Scale without Scope: Firm Specialization and Industry Concentration

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Abstract

U.S. industries have become increasingly concentrated, with large firms accounting for a growing share of economic activity. Using U.S. manufacturing firm-product data from 1990 to 2020, I show that rising concentration is accompanied by increasing specialization among industry leaders. The average number of products produced by the top 1% of firms declines by more than 40%. I develop and structurally estimate an oligopolistic model of multi-product firms, in which firms choose their product scope and invest in scalable, product-specific technologies. As these technologies become more efficient, firms have stronger incentives to invest in their most productive products, while external competition and rising internal investment costs make peripheral products less attractive. Firms can therefore grow larger while producing fewer products. Quantitatively, improvements in scalable technology efficiency increase industry concentration and narrow product portfolios, consistent with the observed trends.

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1 Introduction

U.S. industries have become increasingly concentrated over the past four decades, with a growing share of economic activity accounted for by a small number of large firms (Autor et al. 2020). This shift toward dominant industry leaders is documented across a broad set of industries and has sparked an active debate over the state of market competition and the consequences of rising market power (Covarrubias et al. 2020, De Loecker et al. 2020).[1] In this paper, I study how leading firms come to account for a growing share of industry activity and what this implies for aggregate productivity and welfare.

The existing literature highlights two margins through which firms can expand their industry share. First, as studied in the multi-product firm literature, firms can expand by increasing the number of products they produce, or their *product scope* (Klette and Kortum 2004, Bernard et al. 2010).[2] Second, firms can capture larger shares within the product markets they already serve, as emphasized in studies of superstar firms and market power (Autor et al. 2020, Edmond et al. 2023). These two margins of expansion have different implications for competition. Expanding into additional product markets adds another competing supplier and generates pro-competitive effects in the markets the firm enters. By contrast, concentrating activity in a smaller set of product markets strengthens the firm's market power in the markets it retains. Thus, the same increase in industry concentration can reflect different changes in product-market competition and the allocation of production. Understanding how industry leaders expand is therefore essential for evaluating the productivity and welfare consequences of rising concentration.

This paper proceeds in three steps. First, I provide new empirical evidence on how leading firms have expanded their shares of industry activity using detailed U.S. manufacturing data. I show that the top 1% firms have substantially reduced the number of products they produce even as their industry shares have grown. Second, to explain this pattern, I develop a general equilibrium model of multi-product firms in which firms choose their product scope and make product-specific technology investments. Improvements in technology efficiency change the relationship between firm scale and product

[1] In manufacturing, for example, the sales share of the top 20 firms rose from 68% in 1992 to 71% in 2017. A similar trend occurred in the service sector, where the corresponding share rose from 21% to 28% over the same period (Autor et al. 2023).

[2] Each industry comprises many distinct product markets. For example, the electrical equipment manufacturing industry consists of many narrower product markets, including transformers, motors, and lighting equipment, and many others. It is well documented in the literature that large firms typically operate across several of these markets simultaneously.

scope, allowing firms to become larger while producing fewer products. Third, I estimate the model to quantify the effects of technological progress on industry concentration, aggregate productivity, and welfare. I also examine the role of firms' endogenous investment and product scope choices in shaping these outcomes.

In the first part of the paper, I examine how the product offerings of leading U.S. firms have evolved. Although larger firms produce more products in the cross-section, I find that leading manufacturers have substantially narrowed their product portfolios over time. Using detailed firm-product data covering a near-universe of U.S. manufacturing firms from 1990 to 2020, I show that the average number of products produced by the top 1% of firms falls by more than 40%. I then use the panel structure of the data to examine whether this decline reflects continuing leaders shedding products or firms with narrower portfolios becoming industry leaders. I find that more than half of the decline reflects continuing industry leaders reducing the number of products they produce, while changes in the composition of the top 1% account for a smaller share. These findings motivate the model's focus on understanding why leading firms narrow their own product portfolios while capturing a growing share of industry activity.

In the second part of the paper, I develop a general equilibrium model of multi-product firms to rationalize these facts and study their productivity and welfare implications. Firms choose how many products to develop, as well as the production technology and the scale of production for each product. Across firms, producers are heterogeneous in fundamental productivity. Within a firm, product-level fundamental productivity exhibits a core-periphery structure: the firm is more productive in its core products and less efficient in producing varieties outside its core competence (Eckel and Neary 2010).

In the model, firms choose their production technology by making product-specific investments that lower marginal production costs. In the spirit of Sutton (1991), these investments represent endogenous fixed costs incurred upfront to improve production efficiency. Examples of such fixed costs include product-specific process engineering, digital production blueprints, and custom programming for automated manufacturing. Once made, the same investment can support a larger volume of production without a proportional increase in expenditure.[3] Technology investment is therefore scalable within

[3]Unlike general physical capital, which scales with output, investments such as digital product design and computer-controlled programming (CAD/CAM) require upfront setup and engineering tailored to an individual product specification while lowering unit fabrication costs across larger production runs (Bartel et al. 2007). Similarly, Bustos (2011) studies upfront investments in computerized process controls, custom tooling, and product-level process engineering that reduce unit variable costs within a product line.

each product line.

Firms make decisions in two stages. In the first stage, they choose their product scope, which determines how many product markets to enter. In the second stage, they choose product-level technology investment and compete à la Bertrand within each product market. Conditional on product scope, technology investment determines a firm's marginal cost and therefore its scale of production in each market. The resulting profits determine the value of operating a given product portfolio and feed back into firms' scope choices in the first stage. In equilibrium, these firm-level decisions jointly determine product-market structure, markups, and aggregate productivity.

Two forces govern firms' technology investment in each product. On the benefit side, investment reduces unit labor requirements, generating greater savings over a larger production base. Producers with higher fundamental productivity therefore have stronger incentives to invest, as they tend to operate at a larger scale. On the cost side, technology investment is subject to a common convex cost at the firm level, capturing a within-firm congestion force in the spirit of Lucas (1978).[4] Expanding investment in one product raises the marginal cost of upgrading the rest of the portfolio. Thus, investment in each product depends not only on its own competitive position, but also on investment opportunities elsewhere in the firm's portfolio.

When fixed-cost technology investment is less effective, expanding along the product-scope margin is a central driver of firm size (Klette and Kortum 2004, Bernard et al. 2010). As scalable technology becomes more effective, however, technological progress induces firms to favor intensive expansion within products over extensive expansion across products through two channels. First, endogenous returns to scale strengthen the incentives of the most productive suppliers in each product market to invest and expand. For firms producing multiple products, this increases the return to investment in their core products while reducing the profitability of peripheral products, which face stronger competition from other firms' varieties. Second, the cost linkage across products within a firm reinforces this reallocation. As a firm increases investment in its core products, its marginal cost of investment rises, further reducing the incentive to upgrade peripheral

[4]Manufacturers frequently point to internal congestion over engineering and managerial bandwidth when pruning product lines. For example, following Steve Jobs' return in 1997, Apple eliminated roughly 70% of the projects on its product roadmap and focused on four core computer products. Jobs later explained that this strategy allowed Apple to "put the A team on every single one of them." Similarly, Illinois Tool Works (ITW) uses its "80/20 Front-to-Back" operating system to focus on its largest and most profitable opportunities while exiting less profitable product lines. In its Form 10-K, ITW emphasizes that this approach reduces the "cost, complexity and distractions" associated with additional activities.

products. Together, these forces shift the primary margin of expansion for leading firms from broadening product scope to scaling up core products, allowing them to capture a larger share of industry sales while producing fewer products.

Lastly, I estimate a quantitative version of the model and assess the impact of improvements in scalable technology efficiency on market concentration, aggregate productivity, and welfare. I estimate the key parameters using Simulated Method of Moments (SMM). The estimation targets the firm-employment distribution and the level and size gradient of the revenue-to-variable-cost ratio. I then discipline the historical change in technology efficiency by matching the proportional increase in the aggregate fixed-cost share between 1990 and 2020.

Quantitatively, improvements in the efficiency of scalable technology between 1990 and 2020 account for a substantial share of both the rise in U.S. industry concentration and the decline in leading firms' product scope. Within individual product markets, technological progress strengthens selection. The number of competing suppliers falls, and market shares shift toward leading producers. These changes raise concentration at both the product-market and industry levels. At the aggregate level, technological investment and the reallocation of output toward more productive producers raise productivity by 8.33% and welfare by 5.72%, more than offsetting the losses from reduced variety and higher market power. These results lend quantitative support to the view of "good concentration": rising concentration driven by productivity-enhancing technological progress need not reduce welfare (Autor et al. 2020, Covarrubias et al. 2020).

A natural question is how much of these gains comes directly from technological progress and how much arises from firms' endogenous adjustments. Holding firms' product scope and technology investment fixed at their 1990 levels, improvements in technology efficiency alone raise aggregate productivity by 3.75% and welfare by 3.95%. Allowing firms to adjust their technology investment and product scope generates additional productivity gains of 4.58 percentage points and welfare gains of 1.77 percentage points. These adjustments account for more than half of the total productivity gain and nearly one-third of the total welfare gain. These findings highlight that models treating firm productivity as exogenous can miss an important channel through which technological progress raises aggregate productivity and welfare.

Moreover, explicitly modeling multi-product firms yields markedly different quantitative conclusions from a standard single-product framework. To assess its importance,

I compare the full model with a counterfactual in which firms can increase total technology investment but cannot adjust product scope or vary productivity growth across products. Allowing firms to choose their product scope and allocate investment across products raises aggregate productivity gains by 3.20 percentage points and welfare gains by 1.09 percentage points, accounting for roughly two-thirds of the gains from endogenous firm adjustments. Multi-product firms can withdraw from peripheral products and concentrate investment in their more productive core products. The resulting within-firm reallocation reinforces the reallocation of production toward more productive firms. The quantitative results highlight the importance of modeling product scope and within-firm investment decisions when evaluating the aggregate effects of technological progress.

As a final exercise, I examine whether policies studied in models without endogenous productivity and product scope choices can improve aggregate productivity and welfare in my setting. I find that subsidizing product entry slightly reduces welfare, while a size-dependent subsidy designed to reduce markup dispersion raises welfare by 2.17%.

Related literature. This paper is related to several strands of literature. First, I contribute to the literature on the macroeconomic implications of industry concentration (De Loecker et al. 2020, Aghion et al. 2023, Edmond et al. 2023, De Ridder 2024, and De Loecker et al. 2026). I add to this literature by documenting new empirical evidence on the firm-level adjustments underlying rising industry concentration. In particular, I show that leading firms have substantially reduced the number of products they produce. Building on this finding, I develop a model of multi-product firms within each industry. The model builds on the nested CES demand structure of Atkeson and Burstein (2008) and Gaubert and Itskhoki (2021) but introduces two additional features. First, firms choose product-specific technology investment, making their productivity within each product market endogenous. Second, firms choose their product scope, making the number of competing suppliers in each product market endogenous.

Second, this paper contributes to the large literature on the supply-side drivers of rising industry concentration.[5] In particular, I relate to studies emphasizing the role of technological change (Haskel and Westlake 2018, Baqaee and Farhi 2019, Autor et al. 2020, Covarrubias et al. 2020, Hsieh and Rossi-Hansberg 2023, Kwon et al. 2024). My paper share some key mechanism highlighting the role of scalability of fixed cost invest-

[5] A large literature emphasize the changes in demand-side forces in shaping the industry concentration. For example, Gupta (2020), Ekerdt and Wu (2024), Döpper et al. (2025), Bornstein (2025), among others.

ment in driving up the industry concentration. For example, Hsieh and Rossi-Hansberg (2023) highlights how improvements in ICT allow firms to reuse key inputs across local branches, contributing to rising concentration in the service sector. Other studies emphasize the role of intangibles (Boehm et al. 2022, Kleinman 2022, Crouzet et al. 2022, Ding 2023, Jiang and Rubinton 2024, Argente et al. 2025). I contribute to this literature by incorporating the multi-product nature of firms, motivated by the empirical evidence, and allowing firms to choose product-level technology investment and product scope jointly. My quantitative results show that accounting for these firm-level decisions and the multi-product nature of firms is important for evaluating the effects of technological progress on industry concentration and aggregate welfare.

This paper also contributes to the literature on multi-product firms. Bernard et al. (2010) and Klette and Kortum (2004), among others, emphasize the importance of product scope in explaining firm growth and the firm size distribution. I build on this literature by allowing firms to choose both their product scope and their production technology for each product. While much of the earlier literature focuses on the firm size distribution, I study multi-product firms under oligopolistic competition and examine the implications for industry concentration. Closely related work in international trade studies how trade liberalization affects multi-product firms and welfare (Eckel and Neary 2010, Dhingra 2013, Mayer et al. 2014, Nocke and Yeaple 2014, Mayer et al. 2021). My paper differs from these studies by introducing endogenous product-level technology investment.

Finally, this paper is related to the literature on firm specialization. A longstanding literature in corporate finance documents the decline of conglomerates (Comment and Jarrell 1995, Maksimovic and Phillips 2002). More recently, Autor et al. (2020), Ekerdt and Wu (2024), and Ma (2026) document a secular decline in the number of industries in which U.S. firms operate.[6] While this literature primarily examines firms' activities across industries, I focus on how leading firms adjust their product portfolios within industries and study the implications of these adjustments for rising industry concentration.

The remainder of the paper is organized as follows. Section 2 documents rising specialization among industry leaders. Section 3 presents the model, and Section 4 characterizes investment, scope, and product-market outcomes. Section 5 provides empirical evidence on the mechanism. Section 6 presents the calibration and model validation. Section 7 studies the aggregate implications and policy counterfactuals. Section 8 concludes.

[6] Ma (2026) emphasizes the role of patent markets in facilitating firm specialization, while Ekerdt and Wu (2024) emphasizes nonhomothetic demand as a driver of this trend.

2 Data and Motivating Facts

In this section, I document a set of facts on the rise of firm specialization between 1990 and 2020. These facts reveal a clear change in how leading firms account for industry market share in 2020 compared with the early 1990s. This shift in the pattern of firm expansion motivates the theoretical framework developed below.

2.1 Data

I begin by briefly describing the data used in the motivating facts section. Appendix A provides further details on each dataset and the construction of key variables.

Dun & Bradstreet Data. I use commercial firm- and establishment-level data from Dun & Bradstreet covering the period 1990–2020. The data cover a near-universe of U.S. firms across a broad range of industries. The data provide information on firm structure, the products produced by each establishment, establishment-level employment, industry classifications, and other firm and establishment characteristics. I aggregate the establishment-level information to construct each firm's product portfolio and firm-by-product employment. Appendix A.1 provides further details on the construction of these variables. I next describe how I define industries, firms, and products.

My empirical analysis focuses on U.S. manufacturing because manufactured goods are generally tradable across regions, so competition occurs primarily at the national level. This distinguishes manufacturing from many other sectors, where output is often nontradable and competition takes place in local markets. In these sectors, national concentration can differ substantially from local concentration (Rossi-Hansberg et al. 2021), and it is often challenging to properly define the relevant market. Focusing on manufacturing therefore allows me to examine firms' product scope without introducing a separate geographic dimension.

Industry. I define an industry using a two-digit SIC code. This level of aggregation is broadly comparable to four-digit NAICS industries and is commonly used in the literature on industry concentration (De Loecker et al. 2020). Under this definition, the sample contains 20 manufacturing industries.

Firm. I define a firm as the set of establishments within a two-digit SIC industry that share the same headquarters DUNS number. Under this definition, different industry di-

visions of a multi-industry conglomerate are treated as separate firms. For example, GE's activities in electronic equipment manufacturing and transportation equipment manufacturing are counted separately. Following Crane and Decker (2020) and Rossi-Hansberg et al. (2021), I exclude firms with fewer than 10 employees. Appendix B.4 shows that the main results are robust to a broader definition that groups all establishments sharing the same headquarters DUNS number into a single firm, regardless of industry.

Product. A product is defined as an eight-digit SIC code reported in the Dun & Bradstreet data. For example, within electronic equipment manufacturing (SIC 36), "computer logic modules," "solid-state memory," "magnetic bubble memory," and "light-emitting diodes" are examples of products. Appendix Table A.1 provides a concrete firm-level illustration by listing the products reported for Intel in the Dun & Bradstreet data from 1990 to 2020 in electric equipment manufacturing.

This product definition is more disaggregated than the four- or five-digit SIC classifications commonly used in the multi-product firm literature (e.g., Bernard et al. 2010; Goldberg et al. 2010). In manufacturing, a four-digit SIC definition yields 455 products, while a five-digit SIC definition yields 1,440. By comparison, the eight-digit definition identifies 9,481 unique manufacturing products over 1990–2020.[7]

Nielsen Retail Scanner Data. I complement the main analysis with the Kilts NielsenIQ Retail Scanner Data, covering 2006–2016. These data are widely used in industrial organization to study market structure and concentration (e.g., Döpper et al. 2025) and in macroeconomics and international trade to study firm and product dynamics (e.g., Hottman et al. 2016). The data report weekly unit sales and revenue at the barcode-by-store level for a large sample of retail chains.

The Nielsen data complement the Dun & Bradstreet data by providing alternative, more disaggregated product definitions. My product definition using the eight-digit SIC code is coarser than the narrowly defined product markets often used in the industrial organization literature (e.g., Benkard et al. 2026). Using Nielsen data allows me to construct firm product portfolios using finer classifications at the Nielsen product modules level, and to examine whether the patterns in product scope continue to hold at a more disaggregated level. Appendix A.2 provides further details on the product definitions for

[7]The same product definition is used by Rossi-Hansberg et al. (2021). The exact set of products changes slightly from year to year, potentially reflecting the introduction of new products and the obsolescence of existing ones. Nevertheless, Appendix Figure A.1 shows that the number of unique products remains relatively stable at approximately over the same period.

analysis based on the Nielsen Scanner data.

2.2 Rising Specialization among Top Firms

2.2.1 Fact 1: Declining product scope among top firms

I first document a substantial decline in the product scope of leading firms between 1990 and 2020. In each industry and year, I define leading firms as the top 1% of firms by employment and calculate the average number of products they produce.[8]

Figure 1 documents a substantial decline in the product scope of industry leaders across U.S. manufacturing industries. Panel (a) plots the unweighted average number of products produced by the top 1% of firms and the bottom 99% between 1990 and 2020. Throughout the sample, firms in the top 1% produce substantially more products than those in the bottom 99%, consistent with the multi-product firm literature emphasizing product scope as an important source of firm size variation (Bernard et al. 2010). Over time, however, the average product scope of the top 1% declines sharply. The unweighted average number of products for the top 1% firms falls from 6.02 products in 1990 to 3.85 in 2020. By comparison, firms outside the top 1% produce roughly one product on average throughout the sample.

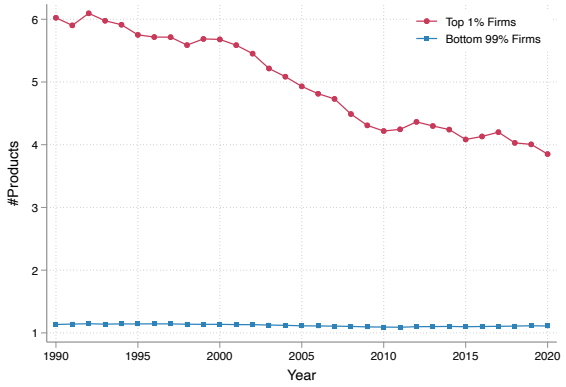
The decline is even more pronounced when weighting firms by employment. Panel (b) shows that the employment-weighted average falls from 9.06 to 5.21 products. The corresponding measure for the bottom 99% remains stable. Overall, product scope declines by 36.1% and 42.5% under the unweighted and employment-weighted measures, respectively. Thus, compared with industry leaders in the early 1990s, leading firms in 2020 produce a substantially narrower range of products.

Appendix B.1 shows that the decline in leading firms' product scope also holds when I define industry leaders as the top 20 firms by employment in each industry, a measure commonly used in the literature (e.g., Autor et al., 2020). Under this definition, average product scope declines by 34.6% without employment weights and by 39.6% when weighted by employment. The results are also robust to an alternative firm definition that counts a firm's products across all manufacturing industries, as shown in Appendix B.4. Finally, Appendix B.5 examines firm product scope using Nielsen Retail Scanner data,

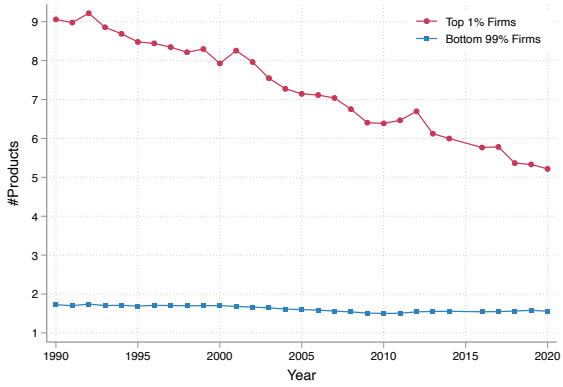
[8]To aggregate these industry-level averages across manufacturing industries, I use each industry's share of total manufacturing employment in 1990 as a fixed weight. Appendix B.3 reports the corresponding results using industry employment shares that vary by year.

Figure 1: Product Scope of Top 1% Firms

(a) Top 1% Firms: Unweighted



(b) Top 1% Firms: Emp weighted



Notes: This figure plots the average number of products produced by the top 1% of firms from 1990 to 2020. A firm is defined as a firm ID by 2-digit SIC industry in the Dun& Bradstreet data. A product is an eight-digit SIC code. For each year, I first compute average product scope among the top 1% of firms within each two-digit SIC industry. I then aggregate these industry-level averages across manufacturing industries, using each industry's share of total manufacturing employment in 1990 as a fixed weight in both panels. Panel (a) plots the resulting aggregate series when firms are equally weighted within each industry, while Panel (b) plots the corresponding series when firms are weighted by their employment.

where products are defined as "product modules." Although these data cover only consumer goods and the shorter period from 2006 to 2016, I find a similar declining trend in product scope among the top 1% of firms.

2.2.2 Fact 2: Declining scope is driven by leading firms shedding products

The decline in product scope documented in Section 2.2.1 is based on repeated cross-sections of the top 1% of firms. It could therefore reflect continuing leaders reducing their own product scope or changes in the composition of industry leaders. In this section, I use the panel structure of the data to examine the sources of the decline between 1990 and 2020. I find that the largest contribution comes from continuing top 1% firms reducing the number of products they produce. Employment reallocation toward continuing leaders with narrower product portfolios and changes in the composition of the top 1% through entry and exit also contribute, but to a lesser extent.

Formally, using a decomposition similar to those in Melitz and Polanec (2015) and Ekerdt and Wu (2024), I decompose the decline in employment-weighted average product scope among the top 1% of firms into three components: (i) continuing leaders reducing

the number of products they produce, (ii) employment shifting toward continuing leaders with narrower product portfolios, and (iii) changes in average product scope as firms with different product portfolios enter and exit the top 1%. The first component captures specialization within continuing leaders. The latter two capture changes in the relative importance and composition of firms with different product portfolios, which can reduce average product scope even without individual firms shedding products.

Let N_t^k denote the employment-weighted mean product scope of leading firms in industry k at date t. In the baseline, I define leading firms as the top 1% of firms by employment within each industry. Then

$$N_t^k = \sum_{i \in \mathcal{L}_t^k} \omega_{it}^k n_{it}^k, \tag{1}$$

where $\mathcal{L}_t^k$ denotes the set of leading firms, n_{it}^k is the number of products produced by firm i, and ω_{it}^k is firm i's employment share among leading firms in industry k: $\omega_{it}^k = \frac{\ell_{it}^k}{\sum_{h \in \mathcal{L}_t^k} \ell_{ht}^k}$. For simplicity, I suppress the industry superscript k throughout this section when there is no risk of confusion.

For a comparison between years t_1 and t_2, let C denote the set of firms that belong to the top 1% in both years. I refer to these firms as continuing leaders. Let E denote firms that enter the top 1% between t_1 and t_2, and let X denote firms that leave the top 1%. For continuing leaders, let ω_{it}^C denote firm i's employment share within C, and let N_t^C denote their employment-weighted mean product scope

$$\omega_{it}^C = \frac{l_{it}}{\sum_{h \in C} \ell_{ht}}, \quad N_t^C = \sum_{i \in C} \omega_{it}^C n_{it}$$

The change in employment-weighted product scope can then be written as

$$\begin{aligned} N_{t_2} - N_{t_1} = & \underbrace{\sum_{i \in C} \frac{\omega_{i,t_2}^C + \omega_{i,t_1}^C}{2} \left(n_{i,t_2} - n_{i,t_1}\right)}_{\text{Scope adjustment}} + \underbrace{\sum_{i \in C} \frac{n_{i,t_2} + n_{i,t_1}}{2} \left(\omega_{i,t_2}^C - \omega_{i,t_1}^C\right)}_{\text{Employment reallocation}} \\ & + \underbrace{\sum_{i \in E} \omega_{i,t_2} \left(n_{i,t_2} - N_{t_2}^C\right) - \sum_{i \in X} \omega_{i,t_1} \left(n_{i,t_1} - N_{t_1}^C\right)}_{\text{Net entry/exit}}. \end{aligned} \tag{2}$$

The first term fixes firms' employment shares within continuers at their average across the two periods while allowing firm i's product scope to change. It captures changes in continuing leaders' contribution that arise from changes in product scope. The term is negative when continuing leaders reduce the number of products they produce. The second term fixes firms' product scope at its average across the two periods while allowing their employment shares within continuers to change. It captures changes due to employment reallocation among continuing leaders. The term is negative when employment shifts toward firms with narrower product portfolios. The final term captures the contribution of firms entering the top 1% net of that of firms leaving the top 1%, with each group's product scope measured relative to the employment-weighted mean scope of continuing leaders in the corresponding year. In the decomposition, I calculate the year-to-year changes for each term in equation (2) and report their cumulative sums from 1990 to 2020.

Table 1 reports the decomposition of the decline in employment-weighted product scope between 1990 and 2020. The first row reports results when industry leaders are defined as the top 1% of firms. Their employment-weighted product scope declines by 3.84 products over this period. Scope adjustment among continuing leaders accounts for 2.36 products, or 61.3% of this decline. Thus, more than half of the decline reflects firms that remain in the top 1% reducing the number of products they produce. Employment reallocation accounts for another 0.98 products, or 25.4%, as employment shifts toward continuing leaders with narrower product portfolios. Net entry and exit account for the remaining 0.51 products, or 13.2%. The decomposition therefore shows that an important part of the aggregate decline reflects continuing industry leaders narrowing their own product portfolios.

The second to the fourth rows repeat the decomposition, defining industry leaders as the top 0.1%, top 5%, the top 10% of firms, and the top 20 firms by employment, respectively. The results are consistent with the top 1% baseline. In all four groups, product-scope reductions among continuing leaders account for a substantial share of the decline in average product scope.

2.3 Summary

To recap, I have shown that the product scope of the top 1% of firms declines substantially between 1990 and 2020, and that much of this decline is driven by continuing

Table 1: Decomposing changes in top firm product scope

Sample	Scope adjustment (1)	Emp reallocation (2)	Net entry (3)	Total change (4)
Top 1% firms	−2.36 (61.3%)	−0.98 (25.4%)	−0.51 (13.2%)	−3.84
Top 5% firms	−1.57 (53.7%)	−1.19 (40.6%)	−0.17 (5.7%)	−2.92
Top 10% firms	−1.37 (51.9%)	−1.21 (45.8%)	−0.06 (2.4%)	−2.64
Top 0.1% firms	−3.59 (66.3%)	−1.29 (23.9%)	−0.53 (9.8%)	−5.42
Top 20 firms	−2.72 (58.5%)	−1.23 (26.4%)	−0.70 (15.1%)	−4.65

Notes: This table reports the decomposition of employment-weighted product scope from 1990 to 2020. Top firms are selected separately within each industry and year. Parentheses report each component's percentage of the total change.

industry leaders reducing the number of products they produce. In Appendix B.6.1, I further show that the product market overlap between top firms declines over time. Together with the rise in industry concentration over the same period, these findings suggest that leading firms are capturing a larger share of their industries while producing fewer products. Rather than growing by broadening their product portfolios, top firms increasingly expand by capturing larger shares within a narrower set of product markets. This raises the question of what drives this shift in the margin of firm growth and how it relates to the rise in industry concentration over the same period.[9]

3 An oligopolistic competition model of multi-product firms

This section develops an oligopolistic model of multi-product firms to study how improvements in scalable production technologies can lead firms to become larger while producing fewer products. In this model, firms make two choices: how many product markets to enter, and how much to invest in fixed-cost, scalable technology for each product. Investment lowers product-level marginal costs through expenditures that are fixed with respect to output. Its implementation across products is subject to a common convex firm-level cost, capturing internal resource constraints. After presenting the model environment and equilibrium in this section, Section 4 characterizes how an increase in the effectiveness of scalable technology alters firms' investment and product scope decisions, and examines the resulting implications for industry concentration.

[9]Specifically, in Section B.6.2, I show that changes in the product scope of the top 1% of firms are not significantly related to the China shock or the broader changes in U.S. manufacturing over the same period.

3.1 Preferences

Households have Cobb-Douglas preferences over industrial output $\{Q^k\}_{k=1}^K$ from K industries indexed by $k \in \{1, \cdots, K\}$. Aggregate utility is given by

$$\log U(Q) = \sum_{k=1}^{K} \alpha^k \log Q^k$$

where $\{\alpha^k\}_{k=1}^K$ are industry expenditure shares that satisfy $\sum_{k=1}^K \alpha^k = 1$ and determine the share of household income spent on consumption across industries.[10]

Each industry k contains a continuum of product markets indexed by $j \in [0,1]$. In each product market j, a finite, endogenously determined set of active firms $\mathcal{M}_j^k$ supplies horizontally differentiated varieties. A firm may participate in several distinct product markets, supplying one differentiated variety in each market it enters. Within each industry, varieties are aggregated into industry output Q^k through a two-tier CES structure. At the lower nest, a competitive product-market assembler combines the horizontally differentiated varieties supplied by firms in $\mathcal{M}_j^k$ into a market-level composite q_j^k. At the upper nest, a competitive final-good producer aggregates the continuum of market-level composites $\{q_j^k\}_{j\in[0,1]}$ into industry output Q^k. The CES quantity aggregators are

$$Q^k = \left(\int_0^1 (q_j^k)^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 1 \tag{3}$$

$$q_j^k = \left(\sum_{i \in \mathcal{M}_j^k} (q_{ij}^k)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \qquad \eta > \sigma > 1 \tag{4}$$

where $\sigma > 1$ is the elasticity of substitution across product markets. q_{ij}^k is the quantity of firm i's variety in market (j,k), and $\eta > 1$ is the elasticity of substitution across varieties within a product market. I assume that $\eta > \sigma > 1$, so that firm-level varieties within a product market are closer substitutes than products within an industry.

With this demand structure, consumer expenditure on product market j in industry k is given by

$$r_j^k = p_j^k q_j^k = S_j^k \alpha^k Y, \qquad \text{with } S_j^k = \left(\frac{p_j^k}{P^k} \right)^{1-\sigma} \tag{5}$$

[10] In the data, I define firms at the firm-division level. The Cobb-Douglas assumption ensures that the decisions of firm divisions operating in different industries are separable.

where p_j^k is the price index of product j in industry k, S_j^k is the within-industry expenditure share of product market j, and Y is aggregate income in the economy. The industry price index P^k satisfies

$$P^k = \left[\int_0^1 (p_j^k)^{1-\sigma} dj \right]^{\frac{1}{1-\sigma}}. \tag{6}$$

The product market price index satisfies

$$p_j^k = \left(\sum_{i \in \mathcal{M}_j^k} (p_{ij}^k)^{1-\eta} \right)^{\frac{1}{1-\eta}} \tag{7}$$

where p_{ij}^k is the price charged by firm i in product market (j,k).

Demand for firm i's variety in product market (j,k) and the corresponding revenue are therefore given by

$$q_{ij}^k = q_j^k \left(\frac{p_{ij}^k}{p_j^k} \right)^{-\eta}, \tag{8}$$

$$r_{ij}^k = p_{ij}^k q_{ij}^k = s_{ij}^k r_j^k = s_{ij}^k S_j^k \alpha^k Y, \qquad \text{with } s_{ij}^k = \left(\frac{p_{ij}^k}{p_j^k} \right)^{1-\eta} \tag{9}$$

where s_{ij}^k is the expenditure share of firm i within product market (j,k).

Two features of this nested-CES structure distinguish this model from standard models of multi-product firms. First, the model abstracts from cannibalization across a firm's own products and instead focuses on the supply-side forces shaping firms' scope and scale decisions. In classical multi-product oligopoly, a firm's varieties compete with one another. In Eckel and Neary (2010), for example, the firm internalizes this demand-side cannibalization when choosing its product portfolio, and cannibalization itself shifts activity toward the firm's core products. In my setting, firms operate a finite number of lines drawn from a continuum of product markets, so the probability that two lines belonging to the same firm appear in the same product market is zero. Products supplied by the same firm therefore do not compete directly in demand. This abstraction is consistent with the empirical definition of a product. Products are broad product categories rather than individual barcodes or narrowly differentiated varieties. For example, "application software" and "operating systems" are treated as distinct products. At this level of aggregation, modeling a firm's products as direct substitutes within the same demand nest is

less natural.

Second, the structure allows a firm to charge different markups across its products. In Hottman et al. (2016), products are nested within firms, so a firm charges a common markup across its product portfolio. I instead organize competition at the product-market level: each product market contains multiple differentiated suppliers, and a multi-product firm may participate in several distinct markets. This formulation is closer to the product-market structure used in the endogenous-growth literature, but differs from quality-ladder models in which a single producer serves each product market and markups are determined by limit pricing, as in Grossman and Helpman (1991) and Peters (2020). Here, multiple firms can coexist within a product market, and a firm's markup on each product depends on its position in that market. I characterize this pricing decision later.

3.2 Production Technology

Each industry k is populated by an exogenous mass N^k of firms. Firm i in industry k produces q_{ij}^k units in product market (j,k) using labor as the only variable input. The production technology is linear

$$q_{ij}^k = z_{ij}^k l_{ij}^k,$$

where productivity satisfies

$$\log z_{ij}^k = \log A_i^k + \log a_{ij}^k + g\left(u_{ij}^k\right), \quad u_{ij}^k \equiv \psi x_{ij}^k \tag{10}$$

Productivity has three components. The first is firm-level process efficiency A_i^k, which applies to every product supplied by the firm. Firm efficiencies are drawn independently from a Pareto distribution with shape parameter ϑ and lower bound one. I assume that $\vartheta > \eta - 1$ following Chaney (2008).

The second component is product-specific fundamental productivity a_{ij}^k. Following Eckel and Neary (2010), I assume that product-specific productivity follows a core competence structure, and product opportunities are ranked within a firm. If product j is the product at rank $d_{ij}^k \in \{0,1,2,...,\lambda_i^k - 1\}$ within firm i, its fundamental productivity is

$$a_{ij}^k = \delta^{d_{ij}^k}, \qquad \delta \in (0,1). \tag{11}$$

with $d_{ij}^k = 0$ corresponding to the firm's core product. The length of the list, λ_i^k, is the

firm's product-scope choice, described in Section 3.3.3. Thus, product-specific fundamental productivity declines with distance from the core. The parameter δ governs the rate of decay.

The third component, $g(u_{ij}^k)$, captures the productivity gain from fixed-cost technology investment. Firm i invests $x_{ij}^k \geq 0$ in product j and obtains an effective stock $u_{ij}^k \equiv \psi x_{ij}^k$. I interpret u_{ij}^k as the productivity-relevant capability embodied in the software, data, logistics, and communication systems used in the production of product j. These technologies facilitate production by improving coordination, information processing, and production efficiency, thereby lowering the variable cost of producing each unit of output. They are scalable in the sense that, once installed, the same capability can be applied to a larger volume of production without being depleted. The parameter $\psi > 0$ measures the effectiveness of fixed-cost technology investment.

I assume that $g : \mathbb{R}_+ \to \mathbb{R}_+$ is increasing and concave, with $g(0) = 0$, $g'(u) > 0$, $g''(u) < 0$, and $g'(u) \to 0$ as $u \to \infty$. Thus, product-specific investment raises log productivity but exhibits diminishing returns.

With the wage normalized to one, marginal cost for firm i in product market (j,k) is

$$c_{ij}^k = \frac{1}{z_{ij}^k} = \frac{1}{A_i^k \delta^{d_{ij}^k} \exp\left[g\left(\psi x_{ij}^k\right)\right]}. \tag{12}$$

so that marginal cost is decreasing in firm efficiency, increasing in distance from the core through $\delta^{-d_{ij}^k} \geq 1$, and decreasing in the product-specific investment gain g.

3.3 Market structure and firm decisions

3.3.1 Timing

Firms choose their product portfolios, investment, and pricing strategies in two stages. In the first stage, each firm chooses the number of products λ_i^k to develop. These λ_i^k products are then randomly assigned to distinct product markets in $[0,1]$. In the second stage, firms observe the realized market structure and choose prices and investments in fixed-cost technologies across their product lines.

Stage 1. In Stage 1, firm i observes its own process efficiency A_i^k and chooses product scope $\lambda_i^k \in \Lambda^k \equiv \{0,1,...,\bar{\lambda}\}$. Product scope is the number of product opportunities the

firm chooses to develop. Developing each product costs F, so the total product development cost is $F\lambda_i^k$, and $\lambda_i^k = 0$ denotes non-production. The product development costs are incurred before product identities, competitor types, and competitors' portfolios are known.

Random product-market draws. Conditional on λ_i^k, firm i receives an ordered list of λ_i^k distinct product-market opportunities. I refer to this assignment mechanism as random anonymous placement. Product identities are drawn uniformly without replacement from a continuum of product markets $j \in [0, 1]$. The first draw is the firm's core line, the second draw has rank one, and so forth. The product at rank d has fundamental productivity δ^d, as defined in equation (11). Every realized opportunity is operated in Stage 2 because there is no fixed operating cost. Thus, λ_i determines how many markets the firm enters, while the random draws determine where it meets competitors.[11] Random anonymous placement rules out strategic portfolio selection. Firms choose product scope before learning product identities and cannot direct entry toward markets with particular competitors or competitive conditions. The realized competition network is therefore generated by random overlap in firms' product portfolios rather than by strategic targeting.

Stage 2. At the beginning of Stage 2, the realized product portfolios, product ranks, and firm efficiencies are publicly observed. Firms then choose prices and investment in fixed-cost technologies across their product lines.

I solve the model by backward induction.

3.3.2 Stage 2: Product-Market Competition and Product-level Investment

At the beginning of Stage 2, product-market placement and productivity draws are realized. Firms' process efficiencies, realized portfolios, and product ranks are publicly

[11] The continuum economy is the large-market limit of economies with J product markets and approximately $N^k J$ firms, where each firm's scope remains bounded as $J \to \infty$. This scaling preserves finite competition in a typical product market. Given a population distribution G^k of the first-stage states (A, λ), the number of suppliers in a typical product market converges to a Poisson random variable with mean

$$\bar{n}^k = N^k \mathbb{E}_{G^k}[\lambda] \tag{13}$$

Appendix C.1 gives the finite-economy construction.

observed. The public information in industry k is summarized by

$$\mathcal{H}^k \equiv \left\{ \left(A_i^k, \mathcal{J}_i^k, \{a_{ij}^k\}_{j \in \mathcal{J}_i^k} \right) \right\}_{i \in \mathcal{I}^k} \tag{14}$$

where $\mathcal{I}^k$ denotes the set of firms in industry k, $\mathcal{J}_i^k$ is firm i's portfolio of product markets, and a_{ij}^k is its product-specific fundamental productivity in market j.

In this stage, the key decisions for firm i are the price charged in each product market and its product-specific investment across products in its portfolio.

Firm problem. Given competitors' prices and investment decisions, firm i chooses $\{p_{ij}^k, x_{ij}^k\}_{j \in \mathcal{J}_i^k}$ to maximize operating profit net of technology investment costs. All firms compete in price à la Bertrand. Specifically, firm i solves the following problem

$$V(A_i^k, \omega_i^k; P^k, Y) = \max_{\{p_{ij}^k, x_{ij}^k\}_{j \in \mathcal{J}_i^k}} \left\{ \sum_{j \in \mathcal{J}_i^k} \left(p_{ij}^k - c_{ij}^k \right) q_{ij}^k - C\left(\sum_{j \in \mathcal{J}_i^k} x_{ij}^k \right) \right\} \tag{15}$$

subject to the marginal cost given by equation (12), demand (8), and total investment cost

$$C(\sum_{j \in \mathcal{J}_i^k} x_{ij}^k) = \phi_1 \left(\sum_{j \in \mathcal{J}_i^k} x_{ij}^k \right)^{\gamma}, \qquad x_{ij}^k \geq 0,\ \phi_1 > 0,\ \gamma > 1$$

Firms are atomistic in each industry since they only operate in a finite number of product markets in an industry with a continuum of products. Therefore, they take the industry-level price index P^k and aggregate income Y as given, while internalizing the effect of their own price on the product-level price index p_j^k.

Here, firms incur a total cost of $C\left(\sum_{j \in \mathcal{J}_i^k} x_{ij}^k\right)$ on their product-level technology investments. The total resource cost is convex in investment across the firm's portfolio. The parameter γ governs how rapidly the marginal cost of investment rises as the firm expands its total fixed-cost technology investment. Convexity ($\gamma > 1$) is the model's central organizational friction. This specification generates a congestion force inside the firm in the spirit of Lucas (1978), reflecting the span-of-control limits that manufacturers often face when coordinating technological upgrades and engineering resources across multiple products. Holding investment elsewhere fixed, greater investment in one product raises the marginal cost of technological upgrading throughout the portfolio. Products

within the firm therefore compete for investment resources, so the cost of investing in a given product depends on investment elsewhere in the firm. When $\gamma = 1$, investment costs are separable across products, and this direct cost linkage disappears.

Two features of the firm's problem are worth emphasizing. First, product-level technology investment is endogenous. By choosing how much to invest in fixed-cost technology for each product, the firm endogenously determines the marginal cost at which that product is produced. Technology investment is therefore an additional strategic margin: firms compete not only through prices, but also through investment decisions that shape their production costs. This differs from models in which productivity or marginal cost is an exogenous state of the pricing problem.[12]

Second, the firm-level convex cost of investment makes technology choices nonseparable across products. A higher return to investment in one product can therefore induce the firm to expand investment there while reducing investment in other products, potentially increasing their marginal production costs.

Moreover, this within-firm linkage connects competitive conditions across product markets. To see this, suppose firms i and ℓ compete in product market j, while firm ℓ also competes with firm h in another market, j'. Firm h's pricing and investment choices in market j' affect firm ℓ's return to investment there. Firm ℓ may then reallocate investment across its portfolio, changing its marginal cost and price in market j. This, in turn, affects firm i's optimal decision in market j. A firm's decision in one product market can therefore affect firms in another market even when they do not compete directly. The interaction between within-market competition and the firm-level convex investment cost thus links firms through overlapping product portfolios.

In the notation of the firm problem (15), although the entire realization $\mathcal{H}^k$ as defined in equation (14) is observed, only a subset of it is relevant for a focal firm i. The relevant environment is summarized by ω_i. Formally, for a focal firm i, define its connected set by

$$\mathcal{C}_i^k \equiv \left\{ \ell \in \mathcal{I}^k : \begin{array}{l} \text{there exist } R \in \mathbb{N}_0 \text{ and firms } i_0, \ldots, i_R, \text{ such that} \\ i_0 = i, \quad i_R = \ell, \quad \mathcal{J}_{i,r-1}^k \cap \mathcal{J}_{i,r}^k \neq \emptyset, \text{ for every } r = 1, \ldots, R \end{array} \right\}.$$

[12] In Bernard et al. (2010), for example, product participation is endogenous, but firm productivity and firm-product appeal are exogenous; conditional on those states, the price of each product is chosen separately. Similarly, in oligopoly models such as Atkeson and Burstein (2008) and Gaubert and Itskhoki (2021), firms compete given their productivity and cost realizations rather than choosing product-level marginal costs through endogenous technology investment.

Thus, $\mathcal{C}_i^k$ contains firm i, its direct competitors, the competitors of those firms in their other product markets, and all firms connected to i through a finite sequence of shared product markets.

Firm i's payoff-relevant environment is the restriction of the industry realization to its connected set $\mathcal{C}_i^k$. Keeping the focal firm's own state A_i^k separate, define its payoff-relevant environment as

$$\omega_i^k \equiv \left(\mathcal{J}_i^k, \{a_{ij}^k\}_{j \in \mathcal{J}_i^k}, \left\{ \left(A_\ell^k, \mathcal{J}_\ell^k, \{a_{\ell j}^k\}_{j \in \mathcal{J}_\ell^k} \right) \right\}_{\ell \in \mathcal{C}_i^k / \{i\}} \right). \tag{16}$$

where ω_i^k contains its realized portfolio and the characteristics and portfolios of the other firms connected to it through product-market competition. Conditional on P^k and Y, firms outside $\mathcal{C}_i^k$ cannot affect firm i through either product-market prices or a chain of investment-allocation responses.

3.3.3 Stage 1: Product Scope Choice

At the beginning of Stage 1, firm i observes its process efficiency A_i^k. It chooses a finite product scope $\lambda_i^k \in \Lambda^k \equiv \{0, 1, ..., \bar{\lambda}\}$ by solving the following Stage-1 problem

$$W\left(A_i^k; \Gamma^k, P^k, Y\right) = \max_{\lambda_i^k \in \Lambda^k} \left\{ \mathbb{E}_{\omega \sim \Gamma^k(\lambda)} \left[V\left(A_i^k, \omega; P^k, Y\right) \right] - F\lambda_i^k \right\}. \tag{17}$$

where $V(A_i^k, \omega; P^k, Y)$ is the firm's Stage-2 profit given a realization of payoff-relevant environment, as defined in (16). This environment is realized only after the firm has chosen its product scope. $F\lambda_i^k$ denotes the fixed cost of developing λ_i^k product opportunities.

The expectation in (17) is taken over the distribution of the firm's payoff-relevant environment. The distribution of the payoff-relevant environment ω when firm i chooses scope λ is written as

$$\omega_i^k(\lambda) \sim \Gamma^k(\lambda), \tag{18}$$

I collect these scope-contingent distributions in

$$\Gamma^k \equiv \left\{ \Gamma^k(\lambda) \right\}_{\lambda \in \Lambda^k}.$$

An individual firm takes the entire family Γ^k as given. Its scope choice selects the distribution $\Gamma^k(\lambda)$ relevant for its own future environment, but does not alter that distribution

since each firm is atomistic in the industry.

The family Γ^k deserves more discussion here. It is a general equilibrium object determined endogenously. Let G^k denote the cross-sectional distribution of firm characteristics (A_i^k, λ_i^k) generated by firms' optimal Stage-1 choices. Given G^k, random product-market placement determines the distribution of firms, product ranks, and portfolios in the competitive environment surrounding a focal firm, and hence determines $\Gamma^k(\lambda)$ for every λ. In equilibrium, the distributions used by firms in (17) coincide with those generated by firms' choices and the random placement process.

3.4 Equilibrium

I close the decentralized economy by imposing labor-market clearing. The representative household supplies $\bar{L}$ units of labor inelastically, and the wage is normalized to one. Labor is used for variable production, technology investment, and product development. Let $X_i^k \equiv \sum_{j \in J_i^k} x_{ij}^k$ denote firm i's total technology investment. Labor-market clearing requires aggregate labor demand to equal aggregate labor supply

$$\bar{L} = \sum_{k=1}^{K} N^k \int \left\{ F\lambda + \mathbb{E}_{\omega \sim \Gamma^k(\lambda)} \left[\sum_{j \in J_i^k} l_{ij}^k + C\left(X_i^k\right) \right] \right\} dG^k(A, \lambda). \tag{19}$$

The three terms on the right-hand side are labor used for product development, variable production, and technology investment, respectively.

A symmetric Bayesian equilibrium consists, for each industry k, of a scope policy $\lambda^k(A)$, an induced distribution of firm characteristics G^k, a family of scope-contingent competitive environments $\{\Gamma^k(\lambda)\}_{\lambda \in \Lambda^k}$, Stage-2 prices and technology investments $\{p_{ij}^k, x_{ij}^k\}$ and the associated quantities $\{q_{ij}^k\}$, and an industry price index P^k, together with aggregate income Y, such that: firms' scope choices solve (17); for every realized competitive environment, each firm's price and technology-investment choices solve its Stage-2 problem, taking competitors' choices and the aggregate objects (P^k, Y) as given; G^k and Γ^k are generated by firms' optimal policies and the random product-market assignment process; demand, production, and price indices are mutually consistent; and the aggregate labor market clears according to (19).

Equilibrium is therefore a fixed point between firms' policies and the competitive environments they generate. Scope policies determine the cross-sectional distribution of

firms and product-market overlap. These distributions determine firms' Stage-2 prices and investments, while aggregate income adjusts so that total labor demand equals the fixed labor supply. Appendix Section C.2 provides the complete system of equilibrium conditions.

4 Model Characterization

This section characterizes firms' investment and product scope choices and their responses to improvements in technology efficiency.

Section 4.1 studies firms' investment and product scope choices in a monopolistic-competition special case. I assume that each firm-product variety is infinitesimal within its product market and allow product scope to be continuous. These simplifications preserve the core–periphery productivity structure and endogenous technology investment, while removing variable markups, strategic interactions, and discrete changes in product scope. I use this special case to characterize firms' responses to a common improvement in technology efficiency and derive an exact marginal condition for product scope. The analysis shows how better fixed-cost technology can allow firms to grow without expanding their product portfolios.

Section 4.2 returns to the full oligopolistic model with a finite number of suppliers in each product market and discrete product scope choices. Section 4.3 relates firms' investment decisions and productivity gains to product-market concentration, markups, and measured productivity.

4.1 Monopolistic competition special case

In this special case, I let the expected number of producers per product market, defined in equation (13), approach infinity. Each firm is therefore infinitesimal not only within its industry but also within each product market. As a result, each firm faces a constant demand elasticity η and charges a constant markup $\mu = \eta/(\eta - 1)$ over marginal cost. In this setting, firm i chooses product scope $\lambda_i \in [0, 1]$, interpreted as the measure of ranked product opportunities it develops. [13]

[13] Under anonymous product-market placement, these opportunities are assigned to a set of distinct product markets of measure λ_i. Because placement is independent of firm characteristics and firms are atomistic, all product markets have the same distribution of supplier types and product ranks.

Suppress the industry superscript and write $E = \alpha Y$. Firm i chooses $\lambda_i \in [0,1]$ and $x_i(r) \geq 0$ for ranks $r \in [0, \lambda_i]$, with $r = 0$ the core. Effective investment is $u_i(r) = \psi x_i(r)$ and productivity is $z_i(r) = A_i \exp(-\log \delta r) e^{g(u_i(r))}$. Operating profit and the common competition index are

$$\pi_i(r) = \frac{E}{\eta \Omega} z_i(r)^{\eta-1}, \qquad \Omega = N \int \int_0^{\lambda(A)} z_A(r)^{\eta-1} \, dr \, dG(A), \tag{20}$$

Here G is the distribution of firm fundamental productivity and N is the mass of potential firms. Ω is aggregate productivity. A larger Ω lowers profitability at given E. Writing $X_i = \int_0^{\lambda_i} x_i(r) dr$ and $C(X_i) = \phi_1 X_i^{\gamma}$, the firm solves

$$\max_{\lambda_i \in [0,1],\, x_i(\cdot) \geq 0} \left\{ \int_0^{\lambda_i} [\pi_i(r) - F] \, dr - C(X_i) \right\} \tag{21}$$

I next characterize the firm's optimal investment and product scope choices.

Optimal product-level investment. Consider first the firm's product-specific fixed-cost technology investment choice. Let $\nu_i = C'(X_i) = \phi_1 \gamma (X_i)^{\gamma-1}$ denote the marginal investment cost for firm i. Since $\frac{\partial ci(r)}{\partial x_i(r)} = -\psi c_i(r) g'(u_i(r))$, the investment optimality condition is

$$\psi q_i(r) c_i(r) g'(u_i(r)) = \psi l_i(r) g'(u_i(r)) \leq \nu_i, \qquad u_i(r) = \psi x_i(r), \quad x_i(r) \geq 0. \tag{22}$$

with equality whenever $x_i(r) > 0$.

Two forces govern this investment condition. First, the benefit from investment depends on the product's production base. The term $q_i(r) c_i(r)$ is the product's total variable cost. Because labor is the only variable input and the wage is normalized to one, this term also equals production employment, $l_i(r)$. The left-hand side of equation (22) therefore measures the labor savings generated by additional product-level investment.

An important feature of technology investment is that it is scale-biased. Holding the marginal investment cost fixed, investment is more valuable for a product with a larger production base. A producer with higher fundamental productivity, $A_i \delta^r$, operates at a larger scale and therefore has a stronger incentive to invest. Higher investment further lowers marginal production costs and expands its production scale, reinforcing its initial advantage. Fixed-cost technology investment can therefore amplify initial productivity

differences across producers.

The second force operates on the cost side. Optimal investment in each product depends on the common marginal investment cost, ν_i, which rises with the firm's total investment when $\gamma > 1$. Greater investment in one product raises the marginal cost of investment throughout the portfolio, inducing the firm to reduce investment elsewhere. In this sense, products within the firm compete for investment resources through the common marginal cost. The firm allocates investment by equating marginal returns across products receiving positive investment. Consequently, investment in a given product depends not only on conditions in its own market, but also on the firm's investment opportunities elsewhere in its portfolio.

Optimal product scope. Consider next the firm's product scope choice.[14] At an interior optimum, the marginal product satisfies

$$\pi_i(\lambda_i) = F + \nu_i x_i(\lambda_i) \tag{23}$$

Let $\frac{\partial X_i}{\partial \lambda_i}$ denote the change in total investment when scope expands and investment on existing products is re-optimized. Then

$$\nu_i x_i(\lambda_i) = \underbrace{\nu_i \frac{\partial X_i}{\partial \lambda_i}}_{\text{additional investment expenditure}} + \underbrace{\nu_i \left(x_i(\lambda_i) - \frac{\partial X_i}{\partial \lambda_i} \right)}_{\text{profit forgone through investment crowd-out}} \tag{24}$$

These conditions make the breadth–depth trade-off explicit. The marginal product's operating profit must cover three costs: the development cost F, additional technology investment expenditure, and operating profits forgone on existing products due to investment crowding out. The third component represents the opportunity cost of investing in the new product. Expanding scope therefore comes partly at the expense of technological upgrading in existing products, raising their unit production costs and weakening their competitive positions. Conversely, narrowing scope relaxes this pressure and allows firms to invest more in their retained products. When investment costs are separable across products, as in the case of linear firm-level investment costs, this internal

[14] The firm chooses scope before its product assignments are realized. Under the monopolistic competition benchmark, however, every assignment delivers the same competitive environment. The scope problem is therefore deterministic.

crowding-out channel disappears. Firms can then expand through product scope without directly crowding out investment in existing products, as in models emphasizing product expansion as a margin of firm growth (Bernard et al. 2011; Klette and Kortum 2004).

Substituting equation (20) into equation (23) gives the implicit scope characterization

$$\lambda_i = \frac{1}{\log \delta}\left[\log A_i + g(u_i^\lambda) + \frac{1}{\eta - 1}\log\left(\frac{E}{\eta\Omega(F + \nu_i x_i^\lambda)}\right)\right]. \tag{25}$$

Higher fundamental productivity favors broader scope, while greater internal congestion limits expansion. The following lemma establishes the net cross-sectional relationship.

Lemma 1 (Scale, scope, and internal congestion)**.** *Suppose g is continuous at zero with $g(0) = 0$, twice continuously differentiable for $u > 0$, and satisfies $g'(u) > 0$ and $g''(u) + (\eta - 1)[g'(u)]^2 < 0$ for all $u > 0$. Holding E/Ω and ψ fixed, firms with higher firm-level productivity A_i have greater total revenue and production employment, choose broader product scope, and make greater total investment.*

Proof: See Appendix C.3.

Comparative statics: response to improvements in technology efficiency. Having characterized firms' optimal choices, I next examine how improvements in technology efficiency affect these choices and the resulting distribution. Specifically, I consider a small, common increase in technology efficiency ψ, holding industry expenditure αY fixed. Both product scope and investment adjust.

The change in ψ affects both competition within product markets and the value of retaining peripheral products. For a continuing supplier, its within-market sales-share responds as

$$\frac{d\log s_{ij}}{d\log \psi} = (\eta - 1)\left(\frac{d\log z_{ij}}{d\log \psi} + \frac{d\log P}{d\log \psi}\right), \tag{26}$$

Defining $\kappa(u) = [g'(u)]^2/[-g''(u)]$, we have

$$\frac{d\log z_{ij}}{d\log \psi} = \underbrace{\frac{\kappa(u_{ij})}{1 - (\eta - 1)\kappa(u_{ij})}}_{\text{technology responsiveness}} \underbrace{\left[1 + (\eta - 1)\frac{d\log P}{d\log \psi} - \frac{d\log \nu_i}{d\log \psi}\right]}_{\substack{\text{investment incentive net of} \\ \text{competition and internal congestion}}}. \tag{27}$$

Equation (26) compares the supplier's productivity gain with the decline in the common price index P: suppliers whose prices fall faster than the index gain market share. Equation (27) states that changes in productivity gaps depend on the shape of the technology, initial investment intensity, and the response of the firm's marginal investment cost. The curvature restriction in Lemma 1 makes the first factor positive. If κ increases with effective investment, it is larger for products that are initially more investment-intensive. The second factor is common within a firm but differs across firms: a faster increase in ν_i dampens all of a firm's productivity gains.

[The technology change also affects firms' scope choices. Differentiating the marginal-product condition (23) and applying the envelope theorem gives

$$(-\log\delta)\frac{d\lambda_i}{d\log\psi} = \underbrace{\left[u_i^\lambda g'(u_i^\lambda) + \frac{d\log P}{d\log\psi}\right]}_{\substack{\text{within-product-market competition:}\\ \text{own gain relative to competitors}}} - \underbrace{u_i^\lambda g'(u_i^\lambda)\frac{d\log\nu_i}{d\log\psi}}_{\text{internal investment congestion}} . \tag{28}$$

Here, $u_i^\lambda = \psi x_i(\lambda_i)$ is effective investment for the firm's marginal variety. The first bracket combines the direct effect of better technology on the marginal variety's optimized contribution with the change in market prices, which reflect changes in competition within the product market. The second captures the change in its internal opportunity cost: higher total investment raises ν_i, making peripheral investment more expensive.

The proposition below formalizes the joint pattern of refocusing, leading-firm specialization, and reallocation toward productive suppliers consistent with the paper's motivating evidence.

Proposition 1 (Scale-biased upgrading and product scope)**.** *Consider a small common increase in ψ, holding industry expenditure fixed. Maintain the conditions of Lemma 1, and suppose $\kappa(u) = [g'(u)]^2/[-g''(u)]$ is strictly increasing, $ug'(u)$ is non-decreasing, and $\gamma > 1$.*

(a) Scale-biased upgrading and competition. Holding the market demand shifter and the firm's marginal investment cost ν_i fixed, an increase in ψ generates larger proportional productivity gains for suppliers with higher initial effective investment.

(b) Within-firm refocusing. Among retained products, those with higher fundamental productivity obtain larger proportional productivity gains and faster revenue growth.

(c) Leading-firm specialization. There exists a finite A^* such that firms with $A_i > A^*$ increase

total investment and sales while reducing scope. Their marginal investment cost rises, and the combined industry sales share of any fixed group $A_i \geq A_0 > A^*$ increases.

Proof. See Appendix C.4.

Proposition 1 connects scale-biased upgrading within product markets to how multi-product firms expand. Fixed-cost technology generates endogenous returns to scale, so suppliers with higher fundamental productivity operate at a larger scale and invest more, amplifying initial productivity differences. When ψ increases, varieties with higher initial effective investment respond more strongly to technological progress if κ is strictly increasing, as shown in Equation (27). In equilibrium, upgrading across suppliers lowers the common product-market price index P, intensifying competition and reducing the operating profits of varieties with smaller productivity gains. Within each firm, the change in ν_i is common across all products. Consequently, higher-productivity core products achieve larger proportional productivity gains and faster revenue growth than retained peripheral varieties.

For sufficiently productive firms ($A_i > A^*$), scale-biased upgrading shifts growth from expanding product scope to scaling up core products. Strong investment incentives in core products lead these firms to increase total technology investment, raising their internal marginal cost of investment ν_i. At the firm's marginal variety in Equation (28), tougher product-market competition and higher marginal investment costs outweigh the direct benefits of better technology, reducing the variety's net contribution below the development cost F. These firms therefore drop peripheral products while expanding their retained core lines. Revenue growth in retained products more than offsets the revenue lost from withdrawn varieties, allowing these firms to increase total sales and capture a larger share of industry sales while producing fewer products.

4.2 Firm choices under oligopolistic competition

I now return to the full oligopoly model, restoring strategic competition among firms within product markets. I characterize firms' optimal pricing decisions in this setting and discuss optimal scope and investment in Appendix C.5.

Optimal pricing and investment. In Bertrand-Nash equilibrium, firm i's price in product

market (j,k) satisfies

$$p_{ij}^k = \mu_{ij}^k c_{ij}^k, \qquad \mu_{ij}^k = \frac{\varepsilon_{ij}^k}{\varepsilon_{ij}^k - 1}, \qquad \varepsilon_{ij}^k \equiv \varepsilon(s_{ij}^k) = \sigma s_{ij}^k + \eta(1 - s_{ij}^k). \tag{29}$$

Here, s_{ij}^k denotes firm i's expenditure share in product market (j,k), as defined in equation (9). Under the nested CES demand system, the residual demand elasticity faced by the firm is a sales-share-weighted average of the across-product elasticity σ and the within-product elasticity η, similar in spirit to Gaubert and Itskhoki (2021). Since $\eta > \sigma$, this elasticity falls with the firm's within-product market share s_{ij}^k. As a result, the markup increases with the firm's market share in product market (j,k).

Because each firm supplies only finitely many products in a continuum of product markets, it takes the industry price index P^k as given. Conditional on marginal costs, pricing interactions are therefore confined to individual product markets. The common investment cost is the only direct link across a firm's products in Stage 2. The investment condition retains the same form as equation (22).

Product scope. Let $\overline{V}_i(n) = \mathbb{E}_{\omega\sim\Gamma(n)}[V(A_i,\omega)]$ be expected Stage-2 profit net of investment but before development costs if the firm were to choose product scope n. The optimal firm scope chooses

$$n_i \in \arg\max_{n\in\Lambda}\{\overline{V}_i(n) - Fn\}. \tag{30}$$

An interior optimal integer n_i necessarily satisfies $\overline{V}_i(n_i) - \overline{V}_i(n_i - 1) \geq F$ and $\overline{V}_i(n_i + 1) - \overline{V}_i(n_i) \leq F$. The full maximization, not just these adjacent comparisons, determines scope.

Appendix C.5 derives the local investment crowd-out and its contribution to the value of an additional product. Proposition 3 in Appendix C.6 derives the response to a common change in technology efficiency.

4.3 Product market outcomes

Holding product portfolios fixed, I relate heterogeneous productivity gains characterized above to concentration, markups, and production productivity.

For each product market j, let $l_j = \sum_i l_{ij}$ and $\ell_{ij} = l_{ij}/l_j$. Define concentration $H_j =$

$\sum_i s_{ij}^2$, the cost-weighted markup $\mu_j = \sum_i \ell_{ij}\mu_{ij} = [\sum_i s_{ij}/\mu_{ij}]^{-1}$, and production productivity $Z_j = q_j/l_j = \mu_j/p_j$. Substituting the pricing rule into the CES price index yields

$$Z_j = \left[\sum_{i\in\mathcal{M}_j}\left(\frac{\mu_{ij}}{\mu_j}\right)^{1-\eta} z_{ij}^{\eta-1}\right]^{1/(\eta-1)}. \tag{31}$$

Equation (31) highlights the relationship between product-market markup dispersion and productivity. With uniform markups, this reduces to the standard power mean $(\sum_i z_{ij}^{\eta-1})^{1/(\eta-1)}$. Markup dispersion distorts the allocation of production across suppliers, reducing product market productivity, as in Edmond et al. (2023). Moreover, the aggregate also reflects a love-of-variety effect: a reduction in the number of suppliers would reduce productivity.

For a common improvement in the efficiency of fixed-cost technology, the proposition below characterizes how product-market concentration, the markup, and productivity respond.

Proposition 2 (Concentration, markups, and productivity)**.** *Define $\bar{\varsigma}_j = \sum_i s_{ij}\varsigma(s_{ij})$ and $w_{ij} = s_{ij}\varsigma(s_{ij})/\bar{\varsigma}_j$. Market-share adding-up implies $G_j = \sum_i w_{ij}G_{ij}$. Write Cov_{w_j} for covariance under these weights, and retain $\varepsilon_{ij} = \varepsilon(s_{ij})$.Along a differentiable equilibrium response with fixed supplier sets*

$$\frac{dH_j}{d\log\psi} = \underbrace{2\bar{\varsigma}_j \mathrm{Cov}_{w_j}\left(s_{ij}, G_{ij}\right)}_{\text{reallocation toward larger suppliers}}, \tag{32}$$

$$\frac{d\log\mu_j}{d\log\psi} = \underbrace{(\eta-\sigma)\mu_j\bar{\varsigma}_j \mathrm{Cov}_{w_j}\left(\frac{s_{ij}}{[\eta-(\eta-\sigma)s_{ij}]^2}, G_{ij}\right)}_{\text{individual markup adjustment}} + \underbrace{\mu_j\bar{\varsigma}_j \mathrm{Cov}_{w_j}\left(\frac{1}{\eta-(\eta-\sigma)s_{ij}}, G_{ij}\right)}_{\text{reallocation across suppliers}},$$

$$\frac{d\log Z_j}{d\log\psi} = \underbrace{\sum_{i\in\mathcal{M}_j}\ell_{ij}G_{ij}}_{\text{technological improvement}} + \underbrace{\frac{\eta\mu_j\bar{\varsigma}_j}{\eta-1}\mathrm{Cov}_{w_j}\left(\frac{1}{\eta-(\eta-\sigma)s_{ij}}, G_{ij}\right)}_{\text{output reallocation}}. \tag{33}$$

If productivity gains are nondecreasing in initial market shares, concentration and cost-weighted markup weakly rise, and output reallocation contributes nonnegatively to productivity.

Proof. See Appendix C.7.

When initially larger suppliers obtain larger productivity gains from technology, ac-

tivity shifts toward them and product-market concentration rises. The cost-weighted markup also rises through two components: individual markup adjustment and expenditure reallocation toward suppliers with higher markups.

The first term in Equation (33) captures the productivity gains from improved technologies. When these gains are larger for initially larger suppliers, the resulting output reallocation provides an additional productivity gain (Baqaee and Farhi 2020). Higher productivity, concentration, and markups can therefore arise jointly from the same distribution of technological gains.

These responses hold product portfolios fixed. Scope adjustment also changes the set of suppliers and the resources devoted to product development. Product withdrawals remove varieties and can strengthen the positions of remaining suppliers, while lower development costs release resources for production. The quantitative analysis evaluates these participation and resource effects jointly with the investment responses characterized here.

5 Empirical Evidence for the Model Mechanism

I next provide reduced-form empirical evidence consistent with the model's key assumptions and predictions, using information technology (IT) as an example of scalable fixed-cost investment. IT is particularly relevant because its adoption increased rapidly over the same period in which industry concentration rose and leading firms' product scope declined (Lashkari et al. 2024). Examples of fixed-cost IT investments include specialized software embedded in production machinery, machine-tool programming, and automated control systems. These IT investments often require upfront expenditures but can support larger production volumes without proportional increases in costs (Crouzet et al. 2022). These features make IT a natural setting for examining the model's mechanism.

Using industry- and firm-level data, I document two main findings. First, industries with larger increases in IT capital per worker experience greater declines in leading firms' product scope. Second, firm-level panel data show that increases in real IT spending are associated with reductions in firms' product scope. Both findings are consistent with the model's specialization mechanism.

5.1 Data

CI Technology Database. I measure firm-level information technology using the Aberdeen CI Technology Database, formerly known as the Harte Hanks CI Technology Database. The database provides establishment-level information on firms' use of information technology from 1998 to 2019. It includes measures of annual expenditures on hardware, software, and communications equipment. The database has been widely used in research examining the role of IT in firm organization and productivity (Bresnahan et al. 2002, Bloom et al. 2012).

The database also reports establishment-level DUNS numbers, which allow me to link its records to the Dun & Bradstreet data. I aggregate these establishment-level records to construct annual firm-level measures of IT spending.

5.2 IT investment and top firm product scope: Industry-level evidence

I first use industry-level data to examine whether industries with larger improvements in IT efficiency experience greater declines in the product scope of their top 1% firms. Because improvements in IT efficiency are not directly observed at the industry level, I follow Michaels et al. (2014) and use growth in IT capital per worker as a proxy for industry exposure to these improvements. The underlying assumption is that improvements in IT efficiency reduce production costs more in industries that rely more heavily on IT for technological reasons. These industries are therefore expected to increase IT adoption more rapidly. Specifically, I measure industry-level IT exposure using the annual log change in IT capital per worker:

$$\Delta\text{Exposure}_{k,t} = \log\left(\frac{\text{IT Capital}_{k,t}}{L_{k,t}}\right) - \log\left(\frac{\text{IT Capital}_{k,t-1}}{L_{k,t-1}}\right), \tag{34}$$

where $\text{IT Capital}_{k,t}$ denotes the KLEMS measure of IT capital in industry k and year t, and $L_{k,t}$ denotes total industry employment. In the KLEMS data, IT capital input is measured as compensation to hardware and communications equipment and is available beginning in 1997. The KLEMS measure is reported at the two-digit NAICS level. I concord two-digit NAICS industries to two-digit SIC industries following Schaller and DeCelles (2021).

I estimate the following regression relating changes in IT exposure to changes in the

product scope of top firms across industries

$$\Delta y_{k,t} = \alpha \Delta \text{Exposure}_{k,t} + X'_{k,t}\beta + \gamma_k + \varepsilon_{k,t}. \tag{35}$$

Here, $\Delta y_{k,t}$ is the change in the product scope of the top 1% of firms in industry k between years $t-1$ and t, and $\Delta \text{Exposure}_{k,t}$ is the change in IT capital per worker over the same period. The vector $X_{k,t}$ contains additional industry-level controls. Industry fixed effects, γ_k, absorb persistent industry-specific differences in changes in product scope, corresponding to industry-specific trends in the level of product scope.

The vector $X_{k,t}$ includes industry-level controls for other factors that may affect changes in firm product scope. First, I control for industry concentration using the industry-level HHI in year $t-1$ and its change between $t-1$ and t. Second, I control for changes in industry value added to account for the change in U.S. manufacturing activity. Finally, I control for import competition from China. As highlighted in the literature, the rapid growth of Chinese imports since the 1990s has substantially affected U.S. manufacturing (Amiti and Heise 2025; Autor et al. 2013). I therefore include the log change in imports from China between $t-1$ and t as a control variable.

Table 2 reports the estimates of equation (35). Column (1) reports the estimated coefficient α without additional controls, weighting industries by employment in 1997. The relationship is negative: industries with larger increases in IT exposure experience larger declines in the product scope of their top 1% firms. A 1 log point increase in IT exposure is associated with a reduction of 0.36 in product scope. Column (2) adds the full set of industry-level controls except the import competition shock, and the negative relationship remains. Column (3) further controls for import competition from China. I find that the China shock is not significantly associated with the reduction in the product scope of top 1% manufacturing firms. Across these specifications, the estimated relationship remains negative and the magnitude of the coefficient is broadly stable.

These industry-level patterns suggest that industries with larger increases in IT exposure experience larger reductions in the product scope of their leading firms. This evidence is consistent with the model prediction in Proposition 1.

Table 2: Top firm scope and IT exposure: industry-level regression

	Outcome: Δ Scope of top 1% firms		
	(1)	(2)	(3)
Δ Log IT per worker	-0.357***	-0.290**	-0.310***
	(0.137)	(0.108)	(0.103)
Initial log HHI		0.091***	0.094***
		(0.020)	(0.019)
Δ HHI		0.109***	0.099***
		(0.037)	(0.034)
Δ log(VA)		0.241	0.136
		(0.167)	(0.179)
Δ log(China Import)			0.010
			(0.077)
Observations	460	460	460
R-squared	0.071	0.101	0.103

Notes: This table reports estimates of equation (35). Column (1) reports the estimated coefficient α without any controls. Column (2) adds the full set of industry-level controls except the import competition shock. Column (3) further controls for the China import shock. Standard errors, clustered at the industry level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 IT investment and firm product scope: Firm-level evidence

A key assumption of the model is that product-specific investments in fixed-cost technology are subject to a common convex firm-level cost. As a result, increasing investment in one product raises the marginal cost of investing in other products. Products therefore compete for investment resources within the firm, creating internal congestion on the supply side. While previous studies have examined competition for resources within firms, I focus on its implications for product scope. Specifically, I use firm-level panel data to examine whether increases in IT investment are associated with firms reducing the number of products they produce.[15]

Specifically, I estimate the following regression to examine how changes in firms' IT adoption are associated with changes in their product scope and employment:

$$\Delta y_{ikt} = \beta \Delta \text{IT}_{ikt} + X'_{ikt}\gamma + \alpha_{kt} + \varepsilon_{ikt}. \tag{36}$$

I estimate this specification separately for two outcomes. The dependent variable, Δy_{ikt},

[15] A strand of literature documents the internal competition across plants. See, for example, Giroud and Mueller (2015); Kehrig and Vincent (2026).

denotes either the change in the number of products produced by firm i in industry k or the log change in its employment between years $t-1$ and t. On the right-hand side, ΔIT_{ikt} denotes the log of firm-level real IT investment over the same period. The vector X_{ikt} includes controls for firm age, initial product scope, initial employment, and initial IT capital in period $t-1$. These controls account for differences in firms' life-cycle stages and initial size and scope. Industry-by-year fixed effects, α_{kt}, absorb industry-specific changes over time in product-scope dynamics.

Table 3 reports the regression results. Standard errors are clustered at the firm level. Column (1) uses the full sample. A doubling of real IT investment is associated with an annual change in product scope that is lower by approximately 0.004 products. Column (2) restricts the sample to firms that belong to the top 1% of their industry's employment distribution in at least one sample year. For these firms, the corresponding difference is approximately 0.010 products.

These firm-level estimates are small relative to the industry-level estimates. This is because the industry- and firm-level estimates capture different aspects of the relationship between IT adoption and product scope. At the industry level, changes in leading firms' product scope reflect both their own technology investment and upgrading by competitors. As competitors invest more, a firm's peripheral products may become less profitable, inducing it to withdraw them. The firm-level regression instead examines whether increases in a firm's own IT investment are associated with reductions in its product scope, controlling for changes common to each industry and year. The negative coefficient shows that this relationship persists even after accounting for common industry-year effects.

The model suggests two opposing effects of a firm's own technology investment on product scope. On the one hand, investment lowers marginal production costs, making existing products more profitable to retain. On the other hand, greater investment in core products raises the common marginal investment cost, making peripheral products less attractive. The negative firm-level association is consistent with this internal competition for investment resources. These opposing forces may also help explain why the estimated relationship is relatively small.

Columns (3) and (4) examine how firms' employment changes with IT investment. I find a positive and statistically significant relationship among firms that have belonged to the top 1% of the employment distribution in at least one year. For these firms, doubling

Table 3: IT Spending, Product Scope, and Employment

	Δ Scope		Δ log Employment	
	(1) Full	(2) Top 1%	(3) Full	(4) Top 1%
Log real IT investment	-0.006*	-0.014**	0.014	0.037*
	(0.003)	(0.006)	(0.010)	(0.019)
Log employment, $t-1$	0.087***	0.093***	-0.481***	-0.515***
	(0.013)	(0.019)	(0.028)	(0.045)
Log real IT capital, $t-1$	-0.006	-0.006	-0.023*	-0.014
	(0.004)	(0.006)	(0.013)	(0.020)
Firm FE	Yes	Yes	Yes	Yes
SIC2 × year FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	911,762	18,353	911,762	18,353

Notes: This table reports regression results of equation (36). Standard errors are clustered at the firm level and reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

IT investment is associated with a 2.6% increase in employment.

A potential concern is endogeneity. As commonly emphasized in the literature, positive unobserved productivity shocks may induce firms to adopt more IT. However, such shocks would also tend to expand firms' product scope, generating an upward bias in the estimated relationship between IT adoption and product scope. Despite this potential upward bias, I find a negative coefficient.

6 Model Calibration

I now estimate the model. I first describe the calibration and structural estimation strategy, then assess how well the model matches targeted and untargeted moments.

6.1 Technology Productivity Function

For the baseline calibration, I specify the productivity gain from fixed-cost investment in equation (10) as

$$g(x_{ij}) = \frac{1}{\eta - 1} \log\left(1 + \psi x_{ij}^{\beta}\right), \quad 0 < \beta < 1 \tag{37}$$

Here, x_{ij} denotes fixed cost investment specific to product j. This functional form satisfies the properties specified in Proposition 3. I normalize fixed-cost technology efficiency in equation (37) to $\psi = 1$ in the baseline calibration.

6.2 Calibration

In the baseline calibration, I calibrate the model to the 2020 economy. I divide the model's parameters into two groups. The first group consists of parameters governing household preferences. These parameters are standard in the literature, so I calibrate them using existing estimates. The second group includes parameters governing production, particularly the technology productivity function, the firm-level investment cost, and the structure of fundamental productivity across products within firms. This block contains new features relative to the existing literature, so I estimate its parameters using the Simulated Method of Moments (SMM).

6.2.1 Externally Calibrated Parameters

The parameters reported in Table 4 are either calibrated externally or taken from existing estimates in the literature. I set σ, the elasticity of substitution across product markets defined at the eight-digit SIC level, to 2.5, according to Broda and Weinstein (2006). I set the elasticity of substitution within product markets to 5.0, according to Hottman et al. (2016). I draw on different sources for the two elasticities because neither paper provides estimates for both margins at the level of aggregation used in my model.[16]

Table 4: Externally Calibrated Parameters

Parameter	Interpretation	Source	Value
σ	EoS across product markets	Broda and Weinstein (2006)	2.5
η	EoS within product markets	Hottman et al. (2016)	5.0
N	Mass of potential entrants	Externally calibrated	30
ψ	Efficiency of production technology	Normalization	1.0

[16] Broda and Weinstein (2006) do not estimate substitution within narrowly defined product markets, while Hottman et al. (2016) do not report an across-product-market elasticity corresponding to our eight-digit SIC definition. Specifically, $\sigma = 2.5$ matches the median elasticity of substitution for disaggregated 3- to 5-digit SITC categories (2.2 to 2.8) and differentiated goods (2.1 to 2.5) estimated by Broda and Weinstein (2006). $\eta = 5.0$ lies between the median cross-firm elasticity (3.9) and median across-barcode elasticity (6.9) within product groups estimated by Hottman et al. (2016), and matches the standard within-market benchmark in quantitative oligopoly models (for example, Atkeson and Burstein (2008)).

Finally, in the simulation, I set the expected number of firms per product market to 30, based on the mean number of firms per product market in the 2020 Dun & Bradstreet data.

6.2.2 Simulated Method of Moments for the Structurally Calibrated Parameters

The remaining six parameters are estimated by indirect inference, matching model-implied moments to their empirical counterparts. These parameters are the shape parameter of the Pareto distribution, ϑ; the rate at which productivity declines along a firm's product ladder, δ; the fixed cost of creating a product, F; and the three parameters governing the productivity and investment cost functions (β, ϕ_1, γ). I collect these parameters in the vector Θ and estimate them jointly using a set of empirical moments.

$$\Theta \equiv \{\vartheta, \delta, F, \beta, \phi_1, \gamma\}$$

I next discuss which moments are most informative about each parameter and describe how key moments are constructed. In practice, however, all moments are jointly determined in equilibrium by the full parameter vector.

I use employment data from Dun & Bradstreet to discipline the parameters $(\vartheta, \delta, \beta)$. The Pareto shape parameter ϑ governs dispersion in fundamental productivity and, in turn, employment across firms. To discipline ϑ, I estimate the slope of the upper tail of the firm-employment distribution. Following Gabaix and Ibragimov (2011), I rank firms by employment within each two-digit SIC industry and estimate

$$\log\left(r_{ik} - \frac{1}{2}\right) = \alpha_k - \zeta_L \log L_{ik} + \varepsilon_{ik}, \tag{38}$$

where r_{ik} is firm i's employment rank within industry k, L_{ik} is its total employment, and α_k denotes industry fixed effects. I estimate the regression using the top 10% of firms by employment within each industry and target the estimated tail exponent $\widehat{\zeta}_L$.

The employment gap between a firm's core and second-ranked products is informative about parameters δ and β. Specifically, the parameter δ governs how quickly productivity declines from a firm's core product to lower-ranked products. I therefore discipline δ using the average employment gap between the core and second-ranked products among multi-product firms in the bottom 50% of the firm size distribution. To discipline

the returns to technology investment, I use differences in the allocation of employment across products among firms of different sizes. The parameter β governs the curvature of productivity gains from product-level investment. I target the difference in the core-to-second product employment gap between firms in the top decile and the bottom half of the employment distribution. This moment captures how the relative scale of a firm's core product varies with firm size and helps discipline the returns to technology investment. Together, these two moments inform the allocation of employment across products within firms.

Specifically, I estimate the following regression:

$$\log L_{i(1)} - \log L_{i(2)} = \alpha + b_1 \mathbb{1}(\text{Top } 10\%_i) + b_2 \mathbb{1}(\text{50th–90th percentiles}_i) + \varepsilon_i, \tag{39}$$

where $L_{i(1)}$ and $L_{i(2)}$ denote employment in firm i's largest and second-largest products, respectively. Employment percentiles are defined within each industry. The first indicator equals one for firms in the top decile, while the second equals one for firms above the median but outside the top decile. Firms in the bottom half of the employment distribution form the omitted group. The constant α therefore measures the mean log employment gap between the largest and second-largest products among firms in the bottom half. The coefficient b_1 measures the difference in this mean gap between top-decile firms and firms in the bottom half.

Table D.1 reports the regression results of equation (39). Column (1) reports unweighted estimates, while column (2) weights each firm by its employment. The estimated intercept α is similar across the two specifications, at 0.993 and 1.029 log points, respectively. This implies an employment gap of approximately one log point between the largest and second-largest products among firms in the reference group. The gap is 0.596 log points larger for firms in the top 10% of the employment distribution than for multi-product firms in the bottom 50% in the unweighted specification. The corresponding difference is 0.595 log points when firms are weighted by employment. Thus, the estimated difference is robust to employment weighting. I use the unweighted estimates from column (1) as the baseline moment targets.

Additionally, I use firm-level revenue and variable-cost data from Compustat data to discipline the investment cost parameters (ϕ_1, γ). The parameter ϕ_1 governs the scale of technology investment costs, while γ determines how rapidly marginal investment costs rise with total firm investment. I target the average revenue-to-variable-cost ratio,

R_i/VC_i, and how this ratio varies with firm size.

Specifically, I estimate

$$\log\left(\frac{R_i}{VC_i}\right) = \alpha_k + b_{RVC}\log R_i + \varepsilon_i, \tag{40}$$

where α_k denotes two-digit SIC industry fixed effects. The average ratio captures the level of revenue relative to variable costs, while the coefficient b_{RVC} measures how this ratio varies with firm revenue. Together with the employment-gap moments, these moments help discipline the parameters governing technology investment. Table D.2 reports the regression results. Doubling revenue is associated with a revenue-to-variable-cost ratio that is approximately 1.76% higher.

Finally, I use the share of multi-product firms to discipline the product development cost F. This parameter governs the cost of expanding a firm's product portfolio.

To estimate Θ, I minimize the loss function

$$\mathcal{L}(\Theta) \equiv \big(m(\Theta) - \tilde{m}\big)' \mathbf{W} \big(m(\Theta) - \tilde{m}\big),$$

where $m(\Theta)$ is the vector of simulated moments implied by the model, and $\tilde{m}$ is the corresponding vector of moments in the 2020 data. The weighting matrix $\mathbf{W}$ determines the relative importance assigned to each moment in estimation.

6.3 Estimation results and model validation

Table 5 reports the estimated parameter values and compares the targeted moments in the model with their empirical counterparts. Panel A lists the targeted moments and their values in the data and the model. The model closely matches moments characterizing the firm employment-size distribution, employment gaps across products within firms, the revenue-to-variable-cost ratio, and how this ratio varies with firm size. Panel B provides a list of the estimated parameters and their values.

Table 5: Estimated parameters using SMM

Panel A. Targeted Moments

Moment	Value (Data/Model)
Firm-employment upper-tail slope	1.16 / 1.16
Share of multi-product firms	0.09 / 0.10
Core-to-second product emp gap: Bottom 50% firms	0.99 / 0.99
Core-to-second product emp gap: Top 10% - Bottom 50% firms	0.60 / 0.60
Revenue/variable cost in Compustat (R/VC)	1.55 / 1.48
Regression slope of $\log(R/VC)$ on log sales	0.03 / 0.03

Panel B. Estimated Parameters

Parameter	Interpretation	Estimate
Firm productivity distribution and fixed cost		
ϑ	Pareto shape parameter	5.866
δ	Speed of productivity decay	0.717
F	Product development cost	0.001
Technology productivity and cost function		
β	Technology productivity curvature	0.902
ϕ_1	Investment cost scalar	0.011
γ	Investment cost curvature	1.161

Notes: This table reports the results of the Simulated Method of Moments (SMM) estimation. Panel A lists the targeted moments and their values in the data and the model. Panel B reports the estimated parameters and their values.

The estimation uses limited information about the distribution of firm product scope and how it varies with firm size. I therefore use these largely untargeted cross-sectional patterns to evaluate the model's quantitative performance.

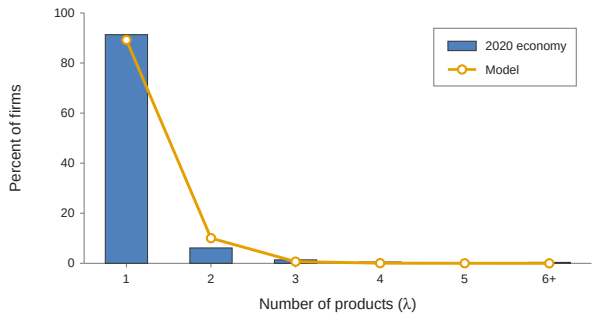
Figure 2a compares the distribution of firm product scope in the data and the calibrated model. I report the share of firms by the number of products they produce, grouping firms with six or more products into a single category. The blue bars represent the 2020 Dun & Bradstreet data, while the orange line with circle markers shows the corresponding model predictions. The share of single-product firms is targeted in the estimation, while the remaining shares are untargeted. The model closely matches the distribution of product scope, including these untargeted moments.

Figure 2b compares average product scope across firm employment deciles in the model and the 2020 data. The orange line reports the model predictions, while the blue bars show the corresponding empirical values. Although these cross-sectional patterns are not directly targeted in the estimation, the model closely reproduces the data. Most firms in the bottom eight deciles produce only one product, a pattern captured by the

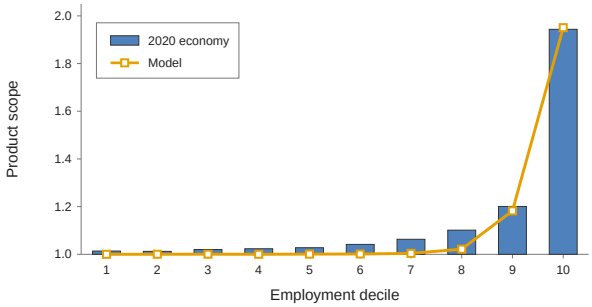
model. Among firms in the top two deciles, where multi-product firms are more common, the model also closely matches the higher average product scope observed in the data.

Figure 2: Product scope distribution and scope-employment relationship: Model vs. data

(a) Product scope



(b) Scope-emp relationship



Notes: This figure compares the calibrated model with the 2020 Dun & Bradstreet data. Panel (a) plots the distribution of the number of products produced by firms, while Panel (b) plots average product scope by firm employment decile. In both panels, the blue bars represent the data, and the orange line represents the corresponding model predictions.

The average markup is also an untargeted moment. The model predicts a cost-weighted average markup of 1.32 across all producers, which falls within the range of estimates reported in the literature (De Loecker et al. 2020).

7 Quantification Exercise

In this section, I use the quantitative model to evaluate how improvements in the efficiency of fixed-cost technology affect aggregate productivity and welfare.

7.1 Changes in technology efficiency: Calibration and implications

The main counterfactual examines the effects of changes in the efficiency of fixed-cost technology. To this end, I calibrate the change in the technology-efficiency parameter ψ between 1990 and 2020 so that the model reproduces the observed increase in the fixed-cost share over this period.

Using Compustat data, I calibrate the change in ψ to match the observed percentage

change in the aggregate fixed-cost share between 1990 and 2020. The calibration implies that ψ in 1990 is 38.61% lower than its 2020 level ($\psi = 1$).

In Sections 7.1.1 and 7.1.2, I compare firms' product scope and revenue, as well as economy-wide concentration and welfare, across these two economies. Together, these exercises quantify the extent to which improvements in technology efficiency from 1990 to 2020 account for the observed decline in firm product scope and rise in industry concentration.

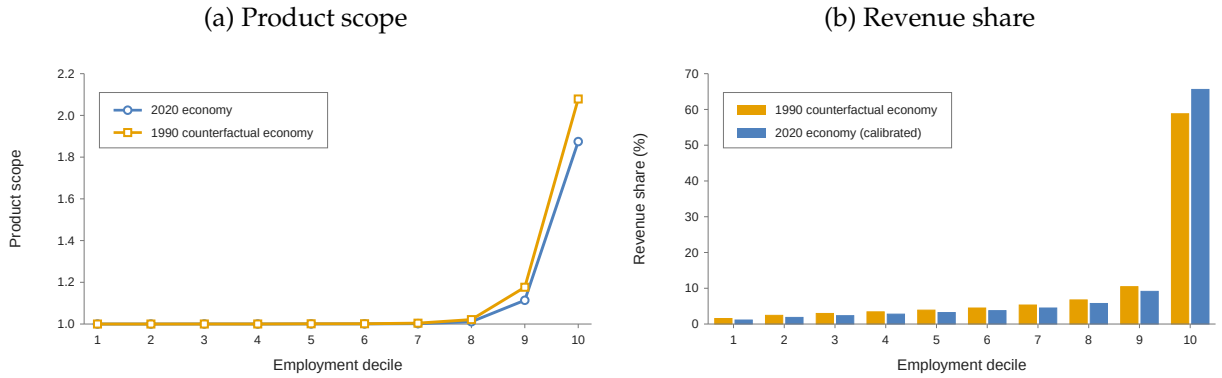
7.1.1 Changes in firm product scope and market share

Figure 3a compares average firm product scope across employment deciles in the 1990 counterfactual economy and the calibrated 2020 economy. The orange line reports average product scope under 1990 technology efficiency, while the blue line reports the corresponding values in the 2020 baseline. Two findings stand out. First, average product scope is lower in the 2020 economy throughout the firm-size distribution. Second, the decline is particularly pronounced among the largest firms. For firms in the top employment decile, average product scope is 7.9% lower in the 2020 baseline than in the 1990 counterfactual. This pattern is qualitatively consistent with the 16.15% decline in product scope observed in the data between 1990 and 2020. These results suggest that improvements in technology efficiency are an important driver of the decline in product scope among leading firms.

Figure 3b compares the distribution of revenue across firm employment deciles in the 1990 counterfactual economy and the calibrated 2020 economy. The orange bars report the revenue share of each employment decile under 1990 technology efficiency, while the blue bars report the corresponding shares in the 2020 baseline. The revenue share declines for firms in each of the bottom nine deciles, while the top decile gains a larger share of total revenue. Specifically, the revenue share of the top 10% of firms rises from 58.79% in the 1990 counterfactual to 65.60% in the 2020 baseline. This pattern is consistent with the observed increase in the share of industry revenue accounted for by leading firms between 1990 and 2020.

Appendix Figures E.1a and E.1b further plot the average productivity and markup by firm employment decile. Productivity and markups are higher in the 2020 baseline, with the increases concentrated in the top decile.

Figure 3: Product scope and revenue share by firm size



Notes: This figure compares firm product scope and revenue shares across employment deciles in the 1990 counterfactual and the 2020 baseline calibration. In the 1990 counterfactual, I reduce technology efficiency ψ by 38.61% relative to its 2020 level to match the observed change in the aggregate fixed-cost share. Panel (a) plots average product scope by firm employment decile. The blue line represents the 2020 baseline calibration, and the orange line represents the 1990 counterfactual. Panel (b) plots each decile's share of total revenue. The blue bars represent the 2020 baseline calibration, and the orange bars represent the 1990 counterfactual.

7.1.2 Economy-wide concentration, productivity, and welfare

What share of the observed increase in aggregate market concentration can be accounted for by improvements in technology efficiency? Table 6 reports the counterfactual results, comparing the calibrated 2020 economy with an economy in which technology efficiency is reduced to its 1990 level.

Table 6: Concentration, Productivity, and Welfare Change from Technology Change

	Δ Model Counterfactual (%)	Δ Data (%)
A. Industry concentration		
Industry HHI	+21.53 %	+23.15%
Observed active firms	-4.91 %	-11.32 %
B. Product-market concentration		
Product market HHI	+30.29 %	–
Suppliers per product	-7.73 %	-11.55 %
C. Fixed costs		
Fixed-cost share (%)	+21.88 %	+22.00 %
D. Product scope		
Top-1% mean scope	-15.43 %	-36.04 %
Top-10% mean scope	-7.92 %	-16.15 %
Multi-product share	-24.06 %	-14.68 %
E. Welfare and productivity		
Welfare, $Q = E/P$	+5.72 %	–
Productivity	+8.33 %	–

Notes: This table compares changes in industry concentration, product-market concentration, fixed-cost shares, and product scope in the model and the data. It also reports the model-implied changes in aggregate productivity and welfare. ΔModel denotes the difference between the calibrated 2020 economy and the counterfactual economy in which technology efficiency ψ is reverted to its 1990 level. ΔData denotes the observed changes between 1990 and 2020. The empirical measures are constructed using Dun & Bradstreet data, except for the fixed-cost share, which is constructed using Compustat data.

First, improvements in technology efficiency generate substantial increases in concentration at both the industry and product levels. Relative to the 1990 counterfactual, the industry HHI in the calibrated 2020 economy is 21.53% higher, while the average product-level HHI increases by 30.29%. The larger increase at the product level suggests that technological progress has a more pronounced effect on concentration within individual products than at the industry level.

Improvements in technology efficiency also affect the number of active firms, both in the aggregate and within individual products. Higher technology efficiency generates stronger selection. Relative to the 1990 counterfactual, the calibrated 2020 economy has 4.91% fewer active firms, reflecting lower participation among less productive firms. This change is consistent with the decline observed in the data, where the number of firms

falls by 11.32% between 1990 and 2020, although the model generates a smaller decline. Similarly, the average number of producers per product is 7.73% lower in the calibrated 2020 economy, compared with a decline of 11.55% in the data. Thus, the model generates declines in the number of active producers both economy-wide and within individual products, consistent with the observed patterns.

Finally, improvements in technology efficiency generate substantial aggregate productivity and welfare gains. Relative to the 1990 counterfactual, aggregate productivity is 8.33% higher and welfare is 5.72% higher in the calibrated 2020 economy. Thus, although technological progress raises industry concentration, it also generates sizable productivity and welfare gains. This finding is consistent with the view that rising concentration can reflect productivity-enhancing technological change (Autor et al. 2020; Covarrubias et al. 2020).

Importantly, this counterfactual isolates the increase in concentration and markups driven by improvements in technology efficiency and endogenous technology adoption. Other forces that weaken competition, such as higher barriers to entry, may also raise concentration and markups without generating comparable productivity and welfare gains. These forces are beyond the scope of this paper.

7.1.3 The role of firm adjustments and multi-product firms

The preceding results show that the model generates changes in industry concentration and firm product scope consistent with the data, along with substantial productivity and welfare gains. However, the preceding comparison does not separate the sources of these gains. How much comes directly from technological progress, and how much arises from firms' endogenous adjustments in technology investment and product scope? In particular, how important is it to model multi-product firms rather than single-product firms when quantifying these effects? To address these questions, I conduct additional counterfactual exercises that separate the direct effects of technological progress from those arising through firms' investment and scope adjustments.

To distinguish these margins, I consider three counterfactuals with different restrictions on firms' technology investment and product scope choices. In the first counterfactual, I isolate the direct effect of technological progress by solving for an economy in which technology efficiency increases to its 2020 level, while firms' product scope and technology investment remain fixed at their 1990 levels. Comparing this economy with

the 1990 counterfactual allows me to quantify the direct contribution of technological progress to changes in concentration, aggregate productivity, and welfare.

Row 2 of Table 7 reports the change in welfare and productivity in this counterfactual. Technological progress alone raises aggregate productivity and welfare by 3.75% and 3.95% respectively. These gains account for 45% of the total productivity gain and 69% of the total welfare gain. The remaining 55% and 31%, respectively, arise from firms' endogenous adjustments in technology investment and product scope.

Second, I solve a counterfactual in which firms can reoptimize technology investment while keeping product scope fixed. However, I require productivity growth to be the same across all products within each firm. This restriction approximates a single-product-firm model, in which firms choose their overall technology investment without allowing different productivity gains across products. Row 3 of Table 7 reports the results. Relative to the first counterfactual, endogenous technology investment adds 0.68 percentage points to the welfare gain and 1.38 percentage points to the productivity gain. These results show that endogenous investment responses generate additional productivity and welfare gains, even in a framework that approximates single-product firms.

Third, I allow firms to adjust their product scope while maintaining the restriction of uniform productivity growth across products. This exercise measures the additional effects of endogenous scope adjustment. Row 4 of Table 7 reports the results. Relative to the second counterfactual, allowing firms to adjust their product scope raises welfare by an additional 0.38 percentage points and aggregate productivity by 1.21 percentage points.

Finally, I return to the full model and allow firms to choose different levels of technology investment across their products. Relative to the third counterfactual, this raises welfare by an additional 0.71 percentage points and aggregate productivity by 1.99 percentage points. Firms allocate more investment toward their most productive products and reduce investment in peripheral ones. These adjustments allow more productive producers to expand production, generating additional productivity and welfare gains.

This result is related to the gains from production reallocation studied by Baqaee and Farhi (2020). In my model, however, production not only reallocate toward more productive suppliers, and these firms also endogenously improve their production technologies. By selectively investing in their stronger products, firms change both the distribution of productivity and the allocation of production across products. These adjustments further

increase aggregate productivity and welfare.

Comparing the full model with the second counterfactual allows me to quantify the additional gains from endogenous product scope and heterogeneous technology investment across products. These two margins are unique to the multi-product setting and help assess the importance of modeling multi-product firms rather than single-product firms. Overall, firms' endogenous adjustments generate additional welfare gains of 1.77 percentage points and productivity gains of 4.58 percentage points. Product-scope adjustment and selective investment across products contribute 1.09 and 3.20 percentage points to these gains, respectively. These represent 19.1% and 38.4% of the total welfare and productivity gains, respectively. Thus, abstracting from the multi-product nature of firms would understate the aggregate productivity and welfare effects of improvements in fixed-cost technology efficiency.

Table 7: Decomposing Welfare and Productivity Changes

	Welfare	Productivity
Baseline: 1990 equilibrium	+0.00% (—)	+0.00% (—)
CF 1. Technology improvement; investment and scope fixed	+3.95% (+3.95%)	+3.75% (+3.75%)
CF 2. Uniform within-firm productivity growth; scope fixed	+4.63% (+0.68%)	+5.13% (+1.38%)
CF 3. Scope adjustment; uniform within-firm productivity growth	+5.01% (+0.38%)	+6.34% (+1.21%)
Full adjustment: 2020 equilibrium	+5.72% (+0.71%)	+8.33% (+1.99%)

Notes: This table reports the decomposition of aggregate productivity and welfare gains across counterfactual exercises. The reference economy is the 1990 counterfactual, in which technology efficiency ψ is 38.61% below its 2020 level. In counterfactual 1 (CF 1), I restore ψ to its 2020 level while holding firms' technology investment and product scope fixed at their 1990 levels. In counterfactual 2 (CF 2), I allow firms to reoptimize technology investment but require productivity growth to be uniform across products within each firm. In counterfactual 3 (CF 3), I further allow firms to adjust their product scope while maintaining the restriction of uniform productivity growth across products. The full adjustment case is the 2020 calibration economy.

7.2 Policy counterfactuals

7.2.1 Subsidizing product creation

I first consider a policy aimed at encouraging the creation of new product varieties. Specifically, I consider a subsidy covering half of firms' product-development costs. The motivation is that the private return to developing a new variety may differ from its social return. Firms do not internalize the benefits to consumers from greater variety and stronger competition, which can lead to too few varieties (Mankiw and Whinston 1986,

Dhingra 2013).[17] These forces make the welfare effects of subsidizing product creation ambiguous.

Specifically, in the counterfactual, the subsidy applies uniformly to expenditure on the entire chosen portfolio. It lowers firms' private development costs without changing the labor required for development. The government finances its payments through a lump-sum tax on the representative household. I hold the calibrated parameters, technology efficiency, and mass of potential firms fixed and re-solve the equilibrium, allowing firms to adjust participation, product scope, technology investment, and prices. The exercise therefore evaluates whether additional variety and changes in competition justify the resources devoted to product development and any crowding out of technology investment in existing products.

Column (1) in Table 8 reports the policy counterfactual results. In the calibrated model, subsidizing product creation reduces welfare. Two forces explain this result. First, expanding product scope crowds out technology investment in firms' core products, lowering overall production productivity. Second, developing additional products requires more labor, leaving fewer resources available for production. Together, these effects reduce aggregate welfare.

Table 8: Policy Counterfactual

	Development subsidy (1)	Markup-targeting transfer (2)
Welfare	-1.05%	$+2.17\%$
Productivity	-0.21%	$+3.55\%$

7.2.2 Policy analysis: Subsidy for high-markup products

I next consider a product-level tax-and-subsidy schedule designed to correct the misallocation arising from markup dispersion, following Edmond et al. (2023). Conditional on technologies and product-market participation, high-markup suppliers produce too little relative to lower-markup suppliers. This creates differences in the marginal social returns to production labor across suppliers. Reallocating labor can therefore raise aggregate output without increasing total production labor. The relevant distortion is markup

[17] On the other hand, firms do not internalize business-stealing effects on competing producers, potentially resulting in excessive supply of varieties.

dispersion, rather than concentration itself. If high-markup suppliers are also more productive, correcting this distortion may increase their market shares and raise concentration.

The policy induces a common price-to-marginal-cost ratio equal to the baseline cost-weighted aggregate markup. It eliminates dispersion in pricing wedges while preserving the baseline aggregate markup, rather than uniformly subsidizing sales. I hold the calibrated parameters, technology efficiency, and mass of potential firms fixed. I then solve for a new equilibrium, allowing firms to adjust their product scope and technology investment. Column (2) of Table 8 reports the counterfactual results. In the calibrated model, eliminating markup dispersion raises aggregate welfare by 2.17% and productivity by 3.55%. These results indicate that markup dispersion generates substantial allocative losses in the calibrated economy.

8 Conclusion

This paper documents new empirical facts that rising industry concentration has been accompanied by greater specialization among leading firms. Using U.S. manufacturing data, I show that much of the decline in product scope reflects continuing industry leaders reducing the number of products they produce. To explain these patterns, I develop a model linking firm specialization to improvements in the efficiency of scalable, product-specific technology investment. These improvements strengthen firms' incentives to invest in their core products, while competition and rising marginal investment costs within the firm make peripheral products less attractive. Firms can therefore account for a larger share of industry activity while producing fewer products.

In the calibrated historical exercise, improvements in technology efficiency raise industry concentration, aggregate productivity, and welfare. Firms' endogenous investment and product scope choices contribute to these aggregate gains. Relative to a counterfactual with fixed product scope and uniform productivity growth across products within each firm, allowing firms to adjust their product scope and allocate investment across products raises productivity gains by 3.20 percentage points and welfare gains by 1.09 percentage points.

These findings highlight the importance of understanding firms' technology investment and product scope decisions when evaluating the consequences of rising industry

concentration. A natural next step is to characterize optimal government policy. The policy exercises suggest that taxes or subsidies on product entry may need to be designed jointly with size-dependent subsidies within product markets, accounting for their effects on both product scope and technology investment. Incorporating product dynamics and innovation would also allow the framework to study how firms' investment and scope choices evolve over time and affect long-run economic growth.

References

Aghion, Philippe, Antonin Bergeaud, Timo Boppart, Peter J Klenow, and Huiyu Li, "A theory of falling growth and rising rents," *Review of Economic Studies*, 2023, *90* (6), 2675–2702.

Amiti, Mary and Sebastian Heise, "US market concentration and import competition," *Review of Economic Studies*, 2025, *92* (2), 737–771.

Argente, David, Munseob Lee, and Sara Moreira, "The life cycle of products: Evidence and implications," *Journal of Political Economy*, 2024, *132* (2), 337–390.

_ , Sara Moreira, Ezra Oberfield, and Venky Venkateswaran, "Scalable Expertise: How Standardization Drives Scale and Scope," Technical Report, National Bureau of Economic Research 2025.

Atkeson, Andrew and Ariel Burstein, "Pricing-to-market, trade costs, and international relative prices," *American Economic Review*, 2008, *98* (5), 1998–2031.

Autor, David, Christina Patterson, and John Van Reenen, "Local and national concentration trends in jobs and sales: The role of structural transformation," Technical Report, National Bureau of Economic Research 2023.

_ , David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen, "The fall of the labor share and the rise of superstar firms," *The Quarterly Journal of Economics*, 2020, *135* (2), 645–709.

Autor, David H, David Dorn, and Gordon H Hanson, "The China syndrome: Local labor market effects of import competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–2168.

Baqaee, David Rezza and Emmanuel Farhi, "The macroeconomic impact of microeconomic shocks: Beyond Hulten's theorem," *Econometrica*, 2019, *87* (4), 1155–1203.

_ and _ , "Productivity and misallocation in general equilibrium," *The Quarterly Journal of Economics*, 2020, *135* (1), 105–163.

Bartel, Ann, Casey Ichniowski, and Kathryn Shaw, "How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement, and worker skills," *The Quarterly Journal of Economics*, 2007, *122* (4), 1721–1758.

Benkard, C Lanier, Ali Yurukoglu, and Anthony Lee Zhang, "Concentration in product markets," *American Economic Journal: Microeconomics*, 2026, *18* (2), 268–292.

Bernard, Andrew B, Stephen J Redding, and Peter K Schott, "Multiple-product firms and product switching," *American Economic Review*, 2010, *100* (1), 70–97.

_ , _ , and _ , "Multiproduct firms and trade liberalization," *The Quarterly journal of economics*, 2011, *126* (3), 1271–1318.

Bloom, Nicholas, Raffaella Sadun, and John Van Reenen, "Americans do IT better: US multinationals and the productivity miracle," *American Economic Review*, 2012, *102* (1), 167–201.

Boehm, Johannes, Swati Dhingra, and John Morrow, "The comparative advantage of firms," *Journal of Political Economy*, 2022, *130* (12), 3025–3100.

Bornstein, Gideon, "Entry and profits in an aging economy: The role of consumer inertia," Technical Report, National Bureau of Economic Research 2025.

Bresnahan, Timothy F, Erik Brynjolfsson, and Lorin M Hitt, "Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence," *The Quarterly Journal of Economics*, 2002, *117* (1), 339–376.

Broda, Christian and David E. Weinstein, "Globalization and the Gains From Variety," *The Quarterly Journal of Economics*, 05 2006, *121* (2), 541–585.

Bustos, Paula, "Trade liberalization, exports, and technology upgrading: Evidence on the impact of MERCOSUR on Argentinian firms," *American Economic Review*, 2011, *101* (1), 304–340.

Chaney, Thomas, "Distorted gravity: the intensive and extensive margins of international trade," *American Economic Review*, 2008, *98* (4), 1707–1721.

Comment, Robert and Gregg A Jarrell, "Corporate focus and stock returns," *Journal of Financial Economics*, 1995, *37* (1), 67–87.

Covarrubias, Matias, Germán Gutiérrez, and Thomas Philippon, "1 From Good to Bad Concentration? US Industries over the Past 30 Years," *NBER Macroeconomics Annual*, 2020, *34*, 1–46.

Crane, Leland D and Ryan A Decker, "Research with private sector business microdata: The case of NETS/D&B," in "Federal Reserve Board Working Paper" 2020.

Crouzet, Nicolas, Janice C Eberly, Andrea L Eisfeldt, and Dimitris Papanikolaou, "The economics of intangible capital," *Journal of Economic Perspectives*, 2022, *36* (3), 29–52.

Dhingra, Swati, "Trading away wide brands for cheap brands," *American Economic Review*, 2013, *103* (6), 2554–2584.

Ding, Xiang, *Industry linkages from joint production*, US Census Bureau, Center for Economic Studies, 2023.

Döpper, Hendrik, Alexander MacKay, Nathan H. Miller, and Joel Stiebale, "Rising Markups and the Role of Consumer Preferences," *Journal of Political Economy*, 2025, *133* (8), 2462–2505.

Eckel, Carsten and J Peter Neary, "Multi-product firms and flexible manufacturing in the global economy," *The Review of Economic Studies*, 2010, *77* (1), 188–217.

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu, "How costly are markups?," *Journal of Political Economy*, 2023, *131* (7), 1619–1675.

Ekerdt, Lorenz KF and Kai-Jie Wu, *The rise of specialized firms*, US Census Bureau, Center for Economic Studies, 2024.

Gabaix, Xavier and Rustam Ibragimov, "Rank – 1/2: A Simple Way to Improve the OLS Estimation of Tail Exponents," *Journal of Business & Economic Statistics*, 2011, *29* (1), 24–39.

Gaubert, Cecile and Oleg Itskhoki, "Granular comparative advantage," *Journal of Political Economy*, 2021, *129* (3), 871–939.

Giroud, Xavier and Holger M Mueller, "Capital and labor reallocation within firms," *The Journal of Finance*, 2015, *70* (4), 1767–1804.

Goldberg, Pinelopi K, Amit K Khandelwal, Nina Pavcnik, and Petia Topalova, "Multiproduct firms and product turnover in the developing world: Evidence from India," *The Review of Economics and Statistics*, 2010, *92* (4), 1042–1049.

Grossman, Gene M and Elhanan Helpman, "Quality ladders in the theory of growth," *The review of economic studies*, 1991, *58* (1), 43–61.

Gupta, Apoorv, "Demand for quality, variable markups and misallocation: Evidence from india," *Variable Markups and Misallocation: Evidence from India (January 1, 2020)*, 2020.

Haskel, Jonathan and Stian Westlake, *Capitalism without capital: The rise of the intangible economy*, Princeton university press, 2018.

Hottman, Colin J., Stephen J. Redding, and David E. Weinstein, "Quantifying the Sources of Firm Heterogeneity," *The Quarterly Journal of Economics*, 08 2016, *131* (3), 1291–1364.

Hsieh, Chang-Tai and Esteban Rossi-Hansberg, "The industrial revolution in services," *Journal of Political Economy Macroeconomics*, 2023, *1* (1), 3–42.

Jiang, Xian and Hannah Rubinton, "The Adoption of Non-Rival Inputs and Firm Scope," 2024.

Kehrig, Matthias and Nicolas Vincent, "Good dispersion, bad dispersion," *Review of Economic Studies*, 2026, *93* (2), 1103–1136.

Kleinman, Benny, "Wage inequality and the spatial expansion of firms," Technical Report, Tech. rep., mimeo 2022.

Klette, Tor Jakob and Samuel Kortum, "Innovating firms and aggregate innovation," *Journal of political economy*, 2004, *112* (5), 986–1018.

Kwon, Spencer Y, Yueran Ma, and Kaspar Zimmermann, "100 years of rising corporate concentration," *American Economic Review*, 2024, *114* (7), 2111–2140.

Lashkari, Danial, Arthur Bauer, and Jocelyn Boussard, "Information technology and returns to scale," *American Economic Review*, 2024, *114* (6), 1769–1815.

Loecker, Jan De, Jan Eeckhout, and Gabriel Unger, "The rise of market power and the macroeconomic implications," *The Quarterly journal of economics*, 2020, *135* (2), 561–644.

_ , _ , and Simon Mongey, "Quantifying market power and business dynamism in the macroeconomy," Technical Report, National Bureau of Economic Research 2026.

Lucas, Jr Robert E, "On the size distribution of business firms," *The Bell Journal of Economics*, 1978, pp. 508–523.

Ma, Yueyuan, "Specialization in a knowledge economy," *Journal of Political Economy Macroeconomics*, 2026, *4* (1), 48–96.

Maksimovic, Vojislav and Gordon Phillips, "Do conglomerate firms allocate resources inefficiently across industries? Theory and evidence," *The Journal of Finance*, 2002, *57* (2), 721–767.

Mankiw, N Gregory and Michael D Whinston, "Free entry and social inefficiency," *The RAND Journal of Economics*, 1986, pp. 48–58.

Mayer, Thierry, Marc J Melitz, and Gianmarco IP Ottaviano, "Market size, competition, and the product mix of exporters," *American Economic Review*, 2014, *104* (2), 495–536.

_ , _ , and _ , "Product mix and firm productivity responses to trade competition," *Review of Economics and Statistics*, 2021, *103* (5), 874–891.

Melitz, Marc J and Sašo Polanec, "Dynamic Olley-Pakes productivity decomposition with entry and exit," *The Rand Journal of Economics*, 2015, *46* (2), 362–375.

Michaels, Guy, Ashwini Natraj, and John Van Reenen, "Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years," *Review of Economics and Statistics*, 2014, *96* (1), 60–77.

Nocke, Volker and Stephen Yeaple, "Globalization and multiproduct firms," *International Economic Review*, 2014, *55* (4), 993–1018.

Peters, Michael, "Heterogeneous markups, growth, and endogenous misallocation," *Econometrica*, 2020, *88* (5), 2037–2073.

Pierce, Justin R and Peter K Schott, "A concordance between ten-digit US harmonized system codes and SIC/NAICS product classes and industries," *Journal of Economic and Social Measurement*, 2012, *37* (1-2), 61–96.

Ridder, Maarten De, "Market power and innovation in the intangible economy," *American Economic Review*, 2024, *114* (1), 199–251.

Rossi-Hansberg, Esteban, Pierre-Daniel Sarte, and Nicholas Trachter, "Diverging trends in national and local concentration," *NBER Macroeconomics Annual*, 2021, *35* (1), 115–150.

Schaller, Zachary and Paul DeCelles, "Weighted crosswalks for NAICS and SIC industry codes," *Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor]*, 2021, pp. 44–76.

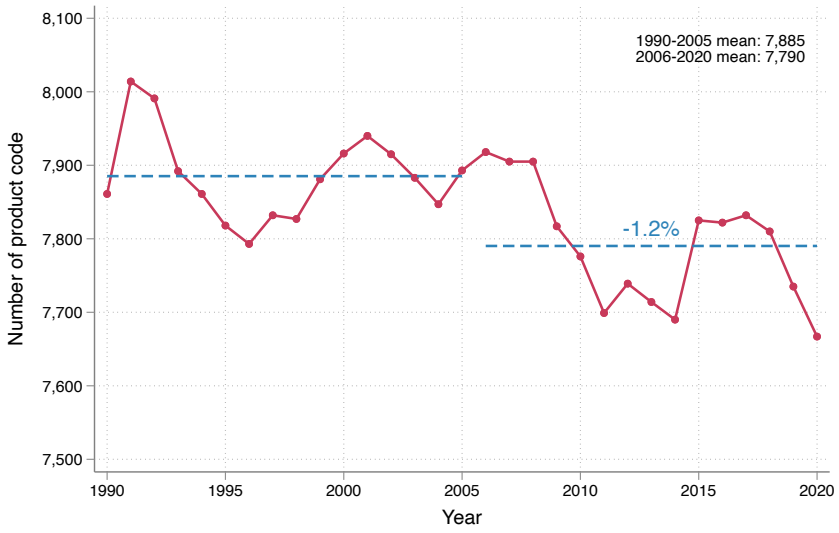
Sutton, John, *Sunk costs and market structure: Price competition, advertising, and the evolution of concentration*, MIT press Cambridge, MA, 1991.

A Data Appendix

A.1 Dun & Bradstreet Data

Number of products In the Dun & Bradstreet data, each product is defined by an eight-digit SIC code. Figure A.1 plots the number of unique products by year. The number declines slightly in the second half of the sample period relative to the first, but the change is small, with roughly 7,800 products per year throughout the sample.

Figure A.1: Number of unique eight-digit SIC code by year



Notes: This figure plots the number of unique eight-digit SIC code by year in the Dun&Bradstreet data.

Imputing product-level employment The data report employment at the plant level and list the products produced by each plant, but do not provide employment by product. Dun&Bradstreet records each plant's products in order of importance, with the first product accounting for the largest share of sales. In the baseline, I assign all plant employment to its primary product. This allocation may overstate the concentration of firm employment in core products. As a robustness check, I alternatively allocate employment equally across all products within each firm and find that the results are robust to this alternative allocation.

A.2 Nielsen Retail Scanner Dataset

My supplementary data source is the Kilts NielsenIQ Retail Scanner Data, covering 2006–2016. The data report weekly unit sales and revenue at the barcode-by-store level for a sample of retail chains. As documented by Argente et al. (2024), total annual sales recorded in the data amount to approximately $220 billion, covering roughly 40% of nationwide consumer goods consumption. The database includes more than 40,000 stores from approximately 90 retail chains across 371 metropolitan statistical areas and 2,500 counties. This extensive coverage provides detailed information on the range of products sold and firms' product portfolios in the consumer goods sector.

The Nielsen data allow me to examine firms' product portfolios at a finer level of disaggregation than the Dun & Bradstreet data. The dataset primarily covers consumer goods, which account for approximately 4% of U.S. GDP. It contains more than one million distinct barcodes, organized into a hierarchical product classification. Each barcode belongs to one of 1,070 product modules, with examples including "ready-to-eat cereals" and "tooth cleaners". Following Hottman et al. (2016), I link individual barcodes to firms using GS1 firm identifiers. Because the Nielsen product classification does not map directly into SIC industries, I define a firm's product scope as the number of distinct product modules in which it sells at least one barcode.[18]

[18] A firm may sell multiple barcodes within the same product module. These barcodes can reflect differences in packaging rather than distinct products. For example, a single can of Coke and a six-pack have different barcodes but belong to the same product category. I therefore count each product module only once when measuring a firm's product scope.

A.3 Example products produced documented in data

Table A.1: List of products produced by Intel in electronic equipment manufacturing

Product code	Short definition	1990	1995	2000	2005	2010	2015	2020
36740201	Computer logic modules	✓	✓	✓	✓	✓	✓	✓
36740204	Solid-state memory	✓	✓	✓	✓	✓	✓	✓
36740207	Microprocessors	✓	✓	✓	✓	✓	✓	✓
36740211	Semiconductor circuit networks	✓	✓	✓	✓	–	–	✓
36770000	Electronic coils/transformers	✓	–	–	–	–	–	–
36790102	Electronic commutators	✓	–	–	–	–	–	–
36720000	Printed circuit boards	✓	–	–	–	–	–	–
36740206	Integrated microcircuits	–	–	✓	✓	✓	✓	✓
36740200	Integrated circuits/networks	–	–	✓	✓	✓	✓	–
36610000	Telephone/telegraph equipment	–	–	✓	–	–	–	–
36619908	Fiber-optic communications equipment	–	–	–	✓	✓	✓	–
Product scope		7	4	7	7	6	6	5

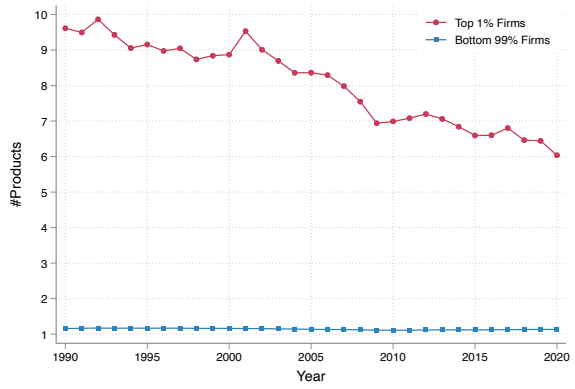
B Additional Stylized Facts

B.1 Product scope of top 20 firms

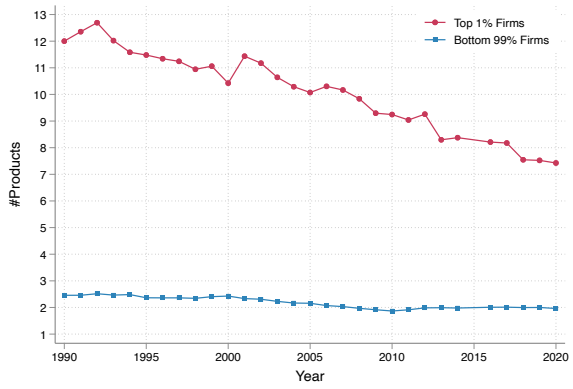
In the baseline, I define industry leaders as the top 1% of firms by employment within each industry. However, the number of firms in each industry changes over time, which can affect the composition and size of the top 1% group. In this section, I examine whether the decline in product scope is robust to an alternative definition of industry leaders. Following Autor et al. (2020), I define leading firms as the top 20 firms by employment in each industry and year. Figure B.1 shows that the decline in product scope is similar to that reported in the main text. Thus, the results are robust to defining industry leaders using a fixed number of firms rather than a fixed percentile of the employment distribution.

Figure B.1: Product Scope of Top 20 Firms

(a) Top 20 Firms: Unweighted



(b) Top 20 Firms: Emp weighted



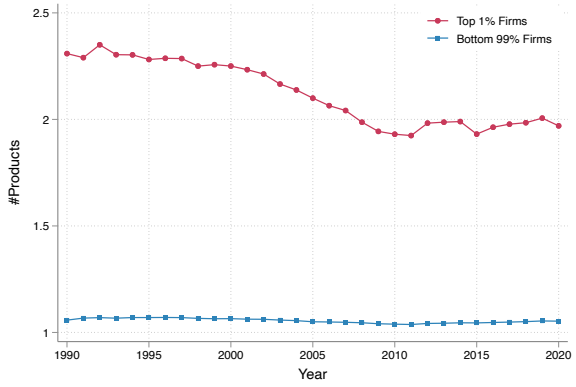
Notes: This figure plots the average number of products produced by the top 20 firms from 1990 to 2020. For each year, I first compute average product scope among the top 1% of firms within each two-digit SIC industry. I then aggregate these industry-level averages across manufacturing industries, using each industry's share of total manufacturing employment in 1990 as a fixed weight in both panels. Panel (a) plots the resulting aggregate series when firms are equally weighted within each industry, while Panel (b) plots the corresponding series when firms are weighted by their employment. We see that there is a substantial decline in the product scope of top 20 firms.

B.2 Product scope of top 10% firms

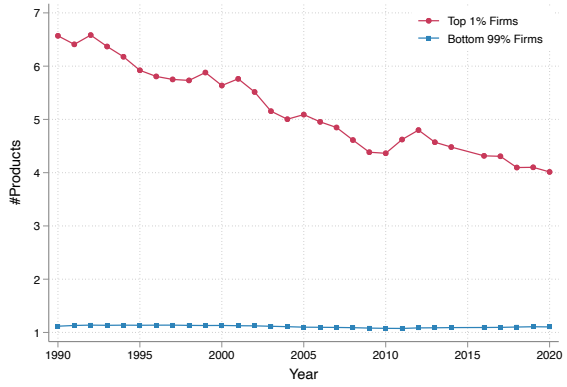
In the baseline, I define industry leaders as the top 1% of firms by employment within each industry. In this section, I examine whether the decline in product scope is robust to an alternative definition of industry leaders. I define leading firms as the top 10% firms by employment in each industry and year. Figure B.2 shows that the decline in product scope is similar to that reported in the main text. We see that there is a substantial decline in the product scope of top 10% firms.

Figure B.2: Product Scope of Top 10% Firms

(a) Top 10% Firms: Unweighted



(b) Top 10% Firms: Emp weighted



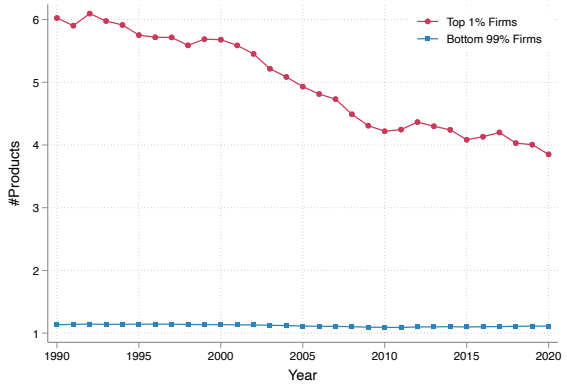
Notes: This figure plots the average number of products produced by the top 10% firms from 1990 to 2020. For each year, I first compute average product scope among the top 1% of firms within each two-digit SIC industry. I then aggregate these industry-level averages across manufacturing industries, using each industry's share of total manufacturing employment in 1990 as a fixed weight in both panels. Panel (a) plots the resulting aggregate series when firms are equally weighted within each industry, while Panel (b) plots the corresponding series when firms are weighted by their employment.

B.3 Product scope of top 1%, Variable Industry Weights

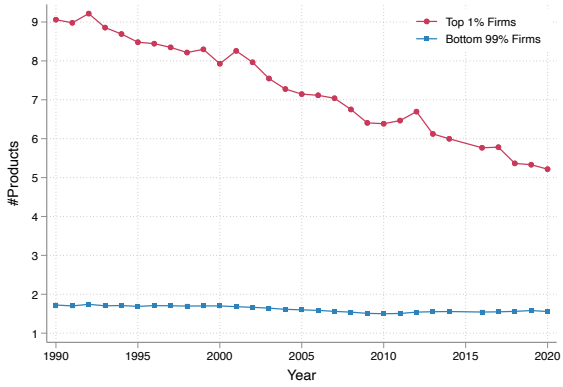
In the baseline, I aggregate industry-level measures of product scope among the top 1% of firms using each industry's share of total manufacturing employment in 1990 as a fixed weight. However, industry employment shares change over time. In this section, I examine whether the results are sensitive to this choice by allowing industry weights to vary each year. Specifically, I use each industry's share of total manufacturing employment in that year. Figure B.3 shows that both the trend and magnitude of the decline in product scope are similar to those reported in the main text. Thus, the decline in product scope among leading firms is not driven by the use of fixed 1990 industry weights.

Figure B.3: Product Scope of Top 1% Firms, Variable Industry Weights

(a) Top 1% Firms: Unweighted



(b) Top 1% Firms: Emp weighted



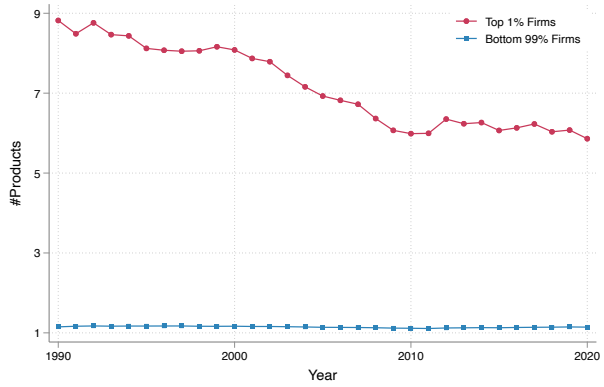
Notes: This figure plots the average number of products produced by the top 1% of firms from 1990 to 2020. For each year, I first compute average product scope among the top 1% of firms within each two-digit SIC industry. I then aggregate these industry-level averages across manufacturing industries, using each industry's share of total manufacturing employment in every year as weight in both panels. Panel (a) plots the resulting aggregate series when firms are equally weighted within each industry, while Panel (b) plots the corresponding series when firms are weighted by their employment. We see that there is a substantial decline in the product scope of top 1% firms.

B.4 Product scope of top 1% Firms, alternative firm definition

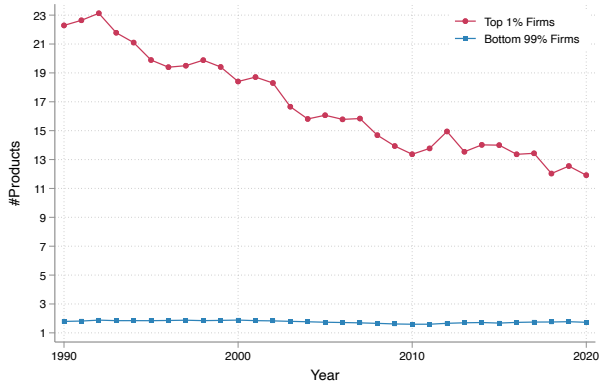
In this section, I examine whether the decline in product scope is robust to an alternative firm definition. In the baseline, I define a firm as the set of establishments sharing the same headquarters DUNS number within a two-digit SIC industry. Here, I instead group all establishments with the same headquarters DUNS number into a single firm and count its products across all manufacturing industries. Figure B.4 plots the average product scope of the top 1% of firms under this broader definition. Panel (a) shows that the unweighted average falls from nearly 9 products in 1990 to fewer than 6 products in 2020. Panel (b) shows a similar decline in employment-weighted average product scope. These results confirm that the decline in product scope among leading firms persists even when their products are counted across all manufacturing industries.

Figure B.4: Product Scope of Top 1% Firms

(a) Top 1% Firms: Unweighted



(b) Top 1% Firms: Emp weighted

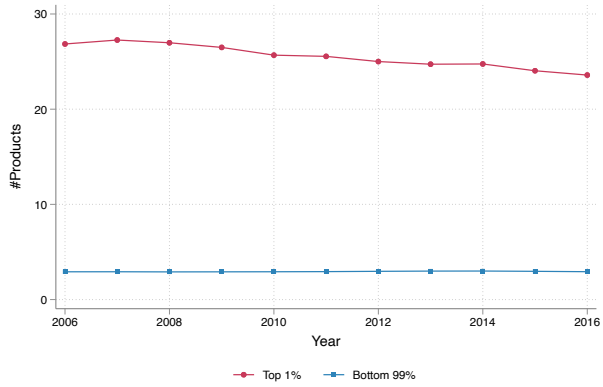


Notes: This figure plots the average number of products produced by the top 1% of firms from 1990 to 2020. Here, I instead group all establishments with the same headquarters DUNS number into a single firm and count its products across all manufacturing industries. For each year, I compute average product scope among the top 1% of firms within manufacturing sector. Panel (a) plots the resulting aggregate series when firms are equally weighted within each industry, while Panel (b) plots the corresponding series when firms are weighted by their employment. We see that there is a substantial decline in the product scope of top 1% firms.

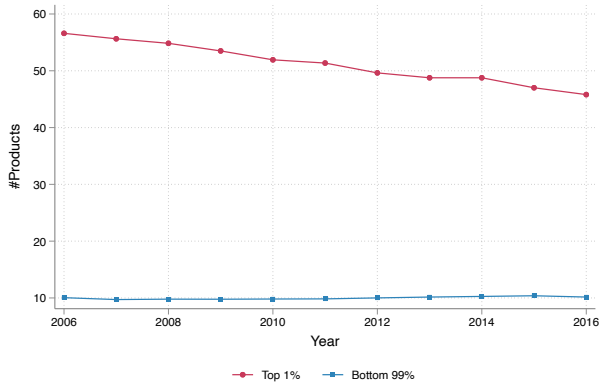
B.5 Product scope results using Nielsen Scanner Dataset

Figure B.5: Product Scope of Top 1% Firms in Nielsen Retail Scanner Data

(a) Top 1% Firms: Unweighted



(b) Top 1% Firms: Sales weighted



Notes: This figure plots the average number of products produced by the top 1% firms in Nielsen Retail Scanner data from 2006 to 2016. For each year, I first compute average product scope among the top 1% of firms by sales. Panel (a) plots the resulting aggregate series when firms are equally weighted, while Panel (b) plots the corresponding series when firms are weighted by their total sales. We see that there is a substantial decline in the product scope of top 1% firms.

B.6 Other stylized facts

B.6.1 Declining product-market overlap among leading firms

I next examine whether leading firms increasingly operate in the same product markets. For each pair of firms i and i' within the same industry, let S_i and $S_{i'}$ denote the sets of products produced by the two firms. I measure product-market overlap using the Jaccard index,

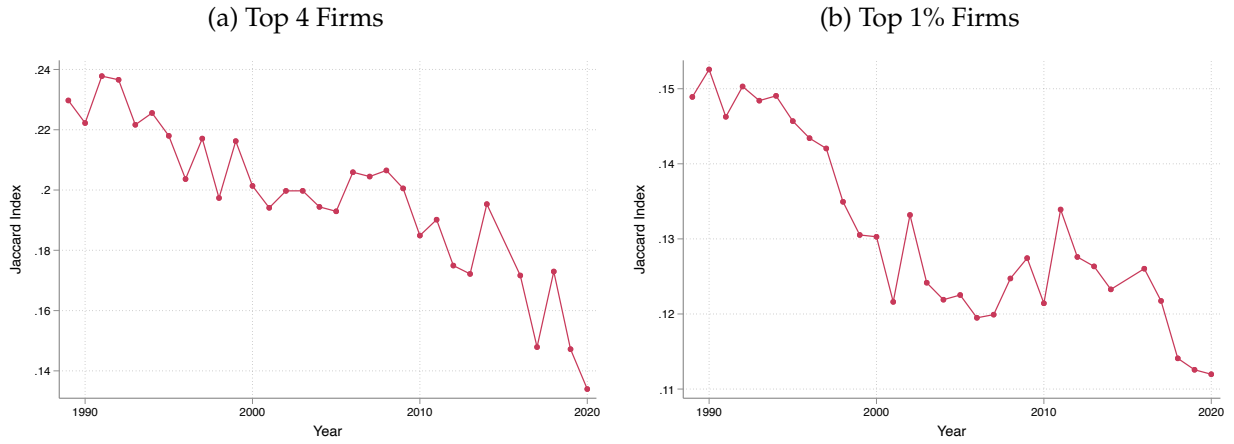
$$J(S_i, S_{i'}) = \frac{|S_i \cap S_{i'}|}{|S_i \cup S_{i'}|}.$$

This index equals zero when two firms produce no common products and equals one when they produce exactly the same set of products. For both the top four firms and the top 1 percent of firms within each industry, I compute the average bilateral Jaccard index across all firm pairs.

Figure B.6 plots the average Jaccard index from 1990 to 2020. Panel (a) reports the

series for the top four firms within each industry, while panel (b) reports the corresponding series for firms in the top 1 percent of the within-industry employment distribution. Product-market overlap among leading firms declines steadily over time. This pattern indicates that leading firms are not increasingly converging toward the same broad product portfolios. Instead, their product portfolios are becoming less similar, consistent with a process of specialization in which top firms narrow their product scope and concentrate on more distinct sets of products.

Figure B.6: Average bilateral Jaccard index



Notes: This figure plots the average bilateral Jaccard index, for the top 4 firms and top 1% firms, respectively.

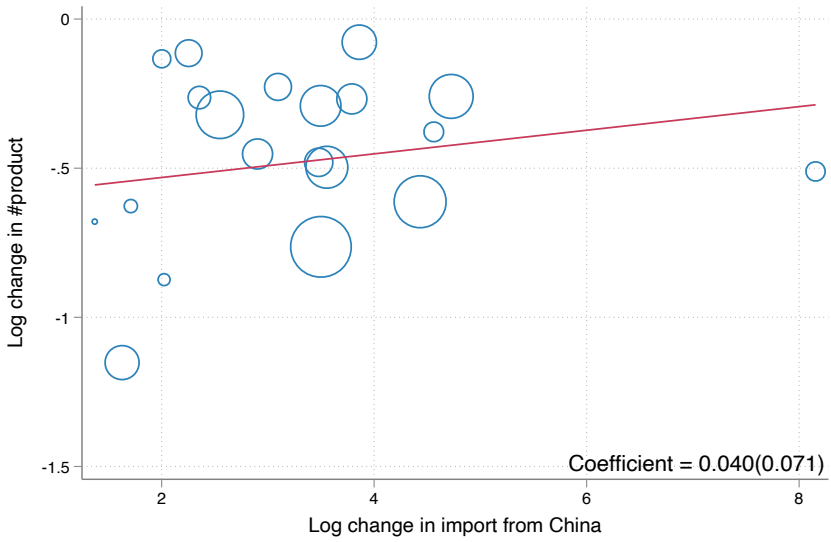
B.6.2 China shock, manufacturing VA & changes in product scope

Figure B.7 plots the industry-level relationship between the log change in imports from China and the log change in average product scope among the top 1% of firms between 1990 and 2019. I end the sample in 2019 to exclude the effects of the COVID-19 pandemic. The estimated relationship is economically small, and statistically insignificant. These results provide little evidence that increased import competition from China is associated with the decline in leading firms' product scope documented in Section 2.2.1.

To construct industry-level imports from China, I first collect annual U.S. import values from China at the ten-digit Harmonized System (HS10) level. I map HS10 products to six-digit NAICS industries using the concordance provided by Pierce and Schott (2012) and harmonize the industry codes to the 1997 NAICS classification. I then use the NAICS6–SIC4 crosswalk provided by Schaller and DeCelles (2021) to allocate each

NAICS6 industry's imports across its corresponding four-digit SIC industries. I aggregate these values to the two-digit SIC level and convert nominal imports to 2019 U.S. dollars using the GDP deflator.

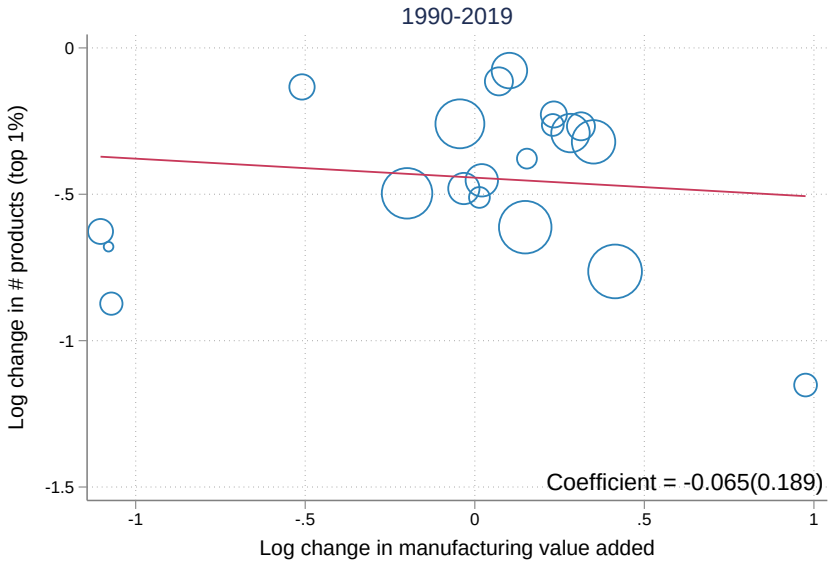
Figure B.7: China import shock & Top 1% product scope



Notes: This figure plots the industry-level relationship between the log change in imports from China and the log change in average product scope among the top 1% of firms between 1990 and 2019. Industries are defined at the two-digit SIC level. The horizontal axis measures the log change in imports from China, expressed in 2019 U.S. dollars. The vertical axis measures the log change in average product scope among the top 1% of firms within each industry.

Furthermore, Figure B.8 plots the relationship between the log change in industry value added and the log change in leading firms' product scope between 1990 and 2019. The estimated relationship is economically small and statistically insignificant. This finding suggests that changes in manufacturing industry size, as measured by value added, are not strongly associated with the decline in product scope documented in Section 2.2.1.

Figure B.8: Log change in industry VA & Top 1% product scope



Notes: This figure plots the relationship between the log change in industry value added and the log change in leading firms' product scope between 1990 and 2019. Industries are defined at the two-digit SIC level. The horizontal axis measures the log change in industry-level value added. The vertical axis measures the log change in average product scope among the top 1% of firms within each industry.

C Theory Appendix

C.1 Random product-market draws

Fix an industry and suppress its index. Consider J product markets and $I_J = \lfloor NJ \rfloor$ potential firms. Assume that their first-stage states $\mathcal{S}_J = \{(A_i, \lambda_i)\}_{i=1}^{I_J}$ have an empirical distribution converging to G, with $\lambda_i \in \{0, \ldots, \bar{\lambda}\}$ for a fixed $\bar{\lambda} < \infty$ and $\mathbb{E}_G[\lambda] > 0$. Conditional on these states, each firm independently draws a uniform ordered list of λ_i distinct markets. The assigned products have ranks $0, \ldots, \lambda_i - 1$.

Let B_{ij} indicate that firm i enters market j, and write $n_j^J = \sum_i B_{ij}$. The indicators are conditionally independent across firms, with $\Pr(B_{ij} = 1 \mid \mathcal{S}_J) = \lambda_i / J$. For $t \in [0, 1]$,

$$\begin{aligned}
\log \mathbb{E}[t^{n_j^J} \mid \mathcal{S}_J] &= \sum_{i=1}^{I_J} \log\left(1 + \frac{\lambda_i}{J}(t-1)\right) \\
&= \frac{t-1}{J} \sum_{i=1}^{I_J} \lambda_i + O(J^{-1}) \\
&\longrightarrow \bar{n}(t-1), \qquad \bar{n} = N\mathbb{E}_G[\lambda].
\end{aligned}$$

The remainder vanishes because $\sum_i \lambda_i^2 / J^2 = O(J^{-1})$. The limiting probability-generating function is that of a Poisson random variable, proving $n_j^J \Rightarrow \text{Poisson}(\bar{n})$ and equation (13). For any fixed collection of distinct markets, the same expansion gives independent limiting counts: the probability that one firm enters any specified pair is $\lambda_i(\lambda_i - 1)/[J(J-1)]$, whose sum across firms tends to zero.

Each rank $d < \lambda_i$ is assigned to market j with probability $1/J$. Applying the same argument to disjoint type–rank classes shows that, conditional on the limiting supplier count, supplier marks are independent draws from

$$H(dA, d\lambda, \{d\}) = \frac{\mathbf{1}\{0 \le d < \lambda\}}{\mathbb{E}_G[\lambda]} \, G(dA, d\lambda).$$

Thus an encountered supplier's parent state has distribution $\lambda G(dA, d\lambda)/\mathbb{E}_G[\lambda]$, and its rank is uniform over $\{0, \ldots, \lambda - 1\}$ conditional on that state.

Conditional on a focal firm's finite set of assignments, excluding that firm leaves the limiting rival distribution unchanged. Each of its markets therefore contains $1 +$ Poisson$(\bar{n})$ suppliers, including itself. Within-firm assignments are distinct for every J.

An unconditionally sampled market is empty with limiting probability $e^{-\bar{n}}$; by convention, such markets have zero quantity and expenditure and price index $+\infty$, contributing zero to $P^{1-\sigma}$. □

C.2 Equilibrium definition

Definition 1 (Symmetric Bayesian Equilibrium) A symmetric Bayesian equilibrium consists of, for each industry k, of a first-stage scope policy function $\lambda^k(A)$, a distribution G^k of first-stage firm characteristics (A_i^k, λ_i^k), a family $\Gamma^k = \{\Gamma^k(\lambda)\}_{\lambda \in \Lambda^k}$ of scope-contingent competitive environments, Stage-2 price, investment, and quantity $\{p_{ij}^k, x_{ij}^k, q_{ij}^k\}_{i \in \mathcal{I}^k}$ for all firms and their products, and an industry price index P^k. Together with aggregate income Y and price index P. These objects satisfy the following conditions.

1. *Stage-2 optimality.* For every realization generated by G^k and the product assignment process, firms' price and investment choices $\{p_{ij}^k, x_{ij}^k\}$ form a Nash equilibrium (15).
2. *Stage-1 optimality.* The stage-1 scope policy function solves the firm problem (17).
3. *Consistency of firm characteristics and competitive environments.* The distribution G^k is induced by the exogenous productivity distribution of A and the scope policy functions $\lambda^k(A)$. For each $\lambda \in \Lambda^k$, $\Gamma^k(\lambda)$ is the distribution of payoff-relevant environments generated when the focal firm chooses product scope λ. The distributions of competitive environments used in Stage-1 problems coincide with the distribution generated by firms' equilibrium choices and the product market assignment process.
4. *Price-index and goods-market consistency.* Product-market and industry price indices satisfy (6) and (7). Quantities satisfy the demand equations (4) and (8). Production follows $q_{ij}^k = z_{ij}^k l_{ij}^k$.
5. *Labor-market clearing.* Investment and product development costs are paid in units of labor. Let
$$X_i^k \equiv \sum_{j \in \mathcal{J}_i^k} x_{ij}^k$$
denote firm i's total technology investment in Stage 2. With the wage normalized to

one, aggregate labor supply $\bar{L}$ satisfies

$$\bar{L} = \sum_{k=1}^{K} N^k \int \left\{ F\lambda + \mathbb{E}_{\omega \sim \Gamma^k(\lambda)} \left[\sum_{j \in \mathcal{J}_i^k} c_{ij}^k q_{ij}^k + C\left(X_i^k\right) \right] \right\} dG^k(A, \lambda). \tag{41}$$

6. *Aggregate income.* Aggregate income is

$$Y = \bar{L} + \Pi, \tag{42}$$

where aggregate profits are

$$\Pi = \sum_{k=1}^{K} N^k \int \left\{ \mathbb{E}_{\omega \sim \Gamma^k(\lambda)} \left[\sum_{j \in \mathcal{J}_i^k} \left(p_{ij}^k - c_{ij}^k\right) q_{ij}^k - C\left(X_i^k\right) \right] - F\lambda \right\} dG^k(A, \lambda). \tag{43}$$

The equilibrium definition therefore closes three fixed points: firms' first-stage choices determine the distribution of realized competitive environments; those environments determine Stage-2 prices and investment decisions; and the resulting allocations determine the aggregate price indices and income taken as given by individual firms.

C.3 Proof of Lemma 1

Suppress the firm subscript within this proof and put $f(u) = e^{(\eta-1)g(u)}$, $a = (\eta - 1)\zeta$, and $b = EA^{\eta-1}/(\eta\Omega)$. Then $\pi(r) = be^{-ar} f(\psi x(r))$ and $f'' < 0$ by the lemma's curvature condition. For fixed scope, the objective is strictly concave in the investment vector. Its first-order condition is $\pi_x(r) = \nu = C'(X)$. At a given shadow price, define $v(y, \nu) = \max_{x \geq 0}\{yf(\psi x) - \nu x\}$. The scope envelope is $v(be^{-a\lambda}, \nu) - F$; hence interior scope satisfies $\pi^\lambda - \nu x^\lambda = F$, proving (23) and (25).

At fixed b, the marginal contribution declines with scope: the last rank is less productive and its shadow cost rises. The interior scope optimum is therefore unique. An expansion of scope increases total investment by

$$\frac{\partial X}{\partial \lambda} = \frac{x^\lambda}{1 - C''(X) \int_0^\lambda \partial x(r)/\partial \nu \, dr} \in (0, x^\lambda),$$

where $\partial x/\partial \nu < 0$. The operating-profit change on existing products is $\nu(\partial X/\partial \lambda - x^\lambda)$.

Adding its negative to the increase in investment expenditure proves (**??**). When $C'' = 0$, investment on existing products is unchanged and $\partial X/\partial\lambda = x^\lambda$.

For the cross-sectional comparison, let $t = \log b$, $J = \int_0^\lambda \partial x(r)/\partial \log(b/\nu)\, dr > 0$, and $k_X = C''(X)/\nu > 0$. Differentiating investment and the scope envelope gives

$$(1 + k_X J)\frac{dX}{dt} = J + x^\lambda \frac{d\lambda}{dt}, \qquad \pi^\lambda \left(1 - a\frac{d\lambda}{dt}\right) = \nu x^\lambda k_X \frac{dX}{dt}.$$

Therefore

$$\frac{d\lambda}{dt} = \frac{\pi^\lambda + k_X JF}{a\pi^\lambda(1 + k_X J) + \nu k_X (x^\lambda)^2} > 0, \qquad \frac{dX}{dt} > 0.$$

The shadow price rises with X. If W is optimized net profit, the envelope is $dW/dt = \int_0^\lambda \pi(r)dr > 0$; since $\int \pi = W + C(X) + F\lambda$, total operating profit, revenue, and production employment increase too. At fixed scope, $d\log\nu/dt = k_X J/(1 + k_X J) < 1$, so investment rises at every rank even though ν adjusts. Boundary scopes replace the strict scope comparison with a weak one. □

C.4 Proof of Proposition 1

General response identities. Write $\widehat{v} = d\log v/d\log\psi$ and $\dot{\lambda}_i = d\lambda_i/d\log\psi$. Put $p = \eta - 1$, $\zeta = -\log\delta > 0$, $a = p\zeta$, and $b_i = EA_i^p/(\eta\Omega)$. Let $f(u) = e^{pg(u)}$, so that $\pi_i(r) = b_i e^{-ar} f(u_i(r))$ and $u_i(r) = \psi x_i(r)$. Constant markups imply $s_{ij} \propto z_{ij}^p/\Omega$ and $\widehat{P} = -\widehat{\Omega}/p$, proving (26). Log-differentiating $\psi l_{ij} g'(u_{ij}) = \nu_i$ gives

$$\widehat{z}_{ij} = \kappa(u_{ij})(1 + \widehat{l}_{ij} - \widehat{\nu}_i), \qquad \widehat{l}_{ij} = p(\widehat{z}_{ij} + \widehat{P}),$$

which proves (27).

For an interior scope choice, the marginal product satisfies $v(b_i e^{-a\lambda_i}, \nu_i; \psi) = F$, where $v(y, \nu; \psi) = \max_{x\geq 0}\{yf(\psi x) - \nu x\}$. Differentiating this condition and applying the envelope theorem gives

$$0 = \pi_i^\lambda \left[-\widehat{\Omega} - a\dot{\lambda}_i + pu_i^\lambda g'(u_i^\lambda)\right] - \nu_i x_i^\lambda \widehat{\nu}_i.$$

Using $\nu_i x_i^\lambda = p\pi_i^\lambda u_i^\lambda g'(u_i^\lambda)$ proves (28). Changes in the marginal product's optimized investment cancel because its marginal return equals its shadow cost. When scope adjusts,

the price-index response also includes changes in the product portfolio:

$$-\widehat{P} = \frac{N}{\Omega}\int\int_0^{\lambda(A)} z_A(r)^p \widehat{z}_A(r)\, dr\, dG(A) + \frac{N}{p\Omega}\int z_A(\lambda(A))^p \dot{\lambda}(A)\, dG(A).$$

With fixed product portfolios, the second term is zero, and the price decline equals the sales-weighted mean of continuing suppliers' productivity gains.

Part (a): conditional scale-biased upgrading. Allow product-level investment to adjust while holding the common market demand shifter, the firm's marginal investment cost, and fundamental productivity fixed. Equation (27) then implies

$$\left.\frac{\partial \log z_{ij}}{\partial \log \psi}\right|_{\Omega,\nu_i,A_i\delta^{r_{ij}}} = \frac{\kappa(u_{ij})}{1-p\kappa(u_{ij})}.$$

The curvature condition in Lemma 1 implies $0 < \kappa(u) < 1/p$. The map $k \mapsto k/(1-pk)$ is strictly increasing on this interval. Since $\kappa(u)$ is strictly increasing, suppliers with higher initial effective investment obtain larger proportional productivity gains under this conditional comparison. Investment is reoptimized in this calculation; holding investment itself fixed would instead give the elasticity $ug'(u)$.

For the static comparison used in the interpretation, write $a_{ij} = A_i\delta^{r_{ij}}$. The investment condition $\psi[E/(\eta\Omega)]a_{ij}^p f'(u_{ij}) = \nu_i$ also gives

$$\left.\frac{\partial \log x_{ij}}{\partial \log a_{ij}}\right|_{\Omega,\nu_i,\psi} = -\frac{pf'(u_{ij})}{u_{ij}f''(u_{ij})} > 0, \qquad \left.\frac{\partial \log z_{ij}}{\partial \log a_{ij}}\right|_{\Omega,\nu_i,\psi} = \frac{1}{1-p\kappa(u_{ij})} > 1.$$

Thus endogenous investment amplifies fundamental-productivity differences at a given marginal investment cost. The equilibrium decline in the common price index is established below, completing part (a).

Additional assumptions for the equilibrium responses. The preceding identities do not by themselves establish the signed equilibrium responses. Maintain the model's lower productivity bound $A \geq 1$, and suppose f is continuous at zero, twice continu-

ously differentiable for $u > 0$, and satisfies

$$\begin{gathered} f(0) = 1, \quad f' > 0, \quad f'' < 0, \quad f'(0^+) = \infty, \\ d(u) \equiv -\frac{uf''(u)}{f'(u)} \in (0,1) \text{ is nonincreasing}, \qquad d(u) \longrightarrow 1-\beta, \\ \frac{f(u)}{u^\beta} \longrightarrow K \in (0,\infty), \qquad 0 < \beta < 1. \end{gathered} \tag{44}$$

Assume $\gamma > 1$, $F, \phi_1 > 0$, and a Pareto upper tail with $\vartheta > m \equiv p\gamma/(\gamma - \beta)$. Consider a finite, differentiable equilibrium response at fixed E, N, and wage. These are sufficient conditions for the analytical results, not restrictions imposed on the numerical oligopoly calibration. The technology conditions hold, for example, for $f(u) = 1 + u^\beta$ and positive finite mixtures $1 + \sum_k b_k u^{\beta_k}$ with $0 < \beta_k \leq \beta < 1$ and $\max_k \beta_k = \beta$.

For part (c), consider the auxiliary uncapped rank problem, with

$$\max_{\lambda_i \geq 0,\, x_i(\cdot) \geq 0} \left\{ \int_0^{\lambda_i} [\pi_i(r) - F] dr - \phi_1 X_i^\gamma \right\}, \qquad X_i = \int_0^{\lambda_i} x_i(r)\, dr.$$

Here scope is the measure of developed product lines, with

$$\pi_i(r) = \frac{E}{\eta\Omega} z_i(r)^p, \qquad \Omega = N \int \int_0^{\lambda(A)} z_A(r)^p \, dr \, dG(A).$$

It is not the measure of a subset of distinct markets in $[0,1]$. We first establish the equilibrium responses for this uncapped problem; the extension of parts (a) and (b) to a finite scope cap is given at the end.

Define

$$h(u) = \frac{uf'(u)}{f(u)}, \qquad e(u) = \frac{1}{d(u)}.$$

Integrating $f'(t) \geq f'(u)(u/t)^{d(u)}$ over $0 < t < u$ gives $0 < h(u) < 1 - d(u) \leq \beta$. Consequently,

$$uh'(u) = h(u)[1 - d(u) - h(u)] > 0, \qquad 1 < e(u) \leq \frac{1}{1-\beta}.$$

The function e is nondecreasing. Concavity and the power-tail limit imply $f'(u) \sim K\beta u^{\beta-1}$, so

$$h(u) \longrightarrow \beta, \qquad e(u) \longrightarrow \frac{1}{1-\beta}, \qquad \kappa(u) = \frac{h(u)e(u)}{p[1 + h(u)e(u)]}.$$

Thus both $ug'(u) = h(u)/p$ and $\kappa(u)$ are strictly increasing.

Every firm has positive, finite scope in the uncapped problem. Since f is unbounded, choose a finite $\bar{x}$ such that $b_i f(\psi\bar{x}) > F$. A sufficiently small portfolio with $x_i(r) = \bar{x}$ yields net profit $\lambda[b_i f(\psi\bar{x}) - F] + o(\lambda) > 0$, since $\gamma > 1$. Moreover, $f(u) \le K_0(1 + u^\beta)$ and Hölder's inequality give

$$\Pi_i^o \equiv \int_0^{\lambda_i} \pi_i(r)\, dr \le K_1 b_i (1 + X_i^\beta).$$

After maximizing $K_1 b_i(1 + X_i^\beta) - \phi_1 X_i^\gamma - F\lambda_i$ over X_i, this bound tends to minus infinity with λ_i. Optimal scope is therefore finite. The Inada condition gives positive investment at every retained rank, so investment and interior scope optimality hold with equality.

Competition and within-firm refocusing. Define

$$h_i = h(u_i^\lambda), \qquad \bar{e}_i = \int_0^{\lambda_i} \frac{x_i(r)}{X_i} e(u_i(r))\, dr, \qquad T_i = \frac{x_i^\lambda}{X_i}.$$

The investment and scope responses satisfy

$$\begin{aligned} \widehat{u}_i(r) &= e(u_i(r))(1 - \widehat{\Omega} - \widehat{\nu}_i), \quad \widehat{\nu}_i = (\gamma - 1)\widehat{X}_i, \\ a\dot{\lambda}_i &= h_i(1 - \widehat{\nu}_i) - \widehat{\Omega}, \\ [1 + (\gamma - 1)\bar{e}_i]\widehat{X}_i &= \bar{e}_i(1 - \widehat{\Omega}) - 1 + T_i\dot{\lambda}_i. \end{aligned} \tag{45}$$

The final equation includes the change in the investment boundary. Investment decreases with rank, while e is nondecreasing, so $\bar{e}_i \ge e(u_i^\lambda)$. Together with $h_i < 1 - d(u_i^\lambda)$, this implies $\bar{e}_i(1 - h_i) > 1$. With $\mathcal{D}_i = a[1 + (\gamma - 1)\bar{e}_i] + (\gamma - 1)h_i T_i > 0$, solving the response system gives

$$\begin{aligned} \dot{\lambda}_i &= \frac{\gamma h_i - \widehat{\Omega}[1 + (\gamma - 1)\bar{e}_i(1 - h_i)]}{\mathcal{D}_i}, \\ \widehat{X}_i &= \frac{a[\bar{e}_i(1 - \widehat{\Omega}) - 1] + T_i(h_i - \widehat{\Omega})}{\mathcal{D}_i}. \end{aligned}$$

Let $W_i = \Pi_i^o - C(X_i) - F\lambda_i$ denote optimized net profit. The envelope theorem gives

$dW_i/d\log\psi = \nu_i X_i - \widehat{\Omega}\Pi_i^o$, hence

$$\frac{d\Pi_i^o}{d\log\psi} = \nu_i X_i(1+\widehat{X}_i) - \widehat{\Omega}\Pi_i^o + F\dot{\lambda}_i, \qquad \nu_i X_i = \int_0^{\lambda_i} \pi_i(r)h(u_i(r))\,dr < \beta\Pi_i^o.$$

At the trial response $\widehat{\Omega} = 0$, both $\widehat{X}_i$ and $\dot{\lambda}_i$ are positive, so operating profit increases. At $\widehat{\Omega} = \beta$, both responses are negative because $\bar{e}_i(1-\beta) \le 1$, $h_i < \beta$, and $\bar{e}_i(1-h_i) > 1$. Operating profit then decreases. Its response is affine and strictly decreasing in $\widehat{\Omega}$.

Differentiation under the aggregate integral is valid. Lemma 1 and $A \ge 1$ give $\lambda_i \ge \lambda(1) > 0$ and $\Pi_i^o \ge \Pi^o(1) > 0$. Since investment decreases with rank, $T_i \le 1/\lambda_i \le 1/\lambda(1)$. The bounds on h_i, $\bar{e}_i$, and T_i uniformly bound $|\widehat{X}_i|$ and $|\dot{\lambda}_i|$ for bounded trial responses of Ω. The operating-profit envelope therefore gives

$$\left|\frac{d\Pi_i^o}{d\log\psi}\right| \le K_2\Pi_i^o.$$

Combining $\Pi_i^o \le K_1 b_i(1+X_i^\beta)$ with $\phi_1\gamma X_i^\gamma = \nu_i X_i < \beta\Pi_i^o$ yields

$$\Pi_i^o \le K_3\left(b_i + b_i^{\gamma/(\gamma-\beta)}\right) \le K_4 A_i^m.$$

The constants are uniform in a compact positive neighborhood of (ψ, Ω). The Pareto restriction thus dominates operating profits and their local derivatives. Differentiating aggregate consistency, $N\int \Pi_A^o\,dG(A) = E/\eta$, and using the opposite signs at the two trial responses gives

$$0 < \widehat{\Omega} < \beta, \qquad \widehat{P} = -\frac{\widehat{\Omega}}{p} < 0.$$

This proves the equilibrium competition statement in part (a).

Substitution into (45) gives

$$B_i \equiv 1 - \widehat{\Omega} - \widehat{\nu}_i = \frac{a(\gamma-\widehat{\Omega}) + (\gamma-1)\widehat{\Omega}T_i(1-h_i)}{\mathcal{D}_i} > 0.$$

Thus effective investment rises on every retained product. Within a firm, higher-fundamental products have higher $u_i(r)$, while B_i is common across products. Since he is strictly increasing,

$$\widehat{z}_i(r) = \frac{h(u_i(r))e(u_i(r))}{p}B_i, \qquad \widehat{R}_i(r) = -\widehat{\Omega} + h(u_i(r))e(u_i(r))B_i$$

are larger for stronger retained products. Here $R_i(r) = \eta \pi_i(r)$. This proves part (b), including when market conditions and marginal investment costs adjust in equilibrium.

Part (c): leading-firm specialization. As $A_i \to \infty$, X_i and ν_i diverge. Otherwise, $\psi b_i e^{-ar} f'(u_i(r)) = \nu_i$ would imply $u_i(r) \to \infty$ uniformly on a fixed core interval inside $[0, \lambda(1)]$, contradicting bounded total investment. At the scope margin, investment and scope optimality give

$$\frac{\nu_i}{\psi} = F \frac{f'(u_i^\lambda)}{f(u_i^\lambda) - u_i^\lambda f'(u_i^\lambda)}.$$

The ratio on the right decreases strictly from infinity to zero: its derivative has the sign of $ff'' < 0$. Hence $u_i^\lambda \to 0$, $h_i \to 0$, $T_i \to 0$, and $b_i e^{-a\lambda_i} \to F$, so $\lambda_i \to \infty$. Let $u_i^0 = u_i(0)$. Investment optimality across ranks implies $\partial \log u_i(r)/\partial r = -ae(u_i(r))$, and therefore

$$a\psi X_i = \int_{u_i^\lambda}^{u_i^0} d(u)\, du, \qquad \bar{e}_i = \frac{u_i^0 - u_i^\lambda}{\int_{u_i^\lambda}^{u_i^0} d(u)\, du} \longrightarrow \frac{1}{1-\beta}.$$

Here $u_i^0 \to \infty$ because $X_i \to \infty$. The response system then gives $\widehat{X}_i \to (\beta - \widehat{\Omega})/(\gamma - \beta) > 0$ and $\dot{\lambda}_i \to -\widehat{\Omega}/a < 0$.

For total revenue, changing variables from rank to effective investment yields the exact identity

$$\Pi_i^o = \frac{\nu_i}{a\psi} \left[\frac{f(u_i^0)}{f'(u_i^0)} - u_i^0 \right] - \frac{F}{a}.$$

To verify it, the derivative of $f/f' - u$ is $-ff''/(f')^2$, and the lower endpoint contributes F/a by the marginal-product condition. Since $f(u)/f'(u) \sim u/\beta$ and $a\psi X_i \sim (1-\beta)u_i^0$, it follows that $\nu_i X_i / \Pi_i^o \to \beta$. Using $R_i = \eta \Pi_i^o$, divide the exact operating-profit envelope by Π_i^o to obtain

$$\widehat{R}_i = \frac{\nu_i X_i}{\Pi_i^o}(1 + \widehat{X}_i) - \widehat{\Omega} + \frac{F\dot{\lambda}_i}{\Pi_i^o} \longrightarrow \frac{\gamma(\beta - \widehat{\Omega})}{\gamma - \beta} > 0.$$

The boundary term is included throughout; its ratio to operating profit tends to zero. Collecting the three limits gives

$$\widehat{X}_i \longrightarrow \frac{\beta - \widehat{\Omega}}{\gamma - \beta} > 0, \qquad \dot{\lambda}_i \longrightarrow -\frac{\widehat{\Omega}}{a} < 0, \qquad \widehat{R}_i \longrightarrow \frac{\gamma(\beta - \widehat{\Omega})}{\gamma - \beta} > 0. \tag{46}$$

The strict limits establish a finite A^* above which all three signs hold. Marginal investment cost rises because $\widehat{\nu}_i = (\gamma - 1)\widehat{X}_i > 0$. For any fixed $A_0 > A^*$, fixed industry expenditure implies

$$\frac{d}{d\log\psi}\left[\frac{N}{E}\int_{A_0}^{\infty} R_A\, dG(A)\right] = \frac{N}{E}\int_{A_0}^{\infty} R_A \widehat{R}_A\, dG(A) > 0.$$

This proves part (c). □

Core expansion and the scope margin. For each fixed core rank r, the bound on e gives $u_i(r) \geq u_i^0 e^{-ar/(1-\beta)} \to \infty$. Consequently, the product-level response equations imply

$$\widehat{x}_i(r) \longrightarrow \frac{\beta - \widehat{\Omega}}{\gamma - \beta} > 0, \qquad \widehat{R}_i(r) \longrightarrow \frac{\gamma(\beta - \widehat{\Omega})}{\gamma - \beta} > 0.$$

This supports the interpretation that sufficiently productive firms increase investment and sales in their retained core lines. Write $v_i(r) = v(b_i e^{-ar}, \nu_i; \psi)$. At the previously marginal rank, holding that rank fixed while allowing investment to reoptimize, the contribution response is

$$\left.\frac{dv_i(r)}{d\log\psi}\right|_{r=\lambda_i^{\text{pre}}} = \pi_i^{\lambda}[-\widehat{\Omega} + h_i(1 - \widehat{\nu}_i)] = a\pi_i^{\lambda}\dot{\lambda}_i < 0.$$

Its contribution therefore falls below F; the new interior margin again satisfies the scope condition. Moreover,

$$\frac{dR_i}{d\log\psi} = \int_0^{\lambda_i} R_i(r)\widehat{R}_i(r)\, dr + R_i(\lambda_i)\dot{\lambda}_i.$$

For leading firms, the total is positive and the boundary term is negative, so revenue gains on retained products more than offset the revenue lost from withdrawals.

Finite scope caps. A fixed finite cap eventually binds as $A_i \to \infty$, so the strict upper-tail scope-contraction statement in part (c) requires the auxiliary uncapped problem. Parts (a) and (b), including the price-index decline, also hold in the capped benchmark. For a firm

whose cap binds locally,

$$\dot{\lambda}_i = 0, \qquad \widehat{X}_i = \frac{\bar{e}_i(1-\widehat{\Omega})-1}{1+(\gamma-1)\bar{e}_i}.$$

Its operating-profit response is positive at the trial $\widehat{\Omega} = 0$ and negative at $\widehat{\Omega} = \beta$, and is affine and strictly decreasing between them. The same aggregate argument therefore gives $0 < \widehat{\Omega} < \beta$. For a capped firm,

$$1 - \widehat{\Omega} - \widehat{\nu}_i = \frac{\gamma - \widehat{\Omega}}{1+(\gamma-1)\bar{e}_i} > 0,$$

so the within-firm ordering also follows. An exact cap-switching type can be treated with one-sided derivatives and has zero mass under the continuous productivity distribution.

C.5 Model Mechanism under Oligopolistic Competition.

Optimal product-level investment. Consider next the firm's product-specific fixed-cost technology investment choice. Let $X_i^k = \sum_{j \in \mathcal{J}_i^j} x_{ij}^k$ and $\nu_i^k = C'\left(X_i^k\right) = \phi_1 \gamma (X_i^k)^{\gamma-1}$ denote total investment and its common marginal cost.

Since $\frac{\partial c_{ij}^k}{\partial x_{ij}^k} = -\psi c_{ij}^k g'\left(\psi x_{ij}^k\right)$, the envelope theorem applied to the firm's optimal pricing decision gives

$$\psi q_{ij}^k c_{ij}^k g'\left(u_{ij}^k\right) = \psi l_{ij}^k g'(u_{ij}^k) \leq \nu_i^k, \qquad u_{ij}^k = \psi x_{ij}^k, \quad x_{ij}^k \geq 0. \tag{47}$$

with equality whenever $x_{ij}^k > 0$.

Two forces govern this investment condition. First, the benefit from investment depends on the product's production base. The term $q_{ij}^k c_{ij}^k$ is the product's total variable cost. Because labor is the only variable input and the wage is normalized to one, this term also equals production employment, l_{ij}^k. The left-hand side of equation (47) therefore measures the labor savings generated by additional product-level investment.

Holding the marginal investment cost fixed, investment is more valuable for a product with a larger production base. A producer with higher fundamental productivity, $A_i a_{ij}$, operates at a larger scale and therefore has a stronger incentive to invest. Higher investment further lowers its marginal cost and expands its production base, reinforcing the in-

centive to invest. Fixed-cost technology investment therefore amplifies initial differences in fundamental productivity and favors producers that are already more productive.

Importantly, the production base within each market is not determined by the firm's own productivity alone. It also depends on competitors' productivity, investment, and pricing decisions, which determine the firm's competitive position in that market. Competition therefore directly shapes the benefit from investment on the left-hand side of equation (47).

The second force operates on the cost side. Optimal investment in each product depends on the common marginal investment cost, ν_i^k, which rises with the firm's total investment when $\gamma > 1$. Greater investment in one product raises the marginal cost of investment throughout the portfolio, inducing the firm to reduce investment elsewhere. In this sense, products within the firm compete for investment resources through the common marginal cost. The firm allocates investment by equating marginal returns across products receiving positive investment. Consequently, investment in a given product depends not only on conditions in its own market, but also on the firm's investment opportunities elsewhere in its portfolio.

Optimal product scope. Consider next the firm's product scope choice. The firm chooses scope before its assignments and competitive environment are realized. To isolate the internal investment competition trade-of, I first consider the value of an additional product conditional on a realized sequence of opportunities, and then return to the expected Stage-1 comparison.

Let $J_{i,n}$ denote the set of product markets associated with firm i's first n product opportunities, with $|\mathcal{J}_{i,n}| = n$. The next opportunity serves market $j_{i,n+1} \notin_{i,n}$, so that $\mathcal{J}_{i,n+1} = \mathcal{J}_{i,n} \cup \{j_{i,n+1}\}$.

Let $\pi_{ij}(x)$ denote operating profit in market j after optimal pricing, but before investment and product-development costs. The firm's optimized profit with n products, net of both investment costs and product creation costs, is

$$W_i^{(n)} = \max_{\{x_{ij} \geq 0\}_{j \in \mathcal{J}_{i,n}}} \left\{ \sum_{j \in \mathcal{J}_{i,n}} \pi_{ij}(x_{ij}^{(n)}) - C\left(\sum_{j \in \mathcal{J}_{i,n}} x_{ij}^{(n)} \right) - nF \right\}. \tag{48}$$

where $x_{ij}^{(n)}$ is the optimal investment under scope n, and define

$$X_i^{(m)} \equiv \sum_{j \in \mathcal{J}_{i,n}} x_{ij}^{(n)}, \qquad \nu_i^{(n)} \equiv C'(X_i^{(n)}), \qquad \pi_{ij}^{(n)} \equiv \pi_{ij}\left(x_{ij}^{(n)}\right).$$

Define $D_{i,n} \equiv W_i^{(n+1)} - W_i^{(n)}$ as the net incremental profit from increasing scope from n to $n+1$. If n is optimal, adding the next product is unprofitable and $D_{i,n} < 0$. The gains from adding product $n+1$, which sells in market $j_{i,n+1}$ is

$$D_{i,n} = \pi_{i,j_{i,n+1}}^{(n+1)} - F - \left[C(X_i^{(n+1)}) - C(X_i^{(n)})\right] - \sum_{h \in \mathcal{J}_{i,n}} \left[\pi_{ih}^{(n)} - \pi_{ih}^{(n+1)}\right]. \tag{49}$$

Adding a product generates additional operating profit but also incurs a development cost and raises the firm's total investment expenditure. When total investment rises, the common marginal cost of investment increases, crowding out investment in existing products. The final term captures the resulting loss of operating profits from these products. Thus, the value of adding a product depends not only on its own profitability but also on the adjustments it induces elsewhere in the firm's portfolio.

To characterize this linkage, I use a small-product approximation. For a sufficiently large portfolio, adding one product can therefore be approximated as a marginal expansion of scope. Investment in the additional product is small relative to investment in the existing portfolio. The following lemma characterizes the resulting investment crowding out and incremental product value.

Lemma 2 (Marginal product value and internal investment competition)**.** *Define*

$$\epsilon_{D,ih} \equiv -\frac{\partial \log x_{ih}(\nu)}{\partial \log \nu} > 0, \qquad \bar{\epsilon}_{D,i} \equiv \sum_{\substack{h \in \mathcal{J}_{i,n} \\ x_{ih}^{(n)} > 0}} \frac{x_{ih}^{(n)}}{X_i^{(n)}} \epsilon_{D,ih}, \qquad \iota_i \equiv \frac{(\gamma-1)\bar{\epsilon}_{D,i}}{1+(\gamma-1)\bar{\epsilon}_{D,i}}.$$

Then, to first order around the initial n-product allocation[19]*,*

[19]For this local calculation, competitors' prices and aggregate demand conditions are held at their initial equilibrium values while the focal firm reoptimizes its prices and investment. The expected Stage-1 comparison below uses equilibrium continuation values under each scope choice and includes the associated competitive responses.

1. *Adding the product crowds out investment in each existing product h by*

$$-\Delta \log x_{ih} \approx \iota_i \frac{\epsilon_{D,ih}}{\bar{\epsilon}_{D,i}} \frac{x^{(n+1)}_{i,j_{i,n+1}}}{X_{i,n}}, \tag{50}$$

where $\Delta \log x_{ih} \equiv \log x^{(n+1)}_{ih} - \log x^{(n)}_{ih}$. *Consequently,*

$$-\sum_{h \in \mathcal{J}_{i,n}} \Delta x_{ih} \approx \iota_i x^{(n+1)}_{i,j_{i,n+1}}, \qquad X^{(n+1)}_i - X^{(n)}_i \approx (1-\iota_i) x^{(n+1)}_{i,j_{i,n+1}}.$$

2. *The net value of producing the additional product is*

$$D_{i,n} \approx \pi^{(n+1)}_{i,j_{i,n+1}} - F - \underbrace{(1-\iota_i)\nu^{(n)}_i x^{(n+1)}_{i,j_{i,n+1}}}_{\text{additional investment expenditure}} - \underbrace{\iota_i \nu^{(n)}_i x^{(n+1)}_{i,j_{i,n+1}}}_{\text{forgone operating profit}} \tag{51}$$

Lemma 2 makes the breadth–depth trade-off explicit. Equation (50) characterizes how adding a new product crowds out investment in existing products. For each unit invested in the new product, investment in existing products falls by approximately ι_i units in total. Products whose investment is more sensitive to the marginal investment cost experience larger proportional reductions. When $\gamma > 1$, expanding scope therefore comes partly at the expense of technological upgrading in existing products. This raises their unit costs and weakens their market positions. Conversely, narrowing scope relaxes this pressure and supports deeper investment in the retained products.

Equation (51) separates the development cost, the increase in total investment expenditure, and operating profits forgone on existing products. The first term, F, captures the cost of creating one additional product. The second term $\nu_i(1-\iota_i)x^{(n+1)}_{i,j_{i,n+1}}$, captures the increase in the firm's total investment cost. The third term, $\nu_i \iota_i x^{(n+1)}_{i,j_{i,n+1}}$, captures the operating profits forgone on existing products due to investment crowding out.

Returning to Stage 1, let $V(A_i, \omega)$ denote equilibrium Stage-2 profit net of investment costs but before product-development costs. Evaluated at the equilibrium associated with a realization ω under scope n, the net payoff defined above is $W^{(n)}_i(\omega) = V(A_i, \omega) - nF$. The expected gain from choosing $n+1$ rather than n products is

$$\begin{aligned} \overline{D}_{i,n} &\equiv \mathbb{E}_{\omega \sim \Gamma(n+1)}\left[W^{(n+1)}_i(\omega)\right] - \mathbb{E}_{\omega \sim \Gamma(n)}\left[W^{(n)}_i(\omega)\right] \\ &= \mathbb{E}_{\omega \sim \Gamma(n+1)}[V(A_i, \omega)] - \mathbb{E}_{\omega \sim \Gamma(n)}[V(A_i, \omega)] - F. \end{aligned} \tag{52}$$

The firm chooses scope to maximize expected net profit. Thus, $\bar{D}_{i,n} < 0$ means thaat adding the next product is unprofitable relative to retaining n products.

C.6 Response to technology shock

I next consider a small, common improvement in technology efficiency around an arbitrary positive value of ψ. This allows me to examine how better scalable technology changes firms' incentives to expand within existing products or across more products. The analysis helps explain why leading firms can capture larger shares of industry activity while producing fewer products.

Proposition 3 (Better technology, product deepening, and scope)**.** *Consider a small improvement in technology efficiency ψ, and holding industry expenditure fixed. Suppose g is increasing and strictly concave, $\kappa(u) = [g'(u)]^2/[-g''(u)]$ is strictly increasing, and $ug'(u)$ is non-decreasing. Define,*

$$G_{ij} \equiv \frac{d\log z_{ij}}{d\log\psi}, \qquad \overline{G}_j \equiv -\frac{d\log p_j}{d\log\psi}, \qquad \overline{G}_P \equiv -\frac{d\log P}{d\log\psi}.$$

(i) (Scale-biased upgrading and market-share selection.) For two suppliers in the same market,

$$x_{ij} > x_{\ell j} \quad \Longleftrightarrow \quad \frac{l_{ij}}{\nu_i} > \frac{l_{\ell j}}{\nu_\ell}. \tag{53}$$

Their market shares respond according to

$$\frac{d\log s_{ij}}{d\log\psi} = \varsigma(s_{ij})(G_{ij} - \overline{G}_j), \qquad \varsigma(s) = \frac{\eta - 1}{1 + (\eta - 1)\dfrac{(\eta - \sigma)s}{\varepsilon(s)[\varepsilon(s) - 1]}} > 0. \tag{54}$$

(ii) (Marginal product value and internal amplification.) Let $j = j_{i,n+1}$ be the additional product and let $\widetilde{D}_{i,n} = \max_{x\geq 0}\{\pi_{ij}(x) - F - \nu_i x\}$ denote the marginal-product approximation underlying Lemma 2. The marginal value of adidtional product is approximately optimized

contribution satisfies

$$\frac{1}{\pi_{ij}}\frac{d\widetilde{D}_{i,n}}{d\log\psi} = \underbrace{(\varepsilon_{ij}-1)u_{ij}g'(u_{ij}) - \left[(\eta-\sigma)\sum_{\ell\in\mathcal{M}_j\setminus\{i\}} s_{\ell j}\left(G_{\ell j} - \frac{d\log\mu_{\ell j}}{d\log\psi}\right) + (\sigma-1)\overline{G}_P\right]}_{\textit{product-market selection}}$$

$$- \underbrace{\frac{\nu_i x_{ij}}{\pi_{ij}}\frac{d\log\nu_i}{d\log\psi}}_{\textit{internal investment competition}}. \tag{55}$$

where

$$\frac{d\log\nu_i}{d\log\psi} = (\gamma-1)\sum_{h\in\mathcal{J}_{i,n}}\omega^x_{ih}\frac{d\log x_{ih}}{d\log\psi}, \qquad \omega^x_{ih} = \frac{x_{ih}}{X_i}. \tag{56}$$

Proposition 3 identifies two forces governing how better technology changes the value of the marginal product: product-market competition and internal competition for investment. The first captures changes in a product's operating profit as its own technology and its competitors' technologies improve. The second captures how investment elsewhere in the firm's portfolio affects its marginal investment cost and the value of adding another product.

Product-market competition operates through scale-dependent returns to technology investment. As equation (47) shows, an investment that reduces unit labor requirements generates greater savings when applied to a larger production base. Under the increasing-$\kappa(u)$ condition, better technology reinforces this scale advantage. Holding the parent's marginal investment cost fixed, larger producers invest more and obtain greater productivity gains. These uneven gains strengthen the competitive positions of larger producers while making weaker producers less competitive. A product can become more productive yet lose market share if its productivity gain falls below the market benchmark, $G_{ij} < \overline{G}_j$. As a result, better technology can therefore reduce the value of retaining a marginal product even before accounting for internal investment competition.

This selection mechanism is related to the product-mix adjustments studied by Bernard et al. (2011) and Mayer et al. (2014). In those settings, changes in the trading environment induce firms to adjust their product portfolios and withdraw marginal products. Here, competitive pressure arises endogenously from technological upgrading. Larger suppliers have stronger incentives to invest, making products with smaller relative productivity gains less attractive.

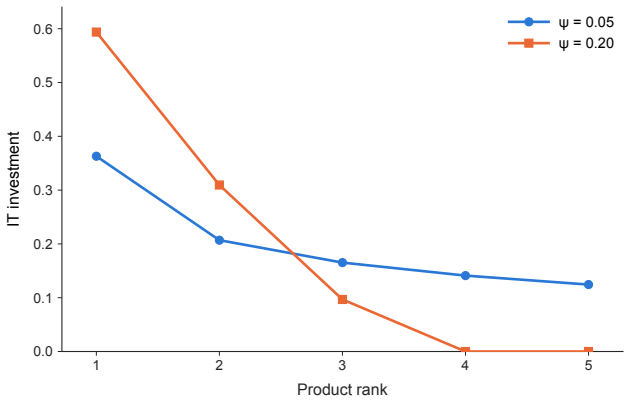
In addition to the selection effects, internal competition for investment can further reduce the value of marginal products when better technology increases investment in the firm's existing products. Because investment costs are convex, this expansion raises the common marginal investment cost, $\nu_i = C'(X_i)$, faced by all products. Equation (56) shows that the increase depends on product-level investment responses weighted by their shares in total firm investment. Greater investment in the firm's largest product lines can therefore raise the cost of investing in other products.

The higher marginal investment cost reduces the value of adding another product. As equation (55) shows, this effect can reinforce losses from product-market competition or outweigh gains from technological upgrading. Importantly, it suggests that a product may remain a strong competitor in its own market yet become unattractive to its parent firm because of more valuable investment opportunities elsewhere in the portfolio.

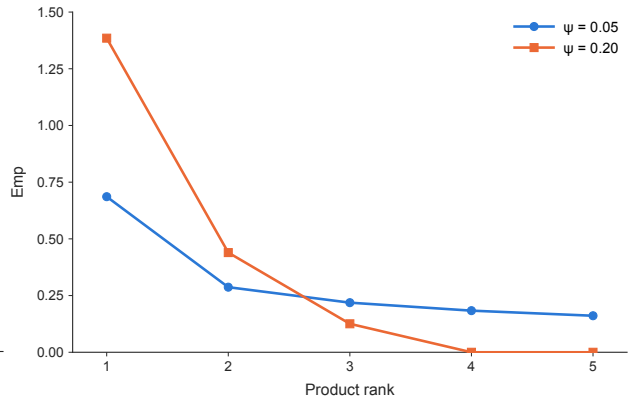
These two forces together reduce scope when they make the expected incremental contribution of another opportunity insufficient to cover its development cost. A decline in $\widetilde{D}_{i,n}$ describes the marginal-product mechanism; the actual Stage-1 decision compares the full expected equilibrium contributions $\overline{D}_{i,n}$. At an adjacent indifference boundary, a decline in $\overline{D}_{i,n}$ favors the narrower portfolio. Away from that boundary, the product can become less valuable without an immediate scope adjustment. Figure C.1 provides a graphical representation of this result. We assume the productivity from fixed-cost technology is $g(u) = \bar{g}\log(1+u^{\beta})$, which satisfies the proposition's shape restrictions at positive investment levels.

Figure C.1: Model mechanism

(a) Fixed-cost investment



(b) Employment size



Notes:

C.7 Proof of Proposition 2.

C.8 Proof of Proposition 2

Write $\widehat{v} = d\log v/d\log\psi$, so that $\rho_{ij} = \widehat{z}_{ij}$ and $\rho_j = -\widehat{p}_j$ denote, respectively, supplier productivity growth and the decline in the product-market price index. All sums below are over the fixed supplier set $\mathcal{M}_j$. Recall $\varepsilon_{ij} = \varepsilon(s_{ij})$, where $\varepsilon(s) = \eta - (\eta-\sigma)s$, and write

$$\varsigma_{ij} = \varsigma(s_{ij}), \qquad \varsigma(s) = \frac{\eta - 1}{1 + (\eta-1)\dfrac{(\eta-\sigma)s}{\varepsilon(s)[\varepsilon(s)-1]}}, \qquad \bar{\varsigma}_j = \sum_i s_{ij}\varsigma_{ij}, \qquad w_{ij} = \frac{s_{ij}\varsigma_{ij}}{\bar{\varsigma}_j}.$$

Let Cov_{w_j} denote covariance across suppliers under the normalized weights w_{ij}.

The market-share response is $\widehat{s}_{ij} = \varsigma_{ij}(\rho_{ij} - \rho_j)$. Market-share adding-up therefore gives $0 = \sum_i s_{ij}\varsigma_{ij}(\rho_{ij} - \rho_j)$, so $\rho_j = \sum_i w_{ij}\rho_{ij}$. Thus, for any initial supplier characteristic v_{ij},

$$\sum_i v_{ij}\frac{ds_{ij}}{d\log\psi} = \bar{\varsigma}_j \,\mathrm{Cov}_{w_j}(v_{ij}, \rho_{ij}). \tag{57}$$

Differentiating $H_j = \sum_i s_{ij}^2$ proves the concentration response in the proposition. Next, $\mu_j^{-1} = 1 - \sum_i s_{ij}/\varepsilon_{ij}$ and $d\varepsilon_{ij} = -(\eta-\sigma)\,ds_{ij}$ give

$$d\log\mu_j = \mu_j \sum_i \left[\frac{1}{\varepsilon_{ij}} + \frac{(\eta-\sigma)s_{ij}}{\varepsilon_{ij}^2}\right] ds_{ij}.$$

Applying the preceding covariance identity gives the markup response in the proposition, separating reallocation across suppliers from individual markup adjustment.

For productivity, $Z_j = \mu_j/p_j$ implies $\widehat{Z}_j = \widehat{\mu}_j + \rho_j$. Using $\ell_{ij} = \mu_j s_{ij}/\mu_{ij}$ and

$$\frac{1}{\varsigma_{ij}} = \frac{1}{\eta-1} + \frac{(\eta-\sigma)s_{ij}}{\varepsilon_{ij}(\varepsilon_{ij}-1)}$$

yields

$$\rho_j - \sum_i \ell_{ij}\rho_{ij} = \mu_j\bar{\varsigma}_j\left[\frac{1}{\eta-1}\,\mathrm{Cov}_{w_j}\left(\frac{1}{\varepsilon_{ij}}, \rho_{ij}\right) - (\eta-\sigma)\,\mathrm{Cov}_{w_j}\left(\frac{s_{ij}}{\varepsilon_{ij}^2}, \rho_{ij}\right)\right].$$

Combining this identity with the markup response proves the productivity response in

the proposition. The functions s, $1/\varepsilon(s)$, and $s/\varepsilon(s)^2$ are increasing when $\eta > \sigma > 1$. If ρ_{ij} is nondecreasing in initial market share s_{ij}, their covariances with ρ_{ij} are nonnegative, proving the sign statements. The direct productivity term is positive when all gains are nonnegative and at least one supplier with positive production labor has a strictly positive gain.

Finally, for given technologies and total production labor, Hölder's inequality implies

$$\left[\sum_i (z_{ij} l_{ij})^{(\eta-1)/\eta}\right]^{\eta/(\eta-1)} \leq \left(\sum_i z_{ij}^{\eta-1}\right)^{1/(\eta-1)} \sum_i l_{ij}.$$

Equality requires $l_{ij}/l_j \propto z_{ij}^{\eta-1}$, which the CES demand allocation delivers exactly when supplier markups are common. This proves the productivity-frontier interpretation in the main text. It does not imply that withdrawing a variety must lower equilibrium productivity after other choices adjust. □

C.9 Proof of proposition 3

Put $\widehat{v} = d\log v/d\log\psi$. From the pricing rule and $c_{ij} = 1/z_{ij}$,

$$\widehat{p}_{ij} = -G_{ij} + \frac{(\eta-\sigma)s_{ij}}{\varepsilon_{ij}(\varepsilon_{ij}-1)}\widehat{s}_{ij}.$$

Differentiate the CES share equation, $\widehat{s}_{ij} = -(\eta-1)(\widehat{p}_{ij} - \widehat{p}_j)$, and substitute to obtain $\widehat{s}_{ij} = \varsigma(s_{ij})(G_{ij} - G_j)$. Together with the investment ranking proved above, this establishes (**??**).

For the marginal-product approximation, the envelope theorem eliminates changes in the focal product's optimized price and investment. At fixed focal choices, the own-technology effect on operating profit is $l_{ij}u_{ij}g'(u_{ij})$. Residual demand is proportional to $EP^{\sigma-1}p_j^{\eta-\sigma}p_{ij}^{-\eta}$, and $\partial\log p_j/\partial\log p_{\ell j} = s_{\ell j}$. Hence

$$\left.\frac{d\pi_{ij}}{d\log\psi}\right|_{\text{envelope}} = l_{ij}u_{ij}g'(u_{ij}) + \pi_{ij}\left[(\eta-\sigma)\sum_{\ell\neq i} s_{\ell j}\widehat{p}_{\ell j} + (\sigma-1)\widehat{P}\right].$$

Subtract $v_i x_{ij}\widehat{v}_i$ and use $l_{ij}/\pi_{ij} = \varepsilon_{ij} - 1$ to prove (**??**). Rivals' prices are fixed in each unilateral optimization; their changes across equilibria enter the envelope as environ-

mental changes. The common marginal-cost response is

$$\widehat{v}_i = (\gamma - 1)\widehat{X}_i = (\gamma - 1) \sum_{h \in \mathcal{J}_{i,n}} \frac{x_{ih}}{X_i} \widehat{x}_{ih},$$

for the fixed existing portfolio used in the local approximation. Thus increased total investment strengthens the congestion term. No global ranking of productivity responses across parents, or automatic discrete scope contraction, is asserted. □

D Calibration Moments

Table D.1 reports regression results by estimating equation (39).

Table D.1: Regression: Core-to-second product employment gap

	(1) Unweighted	(2) Employment weighted
Top 10%	0.596***	0.595***
	(0.057)	(0.075)
50%–90%	0.474***	0.496***
	(0.035)	(0.042)
Constant	0.993***	1.029***
	(0.026)	(0.029)
Observations	10,541	10,541
R-squared	0.021	0.001

Notes: This table reports regression results by estimating equation (39). The dependent variable is $\log L_{i(1)} - \log L_{i(2)}$. Column (1) reports unweighted regression results. Column (2) uses total firm-level employment as analytic weights. I estimate the regression use firms with at least two products. Standard errors are clustered at the industry level and reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.2 reports regression results by estimating equation (40).

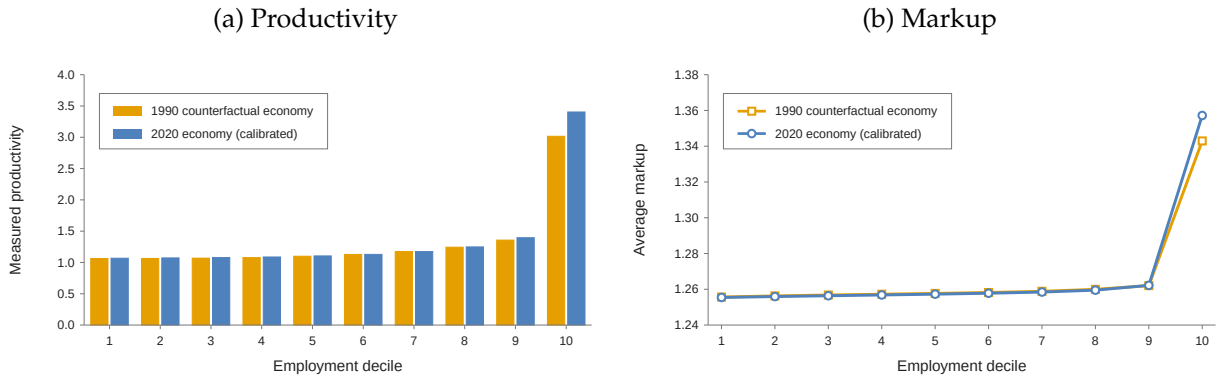
Table D.2: Regression results: Revenue-to-variable-cost ratio

	(1) $\log(R/VC)$
Log revenue	0.0251***
	(0.0056)
Industry fixed effects	Yes
Observations	1,265
R-squared	0.164

Notes: This table reports regression results by estimating equation (40). Standard errors in the parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E Additional Quantification Results

Figure E.1: Productivity and markup by firm size



Notes: This figure compares firm productivity and markup across employment deciles in the 1990 counterfactual and the 2020 baseline calibration. In the 1990 counterfactual, I reduce technology efficiency ψ by 38.61% relative to its 2020 level to match the observed change in the aggregate fixed-cost share. Panel (a) plots average productivity by firm employment decile, the blue bar represents the 2020 baseline calibration, and the orange bar represents the 1990 counterfactual. Panel (b) plots each decile's average markup. In both figures, the blue line represents the 2020 baseline calibration, and the orange line represents the 1990 counterfactual.