for j located at zero and denote this average quality, common to all varieties, by $\bar{q}$:

$$\bar{q} = 2\int_0^{\frac{\pi}{n}} (\chi - \lambda(1-s) - \mu s i) di$$

$$= \frac{2\pi}{n}(\chi - \lambda(1-s)) - \mu s \frac{\pi^2}{n^2}.$$

As a result, combining this expression with the demand function in (B15), we obtain the aggregate demand over all varieties:

$$c = n\bar{q}p^{-\varepsilon} = [2\pi(\chi - \lambda(1-s)) - \mu s \frac{\pi^2}{n}] p^{-\varepsilon}.$$

A.3. Product introduction following process innovation

Let us compare product introduction following foundational and cost-reducing process innovations. The amount of new products introduced after foundational process innovation is $n^*(s+\Delta s)$ – that is, all the new products are located on a new technological frontier:

$$\left(\frac{1}{\varepsilon}\left(\frac{\varepsilon}{\varepsilon-1}\right)^{1-\varepsilon} k^{\varepsilon-1} \mu(s+\Delta s)\pi^2 \right)^{\gamma/(1+\gamma)}.$$

The amount of new products introduced after cost-reducing innovation is $n^*(k+\Delta k) - n^*(k)$, these are the additional varieties introduced on the existing TPF ring:

$$\left(\frac{1}{\varepsilon}\left(\frac{\varepsilon}{\varepsilon-1}\right)^{1-\varepsilon} \mu s \pi^2 \right)^{\gamma/(1+\gamma)} [(k+\Delta k)^{\frac{\gamma(\varepsilon-1)}{1+\gamma}} - k^{\frac{\gamma(\varepsilon-1)}{1+\gamma}}].$$

[27] With homothetic preferences, the ideal price index (Dixit–Stiglitz price index) $P = \left(\int_0^1 q_k p_k^{1-\varepsilon} dk\right)^{\frac{1}{1-\varepsilon}}$ is the minimum cost of buying one unit of aggregate consumption index, such that $PC = E$. Thus if aggregate consumption is the numeraire, this means that $P = 1$ and also that $\int_0^1 q_k p_k^{1-\varepsilon} dk = 1$.

If the following condition is satisfied, the new product introduction following the foundational innovation is higher than the one following the cost-reducing innovation:

$$\left(1+\frac{\Delta s}{s}\right)^{\frac{\gamma}{1+\gamma}} > \left(1+\frac{\Delta k}{k}\right)^{\frac{\gamma(\varepsilon-1)}{1+\gamma}} - 1.$$

The left-hand side is larger than one. For the right-hand side to be larger than one, we need $\frac{\Delta k}{k} > 2^{\frac{\gamma(\varepsilon-1)}{1+\gamma}} - 1$. Substituting $\gamma = 0.5$ (Acemoglu et al., 2018) and $\varepsilon = 5.1$ (Baslandze et al., 2023), we obtain that $\frac{\Delta k}{k} > 1.57$ which implies empirically implausible cost-reducing innovation step sizes. Hence, this inequality will always hold for empirically relevant cases.

A.4. Firm growth after foundational process innovation

For simplicity and expositional convenience, the main text assumes $\lambda = \mu$. The only equation that meaningfully changes as a result of this assumption is (9), so we discuss this equation under a more general case now.

$$\frac{\partial Revenue}{\partial s} = \left(\frac{\varepsilon}{\varepsilon-1}k^{-1}\right)^{1-\varepsilon}\left[\underbrace{2\pi\lambda - \mu\frac{\pi^2}{n}}_{Higher\ quality\ (given\ n)} + \underbrace{\frac{\partial Rev}{\partial n}\frac{\partial n^*(k,s)}{\partial s}}_{More\ varieties\ (given\ p)}\right].$$

When $n > \frac{\pi}{2}\frac{\mu}{\lambda}$, the first component is positive. When $\mu \leq \lambda$ (so, consumers care about vertical distance more or the same way as the horizontal), this condition holds. If $\mu > \lambda$, then n needs to be sufficiently large, so consumers need to be satiated enough with horizontally differentiated products. In such a case, the first term is assured to be positive.

Appendix B. Classifying process and product patents

To construct our process and product innovation measures, we exploit patent office requirements and guidelines for patentees (and their IP lawyers) to carefully choose the wording of patent titles and claims to describe the main subject of the invention. Patent claims define the scope of the protection conferred by a patent. Under the "Guidelines for the Wording of Titles of Invention", WIPO requires that "The patent title should clearly, concisely, and as specifically as possible indicate the main subject to which the invention relates. *If the patent document contains claims in different categories (product, process, apparatus, use), this should be evident from the title.*" Thus, invention titles are carefully scripted to describe the main claims of an invention. The informativeness of the title facilitates an objectively verifiable classification of process and product innovations for over a century across countries.

At the nexus of our new rule-based classification method is the heuristic separation between process and product patents, where the preamble of claims and titles referring to an *activity* (process, method, or use) are classified under process patents, whereas those referring to a *physical entity* (product, device, or apparatus) are classified under product patents. We categorize patents based on their *titles* and *claims* using a "bag-of-words" approach by utilizing an expanding corpus of terms based on the hypernyms of "*activities*" and "*physical entities*" for classification, which does not depend on specific words or predefined word lists. We validate this method with IP experts and patent examiners. Given the long coverage of digitized patent titles (for all patents, from the beginning of patent records), title-based classification allows for every patent to be classified into a product or process patent, while claim-based classification is limited by the availability of digitized claims information.

To overcome the spareness of digitized claim information for international patents, we also use DistilBert (Sanh et al., 2019) to classify patent titles based on patent claims. We train the model to use patent titles as input (features) to predict the classification based on all claims (labels) of USPTO patents.

B.1. Claims-based classification

In a patent (application), the claims define, in technical terms, the extent of the protection conferred (sought) by a patent. Claims are written in a legalistic structured language, and the use of consistent vocabulary in patent claims facilitate the accurate classification of process innovations using textual analysis. Each claim must be written as a single sentence and contains a preamble, a transitional phrase, and a body. The preamble is a general description of the invention (e.g., method or device), the transitional phrase links it to the body (e.g., of, for, by), and the body identifies steps and elements which the assignee claims as the invention. Claims can be independent or dependent. An independent claim stands on its own, while a dependent claim has meaning only when combined with a claim (in the same patent) it refers to.

Claims are informative about the scope and detailed content of the patented invention, while the title provides a high-level description of the invention claimed. For example, the most cited USPTO patent (US4683202 A) is entitled "Process for amplifying nucleic acid sequences", and has 21 claims. The first independent claim is "A process for amplifying at least one specific nucleic acid sequence contained in a nucleic acid ..., " followed by the dependent claim "The process of claim 1, wherein steps (b) and (c) are repeated at least once". Another highly cited USPTO patent (US6294274B1) is titled "Oxide thin film". It has 20 claims, 1 independent and 19 dependent claims, where the first claim is "An oxide thin film formed on a substrate, ... " Therefore, we expect classifying patents into process/product using claims and titles to produce generally similar classifications.

The USPTO only started recording patent data in a digital format, which contains structured full texts, in 1976. Pre-1976 patent information has to be parsed from USPTO patent images in an unstructured format and may contain many optical character recognition (OCR) errors. We find that there are substantial mistakes in OCR-ed patent titles prior to 1900, where 36% of OCR-ed titles are different from the title in the patent document. The rest of the patent text contains even higher error rates and unreadable text. We provide classifications for all patents, however we only include post-1900 patents in our analysis.

For each claim (both independent and dependent), we extract the preamble that recites the class of the invention and follow the same procedure as for titles, both described below, to classify each claim into process and product related based on the preambles. There is 86.5% overlap between claim-based and title-based patent classification for the 1976–2020 sample period. We also classify patents using only the first claim and independent claims and the empirical results remain qualitatively similar.

B.2. Rule-based classification algorithm

This section describes the algorithm to classify process and product patents. The focus is to search for keywords that represent processes or products and define process or product patents based on these keywords.

Titles

1. For each title, change all characters to lower case and lemmatize all words.
2. For each title, remove punctuations and phrases that do not aid in classification such as improvement(s) in, improvement(s) on, improvement(s) of, improvement(s) for, enhancement(s) in, enhancement(s) on, enhancement(s) of, enhancement(s) for.

3. For each **title**, split into **partitions** using the conjunction "and". The conjunction "and" cannot be in the middle of two verbs, e.g., moving and folding; and must be written as a standalone word, e.g., go-and-grab will not be split.
4. For each **partition**, strip off words after prepositions.[28]

```
[of, for, or, having, derived from, from, combi
ned with, with, using,
used, as, to, on, in particular, in, based, via,
prepared by,
performed by, by, characterized, selected, exhi
biting, comprised,
comprising, containing, including, comprised,
consisting, provide,
provided, providing, produced, producing, def
ine, defined, storing,
allowing, enabling, adapted, which, that, where
in, whereby, thereby,
therein, according to, particular]
```

5. For each **partition** from the last step, define it as product-related if the last word in the **partition** is in the *Product-related hypernym word* net or their minor variations.[29]
6. For each **partition** undefined from the last step, define it as process-related if it contains any word(s) that is (are) in the *Process-related hypernym word* net or their minor variations.
7. For each **partition** undefined from the last step, define it as product-related.
8. For each **title**, if it has only process-related partition(s), define it as a process patent.
9. For each **title**, if it has only product-related partition(s), define it as a product patent.
10. For each **title**, if it has both process and product partition(s), define it as a patent that has both process and product component(s).

Claims

1. For each claim, change all characters to lower case and lemmatize all words.
2. For each claim, remove punctuations and phrases that do not aid in classification such as (improvement in/on / of/for; enhancement in/on / of/for), see step 2 in previous section.
3. If the claim contains "by the process" or "by the method" within the first two sentences, define it as a product-by-process claim.
4. For each claim, find the preamble by first striping off words after prepositions, using the same rule as the previous section.
5. For each **preamble** from the last step, define the claim as product-related if the last word in the **preamble** is in the *Product-related hypernym word* net or their minor variations.
6. For each **preamble** undefined from last step, define the claim as a process claim if it contains any word(s) from the *Process-related hypernym word* net or their minor variations.
7. For each **preamble** undefined from last step, define the claim as product claim.

Deep-learning model

We take advantage of the recent advancement in natural language processing (NLP) techniques to classify patent titles to process-related and product-related inventions, using DistilBert. DistilBert is a successful NLP deep-learning, which is an improved version of the popular BERT model that has achieved several state-of-the-art results in various NLP tasks.[30]

We first classify patents into process and product innovation based on their claims. If all patent claims are classified as process claims based on the rule-based classification, then the patent is defined as a process patent. If all patent claims are classified as product claims based on the rule-based classification, then the patent is defined as a product patent. We train the model to use patent titles as input (features) to predict the classification based on claims (labels). We achieve an 88.7% prediction accuracy, which is considered very high in NLP tasks. For comparison, the breakthrough BERT model achieved an 86.6% accuracy in sentence pairing tasks (to determine whether two sentences are paraphrasing each other) when introduced, which was considered highly successful.

B.3. Classification method validation

One may quibble on whether the rules-based classification and word selection truly captures process or product innovation. To validate our classification method, we co-operated with patent experts from Maxval Group Inc. (vendor for Google Patents, referred to us by Tech Lead at Google Patents) and patent examiners in IP Australia (IPA).[31] We asked both sets of experts to classify a randomly selected sample of patents based on independent claims.[32] For each of the eight IPC classes (A-H), 100 USPTO patents and 100 EPO patents from 1976 to 2021 (in total 1600 patents) were randomly drawn for Maxval Group Inc. For each of the eight IPC classes (A-H), 50 Australian patents (400 in total) were randomly drawn for IP Australia examiners. Each patent is classified independently by the patent experts into process only, product only, or both based on independent claims.

Maxval Group Inc. classified 1592 patents and IP Australia returned 389 classified patents for a total of 1887 patents, which are our validation set.[33] We compare the independently classified patents, validation set, with our hypernym rules-based claims classification. There is a 93.3% overlap between our rules-based classification and the validation set classified by IP experts and patent examiners (USPTO 94.5%, EPO 92.8%, IPA 91.5%). The 6.7% error rate comes from three different sources. First, the overall patent classification is different from the individual claim classification. In general, IP experts agree that the terms "means, mechanism, arrangement, measurement system, installation" are processes, however upon reading the totality of the claims they sometimes disagree with how the patent should be classified. They classify these patents as products, even though all the claims are process-based. Second, there are errors in the source documents. For Australian patents, we OCR the PDFs to obtain the claim text, while IP Australia uses their documentations for classification. These two

[28] The list provided here illustrates the most common prepositions in the data. Some prepositions are already captured by regular expression. The full code is available from the authors upon demand.

[29] The exception is the word "system". When "system" appears by itself, we regard it as process and is handled in the next step, if "system" is coupled with an adjective or noun before it (e.g., computer system, optical system, etc.), we classify it as a product. Our results are robust to classifying all system-related patents as either product or process. This choice is informed from discussions with patent experts.

[30] The classification performance is not sensitive to which BERT variation we use (Bert, Albert, RoBerta and a few other models). We choose DistilBert for its speed. The model is available from Huggingface repository https://huggingface.co/leoliu/pat_classifier_distilbert.

[31] Founded in 2004, MaxVal Group, Inc. is a Silicon-Valley based provider of IP software and solutions. Their website is located atwww.maxval.com IP Australia is the Australian Patent and Trademark Office.

[32] There is an 86% correlation between rule based classification using independent claims and titles, 88.7% correlation using the deep learning approach.

[33] We also ask them to provide a confidence from 0 to 100 for their level certainty in the classification. Maxval Group Inc. scored all classifications with 100, and IP Australia scored 295 of 389 patents with 100.

documents are different for a dozen patents. Third, less than 1% of the errors come from parsing the claim preambles.

Appendix C. Patent similarity measure

Each patent document is transformed into a high-dimensional vector using TFIDF. Each dimension corresponds to a term — specifically, a word from a global vocabulary comprising all patent documents in Google Patents. We restrict our analysis to words that appear more than 100 times across over 10 million documents to eliminate terms due to misspelling and data errors, after excluding stopwords. This results in a vector of size of 996,522. The TFIDF score serves as the weight for each term in this vector. The similarity between any two vectors can then be calculated using cosine similarity.

To calculate Term Frequency (TF), we measure the frequency of a term t in a document d, as follows:

$$TF(t,d) = \frac{\text{Number of times term } t \text{ appears in document } d}{\text{Total number of terms in document } d}.$$

The Inverse Document Frequency (IDF) measures the importance of a term t across a set of documents D:

$$IDF(t,D) = \log \frac{\text{Total number of documents in } D}{\text{Number of documents containing term } t}.$$

We use an IDF trained on the complete corpus of patents, encompassing both those filed before and after the focal patent. This approach differs from Kelly et al. (2021), whose strategy is to avoid under-representing emergent terminologies that could appear in the focal patent, as such terminology could signal groundbreaking innovations, which is different from our objective. The TFIDF vector for each patent document is simply the product of TF and IDF:

$$TFIDF(t,d,D) = TF(t,d) \times IDF(t,D).$$

To calculate patent similarity, we use cosine similarity:

$$\text{Cosine Similarity}(\mathbf{A},\mathbf{B}) = \frac{\mathbf{A}\cdot\mathbf{B}}{\|\mathbf{A}\| \times \|\mathbf{B}\|}$$

where $\mathbf{A}\cdot\mathbf{B}$ is the dot product of the vectors, and $\|\mathbf{A}\|$ and $\|\mathbf{B}\|$ are their magnitudes. Due to the computational burden of storing all similarity pairs, which requires the storage of a 10 million by 10 million matrix, following Kelly et al. (2021), we constrain the data to include only patent pairs with a cosine similarity greater than 0.1. This selection criterion is unlikely to affect our analysis, because our measure focuses is on patents with very high similarity.

Finally, we use all this information to calculate q as:

$$q^{\tau}_{i,t} = \frac{FS^{\tau}_{i,t}}{BS^{-\tau}_{i,t}},$$

where FS is the forward similarity with future patents, and BS is backward similarity with past patents.

Appendix D. Patent quality measures

We construct seven common measures of patent quality. These measures can be grouped into two categories: backward-looking (number of claims in a patent, patent scope, backward citations, and originality) and forward-looking (forward citations, generality, and market value).

Backward-looking measures of patent quality capture the relation between a patent and the prior innovation it builds on. We compute four measures: claims, scope, backward citations, and originality. For *claims*, we count the number of claims of each patent. Patent *scope* is defined as the number of unique IPC 4-digit patent classifications assigned to the patent.[34] *Backward citation* is the number of U.S. patents a focal patent cites. They are used to assess the legitimacy of a patent's claims and the patentability of an innovation. *Originality* measures the breadth of the technology fields on which the patent relies (Trajtenberg et al., 1997). It is the Hirschman–Herfindahl Index (HHI) index of the IPC classes of the backward citations of a patent p measured as:

$$Originality_p = 1 - \sum_{j}^{n_p} s^2_{pj},$$

where s_{pj} is the percentage of citations made by patent p to patent class j out of the n_p IPC4 patent classes contained in the patents cited by patent p. A value closer to one implies that a patent has relied on a wide range of patent classes and technology fields, which is more likely to lead to original results (see e.g., Gompers et al., 2005).

Forward-looking measures of patent quality capture the ex-post impact of the patent in terms of invention, which we measure by future citations (number and breadth) and the market reaction to a patent. *Forward citation* is the number of U.S. patents that cite a focal patent. If patent citations spread over several technological fields, the cited patent is considered more "general", because it is used in a wider range of fields (Hall and Trajtenberg, 2004; Layne-Farrar and Lerner, 2011). *Generality* is defined as the HHI of the IPC classes of all forward citations of patent p measured as:

$$Generality_p = 1 - \sum_{j=1}^{M_t}\left(\frac{1}{N}\sum_{i=1}^{N}\frac{T^n_{ji}}{T^n_i}\right)^2,$$

where T^n_i is total number of IPC 7-digit classes in patents (indexed by i) citing patent p. T^n_{ji} is the total number of IPC 7-digit in the j_{th} IPC4 class in each i and j is the cardinal of all IPC4 classes in all i.[35] A value closer to one implies that a patent has influenced innovation in a wide range of patent classes.

Market value (referred to as ξ) is the private economic value of each patent calculated using stock returns around (3-day abnormal stock market reaction) the patent grant date (Kogan et al., 2017). This data is provided by Kogan et al. (2017) and is only available for U.S. publicly-listed firms with stock price information in CRSP from 1926.

NPL is the number of non-patent literature cited by the patent. They refer to any published material, such as research papers, books, articles, conference papers, technical reports, and other academic or scientific documents, that are cited in a patent but are not patents themselves.

Re-assignments, as reported by the USPTO, is the number of times a patent has been sold, which can be considered an indicator of the external value of the patent.

Renewal is an indicator variable equal to one if the patent is renewed after 12 years (to have a full patent term of 20 years) and zero otherwise. The renewal rate after 12 years indicates how valuable a patent is to its holder to merit renewal (Lanjouw et al., 1998).

Appendix E. Additional tables and figures

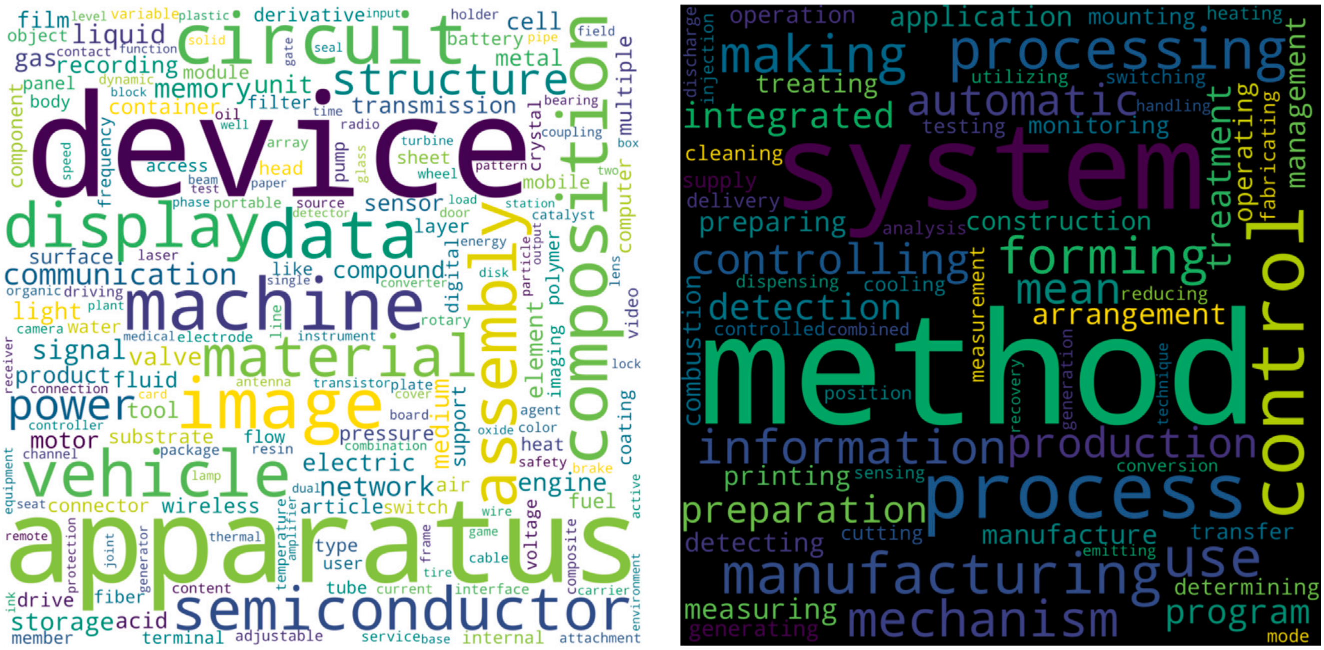
See Figs. E.1 and E.2 and Tables E.1–E.15.

Appendix F. The role of breakthrough products

See Tables F.1–F.4.

[34] The IPC provides a hierarchical system for the classification of patents according to technology areas. The appropriate IPC symbols are indicated on each patent document and are allotted by the national or regional industrial property office that publishes the patent document. The classification is indispensable for the retrieval of patent documents in the search for "prior art", see Lerner (1994) for more details.

[35] This measure is at the IPC4 level but adjusted for the granular distribution within each IPC4.



Panel A. Product related *Panel B. Process related*

Fig. E.1. Word cloud for product- and process-related words.
The figure presents the word cloud for all the words used in classifying product and process USPTO patents, based on patent titles from 1900 to 2020.

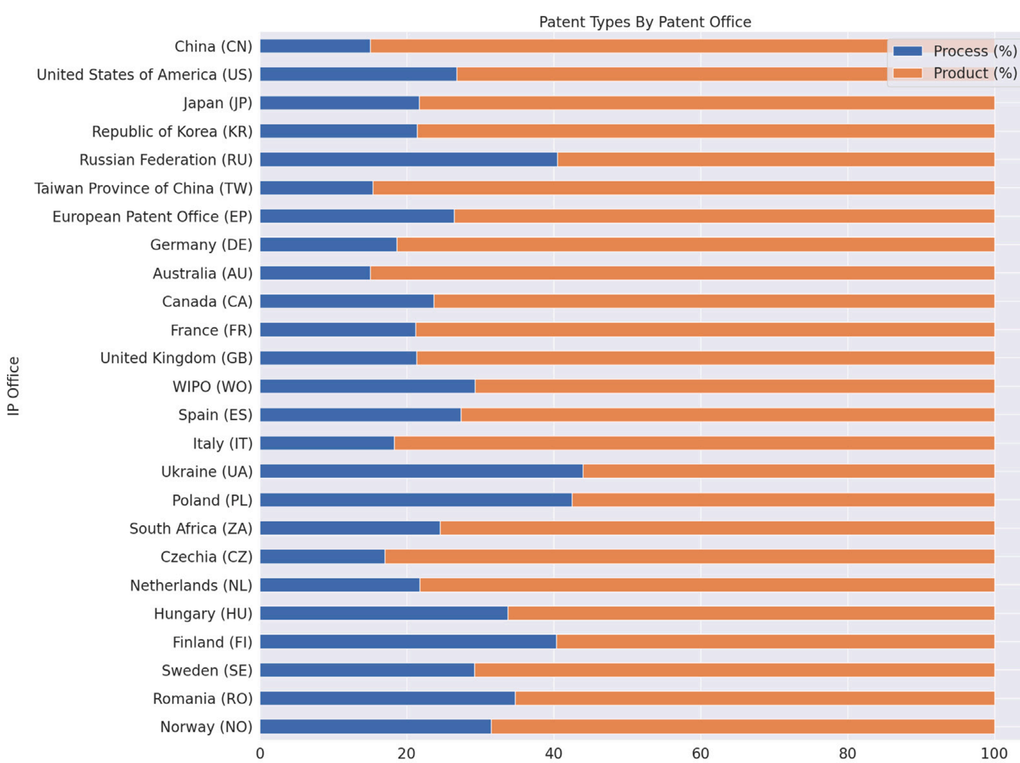


Fig. E.2. Process and product patents by patent office.
The figure presents the variation of process and product granted patents by intellectual property (IP) office for the common sample period from 1984 to 2020. Process and product patents are classified using patent titles. The data is from PATSTAT, 2020 Autumn edition. We present the top 25 IP offices, which grant the highest number of patents during the sample period from 1984 to 2020. IP offices are sorted by the number of granted patents in the sample. The detailed IP office information is available in Table E.5.

Table E.1
Google patent information.

Variable	Description
Publication_number	Patent publication number
Application_number	Application number, formatted to the patent office format where possible.
Country_code	Country the patent is filed at
Kind_code	Kind code, indicating application, grant, search report, correction, etc.
Application_kind	High-level kind of the application: A=patent; U=utility; P=provision; W= PCT; F=design; T=translation.
Pct_number	Patent Cooperation Treaty number
Family_id	ID indicating the patents shared the same priority claims
Title	
Abstract	
Claims	
Description	
Publication_date	Patent publication date
Filing_date	Patent filing date
Grant _date	Patent grant date
Priority_date	The earliest priority date from the priority claims or the filing date
Priority_claim	The application numbers of the priority claims of this patent
Inventor	List of inventor names
Assignee	List of assignee names
Examiner	List of examiner names
USPC	US patent classification
IPC	International patent classification
CPC	Cooperative patent classification
Citation	List of publications that this patent cites

The table presents the list of variables as obtained from Google Patents.

Table E.2
Variable definitions.

Variable name	Abbrev.	Description
Innovation Measures		
Process (θ)	$\theta^{proc}_{i,t}$	Market value of process patents (ξ) aggregated to firm–year scaled by total assets
Product (θ)	$\theta^{prod}_{i,t}$	Market value of product patents (ξ) aggregated to firm–year scaled by total assets
Patent metrics		
Claims		Number of claims in the patent
Scope		Unique number of IPC 4-digit classifications of a patent
Backward		Backward citations, measured as the number of US patents the patent cites
Originality		HHI index of cited patents' IPC4 classes
Forward		Forward citations, measured as number of US patents citing the patent
Generality		HHI index of citing patents' IPC4 classes
ξ		Market value of patent (Kogan et al., 2017)
NPL		The number of non-patent literature cited by the patent [USPTO]
Re-assignments		The number of times a patent has been sold [USPTO]
Renewal		Indicator variable equal to one if the patent is renewed after 12 years (to have a full patent term of 20 years) and zero otherwise [USPTO]
Firm growth		
Profits		Sales minus cost of goods sold [COMPUSTAT: SALE - COGS deflated by CPI]
Capital Stock		[COMPUSTAT: PPEGT deflated by the NIPA price of equipment]
Employment		[COMPUSTAT: EMP]
Total Factor Productivity	TFP	Revenue-based TFP constructed using methodology of Olley and Pakes (1996) applied using the procedure in İmrohoroğlu and Tüzel (2014)
Firm characteristics		
Ln(Total Assets)		Natural log of (1 + Firm's total asset [COMPUSTAT: AT])
Ln(Market Cap)		Natural log of total market capitalization [COMPUSTAT: CSHO × PRCC_F]
Tobin's Q		Sum of total assets plus market value of equity minus book value of equity divided by total assets [COMPUSTAT: (AT+CSHO × PRCC_F - CEQ)/AT)]
Leverage		Firm's total debt divided by total assets [COMPUSTAT: (DLTT + DLC)/AT]
Return on Assets	ROA	Net Income divided by total assets [COMPUSTAT: NI/AT]
Sales Growth		Sales growth from last fiscal year end [COMPUSTAT: ($SALE_t/SALE_{(t-1)}$ −1)]
Cash Holdings		[COMPUSTAT: CHE/AT]
Dividends		Firm's total dividends issued [COMPUSTAT: DVT/AT]
Capital Expenditure	CAPX	Capital expenditures divided by total assets [COMPUSTAT: CAPX/AT]
Property, Plant, and Equipment	PPE	Property, plant, and equipment divided by asset [COMPUSTAT: PPENT/AT]
R&D	R&D	Research and development expenses divided by total assets [COMPUSTAT: XRD/AT]
Missing R&D		Indicator variable equal to 1 if R&D expense is missing, zero otherwise
Idiosyncratic Volatility	$\sigma_{i,t}$	Sum of squared abnormal returns [CRSP DSF: $\sum_{d\in t}(r_i - r_m)^2$]
Abnormal Returns		Annualized monthly returns minus value-weighted NYSE, AMEX and NASDAQ return
Volatility		Standard deviation of 60 prior days' stock returns

Table E.3
Robustness on validation of cost-reducing patents.

Panel A. Accounting outcomes

	1976 — 70th			1976 — 90th			1950 — 80th		
	EMP/PPE	CAPX/AT	PPE/AT	EMP/PPE	CAPX/AT	PPE/AT	EMP/PPE	CAPX/AT	PPE/AT
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Ln(Foundational Stock)	0.002*	0.101***	0.084	0.002	0.063**	−0.042	0.001	0.089***	0.051
	(1.72)	(4.75)	(1.36)	(0.97)	(2.25)	(−0.54)	(1.06)	(3.89)	(0.79)
Ln(Cost-reducing Stock)	−0.011***	−0.091***	−0.156***	−0.007***	−0.009	−0.042	−0.008***	−0.058***	−0.118**
	(−6.21)	(−4.50)	(−2.82)	(−4.27)	(−0.48)	(−0.81)	(−5.27)	(−2.97)	(−2.20)
Ln(Product Stock)$_t$	−0.001	−0.004	0.240**	−0.004	−0.039	0.199*	−0.003	−0.022	0.218**
	(−0.48)	(−0.11)	(2.38)	(−1.50)	(−1.01)	(1.93)	(−1.09)	(−0.60)	(2.12)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	148,220	151,774	153,370	148,220	151,774	153,370	149,004	152,613	154,219
Adj. R^2	0.84	0.55	0.87	0.84	0.55	0.87	0.84	0.55	0.87

Panel B. Company reports 10K/Qs

	70th	90th
	(1)	(2)
Ln(Foundational)	−0.001	−0.004
	(−0.27)	(−0.63)
Ln(Cost-reducing)	0.016***	0.012**
	(3.13)	(2.30)
Ln(Product)	−0.015***	−0.013***
	(−3.21)	(−2.81)
Controls	✓	✓
Year FE	✓	✓
Firm FE	✓	✓
Obs.	127,519	127,519
Adj. R^2	0.45	0.45

This table presents validation analysis for the classification of cost-reducing patents. In Panel A, the dependent variables are capital expenditures (CAPX) and property, plant, and equipment (PPE), both expressed as shares of total assets, and the number of employees per million of PPE. In Panel B, the dependent variable is an indicator variable equal to one when cost-reduction terms are mentioned in firms 10-K/Q filings, and zero otherwise. The search terms include the following and their variants: cost-reducing, reduce cost, operational efficiency, efficiency gain, increase productivity, improve productivity, productivity improvement, process efficiency, cost cutting, reduced labor, operational improvement, overhead reduction, efficiency improvement, cost containment, expense control, workflow optimization, cost control, cost minimization, increase efficiency, improve efficiency, efficiency enhancement, and resource optimization. Foundational and cost-reducing patents are defined using the within-firm q-ratio at the 80th percentile. The included control variables are: Ln(Total assets), Tobin's Q, cash flow, R&D expenditure, and a missing R&D indicator. Standard errors are clustered at the firm level. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. All variable definitions are provided in Table E.2 in the Appendix. The sample period for Panel A is 1976 to 2020, and 1993 to 2020 for Panel B, when 10-K/Q electronic filings are available.

Table E.4
Foundational processes and scientific publications.

	t+1	t+2	t+3	t+4	t+5
Ln(Foundational Stock)	0.559***	0.585***	0.581***	0.561***	0.525***
	(10.05)	(10.82)	(11.01)	(10.28)	(9.32)
Ln(Cost-reducing Stock)	−0.025	−0.099*	−0.147***	−0.205***	−0.234***
	(−0.37)	(−1.67)	(−2.72)	(−3.84)	(−4.21)
Ln(Product Stock)	−0.077	−0.128	−0.160	−0.141	−0.159
	(−0.63)	(−1.06)	(−1.38)	(−1.18)	(−1.31)
Ln(Total Asset)	0.276***	0.247***	0.219***	0.217***	0.213***
	(4.01)	(3.76)	(3.38)	(3.25)	(2.93)
Controls	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Obs.	23,749	22,036	20,465	18,819	17,209

This table presents the relation between firm scientific publications and heterogeneous innovations. The dependent variable is the number of scientific papers, measured by the papers linked to patents. We estimate the following Poisson regression:

$$E(New\ \ Paper_{i,t+\tau}) = Exp(\alpha_0 + \beta_{1,\tau} ln(1 + P^{found}_{i,t}) + \beta_{2,\tau} ln(1 + P^{cost\ \ red}_{i,t}) + \beta_{3,\tau} ln(1 + P^{prod}_{i,t}) + \Gamma X'_{i,t} + \alpha_i + \delta_t + \epsilon_{i,t}).$$

Firm scientific publications are obtained from Reliance on Science (https://relianceonscience.org/patent-paper-pairs). $X'_{i,t}$ is a vector of control variables which includes ln(Total Assets) and R&D intensity, α_i are firm fixed effects and δ_t are time fixed effects. The sample period is 1976 to 2020.

Table E.5
International process and product patents by patent office.

Patent Office	Process (%)	Product (%)	Total Patents	Claims Information	Year First PWT	Year First PATSTAT	Year Last PWT/PATSTAT
China	15.0	85.0	17,150,795	Not Reported	1956	1984	2019
United States (Google Patent)	31.0	68.9	6,540,967	Available	1950	1954	2019
Japan	23.1	76.9	3,948,797	Not Reported	1954	1946	2019
Korea	21.5	78.5	2,065,781	Not Reported	1957	1968	2019
Germany	18.6	81.4	2,026,937	Not Reported	1954	1889	2014
Russian Federation	35.9	64.1	1,870,229	Not Reported	1994	1983	2019
France	20.6	79.4	1,550,841	Not Reported	1954	1902	2017
United Kingdom	19.8	80.2	1,178,560	Not Reported	1954	1782	2019
Taiwan	15.4	84.6	778,736	Not Reported	1955	1983	2019
European Patent Office (EPO)	26.6	73.4	732,046	By Crawling	NA	1978	2019
Spain	28.4	71.6	705,665	Not Reported	1954	1907	2019
Canada	20.2	79.8	474,696	Not Reported	1954	1800	2019
Switzerland	18.1	81.9	385,891	Not Reported	1954	1955	2014
Australia	15.1	84.9	373,270	Not Reported	1954	1904	2019
Italy	18.6	81.4	312,517	Not Reported	1954	1962	2018
Austria	24.2	75.8	296,738	Not Reported	1954	1969	2019
World Intellectual Property Office (WIPO)	29.2	70.8	174,805	Not Reported	NA	1978	2019
Belgium	26.3	73.7	151,054	Not Reported	1954	1926	2009
Poland	40.9	59.1	104,270	Not Reported	1974	1969	2019
Denmark	24.0	76.0	98,030	Not Reported	1954	1964	2019
Ukraine	43.7	56.3	97,335	Not Reported	1994	1975	2019
South Africa	23.9	76.1	85,035	Not Reported	1954	1950	2019
Finland	38.9	61.1	81,644	Not Reported	1954	1973	2019
Netherlands	21.8	78.2	56,019	Not Reported	1954	1916	2019
Romania	35.8	64.2	44,663	Not Reported	1964	1900	2019
Greece	24.5	75.5	41,837	Not Reported	1955	1961	2019
Hungary	35.9	64.1	41,699	Not Reported	1974	1966	2019
Czechia	17.0	83.0	40,843	Not Reported	1994	1966	2019
Sweden	29.2	70.8	40,124	Not Reported	1954	1908	2019
Norway	30.6	69.4	32,724	Not Reported	1954	2002	2019
Brazil	22.5	77.5	32,240	Not Reported	1954	1996	2017
Argentina	21.8	78.2	29,322	Not Reported	1954	1972	1994
Bulgaria	31.0	69.0	27,443	Not Reported	1974	1964	2019
Turkey	21.0	79.0	26,509	Not Reported	1954	2005	2019
India	39.7	60.3	26,362	Not Reported	1954	1912	2019
Mexico	32.7	67.3	19,793	Not Reported	1954	1983	2019
Israel	32.9	67.1	15,567	Not Reported	1954	1958	2019
Portugal	32.2	67.8	14,834	Not Reported	1954	1971	2019
Ireland	25.6	74.4	13,355	Not Reported	1954	1928	2019
Philippines	23.9	76.1	11,772	Not Reported	1954	1966	2019
Malaysia	30.3	69.7	7267	Not Reported	1959	1953	2017
Slovenia	21.6	78.4	6612	Not Reported	1994	1974	2019
Hong Kong	12.9	87.1	6370	Not Reported	1964	1971	2019
Slovakia	27.3	72.7	5542	Not Reported	1994	1978	2019
Moldova	52.5	47.5	5471	Not Reported	1994	1985	2019
Luxembourg	27.0	73.0	5434	Not Reported	1954	1976	2019
Latvia	35.1	64.9	3399	Not Reported	1994	1992	2019
Egypt	32.2	67.8	3029	Not Reported	1954	1967	2013
Lithuania	29.7	70.3	2588	Not Reported	1994	1992	2019
Croatia	16.8	83.2	2045	Not Reported	1994	1992	2019
Estonia	26.5	73.5	1642	Not Reported	1994	1996	2019
Serbia	18.2	81.8	1443	Not Reported	1994	1997	2019
Jordan	31.4	68.6	1236	Not Reported	1958	1968	2019
Iceland	29.3	70.7	1200	Not Reported	1954	2000	2019
Zimbabwe	28.9	71.1	892	Not Reported	1958	1978	1994
Saudi Arabia	26.3	73.7	427	Not Reported	1974	1989	2014
Malta	20.7	79.3	305	Not Reported	1958	1968	2011
Tajikistan	49.3	50.7	253	Not Reported	1994	1992	2007

The table presents the share of process and product patents defined using titles for PATSTAT data by IP office. Countries must have at least 10 years growth and patent data. *Process %* is the share of patents classified as process patents using English patent titles, *Product %* is the share of patents classified as product patents using English patent titles, *Total Patents* is the total number of granted patents. *PWT First Year* is the first year with GDP information in Penn World Tables, *PATSTAT First* is the year of the first English patent information in PATSTAT, and *Year Last* is the last year with data PWT or PATSTAT information, whichever ends first.

Table E.6
Cross-country growth and foundational processes.

	t+1	t+2	t+3	t+4	t+5
	(1)	(2)	(3)	(4)	(5)
Panel A. GDP Growth					
Found/(Prod. + Cost)	0.819**	1.688**	1.970**	2.203*	1.776
	(2.00)	(2.05)	(2.40)	(1.90)	(1.33)
Labor Share	0.000	0.000*	0.000**	0.000**	0.000***
	(1.33)	(1.67)	(2.02)	(2.35)	(2.59)
Capital Share	0.001***	0.003***	0.006***	0.008***	0.011***
	(2.97)	(3.61)	(4.35)	(5.17)	(5.99)
Log GDP	−1.101***	−2.889***	−5.026***	−7.431***	−9.943***
	(−2.75)	(−4.29)	(−5.26)	(−6.13)	(−6.80)
Year FE	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓
Obs.	1380	1358	1336	1314	1292
R^2	0.33	0.38	0.42	0.47	0.52
Panel B. TFP Growth					
Found/(Prod. + Cost)	0.837**	1.328**	1.364**	1.569*	0.820
	(2.24)	(2.03)	(2.13)	(1.69)	(0.76)
Labor Share	0.000	0.000	0.000	0.000	0.000
	(0.87)	(0.98)	(1.15)	(1.34)	(1.40)
Capital Share	0.001	0.001*	0.002**	0.003***	0.004***
	(1.64)	(1.95)	(2.33)	(2.71)	(3.15)
Log TFP	−2.577***	−5.863***	−9.274***	−12.814***	−16.393***
	(−3.86)	(−5.76)	(−6.42)	(−7.36)	(−8.18)
Year FE	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓
Obs.	1380	1358	1336	1314	1292
R^2	0.28	0.36	0.41	0.47	0.53

This table present the relation between GDP and TFP growth and foundational processes. We estimate cross-country growth regressions of the form:

$$\ln(Y_{c,t+\tau}) - \ln(Y_{c,t}) = \alpha_0 + \beta_{,\tau} \frac{\text{Foundational}_{c,t}}{\text{Product}_{c,t} + \text{Cost reducing}_{c,t}} + \gamma ln(Y_{c,t}) + \Lambda X'_{c,t} + \alpha_c + \delta_t + \epsilon_{c,t+\tau}$$

where Y represents the growth measures of real GDP per capita and TFP. *Foundational* is the number of foundational process patents, *Product* is the number of product patents, and*Cost reducing* is the number of cost reducing patents filed in country c in year t. X is a vector of control variables which includes the human capital index and labor share. We estimate from $\tau = 1$ to $\tau = 5$. The foundational and cost reduction patents are identified using patent families with foundational/cost reduction patents in the USPTO. The GDP and TFP data are from the Penn World Tables. The sample period is 1954 to 2019. We consider a foreign patent as foundational if it belongs to the same family as a foundational US patent. Other foreign patents are identified by their inclusion in at least one patent family with a public firm's US patent.

Table E.7
Firm growth — process and product patents, claims-based.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Process (θ)	0.008***	0.020***	0.027***	0.023***	0.027***	0.031***	0.032***	0.032***	0.033***	0.033***
	(2.78)	(3.92)	(3.97)	(2.75)	(3.18)	(3.48)	(3.33)	(3.15)	(2.93)	(3.07)
Product (θ)	0.010***	0.008	0.007	0.015*	0.014*	0.013	0.012	0.015	0.015	0.018
	(2.89)	(1.42)	(0.88)	(1.89)	(1.66)	(1.47)	(1.27)	(1.43)	(1.31)	(1.64)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel B. Sales										
Process (θ)	0.005*	0.018***	0.021***	0.020***	0.025***	0.027***	0.031***	0.031***	0.028***	0.032***
	(1.65)	(4.05)	(3.93)	(3.46)	(3.57)	(3.64)	(3.99)	(4.08)	(3.24)	(3.62)
Product (θ)	0.010***	0.009**	0.009*	0.013**	0.009	0.010	0.006	0.008	0.010	0.010
	(3.71)	(2.29)	(1.77)	(2.10)	(1.28)	(1.31)	(0.79)	(1.07)	(1.10)	(1.08)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel C. Capital										
Process (θ)	0.008***	0.014***	0.018***	0.022***	0.026***	0.027***	0.026***	0.024***	0.026***	0.027***
	(2.77)	(3.97)	(4.76)	(5.27)	(5.29)	(5.06)	(4.36)	(3.79)	(3.82)	(3.72)
Product (θ)	0.007***	0.015***	0.019***	0.020***	0.020***	0.020***	0.020***	0.021***	0.021***	0.019**
	(4.04)	(5.10)	(5.09)	(4.64)	(3.50)	(3.17)	(2.96)	(2.88)	(2.63)	(2.31)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel D. Employment										
Process (θ)	0.005***	0.011***	0.014***	0.015***	0.019***	0.020***	0.020***	0.019***	0.020***	0.021***
	(2.81)	(4.25)	(4.03)	(4.22)	(4.65)	(4.68)	(4.09)	(3.59)	(3.54)	(3.51)
Product (θ)	0.006***	0.010***	0.012***	0.012***	0.009**	0.006	0.007	0.007	0.008	0.007
	(4.53)	(4.17)	(3.44)	(3.15)	(2.02)	(1.26)	(1.28)	(1.27)	(1.34)	(1.17)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013

(*continued on next page*)

Table E.7 (*continued*).

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel E. Total Factor Productivity										
Process (θ)	0.010***	0.016***	0.015***	0.012***	0.015***	0.017***	0.018***	0.018***	0.018***	0.021***
	(4.47)	(4.23)	(3.97)	(2.71)	(3.27)	(3.21)	(3.48)	(3.93)	(3.82)	(4.36)
Product (θ)	0.011***	0.013***	0.003	0.007	0.008	0.006	0.004	0.006	0.010	0.009
	(3.62)	(4.21)	(0.34)	(1.02)	(1.26)	(0.90)	(0.61)	(0.97)	(1.52)	(1.38)
Obs.	98,859	88,409	79,714	72,084	65,481	59,556	54,412	49,688	45,421	41,640

The table presents relation between process and product innovation and firm-level outcomes, where patents are classified using patent claims not titles. We present the coefficients (β_τ) from estimations of the following model:

$$ln(Y_{i,t+\tau}) - ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_\tau^{Pats} \theta_{i,t}^{Pats} + \gamma_1 ln(Y_{i,t}) + \gamma_2 ln(Y_{i,t-1}) + \Lambda X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y are the firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different types of patents ($Pats$) granted to firm i in year t scaled by total assets, $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in \{1, \ldots, 10\}$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. All variable definitions are provided in Table E.2 in the Appendix. The sample period is 1976 to 2020.

Table E.8
Firm growth and foundational processes — robustness with cross-firm Q.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Process, foundational (θ) (θ)	0.007***	0.008***	0.014***	0.015***	0.013***	0.014***	0.015***	0.016***	0.019***	0.020***
	(4.18)	(2.67)	(3.90)	(3.61)	(3.06)	(2.87)	(2.94)	(3.02)	(2.98)	(3.25)
Process, cost-reducing (θ)	0.002	0.012***	0.017***	0.009	0.012	0.013	0.010	0.009	0.006	0.007
	(0.94)	(2.97)	(2.72)	(1.20)	(1.61)	(1.53)	(1.14)	(0.94)	(0.62)	(0.78)
Product (θ)	0.012***	0.011**	0.007	0.017**	0.018**	0.020**	0.020**	0.024**	0.025**	0.027**
	(3.49)	(2.23)	(0.85)	(2.20)	(2.10)	(2.10)	(1.96)	(2.06)	(1.96)	(2.29)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel B. Sales										
Process, foundational (θ) (θ)	0.007***	0.012***	0.014***	0.016***	0.017***	0.022***	0.021***	0.019***	0.020***	0.018***
	(4.18)	(3.79)	(3.86)	(4.21)	(4.21)	(4.65)	(3.96)	(3.61)	(3.91)	(3.13)
Process, cost-reducing (θ)	−0.001	0.010**	0.011*	0.007	0.008	0.003	0.001	0.001	0.001	0.005
	(−0.27)	(2.32)	(1.78)	(1.35)	(1.06)	(0.34)	(0.15)	(0.11)	(0.15)	(0.64)
Product (θ)	0.011***	0.010***	0.011*	0.015**	0.014*	0.018**	0.018**	0.023**	0.021*	0.022**
	(4.55)	(2.70)	(1.92)	(2.42)	(1.71)	(2.07)	(2.13)	(2.45)	(1.90)	(2.07)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel C. Capital										
Process, foundational (θ) (θ)	0.004**	0.010***	0.014***	0.017***	0.020***	0.021***	0.022***	0.023***	0.024***	0.024***
	(2.50)	(4.22)	(4.61)	(4.79)	(5.10)	(5.46)	(5.38)	(5.29)	(5.31)	(5.04)
Process, cost-reducing (θ)	0.004*	0.006**	0.007***	0.007**	0.007	0.005	0.002	−0.000	−0.000	0.002
	(1.82)	(2.02)	(2.67)	(2.13)	(1.62)	(1.11)	(0.33)	(−0.04)	(−0.03)	(0.28)
Product (θ)	0.008***	0.016***	0.022***	0.025***	0.026***	0.027***	0.029***	0.030***	0.029***	0.027***
	(4.54)	(5.40)	(5.39)	(5.01)	(3.96)	(3.72)	(3.54)	(3.38)	(3.20)	(2.93)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel D. Employment										
Process, foundational (θ) (θ)	0.004***	0.006***	0.009***	0.013***	0.014***	0.015***	0.015***	0.014***	0.015***	0.015***
	(2.84)	(3.25)	(3.85)	(4.48)	(4.79)	(5.15)	(4.83)	(4.28)	(4.01)	(4.01)
Process, cost-reducing (θ)	0.003	0.007***	0.008***	0.006**	0.007*	0.007	0.006	0.004	0.005	0.005
	(1.40)	(2.60)	(2.89)	(2.00)	(1.91)	(1.59)	(1.13)	(0.78)	(0.93)	(0.95)
Product (θ)	0.007***	0.011***	0.012***	0.013***	0.012**	0.010*	0.011*	0.013*	0.013**	0.012*
	(4.74)	(4.17)	(3.48)	(3.35)	(2.43)	(1.87)	(1.88)	(1.92)	(1.98)	(1.90)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel E. Total Factor Productivity										
Process, foundational (θ) (θ)	0.003**	0.003	0.008**	0.006**	0.005*	0.006*	0.007**	0.007**	0.006*	0.008***
	(1.96)	(1.12)	(2.17)	(2.05)	(1.77)	(1.95)	(2.12)	(2.24)	(1.88)	(2.77)
Process, cost-reducing (θ)	0.007***	0.008**	0.003	0.007	0.010**	0.010*	0.008	0.011*	0.013**	0.010*
	(2.68)	(2.48)	(0.66)	(1.49)	(2.18)	(1.82)	(1.53)	(1.96)	(2.22)	(1.80)
Product (θ)	0.013***	0.018***	0.008	0.008	0.010*	0.009	0.011*	0.011	0.013*	0.015**
	(4.26)	(5.27)	(1.06)	(1.13)	(1.67)	(1.55)	(1.64)	(1.58)	(1.87)	(2.45)
Obs.	98,859	88,409	79,714	72,084	65,481	59,556	54,412	49,688	45,421	41,640

The table presents relation between foundational, cost-reduction process and product innovation and firm-level outcomes, for foundational patents defined using similarity across all listed firms. Patents are classified using titles. We present the coefficients (β_τ) from estimations of the following model

$$ln(Y_{i,t+\tau}) - ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_\tau^{Pats} \theta_{i,t}^{Pats} + \gamma_1 ln(Y_{i,t}) + \gamma_2 ln(Y_{i,t-1}) + \Lambda X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y are the firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different types of patents ($Pats$, foundational/cost reducing/product patents) granted to firm i in year t scaled by total assets, $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in \{1, \ldots, 10\}$. α_{sic3} and δ_t are industry and year fixed effects. Panel A presents results for gross profits, Panel B for sales, Panel C for capital stock, Panel D for employment, and Panel E for total factor productivity. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. All variable definitions are provided in Table E.2 in the Appendix. The sample period is 1976 to 2020.

Table E.9
Firm growth and foundational processes — robustness top 30% Q.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Process, foundational (θ) (θ)	0.010***	0.017***	0.020***	0.020***	0.020***	0.022***	0.021***	0.020***	0.018**	0.019**
	(4.28)	(4.38)	(3.91)	(3.64)	(3.45)	(3.26)	(3.00)	(2.70)	(2.33)	(2.35)
Process, cost-reducing (θ)	0.001	0.003	0.011*	0.007	0.003	0.003	0.003	0.005	0.009	0.008
	(0.55)	(0.87)	(1.90)	(1.17)	(0.40)	(0.39)	(0.29)	(0.60)	(0.82)	(0.91)
Product (θ)	0.011***	0.012**	0.007	0.014**	0.019**	0.021**	0.020**	0.023**	0.022*	0.025**
	(3.23)	(2.37)	(0.80)	(1.97)	(2.24)	(2.24)	(2.04)	(2.01)	(1.76)	(2.16)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel B. Sales										
Process, foundational (θ) (θ)	0.006***	0.011***	0.015***	0.016***	0.018***	0.019***	0.019***	0.017***	0.017***	0.019***
	(3.46)	(4.25)	(4.40)	(4.17)	(4.21)	(4.12)	(4.08)	(3.62)	(3.16)	(3.40)
Process, cost-reducing (θ)	0.003	0.005	0.006	0.006	0.002	−0.000	−0.005	−0.002	0.001	−0.003
	(1.21)	(1.07)	(0.87)	(0.96)	(0.31)	(−0.06)	(−0.46)	(−0.28)	(0.13)	(−0.29)
Product (θ)	0.009***	0.012***	0.012**	0.015**	0.015*	0.019**	0.020**	0.024**	0.020*	0.023**
	(3.85)	(3.13)	(2.05)	(2.33)	(1.83)	(2.16)	(2.31)	(2.56)	(1.86)	(2.28)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel C. Capital										
Process, foundational (θ) (θ)	0.004***	0.009***	0.014***	0.018***	0.021***	0.023***	0.025***	0.027***	0.027***	0.028***
	(2.79)	(3.47)	(3.88)	(4.07)	(4.12)	(4.27)	(4.40)	(4.46)	(4.57)	(4.68)
Process, cost-reducing (θ)	0.001	0.003	0.005	0.004	0.003	0.001	−0.005	−0.007	−0.005	−0.006
	(0.89)	(1.26)	(1.41)	(1.14)	(0.64)	(0.10)	(−0.81)	(−0.95)	(−0.82)	(−0.79)
Product (θ)	0.010***	0.018***	0.022***	0.024***	0.026***	0.026***	0.029***	0.030***	0.028***	0.026***
	(5.78)	(5.60)	(5.29)	(5.02)	(4.04)	(3.81)	(3.71)	(3.50)	(3.25)	(3.00)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel D. Employment										
Process, foundational (θ) (θ)	0.003***	0.006***	0.010***	0.011***	0.012***	0.014***	0.015***	0.016***	0.017***	0.018***
	(2.72)	(3.29)	(3.80)	(3.86)	(3.78)	(4.08)	(4.12)	(4.29)	(4.34)	(4.42)
Process, cost-reducing (θ)	0.002	0.003	0.005*	0.005	0.006	0.004	0.002	−0.001	0.000	−0.001
	(1.38)	(1.34)	(1.68)	(1.54)	(1.61)	(0.97)	(0.32)	(−0.14)	(0.01)	(−0.10)
Product (θ)	0.007***	0.013***	0.013***	0.013***	0.012**	0.010*	0.012*	0.013**	0.013**	0.012*
	(4.75)	(4.52)	(3.56)	(3.30)	(2.41)	(1.90)	(1.96)	(2.00)	(1.98)	(1.90)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel E. Total Factor Productivity										
Process, foundational (θ) (θ)	0.004***	0.005**	0.009**	0.009***	0.008***	0.010***	0.010***	0.009***	0.008**	0.008***
	(2.84)	(2.43)	(2.50)	(2.72)	(2.74)	(3.39)	(3.44)	(2.83)	(2.47)	(2.80)
Process, cost-reducing (θ)	0.003	0.005	0.005	0.006	0.005	0.002	0.003	0.007	0.008	0.010*
	(1.52)	(1.50)	(1.25)	(1.27)	(1.02)	(0.35)	(0.47)	(1.34)	(1.58)	(1.85)
Product (θ)	0.014***	0.019***	0.005	0.006	0.011*	0.011*	0.011*	0.011	0.014**	0.014**
	(4.60)	(5.20)	(0.55)	(0.85)	(1.79)	(1.87)	(1.82)	(1.61)	(2.13)	(2.28)
Obs.	98,859	88,409	79,714	72,084	65,481	59,556	54,412	49,688	45,421	41,640

The table presents relation between foundational, cost-reduction process and product innovation and firm-level outcomes. Patents are classified using titles and within-firm patent similarity, for a foundational patent cut-off at the 70th percentile. We present coefficients (β_τ) from estimations of the following model

$$ln(Y_{i,t+\tau}) - ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_\tau^{Pats} \theta_{i,t}^{Pats} + \gamma_1 ln(Y_t) + \gamma_2 ln(Y_{t-1}) + \Lambda X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y are the firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different types of patents ($Pats$) granted to firm i in year t scaled by total assets, $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in \{1, \dots, 10\}$. α_{sic3} and δ_t are industry and year fixed effects. Panel A presents results for gross profits, Panel B for sales, Panel C for capital stock, Panel D for employment, and Panel E for total factor productivity. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. All variable definitions are provided in Table E.2 in the Appendix. The sample period is 1976 to 2020.

Table E.10
Firm growth and foundational processes — robustness top 10% Q.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Process, foundational (θ) (θ)	0.008***	0.013***	0.016***	0.017***	0.016***	0.016**	0.015**	0.015**	0.014*	0.014*
	(3.14)	(3.07)	(2.90)	(2.84)	(2.67)	(2.44)	(2.23)	(2.05)	(1.95)	(1.80)
Process, cost-reducing (θ)	0.004*	0.009**	0.016**	0.012*	0.009	0.011	0.012	0.013	0.014	0.015*
	(1.65)	(2.17)	(2.55)	(1.92)	(1.29)	(1.40)	(1.23)	(1.40)	(1.25)	(1.72)
Product (θ)	0.011***	0.011**	0.007	0.014*	0.019**	0.020**	0.020*	0.022*	0.022*	0.025**
	(3.15)	(2.27)	(0.80)	(1.95)	(2.19)	(2.14)	(1.92)	(1.92)	(1.73)	(2.08)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel B. Sales										
Process, foundational (θ) (θ)	0.005***	0.009***	0.013***	0.013***	0.016***	0.017***	0.016***	0.015***	0.015***	0.015***
	(2.68)	(2.96)	(3.19)	(3.09)	(3.43)	(3.53)	(3.22)	(3.08)	(3.05)	(2.91)
Process, cost-reducing (θ)	0.004*	0.007*	0.009	0.010*	0.007	0.005	0.002	0.003	0.005	0.005
	(1.85)	(1.85)	(1.47)	(1.68)	(0.92)	(0.61)	(0.25)	(0.34)	(0.61)	(0.64)
Product (θ)	0.009***	0.012***	0.012**	0.015**	0.015*	0.019**	0.020**	0.024**	0.020*	0.023**

(continued on next page)

Table E.10 (*continued*).

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
	(3.84)	(3.15)	(2.07)	(2.32)	(1.84)	(2.14)	(2.24)	(2.50)	(1.83)	(2.17)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel C. Capital										
Process, foundational (θ) (θ)	0.004**	0.009***	0.012***	0.016***	0.019***	0.021***	0.022***	0.023***	0.023***	0.023***
	(2.46)	(2.77)	(2.91)	(2.99)	(3.07)	(3.10)	(3.13)	(3.19)	(3.27)	(3.33)
Process, cost-reducing (θ)	0.001	0.004*	0.008**	0.008**	0.007	0.006	0.003	0.002	0.005	0.006
	(1.01)	(1.77)	(2.04)	(2.05)	(1.55)	(1.19)	(0.50)	(0.34)	(0.69)	(0.84)
Product (θ)	0.010***	0.018***	0.022***	0.025***	0.026***	0.027***	0.029***	0.029***	0.027***	0.025***
	(5.90)	(5.66)	(5.22)	(4.94)	(3.98)	(3.70)	(3.50)	(3.29)	(3.04)	(2.78)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel D. Employment										
Process, foundational (θ) (θ)	0.004**	0.006***	0.009***	0.010***	0.011***	0.012***	0.013***	0.014***	0.014***	0.014***
	(2.46)	(2.74)	(2.94)	(2.99)	(3.01)	(3.09)	(3.11)	(3.22)	(3.26)	(3.21)
Process, cost-reducing (θ)	0.002	0.004*	0.007**	0.007**	0.008**	0.008*	0.007	0.005	0.006	0.007
	(1.42)	(1.84)	(2.16)	(2.10)	(2.04)	(1.74)	(1.23)	(0.85)	(1.16)	(1.30)
Product (θ)	0.008***	0.013***	0.013***	0.014***	0.012**	0.010*	0.012*	0.013*	0.013*	0.011*
	(4.92)	(4.56)	(3.56)	(3.31)	(2.45)	(1.89)	(1.90)	(1.92)	(1.88)	(1.74)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel E. Total Factor Productivity										
Process, foundational (θ) (θ)	0.003**	0.004*	0.006**	0.006**	0.005**	0.005**	0.005**	0.004**	0.004*	0.005**
	(2.31)	(1.82)	(2.50)	(2.37)	(2.15)	(2.44)	(2.57)	(1.99)	(1.78)	(2.18)
Process, cost-reducing (θ)	0.005**	0.006*	0.009**	0.010**	0.010*	0.009	0.011*	0.014***	0.013***	0.014***
	(2.34)	(1.70)	(2.34)	(2.08)	(1.86)	(1.46)	(1.74)	(2.80)	(2.76)	(2.93)
Product (θ)	0.014***	0.019***	0.004	0.006	0.010	0.009	0.009	0.009	0.012*	0.013*
	(4.26)	(5.13)	(0.48)	(0.74)	(1.54)	(1.36)	(1.27)	(1.17)	(1.74)	(1.93)
Obs.	98,859	88,409	79,714	72,084	65,481	59,556	54,412	49,688	45,421	41,640

The table presents relation between foundational, cost-reduction process and product innovation and firm-level outcomes. Patents are classified using titles and within-firm patent similarity, for a foundational patent cut-off at the 90th percentile. We present coefficients (β_τ) from estimations of the following model

$$ln(Y_{i,t+\tau}) - ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_\tau^{Pats}\theta_{i,t}^{Pats} + \gamma_1 ln(Y_t) + \gamma_2 ln(Y_{t-1}) + \Lambda X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y are the firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different types of patents ($Pats$) granted to firm i in year t scaled by total assets, $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in 1-10$. α_{sic3} and δ_t are industry and year fixed effects. Panel A presents results for gross profits, Panel B for sales, Panel C for capital stock, Panel D for employment, and Panel E for total factor productivity. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. All variable definitions are provided in Table E.2 in the Appendix. The sample period is 1976 to 2020.

Table E.11
Firm growth — foundational, cost-reducing process and product patents, claims-based.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Process, foundational (θ) (θ)	0.008***	0.014***	0.015***	0.015***	0.016***	0.017***	0.016***	0.016**	0.014**	0.016**
	(3.59)	(3.95)	(3.54)	(3.16)	(3.13)	(3.08)	(2.72)	(2.50)	(1.98)	(2.19)
Process, cost-reducing (θ)	0.003	0.007**	0.014***	0.011**	0.010*	0.011*	0.014**	0.014**	0.015*	0.015**
	(1.38)	(1.96)	(2.75)	(2.09)	(1.70)	(1.74)	(2.01)	(1.99)	(1.76)	(2.17)
Product (θ)	0.011***	0.012**	0.011	0.018***	0.019**	0.020**	0.019**	0.021**	0.022**	0.025**
	(3.44)	(2.39)	(1.42)	(2.64)	(2.53)	(2.48)	(2.18)	(2.22)	(2.07)	(2.37)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel B. Sales										
Process, foundational (θ) (θ)	0.005***	0.010***	0.013***	0.013***	0.015***	0.016***	0.016***	0.014***	0.013***	0.015***
	(3.41)	(3.92)	(3.92)	(3.76)	(4.05)	(4.07)	(4.11)	(3.49)	(2.69)	(3.03)
Process, cost-reducing (θ)	0.004**	0.007**	0.010**	0.011**	0.010*	0.009	0.011	0.010	0.010	0.008
	(2.04)	(2.31)	(2.10)	(2.35)	(1.77)	(1.53)	(1.58)	(1.55)	(1.50)	(1.29)
Product (θ)	0.009***	0.013***	0.012***	0.015***	0.014**	0.015**	0.013*	0.016**	0.017*	0.019**
	(4.43)	(4.15)	(2.74)	(2.73)	(2.11)	(2.28)	(1.91)	(2.26)	(1.91)	(2.15)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel C. Capital										
Process, foundational (θ) (θ)	0.003**	0.007***	0.011***	0.014***	0.017***	0.019***	0.021***	0.021***	0.022***	0.024***
	(2.40)	(2.90)	(3.26)	(3.42)	(3.61)	(3.76)	(3.86)	(3.92)	(3.95)	(4.06)
Process, cost-reducing (θ)	0.002	0.005**	0.009***	0.010***	0.010**	0.010**	0.008	0.008	0.010	0.009
	(1.39)	(2.47)	(2.68)	(2.86)	(2.44)	(2.05)	(1.47)	(1.22)	(1.60)	(1.40)
Product (θ)	0.010***	0.018***	0.022***	0.024***	0.024***	0.024***	0.024***	0.024***	0.023***	0.021***
	(7.98)	(7.54)	(6.61)	(6.01)	(4.76)	(4.36)	(3.95)	(3.65)	(3.29)	(2.96)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013

(*continued on next page*)

Table E.11 (*continued*).

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel D. Employment										
Process, foundational (θ) (θ)	0.003***	0.006***	0.009***	0.010***	0.010***	0.012***	0.012***	0.013***	0.014***	0.015***
	(2.68)	(3.07)	(3.47)	(3.46)	(3.50)	(3.69)	(3.61)	(3.70)	(3.72)	(3.79)
Process, cost-reducing (θ)	0.002	0.003**	0.007**	0.008***	0.010***	0.011***	0.010**	0.009*	0.009**	0.008
	(1.46)	(2.01)	(2.36)	(2.68)	(3.26)	(2.92)	(2.31)	(1.89)	(2.09)	(1.61)
Product (θ)	0.008***	0.013***	0.013***	0.013***	0.011***	0.009**	0.010*	0.009*	0.010*	0.010*
	(6.32)	(5.94)	(4.54)	(3.94)	(2.74)	(1.98)	(1.93)	(1.77)	(1.80)	(1.72)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel E. Total Factor Productivity										
Process, foundational (θ) (θ)	0.003***	0.005***	0.008***	0.007**	0.007***	0.008***	0.008***	0.007***	0.005**	0.007***
	(2.67)	(2.74)	(3.05)	(2.53)	(3.05)	(3.60)	(3.55)	(2.74)	(1.99)	(2.76)
Process, cost-reducing (θ)	0.004**	0.006*	0.009***	0.007*	0.007*	0.005	0.008	0.009***	0.010***	0.012***
	(2.37)	(1.91)	(2.88)	(1.88)	(1.96)	(0.98)	(1.60)	(2.82)	(2.86)	(3.14)
Product (θ)	0.015***	0.017***	0.004	0.008	0.011*	0.010*	0.008	0.010*	0.014**	0.014**
	(4.84)	(5.88)	(0.48)	(1.30)	(1.93)	(1.82)	(1.39)	(1.74)	(2.40)	(2.55)
Obs.	98,859	88,409	79,714	72,084	65,481	59,556	54,412	49,688	45,421	41,640

The table presents relation between foundational, cost-reduction process and product innovation and firm-level outcomes. Patents are classified using claims and within-firm patent similarity. We present the coefficients (β_τ) from estimations of the following model

$$ln(Y_{i,t+\tau}) - ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_\tau^{Pats}\theta_{i,t}^{Pats} + \gamma_1 ln(Y_{i,t}) + \gamma_2 ln(Y_{i,t-1}) + \Lambda X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y are the firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different types of patents ($Pats$, foundational, cost-reducing, product) granted to firm i in year t scaled by total assets, $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in \{1,\dots,10\}$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. All variable definitions are provided in Table E.2 in the Appendix. The sample period is 1976 to 2020.

Table E.12
Growth from product innovations: The role of processes.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Product (θ, BS to Process)	0.017***	0.028***	0.026***	0.024**	0.024**	0.026**	0.024*	0.023	0.026	0.023
	(4.21)	(4.07)	(3.11)	(2.46)	(2.17)	(2.09)	(1.79)	(1.55)	(1.56)	(1.37)
Product (θ, BS to Product)	−0.001	−0.004	0.001	0.005	0.008	0.009	0.010	0.014	0.012	0.018
	(−0.33)	(−0.48)	(0.10)	(0.44)	(0.63)	(0.65)	(0.65)	(0.82)	(0.63)	(0.90)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel B. Sales										
Product (θ, BS to Process)	0.005	0.014***	0.017**	0.018**	0.020**	0.022*	0.024**	0.020*	0.022	0.022
	(1.36)	(2.69)	(2.29)	(2.28)	(2.14)	(1.94)	(2.16)	(1.72)	(1.60)	(1.53)
Product (θ, BS to Product)	0.008**	0.009*	0.008	0.010	0.007	0.009	0.005	0.012	0.009	0.012
	(2.08)	(1.65)	(1.08)	(1.07)	(0.62)	(0.65)	(0.35)	(0.85)	(0.53)	(0.68)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013

The table compares the growth effects of knowledge spillovers from process innovation to product innovations. Patents are categorized based on their titles, and market values of product patents are weighted according to their backward similarity to both process and product patents. For instance, if a product patent has a market value of $10 million, with a backward similarity score of 2000 to process patents and 3000 to product patents, 2/5 or $4 million would be attributed to process patents and $6 million to product patents. We present the coefficients (β_1, β_2) from the following regression model:

$$\ln(Y_{i,t+\tau}) - \ln(Y_{i,t}) = \alpha_0 + \beta_{1\tau}\theta_{i,t}^{BS\ to\ process} + \beta_{2\tau}\theta_{i,t}^{BS\ to\ product} + \gamma_1 ln(Y_t) + \gamma_2 ln(Y_{t-1}) + \Lambda X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y represents firm outcomes, and $\theta_{i,t}^{from\ process/from\ product}$ is the aggregated market value (ξ) of product patents granted to firm i in year t, with the value split between process and product patents, scaled by total assets. $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in \{1,\dots,10\}$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. All variable definitions are provided in Table E.2 in the Appendix. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. The sample period is 1976 to 2020.

Table E.13
Growth from product innovations: The role of foundational processes — citation.

Panel A. Process and product										
	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Product (θ, Process based)	0.016***	0.027***	0.028***	0.033***	0.038***	0.038***	0.040***	0.046***	0.045***	0.044***
	(4.54)	(4.85)	(3.66)	(4.23)	(4.28)	(4.00)	(4.26)	(4.76)	(4.74)	(4.31)
Product (θ, Product based)	0.000	−0.005	−0.007	−0.005	−0.007	−0.004	−0.006	−0.008	−0.007	−0.002
	(0.02)	(−1.12)	(−1.09)	(−0.70)	(−0.83)	(−0.45)	(−0.62)	(−0.75)	(−0.65)	(−0.20)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013

(*continued on next page*)

Table E.13 (*continued*).

Panel B. Sales										
Product (θ, Process based)	0.011***	0.017***	0.022***	0.029***	0.030***	0.033***	0.031***	0.036***	0.035***	0.033***
	(3.87)	(4.57)	(4.74)	(5.59)	(4.81)	(4.47)	(3.88)	(4.33)	(4.17)	(3.52)
Product (θ, Product based)	0.004	0.003	0.001	−0.002	−0.005	−0.004	−0.003	−0.003	−0.004	0.001
	(1.37)	(0.98)	(0.23)	(−0.49)	(−0.70)	(−0.48)	(−0.37)	(−0.36)	(−0.38)	(0.04)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013

Panel B. Foundational and cost-reducing

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Product (θ, Foundational based)	0.008***	0.010**	0.008	0.013**	0.015**	0.011	0.015*	0.020**	0.022**	0.021**
	(2.99)	(2.42)	(1.45)	(2.10)	(2.09)	(1.45)	(1.75)	(2.23)	(2.28)	(2.23)
Product (θ, Cost-reducing based)	0.011***	0.017***	0.021***	0.022***	0.025***	0.030***	0.027***	0.028***	0.026**	0.029***
	(3.95)	(3.46)	(3.17)	(3.14)	(3.08)	(3.61)	(3.13)	(3.07)	(2.55)	(2.92)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel B. Sales										
Product (θ, Foundational based)	0.006***	0.008**	0.007	0.009*	0.008	0.002	0.007	0.011	0.011	0.014*
	(3.07)	(2.39)	(1.57)	(1.81)	(1.35)	(0.31)	(0.93)	(1.52)	(1.40)	(1.84)
Product (θ, Cost-reducing based)	0.008***	0.014***	0.019***	0.023***	0.024***	0.034***	0.028***	0.029***	0.027***	0.025***
	(3.20)	(3.54)	(3.98)	(4.24)	(3.69)	(4.98)	(3.66)	(3.70)	(3.34)	(2.95)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013

The table compares the growth effects of products based on processes. Patents are classified using citations, and market values of product patents are weighted according to their backward similarity to different types of processes. For example, if a product patent has a market value of \$10 million, with a backward similarity score of 2000 to foundational patents and 3000 to cost-reducing patents, 2/5 or \$4 million would be attributed to foundational patents and \$6 million to cost-reducing patents. We present the coefficients (β_τ) from the following regression model:

$$\ln(Y_{i,t+\tau}) - \ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_\tau^{Pats} \theta_{i,t}^{Pats} + \gamma_1 ln(Y_{i,t}) + \gamma_2 ln(Y_{i,t-1}) + \Gamma X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y represents firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different types of product patents ($Pats$) granted to firm i in year t, with the market value split between foundational (*BS to Foundational*) and cost-reducing patents (*BS to Cost-reducing*), scaled by total assets. $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in \{1, \dots, 10\}$. α_{sic3} and δ_t are industry and year fixed effects. Panel A presents results for product value weighted based on similarity to process and product patents. Panel B presents results for product similarity to foundational and cost-reducing processes. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. All variable definitions are provided in Table E.2 in the Appendix. ***, **, * indicates significance level at 1%, 5% and 10%, respectively. All unbounded variables are winsorized at 1% level. The sample period is 1976 to 2020.

Table E.14
Growth from product innovations: The role of foundational processes — citation-based with added controls.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Product (θ, Foundational based)	0.006**	0.008*	0.007	0.012	0.014*	0.010	0.012	0.018*	0.020*	0.016
	(2.03)	(1.74)	(1.10)	(1.64)	(1.75)	(1.11)	(1.22)	(1.78)	(1.78)	(1.52)
Product (θ, Cost-reducing based)	0.011***	0.020***	0.025***	0.027***	0.032***	0.035***	0.031***	0.034***	0.031***	0.030***
	(3.80)	(3.61)	(3.70)	(3.37)	(3.42)	(3.61)	(3.17)	(3.35)	(3.06)	(2.97)
Product (θ, Breakthrough Prod. based)	0.005**	0.003	−0.000	0.001	−0.002	−0.004	0.000	−0.006	−0.008	−0.000
	(2.14)	(0.75)	(−0.03)	(0.15)	(−0.33)	(−0.61)	(0.00)	(−0.68)	(−0.73)	(−0.03)
Product (θ, Other Prod. based)	−0.004	−0.008**	−0.008	−0.007	−0.007	−0.004	−0.007	−0.005	−0.003	−0.003
	(−1.25)	(−2.11)	(−1.62)	(−1.12)	(−1.02)	(−0.43)	(−0.72)	(−0.49)	(−0.27)	(−0.21)
Process, foundational (θ)	0.007***	0.013***	0.016***	0.015***	0.015***	0.016**	0.016**	0.014**	0.013*	0.015*
	(3.03)	(3.25)	(3.06)	(2.87)	(2.61)	(2.57)	(2.36)	(2.00)	(1.70)	(1.90)
Cost-reducing	−0.009***	−0.013***	−0.021***	−0.024***	−0.030***	−0.025***	−0.019**	−0.019**	−0.014	−0.014
	(−3.88)	(−3.60)	(−4.52)	(−4.74)	(−3.91)	(−3.29)	(−2.40)	(−2.33)	(−1.56)	(−1.43)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel B. Sales										
Product (θ, Foundational based)	0.006**	0.007*	0.006	0.009	0.007	0.000	0.003	0.009	0.009	0.009
	(2.49)	(1.84)	(1.27)	(1.55)	(0.98)	(0.05)	(0.37)	(1.15)	(0.99)	(1.07)
Product (θ, Cost-reducing based)	0.008***	0.014***	0.021***	0.027***	0.028***	0.038***	0.029***	0.032***	0.031***	0.026***
	(2.60)	(3.24)	(4.37)	(5.04)	(4.58)	(5.49)	(3.38)	(3.61)	(4.13)	(2.84)
Product (θ, Breakthrough Prod. based)	0.001	−0.000	−0.004	−0.006	−0.004	−0.006	−0.002	−0.009	−0.008	−0.001
	(0.39)	(−0.08)	(−0.96)	(−1.00)	(−0.70)	(−1.11)	(−0.32)	(−1.20)	(−0.95)	(−0.21)
Product (θ, Other Prod. based)	0.002	0.003	0.002	−0.001	−0.004	−0.003	−0.003	0.001	−0.001	0.001
	(0.97)	(0.79)	(0.39)	(−0.17)	(−0.65)	(−0.31)	(−0.36)	(0.06)	(−0.07)	(0.06)
Process, foundational (θ)	0.004**	0.009***	0.012***	0.012***	0.014***	0.016***	0.015***	0.013***	0.012**	0.014***
	(2.52)	(3.21)	(3.47)	(3.17)	(3.46)	(3.62)	(3.34)	(2.76)	(2.44)	(2.69)

(*continued on next page*)

Table E.14 (*continued*).

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Cost-reducing	−0.007***	−0.012***	−0.017***	−0.018***	−0.018***	−0.016**	−0.010	−0.011	−0.014	−0.015
	(−4.04)	(−4.49)	(−4.18)	(−3.67)	(−3.20)	(−2.47)	(−1.34)	(−1.44)	(−1.52)	(−1.48)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013

The table compares the growth effect of knowledge spillover from process and product innovation with additional control variables. Patents are classified using citations, and we focus on the market values of product patents, segmented by their backward similarity to other process and product patents. For example, if a product patent has a market value of 10 million and it has a total backward similarity of 2000 with process patents and 3000 with product patents, then 4 million would be attributed to process and 6 million to product. We present the coefficients (β_τ) from the following regression model:

$$\ln(Y_{i,t+\tau}) - \ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_\tau^{Pats} \theta_{i,t}^{Pats} + \gamma_1 ln(Y_{i,t}) + \gamma_2 ln(Y_{i,t-1}) + \Gamma X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y represents firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different types of product patents ($Pats$) granted to firm i in year t, with the market value split between foundational (*BS to Foundational*) and cost-reducing patents (*BS to Cost-reducing*), scaled by total assets. $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in \{1, \ldots, 10\}$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Panel A presents results for firm gross profits (sales minus cost of good sold), Panel B for firm sales. Standard errors are clustered at the firm level. All variable definitions are provided in Table E.2 in the Appendix. ***, **, * indicates significance level at 1%, 5% and 10%, respectively. The sample period is 1976 to 2020.

Table E.15
Growth from product innovations: The role of foundational processes — Cross Q.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Product (θ, BS to Foundational)	0.013***	0.019***	0.017**	0.020***	0.021***	0.026***	0.027***	0.029***	0.030***	0.032***
	(4.81)	(3.95)	(2.50)	(3.04)	(2.92)	(3.24)	(3.02)	(2.98)	(2.89)	(3.07)
Product (θ, BS to Cost-reducing)	0.001	0.000	0.001	0.001	0.000	−0.002	−0.002	−0.003	−0.003	−0.003
	(0.59)	(0.13)	(0.22)	(0.16)	(0.03)	(−0.48)	(−0.54)	(−0.70)	(−0.69)	(−0.77)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013
Panel B. Sales										
Product (θ, BS to Foundational)	0.012***	0.017***	0.018***	0.020***	0.018***	0.020***	0.022***	0.025***	0.024***	0.025***
	(6.75)	(5.55)	(4.03)	(3.89)	(2.99)	(3.00)	(3.23)	(3.44)	(2.77)	(2.94)
Product (θ, BS to Cost-reducing)	−0.000	−0.001	0.000	−0.000	0.001	0.000	0.000	−0.000	−0.000	0.000
	(−0.30)	(−0.36)	(0.08)	(−0.09)	(0.25)	(0.14)	(0.05)	(−0.14)	(−0.04)	(0.02)
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013

The table compares the growth effect of knowledge spillover from process and product innovation, for alternative definition of q. Patents are categorized based on their titles, and market values of product patents are weighted according to their backward similarity to both foundational and cost-reducing process patents. For example, if a product patent has a market value of \$10 million, with a backward similarity score of 2000 to foundational patents and 3000 to cost-reducing patents, 2/5 or \$4 million would be attributed to foundational patents and \$6 million to cost-reducing patents. We present the coefficients (β_τ) from the following regression model:

$$\ln(Y_{i,t+\tau}) - \ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_\tau^{Pats} \theta_{i,t}^{Pats} + \gamma_1 ln(Y_{i,t}) + \gamma_2 ln(Y_{i,t-1}) + \Gamma X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y represents firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different types of product patents ($Pats$) granted to firm i in year t, with the market value split between foundational (*BS to Foundational*) and cost-reducing patents (*BS to Cost-reducing*), scaled by total assets. $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in \{1, \ldots, 10\}$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. All variable definitions are provided in Table E.2 in the Appendix. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. The sample period is 1976 to 2020.

Table F.1
Growth from product innovations: Foundational processes and breakthrough products.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Profits										
Product (θ, BS to Foundational)	0.016***	0.025***	0.015*	0.022***	0.024**	0.027***	0.028**	0.027**	0.029**	0.018
	(3.68)	(3.85)	(1.92)	(2.63)	(2.46)	(2.64)	(2.39)	(2.27)	(2.18)	(1.23)
Product (θ, BS to Cost-reducing)	−0.015***	−0.016**	−0.012	−0.020**	−0.020**	−0.016	−0.017*	−0.017*	−0.019*	−0.016
	(−3.50)	(−2.34)	(−1.27)	(−2.53)	(−2.34)	(−1.57)	(−1.74)	(−1.66)	(−1.69)	(−1.28)
Product (θ, BS to Breakthrough product)	−0.008*	−0.017***	−0.014*	−0.015	−0.017	−0.014	−0.013	−0.011	−0.010	0.002
	(−1.79)	(−2.65)	(−1.66)	(−1.58)	(−1.52)	(−1.05)	(−0.87)	(−0.63)	(−0.54)	(0.11)
Product (θ, BS to Other product)	0.013***	0.011	0.002	0.011	0.011	0.004	0.004	0.003	0.004	−0.001
	(3.05)	(1.43)	(0.17)	(1.22)	(1.12)	(0.35)	(0.43)	(0.27)	(0.37)	(−0.06)
Process, foundational (θ)	0.007***	0.008**	0.018***	0.019***	0.017***	0.018***	0.020***	0.022***	0.025***	0.029***
	(3.18)	(1.98)	(3.79)	(3.47)	(2.88)	(2.65)	(2.60)	(2.92)	(2.62)	(3.27)
Process, cost-reducing (θ)	0.002	0.011***	0.019***	0.012	0.015**	0.015*	0.012	0.013	0.009	0.013
	(1.04)	(2.93)	(3.05)	(1.59)	(2.09)	(1.89)	(1.35)	(1.38)	(0.90)	(1.42)
Diff ($\hat{\beta}^{BS\ to\ Foundational} - \hat{\beta}^{BS\ to\ Breakthrough}$)	0.024***	0.042***	0.029*	0.038**	0.04**	0.041*	0.041*	0.037	0.039	0.016
Wald	8.308	12.036	3.775	4.951	4.422	3.46	2.712	1.948	1.708	0.214
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013

(*continued on next page*)

Table F.1 (*continued*).

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel B. Sales										
Product (θ, BS to Foundational)	0.011***	0.010*	0.011*	0.016**	0.016**	0.014	0.023**	0.023**	0.023*	0.015
	(3.32)	(1.93)	(1.82)	(2.46)	(2.16)	(1.36)	(2.48)	(2.42)	(1.94)	(1.10)
Product (θ, BS to Cost-reducing)	−0.012***	−0.019***	−0.014**	−0.017**	−0.021***	−0.023***	−0.021**	−0.016*	−0.017*	−0.008
	(−3.89)	(−3.52)	(−2.27)	(−2.47)	(−2.92)	(−2.70)	(−2.32)	(−1.69)	(−1.68)	(−0.71)
Product (θ, BS to Breakthrough product)	−0.002	−0.004	−0.005	−0.006	−0.010	−0.005	−0.010	−0.006	−0.007	0.002
	(−0.63)	(−0.77)	(−0.75)	(−0.84)	(−1.07)	(−0.37)	(−0.81)	(−0.46)	(−0.42)	(0.13)
Product (θ, BS to Other product)	0.009***	0.012**	0.006	0.007	0.011	0.011	0.009	0.005	0.005	−0.002
	(2.80)	(2.01)	(0.80)	(0.88)	(1.42)	(1.22)	(1.05)	(0.51)	(0.53)	(−0.18)
Process, foundational (θ)	0.008***	0.016***	0.017***	0.020***	0.022***	0.029***	0.026***	0.023***	0.025***	0.022**
	(3.60)	(3.97)	(3.88)	(4.09)	(4.01)	(4.64)	(3.32)	(3.01)	(3.21)	(2.47)
Process, cost-reducing (θ)	−0.001	0.011**	0.013**	0.009*	0.010	0.006	0.003	0.004	0.004	0.009
	(−0.24)	(2.47)	(2.11)	(1.88)	(1.42)	(0.83)	(0.36)	(0.52)	(0.50)	(1.29)
Diff ($\hat{\beta}^{BS\ to\ Foundational} - \hat{\beta}^{BS\ to\ Breakthrough}$)	0.013**	0.013	0.015	0.022*	0.026*	0.019	0.032*	0.029	0.03	0.012
Wald	4.912	2.189	1.948	2.936	2.76	0.726	2.715	1.858	1.143	0.15
Obs.	154,143	138,424	124,709	112,685	102,065	92,644	84,273	76,798	70,063	64,013

The table compares the growth effects of products based on foundational processes to those based on breakthrough products. Patents are categorized based on their titles, and market values of product patents are weighted according to their backward similarity to foundational and cost-reducing process patents and breakthrough and other product patents. For example, if a product patent has a market value of \$10 million, with a backward similarity score of 2000 to foundational process patents, 3000 to cost-reducing process patents, 4000 to breakthrough product patents and 1000 to other product patents: 2/10 or \$2 million would be attributed to foundational, \$3 million to cost-reducing, \$4 million to breakthrough product, and \$1 million to other product patents. We present the coefficients (β_τ) from estimations of the following regression model:

$$\ln(Y_{i,t+\tau}) - \ln(Y_{i,t}) = \alpha_0 + \sum_{Pats} \beta_\tau^{Pats}\theta_{i,t}^{Pats} + \gamma_1 ln(Y_{i,t}) + \gamma_2 ln(Y_{i,t-1}) + \Gamma X'_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y represents firm outcomes, $\theta_{i,t}^{Pats}$ is the aggregated market value (ξ) of different types of product patents ($Pats$) granted to firm i in year t, with the market value split between foundational (*BS to Foundational*), cost-reducing (*BS to Cost-reducing*), breakthrough (*BS to Breakthrough product*), and other product (*BS to Other product*) patents scaled by total assets. $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in \{1,\ldots,10\}$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. All variable definitions are provided in Table E2 in the Appendix. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. The sample period is 1976 to 2020.

Table F.2
Foundational process-based and breakthrough product-based product patents.

Panel A. All Product Patents

	Claims	Backward	Originality	Forward	Generality	ln(ξ)	NPL	Assignments	Renewal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Foundational	0.088***	0.861***	0.055***	0.289***	0.020***	0.195***	1.016***	0.001	0.012***
	(16.18)	(47.21)	(24.98)	(10.25)	(2.81)	(12.43)	(24.43)	(0.10)	(8.44)
Breakthrough product	0.088***	0.847***	0.065***	0.215***	0.022***	0.125***	0.795***	−0.001	0.014***
	(16.46)	(31.56)	(29.86)	(13.30)	(13.81)	(11.70)	(22.36)	(−0.21)	(10.24)
IPC4 × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Diff. ($\hat{\beta}_1 - \hat{\beta}_2$)	0	0.014	−0.01***	0.074***	−0.002	0.07***	0.221***	0.002	−0.002
Wald	(0.01)	(0.75)	(60.92)	(14.88)	(0.11)	(27.39)	(26.39)	(0.13)	(1.6)
Obs.	1,294,575	1,358,482	1,346,312	1,357,453	1,058,761	1,363,490	1,052,982	1,249,618	1,363,490
R^2			0.25		0.20	0.24			0.40

Panel B. Foundational and Breakthrough Citing Patents Only

	Claims	Scope	Backward	Originality	Forward	Generality	ln(ξ)	NPL	Assignments	Renewal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foundational	0.069***	0.017*	0.666***	0.024***	0.218***	0.014**	0.137***	0.936***	0.002	0.008***
	(23.03)	(1.77)	(34.14)	(22.10)	(8.53)	(2.20)	(9.72)	(18.02)	(0.23)	(5.50)
IPC4 × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	592,457	611,776	611,776	616,940	611,004	496,726	617,817	518,851	575,112	617,817
R^2				0.26		0.22	0.25			0.42

This table presents patent metrics comparing product patents that cite foundational patents with all other patents. We estimate regressions of the form:

$$Product\ Patent\ Quality_p = \beta_0 + \beta_1 I\{Foundational\}_p + \beta_2 I\{BT\,Prod\}_p + \delta_{ipc\times t(p)} + \epsilon_p,$$

Foundational is an indicator variable equal to one for all product patents that cite foundational process patents (own or other firms) and zero otherwise, *Breakthrough product* is an indicator variable equal to one for all product patents that cite breakthrough product patents (own or other firms) and zero otherwise, and $ipc \times t(p)$ are patent class interacted with year fixed effects. Panel A compares product patents that cite foundational process and breakthrough product patents to all other patents. Panel B focuses on the subset of patents that cite either foundational processes or breakthrough products. All patent metrics are described in detail in D. *Claims* is the number of claims by the patent; *Scope* is the unique number of IPC 4-digit classifications of a patent; *Backward* is backward citations measured as the number of U.S. patents the patent cites; *Originality* is the HHI index of IPC4 classes of the backward citations; *Forward* is forward citations measured as number of U.S. patents citing the patent; *Generality* is the HHI index of IPC4 classes of the forward citations; and ξ is the market value of patent as in Kogan et al. (2017). *NPL* is the number of non-patent literature citations. *Re-assignments* is the number of USPTO reported re-assignments of the patent. *Renewal* is an indicator variable equal to 1 when a patent is renewed after 12 years and zero otherwise. Columns 1, 2, 3, 5, 8 and 9 are estimated using a Poisson specification, while columns 4, 6, 7 and 10 use OLS. T-statistics, adjusted for clustered standard errors at the IPC4 level, are reported in parentheses. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. All variable definitions are provided in Table E.2 in the Appendix. The sample period is 1930 to 2020, conditional of variable information availability.

Table F.3
Innovation and product differentiation — Controlling for breakthrough product innovation.

Panel A. Foundational processes and product differentiation

	IPC 3_{t+1}	IPC 4_{t+1}	IPC 6_{t+1}	IPC 7_{t+1}
	(1)	(2)	(3)	(4)
Ln(Foundational Stock)$_t$	0.225***	0.227***	0.266***	0.343***
	(8.00)	(8.65)	(9.32)	(8.56)
Ln(Cost-reducing Stock)$_t$	−0.286***	−0.297***	−0.281***	−0.258***
	(−16.79)	(−17.97)	(−14.44)	(−11.30)
Ln(Breakthrough product Stock)$_t$	0.139***	0.152***	0.162***	0.100*
	(5.74)	(5.95)	(4.87)	(1.89)
Ln(Other product Stock)$_t$	−0.089***	−0.019	0.025	0.065**
	(−4.98)	(−1.12)	(1.30)	(2.54)
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Diff ($\hat{\beta}^{Foundational} - \hat{\beta}^{Breakthrough}$)	0.085*	0.075	0.104*	0.242***
Wald	(3.12)	(2.46)	(3.44)	(8.14)
Obs.	75,261	78,712	81,865	82,932

Panel B. Foundational process contribution to new IPC classes

	New IPC 3	New IPC 4	New IPC 6	New IPC 7
	(1)	(2)	(3)	(4)
BS to Foundational	0.007***	0.017***	0.039***	0.043***
	(2.84)	(2.94)	(3.27)	(3.73)
BS to Cost-reducing	−0.002	−0.006	−0.014	−0.016
	(−0.88)	(−1.15)	(−1.37)	(−1.46)
BS to Breakthrough	−0.010***	−0.023***	−0.051***	−0.067***
	(−3.01)	(−2.98)	(−3.24)	(−3.88)
BS to Other products	−0.004**	−0.011***	−0.025***	−0.035***
	(−2.54)	(−2.97)	(−3.48)	(−4.37)
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Diff. ($\hat{\beta}^{Foundational} - \hat{\beta}^{Breakthrough}$)	0.017***	0.041***	0.090***	0.110***
Wald	(8.83)	(8.99)	(10.93)	(15.21)
Obs.	1,003,543	1,003,543	1,003,543	1,003,543
Adj. R^2	0.18	0.18	0.19	0.18

This table present results of the analysis of the role of foundational process and breakthrough product innovations in expanding the firm's product space. Panel A presents results of regressions of the number of new technology classes measured by 3-digit IPC main classes, 4-, 6-, and 7-digit IPC subclasses at $t+1$ and the stock of different types of patents at time t. The explanatory variables are the natural log of the stock of foundational process, cost-reducing, breakthrough product, and other product patents up to time t. The sample includes firms that have at least one patent in their portfolio, where a patent has a maximum life span of 20 years. Panel B presents analysis at the product patent level. The dependent variable is an indicator equal to one if a patent belongs to a technology class (defined by IPC3, 4, 6 and 7) new to firm i, and zero otherwise. All BS variables measure the backward similarity of the focal patent p to prior foundational, cost-reducing, breakthrough, and other patents; they are standardized to unit standard deviation. All regressions include controls for R&D spending and total assets. Standard errors are clustered at the firm level. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. All variable definitions are provided in Table A3 in the Appendix. The sample period is 1976 to 2020.

Table F.4
FDA drug value and foundational process patents — Controlling for breakthrough product innovation.

	ln(Abnormal Returns)	Priority	Ln(Patient Spending)
	(1)	(2)	(3)
Foundational (Fraction on orange book)	0.586***	0.491***	2.232***
	(2.70)	(3.88)	(11.97)
Cost-reducing (Fraction on orange book)	−0.058	0.160***	−0.458
	(−0.45)	(6.05)	(−0.66)
Breakthrough product (Fraction on orange book)	0.395	0.093	−0.673
	(1.32)	(0.82)	(−0.85)
Other product (Fraction on orange book)	−0.103	0.145**	0.142
	(−1.36)	(2.11)	(0.38)
Firm × Year FE	✓	✓	✓
Diff. ($\hat{\beta}^{Foundational} - \hat{\beta}^{Breakthrough}$)	0.190	0.397*	2.904***
Wald	(0.32)	(3.51)	(18.27)

(*continued on next page*)

Table F.4 (*continued*).

	ln(Abnormal Returns)	Priority	Ln(Patient Spending)
	(1)	(2)	(3)
Obs.	632	632	261
Adj. R^2	0.94	0.68	0.78

This table presents the results on the relation between drug product quality and foundational process and breakthrough product patents. The dataset consists of unique drug products approved and listed in the Orange Book. We examine three key variables: *Abnormal returns* calculated using the methodology of Kogan et al. (2017), which captures the 3-day market reaction to drug approvals; *Priority* an indicator variable equal to one if the drug is under Priority Review by the FDA and zero otherwise; and *Patient Spending* is drug spending in health insurance programs (Part B, Part D, and Medicaid) from 2017 to 2021. Priority Review is reserved for drugs that offer significant advancements in treatment, prevention, or diagnosis of diseases, lack alternative treatments, provide distinct advantages over existing treatments, or address public health emergencies or national health issues. The explanatory variables are the fraction of foundational, cost-reducing, breakthrough, and other product patents listed in the Orange Book. Standard errors are clustered at the firm level. ***, **, * indicate significance level at 1%, 5% and 10%, respectively. All variable definitions are provided in Table E.2 in the Appendix. The sample period is 1982 to 2020.

Appendix G. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfineco.2026.104276.

Data availability

Foundational Processes and Growth (Reference data) (Mendeley Data)

References

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N., Kerr, W., 2018. Innovation, reallocation, and growth. Am. Econ. Rev. 108 (11), 3450–3491.

Aghion, P., Howitt, P., 1992. A model of growth through creative destruction. Econometrica 60, 323–351.

Akcigit, U., Hanley, D., Serrano-Velarde, N., 2020. Back to basics: Basic research spillovers, innovation policy, and growth. Rev. Econ. Stud. 88 (1), 1–43.

Akcigit, U., Kerr, W.R., 2018. Growth through heterogeneous innovations. J. Political Econ. 126 (4), 1374–1443.

Argente, D., Baslandze, S., Hanley, D., Moreira, S., 2020. Patents to Products: Product Innovation and Firm Dynamics. FRB Atlanta Working Paper 2020–4.

Bar-Isaac, H., Caruana, G., Cuñat, V., 2023. Targeted product design. Am. Econ. J.: Microeconomics 15 (2), 157–186.

Baslandze, S., Greenwood, J., Marto, R., Moreira, S., 2023. The expansion of varieties in the new age of advertising. Rev. Econ. Dyn. 50, 171–210.

Bena, J., Ortiz-Molina, H., Simintzi, E., 2022. Shielding firm value: Employment protection and process innovation. J. Financ. Econ. 146, 637–644.

Bena, J., Simintzi, E., 2025. Machines could not compete with Chinese labor: Evidence from U.S. firms' innovation. Rev. Financ. 29 (6), 1619–1661.

Berlingieri, G., Ridder, M.D., Lashkari, D., Rigo, D., 2025. Creative Destruction Through Innovation Bursts. Discussion Papers DP2095, Centre for Economic Performance, LSE.

Bloom, N., Schankerman, M., Van Reenen, J., 2013. Identifying technology spillovers and product market rivalry. Econometrica 81 (4), 1347–1393.

Cavenaile, L., Gaetani, R., Roldan-Blanco, P., Schmitz, T., 2024. Industry Life Cycles in General Equilibrium. Working Paper.

Cohen, W.M., Klepper, S., 1996. Firm size and the nature of innovation within industries: The case of process and product R&D. Rev. Econ. Stat. 78 (2), 232–243.

Crozet, M., Head, K., Mayer, T., 2011. Quality sorting and trade: Firm-level evidence for french wine. Rev. Econ. Stud. 79 (2), 609–644.

Dhingra, S., 2013. Trading away wide brands for cheap brands. Am. Econ. Rev. 103 (6), 2554–2584.

Di Comite, F., Thisse, J.-F., Vandenbussche, H., 2014. Verti-zontal differentiation in export markets. J. Int. Econ. 93 (1), 50–66.

Durvasula, M., Hemphill, C.S., Ouellette, L.L., Sampat, B., Williams, H.L., 2023. The NBER Orange Book Dataset: A user's guide. Res. Policy 52 (7), 1047–1091.

Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. J. Financ. 47 (2), 427–465.

Field, A.J., 2003. The most technologically progressive decade of the century. Am. Econ. Rev. 93 (4), 1399–1413.

Fritsch, M., Meschede, M., 2001. Product innovation, process innovation, and size. Rev. Ind. Organ. 19 (3), 335–350.

Goldberg, P.K., 1995. Product differentiation and oligopoly in international markets: The case of the U.S. automobile industry. Rev. Econ. Stud. 62 (1), 43–61.

Gompers, P., Lerner, J., Scharfstein, D., 2005. Entrepreneurial spawning: Public corporations and the genesis of new ventures, 1986 to 1999. J. Financ. 60 (2), 577–614.

Grossman, G.M., Helpman, E., 1991. Quality ladders in the theory of growth. Rev. Econ. Stud. 58 (1), 43–61.

Hall, B.H., Jaffe, A.B., Trajtenberg, M., 2001. The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools. Tech. Rep., NBER.

Hall, B.H., Trajtenberg, M., 2004. Uncovering GPTs with Patent Data. Tech. Rep., NBER.

İmrohoroğlu, A., Tüzel, Ş., 2014. Firm-level productivity, risk, and return. Manag. Sci. 60 (8), 2073–2090.

Jordà, Ò., 2005. Estimation and inference of impulse responses by local projections. Am. Econ. Rev. 95 (1), 161–182.

Karabarbounis, L., Neiman, B., 2013. The global decline of the labor share. Q. J. Econ. 129 (1), 61–103.

Kelly, B., Papanikolaou, D., Seru, A., Taddy, M., 2021. Measuring technological innovation over the long run. Am. Econ. Rev.: Insights 3 (3), 303–320.

Klepper, S., 1996. Entry, exit, growth, and innovation over the product life cycle. Am. Econ. Rev. 86 (3), 562–583.

Kogan, L., Papanikolaou, D., Schmidt, L.D.W., Song, J., 2020. Technological Innovation and Labor Income Risk. Working Paper 26964, National Bureau of Economic Research.

Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017. Technological innovation, resource allocation, and growth. Q. J. Econ. 132 (2), 665–712.

Krieger, J., Li, D., Papanikolaou, D., 2021. Missing novelty in drug development. Rev. Financ. Stud. 35 (2), 636–679.

Lanjouw, J.O., Pakes, A., Putnam, J., 1998. How to count patents and value intellectual property: The uses of patent renewal and application data. J. Ind. Econ. 46 (4), 405–432.

Layne-Farrar, A., Lerner, J., 2011. To join or not to join: Examining patent pool participation and rent sharing rules. Int. J. Ind. Organ. 29 (2), 294–303.

Lerner, J., 1994. The importance of patent scope: An empirical analysis. Rand J. Econ. 25 (2), 319–333.

Marx, M.M., Scharfmann, E., 2024. Does Patenting Promote the Progress of Science? Working Paper.

Olley, G.S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64 (6), 1263–1297.

Plagborg-Møller, M., Wolf, C.K., 2021. Local projections and VARS estimate the same impulse responses. Econometrica 89 (2), 955–980.

Romer, P.M., 1990. Endogenous technological change. J. Political Econ. 98 (5, Part 2), 71–102.

Salop, S.C., 1979. Monopolistic competition with outside goods. Bell J. Econ. 10 (1), 141–156.

Sanh, V., Debut, L., Chaumond, J., Wolf, T., 2019. DistilBERT, A Distilled Version of BERT: Smaller, Faster, Cheaper and Lighter. Tech. Rep.

Sexton, Z.A., Perl, J.R., Saul, H.R., Trotsyuk, A.A., Pietzsch, J.B., Ruggles, S.W., Nikolov, M.C., Schulman, K.A., Makower, J., 2023. Time from authorization by the US food and drug administration to medicare coverage for novel technologies. JAMA Health Forum 4 (8), e232–260.

Stock, J.H., Watson, M.W., 2018. Identification and estimation of dynamic causal effects in macroeconomics using external instruments. Econ. J. 128 (610), 917–948.

Trajtenberg, M., Henderson, R., Jaffe, A., 1997. University versus corporate patents: A window on the basicness of invention. Econ. Innov. New Technol. 5 (1), 19–50.

Utterback, J.M., Abernathy, W.J., 1975. A dynamic model of process and product innovation. Omega 3 (6), 639–656.