Defensive Innovation and Firm Growth in the U.S.: Impact of International Trade*

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November 22, 2019

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Abstract

I develop a two-country endogenous growth model to show that increasing foreign competition contributes to the recent decline in high-growth firm activities and startup rates in the U.S. by changing the way how firms allocate their innovative effort. Firms improve their existing products through internal innovation, while developing new products through external innovation. A novel friction I consider is that it takes time to learn others' technology, which I denote as an imperfect technology spillover. This friction allows firms to defend themselves from competitors by building technological barriers through internal innovation. Increasing foreign competition induces innovation-intensive and thus fast-growing firms to invest more in internal innovation for defensive reasons. At the same time, foreign competition discourages all firms from undertaking external innovation. This shift in innovation cuts the employment growth of innovation-intensive firms, as external innovation generates more quality improvement than internal innovation and requires firms to hire a new set of workers to produce new products. Entry for potential startups is harder as incumbents build higher technological barriers. By using firm-level data from the U.S. Census Bureau integrated with firm-level patent data, I confirm the model's predictions.

JEL Code: F12, F14, L11, L25, O31, O33, O41
Keywords: job creation, startup rate, endogenous growth, innovation, imperfect technology spillover, foreign competition

*I am indebted to my advisers John Haltiwanger, Nuno Limão, and Felipe Saffie for their invaluable guidance and support. I am grateful to John Shea for his support and advice, and seminar participants at the University of Maryland for their useful feedback. This research is funded by the Ewing Marion Kauffman Foundation. Any opinions and conclusions expressed herein are those of the author and do not necessarily represent the views of the U.S. Census Bureau or the Ewing Marion Kauffman Foundation. All results have been reviewed to ensure that no confidential information is disclosed. The contents of the paper are solely my responsibility. Technical Appendix is available here.

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1 Introduction

The past decades have seen declining business dynamism in the U.S. economy in various measures, such as startup rates, job creation and destruction rates, and activity among high-growth firms, a significant portion of which are young firms (Decker et al., 2014). In the manufacturing sector, for example, the startup rate fell from 8.3% in 1992 to 6.3% in 2007, whereas the employment growth rate of the top decile of firm employment growth declined from 22.5% in 1992 to 17.0% in 2007.[1] Startups and high-growth firms account for 70% of gross job creation in typical years (Decker et al., 2014).[2] Furthermore, high-growth firms also play disproportionately important roles in output growth and productivity growth (Haltiwanger et al., 2016). Thus, the decline in startup rates and the activity of high-growth young firms is a large concern.

Simultaneously, the U.S. economy experienced increasing international trade. Exports of goods and services, for example, rose from 8.0% of GDP in 1992 to 11.5% in 2007, and the import penetration ratio rose from 9.2% in 1992 to 15.5% in 2007.[3] While a significant body of research has examined the link between international trade and macroeconomic outcomes such as output growth and unemployment, less attention has been paid to the impact of international trade on high-growth firm activity.

In this paper, I argue that increasing foreign competition induces high-growth firms, especially innovation-intensive firms, to focus their innovative effort on improving their existing products to defend themselves from competitors, as opposed to entering markets outside of their existing scope and capturing businesses from incumbent firms.[4] This shift of innovation activity causes innovation-intensive firms to grow more slowly and makes it difficult for

[1]The startup rates are Author's calculation from the Business Dynamics Statistics (BDS). The top-decile firm is the 90th percentile firm of the employment-weighted distribution of firm employment growth rates. The two employment growth rates are based on Hodrick-Prescott trend, where data is from Decker et al. (2016). Economy-wide, the two numbers changed from 32.8% in 1992 to 26.3% in 2007.

[2]Here, high-growth firms are defined as firms with employment growth rate more than 25% per year.

[3]Import penetration ratio is defined as the imports of goods and services divided by the total expenditure on goods and services, measured as the GDP minus the exports of goods and services plus the imports of goods and services. Both exports of goods and services per GDP, and import penetration ratio is the author's calculation from FRED economic data in real terms, then Hodrick-Prescott trends are reported. Exports of goods and services per total expenditure rose from 7.9% in 1992 to 11.0% in 2007

[4]Acemoglu et al. (2018) show that among innovative firms, young and small firms have higher innovation intensity than mature firms as measured by the ratio of R&D spending to sales. Also, Graham et al. (2018) show that young patenting firms grow faster and shed fewer jobs compared to non-patenting counterparts.

potential startups to enter into the economy. The key friction that generates these responses is that it takes time to learn another firm's technology.

Broadly, innovation comes in two types: internal and external. Firms improve their product quality and production processes through internal innovation, and use external innovation to take over other firms' product markets. If a firm wants to take over another market through external innovation, it first needs to learn the technology that the existing incumbent is using and then build on top of it.

Importantly, however, there is friction in learning others' technology, in that it takes time to learn. I call this an imperfect technology spillover, and introduce this friction to the endogenous growth literature. Incumbent firms can use this time lag to improve their technology further through defensive internal innovation, which makes it harder for competitors to steal their business. In other words, incumbent firms can build a technological barrier in their markets. In such an environment, individual firms can use internal innovation not only to improve the profitability of firms' products but also to escape competition.

The flip side is that defensive innovation by incumbents makes it difficult to take over another firm's market through external innovation, as firms need to overcome the technological advantage of incumbent firms. This technology barrier can become higher if competition increases, because competition incentivizes incumbents to do more internal innovation.

Akcigit and Kerr (2018) empirically show that external innovation generates more forward citations and is associated with higher employment growth compared to internal innovation. They also show, through the lens of their structural model, that external innovation brings higher product quality improvement, and contributes more to economic growth.[5] These findings suggest that higher product market competition, defined as a larger number of firms trying to enter each product market, can potentially lower an individual firm's employment growth. The key mechanism is that the increased competition decreases firms' incentives to perform product scope expansion through external innovation, while encouraging firms to do internal innovation with defensive motives.[6]

[5] Akcigit and Kerr (2018) use patenting firms in the Longitudinal Business Database (LBD) from 1982 to 1997 to arrive these conclusions both theoretically, and empirically.

[6] Bernard et al. (2010) suggest that product switching contributes to a reallocation of resources within firms toward their most efficient use. Thus, experimentation through external innovation is very important for firm growth.

To formalize the mechanism and analyze it in detail, I extend the Akcigit and Kerr (2018) framework to build a two-country endogenous growth model with international trade and multi-product firms that perform two types of innovation—internal and external—subject to imperfect technology spillover. In this model economy, the imperfect technology spillover exists in the form of lagged learning, in which potential rival firms can only learn the product-specific technology of incumbent firms with a one-period lag. Imperfect spillovers generate a local technology gap, defined as the gap between the current period frontier technology for a given product and the one-period lagged technology that potential rival firms can learn through R&D. Thus, internal innovation is built on the current frontier technology, while external innovation is built on lagged technology.

The imperfect technology spillover provides the owner of each product a technological advantage and allows incumbent firms to use internal innovation to defend their product markets from competitors. In this sense, imperfect technology spillovers allow me to introduce technological distance and the escape-competition effect defined in Aghion et al. (2001) to the Klette and Kortum (2004) framework with heterogeneous innovations. This is the key theoretical contribution of this project to the endogenous growth literature, which helps us to distinguish the impacts of foreign competition on internal versus external innovation. In addition, imperfect technology spillovers imply a novel technological-barrier effect, in which factors that affect defensive internal innovation also affect the success probability of business takeover through external innovation in the economy. Since potential startups need to do external innovation to enter, the technological barrier also affects startup rates.

To my best knowledge, this is the first theoretical model of defensive innovation with two countries that allows individual firms to grow both by improving in their existing markets and by taking other firms' markets through two different types of innovation. Allowing for both internal and external innovation is essential for understanding the impact of foreign competition on firms' innovation decisions, as well as firm-level and aggregate economic growth. Firms have different incentives and purposes for different types of innovation, and they use these strategically to increase their profits and the probability of survival. Also, as explained earlier, the two types of innovation have different effects for both individual firms and the overall economy. Thus, allowing only one type of innovation, while ignoring potential compositional change, could disguise the true effect of foreign competition.

My theoretical framework predicts that when foreign competition increases, incumbent firms that have done more recent innovation increase their internal innovation more, compared to incumbents that have done less innovation recently. These innovation-intensive firms, on average, have technological advantage accumulated through past innovation in their own markets, summarized by the local technology gap, compared to other firms. Thus, it is easier for them to make potential competitors even harder to catch up by improving their products further, and this incentivizes the innovation-intensive firms to escape competition through additional internal innovation. This is the escape-competition effect.

It also predicts that if other firms have done more innovation recently, then individual firms do less external innovation. For an individual firm, the aggregate innovation intensity and the distribution of the local technology gap across other products determine the probability of a successful business takeover for a given amount of external innovation effort. The higher the average local technology gap and the more internal innovation effort of incumbent firms, the harder it is to take over another firm's product market. I define this as the technological-barrier effect. Competition shifts the local technology gap distribution by changing both individual firm's internal innovation decisions and the aggregate external innovation intensity. Thus, competition affects individual firms' optimal external innovation intensity through the technological-barrier effect.

To test these model predictions, I construct a unique dataset by combining firm-level datasets from the U.S. Census Bureau and the United States Patent and Trademark Office (USPTO) patent data from 1976 to 2016. This comprehensive dataset has information for the population of U.S. patenting firms, such as employment, international transaction, and 6-digit NAICS industries each firm operates. I use China's WTO accession as an exogenous change in foreign competition and self-citation ratio as a measure for internal-ness of innovation and provide regression results consistent with the escape-competition effect. The positive association between patenting and employment growth for the innovation-intensive firms falls by one-third after an increase in foreign competition, as they create patents more for internal innovation purposes. I also find regression results consistent with the technological-barrier effect by using the changes in foreign patent growth as a measure for an exogenous variation in the technological barrier.

Quality differences between the same products sold in different countries also matter for firms' internal innovation decisions. When international trade is costly, similar quality products are not traded but instead are produced and consumed domestically. This creates a global technology gap—the gap between a U.S. firm's technology and a foreign firm's technology in each product market. Domestic incumbents with lagging technologies invest more in internal innovation if potential foreign competitors in their markets have technology high enough that they could overcome the trade cost and start exporting their products to the domestic market by performing additional internal innovation. On the other hand, global technological leaders also are motivated to perform internal innovation, which could enable them to overcome the trade cost and become exporters. I find supporting empirical evidence for an enhanced internal innovation incentive for global technological leaders.

A counterfactual exercise of reducing tariff rates bilaterally by 4.16 percentage points in my model shows that firms, on average, shift their innovation activities toward more internal innovation after they are exposed to higher international trade. This causes high-growth, innovation-intensive firms to grow more slowly. Also, startup rates fall as the increased technological advantage incumbent firms accumulate through internal innovation makes it harder for startups to enter the economy through external innovation. I provide industry-level regression results consistent with these predictions.

To this end, this paper contributes to an emerging literature on the decline in business dynamism in the U.S. Decker et al. (2014) and Decker et al. (2016) show that business dynamism in the U.S. has been declining in various measures, and these declines accelerated after around 2000. Previous studies, such as Karahan et al. (2019) and Hopenhayn et al. (2018), studies the effect of demographic changes, while Akcigit and Ates (2019a,b) focus on the effect of decline in knowledge diffusion on the observed decline in various business dynamism measures. To my knowledge, I am the first to propose increasing foreign competition and U.S. firms' endogenous innovation allocation decisions as a channel that explains the decline in high-growth firm activity and startup rates through the lens of a structural model and provide supporting empirical evidence.

This paper also contributes to the literature that investigates the impact of international trade on firm innovation. Existing studies mainly combine internal and external innovation and estimate the effect of trade on firms' overall innovation empirically. The results are mixed. Bloom et al. (2016) show that surviving firms in developed European countries fight Chinese import competition by increasing their overall innovation. Autor et al. (2019), on the other hand, show that publicly traded U.S. firms lower their overall innovation when firms are allowed to exit in the regression sample. Aghion et al. (2017), meanwhile, focuses on French exporters' innovation decisions when competition in the export market increases. They show that more productive exporters do more innovation in response to increasing competition in the export market while less productive firms do less innovation.

Atkeson and Burstein (2010) theoretically investigate the effect of trade liberalization on firm innovation when incumbents do internal innovation while startups are born with new products. In their model, the impact of trade on firm innovation operates through wage changes, and no heterogeneous response is allowed. This paper is closely related to Akcigit et al. (2018), who build a two-country endogenous growth model with step-by-step innovation. Similar to the model developed in this paper, their model distinguishes the competition effect and the market size effect for firm innovation. The difference is that, in my framework, firms are also allowed to grow through product scope expansion by taking over others' markets. With the two types of innovation, firm growth can slow down even if they increase internal innovation to escape competition.

This paper contributes to this large strand of literature in three ways. First, I study the differential effect of international competition on two types of innovation, internal and external, that make asymmetric contributions to firm employment growth and economic growth. This helps us understand the reason for the recent decline in business dynamism in the U.S. economy. Second, I study why firms with different initial characteristics can react differentially to the same trade shocks while explaining the underlying mechanisms through a rich theoretical framework that allows us to decompose the firm's innovation incentives in detail. And lastly, I empirically study the effect of international trade on different types of firm innovation using a population of patenting firms by matching the USPTO patent database to internal Census Bureau datasets. To my own best knowledge, this paper is the first to accomplish these three objectives.

The rest of the paper proceeds as follows. Section 2 develops a two-country baseline general equilibrium model. Section 3 develops a simple three-period model to study the proposed mechanism in detail and derive empirically testable predictions. Section 4 presents empirical results for the effect of international competition on firm innovation composition using the U.S. Census Bureau datasets. Section 5 presents results from quantitative analysis of the general model. Section 6 concludes.

2 Baseline Two-Country Model

Time is discrete. Two countries, home (H) and foreign (F), are endowed with $\overline{L}_H$ and $\overline{L}_F$ units of labor, potentially different. In each country, there is a single final good producer operating in perfectly competitive markets, and a continuum of differentiated good producers operating in monopolistically competitive markets. The mass of differentiated good producers is determined through endogenous entry and exit. In each period, there is a fixed mass of potential startups in the differentiated good sector in each country, and those which successfully take over existing good markets through external innovation enter the economy. Differentiated goods are tradable but subject to variable trade costs, and their producers from the two countries compete for technological leadership in a continuum of measure one goods markets through internal and external innovation. External innovation requires learning another firm's technology, but learning takes time. Thus, there is an imperfect technology spillover in the form of lagged learning, as firms can only learn other firms' past-period technologies. Below I describe the economy mainly for the home country H, and super/subscript H is omitted whenever there is no confusion. Time subscript t is also omitted whenever there is no confusion.[7]

2.1 Representative Household

The representative household has a logarithmic utility function and is populated by a continuum of individuals with total measure $\overline{L}$. Each individual supplies one unit of labor each period inelastically and consumes a portion C_t of a unique final good (consumption bundle)

[7] I use the term technology and product quality interchangeably.

in the economy produced by the final good producer. The household's lifetime utility is

$$U = \sum_{t=0}^{\infty} \beta^t \log(C_t) \,. \tag{2.1}$$

Homogeneous workers are employed in the final goods (L) and differentiated goods ($\widetilde{L}$) sectors. Thus, in each period, the labor market satisfies

$$L + \widetilde{L} = \overline{L} \,. \tag{2.2}$$

The household maximizes its lifetime utility (2.1) subject to the period-by-period budget constraint

$$C_t \leqslant w_t \overline{L} + \Pi_t + \widetilde{\Pi}_t + G_t \,, \tag{2.3}$$

where w_t is wage, Π_t is the final good producer's profits, $\widetilde{\Pi}_t$ is differentiated good producers' total profits net of R&D expenses, and G_t is a government transfers including tariff revenues.

2.2 Final Good Producer

Both countries produce an identical final good. The final good is used for consumption and R&D expenditure for differentiated goods. The final good producer uses labor (L_H) and a continuum of differentiated goods indexed by $j \in [0, 1]$ to produce a final good, where some of the differentiated goods can be produced by foreign exporters. Denote $\mathcal{J}_{cH}$ as an index set for differentiated goods sold in the home country that are produced by firms in country $c \in \{H, F\}$, and y_j^{cH} as the quantity of good j from c to H. Then a constant returns to scale production technology w.r.t. labor and differentiated goods can be written as

$$Y_H = \frac{(L_H)^\theta}{1-\theta} \left[\underbrace{\int_0^1 \left(q_j^H\right)^\theta \left(y_j^{HH}\right)^{1-\theta} \mathcal{I}_{\{j \in \mathcal{J}_{HH}\}} \, dj}_{\text{domestic absorbtion}} + \underbrace{\int_0^1 \left(q_j^F\right)^\theta \left(y_j^{FH}\right)^{1-\theta} \mathcal{I}_{\{j \in \mathcal{J}_{FH}\}} \, dj}_{\text{imports}} \right], \tag{2.4}$$

where q_j^H is the quality of good j in country H, possibly different from that in country F, and $\mathcal{I}_{\{\cdot\}}$ are indicator functions. The final good is produced competitively, and input prices—w_H for labor and p_j^H for good j sold in H—as well as product quality q_j^c are taken as given. When there are multiple potential suppliers for the same good from the home and/or foreign countries, the final good producer chooses a supplier with the combination of product quality and marginal cost of production (adjusted by the trade costs for imported goods) that gives the final good supplier the highest profits.

To simplify the model and allow trade imbalances in the differentiated goods sector, I make the following assumption.

Assumption 1. *The final good is traded without friction and it absorbs possible imbalances in differentiated goods trade.*

The free trade in the final good sector, along with identical final good production in both countries, implies that the final good price in both countries, P_H and P_F, will be the same. I normalize that price to one each period for both countries without loss of generality.

2.3 Differentiated Goods Producers

There is a set of measure $\mathcal{F}_H$ of home firms and a set of measure $\mathcal{F}_{FH}$ of foreign exporters with $\mathcal{F}_H + \mathcal{F}_{FH} \in (0, 1)$, which are determined endogenously in equilibrium. These firms produce differentiated goods each period and sell their products in the home market. Some of the home firms ($\mathcal{F}_{HF} \leqslant \mathcal{F}_H$) export a portion of their products as well, which is also determined endogenously based on their product quality and marginal cost of production. Each good is produced in the producer's own country using local labor. Each operating firm owns at least one product line, and a single firm owns each product line in each country. Thus, a firm f can be characterized by using a collection of its product lines $\mathcal{J}^f = \{j : j \text{ is owned by firm } f\}$, where $n_f \equiv \| \mathcal{J}^f \|$ is the number of products firm f produces.

Because international trade is costly and marginal cost of production can be different across countries, some domestic firms may have zero demand from the foreign final good producer, and foreign demand is absorbed by foreign differentiated good firms. In such cases, the quality of the same product in the home country (q_j^H), along with the ownership of the good j, can be different from that in a foreign country (q_j^F). Then a global technology gap can be defined as $\Delta_{j,t}^G \equiv \frac{q_{j,t}^H}{q_{j,t}^F}$. If a firm in country H exports good j, then $\Delta_{j,t}^G$ is not defined as there is no firm in country F producing good j. In this case, I simply define $\Delta_{j,t}^G = \infty$. In the case where a country F firm exports good j, I define $\Delta_{j,t}^G = -\infty$.

Also, because there is imperfect technology spillover, the current period frontier technology can be different from the last period technology that another firm can learn. The local technology gap for each market j in each country $c \in \{H, F\}$ is defined as $\Delta_{j,t}^c \equiv \frac{q_{j,t}^c}{q_{j,t-1}^c}$. Thus, each product line can be characterized by its quality and technology gaps—local technology gaps in home and foreign markets, and the global technology gap—$\left(q_j, \Delta_j^H, \Delta_j^F, \Delta_j^G\right)$.

Denote y_j^{HH} as the quantity of good j produced by a home firm and supplied to home market j. Each good $j \in [0,1]$ is produced using domestic labor ℓ_j^{HH} with a linear technology

$$y_j^{HH} = \bar{q}_H \, \ell_j^{HH} \,, \tag{2.5}$$

where $\bar{q}_H \equiv \int_{\mathcal{J}_{HH}} q_j^H dj + \int_{\mathcal{J}_{FH}} q_j^F dj$ is the average product quality (average production technology) of differentiated goods traded in home markets. If good j is exported by a home firm to foreign market j, then it is produced using the same technology

$$y_j^{HF} = \bar{q}_H \, \ell_j^{HF}$$

but it is subject to an iceberg cost $d_{HF} > 1$ and an ad-valorem tariff $\tilde{\tau}_{HF} \geqslant 1$. Thus, in order to sell y_j^{HF} units of good j in the foreign market, the home firm needs to ship $\tau_{HF} \times y_j^{HF}$ units, where $\tau_{HF} \equiv \tilde{\tau}_{HF} \times d_{HF}$.

2.4 Innovation by Differentiated Good Producers

The differentiated good producers engage in two types of R&D—internal and external—to increase their profits from the products they currently produce, to protect their product markets from competitors, and to expand their businesses, where the R&D output is product quality (equivalently, production technology) improvement. Innovation outcome is realized at the beginning of the next period. To allow incumbent firms to protect their own product markets from competitors (the escape-competition effect) and to make it more difficult to take over other firms' product markets when overall innovation intensity in the economy is high (the technological-barrier effect), I introduce imperfect technological spillovers, which are captured by lagged learning: firms that don't own product line j can only learn the incumbent's last period technology, $q_{j,t-1}$. Thus, external innovation builds on the past-period technology used in the domestic market. A home firm can learn a foreign firm's technology if and only if that foreign firm sells its products in the home country.

In this setup, learning another firm's technology is costly in a sense that i) outside firms can only learn last period's technology, and ii) learning involves R&D—only firms with strictly positive R&D expenditure can learn another firm's past technology, where undirected learning starts after spending a strictly positive amount on R&D.[8] Product line-specific current period technology $q_{j,t}$, and thus, the local technology gap $\Delta_{j,t} \equiv \frac{q_{j,t}}{q_{j,t-1}}$ are observable only to the firms operating in product line j in that period. However, aggregate variables and the local technology gap distribution (the share of product lines with a certain level of local technology gap) are publicly observable. Thus, a stationary equilibrium can be well defined. When two firms' technologies are neck and neck in one 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. An unused technology (idea) is assumed to depreciate by an amount sufficient to ensure that it becomes unprofitable to innovate on top of it next period.[9]

With the last two assumptions, only the winning firm from the coin toss keeps the product line until it is taken over by another firm through creative destruction (external innovation), while the losing firm never tries to enter the same market through internal innovation in the neck and neck case. Thus, the undirected nature of external innovation is ensured, and only the firm producing a product in a current period is allowed to do internal innovation on that product. Finally, each firm can do only one external innovation in each period regardless of the total number of product lines the firm owns, to maintain the tractability of the model.

[8] Firms do not know which product line technology they will learn prior to their learning. This assumption helps the model tractable.

[9] If you don't recall your skill or idea frequently, you gradually forget about it. This is in some sense consistent with the literature discussing displaced workers' human capital depreciation.

2.4.1 Internal Innovation

Successful internal innovation improves the current quality $q_{j,t}$ for differentiated good j by $\lambda > 1$. The probability of internal innovation, $z_{j,t}$, is determined by the level of R&D expenditure $R^{in}_{j,t}$ in units of the final good:

$$z_{j,t} = \left(\frac{R^{in}_{j,t}}{\widehat{\chi} q_{j,t}} \right)^{\frac{1}{\widehat{\psi}}} ,$$

where $\widehat{\chi} > 0$ and $\widehat{\psi} > 1$. Thus incumbent firm's good j quality realized at the beginning of $t+1$, assuming the firm is not displaced by creative destruction is:[10]

$$\left\{ q^{in}_{j,t+1} \right\} = \begin{cases} \left\{ \lambda q_{j,t} \right\} & \text{with probability } z_{j,t} \\ \left\{ q_{j,t} \right\} & \text{with probability } 1 - z_{j,t} \, . \end{cases}$$

As time is discrete and firms are multi-product firms, internal innovation outcomes follow a binomial process as in Ates and Saffie (2016).

2.4.2 External Innovation

Incumbents and potential startups attempt to take over other incumbents' markets through external innovation. Successful external innovation generates an improvement in product quality by a factor of $\eta > 1$ relative to the incumbent's lagged technology, where R&D results are realized at the beginning of next period. I assume, $\lambda^2 > \eta > \lambda$. This assumption ensures that firms can protect their own product lines from outside firms through internal innovation, while $\eta > \lambda$ reflects the idea that external innovation introduces a new way of producing an existing product more efficiently. Thus, external innovation contributes more to both firm employment and aggregate growth than internal innovation, as found in Akcigit and Kerr (2018). Both potential startups' and incumbent firms' external innovations are undirected in a sense that they are realized in any other product line with equal probability.

[10] Hereafter, I write the quality of good j as a point set. This makes it easy to write the case when external innovation fails and firm does not acquire any product lines, which will be written as product quality set to be an empty set.

Existing firms with at least one product line ($n_f > 0$) decide the probability of external innovation x_t by choosing R&D expenditures R_t^{ex} in units of the final good:

$$x_t = \left(\frac{R_t^{ex}}{\widetilde{\chi}\, \bar{q}_t} \right)^{\frac{1}{\widetilde{\psi}}} ,$$

where $\widetilde{\chi} > 0$, and $\widetilde{\psi} > 1$, and $\bar{q}_t$ is the average quality in the country the firm is located. Thus, for prospective external innovators whose takeover is not pre-empted by the incumbent's successful defensive innovation, the distribution of quality at the start of the next period is:

$$\left\{ q_{j,t+1}^{ex} \right\} = \begin{cases} \left\{ \eta q_{j,t-1} \right\} & \text{with probability } x_t \\ \varnothing & \text{with probability } 1 - x_t \, . \end{cases}$$

With probability $1 - x_t$, the external innovation fails, which implies there is zero probability that the firm will take over product line j. In this case, product quality for product line j for the potential entrant does not exist.

As an outside firm can only learn last period's technology, the local technology gap is an important factor determining an incumbent firm's success/failure at protecting its product line through internal innovation. With the above setup for innovation there are four possible technology gaps in this model economy:

Lemma 1. *There can be four local technology gaps in this economy,* $\Delta^1 = 1$, $\Delta^2 = \lambda$, $\Delta^3 = \eta$, *and* $\Delta^4 = \frac{\eta}{\lambda}$, *where states* Δ^3 *and* Δ^4 *can be reached through external innovation.*
Proof: See Appendix A.1.1.

To better understand firm's innovation decisions, and to show how business takeover through external innovation and escape competition through internal innovation work in detail, the following section graphically illustrates specific cases in a closed economy.

2.5 Business Takeover and Escape Competition, an Illustration

Figure 1 illustrates how firms' product quality portfolio and technology gap portfolio evolve over time. Firm A owns the first three product lines and firm B owns the last four product

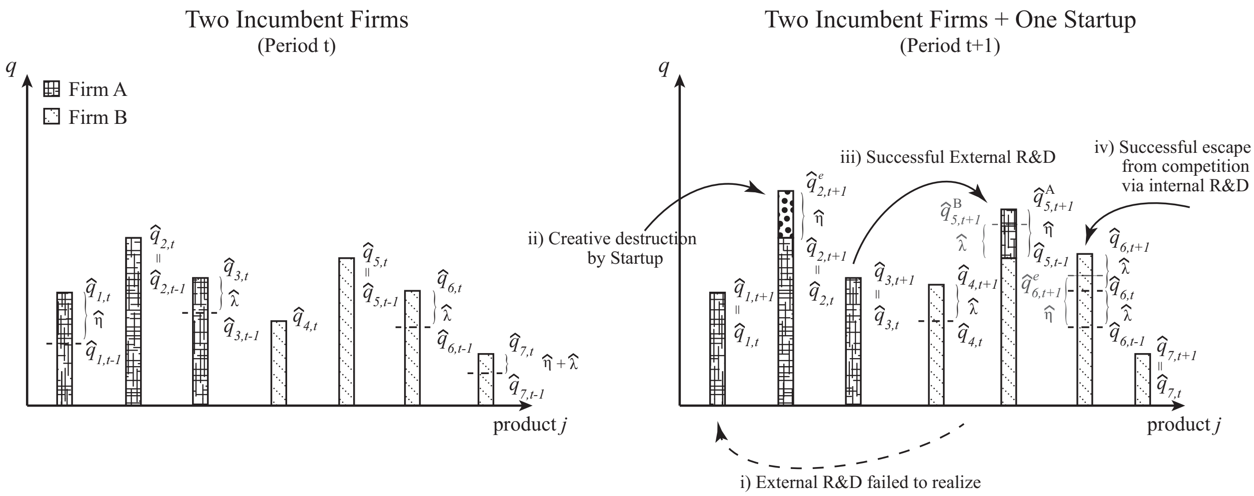

Figure 1: Firms' Innovation and Product Quality Evolution Example

lines in period t. Each bar represents a product and the height of the bar represents the log of product quality for each product, $\widehat{q}_{j,t} \equiv \log(q_{j,t})$ for illustration purposes. In case i), firm B does external innovation in an attempt to take over firm A's product line 1. Firm A took this product line over through successful external innovation at $t-1$, but did not internally innovate at t. So $\Delta_{1,t} = \eta$, and $q^A_{1,t+1} = \eta q_{1,t-1}$ ($\widehat{q}^A_{1,t+1} = \widehat{\eta} + \widehat{q}_{1,t-1}$, where $\widehat{\eta} \equiv \log(\eta)$) for firm A. Firm B, on the other hand, learns $q_{1,t-1}$ in period t and does external innovation so that in period $t+1$, it realizes $q^B_{1,t+1} = \eta q_{1,t-1}$, which is the same as $q^A_{1,t+1}$. A coin is tossed and firm A is the winner. Thus, firm A keeps product line 1. Case ii) illustrates how a firm can lose its existing product line through creative destruction. Firm A failed to do internal innovation on product line 2 in periods $t-1$ and t. Thus, at the beginning of period $t+1$, the quality of product line 2 for firm A is equal to $q^A_{2,t+1} = q_{2,t-1}$. A potential startup learns product line 2's last period technology (quality) by investing in R&D in period t and succeeds in externally innovating the product quality. Thus, at the beginning of period $t+1$, the product quality of product line 2 for the potential startup is equal to $q^e_{2,t+1} = \eta q_{2,t-1}$. Since $q^e_{2,t+1} > q^A_{2,t+1}$, the startup takes over product line 2. Case iii) illustrates how incumbent firm A can take over incumbent firm B's product line through external innovation, despite internal innovation by incumbent firm B. Since there was no internal innovation between $t-1$ and t for product line 5, $q_{5,t} = q_{5,t-1}$. Thus, firm A's quality for product line 5 after external innovation is $q^A_{5,t+1} = \eta q_{5,t}$. Firm B internally innovates product line 5. Thus, firm

B's quality for product line 5 is $q^B_{5,t+1} = \lambda q_{5,t-1}$. Since $\eta > \lambda$, firm A takes over product line 5. Case iv) illustrates how firms can escape from competition (creative destruction) through successful internal innovation. Firm B succeeds in internally innovating its product line 6 for two consecutive periods. Thus, the quality of product line 6 for firm B in period $t+1$ is equal to $q^B_{6,t+1} = \lambda^2 q_{6,t-1}$. Outside firms can increase the quality for product line 6 up to $q^e_{6,t+1} = \eta q_{6,t-1}$. Since $\lambda^2 > \eta$, firm B successfully protects product line 6 from competitors. These examples show an important observation that is unique to the economy with the imperfect technology spillover. Because incumbents can escape competition through internal innovation, not all firms who succeeded in external innovation can successfully take over another firm's business. Thus, the success probability of a business takeover is generally lower than the probability of external innovation.

2.5.1 Entry and Exit in the Differentiated Good Sector

At the beginning of each period, there is an exogenously determined $\mathcal{E}_H$ mass of new potential domestic startups trying to start businesses in the differentiated good sector. To start a business, a potential startup needs to invest in external R&D and take over one of the product lines from an incumbent firm. The potential startups, who have no existing product lines, decide the probability of external innovation $x_{e,t}$ by choosing R&D expenditure R^e_t in units of the final good:

$$x_{e,t} = \left(\frac{R^e_t}{\widetilde{\chi}_e \, \bar{q}_t} \right)^{\frac{1}{\widetilde{\psi}_e}} ,$$

where $\widetilde{\chi}_e > 0$, $\widetilde{\psi}_e > 1$. For potential startups whose takeover attempt is not thwarted by defensive innovation by the incumbent, the distribution of quality at $t+1$ is

$$\left\{ q^e_{j,t+1} \right\} = \begin{cases} \left\{ \eta q_{j,t-1} \right\} & \text{with probability } x_{e,t} \\ \varnothing & \text{with probability } 1 - x_{e,t} \, . \end{cases}$$

Incumbent firms in the differentiated good sector are engaged in internal and external innovation in each period. Thus, not only do they expand by developing improved versions of their existing products, they also expand by adding new product lines to their portfolio. However, as there are other firms engaged in external innovation as well, an individual incumbent firm is always faced with a positive probability of losing some of its own product markets to competitors. As there is a continuum of measure one product lines and a continuum of differentiated good producers, each product line faces the same probability of encountering a competitor. This is called the aggregate endogenous creative destruction arrival rate and it is equal to the average probability of external innovation in the economy:

$$\overline{x} = \underbrace{\mathcal{F}_H x^H + \mathcal{E}_H x_e^H}_{\equiv \overline{x}^H} + \underbrace{\mathcal{F}_F x^F + \mathcal{E}_F x_e^F}_{\equiv \overline{x}^F}, \tag{2.6}$$

where $\mathcal{F}_c$ is a mass of incumbents, $\mathcal{E}_c$ is a mass of potential startups , x^c is the probability of external innovation by incumbents, and x_e^c is the probability of external innovation by potential startups in country c. Here, I write the probability of external innovation for each group of firms as equal across all the firms in the same group. I verify this holds in equilibrium in the later section. Thus, $\overline{x}^c$ is the portion of the aggregate creative destruction arrival rate due to external innovation by firms in country c. An incumbent firm losing all of its product lines to competitors exits the economy, and it receives the value equal to the sum of discounted expected profits from a successful external innovation when it exits. This compensation for the accumulated knowledge stock ensures the incumbents with no product lines optimally not to attempt to perform external innovation to re-enter the economy.

2.6 Equilibrium

2.6.1 Production

The standard profit maximization problem of the final good producer in country $c \in \{H, F\}$ gives us an inverse demand for differentiated good j produced by a firm in country $\widetilde{c} \in \{H, F\}$:

$$p_j^c = P_c^{-1} L_c^{\theta} \left(q_j^{\widetilde{c}}\right)^{\theta} \left(y_j^{\widetilde{c}c}\right)^{-\theta} , \tag{2.7}$$

and demand for labor:

$$L_c = \frac{\theta}{w_c} P_c Y_c\,, \tag{2.8}$$

where p_j^c is the price for differentiated good j sold in country c, and P_c is the final good price in country c, which is equal to one. In deriving demand for good j I assume that each good is supplied by a single firm. However, past incumbent firms in domestic markets that lost technological leadership to the current leader could in principle try to produce and sell their products through limit pricing, as the marginal cost of production is equal across all domestic firms. To avoid such cases and simplify the model, I adopt the following two-stage price-bidding game assumption.

Assumption 2. *In a given product line j in a given country, the current incumbents and any former incumbents in the same line enter a two-stage price-bidding game. In the first stage, each firm pays a fee of $\varepsilon > 0$. In the second stage, all firms that paid the fee announce their prices.*

This assumption ensures that only the technological leader enters the first stage and announces its price in equilibrium. By using (2.7), the profit maximization problem of the differentiated good producer in country c owning product line $j \in [0,1]$ is then

$$\pi^c(q_j^c) = \begin{cases} \max\limits_{y_j^{cc} \geqslant 0} \left\{ P_c^{-1} L_c^{\theta} \left(q_j^c\right)^{\theta} \left(y_j^{cc}\right)^{1-\theta} - \dfrac{w_c}{\overline{q}_c}\, y_j^{cc} \right\} & \text{if not exporter} \\ \max\limits_{y_j^{cc} \geqslant 0} \left\{ \sum\limits_{\hat{c}=c}^{\tilde{c}} \left[P_{\hat{c}}^{-1} L_{\hat{c}}^{\theta} \left(q_j^c\right)^{\theta} \left(y_j^{c\hat{c}}\right)^{1-\theta} - \tau_{c\hat{c}} \dfrac{w_c}{\overline{q}_c}\, y_j^{c\hat{c}} \right] \right\} & \text{if exporter,} \end{cases}$$

where $\tau_{cc} = 1$. The first order conditions of the above problem (and its foreign firm counterpart) yield the optimal price for differentiated good j in country c market:

$$p_j^c = \begin{cases} \dfrac{1}{1-\theta}\, \dfrac{w_c}{\overline{q}_c} & \text{for domestic suppliers} \\ \dfrac{1}{1-\theta}\, \tau_{\tilde{c}c}\, \dfrac{w_{\tilde{c}}}{\overline{q}_{\tilde{c}}} & \text{for imports} \end{cases} \tag{2.9}$$

which is an unconstrained monopoly price given that the seller is the technological leader (taking into account the marginal costs) in each market in each country c. The optimal price is independent of the individual product quality. Optimal quantities supplied by firms in country c are equal to

$$y_j^{cc}(q_j^c) = (1-\theta)^{\frac{1}{\theta}} \, (P_c)^{\frac{1}{\theta}} \, L_c \left(\frac{w_c}{\bar{q}_c}\right)^{-\frac{1}{\theta}} \; q_j^c \tag{2.10}$$

$$y_j^{c\tilde{c}}(q_j^c) = (1-\theta)^{\frac{1}{\theta}} \, (P_{\tilde{c}})^{\frac{1}{\theta}} \, L_{\tilde{c}} \left(\tau_{c\tilde{c}}\frac{w_c}{\bar{q}_c}\right)^{-\frac{1}{\theta}} \; q_j^c \; . \tag{2.11}$$

Then, profits for a firm in country c with technology q_j^c selling to market j in its own country are equal to

$$\pi^{cc}(q_j^c) = \underbrace{\theta(1-\theta)^{\frac{1-\theta}{\theta}} L_c \left(\frac{w_c}{\bar{q}_c}\right)^{-\frac{1-\theta}{\theta}} (P_c)^{\frac{1}{\theta}}}_{\equiv \pi^{cc}} \; q_j^c \; ,$$

and profits for the same firm from selling to market j in country $\tilde{c}$ are equal to

$$\pi^{c\tilde{c}}(q_j^c) = \underbrace{\theta(1-\theta)^{\frac{1-\theta}{\theta}} L_{\tilde{c}} \left(\tau_{c\tilde{c}}\,\frac{w_c}{\bar{q}_c}\right)^{-\frac{1-\theta}{\theta}} (P_{\tilde{c}})^{\frac{1}{\theta}}}_{\equiv \pi^{c\tilde{c}}} \; q_j^c \; .$$

Importantly, both expressions are linear in q_j^c. Notice that product quality of good j sold in country $\tilde{c}$ by a firm in country c is denoted as q_j^c. This is because product quality is firm-specific, in that if a firm produces good j in its own country c with quality q_j^c, then the quality of good j the firm can sell in country $\tilde{c}$ is also equal to q_j^c.

Denote total product quality of goods produced by firms in country $\tilde{c} \in \{H, F\}$ that are sold in country $c \in \{H, F\}$ as

$$\mathcal{Q}_{\tilde{c}c} \equiv \int_0^1 q_j^c \, \mathcal{I}_{\{j \in \mathcal{J}_{\tilde{c}c}\}} dj \; .$$

Then, the wage expressed in units of total quality in country c satisfies the following equation:

$$\frac{w_c}{\overline{q}_c} = \theta(1-\theta)^{\frac{1-2\theta}{\theta}} \left[\left(\frac{w_c}{\overline{q}_c}\right)^{-\frac{1-\theta}{\theta}} \frac{\mathcal{Q}_{cc}}{\overline{q}_c} + \left(\tau_{\tilde{c}c} \frac{w_{\tilde{c}}}{\overline{q}_{\tilde{c}}}\right)^{-\frac{1-\theta}{\theta}} \frac{\mathcal{Q}_{\tilde{c}c}}{\overline{q}_c} \right] (P_c)^{\frac{1}{\theta}} \ . \tag{2.12}$$

Total labor hired by differentiated good producers in country c is equal to

$$\widetilde{L}_c = (1-\theta)^{\frac{1}{\theta}} \left(\frac{w_c}{\overline{q}_c}\right)^{-\frac{1}{\theta}} \left[L_c (P_c)^{\frac{1}{\theta}} \frac{\mathcal{Q}_{cc}}{\overline{q}_c} + L_{\tilde{c}} (P_{\tilde{c}})^{\frac{1}{\theta}} (\tau_{c\tilde{c}})^{-\frac{1}{\theta}} \frac{\mathcal{Q}_{c\tilde{c}}}{\overline{q}_c} \right] , \tag{2.13}$$

and total labor hired by the final good producer is equal to $L_c = \overline{L}_c - \widetilde{L}_c$. The last three equations for the two countries can be solved for w_c, $\widetilde{L}_c$, and L_c as functions of aggregate qualities, price indices, and trade costs.

Total final good output expressed in units of total quality in country c is

$$\frac{Y_c}{\overline{q}_c} = (1-\theta)^{\frac{1-2\theta}{\theta}} (P_c)^{\frac{1-\theta}{\theta}} L_c \left[\left(\frac{w_c}{\overline{q}_c}\right)^{-\frac{1-\theta}{\theta}} \frac{\mathcal{Q}_{cc}}{\overline{q}_c} + \left(\tau_{\tilde{c}c} \frac{w_{\tilde{c}}}{\overline{q}_{\tilde{c}}}\right)^{-\frac{1-\theta}{\theta}} \frac{\mathcal{Q}_{\tilde{c}c}}{\overline{q}_c} \right] . \tag{2.14}$$

Other equations are described in Technical Appendix TA5.

2.6.2 International Trade of Differentiated goods

Denote $MC^H \equiv \frac{w_H}{\overline{q}_H}$ as the marginal cost of production for domestic differentiated good firms, and $MC^F \equiv \frac{w_F}{\overline{q}_F}$ as the foreign counterpart. Recall that τ_{FH} is the trade cost to foreign firms exporting to domestic markets, and τ_{HF} is the trade cost to domestic firms exporting to the foreign country. Proposition 1 shows how these values define ranges of global technology gap Δ^G corresponding to the direction of trade between home and foreign countries, which come from a profit maximizing final good producer that values product quality.

Proposition 1. *Denote threshold home firm to foreign firm marginal cost of production ratios in home and foreign markets as*

$$\underline{\Omega} \equiv \left(\frac{1}{\tau_{FH}}\right)^{\frac{1-\theta}{\theta}} \left(\frac{MC^H}{MC^F}\right)^{\frac{1-\theta}{\theta}} \quad , \quad \overline{\Omega} \equiv (\tau_{HF})^{\frac{1-\theta}{\theta}} \left(\frac{MC^H}{MC^F}\right)^{\frac{1-\theta}{\theta}} \quad , \tag{2.15}$$

and the global technology gap for product j as

$$\Delta_j^G \equiv \frac{q_j}{q_j^F}\,.$$

Then, the home firm exports good j to the foreign country iff

$$\Delta_j^G > \overline{\Omega}\,,$$

while the home final good firm imports j from the foreign country iff

$$\Delta_j^G < \underline{\Omega}\,.$$

There is no trade of good j between the two countries iff $\Delta_j^G \in \left[\underline{\Omega}, \overline{\Omega}\right]$.
Proof: See Technical Appendix TA3.1.

Proposition 1 shows that depending on the relative size of (trade cost-adjusted) marginal costs, which are equivalent to quality-adjusted wages, foreign products with low quality (technology) can be sold in domestic markets. The global technology gap can also be defined by using 2-tuple integers. Denote m as the number internal innovations, and n as the number of external innovations in which home firms advance compared to foreign firms. Assuming that quality of good j in both countries when the economy started were the same, $\Delta_j^G = \frac{q_j^H}{q_j^F} = \lambda^m \times \eta^n$ and this can be written as $\widetilde{\Delta^G}_j = (m, n)$.

As briefly explained earlier, there is free trade in the final good sector, in which all of the trade imbalance in the differentiated good sector is absorbed. Thus,

$$P_c X_c = \int_{j \in \mathcal{J}_{\tilde{c}c}} p_j^c y_j^{\tilde{c}c} dj \; - \; \frac{P_c}{P_{\tilde{c}}} \int_{j \in \mathcal{J}_{c\tilde{c}}} p_j^{\tilde{c}} y_j^{c\tilde{c}} dj\,,$$

which implies

$$X_c = (1-\theta)^{\frac{1-\theta}{\theta}} \left[(P_c)^{\frac{1-\theta}{\theta}} L_c \left(\tau_{\tilde{c}c} \frac{w_{\tilde{c}}}{\overline{q}_{\tilde{c}}} \right)^{1-\frac{1}{\theta}} \mathcal{Q}_{\tilde{c}c} - (P_{\tilde{c}})^{\frac{1-\theta}{\theta}} L_{\tilde{c}} \left(\tau_{c\tilde{c}} \frac{w_c}{\overline{q}_c} \right)^{1-\frac{1}{\theta}} \mathcal{Q}_{c\tilde{c}} \right] \tag{2.16}$$

where X_c is the net quantity of final goods exported by country c. $X_c > 0$ means country

c exports final goods to country $\widetilde{c}$, and $X_c < 0$ means country c imports final goods from country $\widetilde{c}$. The first term in the RHS is the total value of differentiated goods imported from country $\widetilde{c}$, and the second term is the total value of differentiated goods exported to $\widetilde{c}$.

2.6.3 Firm Values and Optimal Innovation Decision

The value of a firm in country c with a production technology portfolio

$$\Phi^f \equiv \left\{ \left(q_j^c \, , \, \Delta_j^H \, , \, \Delta_j^F \, , \, \Delta_j^G \right) \right\}_{j \in \mathcal{J}^f}$$

is equal to

$$V^c \left(\Phi^f \right) = \max_{\left\{ z_j^c \right\}_{j \in \mathcal{J}^f} \, , \, x^c} \left\{ \sum_{j \in \mathcal{J}^f} \pi^c(q_j^c) - \left(\sum_{j \in \mathcal{J}^f} \widehat{\chi} \left(z_j^c \right)^{\widehat{\psi}} \, q_j^c + \widetilde{\chi} \left(x^c \right)^{\widetilde{\psi}} \, \overline{q}_c \right) + \widetilde{\beta} \, \mathbb{E}\Big[V^c \left(\Phi^{f\prime} \mid \Phi^f \, , \, \left\{ z_j^c \right\}_{j \in \mathcal{J}^f} \, , \, x^c \right) \Big] \right\},$$

where

$$\pi^c(q_j^c) = \begin{cases} \left(\pi^{cc} \right) \, q_j^c & \text{if firm is not an exporter} \\ \left(\pi^{cc} + \pi^{c\widetilde{c}} \right) \, q_j^c & \text{if firm is an exporter} \end{cases}$$

are profits from production net of labor costs and tariffs, defined in the previous section, and where the second and third terms in parenthesis are R&D expenses for internal and external innovation. Since all firms are owned by the household, they discount their future profits using households' stochastic discount factor, $\widetilde{\beta} \equiv \frac{P_H' C_H'}{\beta P_H C_H}$. The last conditional expectation term for future values, $\mathbb{E}\Big[V^c \left(\Phi^{f\prime} \mid \Phi^f \, , \, \left\{ z_j^c \right\}_{j \in \mathcal{J}^f} \, , \, x^c \right) \Big]$ is defined in Appendix A.2.1.

Proposition 2. *For a given joint distribution over local technology gaps for home and foreign markets and global technology gaps, the value function of a firm in country c with product quality and technology gap portfolio $\Phi^f \equiv \left\{ \left(q_j^c \, , \, \Delta_j^H \, , \, \Delta_j^F \, , \, \Delta_j^G \right) \right\}_{j \in \mathcal{J}^f}$ is of the form:*

$$V^c \left(\Phi^f \right) = \sum_{j \in \mathcal{J}^f} A^c \left(\Delta_j^H \, , \, \Delta_j^F \, , \, \Delta_j^G \right) q_j^c \; + \; B^c \overline{q}_c \, ,$$

where the coefficient for values from existing products, $A^c\left(\Delta_j^H, \Delta_j^F, \Delta_j^G\right)$, are independent of product quality q_j^c. The values from external innovation is equal to $B^c\overline{q}_c$, which is also equal to the exit value of an incumbent firm, $V^c(\varnothing) = B^c\overline{q}_c$. Furthermore, optimal internal innovation intensity z_j^c also depends only on the technology gap $\left(\Delta_j^H, \Delta_j^F, \Delta_j^G\right)$. Finally, optimal external innovation intensity x^c is independent of firm characteristics and equal across all incumbent firms.

Proof: See Technical Appendix TA4.2.

Analytic expressions for $A^c\left(\Delta_j^H, \Delta_j^F, \Delta_j^G\right)$, $z^c\left(\Delta_j^H, \Delta_j^F, \Delta_j^G\right)$, B^c, and x^c are provided in Technical Appendix TA4.2.

2.6.4 Potential Startups

Let $V^c\left(\left\{q_j\ \Delta_j^H\ \Delta_j^F\ \ \Delta_j^G\right\}\right)$ denote the value of a firm in country c that has only one product line j, with product quality q_j^c, local technology gaps in home and foreign markets Δ_j^H and Δ_j^F, and global technology gap Δ_j^G. Then a potential startup's expected profits from entering through R&D are

$$\Pi_c^e = x_e^c\,\widetilde{\beta}_c\,\mathbb{E}\Big[\ V^c\left(\left\{q_j^{c\prime}\ \Delta_j^{H\prime}\ \Delta_j^{F\prime}\ \ \Delta_j^{G\prime}\right\}\right)\ \Big] - \widetilde{\chi}^e\,(x_e^c)^{\widetilde{\psi}^e}\ \overline{q}_c\,.$$

An analytic expression for optimal external innovation decision rule for the potential startups is derived in Technical Appendix TA4.3.

2.6.5 Evolution of the Technology-Gap Distribution and Aggregate Growth

As shown in the previous section, product j can be completely described by its technology gaps $\left(\Delta_j^H\ \Delta_j^F\ \ \Delta_j^G\right)$ and its quality q_j. Thus, the index for each product, j, is redundant. Furthermore, what matters for firms' optimal decisions are the technology gaps, and firms need to know the distribution of technology gaps across market—local technology gaps in home and foreign markets, Δ^H and Δ^F, and global technology gaps, Δ^G. Denote the technology gap distribution as $\mu\left(\Delta^H, \Delta^F, \Delta^G\right)$. Appendix TA1 shows how technology gaps evolve over time according to firms' innovation decisions for each possible set of local and global technology gaps, $\left(\Delta^H, \Delta^F, \Delta^G\right)$. In a stationary equilibrium, inflow should be equal to outflow for each technology gap state $\mu\left(\Delta^{H}, \Delta^{F}, \Delta^{G}\right)$, where inflows and outflows for each technology gap state are described in Technical Appendix TA1.4.

2.7 Aggregate Quality Evolution

Proposition 3. *Define* $\boldsymbol{\Delta} \equiv \left(\Delta^{H}, \Delta^{F}, \Delta^{G}\right)$ *and* $\boldsymbol{\Delta}' \equiv \left(\Delta^{H\prime}, \Delta^{F\prime}, \Delta^{G\prime}\right)$*. Then for* c *,* $\widetilde{c} \in \{H, F\}$ *with* $c \neq \widetilde{c}$*, and for* $\widehat{c} \in \{c, \widetilde{c}\}$*, aggregate quality along a balanced growth path evolves according to*

$$\begin{aligned}\mathcal{Q}'_{\widehat{c}c} = & \left[\sum_{\boldsymbol{\Delta}}\sum_{\boldsymbol{\Delta}'} \ \Delta^{H\prime} \ \mathcal{I}'_{\widehat{c}c}\left(\Delta^{G\prime}\right) \ \mathcal{I}_{cc}\left(\Delta^{G}\right) \ \mathcal{P}\left(\boldsymbol{\Delta}'|\boldsymbol{\Delta}\right) \ \mu\left(\boldsymbol{\Delta}\right)\right]\mathcal{Q}_{cc} \\ & + \left[\sum_{\boldsymbol{\Delta}}\sum_{\boldsymbol{\Delta}'} \ \Delta^{H\prime} \ \mathcal{I}'_{\widehat{c}c}\left(\Delta^{G\prime}\right) \ \mathcal{I}_{\widetilde{c}c}\left(\Delta^{G}\right) \ \mathcal{P}\left(\boldsymbol{\Delta}'|\boldsymbol{\Delta}\right) \ \mu\left(\boldsymbol{\Delta}\right)\right]\mathcal{Q}_{\widetilde{c}c}\,, \end{aligned} \tag{2.17}$$

where $\mathcal{P}\left(\boldsymbol{\Delta}'|\boldsymbol{\Delta}\right)$ *is the probability of* $\boldsymbol{\Delta}$ *becoming* $\boldsymbol{\Delta}'$*, which is described in Technical Appendix TA1.* $\mathcal{I}_{\breve{c}c}\left(\Delta^{G}\right)$ *is an index function equal to one if* Δ^{G} *falls into the range for which a firm from country* $\breve{c}$ *produces and sells its product in country* c *for* $\breve{c} \in \{c, \widetilde{c}\}$*.* $\mathcal{I}'_{\breve{c}c}\left(\Delta^{G\prime}\right)$ *is the next period counterpart.*

Proof: See Appendix A.2.2.1

A complete description of $\mathcal{P}\left(\boldsymbol{\Delta}'|\boldsymbol{\Delta}\right)$ is provided in Technical Appendix TA1. and a complete description for the evolution of $\mathcal{Q}_{c\widetilde{c}}$ is provided in Technical Appendix TA3.

Equation (2.14) shows that aggregate output growth is determined by the growth of the total technology, $\overline{q}_{c}$. The following lemma characterizes the aggregate growth rate.

Lemma 2. *The aggregate growth rate* g_c *along the balanced growth path is determined by*

$$g_c = \sum_{\boldsymbol{\Delta}}\sum_{\boldsymbol{\Delta}'} \Delta^{c\prime}\, \mathcal{P}\left(\boldsymbol{\Delta}'|\boldsymbol{\Delta}\right) \ \mu(\boldsymbol{\Delta}) - 1\,. \tag{2.18}$$

Proof: This follows from the proof of Proposition 3.

2.7.1 Aggregate Variables and Balanced Growth Path (BGP) Equilibrium

Total R&D expenses in country c, R_c, are

$$\begin{aligned} R_c \; = & \sum_{(\,\Delta^H\,,\,\Delta^F\,,\,\Delta^G\,)} \widehat{\chi}\left(z_j^c\left(\,\Delta^H\,,\,\Delta^F\,,\,\Delta^G\,\right)\right)^{\widehat{\psi}} \mu\left(\,\Delta^H\,,\,\Delta^F\,,\,\Delta^G\,\right)\,\mathcal{Q}_{cc} \\ & + \widetilde{\chi}\,(x^c)^{\widetilde{\psi}}\;\mathcal{F}_c\,\overline{q}_c + \widetilde{\chi}^e\,(x_e^c)^{\widetilde{\psi}^e}\;\mathcal{E}_c\,\overline{q}_c\,, \end{aligned} \tag{2.19}$$

where the first term is the sum of all internal R&D expenses by incumbent firms, the second term is the sum of all external R&D expenses by incumbent firms, and the last term is the sum of all external R&D expenses by potential startups. Note that $z_j^H\left(\,\Delta^H\,,\,\Delta^F\,,\,-\infty\,\right) = 0$ and $z_j^F\left(\,\Delta^H\,,\,\Delta^F\,,\,\infty\,\right) = 0$, $\forall\,\Delta^H,\,\Delta^F\,\in\left\{\,1,\,\frac{\eta}{\lambda},\,\lambda,\,\eta\,\right\}$.

Total profits by incumbent firms net of R&D expenses are then

$$\widetilde{\Pi}_c \;=\; \pi^{cc}\,\mathcal{Q}_{cc} \;+\; \pi^{c\widetilde{c}}\,\mathcal{Q}_{c\widetilde{c}} - P_c R_c\,. \tag{2.20}$$

Since the final good producer is perfectly competitive, its profit is zero, $\Pi_c = 0$.

The government transfer, G_c for $c \neq \widetilde{c}$ is equal to total tariff revenue

$$G_c = \widetilde{\tau}_{\widetilde{c}c}\,(1-\theta)^{\frac{1-\theta}{\theta}}\,(P_c)^{\frac{1}{\theta}}\,L_c\left(\tau_{\widetilde{c}c}\frac{w_{\widetilde{c}}}{\overline{q}_{\widetilde{c}}}\right)^{1-\frac{1}{\theta}}\mathcal{Q}_{\widetilde{c}c}\,.$$

Finally, consumption is determined by the resource constraint

$$P_c C_c = P_c Y_c - P_c X_c - R_c + G_c\,, \tag{2.21}$$

which is equal to the households' total income defined by the households' budget constraint (2.3) with equality. I now close this section by defining the equilibrium.

Definition 1 (Balanced Growth Path Equilibrium). *Let the world economy consist of two countries $c \in \{H, F\}$. A balanced growth path equilibrium of this economy consists of the following tuple for every t, $c, \widetilde{c} \in \{H, F\}$, $j \in [0,1]$, q_j^c and $\overline{q}_c$:*

$$\left\{\, y_j^{c\widetilde{c}*},\, p_j^{c*},\, w_c^*,\, L_c^*,\, \widetilde{L}_c^*,\, x^{c*},\, \{z_j^{c*}(\boldsymbol{\Delta})\}_{\boldsymbol{\Delta}},\, x_e^{c*},\, \overline{x}^{c*},\, \overline{x}^*,\, \mathcal{F}_c^*,\, R_c^*,\, X_c^*,\, Y_c^*,\, C_c^*,\, g_c^*,\, \mathcal{Q}_{c\widetilde{c}},\, \underline{\Omega},\, \overline{\Omega},\, \{\mu^*(\boldsymbol{\Delta})\}_{\boldsymbol{\Delta}} \,\right\}$$

such that (i) $y_j^{c\tilde{c}*}$ *and* p_j^{c*} *satisfy* (2.9)-(2.11)*; (ii)* w_c^**,* L_c^**, and* $\widetilde{L}_c^*$ *satisfy* (2.12)*,* (2.13)*, and* $L_c = \overline{L}_c - \widetilde{L}_c$*; (iii)* x^{c*} *is equal to* (TA4.66)*; (iv)* $\left\{z_j^{c*}(\mathbf{\Delta})\right\}_{\mathbf{\Delta}}$ *is equal to* (TA4.73)-(TA4.78) *and* (TA4.67)-(TA4.72) *according to the value of* $\mathbf{\Delta}$*; (v)* x_e^{c*} *is equal to* (TA4.79)*; (vi)* $\overline{x}^{c*}$ *is as defined in* (2.6)*; (vii)* $\overline{x}^*$ *is equal to* (2.6)*; (viii)* $\mathcal{F}_c^*$ *is consistent with optimal innovation decisions; (ix)* R_c^* *satisfies* (2.19)*; (x)* X_c^* *satisfies* (2.16)*; (xi)* Y_c^* *satisfies* (2.14)*; (xii)* C_c^* *satisfies* (2.21)*; (xiii)* g_c^* *is given by* (2.18)*; (xiv)* $\mathcal{Q}_{c\tilde{c}}$ *evolves according to the evolution of the technology gaps* (2.17)*; (xv)* $\underline{\Omega}$ *and* $\overline{\Omega}$ *satisfy* (2.15)*; and (xvi)* $\{\mu^*(\mathbf{\Delta})\}_{\mathbf{\Delta}}$ *evolves according to the laws of motion* (TA1.18)-(TA1.41) *according to the value of* $\mathbf{\Delta}$*.*

3 Simple Three-Period Heterogeneous Innovation Model

To understand firms' incentives for internal and external innovation, and to derive empirically testable model predictions, we will consider a three-period economy with two product markets and three firms. In period 0, the economy starts with two product markets, market 1 and 2, with initial market-specific technologies $q_{1,0}$, and $q_{2,0}$, and two firms, firm A and B. Product market 1 is given to firm A and is ready for production. Firm A is also given an initial probability of internally innovating product 1, $z_{1,0}$. Firm B, on the other hand, is given only a probability of externally innovating product 2 $x_{2,0}$. Thus, firm B can start operating and producing in period 1 but not in period 0. If external innovation fails, then firm B still keeps market 2 but produces with initial product quality $q_{2,0}$. Thus, at the beginning of period 1, product qualities in the two markets are equal to:

$$q_{1,1} = \begin{cases} \lambda\, q_{1,0} & \text{with probability } z_{1,0} \\ q_{1,0} & \text{with probability } 1 - z_{1,0}\ , \end{cases}$$

and

$$q_{2,1} = \begin{cases} \eta\, q_{2,0} & \text{with probability } x_{2,0} \\ q_{2,0} & \text{with probability } 1 - x_{2,0}\ . \end{cases}$$

where $\lambda^2 > \eta > \lambda > 1$ are innovation step sizes.

In period 1, the main period of interest, there is an outside firm (potentially from a foreign country) that does external innovation hoping to take over the two product markets in period 2. The outside firm succeeds in doing external innovation with probability x_1^e in each product market. Also, there is a news shock about period 2 profit (potentially including an increase in foreign demand) announced in period 1. Afterwards, the two incumbent firms produce using the given technologies, invest in internal innovation to improve the quality of their own products, and invest in external innovation to take over the other firm's product market. At the beginning of period 2, all innovation outcomes are realized. Then, technological competition in each product market takes place, and only the firm with the highest technology in each product market produces. The economy ends after period 2.

In period 1, incumbent firm $i \in \{A, B\}$ invests $R_{j,1}^{in}$ on internal innovation, $j \in \{1, 2\}$ (e.g., for $i = A$, $j = 1$), implying a success probability $z_{j,1}$ using the R&D production function

$$z_{j,1} = \left(\frac{R_{j,1}^{in}}{\widehat{\chi} q_{j,1}} \right)^{\frac{1}{2}} .$$

Successful internal innovation increases the next-period product quality by $\lambda > 1$. Thus, the period 2 product quality for firm i becomes

$$q_{j,2}^i = \begin{cases} \lambda \, q_{j,1} & \text{with probability } z_{j,1} \\ q_{j,1} & \text{with probability } 1 - z_{j,1} \, . \end{cases}$$

Similarly, firm i invests $R_{-j,1}^{ex}$ to learn the period 0 technology used by firm $-i \neq i$, implying a success probability of external innovation $x_{-j,1}$ using the R&D production function

$$x_{-j,1} = \left(\frac{R_{-j,1}^{ex}}{\widetilde{\chi} q_{-j,0}} \right)^{\frac{1}{2}} ,$$

where $-j$ is owned by $-i$. Successful external innovation increases product quality relative to the past-period quality by $\eta > 1$. Thus, product $-j$'s quality in period 2 for firm i becomes

$$q_{-j,2}^i = \begin{cases} \eta \, q_{-j,0} & \text{with probability } x_{-j,1} \\ \varnothing & \text{with probability } 1 - x_{-j,1} \, , \end{cases}$$

where $\varnothing$ means firm i failed to acquire a production technology for product $-j$.

3.1 Optimal Innovation Decisions and Theoretical Predictions

Assume that in each product market j in each period t, firms receive instantaneous profit of $\pi_{j,t}\, q_{j,t}$ where $q_{j,t}$ is the product quality and $\pi_{j,t}$ is a market-period-specific constant known to firms before each period begins. Because there are only two products, incumbents and the outside firm can perform external innovation on the same product. To keep the model simple, further assume that the outside firm can do external innovation only if an incumbent fails to do external innovation, following Garcia-Macia et al. (2019). Then the profit maximization problem of firm i that has product market j with quality $q_{j,1}$ in period 1 can be written as

$$V(q_{j,1}) = \max_{\{z_{j,1},\, x_{-j,1}\}} \left\{ \begin{array}{l} \pi q_{j,1} - \widehat{\chi}(z_{j,1})^2 q_{j,1} - \widetilde{\chi}(x_{-j,1})^2 q_{-j,0} \\ +(1-x_{j,1})(1-x_1^e)\Big[(1-z_{j,1})\pi_{j,2}q_{j,1} + z_{j,1}\pi_{j,2}\lambda q_{j,1}\Big] \\ +\big[x_{j,1} + (1-x_{j,1})\, x_1^e\big]\Big[z_{j,1}\pi_{j,2}\, \lambda\, q_{j,1}\, \mathcal{I}_{\{\lambda q_{j,1} > \eta q_{j,0}\}} \\ \qquad\qquad + \frac{1}{2}(1-z_{j,1})\pi_{j,2}q_{j,1}\, \mathcal{I}_{\{q_{j,1} = \eta q_{j,0}\}}\Big] \\ +x_{-j,1}\Big[(1-z_{-j,1})\,\pi_{-j,2}\,\eta\, q_{-j,0}\,\mathcal{I}_{\{\eta q_{-j,0} > q_{-j,1}\}} \\ \qquad + z_{-j,1}\,\pi_{-j,2}\,\eta\, q_{-j,0}\,\mathcal{I}_{\{\eta q_{-j,0} > \lambda q_{-j,1}\}} \\ \qquad + \frac{1}{2}(1-z_{-j,1})\pi_{-j,2}\eta q_{-j,0}\,\mathcal{I}_{\{\eta q_{-j,0} = q_{-j,1}\}} \\ \qquad + \frac{1}{2} z_{-j,1}\pi_{-j,2}\eta q_{-j,0}\,\mathcal{I}_{\{\eta q_{-j,0} = \lambda q_{-j,1}\}}\Big] \end{array} \right\},$$

where $\mathcal{I}_{\{\cdot\}}$ is an indicator function that captures the possible relationships between the two technologies among the three firms in period 2 in a given market. The first line shows the period 1 profit net of the total R&D cost. The second line represents the incumbent's period 2 expected profit from market j when the other incumbent and the outside firm fail to externally innovate the market j technology. The third and the fourth line represent the period 2 expected profit from market j when one of the two other firms succeeds in externally innovating the market j technology. The fifth to eighth lines represent the period 2 expected profit from market $-j$ when firm i succeeds in externally innovating the market $-j$ technology. The terms following $\frac{1}{2}$ are for the cases in which two firms can produce the same quality product, so that a coin-toss tiebreaker rule applies.

The interior solutions to this problem are

$$z^*_{j,1} = \begin{cases} \dfrac{\pi_{j,2}}{2\,\widehat{\chi}}\,(\lambda-1)(1-x^*_{j,1})(1-x^e_1) & \text{, when } q_{j,1}=q_{j,0} \\ \dfrac{\pi_{j,2}}{2\,\widehat{\chi}}\,\left[\lambda-(1-x^*_{j,1})(1-x^e_1)\right] & \text{, when } q_{j,1}=\lambda\,q_{j,0} \\ \dfrac{\pi_{j,2}}{2\,\widehat{\chi}}\,\left[\lambda-\dfrac{1}{2}-\dfrac{1}{2}(1-x^*_{j,1})(1-x^e_1)\right] & \text{, when } q_{j,1}=\eta\,q_{j,0} \end{cases}$$

and

$$x^*_{-j,1} = \begin{cases} \dfrac{\eta\,\pi_{-j,2}}{2\,\widetilde{\chi}} & \text{, when } q_{-j,1}=q_{-j,0} \\ \dfrac{\eta\,\pi_{-j,2}}{2\,\widetilde{\chi}}\,(1-z^*_{-j,1}) & \text{, when } q_{-j,1}=\lambda\,q_{-j,0} \\ \dfrac{\eta\,\pi_{-j,2}}{2\,\widetilde{\chi}}\,\dfrac{1}{2}(1-z^*_{-j,1}) & \text{, when } q_{-j,1}=\eta\,q_{-j,0}\,. \end{cases}$$

The above results show that the firm's optimal innovation decisions depend on the (expected) future profit, the technology gap in both its own market and the other firm's market, and other firms' internal and external innovation decisions. From these interior solutions, I draw the following results.

Proposition 4. *For each $q_{j,1}$ and for $\lambda^2 > \eta > \lambda > 1$, we can order internal innovation intensities as*

$$z^*_{j,1}\Big|_{q_{j,1}=\lambda q_{j,0}} \quad > \quad z^*_{1,1}\Big|_{q_{j,1}=\eta q_{j,0}} \quad > \quad z^*_{j,1}\Big|_{q_{j,1}=q_{j,0}}\,.$$

Furthermore,

$$\left.\frac{\partial z^*_{j,1}}{\partial x^e_1}\right|_{q_{j,1}=\lambda q_{j,0}} \quad > \quad \left.\frac{\partial z^*_{j,1}}{\partial x^e_1}\right|_{q_{j,1}=\eta q_{j,0}} \quad > \quad 0 \quad > \quad \left.\frac{\partial z^*_{j,1}}{\partial x^e_1}\right|_{q_{j,1}=q_{j,0}}\,.$$

Proof: See Appendix A.2.3

The second part of proposition 4 implies that firms with no local technology gap lower their internal innovation investment when they are faced with a higher probability of creative destruction in their own markets, as they cannot increase the probability of escaping competition by improving their products through internal innovation. On the other hand, if a firm has very high technological advantage, then the firm doesn't increase its internal innovation investment much in response to outsiders' investment in external innovation, because the probability of losing its own product market is small. In the intermediate case, firms increase their internal innovation investment more strongly in response to outsiders' external innovation, as they can lower the probability of losing their market by doing so.

Higher innovation in period 0 increases the probability of having a high local technology gap in period 1 and this helps firms to escape competition. To understand how past innovation intensity affects the firm's current internal innovation decision when the firm is faced with a higher probability of encountering a competitor, x_1^e, define the expected value of internal innovation intensity in period 1 as

$$\overline{z}_1^* = z_{1,1}^*\big|_{q_{1,1}=q_{1,0}} \frac{1}{2}(1 - z_{1,0}) \; + \; z_{2,1}^*\big|_{q_{2,1}=q_{2,0}} \frac{1}{2}(1 - x_{2,0}) \; + \; z_{1,1}^*\big|_{q_{1,1}=\lambda q_{1,0}} \frac{1}{2} z_{1,0} \; + \; z_{2,1}^*\big|_{q_{2,1}=\eta q_{2,0}} \frac{1}{2} x_{2,0} \,,$$

where $\frac{1}{2}$ comes from the fact that there are two products. Then, proposition 4 gives us:

Corollary 1 (**Escape Competition Effect**). *The impact of period 0 innovation intensities, $z_{1,0}$ and $x_{2,0}$ on expected internal innovation in period 1 satisfies:*

$$\frac{\partial \overline{z}_1^*}{\partial x_1^e \partial z_{1,0}} > 0 \,, \;\; \textit{and} \quad \frac{\partial \overline{z}_1^*}{\partial x_1^e \partial x_{2,0}} > 0 \,.$$

Proof: See Appendix A.2.4

Corollary 1 implies that intensive innovation in the previous period induces firms to increase the response of their internal innovation to higher product market competition. As the optimal decision rule shows, firms' external innovation decision also depends on past innovation decisions of other firms:

Proposition 5. *For each $q_{j,1}$ and for $\lambda^2 > \eta > \lambda > 1$, we can order external innovation intensities as*

$$x_{j,1}^*\big|_{q_{j,1}=q_{j,0}} \quad > \quad x_{j,1}^*\big|_{q_{j,1}=\lambda q_{j,0}} \quad > \quad x_{j,1}^*\big|_{q_{j,1}=\eta q_{j,0}}$$

Furthermore,

$$\left.\frac{\partial x^*_{j,1}}{\partial x^e_1}\right|_{q_{j,1}=q_{j,0}} = 0\,, \quad \left.\frac{\partial x^*_{j,1}}{\partial x^e_1}\right|_{q_{j,1}=\lambda q_{j,0}} < 0\,, \quad \textit{and} \quad \left.\frac{\partial x^*_{j,1}}{\partial x^e_1}\right|_{q_{j,1}=\eta q_{j,0}} < 0\,.$$

Proof: See Appendix A.2.3

Proposition 5 implies that firms do less external innovation if other firms have a higher technology advantage, as it becomes more difficult to take over their markets through external innovation. For product markets with a technological barrier (local technology gap > 1), firms also lower their external innovation if the outside firm does more external innovation, as incumbents in these markets will respond by doing more internal innovation with defensive motive (proposition 4). To understand how the past innovation intensity of other firms affects a firm's current external innovation decision, define the expected value of external innovation intensity in period 1 as

$$\overline{x}^*_1 = x^*_{1,1}\big|_{q_{1,1}=q_{1,0}}\,\frac{1}{2}(1-z_{1,0}) \;+\; x^*_{2,1}\big|_{q_{2,1}=q_{2,0}}\,\frac{1}{2}(1-x_{2,0}) \;+\; x^*_{1,1}\big|_{q_{1,1}=\lambda q_{1,0}}\,\frac{1}{2}z_{1,0} \;+\; x^*_{2,1}\big|_{q_{2,1}=\eta q_{2,0}}\,\frac{1}{2}x_{2,0}\,.$$

Then, the first part of proposition 5 implies the following:

Corollary 2 (Technological Barrier Effect). *For a given technology $q_{j,1}$ and period 0 innovation intensities, $z_{1,0}$ and $x_{2,0}$, we have*

$$\frac{\partial \overline{x}^*_1}{\partial z_{1,0}} < 0 \;\;, \textit{and} \;\; \frac{\partial \overline{x}^*_1}{\partial x_{2,0}} < 0\,.$$

Proof: See Appendix A.2.5

Corollary 2 implies that higher technology levels in other markets, which are due to previous innovation, serve as an effective technological barrier that makes it difficult for outside firms to take over another firm's product market. This reduces firms' incentive for external innovation. Because innovation is forward looking, changes in future profit π' are an important factor affecting current period innovation intensity. Proposition 6 summarizes this:

Proposition 6 (Ex-post Schumpeterian Effect)**.** *Given expected period 2 profit $\pi_{j,2}$, we have*

$$\frac{\partial z^*_{j,1}}{\partial \pi_{j,2}} > 0 \,, \quad \forall\, q_{j,1} \ \ , \textit{and} \qquad \frac{\partial x^*_{j,1}}{\partial \pi_{j,2}} > 0 \,, \quad \textit{for} \ \ q_{j,1} = q_{j,0} \,.$$

Signs for $\frac{\partial x^*_{j,1}}{\partial \pi_{j,2}}$ for other local technology gaps are ambiguous.
Proof: See Appendix A.2.6

Proposition 6 implies that any factor that affects future profits may affect firms' internal and external innovation. These include market size changes (such as an opportunity to access foreign markets), changes in input costs, and the future survival probability. More specifically, an increase in the expected profit from one's own market induces firms to increase their internal innovation. However, the effect of increasing expected profit in other markets on firms' external innovation is ambiguous for cases with local technology gap $>$ 1. This is because incumbents in these markets increase their internal innovation in response to increasing expected profit, and this helps them escape competition. For the case with local technology gap $=$ 1, incumbents cannot escape competition through internal innovation. Thus, an increase in expected future profit unambiguously increases external innovation for this case. The above results outline various factors affecting internal, external, and total innovation. The next section tests these predictions empirically.

4 Empirics

In this section, I examine the relationships among firm innovation, firm growth, and international trade for firms with different characteristics empirically. To this end, I identify the causal effect of international trade on the composition of firm innovation (internal vs. external) and test the model predictions. The analysis focuses on the early 1990s to mid-2000s, especially the years after 2000, as this period witnesses changes in the trends for many important economic variables, especially the employment growth rate of high-growth firms and the number of patent applications filed by U.S. firms. The rise of China in the U.S. markets after China's WTO accession, and increased Chinese demand for U.S. products, will be treated as a quasi-experiment.

4.1 Data and Measurement

To construct a comprehensive firm-level dataset with innovation and international trade-related measures, I combine the following seven datasets: the USPTO PatentsView database, the Longitudinal Business Database (LBD), the Longitudinal Firm Trade Transactions Database (LFTTD), the Census of Manufactures (CMF), the UN Comtrade Database, the NBER-CES database, and the data compiled by 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.[11] 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. I aggregate establishment-level information into firm-level observations using these firm identifiers. Firm size is measured by either total employment or total payroll. Firm age is based on 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 associated with the highest level of employment. Time-consistent NAICS codes for the 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 starting from 1992 onward at the firm-level.[12] The LFTTD provides the U.S. dollar value of shipments, and the origin and destination country for each transaction, as well as a related-party flag, which indicates whether the U.S. importer and the foreign exporter are related by ownership of at least 6 percent.

The USPTO PatentsView database tracks all patents ultimately granted by the USPTO from 1976 onward.[13] This database contains detailed information for granted patents including application and grant dates, technology class, other patents cited, and the name and address of patent assignees. It also provides the list of inventors responsible for each patent with their locations. In the following analyses, I use the citation-adjusted number of utility

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

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

[13] See http://www.patentsview.org/download/.

patent applications as the main measure of firm innovation.[14] By using detailed information for each patent, I distinguish domestic innovation from foreign innovation, and measure the extent to which each patent represents internal innovation. The year in which a patent application is filed is used as a proxy for the innovation year. The citation-adjusted average of the internal innovation measure for the flow of patent applications in each firm-year is used as a proxy for the overall extent of internal innovation at each firm in each year. I discuss the measure of internal innovation in detail shortly.

I match the USPTO patent database to the LBD to assign detailed firm-level information and assign firm-industry-level changes in trade flows to each patent. In the following analyses, I compare firms' patenting behavior across different years. Thus, match quality is important – failing to match a firm in the USPTO patent database in a particular year to its LBD counterpart will result in mismeasuring innovation. This problem arises because the USPTO doesn't track a consistent unique firm ID. The USPTO assign patent applications to self-reported firm names. Thus, it is vulnerable to misspelling of firm names. To overcome this match quality issue, I adopt the Autor et al. (2019) methodology that utilizes the machine-learning capacities of the internet search engine. I use all patents granted up to December 26, 2017 during the matching procedure, and use patent applications up to 2007 in the subsequent analyses. Thus, the following analyses are virtually free from the right censoring issue (mismeasuring firms' innovation activities due to the patents applied for but not yet granted). Table A4 in the Appendix reports summary statistics for patenting firms in 1992.

The quinquennial CMF provides detailed information for activities by establishments in the manufacturing sector. It also provides detailed product codes and breaks down the value of shipments for all products each establishment sells. I used five-digit SIC codes for observations up to 1997, and the seven-digit NAICS codes for observations from 2002 onward to measure firms' product choices.

The UN Comtrade Database provides information for world trade flows at the six-digit HS product-level from 1991 to 2016.[15] The six-digit HS codes are concorded to the six-digit 2012 NAICS industries using the Pierce and Schott (2009) and Pierce and Schott (2012)

[14]See Cohen (2010) for a comprehensive review of the literature on the determination of firms' and industries' innovative activity and performance and how patent-related measures are used.

[15]https://comtrade.un.org/db/default.aspx.

crosswalks. I construct the industry-level export shock measure using the UN Comtrade Database. I obtain U.S. tariff schedules from Feenstra et al. (2002) to measure the industry-level Trade Policy Uncertainty (TPU), which is used for foreign competition shock. The construction of the two trade shocks are discussed in detail in the following section.

The NBER CES Manufacturing Industry Database, assembled by Becker et al. (2013), is used to obtain the industry-level deflator for the value of shipments for manufacturing industries from 1976 to 2011.[16] All nominal values are inflated to 1997 U.S. dollars using this industry-level deflator for the value of shipments for manufacturing industries, and the BEA's Consumer Price Index for other industries. In the following analyses, I use subsets of a sample of USPTO patents matched U.S. firms in the LBD and industry-level trade data from 1982 to 2007 for each regression specification.

4.1.1 Measure of Internal of Innovation

In this study, I use the self-citation ratio as a measure of whether the patent is used for internal innovation. Each granted patent is required to cite all prior patents on which it builds. When a cited patent belongs to the owner of the citing patent, these citations are called self-citations. Akcigit and Kerr (2018) use the self-citation ratio—defined as the ratio of self-citations to total citations—as a measure of internal innovation. The idea is that the more an idea is based on the firm's internal knowledge stock (self-citation), the more likely the innovation is used for improving the firm's existing products (internal innovation). A higher self-citation ratio means that a patent is more likely to reflect internal innovation.

4.1.2 Measures for Trade Shocks

As it is shown by Handley and Limão (2017), over one-third of the growth of imports from China to the U.S. in the first half of the 2000s is explained by the U.S. granting permanent normal trade relations (PNTR) to China upon China's 2001 accession to the WTO. Nonmarket economies such as China are subject to relatively high tariff rates originally set under the Smoot-Hawley Tariff Act of 1930, when they export to the U.S. These rates are known as non-Normal Trade Relations (non-NTR) or column 2 tariffs. On the other hand,

[16] http://www.nber.org/nberces/.

the U.S. offers WTO member countries NTR or column 1 tariffs which is substantially lower than non-NTR tariffs. The Trade Act of 1974 allows the President of the United States to grant temporary NTR status to nonmarket countries on an annually renewable basis after approval by Congress. Starting from 1980, U.S. Presidents granted such waivers to China.

While China never lost these waivers and the tariff rates applied to Chinese products were kept low, the process of annual approval by Congress created uncertainty about whether the low tariffs would revert to non-NTR rates. After the Tiananmen Square protests in 1989, Congress voted on a bill to revoke China's temporary NTR status every year from 1990 to 2001. Following the bilateral agreement on China's entry into the WTO between the U.S. and China in 1999, Congress passed a bill granting China PNTR status in October 2000. Upon China's accession to the WTO in December 2001, PNTR became effective and was implemented on January 1, 2002. PNTR removed the uncertainty about U.S. trade policy toward China by permanently setting tariff rates on Chinese products at the NTR levels. This lowered the expected U.S. import tariffs on Chinese products, and eliminated any option value of waiting for firms to incur large fixed costs associated with exporting products from China to the U.S. Thus, PNTR reduced TPU, the more so for industries with a large gap between tariff rates under NTR and non-NTR regimes.

I use the industry-level gap between NTR tariff rates reserved for WTO members and non-NTR tariff rates for non-market economies in the year 1999 as a proxy for the industry-level competition shocks from China occurring in 2001.[17] Thus, for industry j,

$$NTRGap_j = Non\ NTR\ Rate_j \ - \ NTR\ Rate_j \ .$$

Also, following Aghion et al. (2017), I use log differences in advanced countries' (excluding the U.S.) exports to China as a proxy for the exogenous change in Chinese demand for the U.S. products (export shock).[18] Thus,

$$\Delta ExportShock_{j\tau} = \log(EX_{j\tau 1}) - \log(EX_{j\tau 0}) \ ,$$

[17]We can consider the NTR gap as a first-order Taylor approx. of model-based TPU measures, such as Handley and Limão (2017), that is positively related to non-NTR rate and negatively related to NTR rate.

[18]These advanced countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. These are the advanced countries for which we can obtain disaggregated bilateral HS trade data back to 1991, as explained in Autor et al. (2019)

where EX_{jt} represents total exports by eight advanced countries to China in industry j in year t, $\tau \in \{1992 - 1999\ ,\ 2000 - 2007\}$ are the two periods of interest, $\tau 0$ is a start-year for each period, and $\tau 1$ is an end-year for each period. If a firm operates in multiple 6-digit NAICS industries, I use the employment-weighed average $NTRGap_j$ and $\Delta ExportShock_{j\tau}$. I use unweighted average trade shocks and shocks to firms' main industry as robustness checks. Table A1 and Table A2 in the Appendix report summary statistics for each trade shock measure.

4.2 Empirical Strategies and Main Results

The theory developed above provides three empirically testable predictions: i) the escape-competition effect, ii) the technological-barrier effect, and iii) the expected profit effect. I now test these three model predictions.

4.2.1 Corollary 1: Escape-Competition Effect

The first prediction of my model is that firms who have innovated intensively in recent periods increase internal innovation more when they are faced with higher competition, compared to their low innovation counterparts. This is because innovation-intensive firms can escape competition more easily through additional internal innovation, by leveraging their higher-than-average production technologies (technological advantages, or technological barriers) that they built in their own markets through recent intensive innovation.

Following Handley and Limão (2017) and Pierce and Schott (2016), I use a Difference-in-Difference (DD) specification to identify the effect of the China competition shock on U.S. firm innovation for two periods, $p \in \{1992 - 1999\ ,\ 2000 - 2007\}$, for firm i in industry j:

$$\begin{aligned} \Delta y_{ijp} \ &= \beta_1 Post_p \times NTRGap_{ijp0} \times InnovIntens_{ijp0} \\ &+\ \beta_2 Post_p \times NTRGap_{ijp0}\ +\ \beta_3 Post_p \times InnovIntens_{ijp0} \\ &+ \beta_4 NTRGap_{ijp0} \times InnovIntens_{ijp0}\ +\ \beta_5 NTRGap_{ijp0} \\ &+\ \mathbf{X}_{ijp0}\,\gamma_1\ +\ \mathbf{X}_{jp0}\,\gamma_2\ +\ \delta_j\ +\ \delta_p\ +\ \alpha\ +\ \varepsilon_{ijp}\ . \end{aligned} \tag{4.22}$$

In these specifications, firms in low TPU industries are the control group, whereas firms in high TPU industries are the treatment group. I use a 2000 cohort of firms to measure firm innovation before the policy change, which occurred in December 2001. In this way, the composition of firms in terms of their innovation is minimally affected by the policy change.

$Post_p$ is a dummy variable equal to one for the period 2000-2007 and zero otherwise. It captures changes in firm innovation after China's WTO accession. $\mathbf{X}_{ijp0}$ is a vector of firm controls, and $\mathbf{X}_{jp0}$ is a vector of industry controls, both measured at the start-year for each period.[19] δ_j is an industry fixed effect (six-digit NAICS), and δ_p is a period fixed effect. All models are unweighted, and standard errors are clustered on the 6-digit NAICS industries.

Δy_{ijp} is the DHS (Davis et al., 1996) growth rate of either i) the total citation-adjusted number of patents, or ii) the citation-weighted average self-citation ratio between the start-year and end-year for each period $p \in \{1992 - 1999\ ,\ \ 2000 - 2007\}$. An increase in the self-citation ratio means that the firm's innovations became more internal.

To maximize the sample size, I 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, and compute the DHS growth rates for the longest span of years available. I also require firms to have at least one patent before the start-year of each period, or to have age > 0 to avoid the effect coming from the firm entry. The sample includes all LBD firms matched to the USPTO patent database that meet these three criteria, except for the firms in FIRE industries.

$InnovIntens_{ijp0}$ is a continuous variable equal to the past five-year average of the ratio of the number of firms i's patent applications to total employment, measured in the start year for each period $p0$. I control for industry-fixed effects for this measure by dividing it by its time-average at the 2-digit NAICS level. Thus, I am examining the impact of heterogeneity within industries rather than differences across industries. The escape-competition hypothesis predicts β_1 to be positive when changes in the self-citation ratio are used as Δy_{ijp}.

Table 1 shows the estimates of β_1.[20] As indicated in column (4) of Table 1, the estimate for β_1 is positive and statistically significant for the growth of the self-citation ratio as

[19]Firm controls include: firm employment, firm age, past 5-year growth of U.S. patents in the CPC technology classes in which firm operates, and dummy variables for publicly traded firms, exporters, importers, and offshoring firms. Industry control includes NTR rates measured at the start of each period.

[20]To conserve space, Table 1 reports coefficients estimates for triple interaction terms only. Results including coefficients for all the interaction terms are reported in Table A8 in the Appendix.

Table 1: Escape-competition effect

	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite
	(1)	(2)	(3)	(4)
NTR gap × Post × Innovation-intensity	0.077	-0.017	0.732**	0.784***
	(0.231)	(0.233)	(0.299)	(0.268)
Observations	6,500	6,500	6,500	6,500
Fixed effects	j, p	j, p	j, p	j, p
Controls	no	full	no	full

Notes: Full controls include past 5-year U.S. patent growth in firms' own technology fields, log employment, firm age, NTR rate, dummy for publicly traded firms, dummy for firms with total imports > 0, dummy for firms with total exports > 0, and dummy for firms with imports from relative parties > 0. Estimates for industry (j) and the period (p) fixed effects as well as the constant are suppressed. Robust standard errors adjusted for clustering at the level of the firms' major industries are displayed below each coefficient. Observations are unweighted. Observation counts are rounded due to Census Bureau disclosure avoidance procedures. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

a dependent variable, consistent with Corollary 1. The estimated effect is economically important as well. Table A11 in Appendix B.4 shows that for an average firm, creating 4 more patents is associated with a 3.4 percentage points increase in employment growth, but the association becomes smaller in magnitude if the average self-citation ratio of the new patents is high. The estimates in Table 1, combined with Table A11 suggest that the association between patenting and employment growth is decreased by 1.13 percentage points for firms with average innovation intensity following the competition shock from China.

4.2.1.1 Discussion: PNTR as a Competitive Pressure Measure

As discussed extensively in Pierce and Schott (2016) and Facchini et al. (2019), the main channel the removal of trade policy uncertainty affects trade between the U.S. and China is by persuading Chinese firms to export their products to the U.S. The two papers verify this channel by estimating the effect of the removal of TPU on changes in Chinese exports to the U.S. using the LFTTD at the product level, and Chinese Custom Data at the firm level. Table A9 in the Appendix shows OLS estimates of the effect of PNTR on changes in U.S. imports from China from 2000 to 2007 at the 8-digit HS level and the 6-digit NAICS level separately. As indicated in the table, the NTR gap is positively associated with changes in U.S. imports from China regardless of the level of aggregation. However, statistical significance falls from the 1% to the 5% level as we move from the 8-digit HS level to the 6-digit NAICS level, where the latter is the level of aggregation used in this paper.

As is clear from the simple three-period model introduced in Section 3, one critical factor firms consider when they decide how much to invest in innovation is competitive pressure—the probability of encountering competitors in a firm's own market in the near future. In the real world, pressure can come from both realized competition (an increase in the number of competitors) and from possible future competition (an increase in the number of potential entrants) in each product market. Table A10 shows OLS results from regressing the two dependent variables of interest on the realized changes in U.S. imports from China, to estimate the effect of realized competition on firm innovation composition. Here I use the same two seven-year periods used in the previous analysis, 1992-1999 and 2000-2007. As the table indicates, changes in U.S. imports from China from 1992 to 2007 do not have any statistically significant effect on U.S. firms' innovation composition after I control for firm characteristics. This analysis, however, has two concerns: i) changes in U.S. imports from China are endogenous, and ii) successful escape competition by U.S. firms can make realized competition low even competitive pressure is substantial.

The concern i) can be addressed by using the imposition of PNTR as an instrument for changes in imports. However, as Table A9 shows, the NTR gap has low statistical power for predicting U.S. imports from China at the 6-digit NAICS level. Indeed, the F-test from the first stage of the 2SLS estimation exercise shows that NTR gap is a weak instrument. Nonetheless, the 2SLS estimate of β_1 is positive and large.[21]

My model suggests that the second concern is important, and measures for realized competition cannot capture this. The removal of trade policy uncertainty, however, can be an excellent proxy for increased competitive pressure, as it is associated with an increase in Chinese firms' opportunity to enter the U.S. market. For example, Handley and Limão (2017), through the lens of their structural model, show that a reduction in TPU provides greater incentive for incumbents to incur irreversible investments to enter foreign markets. Erten and Leight (2019) further show that the imposition of PNTR induces Chinese manufacturing firms to increase their investment and their value-added per worker. These findings suggest a

[21] The 2SLS regression results are not reviewed by the Census Bureau for disclosure avoidance yet. Thus, they are not released from the Maryland RDC at this moment.

tight relationship between the imposition of PNTR and an increase in potential future competition. Thus, finding direct evidence for this relationship, such as a link between PNTR and the number of Chinese startups or the number of Chinese firms with the ability to export their products to the U.S., is a priority for future research.

4.2.1.2 Validity of the Identification Strategy and Robustness Tests

Previous studies using PNTR with China as a trade shock, such as Pierce and Schott (2016) and Handley and Limão (2017), provide rich evidence for the exogeneity of PNTR for the U.S. firms' decisions in the 1990s and 2000s. Thus, I focus on testing the parallel pre-trends assumption, the key identifying assumption for the DD model. To test the assumption for the dependent variables of interest, I estimate (4.22) for two seven-year periods before the policy change, 1984-1991 and 1992-1999. Table A12 in the Appendix shows the results, which support the validity of the parallel pre-trends assumption.

To further confirm the validity of my results, I perform several robustness checks, with results reported in the Appendix. I find that my results are robust to a variety of different specifications. First I include upstream and downstream trade shocks as covariates in model (4.22). By using the 1992 BEA input-output table, I construct upstream and downstream trade shocks as weighted averages of industry-level trade shocks. The upstream effect of trade is the effect of trade shocks propagating upstream from an industry's buyers, and the downstream effect of trade is the effect of trade shocks propagating downstream from its suppliers.[22] Table A13 in the Appendix shows that including controls for I-O linkages does not change the main results.

The second test uses different weights for constructing firm-level NTR gaps. Because patenting firms are multi-industry firms, I use employment in the start year of each period as weights and construct a weighted average of industry-level NTR gaps for all industries in which each firm operates as the firm-level NTR gap. I also use an unweighted average of this measure, and use industry-level NTR gaps for firms' main industry (the industry with

[22]Following Pierce and Schott (2016), for each 6-digit NAICS industry, I set the I-O weights to zero for both up and downstream industries belonging to the same 3-digit NAICS broad industries while computing the indirect effects to take into account the findings from Bernard et al. (2010) that U.S. manufacturing establishments often produce clusters of products within the same 3-digit NAICS sector.

the most employment) as alternative measures for TPU in model (4.22). Table A15 in the Appendix shows that using these alternative measures do not change the main results.

The third test addresses possible selection bias resulting from including only firms with a positive number of patents granted in the start year and in any of the last four years of each period in the regression analysis. This selection is inevitable as I need to compute the self-citation ratio for two years for each period. I correct for this bias by re-weighting the regression sample using the inverse of the propensity scores from a logit model with an indicator for the analysis sample as the dependent variable as weights. Table A16 in the Appendix shows that this reweighting does not change the results. The fourth test adds the cumulative number of patents as a firm-level control variable in the model (4.22). The self-citation ratio can mechanically increase because the firm's patent stock increases as the firm becomes older. Adding the cumulative number of patents as a firm-level covariate addresses this issue, and Table A17 in the Appendix shows that this does not change the results.

The fifth test clusters standard errors on firms. The second test indicates that most variation in the firm-level NTR gap is at the industry-level. Thus, I cluster standard errors at the six-digit NAICS level in the main analysis. As a robustness check, I cluster standard errors on firms, and Table A18 in the Appendix shows this does not change our inference on the main results. Finally, I test the robustness of my results by using the number of products added as a dependent variable—an alternative measure for external innovation (inverse of internal innovation). Table A19 in the Appendix shows results that support Corollary 1, with the number of products added as an alternative measure of external innovation.

4.2.2 Corollary 2: Technological-Barrier Effect

Another prediction from my model is that firms do less external innovation if other firms have innovated more intensively in the past period. Intensive innovation by other firms raises the technology barrier in other markets on average, which implies that business take over through external innovation becomes more difficult. Thus, firms optimally reduce their external innovation. To test this theoretical prediction, I use the recent increase in the number of foreign patent applications as a proxy for increasing innovation intensity in other markets. Since I don't have product-market information for foreign firms, I use patent technology class (CPC) as a proxy for product in this exercise. Foreign patents are defined as patents filed by foreign firms whose first listed inventor is a foreigner. I use the pre-shock years from period 1989 to 2000 and construct non-overlapping five-year first differences (DHS growth for 1989-1994, and 1995-2000) to estimate the following fixed-effect model:

$$\Delta Y_{ijt+5} = \beta_1 \overline{\Delta S}_{ijt-5}^{Own} + \beta_2 \overline{\Delta S}_{ijt-5}^{Outside} + \mathbf{X}_{ijt}\,\gamma_1 + \delta_{jt+5} + \varepsilon_{ijt+5}$$

ΔY_{ijt+5} is either the 5-year DHS growth rate of the citation-adjusted number of patents or the average self-citation ratio between t and $t+5$, and $\overline{\Delta S}_{ijt-5}^{tech}$ for $tech \in \{Own,\ Outside\}$ is the lagged average 5-year DHS growth rate of foreign patents in each technology class for firm i's own technology space (Own) and outside of firm i's technology space ($Outside$).

To be more specific, for each technology class c in CPC, denote the total number of foreign patents filed in year t as $S_{c,t}$. Then the DHS growth rate of foreign patents belonging to c between year $t-5$ and t can be written as

$$\Delta S_{c,t-5} \equiv \frac{S_{c,t} - S_{c,t-5}}{0.5 \times (S_{c,t} + S_{c,t-5})} \,.$$

Denote Q_t as the set of all the patent technology classes available until year t, and Q_{ijt} as the portfolio of patent technology classes firm i accumulated through year t. This defines the technology space in which firm i operates. Furthermore, denote $\omega_{c,i,j,t}$ the share of patent technology class c in firm i's technology portfolio through year t. Then the lagged growth in innovation intensity in firm i's own space, $\overline{\Delta S}_{ijt-5}^{Own}$, is defined as

$$\overline{\Delta S}_{ijt-5}^{Own} \equiv \sum_{c \in Q_{ijt}} \omega_{i,j,c,t} \Delta S_{c,t-5} \,,$$

and outside of own space counterpart, $\overline{\Delta S}_{ijt-5}^{Outside}$, is defined as

$$\overline{\Delta S}_{ijt-5}^{Outside} \equiv \frac{1}{\|Q_{ijt}^c\|} \sum_{c \in Q_{ijt}^c} \Delta S_{c,t-5} \,,$$

where $Q_{ijt}^c \equiv Q_t \backslash Q_{ijt}$ is the complement of the set Q_{ijt}, and $\|Q_{ijt}^c\|$ is the number of technology

Table 2: Technological-barrier effect

	ΔPatents	ΔSelf-cite
	(1)	(2)
Past 5 year Δforeign patent, outside of firm's own technology fields	-5.984**	9.076***
	(2.756)	(2.711)
Observation	7,600	7,600
Fixed effects	*jp*	*jp*

Notes: Controls include past 5-year U.S. patent growth in firms' own technology fields, log payroll, firm age, dummy for publicly traded firms, dummy for firms with total imports > 0, dummy for firms with total exports > 0, and dummy for firms with imports from relative parties > 0. Estimates for industry-period (jp) fixed effects as well as the constant are suppressed.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.

classes in Q^c_{ijt}. Table A3 in the Appendix reports summary statistics for the technology shock measures. The regression is unweighted and standard errors are clustered by firm. I include industry-period fixed effects to control for industry-level shocks. The theory predicts β_2 to be positive when changes in the self-citation ratio is the dependent variable, and insignificant or negative for changes in the total number of patents.

Table 2 shows estimates of β_2.[23] As the table indicates, U.S. firms create fewer patent applications when recent outside innovation by foreign firms is high, and firms' innovation is more internal in nature. This suggests that U.S. firms perform less external innovation when the technological barrier is high in product markets outside of their own.

4.2.3 Proposition 6: Ex-post Schumpeterian Effect

The final prediction of my model that I test is that firms do more internal innovation if they expect to get higher profits from their current product markets in the near future. To test this prediction, I use the export shock explained previously as a proxy for changes in future profits. Thus, for firm i in industry j in period $p \in \{1992-1999, 2000-2007\}$, I estimate the following regression model:

$$\Delta y_{ijp} = \beta_2 \Delta ExportShock_{jp} + \mathbf{X}_{ijp0}\,\gamma_1 + \delta_j + \delta_p + \alpha + \varepsilon_{ijp}\,, \tag{4.23}$$

[23]Table A20 in the Appendix shows the estimation results for own technology field shock, as well as the results including the interaction with firms' innovation intensities. I also run the same regression specification using concurrent technology shock, and Table A21 in the Appendix shows the results. The results are widely consistent with that of the lagged technology shock.

Table 3: Effect of export shocks on firm innovation composition

	ΔPatents (1)	ΔPatents (2)	ΔSelf-cite (3)	ΔSelf-cite (4)
Export shock	0.046	0.047	-0.013	-0.014
	(0.032)	(0.032)	(0.035)	(0.035)
X Innovation intensity		0.003		0.014*
		(0.008)		(0.008)
Observations	6,500	6,500	6,500	6,500
Fixed effects	j, p	j, p	j, p	j, p

Notes: Controls include past 5-year U.S. patent growth in firms' own technology fields, log employment, firm age, dummy for publicly traded firms, dummy for firms with total imports > 0, dummy for firms with total exports > 0, and dummy for firms with imports from relative parties > 0. Estimates for industry (j) and the period (p) fixed effects as well as the constant are suppressed. Robust standard errors adjusted for clustering at the level of the firms' major industries 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.

where the descriptions for each variable are the same as described in model (4.22).

Table 3 reports the results. As the table indicates, there is no statistically significant effect of the export shock on the average firm's innovation composition. These weak results might be because few U.S. firms were exporting to China even in 2007, and the share of the total value of shipments accounted for by the value of exports to China is quite small, as Table A5 and A6 in the Appendix show. The interaction term with firm-level innovation intensity, however, is statistically significant and positive when changes in the self-citation ratio is the dependent variable. We will see in the quantitative analysis below that this result is consistent with the prediction from the baseline two-country model.

5 Quantitative Analysis

5.1 Calibration

There are nineteen structural parameters (assuming symmetry across the two countries for innovation and production) that I need to calibrate, seven of which I are calibrate internally. Table 4 shows the list of parameters and their values used for counterfactual exercise. I map my two-country model to the U.S. and China. As all the products in my model economy are tradable, I calibrate the model to the U.S. manufacturing sector in 2000.

Table 4: Structural Parameters

	Parameter	Description	Value	Identification
1.	β	Time discount factor	0.9615	Annual interest rate of 4%
2.	$\tilde{\tau}_{HF}$	Tariff rates for exports from H to F	1.0816	External calibration
3.	$\tilde{\tau}_{FH}$	Tariff rates for exports from F to H	1.0816	External calibration
4.	$\mu_0\left(\Delta^G\right)$	Initial global technology gap distribution	Matrix	External calibration
5.	$\hat{\psi}$	Curvature of internal R&D	2	(Akcigit and Kerr, 2018)
6.	$\tilde{\psi}$	Curvature of external R&D	2	(Akcigit and Kerr, 2018)
7.	$\tilde{\psi}^e$	Curvature of external R&D, startup	2	(Akcigit and Kerr, 2018)
8.	θ	Quality share in final good production	0.109	(Akcigit and Kerr, 2018)
9.	$\overline{L}_H$	Mass of labor in country H	1	External calibration
10.	$\overline{L}_F$	Mass of labor in country F	1	External calibration
11.	$\mathcal{E}_H$	Mass of potential startups in H	0.5	External calibration
12.	$\mathcal{E}_F$	Mass of potential startups in F	0.5	External calibration
13.	λ	Quality multiplier of internal innovation	1.044	Indirect inference
14.	η	Quality multiplier of external innovation	1.067	Indirect inference
15.	$\hat{\chi}$	Scale of internal R&D	0.119	Indirect inference
16.	$\tilde{\chi}$	Scale of external R&D	0.714	Indirect inference
17.	$\tilde{\chi}^e$	Scale of external R&D, startup	11.696	Indirect inference
18.	d_{HF}	Iceberg trade cost for exports from H to F	1.01	Indirect inference
19.	d_{FH}	Iceberg trade cost for exports from F to H	1.01	Indirect inference

One complication with this setup is that tariff rates imposed by the U.S. government to Chinese products in 2000 were virtually unchanged after China's WTO accession. However, because there was a possibility of tariff rate increases, the effective tariff rates Chinese firms perceived with before 2001 were higher than the actual values, as discussed in the previous section. To capture this and to run a counterfactual exercise to analyze the effect of trade liberalization on the composition of firm innovation that mimics what happened after China's WTO accession in the U.S., I estimate the effective tariff rate facing Chinese firms in 2000. Specifically, I assume a 13% probability of the tariff rate increasing to the non-NTR rate, as estimated by Handley and Limão (2017), an average non-NTR rate of 36%, and an average NTR rate of 4%, to get an effective tariff rate of 8.16%.

As one period in my model is one year, I set the time discount factor to 0.9615, implying a real interest rate of 4%. I set the mass of labor to 1 and the mass of potential startups to 0.5 in both countries, as the counterfactual exercise will compare the two balanced growth path equilibria before and after China's WTO accession, and this requires the two countries to be symmetric. I set the initial global technology gap distribution to be a symmetric random matrix. This is innocuous as the effect from the initial values of this matrix will be washed away during the simulation. I set the curvature of the R&D cost functions to 2, which is a standard value in the firm innovation literature. I set the quality share in final good production to 0.109, the value estimated by Akcigit and Kerr (2018).

Table 5: Model Fit

	Moment	Data	Model	Source
1.	p90 emp. growth, emp. weighted (%)	19.86	18.46	Decker et al. (2016)
2.	Startup rates (%)	6.68	5.64	BDS
3.	Agg. domestic sales growth (%)	2.14	1.70	NBER-CES
4.	Avg. # of products firms produce	2.27	1.88	CMF
5.	Success prob. of adding a product (%)	29.20	22.68	CMF
6.	Share of US firms exporting to CN (%)	2.30	1.12	LFTTD

5.2 Indirect Inference

There are seven remaining parameters to be estimated: λ, η, $\widehat{\chi}$, $\widetilde{\chi}$, $\widetilde{\chi}^e$, d_{HF}, and d_{FH}. However, as the two countries are symmetric, $d_{HF} = d_{FH}$. Thus, I have six remaining parameters and these are estimated using an indirect inference approach: for each set of six parameter values, I compute six model-generated moments, compare them to the data moments, and find a set of parameter values that minimizes the objective function

$$\min \sum_{i=1}^{6} \frac{\mid \text{model moments}_i - \text{data moments}_i \mid}{\frac{1}{2} \mid \text{model moments}_i \mid + \frac{1}{2} \mid \text{data moments}_i \mid}$$

where the six moments are listed in Table 5.

The six moments are chosen in consideration of both their importance in answering the central question of this paper, and the relationships among the moments and the parameters coming from the choice of functional forms in the model. Although all the parameter values contribute substantially in determining the value for each model-generated moment, the tight relationship between specific sub-groups of parameters and moments can be noted.

Firms perform internal and external R&D to adjust the number of product lines they operate. Since R&D cost is one of the crucial factors determining the level of R&D intensity, and hence the number of product lines the firm owns, I discipline the scale parameter of internal R&D ($\widehat{\chi}$) and external R&D ($\widetilde{\chi}$) using the average number of products firms own. Potential startups learn and improve existing technologies to enter the market, and the success probability of entry is tightly related to the level of R&D expenditure they spend. Thus I discipline the scale of external R&D for startups ($\widetilde{\chi}^e$) using the startup rate.

Firms grow in terms of both sales and the number of employees by improving the qualities of their existing products and/or adding new product lines to their product portfolios. How

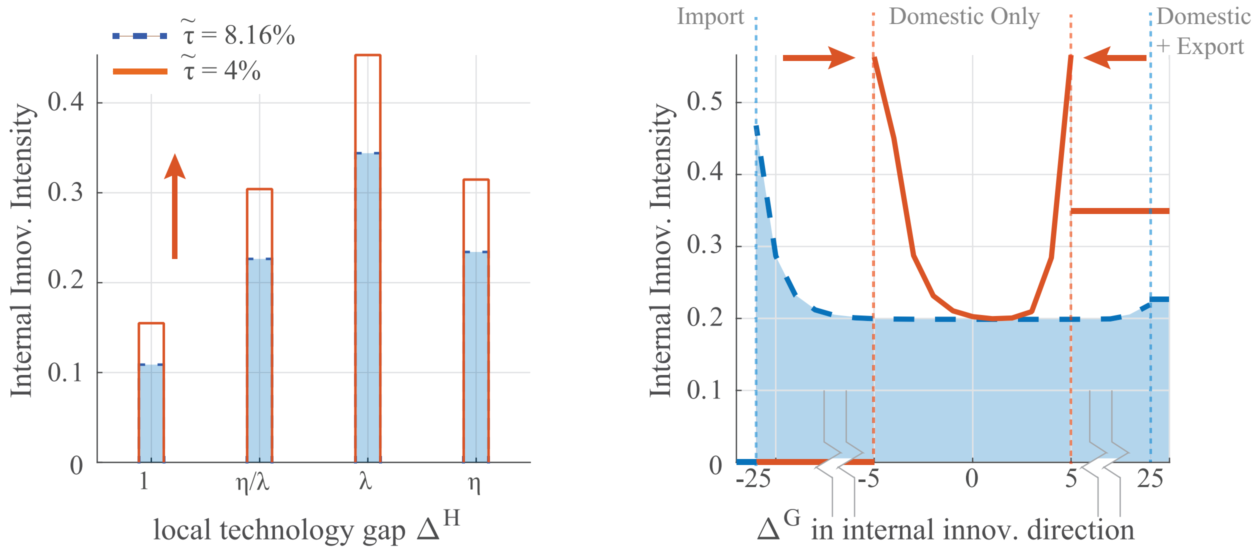

Figure 2: Internal Innovation Decision Rule

quickly they grow depends on how much product quality improvement they can achieve. Thus I discipline the quality multipliers of internal innovation (λ) and external innovation (η) using the average sales growth rate and the employment growth rate at the 90th percentile of the employment-weighted firm employment growth distribution.

How fast firms add a new product to their portfolio depends on the level of external R&D investment. Thus, I discipline the scale of external R&D ($\tilde{\chi}$) using the success probability of adding a product (average number of products added by firms). Finally, I discipline the iceberg trade costs $d_{cc'}$ using the share of U.S. firms exporting to China. Table 5 reports the model generated moments and their empirical counterparts.

5.3 Solution Algorithm

Since I don't have an analytic expression for firm distribution, I pin down values for the mass of firms, $\mathcal{F}_H$ and $\mathcal{F}_F$, through simulation during the numerical solution method. I simulate 200,000 products over 600 years, then take an average across outcomes from the last 200 years to capture the model-implied moments. I solve the model as a fixed point over a vector of growth rates (g^H, g^F). Appendix A.2.7 describes the solution algorithm in detail.

Table 6: Reduction in bilateral tariff rates from 8.16% to 4%

Description	Before	After	% change
Avg. internal innov. intensity z^H (%)	19.28	20.99	8.83
Firm level external innov. intensity x^H (%)	26.63	24.81	-6.84
Success prob. of adding a product (%)	22.68	20.63	-9.04
Technological barrier (%)	14.82	16.83	13.56
p90 emp. growth (%)	18.46	15.15	-17.94
p10 emp. growth (%)	-41.77	-37.89	-9.28
Startup rate (%)	5.64	5.06	-10.26
Aggregate domestic sales growth (%)	1.70	1.69	-0.55
R&D to sales ratio (%)	4.54	4.16	-8.51
Internal R&D expense share	21.84	31.96	46.35
Share of firms exporting (%)	1.12	3.44	206.45
Share of export sales in total sales (%)	0.46	1.64	256.37

5.4 Characteristics of Optimal Innovation Decision Rules

The blue lines in Figure 2 show two cross-sections from the internal innovation decision rule for the baseline parameter values, which is four-dimensional. The left panel shows the average internal innovation decision rule as a function of the local-technology-gap in the home county (Δ^H). As we can see, innovation intensity (success probability of innovation) increases with Δ^H at first, then drops when $\Delta^H = \eta$. In the latter case, incumbents have such a high technological advantage that no competitors can take over their businesses even when incumbents fail at internal innovation. The right panel shows the internal innovation decision rule as a function of the global-technology-gap (Δ^G), which is similar to Akcigit et al. (2018). Internal innovation intensity peaks near two thresholds. Firms have higher incentives to do internal innovation near the export-threshold (right), as additional internal innovation makes firms exporters, which leads to higher profits. Firms also have higher incentives to do internal innovation near the import-threshold (left), as the failure of internal innovation leads to losing the product market to foreign firms.

5.5 Counterfactual Exercise

I run a counterfactual exercise using a 4.16 percentage point drop in the bilateral tariff rate (from 8.16% to 4%) as a trade shock, and compare the two BGP equilibria. Figure 2 shows changes in the optimal internal innovation decision rule, and Table 6 shows the changes in firm and aggregate-level moments. Increasing international competition leads firms to shift their innovation from external to internal, which leads to lower employment growth rates for high-growth firms (firms at the 90th percentile of the firm employment growth distribution). Employment growth of low-growth firms (firms at the 10th percentile of the firm employment growth distribution), however, increases, and this leads to a decline in the skewness of the firm employment growth distribution measured as the p90-p10 differential. Firms become better at protecting their own product market through defensive internal innovation but lose their power of creative destruction. The economy becomes a place where incumbent firms have high technological advantages in their own markets on average. This is reflected as an increased technological barrier (measured as one minus the ratio of the success probability of adding a product divided by the firm-level external innovation intensity). Thus, startup rate also declines as external innovation becomes harder. These results are consistent with industry-level regression results using the imposition of PNTR as a foreign competition shock, as shown in Table A22 in the Appendix.

6 Concluding Remarks

In this paper, I investigate how foreign competition affects firm innovation, high-growth firm activity and firm entry by developing a two-country endogenous growth model with two types of innovation and imperfect technology spillovers, and then testing model predictions empirically. Having different types of innovation and imperfect technology spillovers in the model is crucial in analyzing the relationship between increasing foreign competition and the decline of high-growth firms and firm entry. This is because changes in the composition of firms' innovation in response to increasing foreign competition is the key mechanism affecting firms' growth. An increase in foreign competition lowers firms' incentive to invest in external innovation while it encourages investment in internal innovation for products with high technological advantage. Since innovation-intensive firms have the strongest escape competition, foreign competition affects the growth rate of innovation-intensive high-growth firms more severely. Quantitative analysis using my theoretical framework confirms this mechanism.

A 4.16 percentage point reduction in bilateral tariff rates in my model causes firms to shift their innovation activities toward more internal innovation due to higher foreign competition. Consequently, high-growth firms grow more slowly, as they are less willing to experiment and add new products. Also, the startup rate falls as the heightened technological advantage accumulated by incumbent firms through internal innovation makes it harder to enter the economy through external innovation.

To the best of my knowledge, this is the first attempt to develop a two-country endogenous growth model with an escape-competition effect, in which firms are allowed to grow both through product scope expansion à la Klette and Kortum (2004) and own product quality improvement as in Aghion et al. (2001), and including firm entry and exit. Also, this paper is the first to identify increasing foreign competition as a reason for declining business dynamism in the U.S. economy, and provides supporting empirical evidence.

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A Theory Appendix

A.1 Technology-Gaps Evolution

I show that local technology gap Δ_t can assume only four values, $\Delta^1 = 1$, $\Delta^2 = \lambda$, $\Delta^3 = \eta$, and $\Delta^4 = \frac{\eta}{\lambda}$.

A.1.1 Proof of Lemma 1

Proof. To make argument clearer, let's consider the cases where 1) there is no ownership change between $t-1$ and t, and 2) there is ownership change between $t-1$ and t.

1) No ownership change between $t-1$ and t: In this case, $q_{j,t} = \Delta_{j,t} q_{j,t-1}$ should hold, where only $\Delta_{j,t} \in \{\Delta^1 = 1, \Delta^2 = \lambda\}$ are possible due to the fact that $\Delta_{j,t}$ is an outcome of internal innovation.

2) Ownership change between $t-1$ and t: In this case, $q_{j,t} = \eta q_{j,t-2}$ should hold. Let's consider all potentially possible cases where i. $\Delta_{j,t} = 1$, ii. $\Delta_{j,t} = \lambda$, iii. $\Delta_{j,t} = \eta$, iv. $\Delta_{j,t} = \frac{\eta}{\lambda}$, v. $\Delta_{j,t} = \frac{\eta^n}{\lambda^m}$ with $n \geqslant m > 0$, and vi. $\Delta_{j,t} = \frac{\lambda^n}{\eta^m}$ with $n > m > 0$. These are the only potentially possible values Δ can assume, as there are only three step sizes (1, λ, and η) product quality can change between two periods and there cannot be a technology regression ($q_t < q_{t-1}$). In the end, we will see that only the first four cases are possible.

case 2)-i. $\Delta_{j,t} = 1$

For this to be true, $q_{j,t} = q_{j,t-1}$ should hold. Since $q_{j,t} = \eta q_{j,t-2}$, this implies $q_{j,t-1} = \eta q_{j,t-2}$. This is possible if there was external innovation between $t-2$ and $t-1$, and no internal innovation between $t-3$ and $t-1$, thus $q_{j,t-2} = q_{j,t-3}$. Thus $\Delta_{j,t} = 1$ is possible with ownership change between $t-1$ and t.

case 2)-ii. $\Delta_{j,t} = \lambda$

For this to be true, $\Delta_{j,t-1} = \frac{\eta}{\lambda}$ should hold, as $\Delta_{j,t} = \frac{q_{j,t}}{q_{j,t-1}} = \frac{(\eta) q_{j,t-2}}{\Delta_{j,t-1} q_{j,t-2}}$. This can be possible if there is internal innovation between $t-3$ and $t-2$, and external innovation between $t-2$ and $t-1$, but no internal innovation between $t-2$ and $t-1$. In this case, $q_{j,t-2} = \lambda q_{j,t-3}$, and $q_{j,t-1} = \eta q_{j,t-3}$. Thus $\Delta_{j,t-1} = \frac{q_{j,t-1}}{q_{j,t-2}} = \frac{\eta q_{j,t-3}}{\lambda q_{j,t-3}} = \frac{\eta}{\lambda}$. So I proved both $\Delta_{j,t} = \lambda$ and $\Delta_{j,t} = \frac{\eta}{\lambda}$ are possible and $\Delta_{j,t} = \frac{\eta}{\lambda}$ can be realized only through external innovation between $t-1$ and t.

case 2)-iii. $\Delta_{j,t} = \eta$

For this to be true, $q_{j,t-1} = q_{j,t-2}$ should hold. This is possible if there is no ownership change and no internal innovation between $t-1$ and $t-2$. Thus $\Delta_{j,t} = \eta$ is possible.

case 2)-iv. $\Delta_{j,t} = \frac{\eta}{\lambda}$

The possibility of this case is shown in case 2)-ii.

case 2)-v. $\Delta_{j,t} = \frac{\eta^n}{\lambda^m}$ with $n \geqslant m > 0$

Let's suppose this is the case. Since $\Delta_{j,t} \notin \{\Delta^1 = 1, \Delta^2 = \lambda\}$ there should be an ownership change between $t-1$ and t. Thus $q_{j,t} = \eta q_{j,t-2}$ should hold, and this implies $q_{j,t-1} = \frac{\lambda^m}{\eta^{n-1}} q_{j,t-2}$. $m \leqslant n-1$ is not possible as this implies technology regression. Let's suppose $m > n-1$. Since $n \geqslant m > 0$, this implies $m = n$ should hold. Suppose this is the case, thus $g_{j,t-2} = \frac{\lambda^m}{\eta^{m-1}} q_{j.t-1}$. If the values for λ, η, and m are such that $\frac{\lambda^m}{\eta^{m-1}} < 1$, then this means technology regression, which is not possible. Let's suppose $\frac{\lambda^m}{\eta^{m-1}} > 1$ is true. If $m = 1$, we are back in the case 2)-ii and case 2)-iv. Let's suppose $m > 1$. Since $\frac{\lambda^m}{\eta^{m-1}} \neq 1$ or $1 + \lambda$, there should be an ownership change between $t-2$ and $t-1$. Thus $q_{j,t-1} = \eta q_{j,t-3}$, and this implies $q_{j,t-2} = \frac{\eta^m}{\lambda^m} q_{j,t-3}$.

Thus if $\Delta_{j,t} = \frac{\eta^n}{\lambda^m}$ is possible, then

$$q_{j,t-s} = \begin{cases} \frac{\eta^m}{\lambda^m} q_{j,t-s-1} & , s\text{: even number} \\ \\ \frac{\lambda^m}{\eta^{m-1}} q_{j,t-s-1} & , s\text{: odd number .} \end{cases}$$

Thus in this case, either $q_{j,1} = \frac{\eta^m}{\lambda^m} q_{j,0}$ or $q_{j,1} = \frac{\lambda^m}{\eta^{m-1}} q_{j,0}$ should hold, which is not possible (or I assume this case out). Thus $\Delta_{j,t} = \frac{\eta^n}{\lambda^m}$ with $n \geqslant m > 0$ is not possible.

case 2)-vi. $\Delta_{j,t} = \frac{\lambda^n}{\eta^m}$ with $n > m > 0$

With a similar argument, this case is not possible.

Therefore $\Delta_{j,t}$ can assume only four values, $\left\{1, \lambda, \eta, \frac{\eta}{\lambda}\right\}$. ■

A.2 Value Function

A.2.1 Conditional Expectation

For

$$\Phi^f \equiv \left\{ \; (\, q_j \; , \; \Delta_j^H \; , \; \Delta_j^F \; , \; \Delta_j^G \,) \; \right\}_{j \in \mathcal{J}^f} \; ,$$

conditional expectation term, $\mathbb{E}\Big[V \left(\Phi^{f\prime} \, \middle| \, \Phi^f \; , \; \{z_j\}_{j \in \mathcal{J}^f} \; , \; x \right) \Big]$ is equal to

$$\int_{\Phi_{-j}} \sum_{\mathcal{I}^x = 0}^{1} \; \sum_{\mathcal{I}^{ZH}_{-j} = 0}^{1} \; \sum_{\mathcal{I}^{ZF}_{-j} = 0}^{1} \; \sum_{c - t_{-j} = \text{win}}^{\text{lose}} \; \sum_{\mathcal{I}^Z_i \, , \, \ldots \, , \, \mathcal{I}^Z_{n^f} = 0}^{1} \; \sum_{\mathcal{I}^{ZF}_i \, , \, \ldots \, , \, \mathcal{I}^{ZF}_{n^f} = 0}^{1} \; \sum_{\mathcal{I}^{\overline{x}}_i \, , \, \ldots \, , \, \mathcal{I}^{\overline{x}}_{n^f} = 0}^{2} \; \sum_{c - t_1 \, , \, \ldots \, , \, c - t_{n^f} = \text{win}}^{\text{lose}}$$

$$\mu\left(\Phi_{-j}\right) \; x^{\mathcal{I}^x} (1-x)^{1-\mathcal{I}^x} \; \left(z^H\right)^{\mathcal{I}^{ZH}_{-j}} \left(1 - z^H\right)^{1-\mathcal{I}^{ZH}_{-j}} \; \left(z^F\right)^{\mathcal{I}^{ZF}_{-j}} \left(1 - z^F\right)^{1-\mathcal{I}^{ZF}_{-j}} \; \frac{1}{2}$$

$$\times \prod_{i=1}^{n^f} \left[\; \left(z_{j_i}\right)^{\mathcal{I}^Z_i} \left(1 - z_{j_i}\right)^{1-\mathcal{I}^Z_i} \; \left(z^F_{j_i}\right)^{\mathcal{I}^{ZF}_i} \left(1 - z^F_{j_i}\right)^{1-\mathcal{I}^{ZF}_i} \; \left(1 - \overline{x}\right)^{\mathcal{I}^{\overline{x}0}_i} \; \left(\overline{x}^H\right)^{\mathcal{I}^{\overline{x}1}_i} \; \left(\overline{x}^F\right)^{\mathcal{I}^{\overline{x}2}_i} \; \right] \left(\frac{1}{2}\right)^{n^f}$$

$$\times V\left(\left[\bigcup_{i=1}^{n^f} \left[\left\{ \left(\Delta^{H\prime}_{j_i} q_{j_i} \; , \; \Delta^{H\prime}_{j_i} \; , \; \Delta^{F\prime}_{j_i} \; , \; \Delta^{G\prime}_{j_i} \right) \; \middle| \; \left(q_{j_i} \; , \; \Delta^H_{j_i} \; , \; \Delta^F_{j_i} \; , \; \Delta^G_{j_i} \right) \; , \; \mathcal{I}^Z_i \; , \; \mathcal{I}^{ZF}_i \; , \; \mathcal{I}^{\overline{x}}_i \; , \; c - t_i \right\} \setminus \{\mathbf{0}\} \right] \right] \right.$$

$$\bigcup \left[\left\{ \left(\Delta^{H\prime}_{-j} \, q_{-j} \; , \; \Delta^{H\prime}_{-j} \; , \; \Delta^{F\prime}_{-j} \; , \; \Delta^{G\prime}_{-j} \right) \; \middle| \; \left(q_{-j} \; , \; \Delta^H_{-j} \; , \; \Delta^F_{-j} \; , \; \Delta^G_{-j} \right) \right. \right.$$

$$\left. \left. \left. , \; \mathcal{I}^x \; , \; \mathcal{I}^{ZH}_{-j} \; , \; \mathcal{I}^{ZF}_{-j} \; , \; c - t_{-j} \right\} \setminus \{\mathbf{0}\} \right] \right) \mathbf{d}\left(\Phi_{-j}\right) \; ,$$

where $\mathcal{I}^{\overline{x}k}_i$ is an indicator function equal to 1 if $\mathcal{I}^{\overline{x}}_i = k$ for $k \in \{0, 1, \}$. Note that $\Delta^{H\prime}_{-j} = \frac{1+\eta}{\Delta^H_{-j}}$ for the case when business takeover is successful.

A.2.2 Aggregate Quality Evolution

A.2.2.1 Proof for $\mathcal{Q}$ and $\overline{q}$ Evolution

Proof. Here, I prove Proposition 3 for a general case. Application of proper index functions provides equation (2.17). Pick any product line j with product quality q_j^H and technology gaps $\boldsymbol{\Delta} \equiv \left(\Delta^H \; \Delta^F \; \Delta^G \right)$, $\Delta^G \in [\underline{\Omega}, \overline{\Omega}] \cup \{\infty\}$. Then with $\mathcal{P}\left(\boldsymbol{\Delta}'|\boldsymbol{\Delta}\right)$: probability of $\boldsymbol{\Delta}$ becoming $\boldsymbol{\Delta}'$, which is described in Appendix TA1, the conditional expected value of q_j^H conditioning on $\boldsymbol{\Delta}$ next period is equal to

$$\begin{aligned}
\mathbb{E}_{\boldsymbol{\Delta}'}\left[\, q_j^{H\prime} \,\middle|\, \boldsymbol{\Delta},\, q_j^H \,\right] &= \mathbb{E}_{\boldsymbol{\Delta}'}\left[\, \Delta^{H\prime} q_j^H \,\middle|\, \boldsymbol{\Delta},\, q_j^H \,\right] \\
&= \mathbb{E}_{\boldsymbol{\Delta}'}\left[\, \Delta^{H\prime} \,\middle|\, \boldsymbol{\Delta} \,\right] q_j^H \\
&= \left[\sum_{\boldsymbol{\Delta}'} \Delta^{H\prime} \, \mathcal{P}\left(\boldsymbol{\Delta}'|\boldsymbol{\Delta}\right) \right] q_j^H
\end{aligned}$$

where the second equality follows from $\boldsymbol{\Delta} \perp q_j^H$, thus, $\boldsymbol{\Delta}' \perp q_j^H$ for any j. Then,

$$\begin{aligned}
\mathbb{E}\left[\, q_j^{H\prime} \,\middle|\, q_j^H \,\right] &= \mathbb{E}_{\boldsymbol{\Delta}}\Big[\, \mathbb{E}_{\boldsymbol{\Delta}'}\left[\, q_j^{H\prime} \,\middle|\, \boldsymbol{\Delta},\, q_j^H \,\right] \Big] \\
&= \left[\sum_{\boldsymbol{\Delta}} \sum_{\boldsymbol{\Delta}'} \Delta^{H\prime} \, \mathcal{P}\left(\boldsymbol{\Delta}'|\boldsymbol{\Delta}\right) \, \mu(\boldsymbol{\Delta}) \right] q_j^H \, .
\end{aligned} \tag{A.24}$$

Summation of (A.24) over a proper subset provides law of motion for $\mathcal{Q}_{\tilde{c}H}$ and $\overline{q}_H$. For instance, since $\mathbb{E}\left[q_j^{H\prime}\right] = \overline{q}_H$ in equilibrium, by summing up (A.24) over possible q_j^H, we have

$$\overline{q}_H' = \left[\sum_{\boldsymbol{\Delta}} \sum_{\boldsymbol{\Delta}'} \Delta^{H\prime} \, \mathcal{P}\left(\boldsymbol{\Delta}'|\boldsymbol{\Delta}\right) \, \mu(\boldsymbol{\Delta}) \right] \overline{q}_H \, ,$$

which gives us

$$q_H = \sum_{\boldsymbol{\Delta}} \sum_{\boldsymbol{\Delta}'} \Delta^{H\prime} \, \mathcal{P}\left(\boldsymbol{\Delta}'|\boldsymbol{\Delta}\right) \, \mu(\boldsymbol{\Delta}) - 1 \, .$$

The law of motion for country F can be defined symmetrically. ■

A.2.3 Proof for Proposition 4

Proof. The first part of proposition 4 follows from simple algebra. I prove the second part here. For $q_{j,1} = q_{j,0}$, we have

$$\frac{\partial z_{j,1}}{x_1^e} = -\frac{\pi_{j,2}}{2\widehat{\chi}}(\lambda - 1)\left[(1 - x_{j,1}) + (1 - x_1^e)\frac{\partial x_{j,1}}{\partial x_1^e}\right] ,$$

and

$$\frac{\partial x_{j,1}}{\partial x_1^e} = 0\,.$$

Thus, we have

$$\frac{\partial z_{j,1}}{\partial x_1^e} = -\frac{\pi_{j,2}}{2\widehat{\chi}}(\lambda - 1)(1 - x_{j,1}) < 0\,.$$

For $q_{j,1} = \lambda q_{j,0}$, we have

$$\frac{\partial z_{j,1}}{\partial x_1^e} = \frac{\pi_{j,2}}{2\widehat{\chi}}\left[1 - x_{j,1} + (1 - x_1^e)\frac{\partial x_{j,1}}{\partial x_1^e}\right]\,,$$

and

$$\frac{\partial x_{j,1}}{\partial x_1^e} = -\frac{\eta\pi_{j,2}}{2\widetilde{\chi}}\frac{\partial z_{j,1}}{\partial x_1^e}\,.$$

Thus, we have

$$\frac{\partial z_{j,1}}{\partial x_1^e} = (1 - x_{j,1})\left[\frac{2\widehat{\chi}}{\pi_{j,2}} + \frac{\eta\pi_{j,2}}{2\widetilde{\chi}}(1 - x_1^e)\right]^{-1} > 0\,,$$

hence

$$\frac{\partial x_{j,1}}{\partial x_1^e} = -\frac{\eta\pi_{j,2}}{2\widetilde{\chi}}\frac{\partial z_{j,1}}{\partial x_1^e} < 0\,.$$

For $q_{j,1} = \eta q_{j,0}$, we have

$$\frac{\partial z_{j,1}}{\partial x_1^e} = \frac{\pi_{j,2}}{2\widehat{\chi}}\frac{1}{2}\left[1 - x_{j,1} + (1 - x_1^e)\frac{\partial x_{j,1}}{\partial x_1^e}\right]\,,$$

and

$$\frac{\partial x_{j,1}}{\partial x_1^e} = -\frac{\eta\pi_{j,2}}{2\widetilde{\chi}}\frac{1}{2}\frac{\partial z_{j,1}}{\partial x_1^e}\,.$$

Thus, we have

$$\frac{\partial z_{j,1}}{\partial x_1^e} = (1 - x_{j,1})\left[\frac{4\widehat{\chi}}{\pi_{j,2}} + \frac{\eta\pi_{j,2}}{4\widetilde{\chi}}(1 - x_1^e)\right]^{-1} > 0\,,$$

hence

$$\frac{\partial x_{j,1}}{\partial x_1^e} = -\frac{1}{2}\frac{\eta\pi_{j,2}}{2\widetilde{\chi}}\frac{\partial z_{j,1}}{\partial x_1^e} < 0\,.$$

From $x_{j,1}^*$, we see that $\frac{\eta\pi_{j,2}}{2\widetilde{\chi}} \in (0,1)$. Then, under a parameter restriction $4\widehat{\chi} > \pi_{j,2}$,

$$\frac{4\widehat{\chi}}{\pi_{j,2}} + \frac{\eta\pi_{j,2}}{4\widetilde{\chi}}(1-x_1^e) > \frac{2\widehat{\chi}}{\pi_{j,2}} + \frac{\eta\pi_{j,2}}{2\widetilde{\chi}}(1-x_1^e)\,.$$

Thus, $\left.\frac{\partial z_{j,1}^*}{\partial x_1^e}\right|_{q_{j,1}=\lambda q_{j,0}} > \left.\frac{\partial z_{j,1}^*}{\partial x_1^e}\right|_{q_{j,1}=\eta q_{j,0}}$ ■

A.2.4 Proof of Corollary 1

Proof. From $\overline{z}_1^*$, we know that

$$\frac{\partial\overline{z}_1^*}{\partial z_{1,0}} = \frac{1}{2}\left(z_{1,1}^*\big|_{q_{1,1}=\lambda q_{1,0}} - z_{1,1}^*\big|_{q_{1,1}=q_{1,0}}\right) > 0\,,$$

and

$$\frac{\partial\overline{z}_1^*}{\partial x_{2,0}} = \frac{1}{2}\left(z_{2,1}^*\big|_{q_{2,1}=\eta q_{2,0}} - z_{2,1}^*\big|_{q_{2,1}=q_{2,0}}\right) > 0\,,$$

where the signs of the two derivatives follow from proposition 4. Then, the results follow from proposition 4 ■

A.2.5 Proof of Corollary 2

Proof. From $\overline{x}_1^*$, we have

$$\frac{\partial\overline{x}_1^*}{\partial z_{1,0}} = \frac{1}{2}\left(x_{1,1}^*\big|_{q_{1,1}=\lambda q_{1,0}} - x_{1,1}^*\big|_{q_{1,1}=q_{1,0}}\right) < 0\,,$$

and

$$\frac{\partial\overline{x}_1^*}{\partial x_{2,0}} = \frac{1}{2}\left(x_{2,1}^*\big|_{q_{2,1}=\eta q_{2,0}} - x_{2,1}^*\big|_{q_{2,1}=q_{2,0}}\right) < 0\,,$$

where the signs for the two derivatives follow from proposition 5 ■

A.2.6 Proof of Proposition 6

Proof. For $q_{j,1} = q_{j,0}$,

$$\frac{\partial z_{j,1}}{\partial \pi_{j,2}} = \frac{1}{2\widehat{\chi}}(\lambda - 1)(1 - x_{j,1})(1 - x_1^e) - \frac{\pi_{j,2}}{2\widehat{\chi}}(\lambda - 1)(1 - x_1^e)\frac{\partial x_{j,1}}{\partial \pi_{j,2}} ,$$

and

$$\frac{\partial x_{j,1}}{\partial \pi_{j,2}} = \frac{\eta}{2\widetilde{\chi}}$$

Thus,

$$\frac{\partial z_{j,1}}{\partial \pi_{j,2}} = \frac{1}{2\widehat{\chi}}(\lambda - 1)(1 - 2x_{j,1})(1 - x_1^e) ,$$

and this is positive iff $x_{j,1} < \frac{1}{2}$. $\frac{\partial x_{j,1}}{\partial \pi_{j,2}} > 0$ unambiguously.

For $q_{j,1} = \lambda q_{j,0}$,

$$\frac{\partial z_{j,1}}{\partial \pi_{j,2}} = \frac{1}{2\widehat{\chi}}\big[\lambda - (1 - x_{j,1})(1 - x_1^e)\big] + \frac{\pi_{j,2}}{2\widehat{\chi}}(1 - x_1^e)\frac{\partial x_{j,1}}{\partial \pi_{j,2}} ,$$

and

$$\frac{\partial x_{j,1}}{\partial \pi_{j,2}} = \frac{x_{j,1}}{\pi_{j,2}} - \frac{\eta \pi_{j,2}}{2\widetilde{\chi}}\frac{\partial z_{j,1}}{\partial \pi_{j.2}} .$$

Thus,

$$\frac{\partial z_{j,1}}{\partial \pi_{j,2}} = \big[\lambda - (1 - 2x_{j,1})(1 - x_1^e)\big]\left[2\widehat{\chi} + \frac{\eta(\pi_{j,2})^2}{2\widetilde{\chi}}(1 - x_1^e)\right]^{-1} ,$$

and this is positive unambiguously. The sign for $\frac{\partial x_{j,1}}{\partial \pi_{j,2}}$ is ambiguous.

For $q_{j,1} = \eta q_{j,0}$,

$$\frac{\partial z_{j,1}}{\partial \pi_{j,2}} = \frac{1}{2\widehat{\chi}}\left[\lambda - \frac{1}{2} - \frac{1}{2}(1 - x_{j,1})(1 - x_1^e)\right] + \frac{\pi_{j,2}}{2\widehat{\chi}}\frac{1}{2}(1 - x_1^e)\frac{\partial x_{j,1}}{\partial \pi_{j,2}} ,$$

and

$$\frac{\partial x_{j,1}}{\partial \pi_{j,2}} = \frac{\eta}{2\widetilde{\chi}}\frac{1}{2}(1 - z_{j,1}) - \frac{\eta \pi_{j,2}}{2\widetilde{\chi}}\frac{1}{2}\frac{\partial z_{j,1}}{\partial \pi_{j,2}} .$$

Thus,

$$\frac{\partial z_{j,1}}{\partial \pi_{j,2}} = \left[\lambda - \frac{1}{2} - \frac{1}{2}(1-2x_{j,1})(1-x_1^e)\right]\left[2\widehat{\chi} + \frac{\eta(\pi_{j,2})^2}{2\widetilde{\chi}}\frac{1}{4}(1-x_1^e)\right]^{-1},$$

and this is positive unambiguously. The sign for $\frac{\partial x_{j,1}}{\partial \pi_{j,2}}$ is ambiguous. ■

A.2.7 Solution Algorithm

Solution Algorithm

1. Guess product line stationary distribution $\mu\left(\Delta^H\ \Delta^F\ \Delta^G\right)$, BGP growth rates g^c, total external innovation rates $\overline{x}^c$, and total quality ratios $\frac{\mathcal{Q}_{cc}}{\overline{q}_c}$ for $c \in \{H,F\}$ with $\frac{\mathcal{Q}_{\tilde{c}c}}{\overline{q}_c} = 1 - \frac{\mathcal{Q}_{cc}}{\overline{q}_c}$.

2. Using $\frac{\mathcal{Q}_{cc}}{\overline{q}_c}$ and $\frac{\mathcal{Q}_{\tilde{c}c}}{\overline{q}_c}$ for $c \in \{H,F\}$,

   (a) Compute $\frac{w_c}{\overline{q}_c}$, L_c, and $\widetilde{L}_c$.

   (b) Then, compute $\pi^{c\tilde{c}}$ for $c,\tilde{c} \in \{H,F\}$.

   (c) Compute the two thresholds $\underline{\Omega}$, and $\overline{\Omega}$, and identify the range of $\Delta^G \in \left[\underline{\Omega},\overline{\Omega}\right]$.

3. Using $\overline{x}^c$ and g^c,

   (a) Compute $A^c\left(\Delta^H\ \Delta^F\ \Delta^G\right)$, $z^c\left(\Delta^H\ \Delta^F\ \Delta^G\right)$, x^c and x_e^c for $c \in \{H,F\}$.

   (b) Compute $\mathcal{F}_c = \frac{\overline{x}^c - x_e^c\mathcal{E}_c}{x^c}$. If $\mathcal{F}_c \notin (0,1)$, adjust $\overline{x}^c$ and redo 3a.

4. Simulate to get updates for g^c, $\frac{\mathcal{Q}_{cc}}{\overline{q}_c}$, and $\mathcal{F}_c$ for $c \in \{H,F\}$:

   (a) Draw sample of N_p product lines from a guessed stationary distribution $\mu\left(\Delta^H\ \Delta^F\ \Delta^G\right)$.

   (b) Assign N_f^c number of firms implied by $\mathcal{F}_c$ computed in 3b to the sample product lines randomly.

   (c) Simulate the model while allowing for firm entry and exit until $\| g_{t+1}^c - g_t^c \| < \varepsilon$

   (d) Compute $\frac{\mathcal{Q}_{cc}}{\overline{q}_c}$, $\mathcal{F}_c = \frac{total\ nb\ of\ firms_c}{total\ nb\ of\ products_c}$, and $\overline{x}^c = x^c\mathcal{F}_c + x_e^c\mathcal{E}_c$.

5. Compute a stationary distribution $\mu_\infty\left(\Delta^H\ \Delta^F\ \Delta^G\right)$ by using the law of motion and innovation rates (use z^c and x_e^c from 3a, and $\overline{x}^c$ from 4d).

6. Compare the initial growth rates in 1 with the values from 4. If the values are sufficiently different, update 1 with 5 and 4d, and redo the process 2 through 4. Iterate until the two growth rates converge.

B Data Appendix

B.1 Summary Statistics

Table A1: Trade-shock related measures

	NTR gap	Dnstream NTR gap	Upstream NTR gap	NTR rate	Non-NTR rate	Export shock
Mean	0.291	0.138	0.203	0.027	0.303	1.127
(Std. dev.)	(0.127)	(0.060)	(0.073)	(0.022)	(0.134)	(0.970)
cov(, NTR gap)		0.485	0.434	0.412	0.969	0.214
cov(, Up. NTR gap)		0.204				

Table A2: Firm-level NTR gap constructed using different weights

	NTR gap, unweighted	NTR gap, main industry
Mean	0.333	0.336
(Std. dev.)	(0.107)	(0.116)
cov(, NTR gap)	0.78	0.86
cov(, NTR gap, main industry)	0.906	

Table A3: Technology shocks

	Past 5 years			5 years onward	
	own US shock	own foreign shock	outside f. shock	own f. shock	outside f. shock
Mean	0.388	0.342	0.188	0.344	0.257
(Std. dev.)	(0.306)	(0.299)	(0.064)	(0.304)	(0.161)
cov(, past own f.)	0.593			-0.059	
cov(, past out f.)	-0.191	0.151			-0.991
cov(, onward out f.)				0.541	

Table A4: All patenting firms vs. regression sample patenting firms in 1992

	All patenting firms	Regression sample
Average number of patents	6.15	8.86
	(19.46)	(24.10)
Average self-citation rate	0.0434	0.0540
	(0.0899)	(0.0941)
Innovation intensity	0.055	0.093
	(0.25)	(0.33)
Number of industries operating	2.34	5.43
	(3.67)	(6.94)
Employment	511.7	1988.0
	(1869.0)	(3835.0)
Patent stock	6.45	35.22
	(26.61)	(64.37)
Employment growth	0.07	0.06
	(0.60)	(0.40)
Firm age	12.33	15.65
	(6.76)	(9.42)
7yr patent growth		-0.854
		(1.312)
7yr self-citation ratio growth		0.356
		(1.322)
Number of firms	26,500	3,100

Table A5: Export Share of Total Value of Shipments (CMF exporters)

	1992	2002	2007
Avg. of firm-level exp/vship	4.99%	5.27%	6.41%
Avg. of firm-level CN exp/vship	0.70%	0.89%	1.17%
Aggregate-level exp/vship	7.76%	9.29%	10.46%
Aggregate-level CN exp/vship	0.19%	0.38%	0.64%

Table A6: Share of Exporters (LBD firms)

Year	1992	2002	2007
Share of exporters	15.90%	22.10%	24.00%
Share of firms exporting to CN	0.60%	2.30%	4.00%

B.2 Overall and Escape-Competition Effect

Table A7: Overall Effect

	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite
	(1)	(2)	(3)	(4)
NTR gap $\times$ Post	0.226	0.049	0.025	0.052
	(0.230)	(0.279)	(0.260)	(0.291)
NTR gap	-2.222***	0.569	1.104***	-0.117
	(0.372)	(0.405)	(0.317)	(0.393)
Post	-0.276***	-0.198**	-0.092	-0.021
	(0.077)	(0.082)	(0.080)	(0.084)
Past 5yr Δpat in own tech.		0.170*		0.282***
		(0.087)		(0.091)
Log employment		0.134***		0.014
		(0.013)		(0.014)
Firm age		-0.005**		-0.009***
		(0.002)		(0.002)
NTR rate		-2.273		1.222
		(1.690)		(2.267)
Observations	6,500	6,500	6,500	6,500
Fixed effects	j, p	j, p	j, p	j, p
Controls	no	full	no	full

Notes: Full controls include past 5-year U.S. patent growth in firms' own technology fields, log employment, firm age, NTR rate, dummy for publicly traded firms, dummy for firms with total imports > 0, dummy for firms with total exports > 0, and dummy for firms with imports from relative parties > 0. Estimates for industry (j) and the period (p) fixed effects as well as the constant are suppressed. Robust standard errors adjusted for clustering at the level of the firms' major industries are displayed below each coefficient. Observations are unweighted. Observation counts are rounded due to Census Bureau disclosure avoidance procedures. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Escape-competition effect

	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite
	(1)	(2)	(3)	(4)
NTR gap × Post	0.238	0.054	-0.075	-0.051
	(0.237)	(0.287)	(0.257)	(0.295)
× Innovation-intensity	0.077	-0.017	0.732**	0.784***
	(0.231)	(0.233)	(0.299)	(0.268)
NTR gap	-2.206***	0.593	1.101***	-0.067
	(0.375)	(0.409)	(0.315)	(0.397)
× Innovation intensity	-0.226	-0.213	-0.198	-0.379
	(0.158)	(0.175)	(0.231)	(0.231)
Post	-0.277***	-0.202**	-0.071	-0.002
	(0.078)	(0.083)	(0.080)	(0.083)
× Innovation-intensity	-0.053	0.017	-0.179*	-0.198**
	(0.070)	(0.075)	(0.095)	(0.085)
Innovation-intensity	0.080*	0.057	0.059	0.086
	(0.048)	(0.046)	(0.070)	(0.066)
NTR rate		-2.403		1.021
		(1.703)		(2.272)
× Innovation-intensity		0.593		0.539
		(0.507)		(0.484)
Observations	6,500	6,500	6,500	6,500
Fixed effects	j, p	j, p	j, p	j, p
Controls	no	full	no	full

Notes: Full controls include past 5-year U.S. patent growth in firms' own technology fields, log employment, firm age, NTR rate, dummy for publicly traded firms, dummy for firms with total imports > 0, dummy for firms with total exports > 0, and dummy for firms with imports from relative parties > 0. Estimates for industry (j) and the period (p) fixed effects as well as the constant are suppressed. Robust standard errors adjusted for clustering at the level of the firms' major industries 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.

B.3 Import Competition

Table A9: Effect of PNTR on US imports from China

	ΔCN imp	ΔCN imp
	HS8-level	NAICS6-level
	(1)	(2)
NTR gap	0.209***	0.594**
	(0.059)	(0.243)
ΔNTR rate	-0.043***	-0.204**
	(0.015)	(0.080)
ΔTransport cost	-0.791***	-0.491
	(0.194)	(0.766)
Obsevations	10,089	490

Notes: Table reports results of OLS regressions of US imports from China on NTR gap at the 8-digit HS level, and 6-digit NAICS level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Regression using 7-year changes in the U.S. imports from China

(a) 7-year changes in the US imports from China

	ΔPatents	ΔPatents	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite	ΔSelf-cite	ΔSelf-cite
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
7yr ΔUS imports from CN	-0.273***	-0.041	-0.277***	-0.043	0.082	-0.030	0.081	-0.030
	(0.047)	(0.041)	(0.047)	(0.041)	(0.061)	(0.058)	(0.061)	(0.058)
× Innovation intensity			0.037**	0.017			0.001	-0.001
			(0.017)	(0.015)			(0.020)	(0.015)
Observations	6,500	6,500	6,500	6,500	6,500	6,500	6,500	6,500
Fixed effects	j, p	j, p	j, p	j, p	j, p	j, p	j, p	j, p
Controls	no	full	no	full	no	full	no	full

Notes: Table reports results of OLS regression results estimating the relationship between the U.S. firms' innovation and realized changes in the U.S. imports from China. Full controls include past 5-year U.S. patent growth in firms' own technology fields, log employment, firm age, dummy for publicly traded firms, dummy for firms with total imports > 0, dummy for firms with total exports > 0, and dummy for firms with imports from relative parties > 0. Estimates for industry (j) and the period (p) fixed effects as well as the constant are suppressed. Robust standard errors adjusted for clustering at the level of the firms' major industries are displayed below each coefficient. Observations are unweighted. Observation counts are rounded due to Census Bureau disclosure avoidance procedures. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.4 Firm Growth and Two Types of Innovation

Akcigit and Kerr (2018) show that internal innovation contributes less to firm employment growth by using the LBD. Here, I replicate their result while including firm controls for the Census years: 1982, and 1992 and construct non-overlapping five-year first differences (DHS growth) by using the LBD matched USPTO patent database. I estimate the following fixed-effect regression model:

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

For firm i in industry j, ΔY_{ijt+5} is a 5-year DHS growth rate of i) firm employment growth from year t to $t+5$, and ii) number of six-digit NAICS industries added. Pat_{ijt} is a log of citation adjusted number of patents in year t, and $Internal_{ijt}$ is an citation-adjusted average self-citation ratio in year t. Firm and industry controls include firm age, and log of payroll. The regression is unweighted and standard errors are clustered on firm. Based on Akcigit and Kerr (2018) we expect β_1 to be positive while β_2 to be negative, as internal innovation contributes less to firm employment growth. I run the same regression model with the number of products (seven-digit NAICS product codes) added by using the CMF firms.

Table A11: Real effect of innovation: employment growth, industry add, and product add

	LBD firms		CMF firms
	ΔEmployment	Log nb. of industries added	Log nb. of products added
	(1)	(2)	(3)
Log nb. of patents	0.031***	0.098***	0.078***
	(0.010)	(0.011)	(0.013)
Avg. self-citation	-0.269**	-0.154**	-0.343***
	(0.106)	(0.078)	(0.102)
Log payroll	-0.025***	0.083***	0.154***
	(0.009)	(0.006)	(0.008)
Firm age	-0.004**	-0.004**	-0.007***
	(0.002)	(0.002)	(0.002)
Innovation intensity	0.032	0.009	0.076'***
	(0.029)	(0.015)	(0.017)
Observations	5,400	5,400	5,700
Fixed effects	*jp*	*jp*	*jp*

Notes: Estimates for industry-period (jp) fixed effects as well as the constant are suppressed. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.5 Pre-trend and Robustness

Table A12: Parallel pre-trend test

	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite
	(1)	(2)	(3)	(4)
NTR gap	-0.393	-0.379	-0.559	-0.551
	(0.487)	(0.488)	(0.403)	(0.403)
× Innovation intensity		-0.193		-0.0057
		(0.162)		(0.394)
NTR gap × $\mathcal{I}_{\{1992\}}$	0.520	0.498	0.254	0.261
	(0.355)	(0.361)	(0.294)	(0.290)
× Innovation intensity		0.092		-0.114
		(0.243)		(0.490)
Observations	5,000	5,000	5,000	5,000
Fixed effects	j, p	j, p	j, p	j, p

Notes: Full controls include past 5-year U.S. patent growth in firms' own technology fields, log employment, firm age, and dummy for publicly traded firms. Estimates for industry (j) and the period (p) fixed effects as well as the constant are suppressed. Robust standard errors adjusted for clustering at the level of the firms' major industries are displayed below each coefficient. Observations are unweighted. Observation counts are rounded due to Census Bureau disclosure avoidance procedures. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Foreign competition shock with I-O

	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite
	(1)	(2)	(3)	(4)
NTR gap × Post	-0.111	-0.111	-0.290	-0.415
	(0.332)	(0.343)	(0.355)	(0.354)
× Innovation intensity		0.054		0.825***
		(0.319)		(0.282)
NTR gap	0.580	0.613	-0.096	-0.038
	(0.406)	(0.411)	(0.382)	(0.387)
× Innovation intensity		-0.275		-0.407
		(0.203)		(0.262)
Post	-0.254**	-0.264**	-0.145	-0.137
	(0.110)	(0.111)	(0.122)	(0.123)
× Innovation intensity		0.158		-0.098
		(0.142)		(0.139)
Innovation intensity		0.057		0.089
		(0.047)		(0.068)
NTR rate	-2.314	-2.512	1.129	0.900
	(1.670)	(1.704)	(2.237)	(2.240)
× Innovation intensity		1.027		0.666
		(0.874)		(0.765)
Downstream X Post	0.501	0.492	0.965	0.979
	(0.597)	(0.602)	(0.707)	(0.715)
× Innovation intensity		-0.241		-0.019
		(0.525)		(0.348)
Upstream X Post	0.161	0.196	0.430	0.491
	(0.443)	(0.447)	(0.480)	(0.482)
× Innovation intensity		-0.497		-0.382
		(0.381)		(0.418)
Observations	6,500	6,500	6,500	6,500
Fixed effects	j, p	j, p	j, p	j, p

Notes: Controls include past 5-year U.S. patent growth in firms' own technology fields, log employment, firm age, NTR rate, dummy for publicly traded firms, dummy for firms with total imports > 0, dummy for firms with total exports > 0, and dummy for firms with imports from relative parties > 0. Estimates for industry (j) and the period (p) fixed effects as well as the constant are suppressed. Robust standard errors adjusted for clustering at the level of the firms' major industries 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.

Table A14: Overall response: different weights for firm-level tariff measures

	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite
	(1)	(2)	(3)	(4)
NTR gap × Post	-0.139	-0.017	0.133	0.091
	(0.331)	(0.247)	(0.311)	(0.260)
NTR gap	0.943**	omitted	-0.240	omited
	(0.374)		(0.349)	
Post	-0.146	-0.194***	-0.024	-0.036
	(0.107)	(0.074)	(0.106)	(0.076)
NTR rate	-1.763	-2.360	1.614	0.368
	(1.533)	(1.871)	(1.792)	(2.373)
Observations	6,500	6,500	6,500	6,500
Fixed effects	j, p	j, p	j, p	j, p
Weights for tariffs	unweighted	major indust.	unweighted	major indust.

Notes: Table reports results of OLS generalized difference-in-differences regressions in which firm-level tariff measures are constructed with different weights. Controls include past 5-year U.S. patent growth in firms' own technology fields, log employment, firm age, NTR rate, dummy for publicly traded firms, dummy for firms with total imports > 0, dummy for firms with total exports > 0, and dummy for firms with imports from relative parties > 0 (full controls). Estimates for industry (j) and the period (p) fixed effects as well as the constant are suppressed. Robust standard errors adjusted for clustering at the level of the firms' major industries are displayed below each coefficient. Observations are unweighted. Observation counts are rounded due to Census Bureau disclosure avoidance procedures. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Escape-competition effect: different weights for firm-level tariff measures

	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite
	(1)	(2)	(3)	(4)
NTR gap × Post	-0.131	-0.015	0.017	0.021
	(0.339)	(0.251)	(0.310)	(0.260)
× Innovation intensity	0.038	0.017	0.754***	0.745***
	(0.218)	(0.218)	(0.261)	(0.263)
NTR gap	0.962**	omitted	-0.189	omitted
	(0.376)		(0.350)	
× Innovation intensity	-0.268	-0.235	-0.380*	-0.395*
	(0.168)	(0.173)	(0.228)	(0.229)
Post	-0.150	-0.197***	0.004	-0.024
	(0.109)	(0.074)	(0.105)	(0.075)
× Innovation intensity	0.002	0.008	-0.191**	-0.185**
	(0.071)	(0.071)	(0.082)	(0.083)
Innovation intensity	0.065	0.056	0.085	0.085
	(0.045)	(0.046)	(0.066)	(0.066)
NTR rate	-1.839	-2.482	1.468	0.256
	(1.541)	(1.874)	(1.795)	(2.372)
× Innovation intensity	0.583	0.584	0.576	0.666
	(0.517)	(0.525)	(0.489)	(0.477)
Observations	6,500	6,500	6,500	6,500
Fixed effects	j, p	j, p	j, p	j, p
Weights for tariffs	unweighted	major indust.	unweighted	major indust.

Notes: Table reports results of OLS generalized difference-in-differences regressions in which firm-level tariff measures are constructed with different weights. Full controls are included. Estimates for industry (j) and the period (p) fixed effects as well as the constant are suppressed. Robust standard errors adjusted for clustering at the level of the firms' major industries 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.

Table A16: Use inverse of the propensity scores to re-weight observations

	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite
	(1)	(2)	(3)	(4)
NTR gap × Post	-0.085	-0.058	-0.065	-0.294
	(0.417)	(0.420)	(0.362)	(0.351)
× Innovation intensity		-0.033		0.794***
		(0.271)		(0.269)
Observations	6,500	6,500	6,500	6,500
Fixed effects	j, p	j, p	j, p	j, p
Regression weights	inv. propens.	inv. propens.	inv. propens.	inv. propens.

Notes: Table reports results of OLS generalized difference-in-differences regressions in which observations are weighted by the inverse of the propensity scores from logit model (y = indicator for analysis sample). Full controls are included. Estimates for industry (j) and the period (p) fixed effects as well as the constant are suppressed. Robust standard errors adjusted for clustering at the level of the firms' major industries are displayed below each coefficient. Observation counts are rounded due to Census Bureau disclosure avoidance procedures. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Add the cumulative number of patents as a firm-level control variable

	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite
	(1)	(2)	(3)	(4)
NTR gap × Post	-0.000	0.004	0.088	-0.015
	(0.279)	(0.287)	(0.290)	(0.289)
× Innovation intensity		-0.011		0.786***
		(0.231)		(0.268)
Observations	6,500	6,500	6,500	6,500
Fixed effects	j, p	j, p	j, p	j, p

Notes: Table reports results of OLS generalized difference-in-differences regressions in which firm-level cumulative number of patents are included as a control. Full controls are included. Estimates for industry (j) and the period (p) fixed effects as well as the constant are suppressed. Robust standard errors adjusted for clustering at the level of the firms' major industries are displayed below each coefficient. Observations are unweighted. Observation counts are rounded due to Census Bureau disclosure avoidance procedures. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A18: Cluster standard errors on firms

	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite
	(1)	(2)	(3)	(4)
NTR gap × Post	0.004	0.010	0.103	-0.000
	(0.287)	(0.290)	(0.308)	(0.311)
× Innovation intensity		-0.012		0.784***
		(0.235)		(0.274)
Observations	6,500	6,500	6,500	6,500
Fixed effects	j, p	j, p	j, p	j, p
se. cluster	firmid	firmid	firmid	firmid

Notes: Table reports results of OLS generalized difference-in-differences regressions in which robust standard errors are adjusted for clustering at the firm-level. Full controls are included. Estimates for industry (j) and the period (p) fixed effects as well as the constant are suppressed. Observations are unweighted. Observation counts are rounded due to Census Bureau disclosure avoidance procedures. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A19: Effect of foreign competition on product add

	Log number of products added	Log number of products added
	(1)	(2)
NTR gap × Post	-0.209***	-0.208***
	(0.067)	(0.068)
× Innovation intensity		-0.554***
		(0.196)
Post × Innovation intensity		0.024
		(0.088)
Innovation intensity		0.227***
		(0.042)
Observations	497,000	497,000
Fixed effects	j, p	j, p

Notes: Controls include past 5-year U.S. patent growth in firms' own technology fields, log payroll, firm age, NTR rate and its interaction with innovation intensity, dummy for publicly traded firms, dummy for firms with total imports > 0, dummy for firms with total exports > 0, and dummy for firms with imports from relative parties > 0. Estimates for industry-period (jp) fixed effects as well as the constant are suppressed. Robust standard errors adjusted for clustering at the level of the firms' major industries are displayed below each coefficient. Observations are unweighted. Observation counts are rounded due to Census Bureau disclosure avoidance procedures. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.6 Technological Barrier Effect

Table A20: Technological-barrier effect

	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite
	(1)	(2)	(3)	(4)
Past 5yr Δforeign patent,	-5.984**	-5.209*	9.076***	8.712***
outside of own technology field	(2.756)	(2.733)	(2.711)	(2.740)
× Innovation intensity		0.161		-0.365
		(0.240)		(0.264)
Past 5yr Δforeign patent,	0.005	-0.006	0.033	0.021
inside of own technology field	(0.079)	(0.081)	(0.081)	(0.082)
× Innovation intensity		0.048		0.047
		(0.055)		(0.059)
Observation	7,600	7,600	7,600	7,600
Fixed effects	jp	jp	jp	jp

Notes: Full controls except for the NTR rate are included. Estimates for industry-period (jp) fixed effects as well as the constant are suppressed. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A21: Effect of concurrent technological shocks

	ΔPatents	ΔPatents	ΔSelf-cite	ΔSelf-cite
	(1)	(2)	(3)	(4)
5yr Δforeign patent,	-8.680**	-7.637**	14.15***	13.56***
outside of own technology field	(3.546)	(3.521)	(3.540)	(3.565)
× Innovation intensity		-0.063		0.081
		(0.114)		(0.122)
5yr Δforeign patent,	0.212***	0.228***	0.133*	0.118
inside of own technology field	(0.075)	(0.077)	(0.075)	(0.076)
× Innovation intensity		-0.069		0.067
		(0.062)		(0.074)
Observation	7,600	7,600	7,600	7,600
Fixed effects	jp	jp	jp	jp

Notes: Description the same as Table A20.

B.7 Industry-Level Regression

To estimate the effect of Chinese competition shock on the industry-level business dynamism statistics, I run the following regression model for the years from 1992 to 2007

$$Y_{jt} = \beta_1 PostPNTR \times NTRGap_j + \mathbf{X}_{jt}\,\gamma_1 + \mathbf{X}_{j0}\,\gamma_2 + \delta_j + \delta_t + \alpha + \varepsilon_{jt}\,, \tag{B.25}$$

where Y_{jt} is i) log of employment, ii) young firm share iii) startup rates, iv) exit rates, v) 90th percentile of firm employment growth rates, and vi) 10th percentile of firm employment growth rates.

Table A22: Industry-level effect

	log(Emp)	log(Emp) by young firms	Share of young firms	Startup rate	Exit rate	P90 ΔEmp	P10 ΔEmp
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NTR gap × Post	-0.632***	-0.809**	-0.102**	-0.036***	0.014	-0.718***	-0.014
	(0.231)	(0.364)	(0.047)	(0.012)	(0.010)	(0.195)	(0.134)
Obervations	6,200	6,200	6,200	6,200	6,200	6,200	6,200
Fixed effects	j,t	j,t	j,t	j,t	j,t	j,t	j,t
Reg. Weights	1992 emp.	1992 emp.	1992 emp.	1992 emp.	1992 emp.	1992 emp.	1992 emp.
implied impact	-20.19%	-26.54%	-3.01pp	-1.05pp		-23.24pp	

Notes: Controls include NTR rate. Robust standard errors adjusted for clustering at the industry (j) level are displayed below each coefficient. Estimates for industry and the year (t) fixed effects as well as the constant are suppressed. Observations are weighted by 1992 industry employment. Final row reports the predicted change in the dependent variable implied by the regression coefficient. Observation counts are rounded due to Census Bureau disclosure avoidance procedures. * p < 0.1, ** p < 0.05, *** p < 0.01.