Heterogeneous Innovations and Growth under Imperfect Technology Spillovers*

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April 21, 2025

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Abstract

We study how frictions in learning others' technology, termed "imperfect technology spillovers," impact firm innovation strategies and the aggregate economy through changes in innovation composition. We develop an endogenous growth model that generates strategic innovation decisions, where multi-product firms improve their products via own-innovation and enter new product markets through creative destruction under learning frictions. In our model, firms with technological advantages intensify own-innovation as learning frictions enable them to protect their markets from competitors, thereby reducing creative destruction of rivals. This pattern gets more pronounced when competitive pressure increases exogenously. Importantly, the shift in innovation composition reduces aggregate growth, as creative destruction contributes more to growth. Using U.S. administrative firm-level data, we provide regression results supporting the model predictions.

Keywords: innovation, technology spillover, endogenous growth, competition

JEL Code: L11, L25, O31, O33, O41

*Previously circulated under the title "Competition, Firm Innovation, and Growth under Imperfect Technology Spillovers." We thank David Argente, Murat Alp Celik, Michael Ewens, John Haltiwanger, Munseob Lee, Nuno Limao, Michael Peters, Marta Prato, Benjamin Pugsley, Felipe Saffie, John Shea, Stephen Redding, Bernardo Ribeiro, Maarten De Ridder, Richard Rogerson, Jane Olmstead-Rumsey, Aysegul Sahin, Karthik Sastry, Yongseok Shin, Gianluca Violante, and seminar participants at the University of Maryland, Princeton University, Clemson University, Rutgers University, Drexel University, FRB New York, and the U.S. Census Bureau, as well as participants at several conferences including the ASSA Meeting, AIEA-NBER Conference, BSE Summer Forum, CEPR Macroeconomics and Growth Annual Symposium, Philly Fed Junior Macro workshop, Midwest Macro Meetings, SED, and the STEG-CEPR Annual Conference for their helpful comments. Karam Jo gratefully acknowledges financial support from the Ewing Marion Kauffman Foundation. Any opinions and conclusions herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau, the Ewing Marion Kauffman Foundation, or the Korea Development Institute. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2095. (CBDRB-FY24-0073, CBDRB-FY24-0311)

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1 Introduction

Firm innovation unfolds in two stages: firms first learn about existing technologies (e.g., Lucas and Moll, 2014), and then build upon them. Recent research highlights that innovations vary in type: some enhance a firm's existing products by improving its own technologies, while others leverage technologies developed by other firms to expand into new product markets beyond the firm's current scope. These heterogeneous innovations also differ in their impact on firm performance and aggregate economic outcomes (Akcigit and Kerr, 2018; Garcia-Macia et al., 2019; Peters, 2020; Argente et al., 2024). Importantly, scope-expanding innovations require firms to learn technologies new to them, which takes time. This additional dimension of heterogeneity, the time-consuming nature of a certain innovation type, can have distinct and important macroeconomic implications by generating strategic behavior of incumbent firms.

In this paper, we investigate two key questions: How do firms use different types of innovation when learning others' technology takes time? And how does this process offer new insights into the aggregate implications of firm innovation, particularly through the relationship between innovation composition and growth in the context of increasing competition? Theoretically, we develop an endogenous growth model with two types of innovation and learning frictions. This model offers a micro-foundation for understanding firms' varying innovation incentives and their interactions, as well as how both the level and composition of the two innovation types change when competition intensifies. Empirically, we link U.S. administrative firm-level data to the patent database and document new facts about innovation heterogeneity and compositional changes in response to an exogenous increase in competition. Finally, we calibrate the model and derive the aggregate implications of competition across different economies.

In the model, multi-product firms grow through two types of innovation—"own-innovation" and "creative destruction"—subject to imperfect technology spillovers. Own-innovation improves existing product quality, while creative destruction enables firms to enter new markets by displacing incumbents.[1] In addition, the two innovations differ along two key dimensions: innovation step size and learning. Individual creative destruction contributes more to product quality improvement, thus

[1]An illustrative real-world example of creative destruction is Apple's entry into the cell phone industry with the introduction of the iPhone back in 2007 when its major business was computer manufacturing. An example of own-innovation is Apple's improvement and production of iPhone 16 from iPhone 15.

to firm and aggregate growth than own-innovation.[2,3] Creative destruction also requires learning others' technology, which takes time due to imperfect technology spillovers.

The literature widely acknowledges the time-consuming nature of learning others' technology (e.g., Lucas and Moll, 2014). Accordingly, we conceptualize innovation in two stages: learning existing technology and building on it. Own-innovation bypasses the learning phase, as the firm already knows the technology, while creative destruction requires it. Thus, entering a market through creative destruction involves learning and improving incumbents' technology, which demands substantial time and resources.[4] Our model incorporates lagged learning as a form of imperfect technology spillovers, requiring potential rivals to spend one period learning the frontier technology of incumbents. In other words, creative destruction builds on one-period lagged technology.

Imperfect technology spillovers, a novel feature introduced in this class of models, generate unique mechanisms that reshape firm innovation decisions. Spillover frictions create a technology gap between incumbents' frontier technology and the one-period lagged technology available to rivals. This gap enables incumbents to strategically use own-innovation to defend their markets by improving product quality further and securing a technological advantage—a "*market-protection*" effect.[5] Then, the technological advantages of incumbents act as "*technological barriers*" that deter rivals' entry and stifle creative destruction—a "*technological barrier*" effect. This interaction distinguishes our model from others in the literature on firm innovation and specialization. Competition induces a shift in the composition of firm innovation, driven by the strategic choices of firms and their endogenous interactions. Consequently, the aggregate effect of competition on innovation depends on the relative shifts between the two types of innovation.

The strength of our model lies in capturing the strategic role of own-innovation and its endoge-

[2]As highlighted by Bernard et al. (2010) and Akcigit and Kerr (2018), creative destruction plays a pivotal role in driving growth. It is tightly connected to radical innovation that significantly improves existing technologies.

[3]Garcia-Macia et al. (2019) show that the aggregate-level own-innovation contributes more to the aggregate growth than creative destruction, because the latter succeeds less frequently. Our model aligns with these findings at the aggregate level while also distinguishing the contributions of the two types of innovation at the individual level.

[4]Creative destruction involves recruiting new employees to handle new technology, reallocating resources to new projects, training workers, reverse engineering, and preparing production facilities for new products. For example, Apple took three years to enter the cell phone industry, even after leveraging its previously accumulated knowledge from iPod development and production.

[5]Our market-protection effect differs from the escape-competition effect as it focuses on the innovation incentives of market leaders and competitive pressure from the entry margin. This perspective explains why frontier firms like Google and NVIDIA keep innovating intensely, despite their technological lead over competitors. The standard step-by-step innovation model implies these firms should stop innovating due to the assumption of immediate catch-up by rivals.

nous feedback effects on rivals' creative destruction and market entry. By introducing imperfect technology spillovers into a multi-product firm framework, the model achieves this major theoretical advance.[6] In existing models of multi-product firms growing through product scope expansion, firms cannot protect their markets because rivals can instantly learn and copy frontier technology without any friction (Klette and Kortum, 2004; Akcigit and Kerr, 2018; Peters, 2020).[7] Step-by-step innovation models generate an escape-competition motive, but assume single-product firms that can only do own-innovation (Aghion et al., 2001, 2005; Akcigit et al., 2018).[8] This lacks the feedback effects of incumbents' innovation choices on the innovation of rivals attempting to enter a product market and does not capture the firm-level innovation composition observed in the data.

To this end, our model underscores the important role of innovation composition in understanding the aggregate implications of competition. Unlike earlier frameworks, own-innovation not only improves incumbents' product quality but also suppresses rivals' creative destruction and entry, which contributes to firm and economic growth substantially. Ignoring such shifts in innovation composition obscures the true impact of competition on firms and the aggregate economy.

Next, to validate our model, we construct a unique dataset combining U.S. administrative firm-level data with USPTO patent data from 1976 to 2016. This provides comprehensive information for the entire population of U.S. patenting firms. We use the rise in foreign firm entry into U.S. markets after China's WTO accession in 2001 as an exogenous competition shock, and use the self-citation ratio of patents as a measure of the likelihood that patents are used for own-innovation. We additionally use product-level data to complement our analysis.

Using the pre-shock period (prior to 2000), we document differences between own-innovation and creative destruction in learning time, quality improvement, and economic outcomes. We find that patents closer to creative destruction have a longer duration between their application year and that of backward-cited patents, higher scientific and market values, and greater contributions to firm growth. Furthermore, we find regression results consistent with the model predictions on the "*market-protection*" and "*technological barrier*" effects: heightened competition increases own-innovation among firms with technological advantages but decreases creative destruction

[6] In this sense, our framework brings together quality-ladder and step-by-step innovations.

[7] Akcigit and Kerr (2018), for example, is a special case of our model where firms have no technological advantages. In their setup, firms reduce own-innovation when competition increases.

[8] Cavenaile et al. (2019) is the sole exception, where their extended model adds Klette and Kortum (2004) superstructure to a step-by-step innovation model with oligopolistic competition.

across all firms; firm entry is lower in industries with higher technological barriers, measured by the TFPR gap as in Aghion et al. (2005).

Lastly, to understand the aggregate implications, we calibrate our model to the U.S. manufacturing sector and conduct two counterfactual exercises by increasing competitive pressure by outside firms exogenously: i) in the U.S. economy, and ii) in economies where creative destruction costs exceed those in the U.S.[9,10] Both exercises yield qualitatively similar results at the firm level: firms increase (decrease) own-innovation for products with a (no) technological advantage, while creative destruction drops across all firms. However, the aggregate implications differ.

Overall innovation—the aggregate-level R&D to sales ratio—declines in the U.S., where firms actively engage in creative destruction with lower associated costs. In contrast, economies with higher creative destruction costs see the opposite result, as the initially low levels of creative destruction leave little room for further decline under increased competition. Despite this, the aggregate growth by domestic firms falls in both economies, even though the latter has seen an increase in overall innovation. This occurs because heightened competition endogenously elevates technological barriers and impedes creative destruction by domestic incumbents and firm entry.

Our paper offers a unified framework that facilitates the comparison of the effects of competition across different countries. Changes in innovation composition, driven by firms' strategic choices, are an important margin to understand the heterogeneous impact of competition and its aggregate implications across diverse economic landscapes.

Related Literature

First, our paper is related to an extensive body of research on heterogeneity in innovations. Aghion et al. (2004) and Akcigit et al. (2018) incorporate entry margins and Atkeson and Burstein (2010) explore product and process innovations. However, these models focus on single-product firms that can pursue one innovation type. Klette and Kortum (2004) model multi-product firms but assume a single innovation type. Other studies have expanded the study of multi-product firms, including Bernard et al. (2010) on product switching, Akcigit and Kerr (2018) on the two types of innovation

[9] Such costs include heightened frictions related to R&D or labor mobility for creative destruction.

[10] Additional counterfactual analysis of an increasing domestic firm entry is presented in Online Appendix I.

by multi-product firms with their distinctive role in driving economic growth, Peters (2020) on the role of creative destruction in mitigating market power accumulated by own-innovation, Dhingra (2013) and Argente et al. (2024) on the role of cannibalization in firm innovation decisions, and Acemoglu et al. (2022) on the relationship between managerial characteristics and the choice of innovation types. In addition, Garcia-Macia et al. (2019) and Atkeson and Burstein (2019) explore the impacts of varied innovation types on growth and policy implications. Our contribution arises from adding learning frictions that create firms' strategic use of own-innovation while creating feedback effects on creative destruction and firm entry into a product market. Our research also provides rich empirical evidence on the properties of heterogeneous innovations and the strategic innovation decisions of multi-product firms that drive shifts in innovation composition.

Second, our paper relates to the growing literature on technology gaps and spillovers. Previous studies have shown that technology gaps between firms shape firm innovation incentives and policy implications (Aghion et al., 2001, 2005; Dinopoulos and Syropoulos, 2007; Aghion and Griffith, 2008; Acemoglu and Akcigit, 2012; Akcigit et al., 2018); documented the trend of diminishing knowledge diffusion from market leaders to laggards (Andrews et al., 2016; Bessen et al., 2020; Akcigit and Ates, 2021; Arora et al., 2021; Akcigit and Ates, 2023); and highlighted phenomena consistent with this trend (Shapiro, 2000; De Ridder, 2024; Olmstead-Rumsey, 2019; Cavenaile et al., 2019; Argente et al., 2020; Bessen et al., 2020; Bloom et al., 2020; Aghion et al., 2023; Akcigit and Ates, 2023; Akcigit and Goldschlag, 2023). However, these studies have not identified a definitive mechanism driving this shift. Our contribution is to uncover an underlying endogenous force behind the decline in technology diffusion: firms' strategic responses to increased competition under learning frictions.

Lastly, our paper contributes to the longstanding literature on competition and innovation. The empirical literature reports mixed findings (Aghion et al., 2005; Bloom et al., 2016; Hombert and Matray, 2018; Shu and Steinwender, 2019; Autor et al., 2020).[11] Some explore this dynamic through Schumpeterian growth models featuring step-by-step innovation (Aghion et al., 2001, 2004, 2005, 2009; Akcigit et al., 2018), while others employ trapped-factor models where rising competition reduces innovation's opportunity cost (Bloom et al., 2013, 2021; Medina, 2022).[12] However, their

[11] See Shu and Steinwender (2019) for further details.

[12] The former has the "Schumpeterian effect" (laggards) and the "escape-competition effect" (neck-and-neck firms).

analysis is rooted in several assumptions lacking data support and abstracts from discussing the composition of different innovations.[13,14] We contribute by providing a rich theoretical framework where multi-product firms strategically leverage technological advantages, employ own-innovation, and endogenously affect rivals' creative destruction, along with supportive data evidence. Our framework demonstrates how competition changes innovation composition, generating distinct aggregate effects based on relative shifts. This helps reconcile the prior diverging findings and deepens understanding of complex impact of competition on innovation.

The rest of the paper is organized as follows. Section 2 develops the baseline endogenous growth model. Section 3 presents the empirical strategy and findings. Section 4 provides a quantitative analysis of the model. Section 5 concludes.

2 Baseline Model

We build a discrete-time infinite horizon endogenous growth model with multi-product firms, two types of innovation, imperfect technological spillovers, and an exogenous source of competitive pressure.[15] The model is distinct in the following three dimensions: we i) introduce a novel friction named "imperfect technology spillovers" by assuming that firms can only learn the incumbent's technology lagged by one period in the process of creative destruction; ii) generate incumbent firms' own-innovation decision as an endogenous function of the technology gap—the ratio of the current-period technology $q_{j,t}$ to the previous-period technology $q_{j,t-1}$, $\Delta_{j,t} = \frac{q_{j,t}}{q_{j,t-1}}$, due to the friction; and iii) allow for exogenous shifts of the aggregate creative destruction arrival rate to analyze the effect of increasing competitive pressure on firm innovation and growth. Hereafter, the time subscript is suppressed.[16] The terms product quality and technology are used interchangeably.

[13] The model assumes single-product firms, a single innovation type, or the immediate imitation by the laggards.

[14] Alternative studies include Hombert and Matray (2018) (product differentiation), Dhingra (2013) (process innovation to avoid cannibalization), and Helpman (2023) (ambiguous impacts on innovation by multi-product firms).

[15] Exogenous competitive pressure emanates from firms outside the economy, which could be foreign firms or domestic incumbents in other sectors or states, depending on whether we consider the model economy as an aggregate economy or a specific sector or state.

[16] Superscript $'$ denotes the forward-period $(t+1)$, and subscript -1 is used for the previous-period $(t-1)$.

2.1 Representative Household

A representative household consists of a measure-one continuum of individuals, each supplying one unit of labor inelastically to the final goods sector and consuming a portion C_t of the economy's final goods each period. The household has the following lifetime utility:

$$U = \sum_{t=0}^{\infty} \beta^t \log(C_t).$$

2.2 Final Goods Producer

The final goods producer produces a final good with labor (L) and a continuum of differentiated intermediate goods indexed by $j \in [0,1]$ (produced by either domestic firms $j \in \mathcal{D}$ or outsiders $j \notin \mathcal{D}$). The production function has the constant returns-to-scale technology as follows:

$$Y = \frac{L^\theta}{1-\theta}\left[\int_0^1 q_j^\theta y_j^{1-\theta} \mathcal{I}_{\{j \in \mathcal{D}\}} dj + \int_0^1 q_j^\theta y_j^{1-\theta} \mathcal{I}_{\{j \notin \mathcal{D}\}} dj\right],$$

where y_j and q_j are the quantity and quality of good j, and $\mathcal{I}_{\{\cdot\}}$ is an indicator function. The market is competitive with the price normalized to one, and input prices taken as given.

2.3 Intermediate Producers

Domestic and outside firms have the mass of $\mathcal{F}_d$ and $\mathcal{F}_o$, respectively, with $\mathcal{F} = \mathcal{F}_d + \mathcal{F}_o \in (0,1)$. They produce and sell differentiated intermediate goods in monopolistically competitive domestic markets. Each firm operates with at least one product, and each product is owned by a single firm. Thus, firm f can be characterized by the collection of its products $\mathcal{J}^f = \{j : j \text{ is owned by firm } f\}$. The intermediate good is produced at a unit marginal cost in terms of final goods. In Online Appendix F, we extend the model to a duopoly setting and show that our main results remain robust under this alternative market structure.

2.4 Innovation by Intermediate Producers

Intermediate producers engage in two types of R&D, own-innovation and creative destruction, by spending expenditures in units of final goods. Firms improve the quality of their own products through own-innovation, while taking over other markets through creative destruction.[17] The R&D output manifests as improving product quality and is realized at the beginning of the next period.

On top of this, we introduce a novel friction named "imperfect technology spillovers," under which learning others' technology takes time in the process of creative destruction.[18] We conceptualize it in the form of lagged learning by assuming creative destruction builds on the past-period technology. Thus, only the owner of a product line can observe the frontier level of technology $q_{j,t}$ in the market, while outsider firms can only see the lagged level $q_{j,t-1}$.[19] Following this, a product line can be sufficiently characterized by its quality q_j and technology gap between current and previous periods $\Delta_{j,t} = \frac{q_{j,t}}{q_{j,t-1}}$.[20] This friction induces incumbents to strategically use own-innovation to build technological barriers and protect their markets from competitors. We name it the "market-protection effect."

When two firms are neck and neck in a product line, a coin-toss tiebreaker rule applies as in Acemoglu et al. (2016) to make sure each product is produced by only one firm.[21] Creative destruction is undirected and the targeted product is randomly assigned among the entire set of products with equal probability. For now, we assume that firms can only attempt one creative destruction each period, which aids in deriving analytic solutions for firm decision rules and distributions with minimal assumptions. In the quantitative analysis, we allow multiple creative destructions as in Klette and Kortum (2004). The details are provided in Online Appendix E.

2.4.1 Own-Innovation

Successful own-innovation improves the current quality $q_{j,t}$ of the product by $\lambda > 1$. The quality of good j evolves as follows, conditional on the owning firm not displaced by creative destruction: for

[17] Note that the quality in this model is a marginal cost of production-adjusted measure, and can be improved through either technological advancement or cost reduction. In this sense, our concept of innovation encompasses both product and process innovations. Thus, firms with lower technology can compete with firms with advanced technology if they have a sufficiently lower marginal cost of production.

[18] See Section 3.2 for empirical results consistent with this.

[19] All the aggregate variables and technology gap distribution are publicly observable, and firms make optimal innovation decisions by considering them. In this way, a stationary firm-product distribution is well defined.

[20] This technology gap summarizes the technological advantage incumbents have in their market.

[21] Unused technology is assumed to depreciate sufficiently to make it unprofitable for firms that have done creative destruction to build upon it next period. This approach guarantees the undirected nature of creative destruction and restricts own-innovation to the current owner only.

$\widehat{\chi} > 0$, $\widehat{\psi} > 1$,

$$\left\{q^{\text{in}}_{j,t+1}\right\} = \begin{cases} \left\{\lambda q_{j,t}\right\} & \text{with probability } z_{j,t} \\ \left\{q_{j,t}\right\} & \text{with probability } 1 - z_{j,t}, \end{cases} \qquad z_{j,t} = \left(\frac{R^{\text{in}}_{j,t}}{\widehat{\chi} q_{j,t}}\right)^{\frac{1}{\widehat{\psi}}}.$$

The success probability of own-innovation, $z_{j,t}$, depends on R&D investment $R^{\text{in}}_{j,t}$.[22]

2.4.2 Creative Destruction

Successful creative destruction improves the lagged quality of the obtained product by $\eta > 1$. We assume $\lambda^2 > \eta > \lambda$. $\eta > \lambda$ reflects our empirical findings (in Section 3.2.2) that creative destruction is of higher quality than own-innovation, both in terms of market value (Kogan et al., 2017) and forward citations, and contributes more to firm, hence aggregate growth.[23] The condition $\lambda^2 > \eta$ reflects the idea that consecutive own-innovations have a substantial impact, enabling firms to defend their product lines from rivals through continued innovation efforts. These assumptions are innocuous to our results; rather, they are introduced to simplify the main exposition and minimize computational burden. In Online Appendix D, we extend the model by allowing innovation step sizes (λ and η) to be drawn from probability distributions, as in Garcia-Macia et al. (2019), and confirm the robustness of our main findings without imposing specific assumptions on their relative magnitudes. The results hold even when both step sizes are drawn from the same distribution.

Firms invest in creative destruction and can obtain the following product quality if not pre-empted by the successful own-innovation of the incumbent in their target market: for $\widetilde{\chi} > 0$, $\widetilde{\psi} > 1$,

$$\left\{q^{\text{ex}}_{j,t+1}\right\} = \begin{cases} \left\{\eta q_{j,t-1}\right\} & \text{with probability } x_t \\ \emptyset & \text{with probability } 1 - x_t, \end{cases} \qquad x_t = \left(\frac{R^{\text{ex}}_t}{\widetilde{\chi} \bar{q}_t}\right)^{\frac{1}{\widetilde{\psi}}}.$$

The success probability of creative destruction, x_t, is determined by R&D investment R^{ex}_t and the

[22] Hereafter, we represent the quality of product j as a point set. This makes it easy to describe the case where a firm fails to acquire any product lines—in such cases, the product quality set is an empty set.

[23] This is consistent with the findings of Akcigit and Kerr (2018).

average quality $\bar{q}_t$ in the economy.[24] With probability $1 - x_t$, the creative destruction fails, implying neither product takeover nor quality is obtained. See Online Appendix B.1 for examples illustrating how firms choose own-innovation and creative destruction.

2.4.3 Product Quality Evolution

Imperfect technology spillovers create a gap between current and lagged product quality levels, $\Delta_{j,t} = \frac{q_{j,t}}{q_{j,t-1}}$, which represents the technological advantage incumbent firms hold in their markets. This advantage allows them to defend their product lines through own-innovation. The technology gap can take one of four possible values.

Lemma 1. *There are four possible values for a technology gap: $\Delta^1 = 1$, $\Delta^2 = \lambda$, $\Delta^3 = \eta$, and $\Delta^4 = \frac{\eta}{\lambda}$, with Δ^3 and Δ^4 arising exclusively through creative destruction.*
Proof: See Online Appendix A.1.

Then, incumbents' product quality (conditional on a technology gap) evolves as follows:

$$\left\{q_{j,t+1} \middle| \Delta_{j,t} = \Delta^1\right\} = \begin{cases} \emptyset & \text{, with prob. } \overline{x} \\ \left\{q_{j,t}\right\} & \text{, with prob. } (1-\overline{x})(1-z_j^1) \\ \left\{\lambda q_{j,t}\right\} & \text{, with prob. } (1-\overline{x})z_j^1 \end{cases} \tag{1}$$

$$\left\{q_{j,t+1} \middle| \Delta_{j,t} = \Delta^2\right\} = \begin{cases} \emptyset & \text{, with prob. } \overline{x}(1-z_j^2) \\ \left\{q_{j,t}\right\} & \text{, with prob. } (1-\overline{x})(1-z_j^2) \\ \left\{\lambda q_{j,t}\right\} & \text{, with prob. } z_j^2 \end{cases} \tag{2}$$

$$\left\{q_{j,t+1} \middle| \Delta_{j,t} = \Delta^3\right\} = \begin{cases} \emptyset & \text{, with prob. } \frac{1}{2}\overline{x}(1-z_j^3) \\ \left\{q_{j,t}\right\} & \text{, with prob. } \left(1-\frac{1}{2}\overline{x}\right)(1-z_j^3) \\ \left\{\lambda q_{j,t}\right\} & \text{, with prob. } z_j^3 \end{cases} \tag{3}$$

$$\left\{q_{j,t+1} \middle| \Delta_{j,t} = \Delta^4\right\} = \begin{cases} \emptyset & \text{, with prob. } \overline{x}\left(1-\frac{1}{2}z_j^4\right) \\ \left\{q_{j,t}\right\} & \text{, with prob. } (1-\overline{x})(1-z_j^4) \\ \left\{\lambda q_{j,t}\right\} & \text{, with prob. } \left(1-\frac{1}{2}\overline{x}\right)z_j^4. \end{cases} \tag{4}$$

Note that z_j^ℓ is the optimal own-innovation of the firm owning product j with its technology gap Δ^ℓ, $\ell \in \{1,2,3,4\}$. $\overline{x}$ is the aggregate creative destruction arrival rate, representing the probability

[24]The average quality matters for creative destruction as the target product is randomly assigned.

that a product market faces a rival firm with successful creative destruction. The symbol $\emptyset$ indicates that the firm loses product line j in the next period, and the term $\frac{1}{2}$ in the probabilities reflects a coin-toss tiebreaker in neck-and-neck scenarios.

In the case of $\Delta_{j,t} = 1$, incumbents lack any technological advantage and lose their product lines if a rival firm arrives with successful creative destruction, irrespective of their success in own-innovation.[25] In contrast, for other cases where $\Delta^\ell > 1$, firms can lower the probability of losing their product lines by investing more in own-innovation.[26] Hence, firms are more incentivized to augment their own-innovation efforts for products with technological advantages ($\Delta^\ell > 1$).[27]

For rival firms entering a market, the success probability of product takeover depends not only on the success of creative destruction but also on the technology gap and the own-innovation intensity of the product owner, even after successful creative destruction. Thus, the success probability of product takeover x_{takeover} ($\equiv x\overline{x}_{\text{takeover}}$) can be decomposed into i) the success probability of creative destruction x, and ii) conditional takeover probability $\overline{x}_{\text{takeover}}$, which is defined as

$$\overline{x}_{\text{takeover}} = \mu(\Delta^1) + (1 - z^2)\mu(\Delta^2) + \frac{1}{2}(1 - z^3)\mu(\Delta^3) + \left(1 - \frac{1}{2}z^4\right)\mu(\Delta^4), \tag{5}$$

with technology gap distribution $\left\{\mu(\Delta^\ell)\right\}_{\ell=1}^4$ (the mass of products with a gap Δ^ℓ).[28]

Note that the higher the overall innovation intensity (both own-innovation and creative destruction) is, the wider the average technology gap becomes in the economy (the mass of products with Δ^1 decreases). This makes it difficult for firms to successfully take over product markets.[29] This is referred to as the "technological barrier effect," where increased own-innovation by incumbents or higher $\bar{x}$ dampens creative destruction and slows the growth of firms.[30]

[25] Rivals with successful creative destruction achieve $q^{\text{rival}}_{j,t+1} = \eta q_{j,t-1}$, which is greater than $\lambda q_{j,t-1}$. The model in Akcigit and Kerr (2018) falls into this category.

[26] The extent of the reduction in the probability of product loss is contingent on the technology gap.

[27] See Online Appendix B.2 for the evolution of product quality for rival firms entering a market.

[28] This shows that if a firm succeeds in creative destruction for a product line with a technology gap of Δ^1, then it takes over that product line with a probability of one. For a product line with Δ^2, this probability becomes $1 - z^2$; for Δ^3, it is $\frac{1}{2}(1 - z^3)$; and for Δ^4, it is $1 - \frac{1}{2}z^4$. It is assumed that own-innovation intensity z depends solely on technology gap Δ^ℓ. In the next section, we prove this assumption holds true.

[29] Higher own-innovation intensity widens the technology gap. Simultaneously, higher creative destruction intensity increases the aggregate creative destruction arrival rate, which in turn endogenously strengthens incumbents' incentives to engage in own-innovation more, as discussed earlier.

[30] This technological barrier effect is a novel feature of our model, which is distinct from the well-known Schumpeterian effect. The Schumpeterian effect refers to the decline in firm innovation incentives following an increase in $\bar{x}$ due to reduced expected future profits conditional on successful innovation and business takeover.

2.4.4 Potential Startups

There is a fixed mass of potential domestic startups $\mathcal{E}_d$. To start a business, they invest in creative destruction R&D and attempt to take over a product line from an incumbent firm. Potential startups choose R&D expenditure R_e^{ex} and decide the probability of creative destruction $x_e = \left(R_e^{\text{ex}} / \left(\widetilde{\chi}_e \bar{q}\right)\right)^{\frac{1}{\widetilde{\psi}_e}}$, where $\widetilde{\chi}_e > 0$ and $\widetilde{\psi}_e > 1$.

Let $V(\{(q_j, \Delta_j)\})$ denote the value of a firm that has a product with quality q_j and a technology gap of Δ_j. Then a potential startup's expected profits from entering through R&D is

$$\Pi^e = \widetilde{\beta}\mathbb{E}\left[V(\{(q_j', \Delta_j')\})\middle| x_e\right] - \widetilde{\chi}_e (x_e)^{\widetilde{\psi}_e}\overline{q}, \tag{6}$$

where $\widetilde{\beta}$ is the stochastic discount factor, and the expectation conditioning on x_e is taken over the distribution of incumbents' product quality q_j and technology gap Δ_j due to the undirected nature of creative destruction.[31] Potential startups choose the probability of creative destruction x_e to maximize expected profits from entry. Since potential startups are ex-ante homogeneous, they all choose the same level of creative destruction intensity x_e^*. Hence, the mass of potential domestic startups that succeed in creative destruction and attempt to take over product markets is $\mathcal{E}_d x_e^*$.

2.5 Exogenous Competitive Pressure and Creative Destruction

As explained before, the aggregate creative destruction arrival rate $\overline{x}$ is the probability that an incumbent faces a rival firm (either a domestic startup, incumbent, or an outside firm) with successful creative destruction. The aggregate creative destruction arrival rate is equal to the total mass of firms succeeding in creative destruction given the undirected nature of creative destruction and the continuum of unit mass of product lines.[32] Let $\overline{x}_d$ denote the total mass of domestic firms with successful creative destruction and $\overline{x}_o$ denote the outside firms' counterpart. The creative destruction

[31] $\widetilde{\beta} = \frac{\beta C}{C'}$ as the household owns all firms.

[32] This follows along with the assumption that each firm can do creative destruction at most one product line each period, which makes the total mass of firms with successful creative destruction equivalent to the total mass of product markets for which an incumbent faces a rival firm. This assumption is extended in our full-fledged version, and this result still holds with additional aggregation across products within successful firms.

arrival rate is defined as

$$\overline{x} = \overline{x}_d + \overline{x}_o.$$

Competitive pressure from outside firms is captured by an exogenous increase in $\overline{x}_o$, resulting from either increased creative destruction intensity or a larger mass of outside firms.[33]

2.6 Equilibrium

2.6.1 Optimal Production and Employment

The final goods producers choose labor and intermediate goods inputs. Let p_j denote the price of differentiated product j, and w denote the wage in the domestic economy. The inverse demand for intermediate good j is:

$$p_j = q_j^{\theta} L^{\theta} y_j^{-\theta}. \tag{7}$$

Each product is assumed to be supplied by a single firm. We follow Acemoglu et al. (2012) and Acemoglu et al. (2018) and assume that the current and former incumbents engage in the following two-stage price-bidding game for each product line j: i) each firm pays a fee of ε (> 0), and ii) those that have paid the fee announce their prices.[34]

Intermediate producers take (7) as given and maximize their operating profits $\pi(q_j)$ for each product $j \in \mathcal{J}^f$.[35] The optimal production and price are derived as follows:

$$y_j = (1-\theta)^{\frac{1}{\theta}} q_j \quad \text{and} \quad p_j = \frac{1}{1-\theta}, \tag{8}$$

[33] Jo (2024) extends our baseline model to a two-country framework and endogenizes the changes in $\overline{x}_o$ driven by the changes in bilateral tariff rates.

[34] This is to avoid the case where the former market leader, having lost its leadership to the current leader in a market, attempts to produce and sell its product through limit pricing. This ensures that only the firm with the leading-edge technology enters the first stage and announces its price in equilibrium.

[35] Since each intermediate product incurs a unit marginal cost in terms of final goods, the problem is identical for both domestic and outside firms.

which simplify the equilibrium profit, wage, and final goods output to the following:

$$\pi(q_j) = \underbrace{\theta(1-\theta)^{\frac{1-\theta}{\theta}}}_{\equiv\pi} q_j, \quad w = \theta(1-\theta)^{\frac{1-2\theta}{\theta}}\overline{q}, \quad \text{and} \quad Y = (1-\theta)^{\frac{1-2\theta}{\theta}}\overline{q}. \tag{9}$$

2.6.2 Optimal own-innovation and creative destruction

Let $\Phi^f \equiv \{(q_j, \Delta_j)\}_{j\in\mathcal{J}^f}$ denote the set of product quality and technology gap for intermediate goods producer f. The firm value is:

$$V(\Phi^f) = \max_{\substack{x,\\ \{z_j\}_{j\in\mathcal{J}^f}}} \left\{ \sum_{j\in\mathcal{J}^f} \left[\pi q_j - \hat{\chi} z_j^{\hat{\psi}} q_j\right] - \overline{q}\widetilde{\chi}x^{\widetilde{\psi}} + \widetilde{\beta}\mathbb{E}\left[V(\Phi^{f\prime}\middle|\Phi^f)\middle| x, \{z_j\}_{j\in\mathcal{J}^f}\right] \right\}.$$

The first three terms define the current profits (revenue net of production and R&D costs), and the last term is the discounted future expected value. This expectation is computed over various factors, including the success probabilities of own-innovation and creative destruction, the creative destruction arrival rate, the outcomes of winning or losing coin tosses, the current-period product quality distribution, and the current-period technology gap distribution.

Proposition 1. *The firm value function and optimal innovation choices are derived as:*

$$V(\Phi^f) = \sum_{\ell=1}^{4} A_\ell \left(\sum_{j\in\mathcal{J}^f|\Delta_j=\Delta^\ell} q_j \right) + B\overline{q} \tag{10}$$

$$z^1 = \left[\widetilde{\beta}\left((1-\overline{x})\lambda A_2 - (1-\overline{x})A_1\right) / \left(\widehat{\psi}\widehat{\chi}\right)\right]^{\frac{1}{\widehat{\psi}-1}} \tag{11}$$

$$z^2 = \left[\widetilde{\beta}\left(\lambda A_2 - (1-\overline{x})A_1\right) / \left(\widehat{\psi}\widehat{\chi}\right)\right]^{\frac{1}{\widehat{\psi}-1}} \tag{12}$$

$$z^3 = \left[\widetilde{\beta}\left(\lambda A_2 - (1-\overline{x}/2)\, A_1\right) / \left(\widehat{\psi}\widehat{\chi}\right)\right]^{\frac{1}{\widehat{\psi}-1}} \tag{13}$$

$$z^4 = \left[\widetilde{\beta}\left(\lambda\,(1-\overline{x}/2)\, A_2 - (1-\overline{x})\, A_1\right) / \left(\widehat{\psi}\widehat{\chi}\right)\right]^{\frac{1}{\widehat{\psi}-1}} \tag{14}$$

$$x = \left[\widetilde{\beta}A_{\text{takeover}} / \left(\widetilde{\psi}\widetilde{\chi}\right)\right]^{\frac{1}{\widetilde{\psi}-1}}, \tag{15}$$

where

$$A_1 = \pi - \widehat{\chi}(z^1)^{\widehat{\psi}} + \widetilde{\beta}\left[A_1(1-\overline{x})(1-z^1) + \lambda A_2(1-\overline{x})z^1\right] \tag{16}$$

$$A_2 = \pi - \widehat{\chi}(z^2)^{\widehat{\psi}} + \widetilde{\beta}\left[A_1(1-\overline{x})(1-z^2) + \lambda A_2 z^2\right] \tag{17}$$

$$A_3 = \pi - \widehat{\chi}(z^3)^{\widehat{\psi}} + \widetilde{\beta}\left[A_1\left(1-\overline{x}/2\right)(1-z^3) + \lambda A_2 z^3\right] \tag{18}$$

$$A_4 = \pi - \widehat{\chi}(z^4)^{\widehat{\psi}} + \widetilde{\beta}\left[A_1(1-\overline{x})(1-z^4) + \lambda A_2\left(1-\overline{x}/2\right)z^4\right] \tag{19}$$

$$B = \left(x\widetilde{\beta}A_{\text{takeover}} - \widetilde{\chi}x^{\widetilde{\psi}}\right) / \left(1-\widetilde{\beta}(1+g)\right), \tag{20}$$

g is the growth rate of the average product quality, and A_{takeover} is the ex-ante value of a successful takeover of a product line as follows:

$$A_{\text{takeover}} \equiv \frac{1-z^3}{2}A_1\mu(\Delta^3) + \left(1-\frac{z^4}{2}\right)A_2\lambda\mu(\Delta^4) + A_3\eta\mu(\Delta^1) + (1-z^2)A_4\frac{\eta}{\lambda}\mu(\Delta^2). \tag{21}$$

Proof: See Online Appendix A.2.

Note that A_ℓ is the sum of discounted expected profits from owning a product with a technology gap of Δ^ℓ, normalized by the current-period product quality. The first two terms in (16) through (19) denote the normalized instantaneous profits, net of the optimal R&D spending. The terms inside the brackets are the normalized future value from own-innovation. B is the sum of the discounted expected profits from owning an additional product through creative destruction, normalized by the average product quality.[36]

For the optimal own-innovation (11)-(14), the first term in the brackets (after $\widetilde{\beta}$) in the numerator represents the future value from successful own-innovation with the quality increased by λ, and the second term is the counterpart from no successful own-innovation. Thus, holding $\overline{x}$ fixed, the net future value of successful own-innovation depends on the firm's technology gap, pinning down its optimal choice. Consequently, own-innovation becomes an endogenous function of the technology gap, which is a unique feature of this model due to imperfect technology spillovers.

Corollary 1. *In an equilibrium where $\{z^\ell\}_{\ell=1}^4$ are well defined, the probabilities of own-innovation satisfy $z^2 > z^3 > z^4 > z^1$.*

[36] To understand this variable clearly, we can rewrite (20) as $B\overline{q} = x\widetilde{\beta}A_{\text{takeover}}\overline{q} - \widetilde{\chi}x^{\widetilde{\psi}}\overline{q} + \widetilde{\beta}B(1+g)\overline{q}$. After investing $\widetilde{\chi}x^{\widetilde{\psi}}\overline{q}$ in creative destruction in the current period, the firm receives the discounted expected profit $\widetilde{\beta}A_{\text{takeover}}\overline{q}$ in the next period if the creative destruction succeeds with probability x. Then, the firm plans to invest in creative destruction next period and receive an expected profit of $B\overline{q}'$ in the following period, where $\overline{q}' = (1+g)\overline{q}$. Thus, (20) illustrates that B is the annuity value of an infinite stream of constant payoffs $x\widetilde{\beta}A_{\text{takeover}} - \widetilde{\chi}x^{\widetilde{\psi}}$, evaluated at a constant discount rate of $\widetilde{\beta}(1+g)$, which is the growth rate-adjusted stochastic discount factor.

Proof: See Online Appendix A.3.

Corollary 1 shows that own-innovation increases with the technology gap, which helps firms protect their markets. However, beyond a certain point, a wider technology gap can discourage further investment in own-innovation. This occurs because firms are less likely to lose their product line even without doing additional own-innovation.

Furthermore, the optimal own-innovation also depends on creative destruction arrival rate $\overline{x}$ as shown in Corollary 2, which we label the "market-protection effect."[37,38]

Corollary 2 (Market-Protection Effect)**.** *With $\widetilde{\psi} \in (1, 2]$, the market-protection effect is maximized and is positive for product lines with a technology gap of Δ^2, whereas it is minimized and is negative for product lines with Δ^1. The market-protection effect is positive for the Δ^3 case, whereas its sign is ambiguous for the Δ^4 case. Thus,*

$$\left.\frac{\partial z^2}{\partial \overline{x}}\right|_{A_1,A_2} > \left.\frac{\partial z^3}{\partial \overline{x}}\right|_{A_1,A_2} > 0, \quad \left.\frac{\partial z^3}{\partial \overline{x}}\right|_{A_1,A_2} > \left.\frac{\partial z^4}{\partial \overline{x}}\right|_{A_1,A_2} \lesseqgtr 0, \quad \textit{and} \quad 0 > \left.\frac{\partial z^1}{\partial \overline{x}}\right|_{A_1,A_2}.$$

Proof: See Online Appendix A.4.

In the Δ^1 case, own-innovation fails to effectively protect the firm's product, as shown in (1). Consequently, z^1 decreases as the rate of creative destruction $\overline{x}$ increases. In contrast, the Δ^2 case has the strongest market-protection effect, exerting the highest impact on reducing the probability of losing a product as in (2). In the Δ^3 case, increasing z^3 lowers the probability of product loss, though less than in the Δ^2 case. This results in a positive but diminished market-protection effect. The effect in the Δ^4 case remains ambiguous, where higher z^4 leads to a smaller decrease in the probability of losing the product line. This suggests firms that have innovated intensively previously (and thus larger technology gaps) are more likely to intensify own-innovation in response to increased competition (higher $\overline{x}$) than those with less recent innovation. This highlights another crucial and unique aspect of our model: firms strategically employ own-innovation to defend against competitors, leveraging imperfect technology spillovers.

[37]Note that as A_1 and A_2 also depend on $\overline{x}$, it is difficult to analytically determine the signs of the partial derivatives of $\{z^\ell\}_{\ell=1}^4$ with respect to $\overline{x}$. However, by holding the values of A_1 and A_2 fixed, we can explicitly ascertain these signs as in Corollary 2.

[38]The term A_2 in (11)-(14) reflects the well-known Schumpeterian effect—the lower the expected future profits from keeping the product line through own-innovation, the lower the incentive to invest in own-innovation.

As a result, optimal creative destruction depends on own-innovation, the technology gap distribution among incumbents, and the expected value of products ($\{A_\ell\}_{\ell=1}^4$). Equations (15) and (21) show that higher overall own-innovation and creative destruction intensities reduce firms' incentive for creative destruction in partial equilibrium, with $\{A_\ell\}_{\ell=1}^4$ held constant. This is because increased overall innovation shifts the technology gap distribution, which raises the average technology gap, and hampers firms' market takeover (the "technological barrier effect"). Furthermore, keeping the probabilities of own-innovation and the technology gap distribution constant, a decrease in the expected product values reduces creative destruction (the "Schumpeterian effect").[39] Our simple three-period model in Online Appendix C formally proves these predictions.

Similarly, the optimal creative destruction by potential startups x_e is derived as follows:

$$x_e = \left[\widetilde{\beta}\left(A_{\text{takeover}} + \overline{x}_{\text{takeover}} B(1+g)\right) / \left(\widetilde{\psi}_e \widetilde{\chi}_e\right)\right]^{\frac{1}{\widetilde{\psi}_e - 1}}, \tag{22}$$

with proof provided in Online Appendix A.5.

2.6.3 Aggregate Creative Destruction Arrival Rate

With (15) and (22), the aggregate creative destruction arrival rate in this economy is defined as follows:

$$\overline{x} = \underbrace{\mathcal{F}_d x + \mathcal{E}_d x_e}_{\equiv \overline{x}_d} + \underbrace{\mathcal{F}_o x + \mathcal{E}_o}_{\equiv \overline{x}_o}, \tag{23}$$

where $\mathcal{E}_o$ is the total mass of outside entrants with successful creative destruction, which is exogenously determined.[40,41]

[39]The direction of the changes in the probabilities of own-innovation and creative destruction in response to changes in the aggregate creative destruction arrival rate $\overline{x}$ are ambiguous in general equilibrium. They depend on the relative magnitudes and the directions of the market-protection effect, the technological barrier effect, and the Schumpeterian effect. Nonetheless, results from the numerical exercise in Section 4.2 confirm that the partial equilibrium results, given $\{A_\ell\}_{\ell=1}^4$ and B, still hold in general equilibrium within plausible parameter ranges. Furthermore, $\{A_\ell\}_{\ell=1}^4$ and B decrease with an exogenous increase in $\overline{x}$.

[40]Note that an exogenous increase in $\mathcal{E}_o$ may not increase $\overline{x}$ by the same amount in equilibrium, as the mass of domestic incumbent firms $\mathcal{F}_d$ and the probabilities of creative destruction x and x_e depend on $\overline{x}$. Thus, the level of $\overline{x}$ is endogenously determined, even when $\mathcal{E}_o$ changes exogenously.

[41]The outside firms in domestic markets make the same innovation decisions as the domestic firms.

2.7 Balanced Growth Path

Proposition 2. *The aggregate growth rate g in a Balanced Growth Path is:*

$$
\begin{aligned}
g = & \left[(1-\overline{x})(1-z^1) + \Delta^2(1-\overline{x})z^1 + \Delta^3\overline{x}\right]\mu(\Delta^1) \\
& + \left[(1-\overline{x})(1-z^2) + \Delta^2 z^2 + \Delta^4\overline{x}(1-z^2)\right]\mu(\Delta^2) + \left[1 - z^3 + \Delta^2 z^3\right]\mu(\Delta^3) \\
& + \left[(1-\overline{x})(1-z^4) + \Delta^2(z^4 + \overline{x}(1-z^4))\right]\mu(\Delta^4) - 1, \qquad (24)
\end{aligned}
$$

which can be decomposed into the parts attributed to own-innovation and creative destruction by domestic incumbents and startups (g_d), as well as outside firms (g_o).
Proof: See Online Appendix A.6.

2.8 Firm Distribution

Let $\mathcal{N} = (n_f, n_f^1, n_f^2, n_f^3, n_f^4)$ denote the technology gap composition of firm f, where n_f is the total number of products and n_f^ℓ is the count of products with a technology gap of Δ^ℓ . Let $\widetilde{\mu}(\mathcal{N})$ denote its distribution. Summing $\widetilde{\mu}(\mathcal{N})$ over all possible $\mathcal{N}$ gives the total mass of firms $\mathcal{F}$.

2.8.1 Transition of Technology Gap Portfolio

Consider a firm with technology gap composition given by $\widetilde{\mathcal{N}}(n_f, k) \equiv (n_f, n_f - k, k, 0, 0)$, where $k \in [0, n_f] \cap \mathbb{Z}$ and $n_f > 0$. Ignoring creative destruction, the probability of technology gap composition changing from $\mathcal{N} = \widetilde{\mathcal{N}}(n_f, k)$ to $\mathcal{N}' = \widetilde{\mathcal{N}}(n_f, \widetilde{k})$ is

$$
\begin{aligned}
\widetilde{\mathbb{P}}\left(n_f, \widetilde{k} | n_f, k\right) = & \sum_{\widetilde{k}^1 = \max\{0, \widetilde{k}-k\}}^{\min\{n_f - k, \widetilde{k}\}} \left(\frac{(n_f - k)!}{\widetilde{k}^1!(n_f - k - \widetilde{k}^1)!}\right)\left(\frac{k!}{(\widetilde{k} - \widetilde{k}^1)!(k - (\widetilde{k} - \widetilde{k}^1))!}\right) \\
& \times (1-\overline{x})^{n_f - (\widetilde{k} - \widetilde{k}^1)}(1-z^1)^{n_f - k - \widetilde{k}^1}(z^1)^{\widetilde{k}^1}(1-z^2)^{k - (\widetilde{k} - \widetilde{k}^1)}(z^2)^{\widetilde{k} - \widetilde{k}^1},
\end{aligned}
$$

for $n_f \geq 1$ and $0 \leq \widetilde{k}, k \leq n_f$, and zero, otherwise. This follows a binomial process as in Ates and Saffie (2021).

Using the above, we can track general cases transitioning from $\mathcal{N} = (n_f, n_f^1, n_f^2, n_f^3, n_f^4)$ to $\mathcal{N}' = (n_f', n_f^{1\prime}, n_f^{2\prime}, n_f^{3\prime}, n_f^{4\prime})$ for any $n_f' \leq n_f + 1$ as products with Δ^3 or Δ^4 can only be obtained through creative destruction. Details can be found in Online Appendix B.4.

2.8.2 Technology Gap Distribution

The aggregate distribution of technology gaps is

$$\mu(\Delta^\ell) = \sum_{n_f=1}^{\overline{n}_f} \sum_{n_f^\ell=0}^{n_f} \sum_{n_f^{-\ell}=0}^{n_f} n_f^\ell \widetilde{\mu}(n_f, n_f^1, n_f^2, n_f^3, n_f^4), \text{ for } \ell = 1, 2, 3, 4 \tag{25}$$

where the third summation represents the sum over all possible values for $n_f^{-\ell}$ other than the focal ℓ. Note $\sum_{\ell=1}^4 \mu(\Delta^\ell) = 1$ holds in equilibrium.[42]

2.8.3 Aggregate Variables and Balanced Growth Path

Given the optimal innovation choices (11), (12), (13), (14), (15), and (22), the aggregate domestic R&D expenses becomes

$$R_d = \widehat{\chi} \sum_{\ell=1}^{4} \left[\int_0^1 q_j \mathcal{I}_{\{\Delta_j = \Delta^\ell, j \in \mathcal{D}\}} dj \right] (z^\ell)^{\widehat{\psi}} + \mathcal{F}_d \widetilde{\chi} \overline{q} x^{\widetilde{\psi}} + \mathcal{E}_d \widetilde{\chi}_e (x_e)^{\widetilde{\psi}_e} \overline{q}, \tag{26}$$

where $\mathcal{I}_{\{\Delta_j = \Delta^\ell, j \in \mathcal{D}\}}$ is an indicator for product line j owned by a domestic firm with Δ^ℓ. With (8), the aggregate demand for final goods by domestic intermediate producers is

$$Y_d = \int_0^1 y_j \mathcal{I}_{\{j \in \mathcal{D}\}} dj = (1-\theta)^{\frac{1}{\theta}} \int_0^1 q_j \mathcal{I}_{\{j \in \mathcal{D}\}} dj, \tag{27}$$

and the aggregate consumption is determined by

$$C = Y - \int_{j \notin \mathcal{D}} p_j y_j dj - Y_d - R_d, \tag{28}$$

where the second term is the payments to outside intermediate producers.[43] Lastly, the balanced growth path (BGP) equilibrium is characterized by the following:

Definition 1. *A balanced growth path equilibrium consists of* y_j^*, p_j^*, w^*, L^*, x^*, $\{z^{\ell *}\}_{\ell=1}^4$, $\overline{x}^*$, x_e^*,

[42]This is because each product line is occupied by one incumbent and there is a unit mass of products.

[43]We assume outside firms use final goods from their economy for production and R&D.

$\mathcal{F}^*$, R_d^*, Y^*, C^*, g^*, $\widetilde{\mu}(\mathcal{N})$, $\{\mu(\Delta^\ell)\}_{\ell=1}^4$ for $j \in [0,1]$ with q_j such that: (i) y_j^* and p_j^* satisfy (8); (ii) w^* satisfies (9); (iii) L^* satisfies the labor market clearing condition, $L = 1$; (iv) $\{z^{\ell *}\}_{\ell=1}^4$ satisfy (11)-(14), and x^* satisfies (15); (v) $\overline{x}^*$ satisfies (23); (vi) x_e^* satisfies (22); (vii) Y^* satisfies (9); (viii) R_d^* satisfies (26); (ix) C^* satisfies (28); (x) the BGP growth rate g^* satisfies (24); (xi) the distribution of technology gap portfolio composition $\widetilde{\mu}(\mathcal{N})$ and $\mathcal{F}^*$ satisfy $\mathit{inflow}(\mathcal{N}) = \mathit{outflow}(\mathcal{N})$; and (xii) the technology gap distribution $\{\mu(\Delta^\ell)\}_{\ell=1}^4$ follows (25).

3 Empirics

In this section, we empirically examine innovation heterogeneity and validate model predictions on the "market-protection" and "technology-barrier" effects. We identify the causal effect of competition on firm innovation and composition, and analyze the industry-level association between technological barriers and firm entry. We use the rise in foreign firm entry into U.S. markets after China's WTO accession in 2001 as a quasi-experimental increase in competitive pressure.

3.1 Data and Measurement

To compile comprehensive data on firm innovation and foreign competition shock, we combine the USPTO PatentsView database, the Longitudinal Business Database (LBD), the Longitudinal Firm Trade Transactions Database (LFTTD), the Census of Manufactures (CMF), the Compustat Fundamental Annual database, the NBER-CES database, and the tariff data in Feenstra et al. (2002).

The LBD tracks the universe of establishments and firms in the U.S. non-farm private sector with at least one paid employee annually from 1976 onward.[44] We aggregate establishment-level data into firm-level using firm identifiers.[45] Firm size is measured by total employment or payroll, and firm age by the age of the oldest establishment of the firm when the firm is first observed in the data. The firm's main industry of operation is based on the six-digit North American Industry Classification System (NAICS) code of the establishment with the highest employment.[46]

[44] Details for the LBD and its construction can be found in Jarmin and Miranda (2002).

[45] An establishment corresponds to the physical location where business activity occurs. Establishments that are operated by the same entity, identified through the Economic Census and the Company Organization Survey, are grouped under a common firm identifier.

[46] Time-consistent NAICS codes for LBD establishments are constructed by Fort and Klimek (2018), and the 2012 NAICS codes are used throughout the entire analysis.

The LFTTD tracks all U.S. international trade transactions at the firm level from 1992 onward. It provides information such as the U.S. dollar value of shipments, the origin and destination countries, and a related-party flag indicating whether the U.S. importer and the foreign exporter are related by ownership of at least 6 percent.[47]

The USPTO PatentsView database records all patents ultimately granted by the USPTO from 1976 onward.[48] This database provides comprehensive details for patents, including application and grant dates, technology class, citation, and the name and address of patent assignees. In our analyses, we rely on the citation-adjusted number of utility patents as the main measure of firm innovation.[49] Using the patent-level information, we distinguish domestic innovation from foreign innovation, and assess the extent to which each patent represents own-innovation. The patent application year is used for the innovation year.

We link the USPTO patent database to the LBD to track firm patenting over time. Failure to match a patent assignee with its LBD firm counterpart can mismeasure firm innovation changes.[50] Since the USPTO patent data lacks a longitudinally consistent firm identifier, we build our own crosswalk between the two datasets by adopting the internet search-aided algorithm as in Autor et al. (2020).[51] We pool all patents granted up to December 26, 2017, and use patent applications up to 2007 in our main analyses to avoid a right censoring issue arising from patents applied for but not yet granted. Table J.1 in Online Appendix J.1 reports summary statistics.

The quinquennial CMF provides detailed information about the U.S. manufacturing establishments and products they produce. It contains product-level details such as product codes and the value of shipment. We use five-digit SIC codes (for the pre-2002 years) or seven-digit NAICS codes (for 2002 onward) to define a product. We obtain the U.S. tariff schedules from Feenstra et al. (2002) to measure the industry-level Trade Policy Uncertainty (TPU) as a proxy for foreign competitive pressure. Lastly, all nominal values are converted to 1997 U.S. dollars, using the industry-level deflator from the NBER CES Manufacturing Industry Database for manufacturing industries and

[47] Bernard et al. (2009) describe the LFTTD in greater detail.

[48] See patentsview.org/download/data-download-tables.

[49] See Cohen (2010) for a comprehensive review of the literature on the determination of firm/industry innovative activity and related patent measures.

[50] The USPTO assigns patent applications to self-reported firm names, which are frequently misspelled.

[51] This algorithm utilizes the machine-learning capacities of internet search engines. The entire matching methodology is outlined in our accompanying paper Ding et al. (2022). We also apply it when linking Compustat to USPTO.

the Consumer Price Index from the BEA for other industries.[52]

For our main analyses, we use LBD and Compustat firms matched to USPTO patents, CMF firms, and industry-level trade data spanning from 1982 to 2007.[53]

3.1.1 Own-innovation vs. Creative Destruction

We follow Akcigit and Kerr (2018) and use the self-citation ratio, the ratio of self-citations to total citations, as a measure of the likelihood a patent is used for own-innovation vs. creative destruction.[54] A higher (lower) self-citation ratio implies a greater probability that a patent reflects own-innovation (creative destruction).[55] This is because the more an idea is based on the firm's own knowledge stock (self-citation), the more likely the innovation is used to improve the firm's existing products (own-innovation). Alternatively, we measure own-innovation by the number of patents with a self-citation ratio above a certain threshold (0% or 10%) and within-firm product sales concentration. In addition, we measure creative destruction by the number of new products added.

3.1.2 Exogenous Competition Shock

Following Pierce and Schott (2016) and Handley and Limão (2017), we use the removal of trade policy uncertainty (TPU) as a measure of an exogenous competitive pressure shock. Specifically, we use the following industry-level tariff rate gaps between WTO members and non-market economies in the year 1999 as a proxy for the industry-level competitive pressure shock from China occurring

[52]The NBER CES data are complied by Becker et al. (2013) (www.nber.org/nberces).

[53]Our procedure links patents to the firms initially reported by the USPTO as owners and does not track ownership changes resulting from, for example, M&A activities. We expect our analysis not to be contaminated by firms substituting innovation with acquisitions of other firms, particularly given that U.S. M&A activities began declining around 2000 and did not fully recover by 2007, as shown in Phillips and Zhdanov (2023).

[54]Each granted patent is required to cite all prior patents on which it builds itself. When a cited patent belongs to the owner of the citing patent, these citations are called self-citations.

[55]Thus, 100% self-citation means the patent is used for own-innovation with a 100% probability, and 0% self-citation means the patent is used for creative destruction with a 100% probability.

in 2001.[56]

$$NTRGap_j = Non\ NTR\ Rate_j\ -\ NTR\ Rate_j \text{ (for industry } j).$$

For multi-industry firms, we use the employment-weighted average of it.[57]

The removal of TPU encouraged Chinese firms to enter U.S. markets and export their products (Pierce and Schott, 2016), which captures an exogenous increase in competitive pressure by foreign firms and directly maps into an increase in $\overline{x}_o$ in our model.

3.2 Heterogeneity in Firm Innovation

In this section, we present empirical evidence of innovation heterogeneity in terms of i) learning time, ii) quality improvement, and iii) economic outcomes. In this analysis, we focus on the pre-2000 sample, as the rise in competitive pressure after 2000 changed firm innovation decisions and may influence our empirical results.

3.2.1 Learning Time

Using U.S. patents and assignee data from 1982 to 1999, we demonstrate that learning others' technologies takes time in the process of creative destruction, which is both a key assumption and contribution of our model. Although we have limited data to directly estimate learning time, we infer it from the gap between a patent's application year and the application years of the patents it cites, referred to as backward citation gaps.[58]

Suppose that learning and building on other firms' technologies takes more time. In that

[56]Nonmarket economies such as China are by default subject to relatively high tariff rates, known as non-Normal Trade Relations (non-NTR) or column 2 tariffs, when they export to the U.S. On the other hand, the U.S. offers WTO member countries NTR or column 1 tariffs, which are substantially lower than non-NTR tariffs. Although the U.S. granted temporary NTR status to China from 1980, the U.S. Congress voted on a bill to revoke China's temporary NTR status every year from 1990 to 2001 after the Tiananmen Square protests in 1989. This caused uncertainty about whether the low tariffs would revert to non-NTR rates. Following an agreement on China's entry into the WTO, the U.S. Congress passed a bill granting China permanent NTR (PNTR), and PNTR was implemented on January 1, 2002. The PNTR has reduced trade policy uncertainty, more for industries with a large prior gap between NTR and non-NTR tariff rates. See Pierce and Schott (2016) for details.

[57]Table J.2 in Online Appendix J.1 reports summary statistics of the NTR-related measures.

[58]The granting of a patent legally affirms the embodied idea as a novel and useful advancement over prior knowledge, as reflected in its citations. In principle, a citation of Patent X by Patent Y indicates that X represents prior knowledge upon which Y builds (Jaffe et al., 1993).

Table 1: Backward Citation Gap and Self-Citation Ratio

	Citation gaps	Citation gaps	Citation gaps
Self-citation ratio	-2.277***	-2.434***	-2.575***
	(0.018)	(0.018)	(0.020)
Observations	728,299	728,299	728,299
Fixed effects	none	ct	it, ct

Notes: Constant terms are omitted for brevity. Robust standard errors are displayed below each coefficient. The mean (standard deviation) of the backward-citation gap and self-citation ratio are 6.80 (3.47), and 0.13 (0.22), respectively. Observations are unweighted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

case, the gap between the creation year of a technology (patent) and the creation years of the technologies it builds on (i.e., backward-cited patents) will be larger. As a result, patents representing creative destruction should have larger backward citation gaps compared to those representing own-innovation. To test this hypothesis, we estimate the following regression:

$$CitationGap_{ipct} = \alpha + \beta SelfCite_{ipct} + \delta_{it} + \delta_{ct} + \varepsilon_{ipct}.$$

where $CitationGap_{ipct}$ represents the average backward citation gap for all patents cited by firm i's patent p created in year t and belonging to CPC subsection c; $SelfCite_{ipct}$ denotes the self-citation ratio of patent p; δ_{it} is a firm-year fixed effect; and δ_{ct} is a CPC technology-year fixed effect.

Table 1 shows a negative relationship between the average backward citation gap and the self-citation ratio across various specifications in each column. This indicates that patents involved in creative destruction (with lower self-citation ratios) take longer to develop from existing technologies (larger backward citation gaps).[59]

To rule out alternative explanations that may involve a higher likelihood of citing older patents, regardless of learning, we test the robustness of our results using several variations of the baseline specification. These include: i) calculating citation gaps excluding self-citations, ii) using only non-expired patents to address concerns related to infringement avoidance, and iii) controlling for the technological diversity of cited patents, which may result from the experimental nature of creative destruction. Online Appendix J.2 presents the results. In all cases, our findings remain robust.

[59]While we cannot distinguish between learning time and the time needed for successful creative destruction, this distinction is irrelevant for incumbent firms aiming to protect their markets.

Table 2: Patent Quality and Self-Citation Ratio

	M-value	M-value	M-value	S-value	S-value	S-value
Self-citation	0.192***	-0.289***	-0.027***	-0.110***	-0.082***	-0.047***
	(0.008)	(0.006)	(0.005)	(0.008)	(0.008)	(0.008)
Market cap$_{-1}$		0.431***	0.289***		-0.025***	-0.043***
		(0.001)	(0.003)		(0.001)	(0.005)
Observations	360,750	360,750	360,750	360,750	360,750	360,750
Fixed effects	ct	ct	i, ct	ct	ct	i, ct

Notes: The estimates for firm (i), CPC technology-year (ct) fixed effects, and the constant are suppressed. Robust standard errors are displayed below each coefficient. Observations are unweighted. The mean (standard deviation) of the market value, scientific value, and self-citation ratio are 2.07 (1.32), 2.88 (1.22), and 0.17 (0.24), respectively. * p $<$ 0.1, ** p $<$ 0.05, *** p $<$ 0.01.

3.2.2 Quality Improvement

We also provide empirical evidence on the differentiated quality improvement between own-innovation and creative destruction ($\eta > \lambda$). Innovation quality is measured in two ways: the number of forward citations as a proxy for scientific value and the stock market response to patent news as a measure of market value (Kogan et al., 2017).[60] Since the market value of innovation is available only for publicly traded firms, we limit this analysis to patenting firms in Compustat from 1982 to 1999. To test if patent quality differs by the two innovation types, we estimate the following regression model:

$$Quality_{ipct} = \alpha + \beta_1 SelfCite_{ipct} + \beta_2 X_{it-1} + \delta_{ct} + \varepsilon_{ipct},$$

where $Quality_{ipct}$ represents either the log of market value (M-value) or the log of one plus the number of forward citations (S-value) for patent p by firm i in year t, within CPC subsection c; $SelfCite_{ipct}$ is the self-citation ratio for patent p; X_{it-1} is firm i's market capitalization in period $t-1$ as the baseline measure for firm size; and δ_{ct} is a CPC technology-year fixed effect.[61] δ_{ct} allows for patent quality comparisons within each market, while accounting for varying forward citation trends across technologies and years.[62]

[60]The data is sourced from the paper's website (github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data), updated through 2023.

[61]Market capitalization is calculated as the product of the closing market price (PRCC_F) and the number of common shares outstanding (CSHO).

[62]Due to the lack of product market information for patents, we use the primary CPC subsection as a proxy for product markets.

Table 2 displays the results. Note that patent market value is mechanically correlated with market capitalization (0.67 in our sample), as it is the product of its estimated stock return and the firm's market capitalization (Kogan et al., 2017). Also, larger firms tend to produce patents with higher self-citation ratios (correlation = 0.16). After controlling for these factors, we find a negative relationship between market value and closeness to own-innovation, which remains significant with firm fixed effects (column 2-3). Similar results hold for scientific value (columns 4-6). These findings support the view that creative destructions are of higher quality than own-innovations.[63]

Note that the market value of creative destruction reflects both the addition of a new product and the associated quality improvement, whereas the market value of own-innovation captures only the quality improvement. As a result, the probability that the market value of creative destruction exceeds that of own-innovation should be high. While we cannot separately identify the quality component within market value, the consistency of our findings when using scientific value—an indicator of quality improvement—supports the robustness of our conclusion.

3.2.3 Economic Outcomes

Lastly, we use either LBD firms linked to the USPTO or CMF firms to compare the impacts of the two innovation types on firm performance. We estimate the following regression using census years from 1982 to 1997:

$$\Delta Y_{ijt+5} = \beta_1 Pat_{ijt} + \beta_2 Self_{ijt} + \mathbf{X}_{ijt}\gamma_1 + \delta_{jt+5} + \varepsilon_{ijt+5}.$$

ΔY_{ijt+5} represents the DHS growth of firm employment, the number of industries (six-digit NAICS) added, revenue productivity growth, the number of products added, or the growth in within-firm product market concentration between t and $t+5$; Pat_{ijt} is the citation-adjusted number of patents (in log) at t; and $Self_{ijt}$ is the citation-adjusted average self-citation ratio at t for firm i in industry j. Firm and industry controls include firm age, log payroll, the past five years of U.S. patent growth in firm technology fields, innovation intensity, and public firm status. The regression is unweighted, with standard errors clustered at the firm level.

Table 3 shows that firm patenting is positively associated with the growth of firm-level employ-

[63]The results remain robust across different firm size measures and with firm-year fixed effects. The results are available upon request.

Table 3: Real Effect of Innovation on Employment Growth and Industry Added

	ΔEmployment	#Industries added	ΔTFPR	#Products added	ΔHHI
#patents	0.036***	0.102***	0.118**	0.358**	-0.012
	(0.010)	(0.011)	(0.055)	(0.085)	(0.023)
Avg. self-citation	-0.256**	-0.158**	-0.027	-0.274***	0.154**
	(0.109)	(0.079)	(0.053)	(0.102)	(0.069)
Observations	5,400	5,400	5,700	5,700	5,700
Fixed effects	jt	jt	jt	jt	jt

Notes: The baseline set of controls is included. The first two columns are based on the LBD-USPTO firms, and the last three columns are based on the CMF firms. Robust standard errors adjusted for clustering at the firm-level are displayed below each coefficient. Observations are unweighted. Observation counts are rounded due to Census Bureau disclosure avoidance procedures. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

ment and productivity, as well as the number of industries or products added. However, this association weakens if the new patent has a higher self-citation ratio (or is closer to own-innovation).[64,65] We check the robustness using alternative innovation measures. See Online Appendix J.3.

3.3 Market-Protection Effect

Next, we validate one of the key model predictions: the "market-protection effect." Following Pierce and Schott (2016), we use a Difference-in-Difference (DD) specification to identify the effect of increasing competitive pressure from Chinese firm entry on the U.S. firm innovation, as follows:

$$\begin{aligned}\Delta y_{ijp} =& \beta_1 Post_p \times NTRGap_{ijp0} \times InnovIntens_{ijp0} + \beta_2 Post_p \times NTRGap_{ijp0} \\ & + \beta_3 Post_p \times InnovIntens_{ijp0} + \beta_4 NTRGap_{ijp0} \times InnovIntens_{ijp0} \\ & + \beta_5 NTRGap_{ijp0} + \beta_6 InnovIntens_{ijp0} + \mathbf{X}_{ijp0}\gamma_1 + \mathbf{X}_{jp0}\gamma_2 \\ & + \delta_j + \delta_p + \alpha + \varepsilon_{ijp},\end{aligned} \tag{29}$$

[64]The mean (and standard deviation) of the citation-adjusted logged number of patents is 1.284 (1.125), and the counterpart for the citation-adjusted average self-citation ratio is 0.050 (0.101). The result, along with this, implies that for average firms, creating one more patent is associated with a 1.32 pp (3.6/2.718) increase in their employment growth as exp(1) $\approx$ 2.718. Also, since average firms have the average self-citation ratio of 0.05, an 1% increase in self-citation ratio is associated with a 0.0128 pp (-0.256$\times$0.05$\times$0.01$\times$100) decrease in their employment growth.

[65]Note Akcigit and Kerr (2018) also show that own-innovation contributes less to firm employment growth, which is consistent with our result in the first column of Table 3.

where $p \in \{1992 - 1999,\ 2000 - 2007\}$, y_{ijp} is either i) the total citation-adjusted number of patents (overall innovation), or ii) the citation-weighted average self-citation ratio (closeness to own-innovation) for firm i in industry j, and Δy_{ijp} is the DHS (Davis et al., 1996) growth rate of y between the start-year and end-year for each period p.[66]

To maximize the sample size, we include firms that applied for at least one patent in the start-year and at least one patent in or before the end-year for each period. We compute the DHS growth rates for the longest available span of years. We also require firms to have at least one patent before the start-year of each period, or to have an age greater than 0, to avoid the impact of firm entry. The sample comprises all patenting LBD firms meeting these three criteria and excludes FIRE (finance, insurance, and real estate) industries.

$Post_p$ is a dummy for the post-treatment period (2000-2007). $\mathbf{X}_{ijp0}$ and $\mathbf{X}_{jp0}$ are vectors of firm and industry controls, respectively, measured at the start-year for each period p. As a baseline, we control for firm-level employment size, age, the past five-year growth of U.S. patents in the CPC technology classes in which the firm operates, and a dummy variable for publicly traded firms, and industry-level NTR rates. δ_j is an industry fixed effect (six-digit NAICS), and δ_p is a period fixed effect. The regression is unweighted, and standard errors are clustered by industry (six-digit NAICS). Firms in low TPU industries are the control group, whereas high TPU industry firms are the treatment group. We use the 1992 and 2000 cohorts of firms to gauge firm innovation before and after the policy change in December 2001, minimizing policy-driven changes in firm composition.

$InnovIntens_{ijp0}$ is the lagged five-year average of the ratio of the number of patent applications to total employment for firm i. This proxies the technological advantage the firm has.[67] It is measured in the start year for each period p and is normalized by its time-average at the two-digit NAICS level to control for industry effects. The model predicts $\beta_1 > 0$ when the dependent variable is the changes in self-citation ratio (i.e., the likelihood of patents being used for own-innovation).

Table 4 presents the regression results, which align with our model predictions in several dimensions.[68] First, the first two columns show that the foreign competitive pressure shock has no statistically significant effect on firms' overall innovation, regardless of the firm controls included.

[66]The long-difference regression specification is standard in settings with a slow-moving process, such as innovation or technological progress (e.g., Acemoglu and Restrepo, 2020). This specification controls for firm fixed effects.

[67]In addition, we use alternative measures for technological advantages, as discussed in the following section.

[68]To conserve space, Table 4 reports the main coefficient estimates for the triple interaction and the DD-term only. The full results are available upon request.

Table 4: Market-Protection Effect

	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite
NTR gap $\times$ Post	0.238	0.071	-0.075	-0.062
	(0.237)	(0.283)	(0.257)	(0.291)
$\times$ Innovation intensity	0.077	-0.054	0.732**	0.795***
	(0.231)	(0.242)	(0.299)	(0.277)
Observations	6,500	6,500	6,500	6,500
Fixed effects	j, p	j, p	j, p	j, p
Controls	no	baseline	no	baseline

Notes: Robust standard errors, adjusted for clustering at the level of the firms' major industries, are displayed below each coefficient. Observations are unweighted, and observation counts are rounded due to the Census Bureau disclosure avoidance procedures. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

According to our model, as competition intensifies, firms adjust their own-innovation based on the technological advantages accumulated within their markets. However, firms universally reduce their creative destruction. Considering both changes in own-innovation and creative destruction, the overall effect of competition on firm innovation need not be statistically significant.

However, when examining the effect on own-innovation by substituting the dependent variable with the growth rate of the self-citation ratio, the effect becomes positive and statistically significant, as indicated in the last two columns.[69] This supports the market-protection effect. The estimated coefficient implies a 4.2 percentage points increase in the growth rate of the average self-citation ratio during the period 2000-2007 for a firm with an average lagged innovation intensity (0.18) in an industry with an average NTR gap (0.291). Given that the average value of the seven-year growth rate of the average self-citation ratio between 2000 and 2007 is 28.2 percentage points, this effect corresponds to a 15.0% increase in own-innovation by firms with technological advantages.

The estimated effect is economically important as well. Combined with Table 3, the positive association between firm-level patenting and employment growth decreases by 17.1% (from 1.32pp to 1.10pp) for innovation-intensive firms (with innovation intensity one standard deviation above the average) following the increased competitive pressure. Similar implications can also be inferred for productivity growth and the intensity of adding a new product or entering a new industry.

[69] As firms do not change their overall innovation, the increasing self-citation ratio implies that innovative firms (those above the average innovation intensity) increase their own-innovation while decreasing their creative destruction.

3.3.1 Validity of the Identification Strategy and Robustness Tests

We confirm the validity of our identification and main results across several dimensions: i) parallel pre-trends assumption, ii) industry-level NTR gap measures, iii) input-output network effects, iv) adjustments for sampling bias, v) alternative standard error clustering methods, vi) robustness of innovation intensity measures, vii) alternative measures for technological advantage, viii) alternative measures of the two types of innovations, and ix) additional controls (e.g., cumulative patents, firm payroll, industry-level skill and capital intensities, import/export dummies). More details are provided in Online Appendix J.4 and J.5.

For example, to address concerns about potential correlations between innovation intensity and firm size or age (e.g., Acemoglu et al., 2018), which may confound the effect of technological barriers, we include additional interaction terms between innovation intensity and firm age and size. We also construct an alternative measure of technological advantage, defined as the inverse of the innovation intensity gap relative to the industry frontier, averaged over the past five years. As alternative dependent variables, we directly measure creative destruction by the number of new products added, and own-innovation by the number of patents with a self-citation ratio above 0% or 10%, as well as within-firm product market concentration.[70] Our findings remain robust across all specifications.

3.4 Technological Barrier Effect

To test the "technological barrier effect," we run the following industry-level regression for the four census years in the pre-shock period (1982-1999):

$$FirmEntry_{jt} = \beta TechBarrier_{jt} + \delta_j + \delta_t + \alpha + \varepsilon_{jt}. \tag{30}$$

$FirmEntry_{jt}$ is the firm entry rate, and $TechBarrier_{jt}$ is the technological barrier in industry j at year t. We measure the industry-level technological barrier using the skewness of the firm-level TFPR distribution (normalized by the industry frontier level).[71] Specifically, we use the top 5th or

[70] We also confirm that replacing the dependent variable with changes in within-industry market share yields consistent results: the market share of innovative firms increases following the competition shock. These results are available upon request.

[71] This is the inverse of the TFPR gap in Aghion et al. (2005) (i.e., 1-TFPR gap).

Table 5: Technological Barrier Effect

	Firm entry	Firm entry
Technological barriers	-0.012**	-0.016**
	(0.006)	(0.007)
Observation	1,300	1,300
Fixed effects	j, t	j, t
Tech. barrier thresholds	Top 5%	Top 10%

Notes: Column 1 uses the top 5thpercentile, and Column 2 uses the top 10th percentile of technological barriers. Observations are unweighted. Observation counts are rounded due to Census Bureau disclosure avoidance procedures. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

10th percentile of this distribution to capture how far the technology level of top-performing firms is from that of the average firm within an industry. This measure reflects the intensity of innovation within the industry.

Table 5 indicates that firm entry is lower in industries with higher technological barriers, consistent with the technological barrier effect in the model.

4 Quantitative Analysis

In this section, we examine the aggregate effects of increased competition and shifts in the composition of firm innovation through the channel of imperfect technology spillovers. Specifically, we quantify the resulting changes in aggregate innovation intensity and economic growth. To do so, we calibrate the model to the U.S. manufacturing sector in 1992 and conduct several counterfactual exercises. To better align the model with data, we expand the baseline model in Section 2 by allowing firms to undertake multiple creative destructions simultaneously, depending on the number of products they own, as in Klette and Kortum (2004).[72]

4.1 Calibration

There are eleven structural parameters in the model, as listed in Table 6. The five parameters in the left column are externally calibrated, while the six parameters in the right column are internally calibrated to match moments associated with firm-level variables and the import penetration ratio in

[72] See Online Appendix E and G for further details and the computational algorithms used to solve the model.

Table 6: Parameter Estimates

External calibration			Internal calibration		
Param.	Description	Value	Param.	Description	Value
β	Time discount rate	0.947	$\widehat{\chi}$	Scale, own-innov.	0.044
$\widehat{\psi}$	Curvature, own-innov.	2.000	$\widetilde{\chi}$	Scale, creative destr.	0.405
$\widetilde{\psi}$	Curvature, creative destr.	2.000	$\widetilde{\chi}^e$	Scale, startup R&D	1.689
$\widetilde{\psi}^e$	Curvature, startup R&D	2.000	λ	Step size, own-innov.	1.040
θ	Quality share, final goods	0.109	η	Step size, creative destr.	1.075
			$\mathcal{E}_o$	Mass of outside entrants	0.007

the U.S. manufacturing sector.[73] We use the import penetration ratio because it is an observable moment that partially reflects an exogenous change in competitive pressure.

4.1.1 Externally Calibrated Parameters

The time discount factor (β) is set to 0.947, which corresponds to an annual interest rate of 5.6%. The curvature parameters of the three R&D cost functions ($\widehat{\psi}$, $\widetilde{\psi}$, $\widetilde{\psi}^e$) are taken from Acemoglu et al. (2018) and Akcigit and Kerr (2018). We set the average profit-to-sales ratio θ ($= \int_f \frac{profit_f}{sales_f} df$) to match the quality share in final goods production (10.9%) reported in Akcigit and Kerr (2018). We normalize the mass of potential domestic startups.

4.1.2 Internally Calibrated Parameters

The remaining six parameters are internally calibrated to minimize the objective function,

$$\min \sum_{i=1}^{6} \frac{\left|\text{model moment}_i - \text{data moment}_i\right|}{\frac{1}{2}\left|\text{model moment}_i\right| + \frac{1}{2}\left|\text{data moment}_i\right|},$$

with the six target moments in Table 7. Although the parameters are jointly calibrated, the most relevant moments for each set of parameters can be noted. The R&D scales for own-innovation and creative destruction ($\widehat{\chi}$, $\widetilde{\chi}$) are set to match the average number of products and the number of products added per firm. The startup R&D scale ($\widetilde{\chi}^e$) matches the firm entry rate. We target the average productivity growth rate and the employment growth rate of high-growth firms (90th

[73]The average number of products and the number of products added are from the 1992 CMF. The high-growth firm growth rate is sourced from the LBD (Decker et al., 2016). Data on manufacturing imports and exports for the import penetration ratio come from Schott (2008), while data on manufacturing value added and productivity are from the NBER-CES Manufacturing Industry Database. The firm entry rate is taken from the BDS.

Table 7: Target Moments

Moment	Data	Model	Moment	Data	Model
# of products	2.3	2.3	Avg. productivity growth (%)	1.9	1.9
# of products added	0.3	0.3	High-growth firm growth (%)	22.5	22.3
Firm entry rate (%)	7.6	7.6	Import penetration rate (%)	15.3	15.3

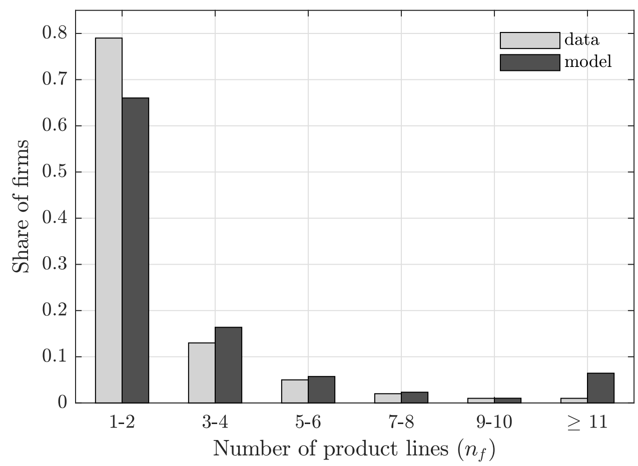

Figure 1: Firm Size Distribution: Theory and Data

percentile) to determine the quality multipliers for own-innovation (λ) and creative destruction (η). Lastly, the mass of potential outside entrants (ε_o) targets the import penetration ratio in manufacturing sector.

4.1.3 Model Properties

The calibration results are presented in Table 7, where our model performs well in matching the target moments overall. In particular, it matches well the number of products and products added. Conditional on the number of products, the number of products added reflects both innovation intensity and the duration for learning the frontier technology in data. These variables may vary across products or technologies, and the learning time may not be strictly annual. By assuming a fixed annual learning duration, the calibration adjusts the R&D cost parameters (innovation intensity) to align the data with the annual frequency of the model.

Targeting the growth of high-growth firms helps us pin down the relative size of the two step sizes λ and η, since creative destruction has a greater impact on the right tail of the firm growth distribution. Our model aligns well with these moments, and the estimated parameter values suggest that creative destruction contributes 1.88 ($\frac{0.075}{0.04}$) times more to growth compared to own-innovation. Also, the estimates satisfy the assumption $\lambda^2 > \eta > \lambda$, even without imposing any parameter restrictions in the calibration process.

As an external validation of our model, Figure 1 compares the firm size distribution (in terms of the number of products) between the model and the data, which is untargeted. While the model exhibits a thicker right tail, indicating more firms with 11 or more products, it aligns closely with the data.[74] Another important untargeted moment is the aggregate R&D to sales ratio.[75] Our model estimate is 4.6%, which is close to the data estimate of 4.1% in Akcigit and Kerr (2018).[76]

4.2 Counterfactual Exercises

Using the calibrated model, we assess the impact of heightened competition on overall firm innovation, the composition of firm innovation, and aggregate growth. To do so, we increase the mass of potential outside entrants $\mathcal{E}_o$ by 83%, corresponding to the rise in import penetration ratio in the U.S. manufacturing sector from 1992 to 2007 (from 15.3% to 25.1%).[77,78]

4.2.1 Increasing Competitive Pressure from Outside Firms

Table 8 shows that an exogenous increase in outside firm entry leads to a rise in the aggregate creative destruction arrival rate $\overline{x}$ and results in three key effects: i) the expected profits of both types of innovations ($\{A_\ell\}_{\ell=1}^4$ and B) decrease, known as the Schumpeterian effect (Panel B); ii) incumbents intensify own-innovation to protect their existing product lines, especially those with a technology gap of $\Delta^\ell > 1$, referred to as the market-protection effect; and iii) the market-protection efforts along with the increase in $\overline{x}$ raise the average technology gap, making it harder

[74] Approximately 60% of firms are single-product firms, but they account for less than 13% of total output (Bernard et al., 2010; Kim and Jo, 2024).

[75] The aggregate R&D to sales ratio is defined as the ratio of total R&D expenses (the sum of R&D expenses for own-innovation and creative destruction) of domestic incumbents to their total sales.

[76] Our model incorporates all resources used for product quality improvement and product scope expansion into R&D expenses, some of which might not be fully captured in the data.

[77] Although we use a trade-related moment in our analysis, we do not intend to assess the effect of trade. We borrow the competition aspect embedded in the trade. For a detailed analysis of the effect of trade on innovation, see Jo (2024), which extends our framework to a two-country model to explore the effects of globalization on business dynamism.

[78] In Online Appendix I, we explore an additional counterfactual analysis involving an increase in the creative destruction arrival rate by domestic startups. This comparison allows us to assess the results in light of varying sources of increased competitive pressure.

Table 8: Counterfactual: Increasing Competitive Pressure in the U.S.

Description	Variables	Before	After	Δ (%)
Panel A: Changes in Firm Innovation				
creative destr. arrival rate by outside firms (%)	$\overline{x}_o$	3.3	5.5	66.4%
aggregate creative destr. arrival rate (%)	$\overline{x}$	21.5	21.9	1.51%
prob. of own-innovation ($\Delta^1 = 1$, %)	z^1	16.9	16.8	-0.43%
prob. of own-innovation ($\Delta^2 = \lambda$, %)	z^2	57.8	57.9	0.19%
prob. of own-innovation ($\Delta^3 = \eta$, %)	z^3	39.7	39.7	0.13%
prob. of own-innovation (%) ($\Delta^4 = \frac{\eta}{\lambda}$, %)	z^4	37.3	37.4	0.05%
prob. of creative destr., incumbents (%)	x	16.8	16.5	-1.33%
prob. of creative destr., potential startups (%)	x_e	4.02	3.97	-1.33%
Panel B: Changes in Innovation Values				
Average of own-innovation values	$\overline{A}$	0.167	0.165	-1.04%
Creative destruction value	B	0.011	0.011	-2.6%
Panel C: Changes in Technology Gap Distribution				
Technology gap distribution (shares)	$\Delta^1 = 1$	0.541	0.539	-0.4%
	$\Delta^2 = \lambda$	0.314	0.314	0.2%
	$\Delta^3 = \eta$	0.116	0.118	1.1%
	$\Delta^4 = \frac{\eta}{\lambda}$	0.028	0.029	1.4%

for firms to take over product markets via creative destruction, labeled as the technological barrier effect (Panel C).[79] This effect arises as creative destruction by outside firms and successful own-innovation shift the technology gap distribution. Specifically, the density of Δ^2, Δ^3, and Δ^4 increases, reducing the conditional takeover probability and the ex-ante value of successful product takeover.[80] Consequently, firm incentives for creative destruction and domestic firm entry get reduced, which contributes to the decline observed in x and x_e in Table 8. Our novel mechanism comes through ii) and iii).

In the general equilibrium, these effects come into play together and interact. For example, the technological barrier effect in iii) additionally influences the aggregate creative destruction arrival rate $\overline{x}$, causing a feedback loop involving i) to iii). The total decline in x and x_e in Table 8 results from the combined impact of the Schumpeterian and technological barrier effects.[81]

Finally, Table 9 summarizes how aggregate variables change in response to the increased compet-

[79] $\overline{A} \equiv \sum_{\ell=1}^{4} A_\ell \mu(\Delta^\ell)$. Table H.1 in Online Appendix H presents details for the changes in $\{A_\ell\}_{\ell=1}^{4}$.

[80] $\overline{x}_{\text{takeover}}$ decreases from 73.2% to 73.0%. The increase in densities $\mu(\Delta^3)$ and $\mu(\Delta^4)$ is solely attributed to increased creative destruction by outside firms. The higher density of Δ^2 reflects both increased own-innovation driven by the market-protection effect and creative destruction by outside firms.

[81] A decomposition reveals that 17.0% and 15.0% of the total change in x and x_e are ascribed to the technological barrier effect (due to the shifts in $\mu(\Delta^\ell)$, given all else equal).

Table 9: Changes in Aggregate Moments

Description	Before	After	% Change
Panel A: Changes in the Aggregate Moments			
R&D to sales ratio (%)	4.6	4.5	-1.6%
Creative destruction R&D intensity (%)	63.9	63.1	-1.2%
Average number of products	2.3	2.2	-5.5%
Total mass of domestic firms	0.39	0.36	-6.4%
Panel B: Changes in the Aggregate Growth and Decomposition			
Average productivity growth by domestic firms (%)	1.9	1.7	-11.0%
Growth from domestic own-innovation (%)	1.0	0.9	-11.4%
Growth from domestic creative destruction (%)	0.7	0.6	-13.0%
Growth from domestic startups (%)	0.2	0.2	-1.7%

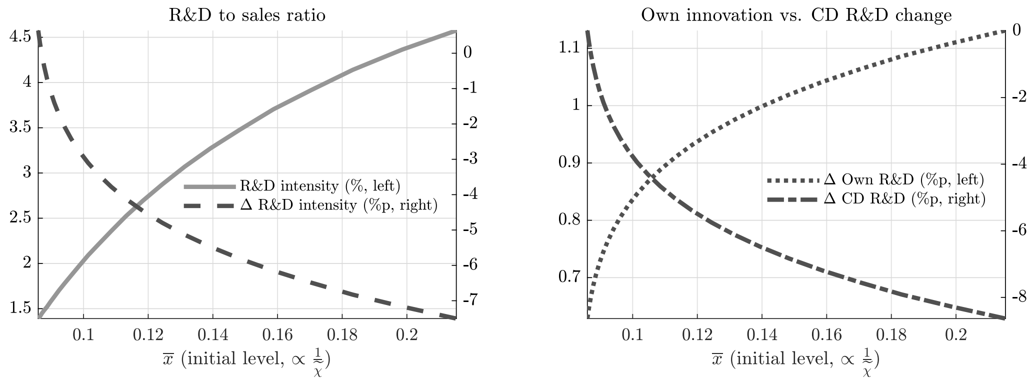

Figure 2: Decomposition of Innovation Change Across different $\widetilde{\chi}$

itive pressure from outside firms. The aggregate R&D to sales ratio of domestic incumbents drops, indicating that the decrease in creative destruction outweighs the increase in own-innovation. Thus, creative destruction R&D intensity—the ratio of domestic R&D expenses for creative destruction to total R&D expenses—decreases. The average number of products per firm falls, aligning with the empirical findings in Bernard et al. (2011). Furthermore, the total number of domestic firms falls.

Most importantly, Panel B shows that the average productivity growth of domestic firms (g_d) declines. This decrease is attributed to shifts in firm-level innovation intensities and the mass of firms. Keeping the mass of domestic incumbents constant, 12.7% of this decline in growth can be attributed to changes in firm-level creative destruction.[82]

[82]For more detailed breakdowns, refer to Tables H.2 and H.3 in Online Appendix H. Note that if taking into account the contribution of outside firms, the aggregate growth rate increases.

Table 10: Aggregate Moment Comparison: U.S. vs. High-Cost Economy

Moment	Baseline	High-Costs	After Shock	Δ (%)
R&D to sales ratio (%)	4.58	1.39	1.41	1.0%
Creative destr. R&D intensity (%)	63.9	8.6	7.8	-9.8%
Average number of products	2.3	1.0	1.0	-0.2%
Avg. growth by domestic firms (%)	1.9	1.4	1.3	-9.7%

4.2.2 Comparison: Economy with High Creative Destruction Costs

To compare implications across environments with different innovation structures, we re-assess the model to hypothetical economies characterized by lower creativity (less creative destruction due to higher frictions) compared to the U.S. Specifically, we increase the parameter associated with creative destruction costs ($\widetilde{\chi}$) from its baseline value of 0.405, while keeping other parameters unchanged. We then perform the same counterfactual analysis.

Figure 2 shows the results across different initial levels of $\overline{x}$ (reflecting different degrees of initial competitive pressure) corresponding to varied values of $\widetilde{\chi}$ (that negatively affects $\overline{x}$). The U.S. economy represents the highest $\overline{x}$ level in the figures. The left panel shows the initial R&D to sales ratios and their changes following a competitive pressure shock, and the right panel breaks down the latter into the changes in own-innovation and creative destruction (CD).

Across all initial values of $\widetilde{\chi}$, own-innovation R&D expenses rise as competitive pressure intensifies, while creative destruction R&D expenses decline. However, the decline in creative destruction R&D is more pronounced when its cost $\widetilde{\chi}$ is low (high initial $\overline{x}$). While both types of innovation respond similarly across different economies, own-innovation increases more than the decline in creative destruction when creative destruction is more costly (lower initial $\overline{x}$), whereas the opposite holds when it is less costly (higher initial $\overline{x}$).[83] Thus, in economies with high creative destruction costs, aggregate R&D rises in response to competitive pressure, in contrast to the U.S. where it declines.

Table 10 compares aggregate moments between the U.S. and an economy with high creative destruction costs ($\widetilde{\chi} \times 80$), as well as the response of the latter economy to a competition shock. The first two columns show that the low creativity economy exhibits lower dynamism than the U.S. with less R&D, fewer products, and lower average productivity growth. The last two columns indicate

[83]See Table H.4 in Online Appendix H for detailed results when $\widetilde{\chi}$ is 80 times higher than the U.S.

that both economies respond similarly to increased foreign competition, except for the R&D to sales ratio, where the difference arises from the initially lower level of creative destruction in the low creativity economy. Despite the increased domestic innovation, the growth attributable to domestic innovation drops in this economy. The reduction is associated with decreases in creative destruction by domestic incumbents and startups, coupled with a decline in the mass of domestic incumbents.[84]

4.2.3 Policy Implications

Our results highlight the importance of examining innovation composition in evaluating the aggregate implications of innovation and informing effective policy design. The two types of innovation contribute differently to the economy, even at the individual level, and interact in ways that shape aggregate outcomes. Increased overall innovation driven by defensive own-innovation may be less beneficial than it appears, as it contributes less to economic growth than creative destruction and restricts firm entry. This underscores the nuanced effects of heightened competition, which, in low-creativity economies, can exacerbate the challenge of insufficient creative destruction.

The differences between the two innovation types extend beyond what is addressed in our paper. Peters (2020), for example, shows that creative destruction reduces misallocation by limiting the accumulation of market power by incumbents. This supports our claim that increases in overall innovation are not always unambiguously beneficial. Given their differing impacts on growth, market power, and resource allocation, policies that fail to account for these distinctions may lead to unintended economic consequences.

Moreover, understanding the composition of innovation can help reconcile disparate findings in the literature. For example, if European economies face higher creative destruction costs due to barriers such as complex approval processes or stringent labor regulations (Peters, 2020; Aghion et al., 2023), our model predicts that increased foreign competition could raise overall innovation in Europe (e.g., Bloom et al., 2016), primarily through shifts in innovation composition. This perspective extends Aghion et al. (2005) by integrating multiple strands of literature and emphasizing compositional changes as a key mechanism in determining the aggregate effects of competition.

[84]The version with a fixed mass of firms is presented in Table H.5 in Online Appendix H. Note that this pattern holds even without the effect of the changes in firm mass.

In summary, our analysis highlights that innovation composition is pivotal in understanding the effects of competition on economic outcomes. Policies that overlook the distinct contributions of own-innovation and creative destruction risk misjudging their aggregate implications.

5 Conclusion

This paper investigates firm innovation incentives in the presence of imperfect technology spillovers and their aggregate implications. We show that learning frictions enable incumbents to strategically use own-innovation to protect their markets, thereby deterring rival entry and stifling creative destruction. Heightened competition amplifies these strategic choices and endogenous interactions, leading to shifts in the composition of innovation. Consequently, the overall impact of competition on innovation depends on the varying magnitudes of these shifts, which can differ across environments with different innovation cost structures. Our paper provides new insights into how firms strategically use innovations under learning frictions and how the strategic innovation decisions of firms impact the composition of innovation and the aggregate outcome. In addition, this framework bridges gaps in the existing literature, reconciles previous findings, and deepens our understanding of the complex relationship between competition and firm innovation.

Supplementary material

Supplementary materials are provided in the Online Appendix.

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