

Heterogeneous Innovations and Growth under Imperfect Technology Spillovers*

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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 learning frictions intensify or competitive pressure rises 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

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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 induce strategic innovation behavior and create distinct and important aggregate implications.

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? 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 in learning frictions or competitive pressure. Empirically, we link U.S. administrative firm-level data to the patent database and document new facts on innovation heterogeneity and compositional responses to exogenous variation in learning time and competition. Finally, we calibrate the model and quantify the aggregate implications of learning frictions and competition across 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 quality and learning. Individual creative destruction contributes more to product quality improvement, thus

¹An 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 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 through creative destruction involves learning and improving incumbents' technology, which demands substantial time and resources.³ Our model features lagged learning as imperfect technology spillovers, requiring potential rivals to spend probabilistically one period learning incumbents' frontier technology. 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.⁴ 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 prior literature. Learning frictions induce strategic innovation behavior and shift the composition of innovation, especially as competitive pressure intensifies. The relative responses of own-innovation and creative destruction therefore shape the aggregate implications importantly.

The strength of our model lies in capturing the strategic role of own-innovation and its feedback effects on rivals' creative destruction and entry. The introduction of imperfect technology spillovers into a multi-product firm framework is a key theoretical advance.⁵ In existing models of multi-

²As 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.

³Creative destruction requires hiring and training workers, reallocating resources, reverse engineering, and preparing facilities for new technologies. For example, despite leveraging iPod-related expertise, Apple still needed about three years to enter the cell phone industry.

⁴Our market-protection effect differs from the escape-competition effect by focusing on leaders' innovation incentives under competitive pressure from entry. This perspective explains why frontier firms such as Google and NVIDIA continue to innovate despite their technological lead, whereas standard step-by-step models with immediate rival catch-up would predict no innovation by such firms.

⁵In this sense, our framework brings together quality-ladder and step-by-step innovations.

product firms growing through product scope expansion, firms cannot protect their markets as rivals instantly learn frontier technology without any frictions (Klette and Kortum, 2004; Akcigit and Kerr, 2018; Peters, 2020).⁶ 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).⁷ This lacks the feedback effects of incumbents’ innovation choices on rivals attempting to enter a product market and does not capture the firm-level innovation composition observed in the data. Our model underscores the central role of innovation composition in understanding the aggregate implications of learning time and competition. Unlike earlier frameworks, own-innovation not only improves incumbent product quality but also suppresses creative destruction and entry, impacting aggregate growth.

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 measure learning time using backward citation gaps—the time between the publication of cited patents and the application of the focal patent—and use self-citation ratio to capture the likelihood that patents are used for own-innovation. To test model predictions, we exploit two quasi-experimental sources of variation: the American Inventors Protection Act (AIPA), which shortened disclosure lags and shifted effective learning time, and the rise in foreign firm entry into U.S. markets following China’s WTO accession in 2001 as an exogenous increase in competitive pressure. We additionally use product-level data to complement our analysis.

Using the pre-shock period, we document differences between own-innovation and creative destruction in learning time, quality improvement, and economic outcomes: patents associated with creative destruction exhibit longer backward citation gaps, higher scientific and market values, and larger contributions to firm growth. Furthermore, we find regression results consistent with the model predictions on learning and “*market-protection*”: lower learning frictions weaken firm incentives for own-innovation, while heightened competition raises own-innovation among firms with technological advantages. We also find supportive evidence for “*technological barrier*” effects

⁶Akcigit and Kerr (2018) is a special case of our model with no technological advantages of firms, implying weaker own-innovation when competition increases.

⁷Cavenaile et al. (2019) is the sole exception, where their model adds Klette and Kortum (2004) superstructure to a step-by-step innovation model with oligopolistic competition.

that strategic own-innovation hampers creative destruction, entry, and slows diffusion.

Lastly, to understand the aggregate implications, we calibrate our model to the U.S. manufacturing sector and conduct counterfactual exercises of changing learning time and increasing exogenous competitive pressure.⁸ First, with lower learning time, firms decrease own-innovation and increase creative destruction, shifting innovation composition. This raises aggregate growth and welfare. We also find that changes in innovation-related factors (e.g., technological shifts), rather than the structural learning probability itself, contributed more to the change in learning time observed between 1992 and 2007. On the other hand, with increased competitive pressure, firms increase (decrease) own-innovation for products with a (no) technological advantage, while creative destruction drops across all firms. This leads to the decline in aggregate growth by domestic firms and welfare. We also compare the latter implication in a hypothetical economy with higher creative costs.⁹ We find qualitatively similar results at the firm level, but overall innovation still goes up in this economy with initially low levels of creative destruction. However, the aggregate growth still falls as in the U.S. as the rise of innovation is driven by strategic own-innovation that elevates technological barriers and impedes creative destruction by domestic incumbents and firm entry.

Our paper develops a unified framework that characterizes firm innovation choices under learning frictions and examines their implications for the aggregate economy. Learning frictions shift the composition of innovation through firms' strategic responses, providing a key margin for understanding the heterogeneous impact of competition and its aggregate consequences across diverse economic environments.

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 with 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 product switching,

⁸Additional counterfactual analysis of an increasing domestic firm entry is presented in Online Appendix H.10.

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

heterogeneous innovations and their roles in growth and market power, and cannibalization effects in innovation decisions (Bernard et al., 2010; Akcigit and Kerr, 2018; Atkeson and Burstein, 2019; Garcia-Macia et al., 2019; Peters, 2020; Dhingra, 2013; Acemoglu et al., 2022). Our contribution stems from introducing learning frictions that generate a strategic role for own-innovation and produce feedback effects on creative destruction and entry and providing rich empirical evidence.

Second, our paper relates to the growing literature on technology gaps and spillovers. Previous studies show 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 (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; Akcigit and Ates, 2023). However, they have not identified a definitive mechanism driving this shift. Another body of work studies knowledge diffusion process altered by patent disclosure policy (Baruffaldi and Simeth, 2020; Hegde et al., 2023). Our paper uncovers an endogenous force behind this shift—firms’ strategic innovation under learning frictions and heightened competition—and quantifies its aggregate implications.

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; Autor et al., 2020). 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).¹⁰ However, their analysis is rooted in several assumptions lacking data support and abstracts from discussing the composition of different innovations.¹¹ We contribute by providing a rich theoretical framework of heterogeneous innovations and learning, along with supportive data evidence, which helps reconcile the prior diverging findings. This deepens our understanding of the complex effects of competition on innovation.

The rest of the paper proceeds as follows: Section 2 develops the baseline endogenous growth

¹⁰The former has the “Schumpeterian effect” (laggards) and the “escape-competition effect” (neck-and-neck firms).

¹¹The model assumes single-product firms, a single innovation type, or the immediate imitation by the laggards.

model. Section 3 presents the empirical analysis. 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.¹² The model is distinct in the following dimensions: we (i) introduce a novel friction named “imperfect technology spillovers” by allowing firms to observe the incumbent’s current frontier technology only with probability ω , and to learn only the incumbent’s one-period-lagged technology with probability $1 - \omega$ 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 $q_{j,t-1}$, $\Delta_{j,t} \equiv \frac{q_{j,t}}{q_{j,t-1}}$ —and the learning probability ω ; 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.¹³ We use product quality and technology interchangeably.

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

¹²Exogenous 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.

¹³Superscripts t and $t - 1$ denote the forward ($t + 1$) and previous ($t - 1$) periods, respectively.

$j \notin \mathcal{D}$). 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.¹⁴ Firm f is characterized by the collection of its products $\mathcal{J}^f = \{j : j \text{ is owned by firm } f\}$. They produce at a unit marginal cost in terms of final goods.

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.¹⁵ The R&D output manifests as improving product quality and is realized in the next period.

On top of this, we introduce a friction of imperfect technology spillovers, under which learning an incumbent's technology takes time in the process of creative destruction.¹⁶ We formalize this as lagged learning, assuming creative destruction builds on the past-period technology $q_{j,t-1}$ with probability $(1 - \omega)$ and only the owner of a product line can observe the frontier level of technology $q_{j,t}$ in the market.¹⁷ Following this, given the learning probability ω , a product line can be sufficiently characterized by its quality q_j and technology gap between current and previous

¹⁴In Online Appendix F, we extend the model to a duopoly setting and show that our main results remain robust.

¹⁵Quality in the model is a marginal-cost-adjusted measure that can improve through technological advances or cost reductions, so innovation encompasses both product and process improvements. Firms with inferior technology can therefore compete with frontier firms if their marginal costs are sufficiently lower.

¹⁶See Section 3.2 for empirical results consistent with this.

¹⁷All the aggregate variables and technology gap distribution are publicly observable, and firms make optimal innovation decisions based on it. In this way, a stationary firm-product distribution is well defined.

periods $\Delta_{j,t} = \frac{q_{j,t}}{q_{j,t-1}}$.¹⁸ This friction induces incumbents to strategically use own-innovation to build technological barriers and protect their markets from competitors, named “market-protection effect.”

When two firms are neck and neck in a product line, we assume that the rival firm wins the market with probability κ , and the incumbent firm wins with probability $1 - \kappa$, to make sure each product is produced by only one firm.¹⁹ 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 for analytical tractability. In the quantitative analysis, we allow multiple creative destruction as in Klette and Kortum (2004).²⁰

2.4.1 Own-Innovation

Successful own-innovation improves the current quality $q_{j,t}$ of the product by $\lambda > 1$. The success probability is $z_{j,t}$, which depends on R&D investment $R_{j,t}^{\text{in}}$.²¹ The quality of good j evolves as follows, conditional on the owning firm not displaced by creative destruction: for $\hat{\chi} > 0, \hat{\psi} > 1$,

$$\{q_{j,t+1}^{\text{in}}\} = \begin{cases} \{\lambda q_{j,t}\} & \text{with probability } z_{j,t} \\ \{q_{j,t}\} & \text{with probability } 1 - z_{j,t}, \end{cases} \quad z_{j,t} = \left(\frac{R_{j,t}^{\text{in}}}{\hat{\chi} q_{j,t}} \right)^{\frac{1}{\hat{\psi}}}.$$

2.4.2 Creative Destruction

Successful creative destruction improves the lagged quality of the obtained product by $\eta > 1$. For analytical tractability and expositional simplicity, we assume $\lambda^2 > \eta > \lambda$. $\eta > \lambda$ reflects our empirical findings (in Online Appendix I.6) that creative destruction is of higher quality than own-innovation, and $\lambda^2 > \eta$ reflects the idea that consecutive own-innovations have a substantial impact, enabling incumbents to defend their product lines.²² These assumptions are innocuous; we

¹⁸The technology gap summarizes the incumbent’s technological advantage in the market.

¹⁹This follows the spirit of the coin-toss tiebreaker in Acemoglu et al. (2016). We assume unused technology depreciates so fast that it cannot be profitably built upon, ensuring that creative destruction is undirected and that own-innovation is limited to the current owner.

²⁰More details are provided in Online Appendix E.

²¹Hereafter, 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.

²² $\eta > \lambda$ is also consistent with the findings of Akcigit and Kerr (2018).

relax them and confirm robustness in Online Appendix D.²³

If there is a technology gap in the target product market, the innovating firm learns the frontier technology with probability ω and the lagged technology with probability $1 - \omega$. 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 $\tilde{\chi} > 0$, $\tilde{\psi} > 1$,

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

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

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.²⁵

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.

²³We allow λ and η to be stochastic (even drawn from the same distributions), as in Garcia-Macia et al. (2019), and verify that our main results continue to hold.

²⁴The average quality matters for creative destruction as it is undirected.

²⁵We assume rivals can only observe the distribution of technology gaps (not the specific gap in a given target market) for tractability. If incumbents could signal their gap, firms with Δ^2 or Δ^4 would have the strongest incentives to signal, while Δ^3 firms would not signal if κ is low enough (e.g., with $\kappa = 0$, they never lose the product), and Δ^1 firms remain not signaling. If the success probability of entering Δ^2 or Δ^4 markets is lower than the probability of meeting a Δ^3 firm in random search, rivals target Δ^2 or Δ^4 , and all types optimally choose not to signal (back to the baseline). Otherwise, only Δ^2 and/or Δ^4 would signal, and rivals randomize between Δ^1 and Δ^3 .

Conditional on a technology gap, the incumbent's product quality evolves as:

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

$$\left\{q_{j,t+1} \mid \Delta_{j,t} = \Delta^2\right\} = \begin{cases} \emptyset & , \text{ with prob. } \bar{x}[1 - (1 - \omega)z_j^2] \\ \{q_{j,t}\} & , \text{ with prob. } (1 - \bar{x})(1 - z_j^2) \\ \{\lambda q_{j,t}\} & , \text{ with prob. } (1 - \omega\bar{x})z_j^2 \end{cases} \quad (2)$$

$$\left\{q_{j,t+1} \mid \Delta_{j,t} = \Delta^3\right\} = \begin{cases} \emptyset & , \text{ with prob. } \bar{x}[\omega + (1 - \omega)\kappa(1 - z_j^3)] \\ \{q_{j,t}\} & , \text{ with prob. } [(1 - \omega)(1 - \kappa)\bar{x} + 1 - \bar{x}](1 - z_j^3) \\ \{\lambda q_{j,t}\} & , \text{ with prob. } (1 - \omega\bar{x})z_j^3 \end{cases} \quad (3)$$

$$\left\{q_{j,t+1} \mid \Delta_{j,t} = \Delta^4\right\} = \begin{cases} \emptyset & , \text{ with prob. } \bar{x}[1 - (1 - \omega)(1 - \kappa)z_j^4] \\ \{q_{j,t}\} & , \text{ with prob. } (1 - \bar{x})(1 - z_j^4) \\ \{\lambda q_{j,t}\} & , \text{ with prob. } [(1 - \omega)(1 - \kappa)\bar{x} + 1 - \bar{x}]z_j^4. \end{cases} \quad (4)$$

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

The probability of losing the product (\emptyset) increases with ω . In the extreme case of $\omega = 1$, firms cannot mitigate this risk by raising own-innovation intensity, and all cases collapse to the case of Δ^1 . In this case, incumbents have no technological advantage and lose the product whenever a rival successfully undertakes creative destruction, regardless of their own-innovation outcome.²⁶ More generally with $\omega < 1$, if $\Delta^\ell > 1$, incumbents can still reduce the probability of losing their product lines by investing more in own-innovation.²⁷ Hence, firms have stronger incentives to raise own-innovation efforts for products with technological advantages ($\Delta^\ell > 1$).

For rival firms entering a market, the success probability of product takeover depends not only

²⁶A rival with successful creative destruction attains $q_{j,t+1}^{\text{rival}} = \eta q_{j,t-1}$, which is greater than $\lambda q_{j,t-1}$. The model in Akcigit and Kerr (2018) falls into this case.

²⁷The extent of this reduction depends on the size of the technology gap.

on the success of creative destruction and learning probability ω , but also on the technology gap and the own-innovation intensity of the product owner, even after successful creative destruction.²⁸ Thus, the success probability of product takeover $x_{\text{takeover}} (\equiv x\bar{x}_{\text{takeover}})$ can be decomposed into (i) the success probability of creative destruction x , and (ii) conditional takeover probability $\bar{x}_{\text{takeover}}$, which is defined as

$$\begin{aligned}\bar{x}_{\text{takeover}} = & \mu(\Delta^1) + [1 - (1 - \omega)z^2] \mu(\Delta^2) + [\omega + (1 - \omega)\kappa(1 - z^3)] \mu(\Delta^3) \\ & + [1 - (1 - \omega)(1 - \kappa)z^4] \mu(\Delta^4),\end{aligned}\tag{5}$$

with technology gap distribution $\{\mu(\Delta^\ell)\}_{\ell=1}^4$ (the mass of products with a gap Δ^ℓ).²⁹ Note that $\bar{x}_{\text{takeover}}$ is an increasing function of ω , and becomes one with $\omega = 1$, where incumbents cannot accumulate technological barriers. Furthermore, higher overall innovation intensity (both own-innovation and creative destruction) widens the average technology gap in the economy (with a lowered mass of products with Δ^1).³⁰ This makes firms harder to successfully take over product markets from incumbents, referred to as the “technological barrier effect.” Thus, increased own-innovation by incumbents or higher \bar{x} dampens creative destruction and slows the growth of firms.³¹

2.4.4 Potential Startups

There is a fixed mass of potential domestic startups \mathcal{E}_d that can enter a market through creative destruction. Potential startups choose R&D expenditure R_e^{ex} and decide creative destruction intensity $x_e = (R_e^{\text{ex}} / (\tilde{\chi}_e \bar{q}))^{\frac{1}{\psi_e}}$, where $\tilde{\chi}_e > 0$ and $\tilde{\psi}_e > 1$.

Let $V(\{(q_j, \Delta_j)\})$ denote the value of a firm that has a product with quality q_j and a technology

²⁸See Online Appendix B.2 for the evolution of product quality for rival firms.

²⁹This 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 $1 - (1 - \omega)z^2$; for Δ^3 , it is $\omega + (1 - \omega)\kappa(1 - z^3)$; and for Δ^4 , it is $1 - (1 - \omega)(1 - \kappa)z^4$. 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.

³⁰Higher 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.

³¹This 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.

gap of Δ_j . Then a potential startup's expected profits from entering through R&D is

$$\Pi^e = \tilde{\beta} \mathbb{E} [V(\{q'_j, \Delta'_j\}) | x_e] - \tilde{\chi}_e(x_e)^{\tilde{\psi}_e} \bar{q}, \quad (6)$$

where $\tilde{\beta}$ 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.³² Potential startups choose creative destruction x_e to maximize expected profits from entry. Given ex-ante firm homogeneity, startups have the same creative destruction intensity x_e^* . The mass of domestic startups attempting to take over product markets with successful creative destruction is $\mathcal{E}_d x_e^*$.

2.5 Exogenous Competitive Pressure and Creative Destruction

As explained before, the aggregate creative destruction arrival rate \bar{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.³³ Let \bar{x}_d denote the total mass of domestic firms with successful creative destruction and \bar{x}_o denote the outside firms' counterpart. The creative destruction arrival rate is $\bar{x} = \bar{x}_d + \bar{x}_o$. Competitive pressure from outside firms is captured by an exogenous increase in \bar{x}_o , resulting from either increased creative destruction intensity or a larger mass of outside firms.³⁴

³² $\tilde{\beta} = \frac{\beta C}{C'}$ as the household owns all firms.

³³This 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 the result still holds with additional aggregation across products within successful firms.

³⁴Jo (2024) extends our baseline model to a two-country framework and endogenizes the changes in \bar{x}_o driven by the changes in bilateral tariff rates.

2.6 Equilibrium

2.6.1 Optimal Production and Employment

The final goods producers choose labor and intermediate goods. Letting p_j and w denote the price of differentiated product j and wage, respectively, the inverse demand for intermediate good j is: $p_j = q_j^\theta L^\theta y_j^{-\theta}$.

Intermediate producers take the demand function as given and maximize their operating profits $\pi(q_j)$ for each product $j \in \mathcal{J}^f$.³⁵ Each product is assumed to be supplied by a single firm, and we follow Acemoglu et al. (2012) and Acemoglu et al. (2018) assuming 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.³⁶ The optimal production and price are derived as:

$$y_j = (1 - \theta)^{\frac{1}{\theta}} q_j \quad \text{and} \quad p_j = \frac{1}{1 - \theta}, \quad (7)$$

which simplifies the equilibrium profit, wage, and final goods output as follows:

$$\pi(q_j) = \underbrace{\theta(1 - \theta)^{\frac{1-\theta}{\theta}} q_j}_{\equiv \pi}, \quad w = \theta(1 - \theta)^{\frac{1-2\theta}{\theta}} \bar{q}, \quad \text{and} \quad Y = (1 - \theta)^{\frac{1-2\theta}{\theta}} \bar{q}. \quad (8)$$

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:

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

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

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

³⁶This 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.

factors, including the success probability of own-innovation and creative destruction, the creative destruction arrival rate, the outcomes of winning or losing product ownership, and the distribution of the current-period product quality and technology gap.

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

$$V(\Phi^f) = \sum_{\ell=1}^4 A_{\ell} \left(\sum_{j \in \mathcal{J}^f | \Delta_j = \Delta^{\ell}} q_j \right) + B\bar{q} \quad (9)$$

$$z^1 = \left[\tilde{\beta} (\lambda A_2 - A_1)(1 - \bar{x}) / (\hat{\psi}\hat{\chi}) \right]^{\frac{1}{\tilde{\psi}-1}} \quad (10)$$

$$z^2 = \left[\tilde{\beta} (\lambda A_2(1 - \omega\bar{x}) - A_1(1 - \bar{x})) / (\hat{\psi}\hat{\chi}) \right]^{\frac{1}{\tilde{\psi}-1}} \quad (11)$$

$$z^3 = \left[\tilde{\beta} (\lambda A_2(1 - \omega\bar{x}) - A_1((1 - \omega)(1 - \kappa)\bar{x} + 1 - \bar{x})) / (\hat{\psi}\hat{\chi}) \right]^{\frac{1}{\tilde{\psi}-1}} \quad (12)$$

$$z^4 = \left[\tilde{\beta} (\lambda A_2((1 - \omega)(1 - \kappa)\bar{x} + 1 - \bar{x}) - A_1(1 - \bar{x})) / (\hat{\psi}\hat{\chi}) \right]^{\frac{1}{\tilde{\psi}-1}} \quad (13)$$

$$x = \left(\tilde{\beta} A_{\text{takeover}} / (\tilde{\psi}\tilde{\chi}) \right)^{\frac{1}{\tilde{\psi}-1}}, \quad (14)$$

where

$$A_1 = \pi - \hat{\chi} (z^1)^{\hat{\psi}} + \tilde{\beta} [A_1(1 - \bar{x})(1 - z^1) + A_2\lambda(1 - \bar{x})z^1] \quad (15)$$

$$A_2 = \pi - \hat{\chi} (z^2)^{\hat{\psi}} + \tilde{\beta} [A_1(1 - \bar{x})(1 - z^2) + A_2\lambda(1 - \omega\bar{x})z^2] \quad (16)$$

$$A_3 = \pi - \hat{\chi} (z^3)^{\hat{\psi}} + \tilde{\beta} [A_1((1 - \omega)(1 - \kappa)\bar{x} + 1 - \bar{x})(1 - z^3) + A_2\lambda(1 - \omega\bar{x})z^3] \quad (17)$$

$$A_4 = \pi - \hat{\chi} (z^4)^{\hat{\psi}} + \tilde{\beta} [A_1(1 - \bar{x})(1 - z^4) + A_2\lambda((1 - \omega)(1 - \kappa)\bar{x} + 1 - \bar{x})z^4] \quad (18)$$

$$B = \left(\tilde{\beta} x A_{\text{takeover}} - \tilde{\chi} x^{\tilde{\psi}} \right) / \left(1 - \tilde{\beta}(1 + g) \right), \quad (19)$$

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:

$$\begin{aligned} A_{\text{takeover}} \equiv & \mu(\Delta^1) A_3 \eta + \mu(\Delta^2) A_4 \frac{\eta}{\lambda} (1 - \omega)(1 - z^2) + \mu(\Delta^3) A_1 (1 - \omega) \kappa (1 - z^3) \\ & + \mu(\Delta^4) A_2 \lambda (1 - \omega) (1 - (1 - \kappa) z^4) + (1 - \mu(\Delta^1)) A_3 \eta \omega. \end{aligned} \quad (20)$$

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 (15) through (18) 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.³⁷

For the optimal own-innovation (10)-(13), the first term in the brackets (after $\tilde{\beta}$) 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 \bar{x} fixed, the net future value of successful own-innovation depends on the firm's technology gap and learning probability, 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 own-innovation intensities satisfy $z^2 \geq z^3, z^4 > z^1$ for $\omega \in [0, 1)$, where $z^2 \geq z^3 > z^4 > z^1$ for $\kappa \in (\frac{A_1}{\lambda A_2 + A_1}, 1]$; and $z^2 \geq z^4 > z^3 > z^1$ for $\kappa \in [0, \frac{A_1}{\lambda A_2 + A_1})$. If $\omega = 1$, $z^\ell = z \forall \ell \in \{1, 2, 3, 4\}$. 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.

Corollary 2 (Learning Effect). *The impact of learning time reduction (immediate learning probability) ω on innovation intensities is $\frac{\partial z^1}{\partial \omega} \Big|_{A_1, A_2} = 0$, $\frac{\partial z^2}{\partial \omega} \Big|_{A_1, A_2} < 0$, $\frac{\partial z^3}{\partial \omega} \Big|_{A_1, A_2} < 0$, $\frac{\partial z^4}{\partial \omega} \Big|_{A_1, A_2} < 0$, and $\frac{\partial x}{\partial \omega} \Big|_{\{A_\ell\}_{\ell=1}^4} > 0$. Proof: See Online Appendix A.4.*

The optimal own-innovation also depends on the learning probability ω , as shown in Corollary 2:

³⁷To clarify the interpretation of B , rewrite (19) as $B\bar{q} = x\tilde{\beta}A_{\text{takeover}}\bar{q} - \tilde{\chi}x^{\tilde{\psi}}\bar{q} + \tilde{\beta}B(1+g)\bar{q}$. A firm invests $\tilde{\chi}x^{\tilde{\psi}}\bar{q}$ today and, if creative destruction succeeds with probability x , earns $\tilde{\beta}A_{\text{takeover}}\bar{q}$ next period. It then continues investing and receives $B\bar{q}'$ in the following period, where $\bar{q}' = (1+g)\bar{q}$. Thus, B is the annuity value of an infinite stream of constant payoffs $x\tilde{\beta}A_{\text{takeover}} - \tilde{\chi}x^{\tilde{\psi}}$, discounted at the growth-adjusted discount factor $\tilde{\beta}(1+g)$.

a higher ω reduces own-innovation intensities across all technology gaps, but promotes creative destruction.

Corollary 3 (Market-Protection Effect). *With $\hat{\psi} \in (1, 2]$, we have*

$$\frac{\partial z^2}{\partial \bar{x}} \Big|_{A_1, A_2} > \frac{\partial z^3}{\partial \bar{x}} \Big|_{A_1, A_2} > \frac{\partial z^1}{\partial \bar{x}}; \quad \frac{\partial z^2}{\partial \bar{x}} \Big|_{A_1, A_2} > \frac{\partial z^4}{\partial \bar{x}} \Big|_{A_1, A_2} > \frac{\partial z^1}{\partial \bar{x}} \Big|_{A_1, A_2},$$

where $\frac{\partial z^1}{\partial \bar{x}} \Big|_{A_1, A_2} < 0$; and the signs of $\frac{\partial z^{2,3,4}}{\partial \bar{x}} \Big|_{A_1, A_2}$ depend on the ranges of ω and κ as follows:
 $\frac{\partial z^3}{\partial \bar{x}} \Big|_{A_1, A_2} > 0$ if $\omega < \frac{\kappa A_1}{\lambda A_2 - (1-\kappa)A_1}$; $\frac{\partial z^2}{\partial \bar{x}} \Big|_{A_1, A_2} > 0 > \frac{\partial z^3}{\partial \bar{x}} \Big|_{A_1, A_2}$ if $\omega \in (\frac{\kappa A_1}{\lambda A_2 - (1-\kappa)A_1}, \frac{A_1}{\lambda A_2})$; $0 > \frac{\partial z^2}{\partial \bar{x}} \Big|_{A_1, A_2}$ if $\omega > \frac{A_1}{\lambda A_2}$; and $\frac{\partial z^3}{\partial \bar{x}} \Big|_{A_1, A_2} \geq \frac{\partial z^4}{\partial \bar{x}} \Big|_{A_1, A_2}$ if $\kappa \geq \frac{\lambda A_2 + A_1}{A_1}$. *Proof: See Online Appendix A.5.*

It also depends on creative destruction arrival rate \bar{x} as shown in Corollary 3, where firms increase own-innovation with a sufficient level of learning friction and technology gap, referred to as “market-protection effect.”^{38,39}

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 \bar{x} increases. With moderate learning frictions (with sufficiently low ω), the firm has a motive to protect its market through own-innovation, and the strength of this motive varies with the size of its technological advantage. The Δ^2 case delivers the largest effect, as own-innovation most strongly reduces the probability of product loss, consistent with (2). For Δ^3 and Δ^4 , the market-protection motive weakens: higher z^3 or z^4 continues to lower the probability of losing a product, but the magnitude of this reduction is smaller. 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 \bar{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. Furthermore, this motive also depends on the degree of learning frictions: when learning frictions are low (with high ω), firms can face a substantially weaker market-protection motive.⁴⁰

³⁸Note that as A_1 and A_2 also depend on \bar{x} , it is difficult to analytically determine the signs of the partial derivatives of $\{z^\ell\}_{\ell=1}^4$ with respect to \bar{x} . However, by holding the values of A_1 and A_2 fixed, we can explicitly ascertain these signs as in Corollary 3.

³⁹The term A_2 in (10)-(13) reflects the well-known Schumpeterian effect—the lower the expected future profits from keeping the product line through own-innovation, the weaker the incentive to invest in own-innovation.

⁴⁰The extreme case is $\omega = 1$, where all firms can instantaneously catch up to the frontier technology, as in Akcigit

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 (14) and (20) 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”).⁴¹ We provide formal proofs of these predictions in Online Appendix C.

Similarly, the optimal creative destruction by potential startups x_e is derived as follows, with proof provided in Online Appendix A.6:

$$x_e = \left[\tilde{\beta} \left(A_{\text{takeover}} + \bar{x}_{\text{takeover}} B(1 + g) \right) / \left(\tilde{\psi}_e \tilde{\chi}_e \right) \right]^{\frac{1}{\tilde{\psi}_e - 1}}. \quad (21)$$

2.6.3 Aggregate Creative Destruction Arrival Rate

With (14) and (21), the aggregate creative destruction arrival rate is

$$\bar{x} = \underbrace{\mathcal{F}_d x + \mathcal{E}_d x_e}_{\equiv \bar{x}_d} + \underbrace{\mathcal{F}_o x + \mathcal{E}_o}_{\equiv \bar{x}_o}, \quad (22)$$

where \mathcal{E}_o is the total mass of outside entrants with successful creative destruction, which is exogenously determined.^{42,43}

and Kerr (2018), and no firm has any market-protection motive.

⁴¹The responses of $\{z^\ell\}_{\ell=1}^4$ and x to changes in \bar{x} are ambiguous in general equilibrium, as they depend on the relative strengths of the market-protection, technological-barrier, and Schumpeterian effects. However, the numerical results in Section 4.2 show that the partial-equilibrium patterns (given $\{A_\ell\}_{\ell=1}^4$ and B) continue to hold under plausible parameter values. Moreover, both $\{A_\ell\}_{\ell=1}^4$ and B decline when \bar{x} increases exogenously.

⁴²Note that an exogenous increase in \mathcal{E}_o may not increase \bar{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 \bar{x} . Thus, the level of \bar{x} is endogenously determined, even when \mathcal{E}_o changes exogenously.

⁴³Outside firms make the same innovation decisions as domestic firms.

2.7 Balanced Growth Path

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

$$\begin{aligned}
g = & \left[(1 - \bar{x})(1 - z^1) + \lambda(1 - \bar{x})z^1 + \eta\bar{x} \right] \mu(\Delta^1) \\
& + \left[(1 - \bar{x})(1 - z^2) + \lambda(1 - \omega\bar{x})z^2 + \eta\omega\bar{x} + (\eta/\lambda)(1 - \omega)\bar{x}(1 - z^2) \right] \mu(\Delta^2) \\
& + \left[(1 - \omega\bar{x})(1 - z^3) + \lambda(1 - \omega\bar{x})z^3 + \eta\omega\bar{x} \right] \mu(\Delta^3) \\
& + \left[(1 - \bar{x})(1 - z^4) + \lambda((1 - \omega)\bar{x} + (1 - \bar{x})z^4) + \eta\omega\bar{x} \right] \mu(\Delta^4) - 1,
\end{aligned} \tag{23}$$

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.7.*

Proposition 3. *If learning time decreases with higher ω , holding the level of own-innovation and creative destruction fixed, the balanced growth rate g increases (direct effect). The overall effect on the growth rate is ambiguous, depending on the responses of own-innovation and creative destruction, and their composition changes. *Proof: See Online Appendix A.8.**

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 $\tilde{\mu}(\mathcal{N})$ denote its distribution. Summing $\tilde{\mu}(\mathcal{N})$ 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 $\tilde{\mathcal{N}}(n_f, k) \equiv (n_f, n_f - k, k, 0, 0)$, where $k \in [0, n_f] \cap \mathbb{Z}$ and $n_f > 0$. Ignoring creative destruction, the probability of technology gap composition changing from $\mathcal{N} = \tilde{\mathcal{N}}(n_f, k)$ to $\mathcal{N}' = \tilde{\mathcal{N}}(n_f, \tilde{k})$ is

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

for $n_f \geq 1$ and $0 \leq \tilde{k}, k \leq n_f$, 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 $\mathcal{N}' = (n'_f, n_f^{1'}, n_f^{2'}, n_f^{3'}, n_f^{4'})$ 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

$$\mu(\Delta^\ell) = \sum_{n_f=1}^{\bar{n}_f} \sum_{n_f^\ell=0}^{n_f} \sum_{n_f^{-\ell}=0}^{n_f} n_f^\ell \tilde{\mu}(n_f, n_f^1, n_f^2, n_f^3, n_f^4), \text{ for } \ell = 1, 2, 3, 4 \quad (24)$$

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.⁴⁴

2.8.3 Aggregate Variables and Balanced Growth Path

Given the optimal innovation choices [\(10\)](#), [\(11\)](#), [\(12\)](#), [\(13\)](#), [\(14\)](#), and [\(21\)](#), the aggregate domestic R&D expenses becomes

$$R_d = \hat{\chi} \sum_{\ell=1}^4 \left[\int_0^1 q_j \mathcal{I}_{\{\Delta_j=\Delta^\ell, j \in \mathcal{D}\}} dj \right] (z^\ell)^{\hat{\psi}} + \mathcal{F}_d \tilde{q} x^{\tilde{\psi}} + \mathcal{E}_d \tilde{\chi}_e (x_e)^{\tilde{\psi}_e} \bar{q}, \quad (25)$$

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 [\(7\)](#), the aggregate demand for final goods by domestic intermediate producers and the aggregate consumption are given by

$$Y_d = \int_0^1 y_j \mathcal{I}_{\{j \in \mathcal{D}\}} dj = (1 - \theta)^{\frac{1}{\theta}} \int_0^1 q_j \mathcal{I}_{\{j \in \mathcal{D}\}} dj, \quad (26)$$

$$C = Y - \int_{j \notin \mathcal{D}} p_j y_j dj - Y_d - R_d, \quad (27)$$

⁴⁴Each product line is occupied by one incumbent and there is a unit mass of products.

respectively.⁴⁵ The average learning time in the economy is defined as

$$\text{1-period} \times [(1 - \omega)p_{\{1-\omega\}}] / [(1 - \omega)p_{\{1-\omega\}} + \omega(1 - \mu(\Delta^1))], \quad (28)$$

where $p_{\{1-\omega\}} \equiv (1 - z^2)\mu(\Delta^2) + \kappa(1 - z^3)\mu(\Delta^3) + (1 - (1 - \kappa)z^4)\mu(\Delta^4)$ denotes the probability of successfully taking over a product without learning the incumbent's frontier technology (the $1 - \omega$ cases). This accounts for all successful takeovers arising from creative destruction either with the immediate-learning (ω) or the lagged-learning ($1 - \omega$).

Lastly, the balanced growth path (BGP) equilibrium is defined as follows:

Definition 1. A balanced growth path equilibrium consists of $y_j^*, p_j^*, w^*, L^*, x^*, \{z^{\ell*}\}_{\ell=1}^4, \bar{x}^*, x_e^*, \mathcal{F}^*, R_d^*, Y^*, C^*, g^*, \tilde{\mu}(\mathcal{N}), \{\mu(\Delta^\ell)\}_{\ell=1}^4$ for $j \in [0, 1]$ with q_j such that: (i) y_j^* and p_j^* satisfy (7); (ii) w^* satisfies (8); (iii) L^* satisfies the labor market clearing condition, $L = 1$; (iv) $\{z^{\ell*}\}_{\ell=1}^4$ satisfy (10)-(13), and x^* satisfies (14); (v) \bar{x}^* satisfies (22); (vi) x_e^* satisfies (21); (vii) Y^* satisfies (8); (viii) R_d^* satisfies (25); (ix) C^* satisfies (27); (x) the BGP growth rate g^* satisfies (23); (xi) the distribution of technology gap portfolio composition $\tilde{\mu}(\mathcal{N})$ and \mathcal{F}^* satisfy $\text{inflow}(\mathcal{N}) = \text{outflow}(\mathcal{N})$; and (xii) the technology gap distribution $\{\mu(\Delta^\ell)\}_{\ell=1}^4$ follows (24).

3 Empirics

3.1 Data and Measurement

To test the model, we construct a comprehensive dataset of the universe of patenting firms or manufacturing sector in the U.S., combining 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. In LBD, we measure firm size using employment

⁴⁵The second term in (26) is the payments to outside intermediate producers, and we assume outside firms use final goods from their economy for production and R&D.

or payroll, and firm age by the age of the oldest establishment at the time the firm first appears in the data. Firm industry is the six-digit NAICS code with the largest employment.

The USPTO dataset records comprehensive information on all patents granted since 1976. We measure firm innovation using the citation-adjusted count of utility patents, indicating innovations by application year. Patents are linked to LBD firms via name–address matching supplemented by the internet-search–aided algorithm of [Autor et al. \(2020\)](#).⁴⁶

The CMF provides detailed quinquennial data on manufacturing firms, including product codes (five-digit SIC or seven-digit NAICS) and shipment values. The LFTTD reports the shipment values, trading partners, and export/import status of firms from 1992. U.S. tariff schedules from [Feenstra et al. \(2002\)](#) are used to construct industry-level Trade Policy Uncertainty as a measure of competitive pressure. All nominal values are normalized at 1997 using industry-level deflators from the NBER CES Manufacturing Industry Database and the CPI for non-manufacturing industries.⁴⁷

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. Further data details are provided in Online Appendix I.1, along with summary statistics reported in Online Appendix I.2.

3.1.1 Own-innovation vs. Creative Destruction

We follow [Akçigit 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. A higher (lower) self-citation ratio implies a greater probability that a patent reflects own-innovation (creative destruction). 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).⁴⁸

⁴⁶See [Ding et al. \(2022\)](#) for details; the same is used for the Compustat–USPTO linkage.

⁴⁷NBER CES data are available at www.nber.org/nberces.

⁴⁸Alternatively, 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. We also measure creative destruction by the number of new products added.

3.1.2 Learning Time

We measure learning time by the gap between a patent’s application year and the publication dates of the patents it cites, referred to as backward citation gaps.⁴⁹ For each patent, we compute either the average or the minimum of its backward citation gaps. Our baseline measure uses the minimum gap, which provides a conservative estimate and mitigates any mechanical increase in backward citation gaps for more recent patents. When counting citations, we exclude those added by examiners, as they may not reflect the assignee’s own learning process. The baseline measure further restricts the sample to non-expired patents to avoid potential biases related to infringement avoidance.⁵⁰

To test the effect of changes in learning probability, we exploit the American Inventors Protection Act (AIPA), which mandates that patents filed after November 28, 2000 be published 18 months after filing. This policy accelerated disclosure and is expected to enhance knowledge diffusion (Hegde et al., 2023), corresponding to a higher ω in the model. We use CPC-group–level variation in the application–grant gap in the pre-AIPA period to capture differential exposure to the policy: because the AIPA disproportionately shortens informational exclusivity for patents with longer pre-grant delays, its impact should be stronger in technologies with longer grant lags.⁵¹

3.1.3 Exogenous Competition Shock

We use the removal of trade policy uncertainty (TPU) as a measure of an exogenous competitive pressure shock as the removal of TPU encouraged Chinese firms to enter U.S. markets and export their products (Pierce and Schott, 2016; Handley and Limão, 2017). This maps into an increase in \bar{x}_o in our model. Specifically, we use the 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 in 2001.⁵² For multi-industry firms, we use the employment-weighted

⁴⁹Patent publication timing varies across institutional regimes. Specifically, for patents applied before 1999, the publication year corresponds to the grant year. For patents applied after 1999, under the American Inventors Protection Act (AIPA), the publication year is defined as the earlier of the grant year and the application year plus 1.5 years.

⁵⁰According to the USPTO, patents granted on continuation, divisional, or continuation-in-part applications filed on or after June 8, 1995, have a term of twenty years from the filing date. For patents in force on June 8, 1995, or issued on applications filed before that date, the term is the longer of twenty years from filing or seventeen years from the grant date. Further details are available at www.uspto.gov/web/offices/pac/mpep/s2701.html. We exclude self-citations except for the analysis in Section 3.2, where self-citations are used for the degree of own-innovation.

⁵¹Baruffaldi and Simeth (2020) and Hegde et al. (2023) use twin patents to identify the causal effect of the AIPA, which is an ideal and more direct strategy when data permit.

⁵²The background for this measure is provided in Online Appendix I.4.

Table 1: Backward Citation Gap and Self-Citation Ratio

	Citation gaps	Citation gaps	Citation gaps	Citation gaps
Self-citation ratio	-1.576*** (0.014)	-1.663*** (0.015)	-1.774*** (0.017)	-1.814*** (0.017)
Observations	740,908	740,908	740,908	740,908
Fixed effects	none	<i>ct</i>	<i>i, t</i>	<i>i, ct</i>

Notes: Constant terms are omitted for brevity. Robust standard errors are displayed below each coefficient. Observations are unweighted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

average of it.

3.2 Learning and Innovation Heterogeneity

One of the key features underlying innovation heterogeneity is learning process, which is the novel ingredient in our model. We present empirical evidence on it.⁵³ We focus on the pre-2000 sample in this analysis, since structural changes after 2000—such as the rise of competition and policy reforms—shifted firm innovation behavior and may confound our results.

Using U.S. patents and assignee data from 1982 to 1999, we test that learning others’ technologies takes time in the process of creative destruction, a key assumption and contribution of our model, with the following regression:

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

where $CitationGap_{ipct}$ represents the minimum 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_i is a firm 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).⁵⁴ We test the robustness of our results using the average backward citation gap, controlling for the technological diversity of cited patents, the number of cited patents,

⁵³We also document innovation heterogeneity in quality improvement and growth in Online Appendix I.6.

⁵⁴While 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.

and the trend in patent filings captured by the number of patents or assignees within a CPC technology group. Online Appendix I.5 presents the robustness of the results.

Firm innovation incentives also depend on the degree of knowledge diffusion and learning probability (Corollary 2). With a higher learning probability, firms reduce own-innovation, while intensifying creative destruction. To test this prediction, we exploit the AIPA-induced change in publication lags and estimate the following firm-level Difference-in-Difference (DD) regression:

$$\Delta y_{icp} = \beta_1 Post_p \times AIPA_c + \beta_2 AIPA_c + \mathbf{X}_{cp0} \gamma + \delta_s + \delta_p + \alpha + \varepsilon_{icp}, \quad (29)$$

where $p \in \{1992-1999, 2000-2007\}$. y_{icp} denotes the citation-weighted average self-citation ratio for firm i in CPC group c , and Δy_{icp} is its DHS (Davis et al., 1996) growth rate between the start and end years of each period p .⁵⁵ $AIPA_c$ measures the average gap between application and grant years over 1995–1999 in the firm’s main CPC group c , capturing the extent of delayed disclosure prior to the AIPA. We control for the number of patent filings and assignees in CPC group c at the beginning of each period through \mathbf{X}_{cp0} , and include CPC-section and year fixed effects, δ_s and δ_p , respectively. 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.

Table 2 presents the results, showing that $\beta_1 < 0$. This supports the model’s prediction that a higher learning probability (triggered by the AIPA) dampens firms’ incentives for own-innovation.⁵⁶

3.3 Market-Protection Effect

Next, we validate the “market-protection effect” in the model (Corollary 3). Following Pierce and Schott (2016), we use a Difference-in-Difference (DD) specification to identify the effect of

⁵⁵The 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.

⁵⁶Due to space limit, Table 2 reports the main coefficient estimates for the DD-term only. The full results are available upon request.

Table 2: AIPA and Innovation Composition

	$\Delta\text{Self-cite}$	$\Delta\text{Self-cite}$	$\Delta\text{Self-cite}$	$\Delta\text{Self-cite}$
AIPA \times Post	-0.652*** (0.215)	-0.646*** (0.228)	-0.635*** (0.218)	-0.620*** (0.227)
Observations	10,108	10,108	10,108	10,108
Fixed effects	p	p	s, p	s, p
Controls	no	baseline	no	baseline

Notes: Robust standard errors, clustered at the CPC technology group level, are reported below each coefficient. The first two columns include period fixed effects only, while the remaining columns include both CPC section and period fixed effects. Baseline controls include the number of patents and assignees in each CPC group at the beginning of the period. Observations are unweighted. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

increasing competitive pressure from Chinese firm entry on the U.S. firm innovation, as follows:

$$\begin{aligned}
\Delta y_{ijp} = & \beta_1 Post_p \times NTRGap_{ijp0} \times InnovIntens_{ijp0} + \beta_2 Post_p \times NTRGap_{ijp0} \\
& + \beta_3 Post_p \times InnovIntens_{ijp0} + \beta_4 NTRGap_{ijp0} \times InnovIntens_{ijp0} \\
& + \beta_5 NTRGap_{ijp0} + \beta_6 InnovIntens_{ijp0} + \mathbf{X}_{ijp0}\gamma_1 + \mathbf{X}_{jp0}\gamma_2 \\
& + \delta_j + \delta_p + \alpha + \varepsilon_{ijp},
\end{aligned} \tag{30}$$

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 (own-innovation intensity) for firm i in industry j , and Δy_{ijp} is the DHS growth rate of y between the start-year and end-year for each period p . The sample comprises all patenting LBD firms meeting the same sampling criteria as before and excludes the FIRE 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, and δ_p is a period fixed effect. 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

Table 3: Market-Protection Effect

	$\Delta\text{Patents}$	$\Delta\text{Patents}$	$\Delta\text{Self-cite}$	$\Delta\text{Self-cite}$
NTR gap \times Post	0.238 (0.237)	0.071 (0.283)	-0.075 (0.257)	-0.062 (0.291)
\times Innovation intensity	0.077 (0.231)	-0.054 (0.242)	0.732** (0.299)	0.795*** (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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

to total employment for firm i . This proxies the technological advantage the firm has. 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.

Table 3 presents the regression results, which align with our model predictions in several dimensions.⁵⁷ 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. 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, the last two columns show the positive and statistically significant effect on own-innovation.⁵⁸ 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.

⁵⁷To conserve space, Table 3 reports the main coefficient estimates for the triple interaction and the DD-term only. The full results are available upon request.

⁵⁸As 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.

The estimated effect is economically important as well. In Online Appendix Table I.11, we document a positive association between firm-level patenting and employment growth. The market-protection effect indicates that the association 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.⁵⁹

In Online Appendix I.7 and I.8, we confirm the validity of our identification and the robustness of the results across several dimensions. In Online Appendix I.9, we also test the consequences of market-protection effect in the model, which raises “technological barrier” to competitors. We find that this increases learning times and reduces firm entry into a market.

4 Quantitative Analysis

We calibrate the model to the U.S. manufacturing sector in 1992 and conduct several counterfactual exercises. We now expand the baseline model in Section 2 by allowing multiple simultaneous creative-destruction, depending on a firm’s number of products, as in Klette and Kortum (2004).⁶⁰

4.1 Calibration

There are fourteen parameters in the model, as listed in the upper panel of Table 4. The seven parameters in the left column are externally calibrated, while the seven parameters in the right column are internally calibrated to match moments associated with firm-level variables and the import penetration ratio in the U.S. manufacturing sector.⁶¹ We use the import penetration ratio because it is an observable moment that partially reflects an exogenous change in competitive pressure. One period in the model corresponds to six years, and we report annualized values for target moments.

⁵⁹Similar implications can also be inferred for productivity growth and the intensity of adding a new product or entering a new industry, which proxy creative destruction.

⁶⁰See Online Appendix E and G for further details and computational algorithms.

⁶¹The 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. The average learning time is taken from the USPTO PatentsView database.

Table 4: Parameter Estimates and Target Moments

Panel A: Parameter estimates					
External calibration			Internal calibration		
Param.	Description	Value	Param.	Description	Value
β	Time discount rate	0.721	$\hat{\chi}$	Scale, own-innov.	0.016
$\hat{\psi}$	Curvature, own-innov.	2.000	$\tilde{\chi}$	Scale, creative dest.	0.024
$\tilde{\psi}$	Curvature, creative dest.	2.000	$\tilde{\chi}^e$	Scale, startup R&D	0.126
$\tilde{\psi}^e$	Curvature, startup R&D	2.000	λ	Step size, own-innov.	1.123
θ	Qual. share, final goods	0.109	η	Step size, creative dest.	1.239
κ	Coin toss winning prob.	0.500	ω	Learning prob.	0.296
\mathcal{E}_d	Mass of dome. startups	1.000	\mathcal{E}_o	Mass of out. entrants	0.021

Panel B: Target moments					
Moment	Data	Model	Moment	Data	Model
# of products	2.3	2.1	Productivity growth (%)	1.9	1.9
# of products added	0.3	0.2	High-growth firm growth (%)	22.5	22.5
Firm entry rate (%)	7.6	7.6	Average learning time	2.3	2.2
			Import penetration rate (%)	15.3	15.3

The discount factor (β) is set to 0.721, mapping into an annual interest rate of 5.6% over a six-year horizon. The curvature parameters of the three R&D cost functions ($\hat{\psi}$, $\tilde{\psi}$, $\tilde{\psi}^e$) are taken from [Acemoglu et al. \(2018\)](#) and [Akcigit and Kerr \(2018\)](#). We set the average profit-to-sales ratio θ ($= \int_f \frac{\text{profit}_f}{\text{sales}_f} df$) to match the quality share in final goods production (10.9%) reported in [Akcigit and Kerr \(2018\)](#). The baseline coin-toss winning probability (κ) is set to 0.5, and we show in Online Appendix H.3 and H.6 that setting it to zero (giving incumbents full product-retention probability) does not materially affect the results. We normalize the mass of potential domestic startups (\mathcal{E}_d).

The remaining seven parameters are internally calibrated to minimize the objective function, $\min \sum_{i=1}^7 \frac{|\text{model moment}_i - \text{data moment}_i|}{\frac{1}{2}|\text{model moment}_i| + \frac{1}{2}|\text{data moment}_i|}$, with the seven target moments in the lower panel of Table 4. 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 ($\hat{\chi}$, $\tilde{\chi}$) are set to match the average number of products and the number of products added per firm. The startup R&D scale ($\tilde{\chi}^e$) matches the firm entry rate. We target the average productivity growth rate and the employment growth rate of high-growth firms (90th percentile) to determine the quality multipliers for own-innovation (λ) and creative destruction (η). The immediate learning probability (ω) targets the average learning time, 2.3 years, estimated in the patent data.⁶² Lastly, the mass of

⁶²The 10th/90th percentiles of learning time distribution is 0.17, 6.17 years, respectively, and the average is 2.47

potential outside entrants (ε_o) targets the import penetration ratio in manufacturing sector.

The calibration results are presented in the bottom panel of Table 4, where our model performs well in matching the target moments overall. 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 1.94 ($\frac{0.239}{0.123}$) 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.

We further validate the model using several untargeted moments. The model generates an aggregate R&D-to-sales ratio of 4.1% and an R&D-to-GDP ratio of 2.8%, which closely match the data counterparts of 4.1% and 2.5%.⁶³ We also find that the size distribution of firms—measured by the number of products—matches the data well, as shown in Online Appendix H.1.

4.2 Counterfactual Exercises

We consider two counterfactual exercises: (i) changing learning probability and (ii) increasing exogenous competitive pressure in the U.S. vs. non-U.S.

4.2.1 Changing Learning Probability

As a counterfactual, we increase the probability of learning, ω , by 63.5%, which reduces the average learning time by 19.1%.⁶⁴ Table 5 presents the results. First, we find lower R&D investment in own-innovation (across all technology gaps) but higher creative destruction (Panel A). This is because incumbents' ability to protect their markets by leveraging accumulated technological advantage is weakened with the reduction in learning time. This pattern is consistent with Corollary 2. Since creative destruction contributes 1.94 times more to growth than own-innovation, the shift raises the

years over 1982–1999. Normalizing the three values with 0.17, we set in our model that one period is six years, and the average learning time is 2.3 years.

⁶³We use the aggregate R&D-to-sales ratio from Akcigit and Kerr (2018), computed for firms with positive R&D spending, and measure the R&D-to-GDP from the U.S. National Science Foundation's National Patterns of R&D Resources.

⁶⁴This corresponds to the AIPA-induced reduction in average disclosure lags observed in USPTO patent data between 1992 and the post-AIPA period. The counterfactual therefore isolates the effect of the AIPA after 2000, assuming expedited disclosure proportionally shortens learning time.

Table 5: Counterfactual: Decreasing Average Learning Time in the U.S.

Description	Variables	Before	After	Δ (%)
Panel A: Changes in Firm Innovation				
aggregate creative destr. arrival rate (%)	\bar{x}	76.8	93.7	22.1%
prob. of own-innovation ($\Delta^1 = 1$, %)	z^1	8.10	1.29	-84.1%
prob. of own-innovation ($\Delta^2 = \lambda$, %)	z^2	80.4	52.5	-34.7%
prob. of own-innovation ($\Delta^3 = \eta$, %)	z^3	53.7	31.8	-40.9%
prob. of own-innovation ($\Delta^4 = \frac{\eta}{\lambda}$, %)	z^4	44.3	26.9	-39.3%
prob. of creative destr., incumbents (%)	x	62.6	77.2	23.4%
prob. of creative destr., potential startups (%)	x_e	11.8	14.6	23.4%
Panel B: Changes in Aggregate Moments				
R&D to sales ratio (%)		4.1	4.1	0.6%
Average number of products		2.1	1.6	-23.8%
Panel C: Changes in Aggregate Growth and Decomposition				
Avg. productivity growth by domestic firms (%)		1.9	2.3	19.7%
Growth from domestic own-innovation (%)		0.7	0.3	-64.0%
Growth from domestic creative destruction (%)		1.0	1.7	72.3%
Growth from domestic startups (%)		0.2	0.4	67.3%

Table 6: Counterfactual: Setting ω to Its 1992 Value in the 2007 U.S. Economy

Description	Variables	1992	2007	w/ ω_{1992}	Δ (%)
Learning probability	ω	0.275	0.329	0.275	19.6%
Panel A: Changes in Firm Innovation					
Avg. prob. of own-innovation (%)	\bar{z}	56.9	37.2	40.4	8.7%
prob. of creative destr., incumbents (%)	x	62.6	27.4	26.6	-2.8%
Panel B: Changes in Aggregate Moments					
Avg. growth by domestic firms (%)		1.94	0.93	0.92	-0.6%
Average number of products		2.12	1.77	1.78	0.5%
R&D to sales ratio (%)		4.09	2.60	2.64	1.7%
Average learning time		2.20	2.58	2.73	5.9%

aggregate growth rate accounted for by domestic firms by 19.7% (Panel C).⁶⁵ These changes raise welfare by 1.4% in consumption-equivalent terms. The R&D-to-sales ratio increases by 0.6% as the rise in creative destruction R&D exceeds the decline in R&D spending on own-innovation (Panel B). We provide more details in Online Appendix H.2.

Furthermore, the U.S. economy exhibited notable structural changes in 2007 relative to 1992: lower growth (0.9% vs. 1.9%), reduced creative destruction (1.8 vs. 2.3 products per firm), and longer learning times (2.6 vs. 2.3 years).⁶⁶ To assess the role of learning probability ω in accounting

⁶⁵This decrease is attributed to shifts in firm-level innovation intensities and the mass of firms. More detailed breakdowns are shown in Online Appendix H.2.

⁶⁶In Online Appendix I.3, we provide details on the time-series pattern of learning time.

for these changes, we recalibrate the model to the 2007 U.S. manufacturing sector and conduct a counterfactual that resets only ω to its 1992 value.⁶⁷

Table 6 summarizes the results. In 2007, both types of innovation are lower, and aggregate growth, the R&D-to-sales ratio, and the number of products all decline relative to 1992, implying a welfare loss of 1.19%. Average learning time is higher in 2007 despite the learning probability ω (0.329) being calibrated about 20% above its 1992 value (0.275). This suggests that other technological forces offset the direct effect of a higher ω on learning time. If ω were the primary driver, resetting it to its 1992 level should move the economy closer to 1992. Instead, the final two columns show that lowering ω does not close the gap, indicating that forces beyond the structural learning parameter drove the economy's shift during this period.

4.2.2 Increasing Competitive Pressure from Outside Firms

As another exercise, we increase competitive pressure by raising the mass of potential outside entrants \mathcal{E}_o by 84%, corresponding to the rise in import penetration ratio in the U.S. manufacturing sector from 1992 to 2007 (from 15.3% to 25.1%).^{68,69} Table 7 shows that this leads to a rise in the aggregate creative destruction arrival rate \bar{x} and results in three key effects: (i) the expected profits of both types of innovations decrease, known as the Schumpeterian effect; (ii) incumbents intensify own-innovation to protect their existing product lines, especially those with a technology gap of $\Delta^2, \Delta^3 > 1$, referred to as the market-protection effect; and (iii) the market-protection efforts along with the increase in \bar{x} raise the average technology gap, making it harder for firms to take over product markets via creative destruction, labeled as the technological barrier effect. 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. Consequently, firm incentives for creative destruction and domestic firm entry get reduced, which contributes to

⁶⁷Calibration results are provided in Online Appendix H.4.

⁶⁸We do not intend to assess the effect of trade here but just 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.

⁶⁹In Online Appendix H.10, 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 7: 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 (%)	\bar{x}_o	11.7	19.5	66.6%
aggregate creative destr. arrival rate (%)	\bar{x}	76.8	77.9	1.5%
prob. of own-innovation ($\Delta^1 = 1$, %)	z^1	8.1	7.8	-4.3%
prob. of own-innovation ($\Delta^2 = \lambda$, %)	z^2	80.4	80.6	0.3%
prob. of own-innovation ($\Delta^3 = \eta$, %)	z^3	53.7	53.8	0.1%
prob. of own-innovation ($\Delta^4 = \frac{\eta}{\lambda}$, %)	z^4	44.3	44.2	-0.2%
prob. of creative destr., incumbents (%)	x	62.6	61.8	-1.3%
prob. of creative destr., potential startups (%)	x_e	11.8	11.7	-1.3%
Panel B: Changes in Aggregate Moments				
R&D to sales ratio (%)		4.1	4.0	-1.3%
Creative destruction R&D intensity (%)		58.7	57.9	-1.5%
Average number of products		2.1	2.0	-5.3%
Panel C: Changes in Aggregate Growth and Decomposition				
Avg. productivity growth by domestic firms (%)		1.9	1.7	-11.4%
Growth from domestic own-innovation (%)		0.74	0.65	-11.8%
Growth from domestic creative destruction (%)		1.0	0.9	-13.2%
Growth from domestic startups (%)		0.2	0.2	-1.7%

the decline observed in x and x_e in Table 7. Our novel mechanism comes through (ii) and (iii).⁷⁰ The total decline in x and x_e in Table 7 results from the combined impact of the Schumpeterian and technological barrier effects.⁷¹

As a result, the aggregate R&D to sales ratio of domestic incumbents drops, indicating that the decrease in creative destruction outweighs the increase in own-innovation (Panel B). Most importantly, the aggregate growth rate by domestic firms declines (Panel C). As a result, welfare falls by 4.0% in consumption-equivalent terms. Online Appendix H.5 describes further discussion. Note that similar qualitative results are obtained in a simplified environment with one-period learning lag (i.e., $\omega = 0$) in Online Appendix H.7.⁷²

⁷⁰In the general equilibrium, these effects come into play together and interact. The technological barrier effect in (iii) additionally influences the aggregate creative destruction arrival rate \bar{x} , causing a feedback loop involving (i) to (iii).

⁷¹A decomposition reveals that 35.3% and 26.4% 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).

⁷²In Online Appendix H.8, we consider the other case of no learning ($\omega = 1$) by recalibrating the model and show that learning frictions are essential to generate the observed compositional shift in innovation.

Table 8: Aggregate Moment Comparison: U.S. vs. High-Cost Economy

Moment	Baseline	High-Costs	After Shock	Δ (%)
R&D to sales ratio (%)	4.1	1.13	1.19	5.2%
Creative destr. R&D intensity (%)	58.7	8.8	7.9	-10.6%
Average number of products	2.1	1.0	1.0	-0.3%
Avg. growth by domestic firms (%)	1.9	1.3	1.1	-9.1%

4.2.3 Comparison: Economy with High Creative Destruction Costs

To compare economies with different innovation structures, we re-evaluate the model in hypothetical environments with lower creativity—that is, less creative destruction due to higher frictions. Specifically, we raise the creative-destruction cost parameter ($\tilde{\chi}$) from its baseline value of 0.024 while holding all other parameters fixed, and then conduct the same counterfactual analysis.

As an example, we set an economy with high creative destruction costs ($\tilde{\chi} \times 80$) than the U.S.⁷³ Table 8 compares aggregate moments between the U.S. and this economy, as well as the response of the aggregate moments to a competition shock in the latter. 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 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 firms, coupled with a decline in the mass of domestic incumbents.⁷⁴ As a consequence, welfare declines by 5.2% in this economy.

4.2.4 Policy Implications

Our results highlight the central role of learning frictions in shaping the composition of innovation and, in turn, aggregate outcomes, which informs important policy design. Faster learning raises the return to creative destruction, shifts effort away from defensive own-innovation, and strengthens the growth contribution of innovation. Policies that ease knowledge diffusion can therefore improve

⁷³In Online Appendix H.9, we examine a range of more $\tilde{\chi}$ values and confirm that the same qualitative pattern appears.

⁷⁴The version with a fixed mass of firms is presented in Online Appendix H.9.

aggregate outcomes and welfare by reallocating it toward the more growth-enhancing innovation.⁷⁵

The paper also underscores the nuanced effects of competition when interacting with learning frictions. Under learning frictions, intensified competition raises defensive own-innovation, which can decrease or increase overall innovation but definitely lowers creative destruction and growth. This suggests that higher innovation is not necessarily beneficial when driven by strategic motives, which dampens creative destruction and growth. Indeed, it makes it more challenging for low-creativity economies. This highlights compositional changes as a key mechanism in determining the aggregate effects of competition, which needs to be carefully considered for effective policy design.

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 entry and creative destruction. Heightened learning frictions or competition amplifies strategic innovation, leading to endogenous impacts on creative destruction and shifts in innovation composition. Consequently, the aggregate impact depends on the varying magnitudes of these shifts. Our paper provides new insights into how firms strategically use innovations under learning frictions, impacting the composition of innovation and the aggregate outcome.

Supplementary material

Supplementary materials are provided in the [Online Appendix](#).

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⁷⁵Accelerated creative destruction can also raise job loss and instability and weaken incumbents' incentives to innovate. Although beyond the scope of this paper, the optimal degree of knowledge diffusion must balance growth gains against other potential costs.

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