From Research to Development: How Globalization Shapes Corporate Innovation

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Abstract

I show that globalization has shifted U.S. corporate innovation from scientific research to commercial development. Analyzing data from publicly traded firms, I find that substantial tariff reductions at export destinations following the "Uruguay Round" led U.S. firms to focus on a narrower range of technologies, reducing their emphasis on scientific research. To explain these findings, I develop a multi-product firm model that distinguishes between research and development. Globalization—represented by expanded market size or lower trade costs—reallocates profits toward products for which firms hold a competitive advantage. Consequently, firms increasingly prioritize developing core products over broader research. The model embeds a crucial welfare trade-off: development increases the supply of high-productivity products, but research enhances the overall innovation efficiency of the economy through knowledge spillovers. Calibration to U.S. manufacturing firms shows that allowing separate decisions on research versus development amplifies the productivity gains from globalization but reduces welfare gains. The welfare-maximizing policy suggests that research subsidies should exceed development subsidies, particularly after globalization, to counteract the decline in research share.

Keywords: Scientific Research and Development, Globalization, Specialization, Innovation Policy

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1. Introduction

Not all innovation is the same. While research and development are often grouped together, they are distinct activities. Research generates new scientific knowledge, while development focuses on improving or creating specific products and processes (OECD, 2005). Recent decades have seen a notable decline in research intensity within U.S. corporate innovation. Figure 1 illustrates this trend, showing a marked decrease in the share of research within R&D expenditures and a decline in scientific publications relative to patents by U.S. companies.[1]

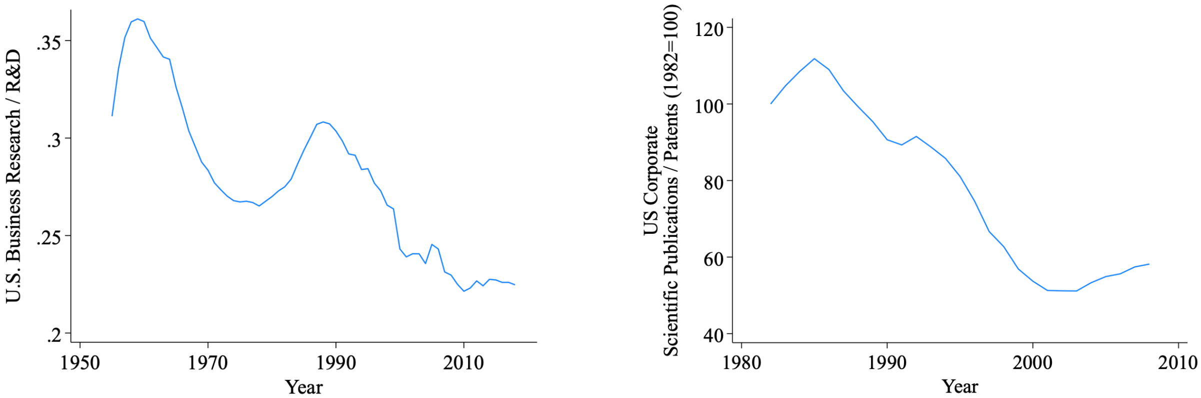
Understanding the forces behind this trend is crucial because, even with the same total R&D investment, how firms allocate resources between research and development can lead to very different economic outcomes (e.g., Young, 1998). Therefore, it is essential to explore how market conditions influence this balance, and how these shifts affect economic outcomes. Despite its importance, the drivers of this change and its implications are not fully understood in the literature.

This paper investigates how globalization has contributed to the decline in research intensity among U.S. firms. I find that U.S. publicly traded firms facing larger tariff cuts in export markets in the 1990s increasingly specialized in specific innovation areas while reducing research efforts. To explain these findings, I develop a multi-product firm model that distinguishes between research and development. In this setting, globalization redirects profits toward core products for which firms hold a production advantage, leading them to prioritize development, which more effectively targets these products. Although this shift leads to better products, it also diminishes aggregate innovation efficiency by reducing investment in research and limiting knowledge spillovers. Calibration to U.S. manufacturing firms reveals that these innovation decisions amplify productivity gains from globalization but reduce welfare gains, suggesting that treating research and development as one activity may overestimate the welfare gains from trade. The welfare-maximizing policy calls for higher research subsidies, particularly after globalization, to counteract the decline in research share.

I first document trends in the innovation specialization of U.S. firms. I introduce two novel metrics based on patent data to measure the technological diversification of U.S. firms registered with the United States Patent and Trademark Office (USPTO). The first metric measures the diversity of a firm's patent portfolio by examining the distribution

[1] In the 1950s and 60s, companies like AT&T's Bell Labs and DuPont made significant scientific contributions through substantial research investments. However, these firms have since downsized or closed their central labs, and no new companies have emerged to fill this gap.

Figure 1: U.S. Corporate Research Intensity



(a) Research Expenditure Share **(b)** Scientific Publications Relative To Patents

The left panel shows the proportion of U.S. domestic research expenditures by businesses relative to total U.S. business-sourced R&D expenditures. The ratio is smoothed using a five-year moving average. Data are from the National Center for Science and Engineering Statistics. The right panel displays the ratio of scientific publications to patents by U.S. public firms in Compustat, compiled by Arora et al. (2021a).

of patents across different patent classes. The second metric evaluates the textual diversity of patents, utilizing a language model to capture semantic similarities between patent descriptions. Results from both measures reveal a rapid decline in the average technological diversity of U.S. corporate innovation during the 1990s. This decline in innovation diversification closely mirrors the increase in U.S. companies' production specialization, as documented by Ekerdt and Wu (2024), and parallels the observed decrease in research intensity (Figure 1).[2] Furthermore, from an analysis of U.S. firms in Compustat, I find that these three outcomes–technology diversity, production diversity, and research intensity–are strongly correlated within firms, even after accounting for potential scale effects, indicating close linkages among these decisions.

I then examine if these changes can be attributed to globalization. Specifically, I analyze the rapid tariff reductions associated with the Uruguay Round and the creation of the WTO in the 1990s. The firm-level globalization shock is measured by the decrease in destination countries' tariff rates, with the importance of each destination calculated based on the firm's pre-period foreign patenting activities, measured using Google Patent data (Aghion et al., 2016; Coelli et al., 2022). I find that firms exposed to larger tariff reductions experienced greater declines in both product and innovation diversity, as well as research intensity.

Building on the empirical findings, I develop a multi-product firm model that in-

[2] Ekerdt and Wu (2024) used U.S. Census data to show that U.S. firms have become increasingly specialized in their production, particularly during the 1990s. For instance, the average number of NAICS 6-digit manufacturing industries in which a U.S. firm is active decreased from approximately 11 in 1980 to 6 in 2000.

corporates endogenous reallocation between research and development. In the model, globalization affects corporate research intensity by narrowing firms' product scope, drawing on two insights from the literature. The first insight comes from the trade literature, which finds that globalization drives firms to specialize in their strongest products (Bernard et al., 2011; Mayer et al., 2014). The second, proposed by Nelson (1959), is the hypothesis that "firms that have their fingers in many pies" are more likely to engage in research. Because research outcomes are less predictable, firms with diversified products or industries invest relatively more in research, as they can better capture its wide-ranging benefits. By combining these two insights, the model provides a mechanism for how globalization can lead firms to reallocate investment toward the development of a narrower set of core products and away from broader research.

In the model, a firm invests in both research and development to create products with varying profitability. The key distinction between research and development lies in the variability of the value that their ideas add to each product's probability of creation. Development is associated with lower variability, giving more predictable outcomes. As a result, development efforts are predominantly applied to high-productivity products, due to their larger profit margins. Therefore, incentives to invest in development are closely tied to these high-productivity products, while incentives to invest in research are spread across a broader range of products, reflecting the insights of Nelson (1959).

Globalization, represented as an increase in market size or lower trade costs between countries, impacts R&D incentives by altering the distribution of products' profits within firms. The model assumes variable elasticity of substitution preferences, whereby low-productivity products have higher demand elasticity, making them more susceptible to competition. Consequently, globalization shifts profits towards a firm's top-performing products. This reallocation of profits, known as the "Matthew effect" (Mrázová and Neary, 2017), encourages firms to allocate more of their innovation investment towards development rather than research and to concentrate their efforts on creating products that align with their core competencies.

The endogenous reallocation of innovation in response to globalization has important implications for welfare and aggregate productivity. According to the literature, research generates larger knowledge spillovers compared to development (Griliches, 1986; Arora et al., 2021a). Consequently, a decrease in research intensity due to globalization reduces the overall R&D efficiency of the economy by diminishing the extent of knowledge spillovers. Conversely, the reallocation of innovation efforts toward high-productivity products increases the share of products that contribute more significantly to welfare. The overall impact of globalization on welfare and aggregate productivity is determined by these two opposing effects.

To assess how these channels contributed to the effects of globalization between 1990 and 2007, I calibrate the model to the 1990 U.S. economy and simulate responses to changes in market size and trade costs to their 2007 levels. I compare the outcomes of this baseline model with those from models that fix innovation decisions at their 1990 levels. The counterfactual exercises reveal that allowing for endogenous innovation decisions significantly amplifies aggregate productivity gains from globalization by shifting firms' innovation efforts toward their better-performing products. However, these productivity gains do not translate into corresponding welfare improvements, as the reduction in knowledge spillovers from decreased research intensity outweighs the benefits of having more high-productivity products. This suggests that models without endogenous innovation decisions, or those that do not differentiate between research and development, may overestimate the welfare gains from trade.

In addition, I analyze the effects of innovation policy using the calibrated model to identify the welfare-maximizing mix of research and development subsidies. The findings suggest that research subsidies should be higher than development subsidies, given research's significant impact on welfare through the knowledge spillover channel. As knowledge spillovers from research become more crucial, the optimal subsidy mix requires an even larger gap between research and development subsidies. Globalization further increases the need for policies that prioritize research over development to counteract firms' incentives to shift away from research.

The rest of the paper proceeds as follows. In Section 2, I describe the data and the measurement of key variables. With these measures, I provide empirical evidence on how globalization induces specialization and reduces research intensity in Section 3. In Section 4, I describe a multi-product firm model with separate research and development decisions, and establish analytic results on the effect of globalization on specialization and research intensity. In Section 5, I calibrate the model, quantify the welfare implications, and discuss optimal innovation policies, highlighting the interactions among globalization, specialization, and knowledge spillovers. Finally, I conclude in Section 6.

1.1. Related Literature

The idea that a firm with more diversified profit sources is more likely to invest in research was initially proposed by Nelson (1959). This idea has recently been empirically validated by Akcigit et al. (2021), who documented a close relationship between the scope of firms' production and their basic research intensity using data on French firms.[3] This paper extends this insight to explore how globalization has contributed to a decrease in corporate research intensity in the U.S. by concentrating profit opportunities within a narrower range of products.

The model predicts close relationships among research intensity, production diversity, and innovation diversity. Two recent studies (Ekerdt and Wu, 2024; Ma, 2022) have documented rising production specialization in the U.S. The empirical findings in this paper reveal a similar trend of innovation specialization among U.S. firms during the same period. Specifically, I adapt the measure of production diversification used by Ekerdt and Wu (2024) to assess technological diversification and introduce a new measure based on the diversity of textual content in a firm's patents. The trend of technological specialization suggested by these two measures is similar to the trend in production specialization. The fact that specialization in production and innovation follow similar aggregate trends in the U.S. further validates the empirical findings presented in my paper.

This paper also relates to two strands of the international trade literature. First, it complements the growing body of research on international trade and innovation (Akcigit and Melitz, 2022), by distinguishing research from development. The existing literature has shown how international trade impacts overall innovation by affecting market size, competition, and access to inputs.[4] This paper contributes to the literature by investigating research and development separately and highlighting the role of competition in determining the mix of corporate innovation.[5] I find that neglecting this distinction may lead to overestimating the welfare gains from trade. Secondly, this paper contributes to the literature that examines the impact of international trade on firms' decisions regarding scope. The trade literature finds that increased competition reduces the product scope of exporters (Mayer et al., 2014, 2021) and firms exposed to increased imports (Liu, 2010; Limão and Xu, 2021). Specifically, I extend the model of multi-product firms of Mayer et al. (2014) and Ding (2023) to explain how the reallocation of profits within firms toward better-performing products affects innovation decisions and, in turn, product scope. This interaction between product scope and innovation has important implications for welfare

[3] Several alternative factors have also been identified as determinants of corporate research investment. These include the quality of universities as research organizations (Arora et al., 2021c; Akcigit et al., 2021), anti-trust policies (Mowery, 2009), patent transactability (Ma, 2022), and technological opportunity (Barge-Gil and López, 2015).

[4] For a comprehensive review, refer to Melitz and Redding (2021) and Akcigit and Melitz (2022).

[5] Similar to this study, there are studies that focus on different aspects of heterogeneity within corporate innovation. Dhingra (2013) highlights the different determinants that influence process and product information and how they are impacted by globalization. Bena and Simintzi (2022) propose a new method for identifying patents related to process innovation.

and aggregate productivity.

Lastly, by including endogenous decisions on the composition of innovation, the model generates unique welfare implications related to market size. A substantial body of literature examines the welfare effects of increases in market size (e.g., Krugman 1979). Recent studies show that market expansion reallocates consumer demand toward high-productivity, high-markup firms and varieties, resulting in significant gains in welfare (Dhingra and Morrow, 2019; Baqaee et al., 2024) and improvements in firm-level productivity (Mayer et al., 2014, 2021). While these studies assume a fixed productivity distribution, this paper endogenizes innovation decisions, allowing an increase in market size to lead firms to reallocate innovation efforts toward high-productivity products, thereby increasing their share within the productivity distribution. This reallocation further enhances welfare and boosts aggregate productivity. However, globalization also reduces research intensity, which lowers welfare by reducing innovation efficiency. This decline in innovation efficiency aligns with the observed decrease in R&D productivity (Bloom et al., 2020) and the rise in less creative, derivative patents (Kalyani, 2024) in recent decades, suggesting that these trends may stem from firms' excessive focus on development over research in response to globalization. By formalizing and quantifying these effects, this paper introduces new channels through which increases in market size affect welfare within the literature.

2. Data and Measurements of Key Variables

This section introduces the data and key variables used to measure firms' research intensity and their innovation and production diversification.

2.1. Data Sources

Due to the lack of publicly available firm-level data that separates research and development expenditures, I use two measures of innovation output: patents and scientific publications. In line with the innovation literature, I use patents as an indicator of a firm's overall investment in innovation, which includes both research and development activities.[6] I use a firm's scientific journal publications as a proxy for its research investment, given the well-established relationship between research efforts and scientific output in

[6]Corporate patenting strongly correlates with overall innovation investment (Griliches, 1998). Therefore, examining a firm's patents can help identify its innovation decisions and knowledge base (Jaffe et al., 1993; Kim and Kogut, 1996).

the literature.[7]

Patent data is sourced from the USPTO and accessed through the PatentsView platform. I focus on all utility patents granted to U.S. corporate entities filed between 1976 and 2015.[8] For firm-level analysis, I link the patent data to U.S. publicly traded manufacturing firms listed in Compustat, using a crosswalk from Arora et al. (2021b) covering the years 1980 to 2015. Additionally, I incorporate data on patents filed by these firms in foreign patent offices using information from Google Patents.[9]

The scientific publications data comes from a dataset compiled by Arora et al. (2021a), which contains over 800,000 publications from about 3,800 U.S. publicly traded manufacturing firms in the Compustat database, spanning the years 1980 to 2015. This dataset provides the number of articles each firm published in scientific journals each year.[10] Some scientific publications are also patented, known as 'PPP' (Patent-Paper Pairs) in the innovation literature. These patents are more likely to result from scientific research rather than development. I use the dataset compiled by Marx and Scharfmann (2024), which identifies approximately 500,000 USPTO patents that are also published as scientific articles.

Finally, business performance metrics, including sales and R&D expenditures for each U.S. publicly traded firm, are sourced from Compustat. To measure production diversity for each firm, I utilize Compustat's Segment data, which provides information on sales and employment at the 4-digit SIC level within each firm.[11]

2.2. Measures of Firm-level Innovation Diversity

I propose two measures of innovation diversity based on patents. The first measure evaluates the diversity and evenness of technological classes within a firm's patent portfolio. A firm with patents spread evenly across various classes is seen as innovating across a broad technological spectrum. However, patents can be technically similar even if they

[7] Adams and Clemmons (2008) demonstrate a positive relationship between research spending and scientific publications among the top 200 U.S. R&D firms. Similarly, Roach and Cohen (2013) find a strong correlation between patent citations to scientific publications and research lab managers' reliance on science. More recently, Arora et al. (2021a) confirm that scientific publication data can successfully replicate findings based on research expenditure data.

[8] The PatentsView dataset starts in 1976. I select 2015 as the cutoff year to account for right truncation issues related to the time it takes for patents to be granted.

[9] Liu and Ma (2021) compared Google Patents with European Patent Office data, which is widely used in studies of global patenting activities, and confirmed the high reliability of Google Patents data.

[10] The dataset includes journals listed in the 'Science Citation Index' and 'Conference Proceedings Citation Index–Science,' but excludes articles in the social sciences, arts, and humanities.

[11] Bens et al. (2011) raises an under-reporting issue with Compustat Segment data. However, other studies have validated their accuracy. For example, Bloom et al. (2013) observes similar results regarding technology spillovers when using Compustat Segment Data in conjunction with Bureau Van Dijk data.

belong to different classes, and vice versa. Thus, I introduce a second measure that assesses technological diversification by calculating the textual differences among patents. This measure reflects a firm's technology scope, as a wider range implies more varied patent descriptions. The second measure doesn't rely on specific patent classifications, but textual similarity might be a noisy proxy for technological similarity. Therefore, I use both measures to ensure a comprehensive assessment of a firm's innovation diversity.

Effective Number of CPCs (ENC). A measure of technology diversification should reflect both the number of patent classes and the distribution of patents across these classes. For example, consider two firms: one holds 5 patents in two distinct classes (5/5), while the other holds 9 patents in one class and 1 patent in another (9/1). Although both firms patent in two classes, the first firm's even distribution suggests a broader technology scope. The first measure of firm-level technology scope, the effective number of Cooperative Patent Classification (CPC) classes, or ENC, captures this distributional effect.[12] For a given period, firm *i*'s ENC is defined as the following:

$$\texttt{ENC}_i \equiv \left[\sum_{c \in \texttt{CPC}} \left(\frac{x_{ic}}{x_i} \right)^q \right]^{\frac{1}{1-q}},$$

where x_{ic} and x_i denote the number of firm *i*'s patents in CPC class c and the total number of firm i's patents, respectively. CPC represents the set of all CPC classes. Note that this measure considers both the number of classes and the distribution of patents across classes within a firm's patent portfolio. ENC takes values between one and $|C_i|$, which is the number of unique CPC classes of firm *i*'s patents. Note that firm *i*'s ENC is equal to its number of unique technologies ($|C_i|$) only when the patent share of each CPC class (x_{ic}/x_i) is the same across CPC classes. Otherwise, when firm *i*'s patents are more concentrated in some CPC classes, the ENC will become smaller than $|C_i|$, and approaches 1 in the limiting case in which almost all of its patents are concentrated in one CPC class. The penalty on unevenness of the patent distribution is governed by $q \geq 0$, where a higher q means a higher penalty.

Similar measures have been widely used in the ecology and politics literatures to measure diversity of species and political parties. In the economics literature, Ekerdt and Wu (2024) introduced the same concept to measure the degree of production diversity of

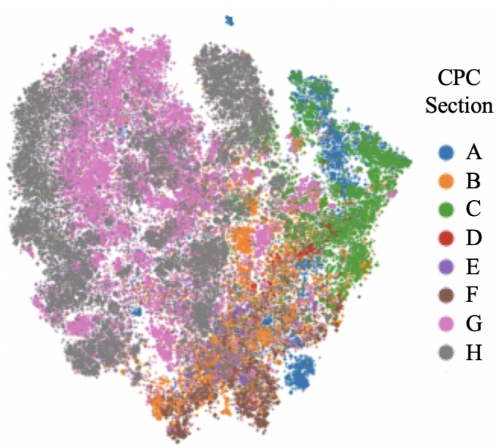
[12] The Cooperative Patent Classification (CPC) system is used jointly by the European Patent Office (EPO) and the USPTO, with a structure similar to the International Patent Classification (IPC). The structure of CPC has the following hierarchy: Section (one letter A to H) $\rightarrow$ Class (two digits) $\rightarrow$ Subclass (one letter) $\rightarrow$ Group (one to three digits) $\rightarrow$ Main group and subgroups (at least two digits). In an example of A01B33/00, A is the Section, 01 is the Class, B is the subclass, 33 is the Group, and 00 is the Main group.

U.S. manufacturing firms, using U.S. Census data. As a baseline, I set $q = 2$, in which case ENC becomes the reciprocal of the Herfindahl-Hirschman Index (HHI), a well-established measure of concentration in the economics literature.[13]

To ensure meaningful variation, I measure ENC at the 4-digit CPC subclass level.[14] There are around 650 CPC subclasses, comparable to 5-digit (around 700 industries) or 6-digit NAICS (around 928 industries). Also, following the innovation literature (Liu and Ma, 2021), when a patent has multiple CPC codes, I define the first CPC listed as its main CPC and use it for the calculation of ENC.

Textual Differences Between Patents (Text-Diff). As an alternative measure of technological diversification, I introduce a measure based on text-based semantic differences between patents. Specifically, for any two patents, I calculate the similarity in their textual content, using the background and summary of the invention.[15] The key assumptions are that a patent's summary text effectively captures its technological content and that patents using words with similar meanings in their summaries likely share similar technologies.

Figure 2: Visualization of Patent Vectors



Notes: The figure shows semantic vectors of all patents granted from applications filed in 1998, with colors representing different one-digit CPC Sections. The original 300-dimensional vectors were reduced to two dimensions for visualization using principal component analysis.

To calculate textual similarities between patents, I use the Word2Vec model, which

[13]Henderson and Cockburn (1996) also used the HHI of innovation spending across different R&D projects to measure a firm's innovation scope and focus.

[14]Examples of CPC subclasses belonging to CPC class A23 (Foods or foodstuffs) are A23B (Preserving), A23C (Dairy products), A23D (Edible oils or fats), A23F (Cofee; Tea; Their substitutes), A23G (Cocoa; Cocoa products), A23J (Protein compositions for foodstuffs), etc.

[15]This "summary" section of a patent application describes the invention's purpose and benefits, often highlighting how it addresses existing problems. It is typically around 1,000 words, providing more detail than the patent abstract.

effectively captures the semantic meanings of words (Mikolov et al., 2013). Word2Vec maps each word to a vector, with vectors of semantically similar words positioned closer together. It's important to note that in the context of patent documents, some words may have meanings that differ from their everyday usage. To account for these specific semantic nuances, I train a Word2Vec word embedding using patent text data, rather than relying on off-the-shelf pretrained embeddings.

The trained Word2Vec model assigns a 300-dimensional vector to each word in the summary texts, enabling the measurement of semantic similarities between words. For example, the vectors for 'microprocessor' and 'CPU' exhibit the highest cosine similarity to the vector for 'processor' among all words used in sample patents. Although these words are distinct, the word vectors effectively capture their similar meanings. Since patents using these words are likely to be technologically related, the similarity measured from these vectors can serve as a proxy for technological similarity.

I define a patent vector, $\texttt{PV}_p$, as the element-wise mean of the 300-dimensional vectors of all words contained in the summary text:

$$\texttt{PV}_p \equiv \frac{1}{N}\sum_{l=1}^{N}\texttt{WV}_l^p,$$

where N is the total number of words used in patent p's summary text and $\texttt{WV}_l^p$ represents the vector of the l-th word in this summary text. Consequently, each patent is represented by a 300-dimensional vector.[16] To visualize this semantic vector space, Figure 2 shows the semantic vectors of all patents granted from the 1998 applications, with each color corresponding to a different one-digit CPC Section. In general, patents belonging to the same section are clustered together, implying similarity in their textual contents.[17]

The similarity between two patent summary texts is calculated as the cosine similarity between their patent vectors. A higher cosine similarity indicates that the patents use words with more similar meanings. Based on the intuitive negative relationship between technology diversity and textual similarities among patents, I define the second measure of a firm's technology scope as the inverse of the average pair-wise cosine similarity among

[16]The i-th element of the patent vector is given by $\frac{\sum_{l=1}^{N} a_{l,i}}{N}$ where $a_{l,i}$ denotes the i-th element of the l-th word vector in the patent's summary.

[17]These vectors, originally in 300 dimensions, are reduced to two dimensions in Figure 2 using Principal component analysis for visualization purposes. Hence, the distance between two points in Figure 2 may not be exactly proportional to the distance between the original 300-dimensional vectors associated with them.

its patent vectors:

$$\texttt{Text-Diff}_i \equiv \left[\left(\sum_{j \in P_i} \sum_{k \in P_i, k \neq j} \frac{\texttt{PV}_j \cdot \texttt{PV}_k}{\|\texttt{PV}_j\| \|\texttt{PV}_k\|} \right) / \left(|P_i| \left(|P_i| - 1 \right) \right) \right]^{-1} \quad \text{if } |P_i| \geq 2,$$

where P_i is the set of firm i's patents and $|P_i|$ denotes the number of patents in this set. The operators $\|\cdot\|$ and $\cdot$ represent the Euclidean norm and the inner product, respectively. The higher the `Text-Diff` value, the greater the textual difference among a firm's patents, indicating higher technological diversity within the firm's portfolio.[18]

2.3. Other Key Variables

The primary measure of research intensity (`ResearchIntensity`) is the ratio of scientific publications to a firm's total sales. A higher reliance on research-based innovation will result in a higher ratio of scientific publications to sales. An alternative measure is the ratio of scientific publications to the sum of scientific publications and patents: $\frac{\texttt{Publication}_{it}}{\texttt{Publication}_{it} + \texttt{Patent}_{it}}$, where $\texttt{Publication}_{it}$ and $\texttt{Patent}_{it}$ represent the numbers of scientific publications and patents by firm i in year t, respectively.

For product diversity, I employ a measure analogous to `ENC`, utilizing shares of sales across 4-digit SIC segments within a firm, instead of patents. Formally, I define the effective number of SIC industries for firm i ($\texttt{ENS}_i$) as follows:

$$\texttt{ENS}_i \equiv \left[\sum_{c \in \texttt{SIC}} \left(\frac{s_{ic}}{s_i} \right)^2 \right]^{-1},$$

where s_{ic} represents the sales from SIC industry c and s_i denotes the total sales of the firm. The set `SIC` denotes the set of all 4-digit SIC industries.

3. Empirical Analysis

With the measures of research intensity and diversity established in Section 2, I next present empirical findings that will guide the choice of model in Section 4. First, I show that there was a marked decline in innovation diversity among U.S. firms during the 1990s. This trend coincides with significant decreases in research intensity (Figure 1a) and product specialization, as evidenced by Ekerdt and Wu (2024) using U.S. census data. In Subsection

[18]The definition of `Text-Diff` applies only to firms with more than one patent. For firms with a single patent, `Text-Diff` is defined as 1, representing the minimal value of the measure.

3.2, I establish strong correlations among these variables at the firm level. Lastly, I explore how the rapid globalization in the 1990s contributed to these trends in Subsection 3.3.

3.1. Innovation Specialization of U.S. Firms

I examine the historical changes in technology diversification among U.S. firms over three decades, from 1980 to 2009.[19] The sample includes all U.S. companies that have ever applied for U.S. patents and are classified as 'US Company or Corporation' by the USPTO.

I first calculate the two firm-level innovation diversity measures using all granted utility patents assigned to these U.S. firms, regardless of inventors' locations.[20] Since innovation outcomes can be unpredictable and may deviate from expected results or timelines, I measure innovation diversification by aggregating all patents a firm applied for within each 3-year period. Next, for each of these periods, I calculate the patent-weighted average of technology diversification across all innovating U.S. firms, providing an estimate of overall U.S. corporate technology diversification.

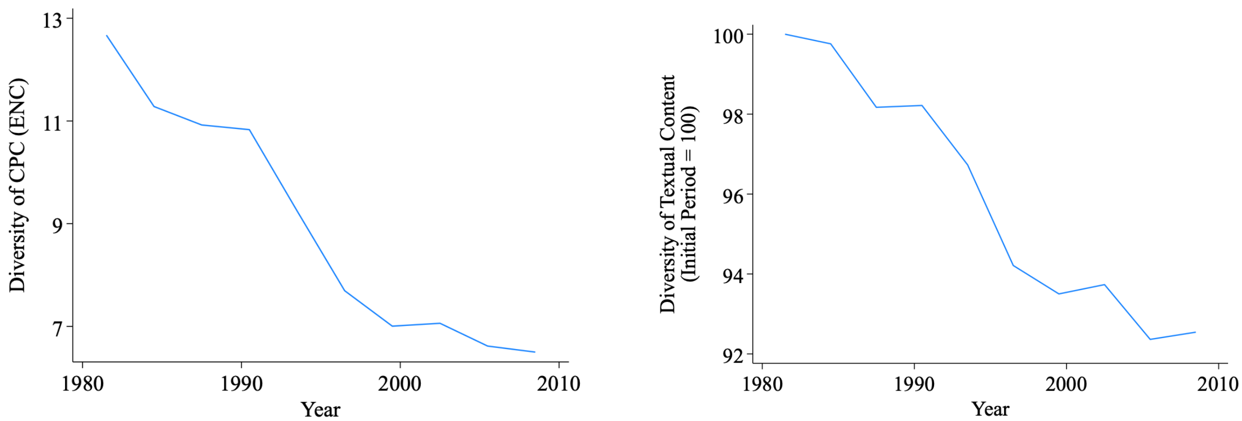
Figure 3 illustrates the aggregate trends in technology diversification among U.S. corporations. Both measures show a decline in technology diversification over time, a trend which I refer to as the innovation specialization of U.S. companies. This trend was particularly pronounced during the 1990s and slowed after 2000. For example, the left panel of the figure shows that the average (effective) number of CPC subclasses in which firms innovated dropped from 12.7 in the initial three-year period (1980-1982) to 6.5 in the final three-year period (2007-2009). Notably, this decrease was most pronounced in the 1990s, with the number falling from 10.8 in the period 1989-1991 to 7.0 in the period 1998-2001. Additionally, Appendix B.2 shows that this rising trend of innovation specialization is consistent across all CPC 1-digit sections, with additional decomposition analysis revealing that this trend was primarily driven by the accelerated specialization of large innovative firms.

These findings remain robust across (1) different sample intervals, such as 1-year or 5-year periods, (2) limiting the sample to patents with above-median forward citations, to address concerns about increasing strategic patenting, (3) restricting the sample to U.S.

[19] I focus on this period to ensure comparability with firm-level analyses that use the crosswalk between Compustat firms and patents compiled by Arora et al. (2021b), which covers 1980 to 2015. To avoid data truncation issues related to the timing of patent grants, the final five years of the period are excluded from the analysis.

[20] This approach differs from analyzing patents created solely by domestic U.S. inventors. Some patents granted by the USPTO may be attributed to U.S.-based inventors working for foreign firms or to inventors located abroad who are employed by U.S. firms through offshore R&D activities (Fan, 2019). By focusing on patents assigned to U.S. firms, I aim to measure innovation diversity within these firms, irrespective of the inventors' geographical locations.

Figure 3: U.S. Average Firm-level Innovation Diversity



Data source: USPTO. The figures illustrate the average innovation scope of all US firms, using patent data from 1980 to 2009. This scope is measured by two metrics, calculated for each firm for every 3-year interval within this period. The left figure measures the scope using the inverse of the HHI at the main 4-digit CPC level (`ENC`). The right figure uses the textual differences between each pair of patents' summary texts (`Text-Diff`). Refer to subsection 2.2 for details on these measures. The number of patents of each firm is used as a weight to calculate the weighted average.

Compustat firms, and (4) excluding patents by foreign inventors. Additionally, I find that U.S. universities increased their technological diversity over the same sample period. This suggests that the trend of corporate innovation specialization is less likely to be driven by purely technical factors, such as changes in the CPC over time. Detailed analyses and figures on these results are provided in Appendix B.1.

3.2. Correlation between Specialization and Research Intensity

The previous subsection highlighted the trend of rising innovation specialization among U.S. firms, coinciding with a decline in research intensity and increased product specialization. Here, I present evidence showing that these outcomes are also closely interconnected within firms. This analysis focuses on publicly traded U.S. firms in Compustat, for which detailed information on these metrics is available.

3.2.1. Specialization and Research Intensity are Correlated within Firms

This analysis focuses on U.S. publicly traded firms in Compustat. To utilize within-firm variation, I limit the sample to firms that registered at least one patent and one scientific publication during the sample period (1980-2009). Collectively, these firms account for approximately 660,000 scientific publications and 1,139,000 patents, representing more than 98% of the total scientific publications and patents recorded in the dataset compiled by Arora et al. (2021a).

I explore the within-firm relationship between research intensity and specialization using the following regression for each firm (i) and year (t):

$$\text{IHS}(\texttt{ResearchIntensity}_{it}) = \beta \ln(\texttt{Diversity}_{it}) + \gamma \mathbf{C}_{it} + \delta_i + \delta_{ct} + \epsilon_{it}, \tag{1}$$

where the outcome variable, $\text{IHS}(\texttt{ResearchIntensity}_{\texttt{it}})$, represents the inverse hyperbolic sine (IHS) transformation of firm i's research intensity in period t.[21] The main independent variable is either innovation diversity (ENC or Text-Diff) or product diversity (ENS). To account for stochastic components in innovation outcomes, I calculate research intensity and specialization measures over a three-year period (from $t-2$ to t), similar to the calculation of aggregate innovation diversity in the previous subsection. To focus on within-firm variation, I include firm-level fixed effects (δ_i). Additionally, the fixed effect $\delta_{c,t}$ captures common changes, such as technology shocks, that occur over time within the firm's primary 4-digit SIC industry c. Lastly, the vector of control variables, $\mathbf{C}_{it}$, includes the IHS-transformed aggregated sum of the number of patents, total R&D expenditures, and total sales over the three-year period from $t-2$ to t. These controls account for potential scale effects influencing both research intensity and firm-level diversity measures.

I then explore the firm-level relationship between product diversity and innovation diversity using the following regression equation for each firm (i) and year (t):

$$\ln(\texttt{ProductDiversity}_{it}) = \beta \ln(\texttt{InnovationDiversity}_{it}) + \gamma \mathbf{C}_{it} + \delta_i + \delta_{ct} + \epsilon_{it}, \tag{2}$$

where I use the logarithm of the firm-level product diversification ($\texttt{ENS}_{\texttt{it}}$) as the outcome variable. The rest of the variables are defined in the same way as Equation (1).

Table 1 summarizes the estimated coefficients from the regressions outlined in Equations (1) and (2). Columns (1) - (8) illustrate statistically significant positive correlations between research intensity, product diversity, and innovation diversity across time within firms.

3.2.2. Research Leads to Higher Innovation Diversity

The previous analysis reveals strong correlations in aggregate and firm-level data between innovation diversity and research intensity. Here, I shed light on the mechanism behind

[21] The IHS transformation is frequently used as an alternative to the logarithmic transformation, particularly for datasets that include zero values. This approach has been applied in recent studies such as Arora et al. (2021a), Azoulay et al. (2019), and Moretti (2021) to handle patent applications and scientific publications, which often contain zero values.

Table 1: Within Firm Relationship

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Research Intensity						Product Diversity	
VARIABLES	$\text{IHS}(\frac{\texttt{Publication}}{\texttt{Sales}})$			$\text{IHS}(\frac{\texttt{Publication}}{\texttt{Publication+Patent}})$			$\ln(\texttt{ENS})$	
Innovation Diversity								
$\ln(\texttt{ENC})$	0.025***			0.010**			0.024***	
	(0.008)			(0.005)			(0.009)	
$\ln(\texttt{Text-Diff})$		0.031**			0.042***			0.032***
		(0.015)			(0.010)			(0.012)
Product Diversity								
$\ln(\texttt{ENS})$			0.071***			0.025**		
			(0.015)			(0.011)		
Number of Firms	2,203	2,203	2,274	2,233	2,233	2,264	2,183	2,183
Observations	27,617	27,617	33,959	28,005	28,005	30,024	26,264	26,264
R-squared	0.836	0.836	0.777	0.794	0.795	0.787	0.825	0.825
Controls	√	√	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√	√	√
SIC4d-Year FE	√	√	√	√	√	√	√	√

Notes: The dependent variables are the inverse hyperbolic sine-transformed `ResearchIntensity`, measured by the ratio of scientific publications to sales (columns 1-3), and by the ratio of scientific publications to the sum of publications and patents (columns 4-6); and the logarithm of product diversity (columns (7-8)). Independent variables include the logarithm of innovation diversity ($\ln(\texttt{ENC})$ and $\ln(\texttt{Text-Diff})$), and product diversity. Controls cover the logarithms of R&D expenditures, patents, and sales from the current and past two years. *p<0.1, **p<0.05, ***p<0.01. Standard errors (in parentheses) are corrected for arbitrary correlation within each firm.

Table 2: Differences in Innovation Diversity Between Research and Development

VARIABLES	(1) $\ln(\texttt{ENC})$	(2) $\ln(\texttt{Text-Diff})$	(3) `ENC`
`Patent-Paper-Pair` (`PPP`)	0.305***	0.080*	5.096**
	(0.111)	(0.046)	(2.064)
Sample Period	1980-2010	1980-2010	1989-1991
Observations	4,878	4,878	220
R-squared	0.956	0.741	0.948
Controls	√	√	√
Firm-Period FE	√	√	-
Firm FE	-	-	√

The dependent variables in Columns (1) to (3) are the logarithms of `ENC` and `Text-Diff`, as well as `ENC`, respectively. The main independent variable, `PPP`, is an indicator equal to one for PPP patents and zero otherwise. Control variables in Columns (1) and (2) include the logarithms of the number of patents and unique CPCs, while in Column (3), controls are the number of patents and unique CPCs. Regressions are weighted by the number of patents in each firm-period pair. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within firms and 2 digit SIC industries, for Columns (1)-(2) and Column (3), respectively.

this correlation, by showing that research outputs inherently exhibit wider innovation diversity. Specifically, I show that patents also published in scientific journals are applied to more diversified technologies than other patents, even within the same firm and time period. This comparison provides direct evidence that research outputs exhibit greater innovation diversity, as comparing within firm-period pairs effectively accounts for firm-level factors, such as production scope, that influence overall innovation diversity.

I employ the following specification to examine the diversity of research outputs:

$$\ln(\texttt{InnovationDiversity}_{it}^{g}) = \beta \texttt{PPP}_{it}^{g} + \gamma_1 \ln(\texttt{Patents}_{it}^{g}) + \gamma_2 \ln(\texttt{Unique}_{it}^{g}) + \delta_{it} + \epsilon_{it}^{g}. \quad (3)$$

I use the same sample as in regression equation (2). I divide each firm's patents into two groups (g): those also published in scientific journals (PPP) and those that are not (non-PPP). For each firm-year pair, I calculate both measures of innovation diversity, the number of patents (`Patents`), and the number of unique CPCs (`Unique`) for both PPP and non-PPP groups over a three-year period (from $t-2$ to t). This specification effectively controls for firm-level factors, such as product scope and innovation scale, that commonly influence overall innovation diversity, using firm-by-time fixed effects as well as group-specific controls for patent scale and scope. The coefficient of interest, β, on the `PPP` indicator (equal to one for the PPP group), tests whether scientific outcomes (PPP patents) exhibit greater innovation diversity than development outcomes (non-PPP patents).

Columns (1) and (2) in Table 2 present the estimated coefficients from the regressions outlined in Equation (3), highlighting the significant positive effects of the PPP indicator, which indicate that research outputs have broader applicability than development outputs. Column (3) restricts the sample period to 3 years around 1990 (from 1989 to 1991) and estimates the difference in levels of `ENC` between PPP and non-PPP groups, which will be used below to calibrate the model to the US economy in 1990.

3.3. Impacts of Globalization on Specialization and Research Intensity

The previous subsections highlighted the rapid specialization and reduction in research intensity among U.S. firms in recent decades, particularly during the 1990s. This subsection provides empirical evidence that globalization in the 1990s contributed to these trends.

The 1990s saw a rapid decline in trade barriers, often referred to as the "Great Liberalization" in the trade literature (Estevadeordal and Taylor, 2013; Coelli et al., 2022). This period featured substantial tariff reductions following the completion of the GATT Uruguay Round in 1994. From 1995 to 2000, average tariffs dropped in developed countries from about 6% to 3%, and in developing countries from around 20% to 13% (Coelli et al., 2022).

I leverage the substantial reduction in Most-Favored-Nation (MFN) tariffs during the 1990s to examine the impact of globalization on U.S. firms' research intensity and specialization. For each US Compustat firm (i), I construct a measure of exposure to tariff reductions in period t as a proxy for globalization shocks ($\texttt{Globalization}$), calculated as the negative of the weighted average tariffs faced by each firm in their export markets:

$$\texttt{Globalization}_{it} = -\sum_{d \in D \setminus US} \sum_{s \in SIC} \omega_{id} \times \omega_{is} \times \texttt{MFN}_{dst}, \tag{4}$$

where $\texttt{MFN}_{dst}$ represents the MFN tariffs of country d in SIC 4-digit industry s in year t. The set D represents all destination countries. I use MFN tariffs as they apply to all WTO member countries and are likely relatively exogenous with respect to U.S. firms' lobbying efforts (Coelli et al., 2022). The data for MFN tariffs is sourced from the UNCTAD Trade Analysis and Information System (TRAINS), which provides highly disaggregated tariff data for over 150 countries.

Weights for each destination-industry pair reflect the importance of each destination-industry market. First, the firm-country level weight, ω_{id}, captures the relative significance of destination d to firm i. Following Aghion et al. (2016) and Coelli et al. (2022), the firm-destination weight is calculated as:

$$\omega_{id} \equiv \frac{x_{id}}{\sum_{d \in D} x_{id}},$$

where x_{id} represents the number of patents applied for by firm i in country d between 1980 and 1989. Patents are used as weights because they likely reflect the firm's expectations of future market presence and correlate strongly with sales weights over time (Aghion et al., 2016; Coelli et al., 2022).[22] Firms with predominantly US-applied patents generally have lower firm-country weights across foreign destinations. Secondly, the firm-industry level weight ω_{is} is determined by the share of sales from industry s relative to firm i's total sales during the 1980s, using Compustat segment data for each firm.

I employ the following regression model to examine the impact of globalization on specialization and research intensity:

$$Y_{it} = \beta_0 \texttt{Globalization}_{it} + \beta_1 \texttt{Globalization}_{it} \times \texttt{Large}_i^{1989} + \gamma \mathbf{C}_{it} + \delta_i + \delta_{s(i)t} + \epsilon_{it}, \tag{5}$$

[22] Seeking intellectual property rights in a specific country is typically motivated by anticipated future sales in that market. There is robust empirical evidence supporting that patent weights are highly correlated with sales weights, and these correlations remain remarkably consistent over time, even across a span of 20 years (Aghion et al., 2016; Coelli et al., 2022).

where Y_{it} represents the logarithm of specialization or research intensity. The impact of globalization is assessed by coefficients β_0 and β_1, which are identified from the within-firm variation in the globalization metric. The decomposition analysis in Appendix B.2 shows that the trend of innovation specialization is primarily driven by the rapid specialization of large innovative firms.[23] To address potential size-related heterogeneity, I incorporate an interaction term between the globalization measure and an indicator for whether the firm's R&D investment or sales in 1989—the pre-period year used in the regression—was larger than the median value of the sample firms ($\texttt{Large}_i^{1989}$). The controls $\mathbf{C}_{it}$ account for potential scale effects on diversity and research intensity outcomes by incorporating the IHS transformed sales, patent counts, and R&D expenditures. Additionally, the industry-by-time fixed effects, denoted as $\delta_{s(i)t}$, help control for common shocks that affect each sector uniformly, such as changes in the propensity to patent or publish scientific works, as well as other technological changes.

The sample is limited to U.S.-based Compustat firms that held any foreign patents from 1980 to 1989, to construct firm-level weights for the globalization metrics. Furthermore, when research intensity is the outcome variable, I exclude firms that did not generate any scientific publications during the sample period.

Table 3 displays the estimated coefficients from equation (5). The negative estimated values of β_1 indicate that globalization leads larger firms to reduce their innovation diversity (Columns (1) and (2)), production diversity (Column (3)), and research intensity (Column (4)). In contrast, the estimated values of β_0 are relatively small and not statistically significant, suggesting little impact of globalization on the shape of innovation for smaller firms. During the sample period, the median change in the firm-level globalization measure was approximately 0.015. The estimated coefficients suggest that a hypothetical firm whose R&D investment exceeded the median level in 1989 would have experienced a decline in innovation diversity, as measured by `ENC` and `Text-Diff`, of 7.5% and 2.2%, respectively, during the sample period, excluding any scale effects.[24]

Appendix B.3 provides robustness checks for these results. Appendix Table B1 replaces the binary indicator for large firms in Table 3 with a continuous measure of firm size, using the IHS transformation of R&D and sales data from 1989. The results remain robust, indicating that globalization led to increased specialization and a reduction in research intensity, particularly among larger firms.

[23] Ekerdt and Wu (2024) also show that the decline in production diversity among U.S. firms during the 1990s was predominantly driven by larger firms.

[24] These numbers are derived from the calculations $(-0.224 - 4.717) \times -1.5\%$ and $(0.268 - 1.726) \times -1.5\%$, respectively.

Table 3: Effects of Globalization on Specialization and Research Intensity

	(1)	(2)	(3)	(4)
	Innovation Diversity		Product Diversity	Research Intensity
VARIABLES	$\ln(\texttt{ENC})$	$\ln(\texttt{Text-Diff})$	$\ln(\texttt{ENS})$	$\text{IHS}(\frac{\texttt{Publication}}{\texttt{Sales}})$
$\texttt{Globalization}$	-0.224	0.268	0.940	0.718
	(1.476)	(0.713)	(1.062)	(1.682)
$\texttt{Globalization} \times 1_{\{\text{R\&D}^{1989} > \text{R\&D}^{1989}_{\text{median}}\}}$	-4.717**	-1.726**		-2.708***
	(2.320)	(0.816)		(1.043)
$\texttt{Globalization} \times 1_{\{\text{Sales}^{1989} > \text{Sales}^{1989}_{\text{median}}\}}$			-4.610**	
			(1.879)	
Observations	7,464	7,464	7,185	6,215
R-squared	0.917	0.707	0.852	0.844
Controls for Scale	√	√	√	√
Firm FE	√	√	√	√
SIC4d-Year FE	√	√	√	√

Notes: Dependent variables in the regression include the logarithms of innovation and product diversity measures ($\texttt{ENC}$, $\texttt{Text-Diff}$, and $\texttt{ENS}$), along with the IHS transformed research intensity ($\frac{\texttt{Publication}}{\texttt{Sales}}$) (see Subsection 3.2. for their definitions). $\texttt{Globalization}$ represents the firm-level globalization shock as defined by Equation (4). Control variables include the IHS transformed R&D expenditure, total counts of patents, and sales. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within each firm.

4. Theoretical Model

This section introduces a model that explains the close relationship between specialization and research intensity documented in Section 3. The model builds on the widely-used multi-product firm framework with variable elasticity of substitution preferences, developed by Mayer et al. (2014) (hereafter MMO). Unlike the original MMO model, in which firms start with multiple products, my model requires firms to first invest in research and development to create these products. This extension connects demand shocks in export markets to specialization and reduced research intensity, allowing for an evaluation of the effects of globalization and innovation reallocation on welfare, productivity, and markups. I first examine a closed economy, in which globalization is represented by an increase in market size, simulating complete economic integration. I then show that similar predictions hold in an open economy model, in which globalization is captured by a reduction in iceberg export costs.

4.1. Market Structure and Production Technologies

I develop a general equilibrium model with a single differentiated goods sector, following the market structure and production technologies of the MMO model. The model is set in a closed economy, where monopolistically competitive firms sell products to consumers. Through innovation, these firms can potentially offer multiple products. The model takes place in a single period, in which firms make innovation and production decisions sequentially.

Consumer Preference. The economy has L identical consumers. The representative consumer's preference is given as an additively separable utility function, $U = \int_0^T u(q_j)dj$, over a continuum of imperfectly substitutable products. Products are indexed by $j \in [0, T]$, where T is the measure of available products. Note that, as in the MMO model, I assume that consumers do not exhibit different substitution patterns between products within a firm or across different firms.[25]

Each consumer inelastically provides one unit of labor, which can be used in either production or R&D activities, and in return, she earns a wage, denoted by w. I choose labor as the numeraire, setting the wage at $w = 1$. Consumers then solve a standard maximization problem: $\max_{q_j} \int_0^T u(q_j)dj$ s.t. $\int_0^T p_j q_j dj = 1$. The first-order condition yields the consumer's residual inverse demand for each product:

$$p(q_j) = \frac{u'(q_j)}{\lambda}, \tag{6}$$

where $\lambda \equiv \int_0^T u'(q_j)q_j dj > 0$ represents the marginal utility of income. This serves as the unique endogenous aggregate demand shifter in the model, where a higher λ shifts all residual demand curves inward.[26] Therefore, following MMO, I interpret λ as the level of competition in the economy. Later, I will show that globalization, modeled as an increase in market size L, endogenously increases competition (λ) and reduces demand for each good. Additionally, I assume that $u'(0) < \infty$, indicating the existence of a finite choke price, $p(0) = u'(0)/\lambda$.[27] Any product with a marginal cost higher than this choke price cannot make positive profits. An increase in competition (a higher λ) reduces the choke

[25] I also assume that the standard conditions on sub-utility u hold, ensuring that the consumer's maximization problem is well-defined. Additionally, I assume that the elasticity of utility $(q_j u'(q_j)/u(q_j))$ and the elasticity of marginal utility $(q_j u''(q_j)/u'(q_j))$ are bounded below and above by $m > 0$ and $1 - m < 1$ following Dhingra and Morrow (2019).

[26] For example, when the assumed demand follows the CES, the marginal utility of income, λ, corresponds exactly to the inverse of the CES aggregate price index.

[27] Alternatively, one could assume a positive fixed cost for selling a product instead of this assumption.

price, making an additional set of products no longer profitable.

Following MMO, I assume that preferences satisfy Marshall's Second Law of Demand (MSLD), which requires that the absolute value of the elasticity of demand decreases as the quantity demanded increases.[28] This assumption is both necessary and sufficient for a model of monopolistic competition to exhibit endogenous markups that are higher for products with larger sales, decrease with tougher competition, and show incomplete pass-through to cost shocks—features that have substantial empirical support but are not captured by CES preferences (Mrázová and Neary, 2017; Mayer et al., 2021).[29]

Production Technology. Upon entry, each firm has a set of potential products that can be created through innovation and sold to consumers. These products vary in how efficiently the firm can produce them. I order these products by their marginal costs (denoted as c_k), which increase with the product index k.[30] The first product ($k = 1$), having the lowest marginal cost, is the one the firm is most proficient at producing and is therefore referred to as the core product. For simplicity, I follow the MMO model and assume that marginal costs are given by $c_k = c\delta^{k-1}$, where $\delta > 1$ indicates the rate at which marginal costs increase with each step away from the core product.[31]

4.2. Innovation: Research and Development

A key departure from the MMO model is that firms must engage in innovation to bring products to market. Figure 4 outlines the sequence of innovation decisions that occur before the production phase. During the innovation stage, firms first determine their separate levels of investment in research and development, which generate ideas. Firms then allocate each idea to a single product, which increases its probability of successful creation. As a result of the innovation stage, the firm ends up with a set of successfully created products based on these probabilities. During the ensuing production stage, these products generate profits according to the original MMO model. The innovation framework in this paper builds on the shareable inputs model explored by Ding (2023).

[28] Mrázová and Neary (2017) referred to these preferences as subconvex. Many authors, including Dixit and Stiglitz (1977) and Krugman (1979), have argued that subconvexity is more intuitively plausible.

[29] De Loecker et al. (2016) and Dhyne et al. (2017) showed a positive correlation between product-level markups and firm performance. Additionally, a substantial body of work has documented incomplete pass-through, particularly for exchange rate shocks (see Burstein and Gopinath (2014) for a survey)

[30] Firms use a production technology with constant returns to scale, where producing the k-th product requires c_k units of labor.

[31] The model's propositions do not rely on this specific assumption regarding the marginal cost structure.

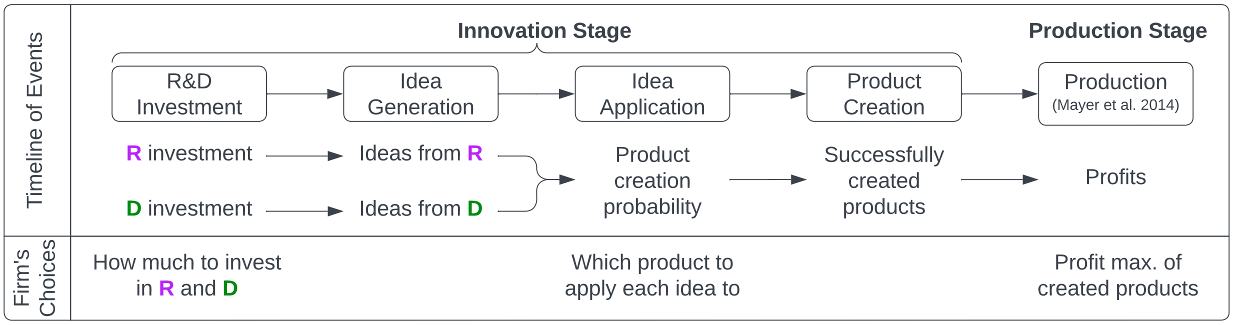


Figure 4: Overview of Key Decisions in the Model

Idea Generation. The firm chooses separate levels of investment for research and development (x_r and x_d) which generate continuums of research ideas and development ideas, respectively. I assume that the masses of ideas from research and development, A_r and A_d, increase with the level of investment, but are subject to diminishing returns to scale as follows:

$$A_m = \frac{1}{\rho} Z_m x_m^{\rho}, \quad m \in \{r, d\}. \tag{7}$$

Increasing the level of investment for research (x_r) or development (x_d) leads to a larger mass of ideas from each innovation margin. The returns to scale of innovation investment are governed by $\rho \in (0, 1)$.[32] A lower ρ implies greater diminishing returns to a firm's R&D effort, in which case changes in market conditions will have smaller effects on the optimal levels of innovation effort. Lastly, Z_m is the efficiency of idea creation.

Idea Application. Each idea i generated by innovation method m has a match-specific value $\phi_{m,i,k}$ when applied to the k-th product. I assume that each idea can be applied to only one product, although multiple ideas can be applied to the same product. Accounting for the randomness in innovation outcomes, these match-specific values are i.i.d. draws from a Fréchet distribution: $Pr(\phi_{m,i,k} \leq v) = e^{-v^{-\theta_m}}$, where $\theta_m \in (1, \infty)$ represents the shape parameter of innovation method m, and is inversely related to the variability of match-specific values.

If the firm chooses to apply idea i to the k-th product (denoted by indicator $\mathbf{1}_{m,i,k} = 1$), it increases the probability of successful creation of the k-th product, I_k, by its match specific value $\phi_{m,i,k}$ multiplied by a shift parameter $B > 0$, which is assumed to be small enough so that product creation probabilities are smaller than 1. Hence, the probability of successful creation for product k is the sum of match-specific values from all ideas generated either

[32]For simplicity, I assume that the return to scale parameter is the same for both research and development. Assuming different return to scale parameters introduces the scale effect of globalization. Appendix A.1 provides more generalized results by relaxing this assumption.

through research or development that are applied to that product:

$$I_k = B \times \left[\sum_{m \in \{r,d\}} \int_0^{A_m} \phi_{m,i,k} \mathbf{1}_{m,i,k} di \right]. \tag{8}$$

The two innovation margins, research and development, differ in their Fréchet shape parameters. Specifically, I assume that research has a smaller shape parameter ($\theta_r < \theta_d$), indicating that research generates ideas with more variable match-specific values—ideas that are more likely to yield either very low or very high values for a product. In contrast, ideas from development have more predictable values. This distinction aligns with findings in the innovation literature that research outputs are less predictable but more often lead to high-value breakthroughs. Later, when considering the firm's optimal decisions, the size of the shape parameter will determine how sensitively the application of ideas responds to profits.

4.3. Firms' Optimal Choices

Firms make optimal decisions at each stage of innovation and production to maximize expected profits. I explain the stages in reverse order, beginning with the production stage. I omit firm subscripts for simplicity, but note that firms can have different core marginal costs, c.

4.3.1. Production Stage

In the production stage, the firm maximizes profits from products that were successfully created during the innovation stage. Since production and consumer demand are independent across products, the firm can maximize profits separately for each product. Assuming the firm successfully created its k-th product in the innovation stage, it solves a standard profit maximization problem:

$$\max_{q_k \geq 0} L \left[\frac{u'(q_k)}{\lambda} - c_k \right] q_k.$$

Let $\pi_k(\lambda)$ denote the optimized per-consumer profit of product k.[33] As the product index increases, profits decline due to rising marginal costs. Furthermore, products with marginal costs greater than the choke price ($c > u'(0)/\lambda$) cannot generate profits. Letting N represent

[33]Since the total profit from selling product k to all consumers is simply the market size multiplied by the per-consumer profit, $L \times \pi_k(\lambda)$, the following discussion will focus on per-consumer profits.

the largest product index that can still yield positive profits, the N-dimensional vector of positive potential per-consumer profits, $\Pi(\lambda) \equiv [\pi_1(\lambda), \pi_2(\lambda), \ldots, \pi_N(\lambda)]$, summarizes the potential returns to innovation for each product, conditional on its successful creation.[34] An increase in competition reduces profits ($\partial\pi/\partial\lambda \leq 0$) and lowers the choke price, potentially making fewer products profitable.

4.3.2. Innovation Stage

Given these optimized profits in the production stage, firms engage in innovation activities to maximize expected profits by determining the probabilities of product creation. Specifically, firms make two key decisions: how many ideas to generate (idea generation) and how to allocate those ideas to products (idea application). I will first describe the firm's optimal decisions regarding idea application, then analyze idea generation.

Optimal Idea Application. Once ideas are generated from the firm's investment in research and development, each idea is applied to a single product to increase the probability of its creation. The linear functional form of product creation probability (Equation (8)) implies that the increase from one idea's application is independent of the assignment of other ideas, allowing each idea to be analyzed separately. Specifically, applying idea i generated by innovation method m to product k increases the firm's expected profits by the product of its match-specific value and the profits of product k conditional on its successful introduction, $\phi_{m,i,k} \times (L\pi_k)$. Consequently, the firm will allocate each idea to the product that maximizes the expected increase in profits.

$$\mathbf{1}_{m,i,k} = \begin{cases} 1 & k = \arg\max_{j \in \{1,2,\ldots,N\}} \{\phi_{m,i,j} \times \pi_j(\lambda)\} \\ 0 & o.w. \end{cases} \tag{9}$$

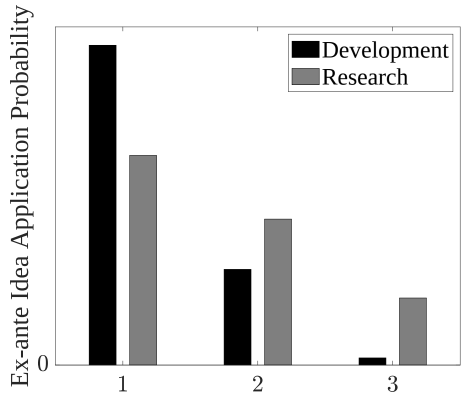
Before the match-specific values are realized, the ex-ante probability that an idea from innovation method m will be optimally applied to the k-th product ($\chi_{m,k}$) can be derived based on the assumption of a Fréchet distribution:

$$\chi_{m,k} = Pr(\mathbf{1}_{m,i,k} = 1) = \frac{\pi_k(\lambda)^{\theta_m}}{\sum_{j=1}^{N} \pi_j(\lambda)^{\theta_m}}. \tag{10}$$

The application probability is higher for products with greater profits (lower k) because higher profitability encourages firms to apply a broader range of ideas, even those with

[34] Under the assumed marginal cost structure, the maximum product index N can be calculated as $N = \max_k \{k \in \{1, 2, 3, \ldots\} | c\delta^{k-1} < u'(0)/\lambda\}$.

Figure 5: Ex-ante Idea Application Probability ($\chi_{m,k}$)



The figure shows the ex-ante probability of an idea being applied to each product before the match-specific values (ϕ) are drawn. The product index is displayed on the horizontal axis, with shape parameters chosen to reflect the assumption that $\theta_r < \theta_d$. Grey bars represent the application probabilities for research ideas, while black bars indicate those for development ideas. The parameters used to generate this figure are $\theta_r = 1.2$ and $\theta_d = 4$.

lower match-specific values. A higher θ_m amplifies this effect, as greater similarity in match-specific ϕ values across products (higher θ_m) makes profitability differences more critical in idea allocation. As a result, development ideas, which have lower variability, tend to focus on high-profit products, while research ideas are applied more broadly. In other words, the benefits of development are more specifically targeted toward high-performing products. Figure 5 illustrates this result for $N = 3$, showing that development ideas are concentrated on core and near-core products, whereas research ideas are applied more widely. This pattern aligns with the hypothesis of Nelson (1959) and the empirical finding in Section 3 that patents generated from research tend to exhibit greater technological diversity.

Optimal Idea Generation. Given the optimal allocation of ideas to products, firms choose the optimal levels of investment in research and development. I assume that each unit of investment in research (x_r) or development (x_d) requires one unit of labor. The firm maximizes expected profits net of innovation costs:

$$\max_{x_r, x_d} L \sum_{k=1}^{N} I_k \pi_k(\lambda) - (x_r + x_d). \tag{11}$$

Each additional unit of labor in research or development increases the number of ideas. Since each idea independently affects the probability of product creation, the expected increase in profits per idea remains constant. However, due to diminishing returns in idea generation ($\rho < 1$), the number of ideas grows at a decreasing rate as investment increases. As a result, the gain in expected profits diminishes with each additional unit of investment, and firms continue hiring labor until the marginal gain in expected profits equals the marginal cost, which is the wage ($w = 1$).

Appendix A.2 shows that the method-specific expected per-consumer profits per idea, Δ_m, can be calculated as the expected increase in profits upon optimal idea application:

$$\Delta_m \equiv \mathbb{E}\left[\max_j B\phi_{m,i,j}\pi_j(\lambda)\right] = B\Gamma(1 - 1/\theta_m)\|\Pi(\lambda)\|_{\theta_m}, \quad \|\Pi(\lambda)\|_{\theta_m} \equiv \left(\sum_{j=1}^{N} \pi_j(\lambda)^{\theta_m}\right)^{1/\theta_m}, \tag{12}$$

where Γ denotes the gamma function and $\|\Pi(\lambda)\|_{\theta_m}$ denotes the θ_m-norm of the profit vector $\Pi(\lambda)$. Note that as θ_m increases, the θ_m-norm places more emphasis on the larger elements in a vector. For example, in the extreme case where θ_m approaches infinity, the θ_m-norm depends solely on the maximum profit, which corresponds to the core product ($\|\Pi(\lambda)\|_{\theta_m} \to \pi_1$ as $\theta_m \to \infty$). Conversely, when θ_m is close to 1, the θ_m-norm depends linearly on the profits of all products ($\|\Pi(\lambda)\|_{\theta_m} \to \sum_{j=1}^{N} \pi_j$ as $\theta_m \to 1$).

With this expression, the expected profits from investing in innovation, the first term in Equation (11) can be rewritten as:

$$L\sum_{k=1}^{N} I_k \pi_k(\lambda) = L \sum_{m\in\{r,d\}} \frac{1}{\rho} Z_m x_m^{\rho} \Delta_m, \tag{13}$$

which is simply the sum across the two innovation margins of the product of the mass of ideas and the expected per-consumer profits per idea, multiplied by the number of consumers. Substituting this expression for the expected profits into Equation (11), the first-order condition gives the optimal level of investment in each innovation margin:

$$x_m = (LZ_m\Delta_m)^{\tilde{\rho}}, \tag{14}$$

where $\tilde{\rho} \equiv 1/(1-\rho) > 0$. The optimal investment in innovation increases with market size, greater efficiency in idea generation, and higher expected benefits from each idea. Additionally, the impact of these factors on optimal investment is stronger when idea generation is less affected by diminishing returns to scale (i.e., when ρ is high).

The resulting probability of creation for product k can be expressed as the product of the mass of ideas applied to k and the expected increase in probability per applied idea:

$$I_k = \sum_{m\in\{r,d\}} \underbrace{A_m \chi_{m,k}}_{\text{Mass of Applied Ideas}} \underbrace{\mathbb{E}\left[B\phi_{m,i,k} | k = \max_j \phi_{m,i,j}\pi_j(\lambda)\right]}_{\text{Expected Increase in } I_k \text{ per Applied Idea}}. \tag{15}$$

Appendix A.3 shows that the second term simplifies to Δ_m/π_k. This value is smaller for core products, because even low-value ideas (those with low ϕ) are applied to them due to their high profitability. However, core products have a higher idea application probability ($\chi_{m,k}$), and this effect outweighs the former, resulting in a higher product creation probability. Additionally, since research ideas have more uniform application probabilities across products, research contributes more evenly to these probabilities compared to development.

4.4. Free Entry and Equilibrium

Entry is unrestricted but subject to a sunk entry cost f_e. In equilibrium, the expected profits of an entrant equal the entry cost. Substituting Equations (13) and (14) into Equation (11) results in the following free entry condition:

$$f_e = \frac{1-\rho}{\rho} \sum_{m\in\{r,d\}} (LZ_m\Delta_m)^{\tilde{\rho}}. \tag{16}$$

This expression highlights how market size and competition affect expected profits for entrants. A larger market increases expected profits by increasing the number of consumers, while higher competition reduces per-consumer profits from each idea generated through research or development (Δ_m). In general equilibrium, competition is endogenously determined by market size, satisfying the free entry condition.

I conclude this subsection by defining a general equilibrium where all potential entrants share the same core productivity.[35] Given consumer preferences, the normalization $w = 1$, innovation technology parameters $(B, \rho, \{\bar{Z}_m, \theta_m\}_{m\in\{r,d\}})$, the number of consumers (L), and the fixed entry cost (f_e), a general equilibrium is defined by allocations ($\{q_j\}_{j\in[0,T]}$), prices ($\{p_j\}_{j\in[0,T]}$), optimal product creation probabilities ($\{I_k\}_{k=1}^N$), and aggregate variables $\{\lambda, M, T\}$ that satisfy the following conditions:

(a) Given w and $\{p_j\}$, $\{q_j\}$ solves the consumer's maximization problem, where $\lambda \equiv \int_0^T u'(q_j)q_j dj$.

[35] Appendix A.7 provides a general equilibrium definition where entrants have varying core productivity, following a productivity distribution.

(b) Given λ, $\{p_j\}$ and $\{q_j\}$ solve the firms' profit maximization problem.

(c) Given λ, $\{I_k\}_{k=1}^{N}$ solve the firm's innovation problem, where $N = \max_k\{k \in \mathbb{N} | c\delta^{k-1} < u'(0)/\lambda\}$ and $T = M \sum_{k=1}^{N} I_k$.

(d) The free entry condition (eq (16)) is satisfied.

4.5. Effects of Globalization on Research Intensity and Specialization

I explore how globalization impacts firms' innovation decisions by examining two distinct globalization shocks. In this subsection, I model globalization as an increase in market size. Specifically, doubling the market size, L, represents full integration between two symmetric countries, moving from autarky to free trade without trade costs. A larger market size affects innovation in two ways: by providing access to a wider consumer base and by intensifying competition in equilibrium. I present propositions showing how these factors reduce research intensity and innovation diversity. In the next subsection, I extend the model to include trade costs between the symmetric countries, and model globalization as a reduction in these costs. This setup reflects partial integration. I demonstrate that a reduction in trade costs starting from autarky has similar effects on these innovation decisions.

First, I demonstrate that an increase in market size leads to more competition in equilibrium. In equilibrium, for the free entry condition to hold, competition must rise to offset the increased profits from a larger market. The intuition behind this result is that each consumer gains access to a greater variety of products as the total number of firms rises with market size. Consequently, demand for each individual variety from each consumer decreases, reflecting an increase in competition.[36]

Proposition 1 *An increase in market size L leads to an increase in competition λ.*

Proof. Suppose not. Since Δ_m is strictly decreasing in λ, the right-hand side of equation (16) would rise with an increase in L, which would violate the free-entry condition. ■

Therefore, a larger market size influences innovation not only through its direct market size effect but also by intensifying competition. This increased competition has important implications for a firm's research intensity. I define research intensity in the model as the ratio of research expenditure to development expenditure, which can be calculated using the expression for optimal innovation expenditure (eq (14)).

[36]It can be shown that as market size increases, each consumer gains access to a wider variety of products because the number of firms grows faster than the reduction in profitable products per firm due to heightened competition.

$$\mathtt{RI} \equiv \frac{x_r}{x_d} = A\left[\frac{\|\Pi(\lambda)\|_{\theta_r}}{\|\Pi(\lambda)\|_{\theta_d}}\right]^{\tilde{\rho}}, \tag{17}$$

where $A \equiv \left(\frac{Z_r\Gamma(1-1/\theta_r)}{Z_d\Gamma(1-1/\theta_d)}\right)^{\tilde{\rho}}$ denotes a constant representing the relative efficiency of research compared to development in the idea generation and application steps, which are unaffected by market conditions.

Note that market size does not have a direct effect in Equation (17), as an increase in market size holding λ constant leads to the same proportional increase in investment across both innovation margins.[37] Instead, market size affects research intensity only indirectly, through its impact on competition. The total derivative of research intensity with respect to market size is:

$$\frac{d\ln \mathtt{RI}}{d\ln L} = \tilde{\rho}\underbrace{\left[\frac{d\ln\|\Pi(\lambda)\|_{\theta_r}}{d\ln\lambda} - \frac{d\ln\|\Pi(\lambda)\|_{\theta_d}}{d\ln\lambda}\right]}_{=:\zeta}\underbrace{\frac{d\ln\lambda}{d\ln L}}_{>0}. \tag{18}$$

The effects of globalization on research intensity depend on how competition influences the relative θ_m-norm of the profit vector $\Pi(\lambda)$, comparing research and development, which in turn depends on two key factors: how competition impacts the profit of each product and how these changes aggregate at different levels of θ.

First, increased competition concentrates profits on a firm's better-performing products. It can be shown that $\partial \ln \pi_k/\partial \ln \lambda = -\epsilon_k < 0$, where $\epsilon_k \equiv -\frac{\partial q_k}{\partial p_k}\frac{p_k}{q_k}$ is the demand elasticity for product k. Thus, while competition reduces profits across all products, it has a larger impact on those with higher demand elasticity. Under the assumed MSLD preferences, products with lower demand have higher elasticities, which means that higher marginal cost products experience a larger relative decline in profits, leading to a concentration around the firm's core products.[38]

This increased concentration of profits reduces the firm's research intensity. As θ increases, the θ-norm of the profit vector becomes increasingly dependent on the core product (in the extreme case, $\|\Pi\|_\theta \to \pi_1$ as $\theta \to \infty$). Since core products experience the

[37]This is because of the assumption that both innovation margins have the same degree of diminishing returns. Appendix A.1 explores a scenario where the diminishing returns to scale differ between the two innovation margins. In that case, an increase in market size has a straightforward effect: larger profit opportunities from a bigger market lead to greater investment in the innovation margin that scales more easily.

[38]This reallocation of profits towards higher-markup (lower demand elasticity) products due to increased competition is referred to as the "Darwinian force" by Baqaee et al. (2024). Under MSLD preferences, since high-productivity products have higher markups, profits are reallocated towards better-performing products, a phenomenon known as the "Matthew Effect" in Mrázová and Neary (2019).

smallest reduction in profits, the overall reduction in the θ-norm is smaller for higher values of θ. Thus, the firm's incentive to invest in research decreases faster than its incentive to invest in development, due to the assumption that $\theta_r < \theta_d$, resulting in lower research intensity. Appendix A.4 offers a formal proof of this effect, showing that:

$$\frac{\partial^2 \ln\|\Pi\|_\theta}{\partial \ln \lambda \partial \ln \theta} \begin{cases} > 0 & \text{if } \epsilon' < 0 \text{ (i.e., } u \text{ is MSLD (subconvex))} \\ = 0 & \text{if } \epsilon' = 0 \text{ (i.e., } u \text{ is CES)} \\ < 0 & \text{if } \epsilon' > 0 \text{ (i.e., } u \text{ is superconvex),} \end{cases} \tag{19}$$

where ϵ' represents the derivative of demand elasticity with respect to quantity. Equation (19) shows that under MSLD preferences, increased competition reduces the incentive to invest in research more so than in development ($\zeta < 0$).[39] Moreover, this reduction in research intensity due to increased competition is more pronounced when the shape parameter for research is smaller, the shape parameter for development is larger, or when innovation faces less severe diminishing returns to scale (higher ρ).

Proposition 2 *Globalization reduces research intensity.*

Proof. It can be shown that $d \ln \mathtt{RI}/d \ln L < 0$ by combining the results from Proposition 1 and Equation (19), as demonstrated in Equation (18). ■

Along with declining research intensity, the application of ideas also becomes increasingly concentrated on firms' better-performing products as competition intensifies, a phenomenon I refer to as innovation specialization. The effects of increased competition on the share of ideas applied to the k-th product ($S_k \equiv \frac{A_r \chi_{r,k} + A_d \chi_{d,k}}{A_r + A_d}$) can be decomposed into the following two channels:

$$\frac{\partial S_k}{\partial \lambda} = \underbrace{\frac{\partial A_d/(A_r + A_d)}{\partial \lambda} (\chi_{d,k} - \chi_{r,k})}_{\text{Lower Research Intensity}} + \sum_{m \in \{r,d\}} \underbrace{\frac{A_m}{A_r + A_d} \frac{\partial}{\partial \lambda} \chi_{m,k}}_{\text{Concentrated Idea Application}} \tag{20}$$

The first term on the right-hand side reflects the effects of lower research intensity on how ideas are allocated. Recall that development ideas are more likely than research ideas to be applied to better-performing products ($\chi_{d,k} > \chi_{r,k}$ for sufficiently low k). As more ideas are generated from development than from research ($\frac{\partial A_d/(A_r + A_d)}{\partial \lambda} > 0$), better-performing products capture a larger share of ideas due to this shift. Secondly,

[39] On the contrary, when preferences are superconvex, profits become more evenly distributed with increased competition, leading to higher research intensity. In contrast, when consumer preferences follow CES, all products experience the same change in profits, causing the incentives to invest in research and development to shift proportionally.

globalization leads to more concentrated application of ideas for both innovation margins, as represented by the second term. As profits become more concentrated within the firm due to globalization, better-performing products receive a greater share of ideas from both research and development ($\frac{\partial \chi_{m,k}}{\partial \lambda} > 0$ for sufficiently low k), while other products lose share. Combining these two effects, the following proposition shows that globalization leads to innovation specialization.[40]

Proposition 3 ***(Innovation Specialization)*** *Globalization leads to a greater share of ideas from R&D applied to better-performing products, i.e.,* $\frac{\partial}{\partial \lambda}\sum_{k=1}^{K} S_k \geq 0, \forall K \in \{1, 2, ..., N-1\}$.

Proof. Appendix A.5 shows that both $\chi_{d,k} - \chi_{r,k}$ and $\frac{\partial \chi_{m,k}}{\partial \lambda}$ decrease as k increases. Therefore, $\frac{\partial S_1}{\partial \lambda} \geq \frac{\partial S_2}{\partial \lambda} \geq ... \geq \frac{\partial S_N}{\partial \lambda}$. ■

Appendix B.4 provides empirical evidence that when U.S. firms face an increase in market size (as measured by real GDP) in a destination country, they reduce the innovation diversity of patent applications in that country, aligning with this model's prediction.

Rising innovation specialization leads to further specialization in firms' production. Globalization affects the share of expected profits of the k-th product ($S_k^{\pi} \equiv I_k \pi_k / (\sum_{j=1}^{N} I_j \pi_j)$) in a manner similar to the application of ideas:

$$\frac{\partial S_k^{\pi}}{\partial \lambda} = \frac{\partial A_d \Delta_d / (A_r \Delta_r + A_d \Delta_d)}{\partial \lambda} (\chi_{d,k} - \chi_{r,k}) + \sum_{m \in \{r,d\}} \frac{A_m \Delta_m}{A_r \Delta_r + A_d \Delta_d} \frac{\partial}{\partial \lambda} \chi_{m,k} \tag{21}$$

After globalization, more value is created from development ($\frac{\partial A_d \Delta_d / (A_r \Delta_r + A_d \Delta_d)}{\partial \lambda} > 0$), which disproportionately benefits better-performing products. Furthermore, ideas from both innovation margins become increasingly concentrated on creating these high-profit products.[41]

Proposition 4 ***(Product Specialization)*** *Globalization leads to a greater share of expected profits from top products, i.e.,* $\frac{\partial}{\partial \lambda}\sum_{k=1}^{K} S_k^{\pi} \geq 0, \forall K \in \{1, 2, ..., N-1\}$.

Proof. Appendix A.5 shows that both $\chi_{d,k} - \chi_{r,k}$ and $\frac{\partial \chi_{m,k}}{\partial \lambda}$ decrease as k increases. Therefore, $\frac{\partial S_1^{\pi}}{\partial \lambda} \geq \frac{\partial S_2^{\pi}}{\partial \lambda} \geq ... \geq \frac{\partial S_N^{\pi}}{\partial \lambda}$. ■

[40] Appendix A.5 shows that the relative size of better-performing products' creation probabilities increases with globalization ($\frac{\partial}{\partial \lambda}\left(\sum_{k=1}^{K} I_k / \sum_{j=1}^{N} I_j\right) \geq 0, \forall K \in \{1, 2, ..., N-1\}$) as long as the diminishing returns to scale parameter (ρ) is not too small.

[41] Appendix A.5 shows that under a slightly more restrictive condition than the MSLD condition—that is, the elasticity of marginal revenue increases with quantity demanded— Proposition 4 can be rewritten in terms of expected sales: $\frac{\partial}{\partial \lambda}\left(\sum_{k=1}^{K} I_k p_k q_k / \sum_{j=1}^{N} I_j p_j q_j\right) \geq 0, \forall K \in \{1, 2, ..., N-1\}$.

4.6. Effects of Reductions in Trade Costs

The previous subsection examined the effects of globalization, modeled as complete market integration between symmetric countries. In this subsection, I extend the model to include trade costs between these countries and show that, starting from autarky, reductions in trade costs (representing partial market integration) yield the same qualitative impacts on research intensity and specialization as outlined in Propositions 2- 4.

I consider a scenario in which N_c symmetric countries engage in trade, facing symmetric iceberg trade costs, denoted by $\tau \geq 1$. All countries are symmetric, with L identical consumers, and firms that share the same production and innovation technologies. Given this symmetry, all endogenous variables—such as firms' innovation decisions and levels of competition—are identical across countries in equilibrium. Therefore, I focus on the perspective of a single country, omitting country subscripts for simplicity.

The key difference in this open economy setup is that firms now consider iceberg export costs when making export decisions. For a given foreign market, a firm maximizes the profit of its k-th product, whose marginal cost effectively increases by τ, by solving the following optimization problem: $\max_{q_k \geq 0} L \left[\frac{u'(q_k)}{\lambda} - \tau c \delta^{k-1}\right] q_k$. When iceberg costs are high enough, only high-productivity products with index $k \leq N^* \equiv \max\{k = 1, 2, 3, ...|\tau c \delta^{k-1} < u'(0)/\lambda\}$ can be exported.

Research intensity in this open economy takes the same form as in the closed economy (eq (17)), but the per-consumer profit vector is now also affected by iceberg costs:

$$\|\Pi(\tau,\lambda)\|_{\theta_m} = \left(\sum_{k=1}^{N}\left(\underbrace{\pi(c_k,\lambda)}_{\text{Domestic Profits}} + \underbrace{(N_c-1)1_{\{k\leq N^*\}}\pi(\tau c_k,\lambda)}_{\text{Export Profits}}\right)^{\theta_m}\right)^{1/\theta_m},$$

where $\pi(c,\lambda)$ denotes the maximized per-consumer profit of a product with marginal cost c, in a market with competition level λ.

Changes in trade costs affect research intensity in two ways: an indirect effect through competition, similar to the impact of market size (eq (18)), and a direct effect by altering the relative profits of different products:

$$\frac{d\ln \texttt{RI}}{d\ln\tau} = \tilde{\rho}\left\{\underbrace{\left[\frac{\partial\ln\|\Pi(\tau,\lambda)\|_{\theta_r}}{\partial\ln\lambda} - \frac{\partial\ln\|\Pi(\tau,\lambda)\|_{\theta_d}}{\partial\ln\lambda}\right]\frac{d\ln\lambda}{d\ln\tau}}_{\text{Indirect Effect Through Competition}} + \underbrace{\left[\frac{\partial\ln\|\Pi(\tau,\lambda)\|_{\theta_r}}{\partial\ln\tau} - \frac{\partial\ln\|\Pi(\tau,\lambda)\|_{\theta_d}}{\partial\ln\tau}\right]}_{\text{Direct Effect of Trade Costs}}\right\}.$$

First, consider the indirect effect of trade costs on research intensity through competition. If no products are traded (i.e., if trade costs are at the prohibitive level $\tau \geq \tau^a = \frac{1}{c}\frac{u'(0)}{\lambda}$), or if all products are freely traded ($\tau = 1$), the economy mirrors the closed economy, in which increased competition reduces research intensity. Furthermore, to satisfy the free entry condition, decreases in trade costs increase competition ($\frac{d\ln\lambda}{d\ln\tau} \leq 0$) for all trade costs $\tau \in (1, \tau^a)$. As a result, reductions in trade costs decrease research intensity by concentrating profits on better-performing products in all scenarios.

Conversely, the direct effects of trade costs on research intensity depend on the initial level of trade costs. When trade costs are high, reductions in trade costs decrease research intensity, as the profits of better-performing products increase while less competitive products remain unexported. This concentration of profits increases incentives to invest in development over research. However, when trade costs are low and all products are already traded, reductions in trade costs lead to relatively larger export increases for lower-productivity products due to their higher demand elasticity. This results in a more balanced profit distribution across products, increasing the relative benefits of research compared to development.

Thus, when trade costs are high, reductions decrease research intensity through both channels. In contrast, as trade costs approach free-trade levels, the relative magnitude of the two effects determines the outcome. The proof of Proposition 5 (Appendix A.8) shows that the direct effects dominate the indirect effects when trade costs are sufficiently low, leading to an increase in research intensity.

Proposition 5 *A reduction in trade costs decreases the research share when initial trade costs are sufficiently high. Conversely, a reduction in trade costs increases the research share when an economy is near free trade. i.e.,* $1 < \exists\underline{\tau} < \exists\bar{\tau} < \tau^a$ *s.t.* $\frac{d\ln \mathtt{RI}}{d\ln\tau} \begin{cases} > 0 & \forall\tau \in (\bar{\tau}, \tau^a) \\ < 0 & \forall\tau \in (1, \underline{\tau}) \end{cases}$

Proof. See Appendix A.8. ■

Additionally, a reduction in trade costs starting from autarky increases both innovation and product specialization. First, it lowers research intensity and intensifies competition, which drives specialization, as shown in Equations (20) and (21). Moreover, this reduction in trade costs creates export opportunities primarily for the most productive products, boosting their relative profits. As a result, this direct effect further contributes to increased innovation and product specialization.

Overall, the effect of trade costs on research intensity and specialization depends on key model parameters, including the level of trade costs. When trade costs are relatively high, reducing them will lower research intensity and innovation diversity. In the next section, I calibrate the model to U.S. manufacturing industries in 1990 and show that reductions in trade costs during the 1990s, combined with market size growth, led to a decline in research intensity.

5. Quantitative Analysis

In this section, I calibrate the open economy model to U.S. manufacturing industries in 1990 to quantitatively evaluate the effects of globalization—both the increase in market size and the reduction in trade costs—as well as innovation subsidies. I begin by extending the model to incorporate knowledge spillovers from economy-wide investment in research and development. Next, I introduce the consumer preferences used in the calibration, followed by an explanation of the calibration procedure. Finally, I use the calibrated model to assess the impact of globalization and innovation subsidies on welfare and aggregate productivity.

5.1. Extension: Knowledge Spillovers and R&D Subsidies

The innovation literature finds that research often generates larger knowledge spillovers across firms than development (Griliches, 1986; Akcigit et al., 2021; Arora et al., 2021a). To incorporate knowledge spillovers into the model, I assume that it becomes easier for each firm to generate ideas as the economy's overall levels of research and development investment increase. Specifically, I assume $Z_m = \bar{Z}_m \times \mathbf{X}_r^{\alpha_r} \times \mathbf{X}_d^{\alpha_d}$, where $\mathbf{X}_r$ and $\mathbf{X}_d$ represent the economy-wide average research and development levels, and $\bar{Z}_m$ is a constant that shifts overall innovation efficiency. A higher value of $\alpha_m \in (0, 1-\rho)$ indicates greater knowledge spillovers. In line with the literature's findings that research generates larger spillovers, I assume $\alpha_r > \alpha_d$.

Since firms do not internalize knowledge spillovers or product market externalities, equilibrium R&D investment may diverge from the welfare-maximizing level. A commonly proposed solution in the literature is to implement innovation policies, such as subsidizing or taxing research and development (e.g., Akcigit et al. 2021). To examine the impact of these policies, I introduce taxes or subsidies on each innovation margin into the model. Specifically, the firm's innovation cost becomes $(1 - t_m)$, where t_m represents a subsidy (or a tax if $t_m < 0$) for innovation method m. I assume that subsidies (or taxes) are redistributed to consumers as lump-sum transfers. Consequently, consumer income is given by $e = 1 - (M/L) \sum_{m \in r,d} x_m t_m$.

Under these extensions, the expressions for optimal innovation remain similar, but now account for the effects of subsidies and knowledge spillovers:

$$x_m = \left(\frac{L\mathbf{K}\bar{Z}_m \Delta_m}{1 - t_m} \right)^{\tilde{\rho}}, \quad m \in \{r, d\}, \tag{22}$$

where $\mathbf{K} \equiv \mathbf{X}_r^{\alpha_r} \mathbf{X}_d^{\alpha_d}$ represents the size of the knowledge spillovers. Appendix A.6 shows that all propositions in Subsections 4.5 and 4.6 still hold with these extensions.[42]

5.2. Consumer Preference

Section 4 showed that MSLD preferences are necessary to capture the observed effects of globalization on research intensity and specialization, as shown in Section 3. I adopt the constant pass-through preference from Mrázová and Neary (2017), where the representative consumer's marginal subutility is:

$$u'(q_j) = \frac{1}{q_j} \left(q_j^{\frac{\kappa-1}{\kappa}} + \gamma \right)^{\frac{\kappa}{\kappa-1}},$$

where $\gamma > 0$ is a quantity shifter and κ governs the curvature of demand. When $\kappa < 1$, the demand function meets the MSLD condition.[43] For a product with marginal cost c, the markup μ is:

$$\mu \equiv p/c = (c_d/c)^{1-\kappa}, \tag{23}$$

where $c_d = 1/\lambda = e \times \left(\int_0^T \left(q_j^{\frac{\kappa-1}{\kappa}} + \gamma \right)^{\frac{\kappa}{\kappa-1}} dj \right)^{-1}$ represents the choke price, which decreases as competition increases. Additionally, the elasticity of pass-through $d \log p / d \log c = \kappa$ is constant. When $\kappa < 1$, better-performing products have higher markups, and pass-through is incomplete, meaning firms pass through only $\kappa \times 100\%$ of cost increases to consumers.[44]

5.3. Calibration

I calibrate the model to the US manufacturing sector in 1990, a period characterized by the onset of rapid globalization and a notable decline in research intensity. To emphasize within-firm innovation decisions, I assume homogeneous firms. The model is calibrated at the NAICS 6-digit manufacturing industry level, where each industry corresponds to a product in the baseline model, and firms can innovate to produce up to one product

[42] Appendix A.7 provides a general equilibrium definition with these extensions.

[43] As $\kappa \to 1$, the demand converges to CES, and at $\kappa = 0.5$, it becomes Stone-Geary. When $\kappa > 1$, preferences exhibit superconvexity.

[44] When $\kappa \to 1$, markups remain constant across productivity levels, whereas for $\kappa > 1$, higher productivity products charge lower markups.

per industry. The product index k represents the firm's productivity ranking across these industries. At this level of aggregation, δ captures marginal cost differences across industries, while θ governs the application of ideas across industries.[45]

There are nineteen parameters in the model that need to be calibrated. Table 4 provides a comprehensive list of these parameters. The first group consists of seven parameters that are externally calibrated based on existing literature and model assumptions. The second group includes seven parameters that are internally calibrated to match target moments in the U.S. aggregate economy. The last group includes five parameters that are normalized.

The first set of seven parameters is externally calibrated. I calibrate the demand function curvature, κ, using pass-through estimates from Ganapati et al. (2020).[46] For R&D subsidy rates, I rely on effective tax credit rates in the US in 1990, as calculated by Hall (1993). The returns to scale parameter for idea generation is adopted from Blundell and Bond (2000), who identify the returns to scale between R&D investment and patent output. The parameter for knowledge spillovers from research is derived from Arora et al. (2021a), based on their estimates of how scientific publications by other firms impact a focal firm's patent generation. For development spillovers, I use various values, ensuring that they are smaller than research spillovers. The baseline results use $\alpha_d = 0.1$, with results for other values provided in the Appendix. Lastly, the number of symmetric countries is set to 4, reflecting the U.S. share of global income in 1990, which was approximately 25%.

The second group of seven parameters are estimated using an indirect inference approach. For a given set of parameter values, I compute seven model-generated moments, compare them to the target moments from data, and find a set of parameter values that minimizes the following objective function:

$$\min \sum_{i=1}^{7} \left[\ln(\text{model moment}_i) - \ln(\text{data moment}_i)\right]^2$$

The seven moments used for calibration are presented in Table 5. Although the seven parameters are calibrated jointly, specific moments are particularly relevant to certain parameters. The overall efficiency in idea applications, B, is calibrated to match the R&D-to-sales ratio. The quantity shifter, γ, reflects the level of competition in the economy,

[45] For simplicity, I assume that the representative consumer demands products symmetrically across industries and that each firm is randomly assigned a ranking across different industries. Since all industries are symmetric, an equal mass of firms occupies each rank ($k = 1, 2, ...$) within every industry. Consequently, ex-post, all industries exhibit an identical productivity distribution of successfully created products.

[46] Although pass-through estimates vary widely, from 0.3 (De Loecker et al., 2016) to a full pass-through of 1, I chose estimates from Ganapati et al. (2020) as they are based on US manufacturing industries around 1990 and fall within the median range. For a comprehensive review of pass-through estimates in the literature, particularly concerning exchange rates, see Fajgelbaum and Khandelwal (2022).

Table 4: List of Parameters

Parameter	Description	Value	Identification
κ	demand function curvature	0.63	Ganapati et al. (2020)
t_d, t_r	R&D subsidy rates	0.1	Hall (1993)
ρ	returns to scale of idea generation	0.5	Blundell and Bond (2000)
α_r	knowledge spillovers from research	0.2	Arora et al. (2021a)
α_d	knowledge spillovers from development	{0, 0.1, 0.15}	assumption ($\alpha_d < \alpha_r$)
N_c	number of countries	4	U.S. share of world income: 1/4
B	overall efficiency in idea applications	0.07	indirect inference
$\bar{Z}_d$	efficiency of development idea generation	10.51	indirect inference
γ	demand quantity shifter	0.68	indirect inference
δ	marginal cost gap between industries	1.17	indirect inference
θ_r	inverse variability of research values	1.12	indirect inference
θ_d	inverse variability of development values	1.87	indirect inference
τ	iceberg export costs	2.37	indirect inference
f_e	fixed entry costs	0.13	normalization
$\bar{Z}_r$	efficiency of research idea generation	1	normalization
c	core industry's marginal cost	1	normalization
M	mass of entrants	1	normalization
L	initial mass of consumers	1	normalization

as indicated by the average markup. The efficiency of idea generation for development, relative to research (where research efficiency is normalized to one), is calibrated to match the research expenditure share. Finally, the iceberg trade cost is calibrated to match the average export intensity (exports over shipments) of U.S. manufacturing industries.

The productivity gap and the variability of the two innovation margins are calibrated to match observed moments regarding the diversity of production (ENI: effective number of manufacturing 6-digit NAICS) and innovation (ENC: effective number of 4-digit CPC):

$$\mathtt{ENC}^{\mathtt{model}} \equiv \left[\sum_{j=1}^{N}\left(\frac{I_j}{\sum_{l=1}^{N} I_l}\right)^2\right]^{-1}, \quad \mathtt{ENI}^{\mathtt{model}} \equiv \left[\sum_{j=1}^{N}\left(\frac{I_j s_j}{\sum_{l=1}^{N} I_l s_l}\right)^2\right]^{-1}.$$

The overall levels of θ and δ are determined by the extent of innovation and production diversity.[47] The difference in the two θ parameters is based on the observed difference in innovation diversity between research and development outputs. A larger difference in innovation diversity leads to greater differences in the two θ parameters, and is estimated using the observed difference in the diversity of patents based on scientific publications versus other patents (Table 2).

I normalize the efficiency of research idea generation, $\bar{Z}_r$, to one, as it cannot be sepa-

[47]To account for the difference between the number of 4-digit CPC categories (approximately 650) and 6-digit manufacturing NAICS industries (354), I adjust the ENC target moments by a factor of 0.56 (354/650). This adjustment allows the number of industries to be interpreted as equivalent to the 6-digit NAICS manufacturing industries.

Table 5: Target Moments

Moment	Data	Model	Source
innovation diversity (ENC)	5.34	5.31	own calculation (data source: USPTO)
innovation diversity difference ($\mathtt{ENC}_r - \mathtt{ENC}_d$)	2.86	2.86	own calculation (data source: USPTO)
production diversity (ENI)	3	3.02	Ekerdt and Wu (2024)
R&D to sales ratio (%)	4.1	4.10	Akcigit et al. (2022)
average markup	1.38	1.38	De Loecker et al. (2020)
research expenditure share (%)	31	31.00	own calculation (data source: NSF)
export intensity (%)	10.5	10.50	Limão and Xu (2021)

Notes: The table summarizes the seven moments used in the calibration. The columns "Data" and "Model" represent the values of the moments observed in the data and those generated by the model, respectively.

rately identified from the overall efficiency parameter B and the efficiency of development idea generation, $\bar{Z}_d$. Similarly, the core industry's productivity is normalized to one, since firm-level outcomes depend on marginal costs relative to the choke price, c_d, which is endogenously determined in the model. The total mass of entrants, M, is normalized to one, with fixed entry costs calibrated to ensure this normalization. Lastly, the mass of consumers in each country in 1990 is normalized to one.

5.4. Counterfactual Exercises

Using the calibrated model, I examine how observed changes in trade costs and market size from 1990 to 2007 contributed to the decline in research intensity and specialization in the U.S. I quantify impacts on welfare and productivity and discuss how welfare-maximizing innovation policies evolve with globalization. To focus on the effects of allocation between research and development, I hold the scale of innovation (each firm's total R&D investment) constant across different market sizes and trade costs.[48]

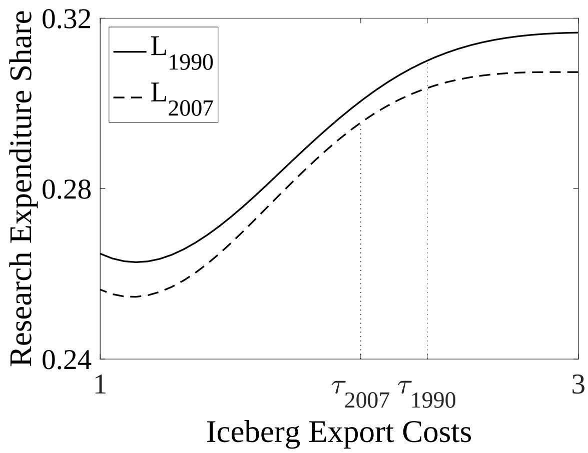
5.4.1. Impacts of Globalization

I analyze the impact of globalization by examining how model outcomes shift with changes in market size and trade costs, holding other parameters constant. From 1990 to 2007, U.S. manufacturing firms' export intensity rose to 16.3%, and the world population grew by 27%.[49] To reflect these changes in the model, I adjust the market size L from 1 to 1.27 and re-calibrate τ to match the 2007 export intensity of 16.3%. The trade cost in 2007 (τ_{2007}) is calibrated at 2.09, corresponding to a 12.5 log-point decrease from 1990, in line with the

[48]The scale remains constant because the free-entry condition ensures that total R&D investment stays fixed, provided that fixed costs, the innovation scale parameter (ρ), and uniform subsidy or tax rates on research and development ($t_r = t_d = \bar{t}$) remain unchanged ($x_r + x_d = f_e\rho/(1-\rho)(1-\bar{t})^{-1}$).

[49]During this period, world GDP—another common proxy for market size—increased by 71%, making 27% a conservative estimate for increases in market size.

Figure 6: Impacts of Globalization on Research Intensity and Specialization



The figure displays the research expenditure share under varying trade costs, for market sizes calibrated to 1990 (L_{1990}) and 2007 (L_{2007}). The calibrated iceberg trade costs for 1990 and 2007 are denoted as τ_{1990} and τ_{2007}, respectively.

decline in trade costs observed in the literature (e.g., Limão and Xu (2021)).

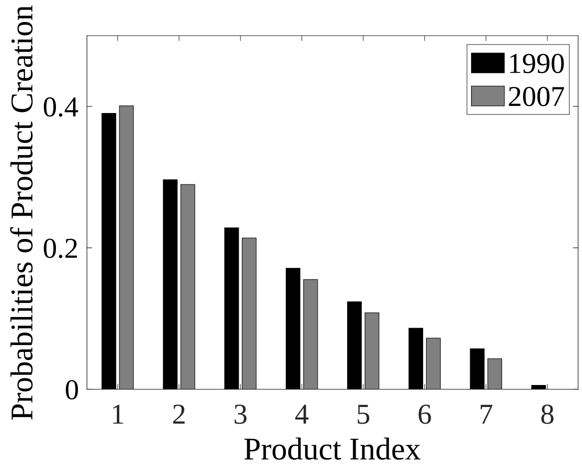
Figure 6 illustrates how these globalization shocks affected research intensity. In 1990, the initial trade cost (τ_{1990}) was relatively high, and its subsequent reduction led to a decline in research intensity, as predicted by Proposition 5.[50] Alongside this, the expansion in market size from 1990 to 2007 further contributed to the decline in research intensity. Together, these factors caused the research expenditure share to fall from 31% to 29.6%, accounting for roughly one-fifth of the total reduction observed in the data.

The reduction in research expenditure share is accompanied by increasing innovation specialization. Figure 7 shows the probabilities of product creation in the 1990 and 2007 economies. As research intensity declines, the probability of product creation decreases. With fewer knowledge spillovers, the number of ideas generated from the same R&D investment drops by 0.75%, which by itself leads to a uniform 0.75% reduction in the probability of product creation. However, low-productivity products experience an even greater reduction, as firms increasingly concentrate ideas on higher-performing products that would have otherwise been applied to lower-performing ones. Consequently, core products see a higher probability of creation after globalization, partially offsetting the decline in knowledge spillovers. As a result, innovation diversity (`ENC`) falls by 7%, also accounting for roughly one-fifth of the total reduction observed in the data.

These changes in creation probabilities affect both welfare and aggregate productiv-

[50]On the contrary, as shown in Proposition 5 when trade costs are very low, further reductions can increase the research expenditure share.

Figure 7: Impacts of Globalization on Product Creation Probabilities (I_k)



Notes: The figure illustrates the probabilities of product creation for each product, depicted as black and gray bars for the calibrated model with market size and trade costs for 1990 and 2007, respectively.

ity by determining which products are sold in the market.[51] To quantify these effects, I compare the outcomes of three economies facing the same globalization shocks. In the first scenario, firms adjust their innovation decisions freely, as in the baseline model. In the second scenario, all innovation decisions are fixed at their 1990 levels, keeping the probability of product creation constant, similar to standard models without endogenous innovation, in which the productivity distribution remains fixed. Consequently, any changes in welfare and aggregate outcomes result from non-innovation-related mechanisms, such as an increase in the number of varieties and the reallocation of production toward high-productivity products, as explored in works like MMO and Dhingra and Morrow (2019). Finally, in the third scenario, firms maintain the same research expenditure share as in 1990, but firms can adjust how they allocate ideas across products, conceptually representing models with endogenous innovation but without distinctions between research and development.

Table 6 summarizes the outcomes for the three economies. Columns (3) to (5) show the percentage changes in each outcome relative to the 1990 economy as market size and trade costs shift from 1990 to 2007 levels across the three scenarios. For the second economy (Column (4)), which represents conventional trade models without endogenous innovation, aggregate sales-weighted productivity increases by 1.48% after globalization. This increase

[51] Appendix A.9 shows that innovation specialization can increase aggregate productivity and consumer welfare by reallocating product creation probabilities toward core products, which have higher productivity and contribute more effectively to welfare per unit of resource. However, the decline in research intensity reduces the total number of products in the market, diminishing competition and negatively impacting both aggregate productivity and welfare.

Table 6: Effects of Globalization on Key Outcomes

(1) Description	(2) Variables	(3) Baseline	(4) Exogenous Innovation	(5) Fixed Research Intensity
welfare	U	6.22%	6.26%	6.39%
aggregate productivity	$\tilde{\phi}$	2.24%	1.48%	2.20%
aggregate markups	$\tilde{\mu}$	-3.21%	-3.39%	-3.25%
innovation diversity	ENC	-7.01%	–	-6.58%
production diversity	ENI	-5.89%	-3.99%	-5.53%
competition	λ	8.16%	8.31%	8.35%
knowledge spillovers	$\mathbf{K}$	-0.75%	–	0%

Notes: Columns (3)–(5) report the percentage changes in each variable due to changes in market size and iceberg trade costs between 1990 and 2007. Column (3) represents the baseline model, where innovation decisions adjust freely without restrictions. Columns (4) and (5) present outcomes when product creation probabilities and the share of research are held constant at their baseline levels from 1990, respectively. Aggregate productivity and aggregate markups are calculated as sales-weighted averages of productivity and markups.

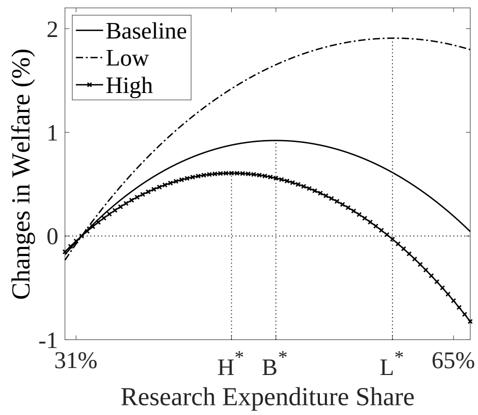
is driven by increased competition, which reallocates demand toward lower-cost products, thereby boosting aggregate productivity. Adding back endogenous innovation decisions as in the baseline model (Column (3)), aggregate productivity rises by 0.76 additional percentage points (pp) (from 1.48% to 2.24%). This is because innovation endogenously becomes more specialized, making product creation increasingly likely for core products compared to peripheral ones.

However, these additional productivity gains do not translate into larger welfare gains. In fact, welfare gains in the baseline model are smaller than those in the conventional model without endogenous innovation. This is because the baseline economy experiences a reduction in knowledge spillovers due to lower research intensity, which outweighs the welfare gains from having more high-productivity products. As a result, the third economy, which maintains a constant research expenditure share while allowing endogenous application of ideas, preserves knowledge spillovers and achieves the highest welfare gains (Column (5)).[52] Consequently, trade models with endogenous innovation that ignore the distinction between research and development may overestimate welfare gains from trade, because they ignore the negative effects of globalization on research intensity.

Appendix Table C3 demonstrates that these patterns hold for different values of the knowledge spillover parameter for development (α_d). As knowledge spillovers from development decrease, the reduction in research intensity leads to an even greater decline in overall knowledge spillovers within the economy, amplifying the resulting negative

[52]Even with a constant research expenditure share, innovation diversity decreases in Column (5). This occurs because, while research intensity remains unchanged, the application of ideas from both research and development becomes more concentrated on core products, as shown in Proposition 2.

Figure 8: Impacts of Research Expenditure Share on Welfare



The figure illustrates the changes in welfare when firms are required to invest in research and development at varying levels, compared to the welfare at the baseline research expenditure share of 31% in the 1990 economy. Each line represents welfare gains under different knowledge spillover parameters for development, where "Low," "Baseline," and "High" correspond to α_d values of 0, 0.1, and 0.15, respectively. L^*, B^*, and H^* indicate the research expenditure levels that maximize welfare for the Low, Baseline, and High cases, respectively.

impacts on welfare. Therefore, the welfare gains from trade in the baseline model become even smaller than in the model without innovation decisions. For example, when development generates no knowledge spillovers ($\alpha_d = 0$), the decline in knowledge spillovers in the baseline model reaches -0.95%, resulting in welfare gains from trade of only 6.17%.

5.4.2. Impacts of Innovation Subsidies

I analyze the impact of research and development subsidies on welfare, focusing on the trade-offs between research and development. To illustrate these trade-offs, I begin by fixing total investment in R&D and then assess how the allocation of innovation effort between research and development affects welfare. Specifically, I calculate the welfare of an economy where firms allocate their investments between research and development based on a given share, while optimally applying ideas to products according to Equation (10).[53]

Figure 8 illustrates the changes in welfare for different shares of research expenditure. The welfare outcomes are normalized to 1 for the baseline economy, where the research expenditure share is 31%. The figure indicates that the economy can improve welfare by increasing the research share, up to a point. This suggests that larger knowledge spillovers outweigh the potential gains from having a relatively higher share of low-cost products. Figure 8 presents results for three levels of knowledge spillovers for development: Baseline ($\alpha_d = 0.1$), Low ($\alpha_d = 0$), and High ($\alpha_d = 0.15$). In all cases, the optimal research share is

[53] As the expenditure share changes, the levels of entry and competition in the economy adjust accordingly within the general equilibrium.

Table 7: Welfare Maximizing Innovation Subsidies

(1) Market Condition	(2) D Spillover	(3) D Subsidy	(4) R Subsidy	(5) Δ Welfare (%)
1990	Baseline ($\alpha_d = 0.1$)	26.7%	50.8%	2.04%
1990	Low ($\alpha_d = 0$)	0.4%	45.8%	2.30%
2007	Baseline ($\alpha_d = 0.1$)	26.6%	51.8%	1.91%
2007	Low ($\alpha_d = 0$)	-0.3%	46.4%	2.16%

Notes: Each row reports the welfare-maximizing innovation subsidies. Columns (3)–(5) present the welfare-maximizing rates for development and research subsidies (or taxes if negative) and the resulting welfare increases, expressed as a percentage compared to the welfare under the baseline scenario of 10% subsidies for both research and development. The results are shown under varying market conditions (different levels of L and τ for 1990 and 2007; Column (1)) and different sizes of spillover effects (α_d; Column (2)).

higher than 31%, but the highest optimal share occurring when knowledge spillovers from development are at their lowest.

The strong knowledge spillover effects suggest that offering larger subsidies for research compared to development can enhance welfare. Table 7 presents the welfare-maximizing subsidy rates for research and development in the U.S. economy for 1990 and 2007, across varying levels of development knowledge spillovers.[54] In all cases, the optimal subsidy rates are higher for research than for development, capitalizing on the benefits of knowledge spillovers.

Comparing the first two rows in the table, lower knowledge spillover potential from development leads to a wider gap between the optimal research and development subsidy rates, with more significant welfare increases.[55] Additionally, comparing the first two rows with the last two shows that globalization generally leads to lower development subsidies and higher research subsidies. This is because research intensity declines as market size increases in an economy without subsidies. Therefore, in a globalized economy, prioritizing research subsidies becomes even more critical for improving welfare and fully capitalizing on the benefits of knowledge spillovers.

6. Conclusion

Corporate innovation in the United States has seen a marked decline in scientific research over recent decades. Research labs of major firms like AT&T and DuPont, which once

[54] In the analysis of welfare-maximizing subsidies, the total scale of innovation may change based on subsidy levels. For instance, if both research and development subsidies increase uniformly by $x\%$, it has the effect of raising entry costs by $x\%$ (see Equation (16)). As a result, fewer firms enter the market, but those that do invest more heavily in R&D. For a detailed analysis of the interaction between trade policies and the overall scale of optimal R&D subsidies, see Akcigit et al. (2022).

[55] When the potential for development spillovers is smaller, the optimal policy may even involve taxing development while subsidizing research, as shown in the fourth row of the table.

played pivotal roles in advancing science during the 1950s, have seen their influence wane without new replacements emerging. This paper explores how globalization has contributed to this decline in research intensity, providing both empirical and theoretical analysis.

Empirically, I present evidence of rising specialization and a shift from research to development in U.S. corporate innovation during the 1990s, a period marked by substantial reductions in trade barriers following the Uruguay Round. Using novel measures of firm-level innovation diversity, I observe a rapid decline in innovation diversity, accompanied by reductions in research intensity (Arora et al., 2021a) and product diversity (Ekerdt and Wu, 2024). Analysis using Compustat data on publicly traded U.S. firms further reveals a strong correlation among these outcomes within firms over time. Moreover, firms that experienced larger tariff reductions due to the Uruguay Round exhibited more pronounced increases in specialization and a greater decline in research intensity.

Building on these empirical observations, the multi-product firm model developed in this paper provides insights into how globalization accelerates specialization and shifts from research to development. Globalization intensifies competition and shifts profits towards firms' core products, which have lower demand elasticities. Development investments yield more predictable outcomes, making them easier to target toward these core products. Consequently, firms allocate a greater portion of their innovation resources to development post-globalization, concentrating on creating more core products.

This model captures a crucial trade-off in how globalization impacts innovation decisions. On the one hand, globalization decreases research intensity, leading to fewer knowledge spillovers within the economy. This makes overall R&D less efficient, reducing the welfare gains from globalization. On the other hand, globalization prompts firms to shift their innovation efforts toward creating more products that have lower costs and higher productivity, amplifying welfare gains from the traditional reallocation channel seen in models without innovation decisions (e.g., Dhingra and Morrow 2019; Baqaee et al. 2024).

By calibrating the model to the 1990 U.S. economy, I quantify these two distinct effects of globalization through 2007. While the shift of innovation efforts toward better-performing products boosts aggregate productivity, the reduction in knowledge spillovers decreases innovation efficiency, ultimately diminishing the overall welfare gains from globalization compared to conventional trade models. This result is also supported by the observed decline in R&D productivity (Bloom et al., 2020) and the rise in less creative, derivative patents (Kalyani, 2024) in recent decades, suggesting that these trends may be linked to firms' excessive focus on development over research in response to globalization.

Subsidies for research and development highlight the importance of carefully balancing this trade-off in policy decisions. Knowledge spillovers play a crucial role in justifying higher subsidies for research compared to development. As the potential for spillovers from development decreases relative to research, the optimal gap between these subsidies widens. In cases where development generates minimal knowledge spillovers, it may even be optimal to tax development while continuing to subsidize research. As globalization advances, optimal innovation policies will need to further expand the gap between research and development subsidies to counter the decline in research intensity driven by globalization. These findings highlight the distinct roles of research and development and their interaction with globalization. By designing innovation subsidies that account for these dynamics, policymakers can enhance welfare and adapt to the economic landscape shaped by globalization.

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APPENDIX

A. Theory Appendix

A.1. Different Returns to Scale for Research and Development

Here, I allow investments in research and development to have different diminishing returns to scale. As in the main model in Section 4, I assume that the mass of ideas from research and development, A_r and A_d, increases with the level of investment but is subject to diminishing returns to scale as follows:

$$A_m = \frac{1}{\rho_m} Z_m x_m^{\rho_m}, \quad m \in \{r, d\}, \tag{A1}$$

where $\rho_r \in (0,1)$ and $\rho_d \in (0,1)$ represent the diminishing returns to scale for research and development investment, respectively. I now allow these to be different. Other than this, I assume the same structure as the main text.

The optimal amount of investment in each innovation margin in equation (14) and research intensity in equation (17) now become:

$$x_m = (LZ_m\Delta_m)^{\tilde{\rho}_m}, \quad \frac{x_r}{x_d} = AL^{\tilde{\rho}_r - \tilde{\rho}_d} \frac{\|\Pi(\lambda)\|_{\theta_r}^{\tilde{\rho}_r}}{\|\Pi(\lambda)\|_{\theta_d}^{\tilde{\rho}_d}},$$

where $\tilde{\rho}_m \equiv 1/(1-\rho_m)$ and $A \equiv \frac{(B\Gamma(1-1/\theta_r))^{\tilde{\rho}_r}}{(B\Gamma(1-1/\theta_d))^{\tilde{\rho}_d}}$. Note that $\tilde{\rho}_m$ increases with ρ_m. Note that $\tilde{\rho}_m$ increases with ρ_m. When an innovation investment faces less diminishing returns to scale (a higher ρ_m), the optimal innovation investment reacts more to economic conditions (L and Δ_m). For this reason, I label $\tilde{\rho}_m$ as the scalability of innovation margin m.

Similarly, taking the total derivative of research intensity with respect to market size L gives the effects of market size on research intensity as follows:

$$\frac{d \ln RI}{d \ln L} = \underbrace{[\tilde{\rho}_r - \tilde{\tilde{\rho}}_d]}_{\text{market size effect}} \underbrace{+\tilde{\rho}_r \frac{d \ln\|\Pi(\lambda)\|_{\theta_r}}{d \ln \lambda} \left[1 - \frac{\tilde{\rho}_d}{\tilde{\rho}_r}\left(\frac{d \ln\|\Pi(\lambda)\|_{\theta_d}}{d \ln \lambda} \Big/ \frac{d \ln\|\Pi(\lambda)\|_{\theta_r}}{d \ln \lambda}\right)\right] \frac{d \ln \lambda}{d \ln L}}_{\text{competition effect}}. \tag{A2}$$

Now, I have an additional term (the first bracket) representing the direct effects of market size. A larger market size encourages firms to expand both margins of innovation by providing larger profits, but the extent of the increase depends on the scalability of each innovation margin. If development can be scaled up with less diminishing returns to scale than research ($\tilde{\rho}_d > \tilde{\rho}_r$), firms will increase development relatively more in response to an increased market size, resulting in lower research intensity.

The competition effect is also influenced by the scalability parameters. As in the main text, increased competition reduces per-consumer profits, thus reducing the incentive to invest in both innovation margins. Similarly, equation (19) implies that increased competition decreases the incentive to invest in research more than in development ($|d \ln \|\Pi(\lambda)\|_{\theta_r} / d \ln \lambda| > |d \ln \|\Pi(\lambda)\|_{\theta_d} / d \ln \lambda|$). implies that increased competition decreases the incentive to invest in research more than in development ($|d \ln \|\Pi(\lambda)\|_{\theta_r} / d \ln \lambda| > |d \ln \|\Pi(\lambda)\|_{\theta_d} / d \ln \lambda|$). Unless the scalability of research is significantly lower than that of development, such relative decreases in research incentives will actually induce the firm to reduce research investment more than development investment. Additionally, a higher scalability of research will amplify the effects of competition on research intensity.

More formally, if the following condition is met, the second bracket will be positive, meaning higher competition decreases research intensity:

$$\tilde{\rho}_r / \tilde{\rho}_d > \frac{d \ln \|\Pi(\lambda)\|_{\theta_d}}{d \ln \lambda} \Big/ \frac{d \ln \|\Pi(\lambda)\|_{\theta_r}}{d \ln \lambda}.$$

Since the right-hand side is smaller than 1, this condition is satisfied unless the scalability of development is disproportionately larger than research. Additionally, holding other factors constant, this condition is more likely to be met when the variability of the ideas' value is more different between the two innovation margins (i.e., the difference between the two θ's is larger).

The following proposition on the effect of globalization on research intensity generalizes the second proposition in the main text to account for different scalability of innovation margins.

Proposition 6 *Effects of globalization on research intensity*

1. ***Market Size Effect:*** *If research encounters more (or less) scalable than development, a growth in market size L from globalization will raise (or lower) research intensity.*

2. ***Competition Effect:*** *A rise in competition level λ from globalization reduces research intensity unless research is significantly less scalable than development. This decrease in research intensity is greater when the value of research ideas becomes more volatile or the scalability of research is larger, or when the value of development ideas becomes less volatile or the scalability of development is smaller.*

In a special case where the scalability is the same for both research and development, globalization will always decrease research intensity due to the competition effect.

A.2. Derivation of Expected Increases in Profits (Δ_m) in Equation (12)

Given the mean-preserving property of Fréchet distributions, the cumulative distribution of the maximum of independent variables with Fréchet distributions with identical shape parameters also follows a Fréchet distribution. Consequently, the cumulative distribution of maximum profit increases can be represented by the following Fréchet distribution:

$$\begin{aligned} Pr(\max\{\pi_j\phi_j\}_{j=1}^{N} \leq x) &= \Pi_{j=1}^{N} exp\left(-(x/\pi_j)^{-\theta_m}\right) \\ &= exp\left(-\sum_{j=1}^{N} \pi_j^{\theta_m} x^{-\theta_m}\right) \end{aligned}$$

Therefore, the expected increase in profits for each idea is simply the mean of this combined Frechet distribution.

$$\mathbb{E}\left[\max_j B\phi_j\pi_j\right] = B\left(\sum_{j=1}^{N} \pi_j^{\theta_m}\right)^{1/\theta_m} \Gamma(1-1/\theta_m)$$

A.3. Derivation of Probability of Product Creation in Equation (15)

The expected increase in the expected probability of product k's creation from each idea can be computed as the product of the expected increase in the probability of product creation conditional on an idea is applied to product k and the ex-ante probability that an idea is applied to product k:

$$\Delta_{I_k}^{m} = \mathbb{E}\left[B\phi_{i,m,k} | k = \arg\max_j \{\pi_j\phi_{i,m,j}\}_{j\in\tilde{N}}\right] \times Pr(k = \arg\max_j \{\pi_j\phi_{i,m,j}\}_{j\in\tilde{N}}),$$

where $\Delta_{I_k}^{m}$ is the expected increase in the probability of product k's introduction from each idea generated by innovation method m and $\tilde{N}$ denotes the set of product indices that yield positive profits.

$$
\begin{aligned}
\Delta_{I_k,m} &= B\int_0^\infty xPr(\max\{\pi_j\phi_j\}_{j\in\tilde{N}\backslash k}\leq x\pi_k)\frac{exp\left(-x^{-\theta_m}\right)}{dx}dx\\
&= B\int_0^\infty xexp\left(-\sum_{j\in\tilde{N}\backslash k}\pi_j^{\theta_m}\left(x\pi_k\right)^{-\theta_m}\right)\theta_m x^{-\theta_m-1}exp\left(-x^{-\theta_m}\right)dx\\
&= B\frac{\pi_k^{\theta_m}}{\sum_{j\in\tilde{N}}\pi_j^{\theta_m}}\int_0^\infty xexp\left(-\pi_k^{-\theta_m}\left(\sum_{j\in\tilde{N}}\pi_j^{\theta_m}\right)x^{-\theta_m}\right)\pi_k^{-\theta_m}\left(\sum_{j\in\tilde{N}}\pi_j^{\theta_m}\right)\theta_m x^{-\theta_m-1}dx\\
&= \chi_{m,k}\pi_k^{-1}\Delta_m
\end{aligned}
$$

A.4. Proof of Equation (19)

I assume that $N\geq 2$. I want to show the following:

$$
\frac{\partial^2\ln\|\Pi\|_\theta}{\partial\ln\lambda\partial\ln\theta}\begin{cases}>0 & \text{if } \epsilon_q<0\ (u \text{ is subconvex; MSLD})\\ =0 & \text{if } \epsilon_q=0\ (u\text{ is CES})\\ <0 & \text{if } \epsilon_q>0\ (u\text{ is superconvex})\end{cases},
$$

where ϵ_q is the derivative of demand elasticity $(-\frac{\partial q}{\partial p}\frac{p}{q})$ with respect to quantity. First, I rewrite the θ-norm:

$$
\|\Pi\|_\theta=\left(\sum_{i=1}^N\pi_i^\theta\right)^{1/\theta}=\pi_1\left(\sum_{i=1}^N\tilde{\pi}_i^\theta\right)^{1/\theta},\tilde{\pi}\equiv\pi_i/\pi_1
$$

The derivative of log of θ-norm with respect to $\ln\lambda$ is:

$$
\frac{\partial\ln\|\Pi\|_\theta}{\partial\ln\lambda}=\frac{\partial\ln\pi_1}{\partial\ln\lambda}+\frac{\sum_{i=1}^N\frac{\partial\ln\tilde{\pi}_i}{\partial\ln\lambda}\tilde{\pi}_i^\theta}{\sum_{i=1}^N\tilde{\pi}_i^\theta}<0\quad(\because\ln\tilde{\pi}_i<0,\quad 2\leq\forall i\leq N)
$$

The cross partial derivative with respect to $\ln\theta$ is:

$$
\begin{aligned}
\frac{\partial}{\partial\ln\theta}\frac{\partial\ln\|\Pi\|_\theta}{\partial\ln\lambda} &= \left(\sum_{i=1}^N\tilde{\pi}_i^\theta\right)^{-2}\left[\left(\sum_{i=1}^N\tilde{\pi}_i^\theta\right)\left[\sum_{i=1}^N\frac{\partial\ln\tilde{\pi}_i}{\partial\ln\lambda}\left(\ln\tilde{\pi}_i\right)\tilde{\pi}_i^\theta\right]-\left(\sum_{i=1}^N\left(\ln\tilde{\pi}_i\right)\tilde{\pi}_i^\theta\right)\left(\sum_{i=1}^N\frac{\partial\ln\tilde{\pi}_i}{\partial\ln\lambda}\tilde{\pi}_i^\theta\right)\right]\\
&= \left(\sum_{i=1}^N\tilde{\pi}_i^\theta\right)^{-2}\sum_{k=1}^N\sum_{i=1,i\neq k}^N\left(\tilde{\pi}_i\tilde{\pi}_k\right)^\theta\left[\left(\frac{\partial\ln\tilde{\pi}_i}{\partial\ln\lambda}-\frac{\partial\ln\tilde{\pi}_k}{\partial\ln\lambda}\right)\left(\ln\tilde{\pi}_i-\ln\tilde{\pi}_k\right)\right]
\end{aligned}
$$

Note that $\frac{\partial\ln\tilde{\pi}_i}{\partial\ln\lambda}-\frac{\partial\ln\tilde{\pi}_k}{\partial\ln\lambda}=\epsilon_k-\epsilon_i$, where ϵ_i represents the demand elasticity for product i. Therefore, if demand elasticity decreases as demand quantity increases, $\frac{\partial\ln\tilde{\pi}_i}{\partial\ln\lambda}-\frac{\partial\ln\tilde{\pi}_k}{\partial\ln\lambda}$ will be positive when $i<k$. Since $\ln\tilde{\pi}_i-\ln\tilde{\pi}_k>0$ when $i<k$ by the construction of the product index, the sign of the bracket is positive. When $i>k$, both parts become negative, resulting in a positive bracket again.

Thus, this cross-partial derivative is positive. By following the same reasoning, the proposition holds for both the CES and superconvex cases as well.

A.5. Proof of Propositions 3 and 4

First, I demonstrate that $\chi_{d,k} - \chi_{r,k}$ decreases as the product index k increases. To do this, it suffices to show that $\frac{\partial \chi_k(\theta)}{\partial \theta}$ decreases with k, where $\chi_k(\theta) \equiv \frac{\pi_k^\theta}{\sum \pi_j^\theta}$. Since π_k decreases with k, I can prove that $\frac{\partial \chi_k(\theta)}{\partial \theta}$ decreases with k from the following expression:

$$\frac{\partial \chi_k(\theta)}{\partial \theta} = \frac{\pi_k^\theta \left(\sum_j \pi_j^\theta\right) \ln \pi_k - \pi_k^\theta \left(\sum_j \pi_j^\theta \ln \pi_j\right)}{\left(\sum_j \pi_j^\theta\right)^2} = \frac{\pi_k^\theta}{\left(\sum_j \pi_j^\theta\right)^2} \left(\sum_j \pi_j^\theta \ln \pi_k / \pi_j\right)$$

Next, I demonstrate that $\frac{\partial}{\partial \lambda}\chi_{m,k}$ decreases with k:

$$\frac{\partial}{\partial \lambda}\chi_{m,k} = \left(\theta_m \pi_k^{\theta_m - 1} \frac{\partial \pi_k}{\partial \lambda} \sum \pi_j^{\theta_m} - \theta_m \sum \pi_j^{\theta_m - 1} \frac{\partial \pi_j}{\partial \lambda} \pi_k^{\theta_m}\right) / \left(\sum \pi_j^{\theta_m}\right)^2 \tag{A3}$$

$$= \frac{\theta_m \pi_k^{\theta_m}}{\lambda} \sum \left(\epsilon_{\pi_k,\lambda} - \epsilon_{\pi_j,\lambda}\right) \pi_j^{\theta_m} / \left(\sum \pi_j^{\theta_m}\right)^2, \tag{A4}$$

where $\epsilon_{\pi_k,\lambda} \equiv \frac{\partial \ln \pi_k}{\partial \ln \lambda}$ is the elasticity of profits with respect to competition. Equation (**??**) shows that this elasticity decreases with k. This completes the proof that $\frac{\partial}{\partial \lambda}\chi_{m,k}$ decreases with k. Lastly, I demonstrate the concentration in product creation probabilities after globalization.

$$S_k^I \equiv \frac{I_k}{\sum I_j} = \frac{\sum_m \Delta_m^{\tilde{\rho}} \xi_m (\pi_k^{\theta_m - 1} / \sum \pi_j^{\theta_m - 1})}{\sum_m \Delta_m^{\tilde{\rho}} \xi_m}, \quad \xi_m \equiv \frac{\sum \pi_j^{\theta_m - 1}}{\sum \pi_j^{\theta_m}}$$

Similarly, this can be decomposed into the following:

$$S_k^I = \frac{\partial \Delta_d^{\tilde{\rho}} \xi_d / (\Delta_r^{\tilde{\rho}} \xi_r + \Delta_d^{\tilde{\rho}} \xi_d)}{\partial \lambda} \left(\pi_k^{\theta_d - 1} / \sum \pi_j^{\theta_d - 1} - \pi_k^{\theta_r - 1} / \sum \pi_j^{\theta_r - 1}\right) + \sum_{m \in \{r,d\}} \frac{\Delta_m^{\tilde{\rho}} \xi_m}{\Delta_r^{\tilde{\rho}} \xi_r + \Delta_d^{\tilde{\rho}} \xi_d} \frac{\partial}{\partial \lambda} \pi_k^{\theta_m - 1} / \sum \pi_j^{\theta_m - 1}$$

From the above, both $\left(\pi_k^{\theta_d - 1} / \sum \pi_j^{\theta_d - 1} - \pi_k^{\theta_r - 1} / \sum \pi_j^{\theta_r - 1}\right)$ and $\frac{\partial}{\partial \lambda} \pi_k^{\theta_m - 1} / \sum \pi_j^{\theta_m - 1}$ are positive. Lastly, since $\frac{\partial \Delta_d / \Delta_r}{\partial \lambda} > 0$, $\frac{\partial \Delta_d^{\tilde{\rho}} \xi_d / (\Delta_r^{\tilde{\rho}} \xi_r + \Delta_d^{\tilde{\rho}} \xi_d)}{\partial \lambda} > 0$ as long as ρ is large enough.

A.6. Endogenous Innovation Decisions Under Knowledge Spillover

Globalization affects research intensity under general equilibrium in the same way as described in the model in Section 4. The research intensity under general equilibrium is given by:

$$\frac{x_r^{GE}}{x_d^{GE}} = \tilde{A} \left[\frac{\|\Pi(\lambda)\|_{\theta_r}}{\|\Pi(\lambda)\|_{\theta_d}}\right]^{\tilde{\rho}}$$

where $\tilde{A} \equiv \left(\frac{\bar{Z}_r \Gamma(1-1/\theta_r)}{\bar{Z}_d \Gamma(1-1/\theta_d)} \frac{1-t_d}{1-t_r}\right)^{\tilde{\rho}}$ represents the relative overall efficiency of investing in research compared to development. This efficiency accounts for the relative effectiveness at both the idea generation and application stages, as well as tax incentives, which are not influenced by market conditions. Since the effect of knowledge spillovers is proportionally the same for both research and development, globalization impacts research intensity only through increased competition, as described in the model in Section 4.

Similarly, the equilibrium level of competition increases with market size. For the free-entry condition (Equation (A6)) to to hold, the rise in profits resulting from a larger market must be offset by a reduction in $Z_m \Delta_m$. Now, suppose the level of competition decreases. In this case, the economy's research intensity increases, leading to a rise in Z_m due to greater knowledge spillovers, and Δ_m also increases. As a result, a decrease in competition would violate the free-entry condition. Therefore, an increase in market size leads to a higher equilibrium level of competition.

A.7. Equilibrium Definition Under Firm Heterogeneity

Given consumer preference, normalization of wage ($w = 1$), the distribution of firms' core marginal cost (H), innovation technology parameters ($B, \rho, \{\bar{Z}_m, \theta_m\}_{m \in \{r,d\}}$), the number of consumers (L), the fixed cost of entry (f_e), and innovation taxes or subsidies (t_r, t_d), equilibrium is defined by the optimal choices at the firm level, $\{x_r, x_d, \mathbf{1}_{m,i,k}\}$, and aggregate variables $\{\mathbf{X}_r, \mathbf{X}_d, \lambda, M\}$ that satisfy the following conditions:

Optimal Innovation Decisions. Since firms do not internalize knowledge spillovers, the optimal innovation expressions are similar, but now include the effects of subsidies:

$$x_m(c) = \left(\frac{L\mathbf{K}\bar{Z}_m \Delta_m(c)}{1 - t_m}\right)^{\tilde{\rho}}, \quad m \in \{r, d\}, \tag{A5}$$

where c denotes the firm's core product marginal cost, and $\mathbf{K} \equiv \mathbf{X}_r^{\alpha_r} \mathbf{X}_d^{\alpha_d}$ represents the size of the knowledge spillover. Additionally, applications of ideas $\mathbf{1}_{m,i,k}$ follow Equation (9).

Free Entry Condition. Entrants compare their ex-ante expected profits to the fixed cost of entry, which I assume is paid in labor. The free-entry condition is:

$$f_e = \frac{1-\rho}{\rho} \sum_{m \in \{r,d\}} (1 - t_m) \left(\frac{LZ_m}{1 - t_m}\right)^{\tilde{\rho}} \int_0^{\bar{c}} \Delta_m(c)^{\tilde{\rho}} dH(c), \tag{A6}$$

where $\bar{c}$ represents the marginal cost cutoff for innovating firms. Firms with core marginal costs higher than the choke price ($u'(0)/\lambda$) cannot profitably produce any varieties ($\Delta_m(c) = 0$ for all $c > u'(0)/\lambda$) and, as a result, do not engage in innovation and exit the market. Conversely, firms with core marginal costs lower than $u'(0)/\lambda$ opt to innovate. Therefore, the marginal cost cutoff for innovation is equal to $u'(0)/\lambda$.

Level of Competition. The equilibrium competition level, λ, is determined from the consumer's maximization problem.

$$\lambda = \frac{1}{e} \times M \times \int_0^{\bar{c}} \sum_{k=1}^{N(c,\lambda)} u'(q_k(c))q_k(c)I_k(c)dH(c),$$

where $N(c, \lambda)$ denotes the maximum product index with positive profits for a firm with a core marginal cost of c given the level of competition, and M represents the mass of entrants, endogenously determined in the equilibrium. The consumption quantity of the k-th product of a firm whose core marginal cost is c is denoted as $q_k(c)$. The probability of the k-th product's successful creation, $I_k(c)$, can be computed from Equation (15). Lastly, consumer income, $e = 1 - L^{-1}M \sum_{m\in\{r,d\}} t_m \int_0^{\bar{c}} x_m(c)dH(c)$, is the normalized wage and lump-sum transfer of innovation subsidies.

Average R&D Level. The economy-wide average research or development level by innovating firms is:

$$\mathbf{X}_m = \frac{1}{H(\bar{c})} \int_0^{\bar{c}} x_m(c)dH(c), \quad m \in \{r, d\},$$

where $H(\bar{c})$ is the probability that an entrant will innovate.

A.8. Proof of Proposition 5

First, I show that a reduction in trade costs increases competition, i.e., $\eta_\tau \equiv \frac{d\ln\lambda}{d\ln\tau} < 0, \forall\tau \in [1, \tau^a]$:

$$\begin{aligned}
\eta_\tau &= -\left(\sum_m \frac{x_m}{x_r + x_d} \frac{\partial \ln\|\Pi(\tau,\lambda)\|_{\theta_m}}{\partial \ln\tau}\right)\left(\sum_m \frac{x_m}{x_r + x_d} \frac{\partial \ln\|\Pi(\tau,\lambda)\|_{\theta_m}}{\partial \ln\lambda}\right)^{-1} \\
&= \left(\sum_m \frac{x_m}{x_r + x_d} \sum_j \chi_{m,j} \frac{\pi_j^e}{\pi_j} \underbrace{(1 - \epsilon(\tau c_j, \lambda))}_{<0}\right)\left(\sum_m \frac{x_m}{x_r + x_d} \sum_j \chi_{m,j} \left(\frac{\pi_j^d}{\pi_j}\epsilon(c_j, \lambda) + \frac{\pi_j^e}{\pi_j}\epsilon(\tau c_j, \lambda)\right)\right)^{-1} \\
&< 0,
\end{aligned}$$

where $x = x_r + x_d$. $\epsilon(c_j, \lambda) = -\frac{\partial u(q_j)}{p_j}\frac{p_j}{q_j} > 1$ represents the demand elasticity of a product whose marginal cost is c_j when competition level is λ. The last inequality holds because $\epsilon > 1$. Note that this uses the following:

$$\frac{\partial \ln\|\Pi(\tau,\lambda)\|_{\theta_m}}{\partial \ln\tau} = \sum_j \chi_{m,j} \frac{\pi_j^e}{\pi_j}(1 - \epsilon(\tau c_j, \lambda)) < 0$$

$$\frac{\partial \ln\|\Pi(\tau,\lambda)\|_{\theta_m}}{\partial \ln \lambda} = -\sum_j \chi_{m,j}\left(\frac{\pi_j^d}{\pi_j}\epsilon(c_j,\lambda) + \frac{\pi_j^e}{\pi_j}\epsilon(\tau c_j,\lambda)\right) < 0,$$

where $\pi_j \equiv \pi_j^d + \pi_j^e = \pi(c_j,\lambda) + (\mathsf{N_c}-1)1_{\{\mathsf{j}\leq\mathsf{N}^*\}}\pi(\tau c_j,\lambda)$ represents the total per-consumer profit of product j, and π_j^d and π_j^e represent the profits from domestic and foreign markets, respectively. $\chi_{m,j}$ represents the idea application probability of an idea from innovation method m on product j.

The effects of tariffs on research intensity depend on how the relative incentives to invest in research versus development react to changes in profits from competition, $\zeta_\lambda \equiv \frac{\partial \ln\|\Pi(\tau,\lambda)\|_{\theta_r}}{\partial \ln \lambda} - \frac{\partial \ln\|\Pi(\tau,\lambda)\|_{\theta_d}}{\partial \ln \lambda}$, and trade costs, $\zeta_\tau \equiv \frac{\partial \ln\|\Pi(\tau,\lambda)\|_{\theta_r}}{\partial \ln \tau} - \frac{\partial \ln\|\Pi(\tau,\lambda)\|_{\theta_d}}{\partial \ln \tau}$. For the effects of competition, when trade costs are either very large ($\tau = \tau^a$) or very low ($\tau = 1$), the economy mirrors the closed economy setup. Therefore, Proposition 2 shows that:

$$\zeta_\lambda|_{\tau=\tau^a} = \zeta_\lambda|_{\tau=1} = \sum_j (\chi_{d,j} - \chi_{r,j})\left(\frac{\pi_j^d}{\pi_j}\epsilon(c_j,\lambda) + \frac{\pi_j^e}{\pi_j}\epsilon(\tau c_j,\lambda)\right) = \sum_j (\chi_{d,j} - \chi_{r,j})\left(\epsilon(c_j,\lambda)\right) < 0$$

Conversely, the effects of trade costs depend on the initial trade costs:

$$\zeta_\tau = \sum_j (\chi_{r,j} - \chi_{d,j})\frac{\pi_j^e}{\pi_j}(1 - \epsilon(\tau c_j,\lambda)).$$

When τ is close to the prohibitive level, $\zeta_\tau > 0$. For instance, when τ is higher than $\tau_1 \equiv \frac{1}{c\delta}\frac{u'(0)}{\lambda}$ but lower than τ^a, only the core product is exported. Since the application probability for the core product is higher for development ideas than for research ideas ($\chi_{r,j} < \chi_{d,j}$), it follows that $\zeta_\tau > 0$ when $\tau \in [\tau_1, \tau^a)$. In contrast, when $\tau = 1$, $\zeta_\tau = -\frac{1}{2}\sum_j (\chi_{r,j} - \chi_{d,j})\,\epsilon(c_j,\lambda)$. Again from Proposition 2, this has a negative sign.

Thus, the overall effect is positive ($\tilde{\rho}\,\{\zeta_\lambda\eta_\tau + \zeta_\tau\} > 0$) when $\tau = \tau^a$. Additionally, it can be shown that the overall effect is negative when $\tau = 1$. Since $\zeta_\tau = \frac{1}{2}\zeta_\lambda$ when $\tau = 1$, it is sufficient to show that $\eta_\tau > -1/2$. The following proves it:

$$\begin{aligned}
\eta_\tau|_{\tau=1} &= \frac{1}{2}\left(1 - \sum \frac{x_m}{x_r + x_d}\sum_j \chi_{m,j}\epsilon(c_j,\lambda|_{\tau=1})\right)\left(\sum \frac{x_m}{x_r + x_d}\sum_j \chi_{m,j}\epsilon(c_j,\lambda|_{\tau=1})\right)^{-1} \\
&= \frac{1}{2}\left(\underbrace{\sum \frac{x_m}{x_r + x_d}\sum_j \chi_{m,j}\epsilon(c_j,\lambda|_{\tau=1})}_{>1}\right)^{-1} - \frac{1}{2} \\
&> -\frac{1}{2}
\end{aligned}$$

Hence, I conclude:

$$\tilde{\rho}\left\{\zeta_\lambda \eta_\tau + \zeta_\tau\right\} \begin{cases} > 0 & \tau = \tau^a \\ < 0 & \tau = 1 \end{cases}.$$

Finally, under the regularity conditions on u in the main text, it can be shown that $\zeta_\lambda \eta_\tau + \zeta_\gamma$ is continuous. Therefore, we can always find $\epsilon_1 > 0$ and $\epsilon_2 > 0$ such that $\tilde{\rho}\left\{\zeta_\lambda \eta_\tau + \zeta_\tau\right\} > 0, \forall \tau \in (\tau^a - \epsilon_1, \tau^a]$ and $\tilde{\rho}\left\{\zeta_\lambda \eta_\tau + \zeta_\tau\right\} < 0, \forall \tau \in [1, 1 + \epsilon_2]$. Setting $\bar{\tau} = \tau^a - \epsilon_1$ and $\underline{\tau} = 1 + \epsilon_2$ proves the proposition.

A.9. Implications of Endogenous Innovation Decisions

The empirical findings in Section 3 and the model in Section 4 demonstrate that globalization leads to increased innovation specialization and a reduction in research intensity. These endogenous innovation reactions can have significant implications for both welfare and aggregate productivity. By reallocating more innovation efforts toward more productive products, aggregate productivity can be enhanced, potentially improving consumer welfare. Conversely, less emphasis in research can lead to less knowledge spillovers that may hurt the economy, by making overall innovation to be less efficient. The effects of globalization on welfare and aggregate outcomes will depend on these channels, and subsidies targeting research or development can also impact these trade-offs. In this subsection, I examine the implications of these two channels in detail.

This subsection examines the implications of these endogenous R&D decisions on welfare, aggregate productivity, and markups within the model. To focus on the innovation decisions within firms, I assume homogeneous firms with identical core productivity. Despite this assumption, the economy still exhibits heterogeneity due to variations in productivity across different products based on their proximity to the firm's core competence.

Changes in a firm's innovation composition affect welfare and aggregate outcomes by affecting the probabilities of product creation, which can be divided into two components: $d \ln I_k = d \ln \mathbf{K} + d \ln \tilde{I}_k$. Globalization impacts both components. By reducing research intensity, it diminishes knowledge spillovers ($\mathbf{K}$), uniformly lowering all probabilities of product creation.[56] Additionally, as shown in Proposition 3, globalization reallocates product creation probabilities toward core products, causing a shift in probabilities ($\tilde{I}_k \equiv I_k/\mathbf{K}$). I refer to these globalization-driven changes in $\mathbf{K}$ and $\tilde{I}$ as the knowledge spillover channel and the innovation reallocation channel, respectively.

Effects on Welfare. Endogenous innovation decisions in the model affect welfare through these two channels. Consumer welfare can be rewritten as $U = M \times \sum_{k=1}^{N} I_k u_k$, with changes in welfare

[56] In the model, the scale of innovation (each firm's total R&D investment) is fixed across different market sizes. Consequently, a reduction in research intensity leads to lower knowledge spillovers. The scale remains fixed because the free-entry condition ensures that total R&D investment stays constant, provided that fixed costs, the innovation scale parameter (ρ), and uniform subsidy or tax rates on research and development ($t_r = t_d = \bar{t}$) remain unchanged ($x_r + x_d = f_e \rho/(1-\rho)(1-\bar{t})^{-1}$).

decomposed into changes in entrants, consumption quantities, and product creation probabilities: $d\ln U = d\ln M + \sum_{k=1}^{N}\tilde{u}_k\left[\eta_k d\ln q_k + d\ln I_k\right]$, where $\tilde{u}_k \equiv \frac{I_k u(q_k)}{\sum_j I_j u(q_j)}$ is the share of welfare derived from product k and $\eta_k \equiv \frac{u'(q_k)q_k}{u(q_k)}$ is the elasticity of utility. Changes in innovation decisions directly affect probabilities of product creation and also impact the mass of firms and competition in general equilibrium. The first channel, the impact of knowledge spillover on welfare, can be analyzed as:

$$\frac{d\ln U}{d\ln \mathbf{K}} = \underbrace{\frac{d\ln M}{d\ln \mathbf{K}} + \sum_{k=1}^{N}\tilde{u}_k}_{=0} + \frac{d\ln U}{d\ln\lambda}\frac{d\ln\lambda}{d\ln \mathbf{K}}.$$

The knowledge spillover channel influences welfare only through affecting competition. Since larger spillovers always increase competition ($\frac{\partial\ln\lambda}{\partial\ln\mathbf{K}} > 0$), globalization could reduce welfare through this channel if lower competition results in a welfare decline.[57]

The innovation reallocation channel has an additional impact on welfare. When the probability of creating product k increases, the effect on welfare is given by:

$$\frac{d\ln U}{d\ln \tilde{I}_k} = \frac{I_k u_k\left(\bar{\eta}-\eta_k\right)}{\sum_{k=1}^{N} I_j u_j \eta_j} + \frac{d\ln U}{d\ln\lambda}\frac{d\ln\lambda}{d\ln \tilde{I}_k},$$

where $\bar{\eta}$ is the average elasticity of utility, weighted by each product's utility share. The first term captures the combined welfare effects of increasing the probability of product k's creation: the gain from consuming more of it and the loss from fewer entrants as the expected number of products per firm rises. Dhingra and Morrow (2019) showed that $(1-\eta_k)$ represents the social markup, reflecting the net utility from consuming a product after accounting for its resource cost, and that better-performing products have a larger social markup (lower η) under MSLD preferences. Hence, the innovation reallocation channel can enhance welfare by increasing product creation probabilities for better-performing products ($\eta_k < \bar{\eta}$) while decreasing them for lower-productivity ones ($\eta_k > \bar{\eta}$). The remaining impact on welfare depends on how this channel affects competition ($\sum_{k=1}^{N}\frac{\partial\ln\lambda}{\partial\ln\tilde{I}_k}d\ln\tilde{I}_k$).

Effects on Aggregate Productivity and Aggregate Markups. I analyze sales-weighted product-level productivity as a measure of aggregate productivity: $\tilde{\phi} \equiv \sum_{k=1}^{N}\frac{I_k s_k}{\sum_{j=1}^{N} I_j s_j}\phi_k$, where ϕ_k represents the productivity of product k ($\phi_k = 1/c_k$) and s_k is its sales. In the original MMO model, globalization improves aggregate productivity as high-productivity products capture a larger share of total sales with increased competition.

In my model, innovation decisions introduce additional effects through two channels. First, globalization reduces knowledge spillovers, lowering aggregate productivity by reducing competition. More importantly, the innovation reallocation channel affects aggregate productivity by

[57] The literature generally shows that competition boosts welfare in similar setups. For example, Baqaee et al. (2024) find large welfare gains from increased competition in their calibrated model.

adjusting sales weights and competition:

$$\frac{\partial \ln \tilde{\phi}}{\partial \ln \tilde{I}_k} = \frac{I_k s_k(\phi_k - \tilde{\phi})}{\sum_{j=1}^{N} I_j s_j \phi_j} + \frac{\partial \ln \tilde{\phi}}{\partial \ln \lambda}\frac{\partial \ln \lambda}{\partial \ln \tilde{I}_k}$$

Through the second channel, globalization can further increase aggregate productivity beyond the effects of the MMO model by reallocating product creation from less productive products ($\phi_k < \tilde{\phi}$) to more productive ones ($\phi_k > \tilde{\phi}$).

Similarly, I analyze sales-weighted product-level markups: $\tilde{\mu} \equiv \sum_{k=1}^{N} \frac{I_k s_k}{\sum_{j=1}^{N} I_j s_j}\mu_k$, where μ_k is the markup of product k ($\mu_k = p_k/c_k$). In the MMO model, the effects of competition on aggregate markups are ambiguous. On one hand, the pro-competitive effect lowers markups for all products ($\frac{\partial \mu_k}{\partial \lambda} < 0, \forall k$). On the other hand, as sales concentrate on better-performing products, the higher markups of these firms carry more weight, raising aggregate markups. Thus, the net effect of competition on aggregate markups depends on the balance of these forces. In my model, the two innovation channels—knowledge spillovers and innovation reallocation—impact aggregate markups similarly to how they affect aggregate productivity. While the knowledge spillover channel reduces competition, the innovation reallocation channel may increase aggregate markups by shifting product creation probabilities toward better-performing products.

B. Additional Empirical Evidence

B.1. Technological Specialization of U.S. Firms (Robustness)

Different Intervals. The rising trend of U.S. corporate technological specialization is robust to splitting the sample period into different lengths of time, such as 1-year (Figure B1a) or 5-year periods.

Defensive Patents. There is a concern that patents generated in recent periods may be different from those in the 1980s or 1990s in that they were generated for strategic purposes rather than representing true innovation outcomes. To address this concern, I limit the analysis to patents whose forward citations (received citations) are greater than the median citation for each pair of CPC subclass and year, based on the assumption that the number of citations received is correlated with the value of patents (Figure B1b). The rising trend of specialization is still evident among this subset of patents.

Entity Disambiguation. Another concern may be the credibility of the disambiguation process used by PatentsView. While patent-firm matched datasets commonly used in the economics literature mainly focus on relatively large firms (e.g., Compustat), PatentsView's disambiguation algorithm identifies all assignees, including small firms and startups. This broader range of identified assignees allows for analysis of the universe of innovating firms in the US, but the process of identifying small firms based on their name is likely to be noisy. To address this concern, I limit the sample to Compustat firms that have matched patent data from Arora et al. (2021a) (Figure B1c). Again, the aggregate trend of technological specialization is very similar to that found in the full sample.

Other Technical Factors. Finally, the observed aggregate trend of US corporate technology specialization may be driven purely by technical factors, such as changes in patent class assignment procedures over time, which are irrelevant to firms' economic decisions regarding technology diversification. If technical factors are the main drivers of the observed trend, the technological specialization trend should also appear for non-corporate innovators. To test this possibility, I calculate the average ENC for U.S. universities instead of US corporations. Figure B1d shows that universities, on average, have increased their technological diversity, which alleviates concerns that the observed U.S. corporate technology specialization is purely driven by technical factors that affect all patents.

Foreign Inventor Patents. The results remain quantitatively unchanged when excluding patents from U.S. firms that were created by inventors located in foreign countries.

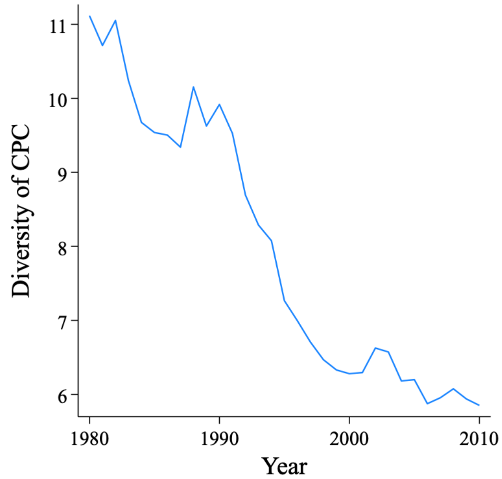
B.2. More Details on Technological Specialization of U.S. Firms

Sector Heterogeneity. The observed trend of technological specialization is common for most sections of CPC. Each graph in Figure B2 shows the average patent-weighted ENC of firms whose main innovation area is in each CPC section. Specifically, a firm's main innovation area is defined as the CPC section in which the firm has the most granted patents during the sample period.[58] All sections, except for section B (Operations and Transport), exhibit an overall trend of technological specialization. Additionally, almost all sections experienced a slowdown in technological specialization or even technological diversification around 2000 and onward. This indicates that the aggregate technological specialization trend is not mainly driven by few specific types of technologies, or by patent reallocation toward more specialized technology classes.

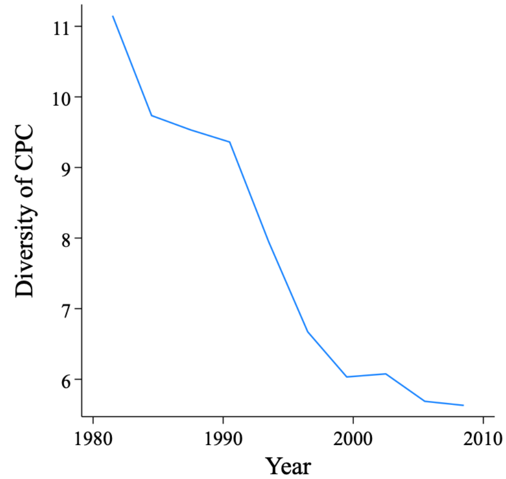
Role of Large Innovative Firms. Here, I provide evidence that major corporate innovators with a large stock of patents have become increasingly technologically specialized compared to their historical counterparts. This technological specialization among leading innovators accounts for most of the aggregate specialization trend.

[58] During the sample period, for example, if a firm has five, two, and one patents in CPC sections A, B, and C, respectively, its main innovation area is A. Around 10% of the entire sample of US corporations have more than one main innovating area, and I include them in calculating the average ENC of all their main sections.

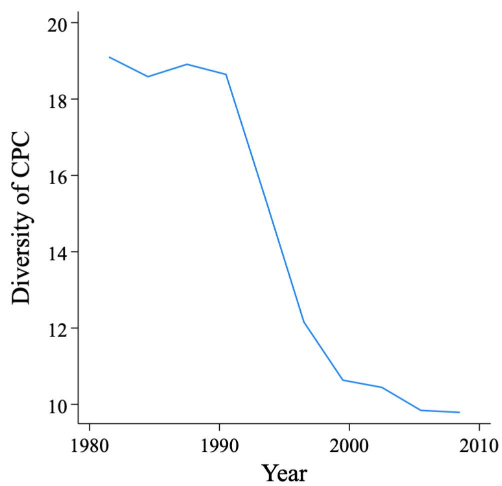
Figure B1: Robustness of US Corporate Technological Specialization Trend



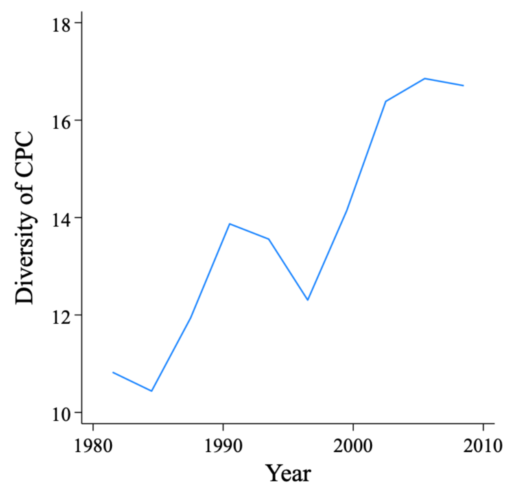
(a) Year-to-Year



(b) Over-Median Patents



(c) Compustat



(d) Universities

Notes: The figure in the top left shows the patent-weighted average ENC of US corporations for each year, rather than a 5-year period. The top right figure displays the same average `ENC`, but only includes patents whose total number of forward citations is greater than the median citation calculated for each year and CPC subclass pair. The bottom left and right figures repeat this exercise for the Compustat firms with matched patent and scientific publication data from Arora et al. (2021a) and for U.S. universities using patent data from Aghion et al. (2019).

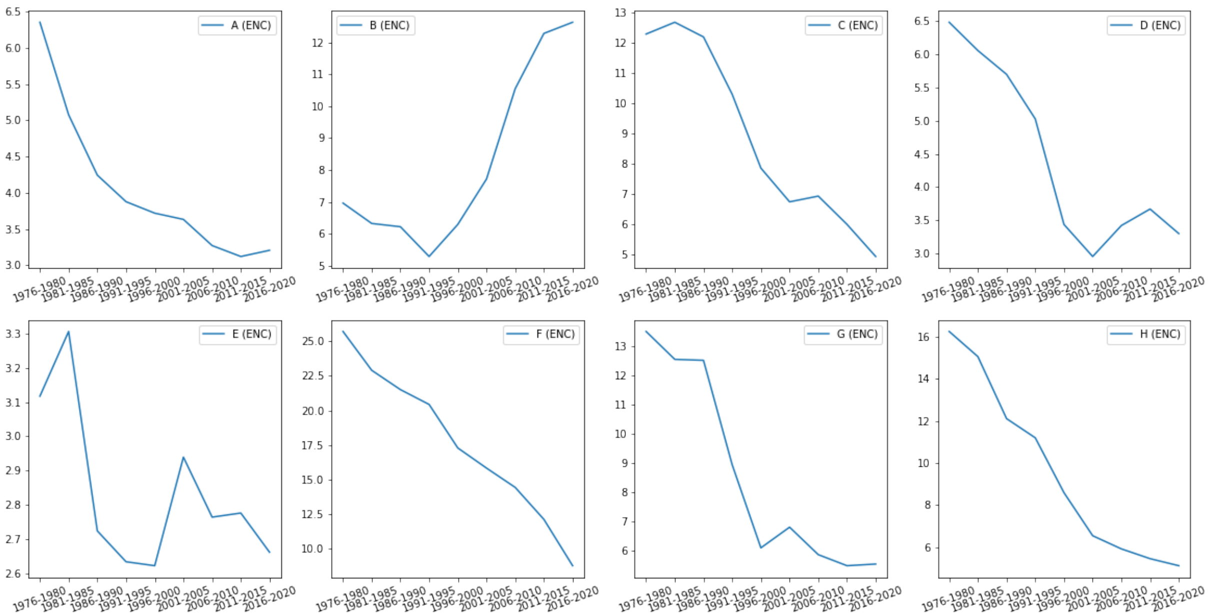


Figure B2: Section Heterogeneity (ENC)

Each figure shows the patent-weighted ENC, focusing on firms with the most patents in each CPC section. The sections include: A: Human Necessities, B: Operations and Transport, C: Chemistry and Metallurgy, D: Textiles, E: Fixed Constructions, F: Mechanical Engineering, G: Physics, and H: Electricity.

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Figure B3 illustrates the logarithm of the ENC values for the top 10 firms with the highest number of granted patents in each 5-year period. These firms are major contributors to U.S. corporate innovation. The figure indicates that the log(ENC) values for these key innovators have generally decreased over time, especially in the 1990s, reflecting a trend towards aggregate technological specialization. Two major factors drive this trend among top innovators. First, the composition of the top 10 innovators has changed consistently over time. Notably, newer top innovators in recent periods are more technologically specialized than their historical counterparts. While recent tech giants like Apple, Google, and Amazon are known for innovation across various fields, their technological diversification is less compared to historical conglomerates like General Electric or DuPont. Second, the figure reveals a decrease in technological diversification within firms that remain major innovators for more than two consecutive 5-year periods. This suggests that the technological specialization of major U.S. corporate innovators is likely a significant driver of the aggregate specialization trend.

From a slightly different angle, Figure B4 illustrates the economic significance of firms with high ENC over each 5-year period. Specifically, I divide these high ENC firms into five groups based on their log(ENC) levels and examine how their share in the total number of firms and patents among all innovating firms has evolved over time. Comparing the number share (Figure B4a) with the patent share (Figure B4b), it is evident that these high ENC firms are the major corporate

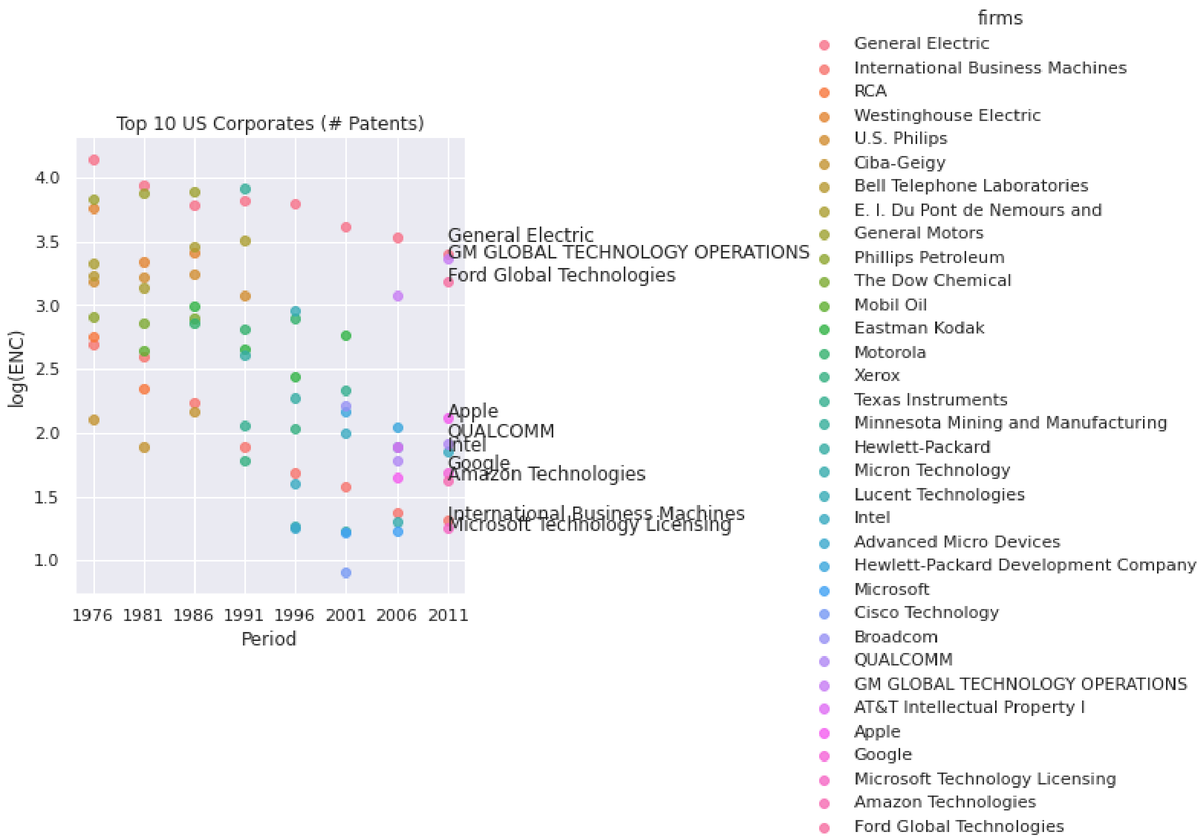

Figure B3: Top 10 US Corporate Innovators' log(ENC)

The figure displays the logarithm of the ENC of the top 10 firms, ranked by the number of granted patents, for each 5-year period. The x-axis represents the initial year of each period. Each firm is represented by a unique color in the legend on the right side of the figure. In the last 5-year period, the names of the firms are also displayed.

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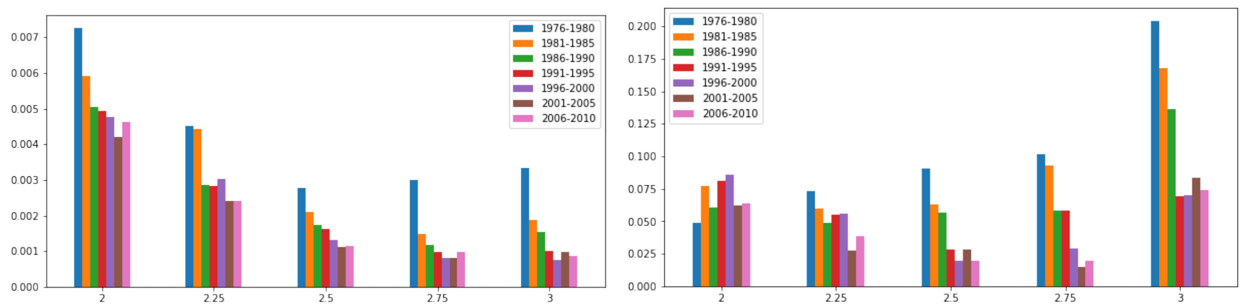
innovators in the U.S. economy. In the first period (1976-1980), these firms generated more than half of all patents despite accounting for less than 2% of the total number of firms. Another striking observation is that both their patent and number shares have decreased over time, consistent with the trend of technological specialization among major innovators suggested by Figure B3.

Motivated by these findings, I formally measure the impacts of technological specialization among major innovators on the aggregate trend. Specifically, I decompose the changes in aggregate log(ENC) using the dynamic decomposition method suggested by Melitz and Polanec (2015) (MP decompositon). According to the MP decomposition, the changes in the aggregate patent-weighted average log(ENC) (denoted as n) from one 5-year period to the next can be broken down into the



(a) Share of Firms by log(`ENC`) **(b)** Share of Patents by log(`ENC`)

Figure B4: Economic Share of High `ENC` Firms

Note: The left panel displays the share of firms, while the right panel shows the share of their patents among all innovating firms and their patents, respectively. Firms are grouped by their log(`ENC`) values. The cutoffs for the first four groups are set at 2.25, 2.5, 2.75, and 3, where each group includes firms whose log(`ENC`) is less than or equal to the cutoff and greater than the previous cutoff. To ensure clarity in visualization, all firms with a log(`ENC`) greater than 3 are aggregated into the final group.

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following components:

$$\Delta n = \underbrace{\left[S_2^E(n_2^E - n_2^C) - S_1^X(n_1^X - n_1^C)\right]}_{\text{Net Entry}} + \underbrace{\overbrace{\Delta \bar{n}^C}^{\text{Within}} + \overbrace{\Delta cov_C\left(\frac{x_i}{\bar{x}^C}, n_i\right)}^{\text{Between}}}_{\text{Continuers}}, \tag{B7}$$

where Δy represents the change between two 5-year periods ($\Delta y \equiv y_2 - y_1$, where y_t is the value of y in period t). The terms E, X, C represent entrants, exiters, and continuers, respectively.[59] n_t^G and S_t^G are the patent-weighted log(`ENC`) and patent share of group G in period t, respectively. The first bracket represents the impacts of net entry, with the first term accounting for the contribution of entrants to changes in aggregate log(`ENC`). If the technological diversification of entrants is greater than that of continuers ($n_2^E > n_2^C$), entrants increase aggregate patent-weighted technological diversification, with a greater effect when entrants generate a larger share of patents (S_2^E). The second term accounts for the impacts of exiters, similarly dependent on their technological diversification relative to continuers and their patent share. The combined effect of these two terms captures the impact of net entry.

The last two terms represent the effects of continuers. The first of these, marked as the within effect, represents the overall changes in diversification among continuers and is defined as the difference between the simple average of technological diversification in two periods. This term conceptually represents changes in diversification common to all firms, regardless of patent size.

[59]Entrants are firms that did not apply for any patents in period 1 but did so in period 2. Exiters are firms that applied for at least one patent in period 1 but did not in period 2. Continuers are firms that applied for at least one patent in both periods 1 and 2.

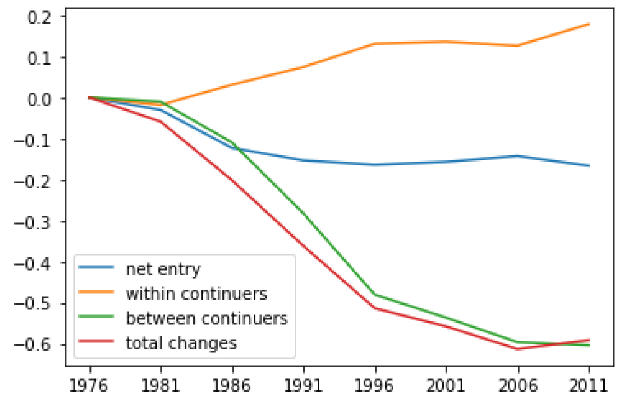

Figure B5: Melitz and Polanec (2015) Decomposition of log(ENC)

Notes: Each line represents the contribution of each term in Equation B7 for a 5-year period, with the starting year indicated on the x-axis, compared to the previous 5-year period. For instance, the value of the line labeled "net entry" in 1981 represents the contribution of the net entry term to the changes in the aggregate log(ENC) between the two 5-year periods, 1976-1980 and 1981-1985.

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Conversely, the last term, the between effect, captures the heterogeneity in changes in diversification based on firms' patent sizes. Mathematically, it is the difference in the covariance between relative firm-level patent size ($x_i/\bar{x}^C$, where x_i is the number of patent from firm *i* and $\bar{x}^C$ is the average number of patents for all continuers) and log(ENC) across all continuers for each period. If firms with a larger number of patents in period 2 tend to be more technologically specialized, the covariance term will be smaller in period 2, leading to negative values in the between effect term. Thus, if differential technological specialization among major innovators has been the primary driver of the aggregate trend, the between continuers term will capture such effects and explain most of the changes in aggregate log(ENC).

Figure B5 presents the results of the MP decomposition of changes in the patent-weighted $\log(ENC)$ throughout the sample period. The figure demonstrates that the "between-continuers" effect nearly accounts for the entire aggregate trend in technological specialization. While the net entry effect—driven by either the entry of more specialized firms or the exit of more diversified firms—contributes somewhat to the trend, particularly in the early 1980s, the overall increase in diversification among continuing firms offsets this effect. This evidence indicates that the technological specialization of major corporate innovators over time almost entirely explains the aggregate trend and closely follows it.

Table B1: Effects of Globalization

	(1)	(2)	(3)	(4)
	Innovation Diversity		Product Diversity	Research Intensity
VARIABLES	ln(`ENC`)	ln(`Text-Diff`)	ln(`ENS`)	IHS($\frac{\texttt{S}}{\texttt{Sales}}$)
`Globalization`	0.350	0.309	2.152	0.489
	(1.609)	(0.758)	(1.614)	(1.495)
`Globalization`×IHS(`R&D`^{1989})	-1.146**	-0.336*		-0.441**
	(0.512)	(0.202)		(0.175)
`Globalization`×IHS(`Sale`^{1989})			-0.667**	
			(0.305)	
Observations	7,464	7,464	7,185	6,215
R-squared	0.917	0.707	0.852	0.844
Controls for Scale	√	√	√	√
Firm FE	√	√	√	√
SIC4d-Year FE	√	√	√	√

Notes: Dependent variables in the regression include the logarithms of innovation and product diversity measures (`ENC`, `Text-Diff`, and `ENS`), along with the IHS transformed research intensity ($\frac{\texttt{S}}{\texttt{Sales}}$) (see Subsection 3.2. for their definitions). `Globalization` represents the firm-level globalization shock as defined by Equation (4). Control variables include the IHS transformed R&D expenditure, total counts of patents, and Sales. *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within each firm.

B.3. Impacts of Globalization on Specialization and Research Intensity (Robustness)

Table B1 replaces the binary indicator for large firms used in Table 3 with a continuous measure. Specifically, the size of firms is measured using the inverse hyperbolic sine (IHS) transformation of R&D and sales data from 1989.

B.4. Increases in Market Size and Innovation Diversity

The model predicts that larger market sizes result in lower innovation and production diversities. Mayer et al. (2014) find that increases in destination market size, measured by the real GDP of the destination country, lead to reduced product diversification in exports to that country. I complement this finding by employing a similar regression approach to examine whether the expansion of a destination market prompts US firms to decrease their innovation diversity within that market context.

Regression Specification. I proxy the market size using real GDP (`RGDP`) and use the following regression to examine the relationship between market size and innovation diversity at the

Table B2: Effects of Increases in Market Size on Innovation Diversity

VARIABLES	(1) $\Delta\ln(\texttt{Patents})$	(2) $\Delta\ln(\texttt{ENC})$	(3) $\Delta\ln(\texttt{Text-Diff})$	(4) $\Delta\ln(\texttt{ENC})$	(5) $\Delta\ln(\texttt{Text-Diff})$
$\Delta\ln(\texttt{RGDP})$	0.557***	-0.087***	-0.098***	-0.085***	-0.097***
	(0.073)	(0.032)	(0.031)	(0.017)	(0.030)
Observations	110,000	110,000	110,000	110,000	110,000
R-squared	0.590	0.669	0.428	0.896	0.459
Controls	-	$\Delta\ln(\texttt{Patents})$	$\Delta\ln(\texttt{Patents})$	$+\Delta\ln(\texttt{Unique})$	$+\Delta\ln(\texttt{Unique})$
Firm-Destination FE	√	√	√	√	√
Firm-Year FE	√	√	√	√	√

Notes: Dependent variables include the differences in the logarithm of the number of patents (`Patents`) and the measures of two innovation diversities (`ENC` and `Text-Diff`), which are assessed at the firm-destination-period level. Δ denotes the difference between year t and year $t-1$. Control variables consist of the logarithms of the number of patents (`Patents`) and the number of unique CPCs (`Unique`). *p<0.1, **p<0.05, ***p<0.01. Standard errors in parenthesis are corrected for arbitrary correlation within each firm.

destination (d)-firm (i)-period (t) level:

$$\Delta\ln(Y_{idt}) = \beta\Delta\ln(\texttt{RGDP}_{dt}) + \gamma\Delta\mathbf{C}_{idt} + \delta_{id} + \delta_{it} + \epsilon_{idt}. \tag{B8}$$

The dependent variables Y include the number of patents and two types of innovation diversities, defined similarly as before but measured at the destination-firm-period level. For example, ENC_{idt} measures the effective number of CPCs of patents applied to destination d by firm i during the years from $t-1$ to $t+1$.

This specification examines whether changes in a destination's GDP affect the number or diversity of patents applied in that destination. When innovation diversities are used as outcomes, controls include changes in the logarithms of `Patents` and `Unique` to account for potential scale effects. Additionally, the fixed effects account for firm-destination and firm-period specific factors, such as changes in overall firm R&D behavior. The coefficient of interest is β, indicating the effect of market size on the outcomes.

Results. Table B2 presents the estimates of β from Equation (3). Column (1) shows that increases in destination market size correlate with firms filing more patents in those markets. This finding aligns with previous research linking firms' patenting activities to their export strategies, as documented by Aghion et al. (2016) and Coelli et al. (2022). Columns (2) to (4) demonstrate that firms tend to reduce innovation diversity while increasing their patenting activities in destinations experiencing market size expansions. This outcome complements the findings of Mayer et al. (2014), who observed that larger market sizes lead to reduced product diversities. Together, these findings provide empirical support for the predictions of the model.

Table C3: Effects of Globalization on Key outcomes

(1) Description	(2) Variables	(3) $\alpha_d = 0.15$	(4) $\alpha_d = 0.1$	(5) $\alpha_d = 0.05$	(6) $\alpha_d = 0$
welfare	U	6.24%	6.22%	6.19%	6.17%
aggregate productivity	$\tilde{\phi}$	2.25%	2.24%	2.24%	2.24%
aggregate markups	$\tilde{\mu}$	-3.21%	-3.21%	-3.21%	-3.20%
innovation diversity	$\texttt{ENC}$	-7.02%	-7.01%	-7.00%	-6.98%
production diversity	$\texttt{ENI}$	-5.86%	-5.89%	-5.93%	-5.96%
competition	λ	8.18%	8.16%	8.13%	8.10%
knowledge spillover	$\mathbf{K}$	-0.65%	-0.75%	-0.85%	-0.95%

Notes: The table presents the outcomes of the baseline model in Column (3) of Table 6, using alternative values for the knowledge spillover parameter for development (α_d) of 0.15, 0.1, 0.05, and 0 for Columns (3) - (6), respectively.

C. Quantitative Results from Alternative Spillover Parameters

Table C3 repeats the analysis from Table 6 using alternative values for the development spillover parameters (α_d).