Understanding Firm Dynamics

Literature review along with a data exercise on manufacturing firms in India

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1 Introduction

This independent study module aimed to understand the evolution of firm dynamics in Indian manufacturing by combining insights from the broader literature with a replication and extension of an influential empirical study. The motivation lies in examining how product scope, diversification, and reallocation within firms have evolved over time, and what this reveals about the nature of productivity growth and creative destruction in India's manufacturing sector. Despite decades of policy reform and trade liberalization, questions remain about whether Indian firms have become more dynamic and competitive or whether structural rigidities continue to constrain their evolution.

The first part of this study presents a detailed synthesis of key papers that collectively frame the debate on firm productivity, management, trade liberalization, and industrial policy. Bloom et al. (2013) show that management quality alone can account for large productivity gaps, emphasizing how better organizational practices can transform firm performance. Chakraborty, Singh, and Soundararajan (2023) highlight how exposure to import competition from China pushed resources toward the formal sector, raising aggregate productivity even as total employment fell. Akcigit and Ates (2021) situate the discussion within a broader theoretical context, linking the global decline in business dynamism to weakened knowledge diffusion and rising market concentration. Goldberg and co-authors (2010a, 2010b) provide the central empirical foundation for this study, analyzing multiproduct firms in India and how trade liberalization affected product turnover and firm scope. Complementary evidence from Martin, Nataraj, and Harrison (2017) demonstrates how removing size-based restrictions under India's small-scale industry policy reallocated activity toward more efficient firms, while recent studies on semiconductor industrial policy (Bown and Wang, 2024; Goldberg et al., 2024) illustrate how governments continue to shape industrial structure through targeted interventions. Finally, Chatterjee et al. (2025) highlight the persistence of exit barriers that prevent unproductive firms from leaving the market, reinforcing the structural frictions that inhibit creative destruction.

Together, these papers paint a comprehensive picture of how competition, management, trade, and policy jointly influence firm behavior and productivity. They point to an economy where efficiency gains are often achieved through reallocation rather than innovation, where exit remains costly, and where market concentration coexists with a long tail of small, stagnant firms. These insights directly motivate the second part of the paper—a data exercise that updates and extends Goldberg, Khandelwal, Pavcnik, and Topalova's (2010) analysis of Indian multiproduct firms using CMIE's Prowess dataset from 2010 to 2024.

The replication reveals several striking trends. Single-product firms overwhelmingly dominate Indian manufacturing, accounting for over three-quarters of all firms and more than four-fifths of total output. Even multiproduct firms remain heavily concentrated around their primary products, with non-core products contributing little to overall revenue. Product churning—measured by additions and drops—has declined sharply since 2010, indicating weakening business dynamism. A brief but steep rise in product drops around 2011–2013 suggests a temporary episode of consolidation, possibly linked to external shocks. Growth decomposition further confirms that firm expansion is driven almost entirely by the intensive margin—sales growth in continuing products—rather than by new product introductions. Transition probabilities reinforce this inertia: firms largely maintain their portfolio sizes over time, rarely adding or experimenting with new lines.

2 Paper Summaries

2.1 Does Management Matter?

Research Question

The study examines whether differences in basic management practices can explain large productivity gaps among firms in a developing-country setting. The authors run a field experiment on large Indian textile firms to directly test whether improving management causes measurable performance gains. The question is motivated by India's low aggregate productivity—around 40% of the US level—despite strong economic growth.

Intervention

Plants were randomly assigned to treatment and control groups. Treatment plants received intensive, hands-on consulting on core management practices such as lean production, quality control, inventory tracking, and standardized processes. Control plants received only short and largely ineffective diagnostic visits. Both groups were given some form of consulting to reduce the risk of Hawthorne effects.

Productivity Gains

Firms that adopted the recommended practices experienced large improvements. Productivity increased by roughly 17% on average, driven by fewer defects, smoother production flows, and lower inventory holdings. Profits rose significantly, showing that the gains were economically meaningful rather than statistical artefacts.

Organizational Changes

Better management changed how firms were run. Decision-making became more decentralized as owners delegated more authority to middle managers and relied on systematic information flows. Firms also increased their use of computers and data systems for monitoring operations. These adjustments reflected a move toward more modern organizational structures.

Why Weren't Firms Already Doing This?

Despite the clear benefits, many firms had never adopted these practices. The main barriers were limited information about modern management and weak understanding of its value. In addition, India's business environment—characterized by low competitive pressure and constraints on entry and expansion—allowed poorly managed firms to survive without being forced to upgrade.

Conclusion and Implications

The experiment shows that management quality is a key driver of firm performance. Even in traditional manufacturing, improvements in basic managerial "technology" can generate large productivity gains. This suggests that targeted consulting or training programs may help underperforming firms grow, and that stronger product-market competition could, over time, encourage better management through creative destruction.

2.2 Import Competition, Formalization, and the Role of Contract Labor (India)

Overview

This paper studies how rising import competition from China reshaped India's manufacturing workforce in the 2000s. India has a large informal sector with many small, low-productivity firms. When imports rise, weaker firms may contract or exit, while stronger formal firms expand. The central question is whether this shift pushed workers toward more productive formal employment, and how these movements affected aggregate productivity.

Main Findings

Chinese import competition caused a clear move toward formal employment between 2000–01 and 2005–06. The share of formal jobs increased by about 3.7 percentage points. This occurred because many informal firms shrank or closed, while more productive formal firms absorbed displaced workers. Most of the additional formal jobs were in contract positions, which gave firms the flexibility to hire without facing strict firing rules.

However, overall employment in affected industries fell, since informal job losses were larger than formal job gains. Aggregate labor productivity rose by roughly 2.87 percent, driven mainly by the reallocation of resources from low-productivity informal firms to higher-productivity formal firms. States with stricter labor laws and stronger unions saw especially large shifts toward formality. Worker-level data indicate that employees became more likely to find work in formal firms, benefiting from better security and a higher chance of receiving retirement benefits.

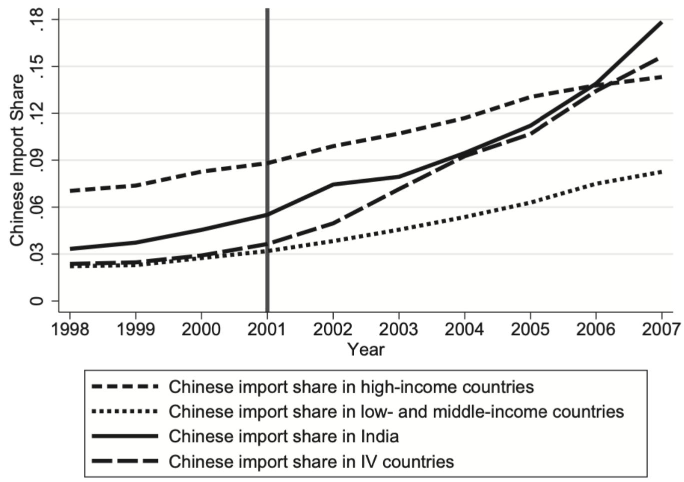


Figure 1: Growth of Chinese Import Share in Indian Manufacturing

Mechanism

The adjustment operated mainly through firm heterogeneity. Low-productivity informal firms were most exposed to import pressure and reduced employment sharply. Formal firms, especially larger and more productive ones, expanded by hiring contract workers. Contract labor helped firms bypass rigid dismissal rules for regular workers, allowing employment to adjust quickly while maintaining compliance with labor laws. This flexibility was central to the reallocation of labor toward more productive firms.

Data

The analysis combines multiple datasets: NSS unorganized manufacturing surveys to track informal firms; ASI data for formal plants; NSS Employment and Unemployment Survey for worker outcomes; COMTRADE import data; and state-level indices capturing variation in labor regulations and union strength.

Methodology

Import competition is measured as Chinese imports divided by domestic absorption at the industry level. To address endogeneity, the authors use Chinese exports to a selected group of Latin American countries as an instrument, capturing global supply shocks unrelated to Indian demand. Firm-level panel regressions track within-firm changes in regular and contract employment under rising import pressure. Productivity effects are studied using an Olley–Pakes decomposition, separating within-firm changes from reallocations across firms. A development-accounting exercise links these reallocations to aggregate productivity gains.

Productivity Effects

Productivity improvements came mainly from reallocation. The covariance term in the Olley–Pakes decomposition explains most of the gain, showing that labor moved toward more productive firms rather than firms becoming more productive internally. Depending on adjustments for hours, human capital, prices, and output elasticities, the aggregate gain ranges from 0.8 to 2.87 percent.

Implications

The results show that rising import competition can promote formalization in economies where informal firms are small, protected, and inefficient. Even though total employment may fall in the short run, workers who move into the formal sector gain more stable jobs and benefits. For policymakers, the findings highlight how trade shocks interact with labor regulations. Strict firing rules encourage firms to expand through contract workers rather than regular employees, shaping the form of formalization. More broadly, the paper shows how external competition can support long-run productivity improvements by reallocating activity toward more productive firms.

2.3 Ten Facts on Declining Business Dynamism and Lessons from Endogenous Growth Theory

Motivation

Over the past few decades, the United States has seen a broad decline in business dynamism. New firm entry has slowed, job reallocation has weakened, market concentration and markups have increased, the labor share has dropped, and productivity growth has been subdued. The paper brings these trends together and proposes a unified endogenous-growth framework—built around strategic R&D races, endogenous markups, and knowledge diffusion between leading and lagging firms—to explain the facts jointly and evaluate potential causes, with particular attention to changes in knowledge diffusion.

Ten Stylized Facts

Using a wide literature and macro and firm-level evidence, the paper highlights: rising market concentration and higher markups; an increase in the profit share paired with a decline in the labor share, which is negatively linked to concentration; a widening productivity gap between frontier and laggard firms; a fall in entry and a shrinking role for young firms; lower job reallocation and a decline in the dispersion of firm growth; and a slowdown in aggregate productivity growth, with a temporary acceleration during the mid-1990s to mid-2000s.

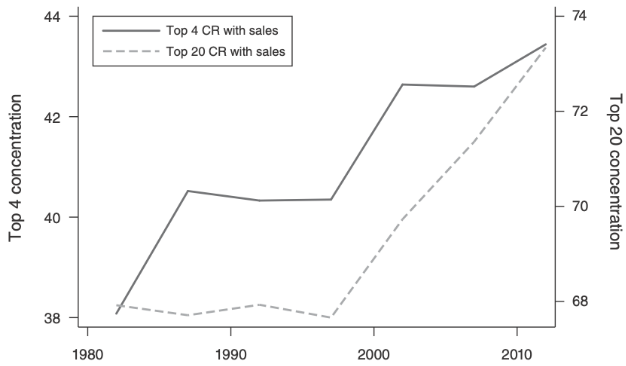


Figure 1. Market Concentration

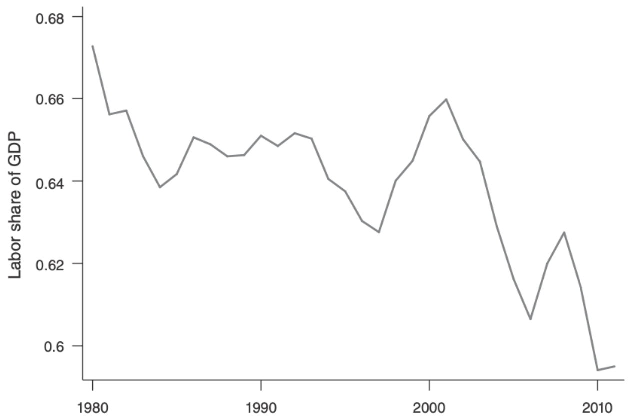


Figure 4. Labor Share

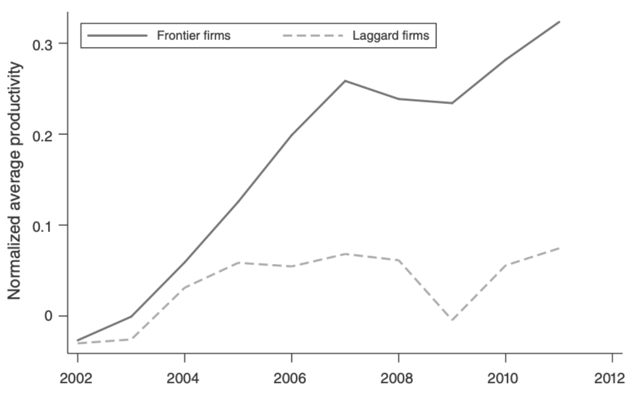


Figure 6. Labor Productivity of Frontier and Laggard Firms

Theory in Brief

The economy has a continuum of product lines. In each line, two incumbent firms compete in prices and try to innovate step by step. The leading firm earns a markup that depends on how far ahead it is. When both firms have the same technology, competition is strongest and markups fall to zero. Firms choose innovation rates strategically. Knowledge can also flow from leader to follower at an exogenous rate δ, which pushes the line back to a neck-and-neck state. The share of unleveled sectors μ (those with a clear leader) determines market concentration, average markups, the labor share, and the profit share. Long-run growth comes from innovation by neck-and-neck firms.

Core Mechanism and Predictions

When knowledge diffusion weakens (a lower δ), the value of being a leader rises. Neck-and-neck firms respond more strongly and innovate at higher rates, trying to "escape" competition. Over time, more sectors move into the unleveled state and μ increases. On the balanced growth path, this shift implies:

- Higher concentration, higher markups, a larger profit share, and a lower labor share.
- A wider productivity gap between frontier and laggard firms.
- Mixed effects on job reallocation, growth dispersion, and aggregate growth, because a stronger incentive to innovate in neck-and-neck sectors works against a compositional shift that reduces the share of such sectors.

During the transition, a fall in δ generates a hump-shaped pattern in productivity growth: it rises at first due to stronger innovation incentives but slows later as the economy becomes more concentrated.

Interpretation of the Diffusion Margin

A decline in effective diffusion can arise from several forces. Data-intensive production and proprietary data can limit spillovers. Regulatory changes such as weaker antitrust enforcement, more licensing and noncompete rules, and reduced worker mobility can also restrict learning. Offshoring may weaken knowledge flows by increasing distance from the frontier. Thicker IP barriers, including patent thickets and defensive patent acquisitions, can further slow diffusion. Evidence from patent filings and reassignment patterns supports rising concentration of innovative activity among the largest firms.

Policy Takeaways

If weaker diffusion is an important driver, policy should aim to make knowledge flow more easily while still supporting innovation at the frontier. This can include data-portability or interoperability rules, stronger antitrust and IP oversight, and labor-market policies that allow greater mobility. The aim is to reduce barriers to diffusion without undermining the incentives that sustain high-quality R&D.

2.4 Investmentless Growth: An Empirical Investigation

Motivation

The paper investigates a central puzzle in the recent U.S. growth experience: private fixed investment has been unusually weak since the early 2000s, even though profitability, cash holdings, and market valuations have been historically high. Using industry- and firm-level data, the authors ask why investment has not responded to strong balance sheets and elevated Tobin's Q. The key distinction is between explanations that predict low investment when Q is low, versus explanations in which investment stays weak despite high Q because of structural features of market power, ownership, and intangibility. The evidence overwhelmingly favors the second class.

Empirical Patterns

Four broad facts frame the analysis. First, profits in the nonfinancial corporate sector have remained high, but reinvestment rates have fallen to roughly half of their pre-2000 levels. Second, investment relative to Tobin's Q shows a persistent decline after 2000, creating a large gap between expected and observed investment. Third, business dynamism has slowed: entry, exit, job reallocation, and IPO activity have all declined, consistent with rising concentration and markups. Fourth, payouts through buybacks and dividends have increased sharply, especially in firms with high passive institutional ownership. Taken together, these patterns suggest a shift away from investment-led growth toward cash distribution and financialization.

Figure 1. Net Investment Relative to Net Operating Surplus, 1962–2015[a]

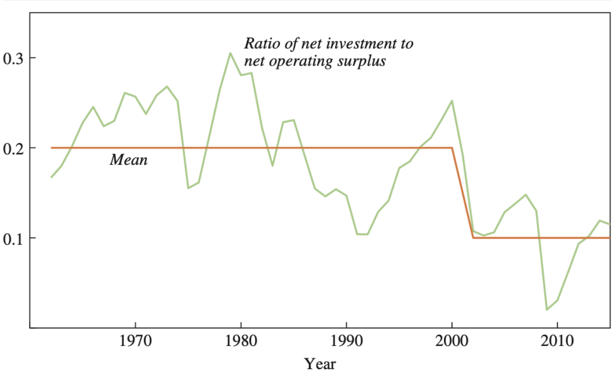
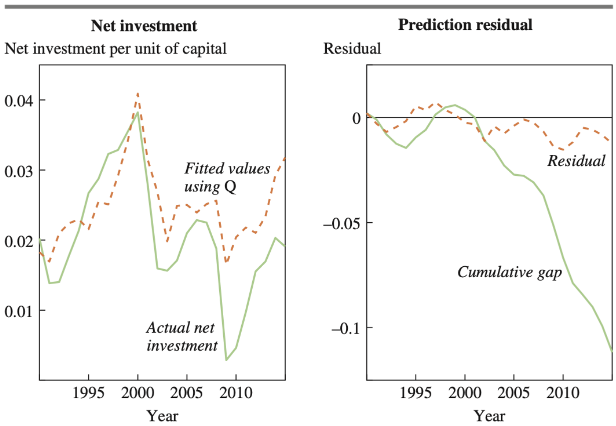


Figure 3. Net Investment versus *Q*, 1990–2015[a]



Empirical Approach

To discriminate among competing explanations, the paper estimates regressions at both firm and industry levels, controlling for profitability, size, age, and errors-in-variables using the cumulant estimator of Erickson, Jiang and Whited (2014). The hypotheses fall into four categories: financial frictions; the changing nature and location of investment; competition and market power; and corporate governance. The results systematically reject financial constraints as a primary driver and instead support explanations rooted in rising intangibles, increased concentration, and changes in ownership structure.

Main Findings

A substantial part of the investment gap reflects the growing importance of intangible assets (software, R&D, and brand capital) that are imperfectly measured and slow to accumulate. Rising intangibility increases equilibrium Q and makes tangible investment appear weaker. Beyond this, the strongest evidence points to declining competition. Industries with higher concentration, higher markups, and greater common ownership invest less, even conditional on fundamentals. Firms with high quasi-indexer ownership also tend to invest less and return more cash to shareholders, indicating governance structures that emphasize short-term financial performance. Alternative explanations such as regulatory burdens, safe-asset scarcity, or financing constraints do not survive once concentration and governance are accounted for.

Macroeconomic Implications

The findings imply that weaker capital formation and slower productivity growth reflect endogenous changes in market structure rather than a deterioration in fundamentals. Higher markups distort investment incentives and alter the distribution of value added: profits rise, labor shares fall, and capital deepening slows. Simulations with a DSGE model show that higher markups reduce measured TFP and investment, even if underlying technology is unchanged. This pattern matches broader concerns about secular stagnation, rising inequality, and the weakening link between corporate profitability and real economic activity.

Conclusion

The paper argues that the post-2000 decline in investment is a structural feature of the modern U.S. economy. Firms remain profitable but invest less because market power, intangibles, and governance practices change the relationship between Q and investment. Growth becomes less tied to capital formation and more dependent on financial returns. The authors emphasise the need for stronger competition policy and governance reforms that may redirect incentives toward long-term productive investment.

2.5 Imported Intermediate Inputs and Domestic Product Growth: Evidence from India

Motivation

Many trade and growth models predict that access to new imported intermediate inputs generates both static gains (through cheaper/better inputs) and dynamic gains (through new domestic product creation). India's 1991 trade liberalization provides a sharp setting to test these mechanisms. During the 1990s, India saw two striking trends: (i) a surge in imported intermediates-over two-thirds of growth came from entirely *new* imported varieties; and (ii) a rapid expansion in domestic product scope, with new products accounting for roughly one-quarter of manufacturing output growth. The central question is whether input tariff reductions, by giving firms access to new intermediate varieties, enabled domestic firms to introduce new products.

Main Findings

Reduced-form evidence shows that industries facing larger cuts in input tariffs experienced significantly greater expansion in firms' product scope. A 10 percentage point fall in input tariffs increased a firm's number of products by about 3.2%. Since input tariffs fell on average by 24 percentage points, tariff liberalization explains roughly 31% of the observed increase in product scope between 1989 and 1997. Firms in these industries also expanded output, improved measured productivity, and raised R&D spending (especially among larger firms), consistent with models linking imported inputs to productivity and innovation.

When the authors decompose input-price movements into a conventional (price) component and a variety component, they find that the extensive margin of input imports played a dominant role. Access to new imported varieties lowered the exact intermediate-input price index by an additional 4.7% per year relative to traditional price effects. Instrumental-variable estimates confirm that increases in imported-variety availability—not just cheaper existing imports—were a key driver of the domestic product expansion.

Mechanism

Input tariffs shape firm behaviour through two channels: (i) *price effects*, which reduce the cost of existing imported inputs; and (ii) *variety effects*, which give firms access to new intermediate inputs that were technologically unavailable before liberalization. If certain inputs are essential or poorly substitutable, new varieties relax technological constraints and make new products economically viable. The structural framework, using Feenstra-style exact price indices, shows that the variety channel has a particularly strong effect on firms' minimum cost of production and thus on the decision to introduce new products.

Data

The analysis combines multiple sources:

- **Firm-level data:** CMIE Prowess panel (1989–1997) with detailed product-level information, enabling direct measurement of changes in firm scope.
- **Trade data:** HS8-level import and tariff data (1987–2001), capturing prices, quantities, and new imported varieties.
- **Input–Output data:** India's 1993–94 IO table (and robustness using 1998–99 IO table) to construct input tariffs and sector-specific price/variety indices.
- **Tariffs:** Differential reductions in input tariffs formed the core policy variation; reforms were unanticipated and not correlated with prereform firm characteristics.

Methodology

The empirical strategy has two components:

Reduced Form.

Firm scope is regressed on lagged input tariffs, with firm and year fixed effects. Robustness checks include NIC–year interactions, prereform trends, firm-size controls, Poisson models, and long-difference specifications.

Structural Decomposition.

The authors construct exact input price indices following Feenstra (1994) and Broda–Weinstein (2006), separating:

(i) conventional price effects, (ii) variety effects from new imported inputs.

These indices are then mapped to firms via input–output weights. Endogeneity concerns are addressed using two instruments: (a) input-tariff declines; and (b) an interaction of tariff declines with a "proximity" measure capturing fixed-cost advantages of English-speaking RCA partners. These instruments separately identify price and variety channels.

Channels and Quantification

Instrumental-variable results show that:

- Lower input prices of existing varieties have limited explanatory power.
- Increased access to new intermediate varieties is the primary driver of firm scope expansion.

A 1% decline in the variety index increases firm scope by roughly 13% (IV estimate). Given observed tariff changes, this mechanism raised product scope by about 3.4% for the average firm—consistent with reduced-form estimates.

Implications

The results provide direct microeconomic evidence for new-variety gains from trade. Input liberalization did not merely lower production costs, it expanded the technological possibilities of firms by giving them access to intermediate inputs previously unavailable in India. This access enabled firms to introduce new products, driving a substantial portion of manufacturing output growth in the 1990s.

More broadly, the findings support endogenous-growth models in which imported input varieties stimulate domestic innovation. They also suggest that the dynamic gains from trade—through firm-level experimentation, product variety expansion, and innovation—are likely to be quantitatively important in developing-country liberalizations.

2.6 In with the Big, Out with the Small

Overview

The paper studies the impact of removing India's SSI reservation policy, under which certain products could only be produced by small firms. Between 1997 and 2007, almost all such products were deregulated. The authors examine how this sudden removal affected employment, output, investment, wages, plant entry and exit, and the broader structure of Indian manufacturing.

The deregulation offers a natural setting to test whether lifting size-based restrictions helps or harms employment and growth.

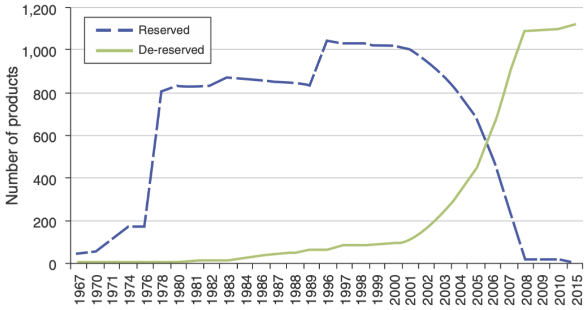


Figure 2
A plot of the number of reserved products over time (sharp fall from 1997–2007)

Data and empirical approach

The analysis uses the Annual Survey of Industries (ASI) panel from 2000–2007. Two complementary strategies are used:

- Establishment-level difference-in-differences using precise dates when each product was deregulated.
- District-level long differences, based on how exposed each district was to products that were later deregulated, using its pre-2000 product mix.

TABLE 3—IMPACT OF DE-RESERVATION ON ESTABLISHMENT-LEVEL OUTCOMES, CONTROLLING FOR TIME TREND

	log(labor)	log(output)	log(capital)	log(wage)	log(Q/L)
Panel A. Aggregate results					
$t \geq$ year de-reserved	−0.000590	0.0371	−0.00954	0.0129	0.0232
	(0.00896)	(0.0125)	(0.0106)	(0.00511)	(0.0103)
Time relative to de-reservation	−0.00151	−0.00566	0.00645	0.00009	−0.00302
	(0.00182)	(0.00268)	(0.00252)	(0.00101)	(0.00213)
Establishment fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	298,984	294,157	292,998	296,575	294,157
Establishments	130,397	128,033	127,822	128,986	128,033
R^2	0.006	0.011	0.003	0.026	0.007
Panel B. Incumbents versus entrants					
Incumbent $\times$ $t \geq$ year de-reserved	−0.0146	−0.000433	−0.0244	0.00117	−0.00566
	(0.00976)	(0.0132)	(0.0113)	(0.00536)	(0.0107)
Entrant $\times$ $t \geq$ year de-reserved	0.0798	0.249	0.0718	0.0704	0.189
	(0.0196)	(0.0327)	(0.0257)	(0.0138)	(0.0277)
Time relative to de-reservation	−0.00264	−0.00732	0.00545	−0.00004	−0.00386
	(0.00182)	(0.00269)	(0.00253)	(0.00101)	(0.00214)
Establishment fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Year of entry $\times$ year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	298,984	294,157	292,998	296,575	294,157
Establishments	130,397	128,033	127,822	128,986	128,033
R^2	0.008	0.014	0.004	0.027	0.009

Figure 3

Main plant-level results

The effects differ sharply across types of plants.

- New entrants into previously reserved product categories expand rapidly. They increase employment, output, capital, wages, and productivity.

- Larger incumbents that had been restricted by SSI size limits also expand. These establishments increase investment, output, and hiring once restrictions are removed.
- Small, older incumbents shrink. These plants lose employment after deregulation, suggesting they were protected by the old system.
- The strongest growth is concentrated among younger and larger plants, consistent with models where competition reallocates activity toward more productive firms.

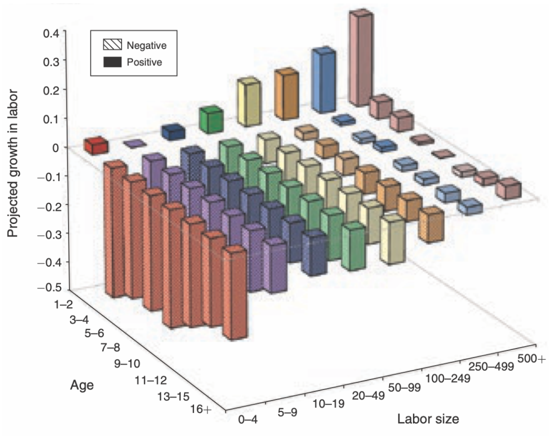


Figure 5. Projected Employment Growth by Size and Age

Results from product-level analysis

When outcomes are aggregated at the product level, deregulation leads to substantial increases in:

employment, output, investment, number of establishments, and wages. Productivity falls at this level because employment grows faster than output, reflecting the entry of many new plants.

Tests for pretrends and placebo exercises show that deregulation timing was not correlated with prior growth.

District-level outcomes

- Districts that were more exposed to products that got deregulated (based on their 2000 production composition) experienced higher employment and output growth from 2000–2007.
- The average district saw a 6 percent rise in manufacturing employment due to deregulation.
- There is no evidence that deregulation forced workers into informal manufacturing; if anything, workers shifted into formal employment.

Interpretation

The findings align with heterogeneous-firm models. Deregulation lowers barriers to entry and scale, causing resources to shift from less productive to more productive firms. The reservation policy had been holding back high-potential firms and limiting competitive pressure. Once removed, markets adjust through entry, expansion of constrained incumbents, and contraction of inefficient plants.

2.7 Semiconductors and Modern Industrial Policy

Overview

This paper serves as a qualitative overview of the semiconductor industry. It explains how the industry developed, why its supply chain is now heavily concentrated in East Asia, and why governments are using large industrial policies to reshape it.

Core ideas

Chips are expensive to manufacture and rely on learning-by-doing, scale economies and local technological spillovers, which makes them a natural target for industrial policy.

Modern production is split across firms, with design and manufacturing often carried out by different companies.

The supply chain is global, but manufacturing capacity has shifted strongly toward East Asia, while the United States and Europe continue to dominate design tools, equipment production and intellectual property.

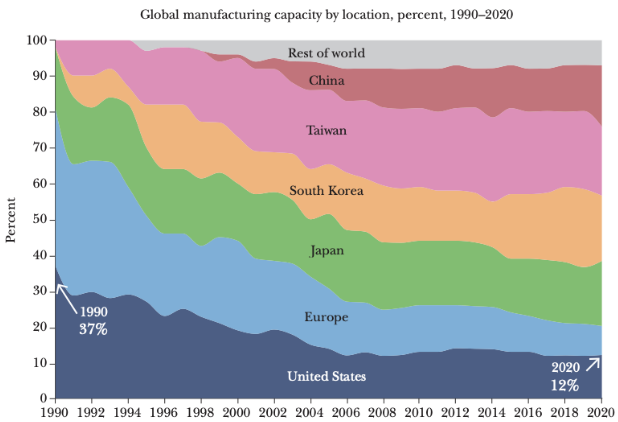
Historical development

In the early decades of the industry, firms in the United States were the global leaders. They benefited from defence and space-related procurement that supported early innovation and large-scale production. During the 1970s and 1980s, Japanese firms became major competitors as a result of coordinated industrial policies and close ties to banks and large electronics producers. This competition led the United States to use trade policy aggressively and opened the door for Taiwan and South Korea, which later developed significant semiconductor capabilities of their own.

Changes in industry structure

Over time, the structure of the industry changed. The fabless–foundry model became the standard, with specialist firms focusing on chip design and others concentrating solely on manufacturing. A small number of firms came to dominate specific stages of production. Manufacturing and downstream activities such as assembly, testing and packaging increasingly moved to Asia, especially Taiwan, South Korea, China and countries in Southeast Asia.

Figure 3
Over time, the supply of semiconductor manufacturing capacity shifted toward Asia



Two major current pressures

Two forces now shape global semiconductor policy. China has expanded subsidies and support programmes to build its own semiconductor base. At the same time, production of the most advanced chips is heavily concentrated in Taiwan and South Korea. This concentration creates risks because any climate shock, geopolitical event, or supply disruption in these economies can affect the entire world.

Policy responses

Governments have reacted with large industrial policy packages. In the United States, the CHIPS Act offers subsidies, tax credits, research funding and limits on investment in China, strict export controls on advanced chips and manufacturing equipment. The European Union, Japan, South Korea and Taiwan have also launched major programmes to attract new fabs or retain existing ones. Export controls, particularly for advanced semiconductor equipment, are now coordinated among the United States, Japan and the Netherlands.

Trade-offs and open questions

These policy choices involve several trade-offs. Shifting production across regions reduces the risks that come from geographic concentration, but it also raises costs and may weaken the efficiency benefits that arise when firms cluster together. The current global investment boom may also exceed future demand, creating excess capacity in some parts of the market. China, if unable to access advanced tools, may instead scale up production of legacy chips, which could require new policy responses.

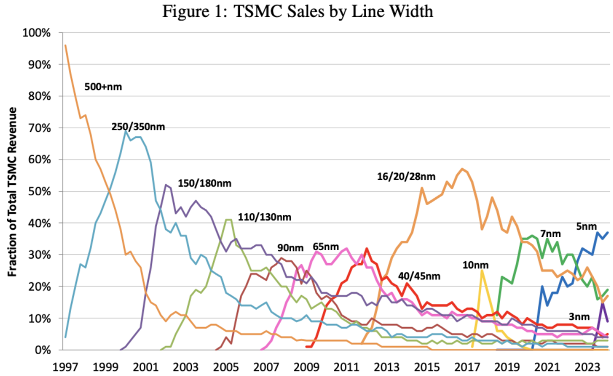
Lastly, the paper also highlights a key problem of the lack of reliable data to measure the size of subsidies, the scope of export controls and their effects on firms and supply chains.

2.8 Industrial Policy in the Global Semiconductor Sector (Goldberg)

Overview

The paper examines why governments heavily support the semiconductor industry, how this support is measured, and what effects it has within and across countries.

Figure 1: TSMC Sales by Line Width

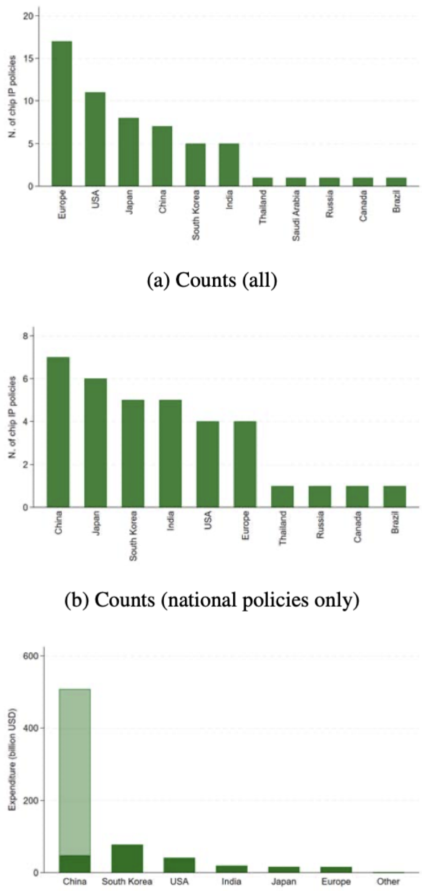


Data and Empirical Approach

The study combines both qualitative and quantitative elements. It begins with a historical account of government support across major semiconductor-producing economies. This is followed by an NLP-based identification of semiconductor-related industrial policies in the Global Trade Alert dataset for the years 2010 to 2022. Here policies are detected using keyword dictionaries and HS codes. The third component is a structural model of foundry pricing and costs, supported by wafer-level data from the Global Semiconductor Alliance. In this model, production subsidies are inferred as the part of observed marginal costs that cannot be explained by wages, technology, experience or other measurable cost drivers.

Patterns of Government Support

The paper documents widespread and rising support for the semiconductor sector. Six major jurisdictions account for most of the activity: China, Japan, South Korea, Europe, the United States and India. Support accelerates after 2020 with the introduction of new funding programmes, national semiconductor strategies and various resilience-oriented plans. Governments intervene at every stage of the value chain, including raw materials, design, fabrication and assembly. Although China appears highly active, its support level is not unusual once scaled to the size of its economy. India stands out for committing substantial resources despite not having an established domestic industry.



(a) Counts (all)

(b) Counts (national policies only)

(c) Monetary values (billions nominal USD)

Figure 3: Industrial policy by country

Policy Instruments and Objectives

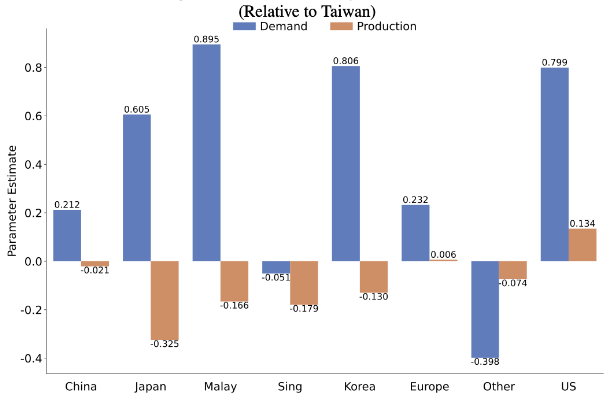
Subsidies are the dominant tool. These include grants, tax credits, concessional loans, equity injections, and incentives for new fabrication plants. Other instruments include FDI incentives, local content requirements, and trade measures. Some policy incentives described by the paper are growth, technology upgrading, competitiveness, supply chain resilience, and national security.

Model-Based Findings

The model provides insight into learning and cost patterns in the industry.

- Learning by doing exists but is smaller than often believed at the level of a specific chip technology.
- Learning is stronger across technologies within the same firm, showing economies of scope.
- Learning spillovers across countries are large. These likely come from shared suppliers, buyer-foundry interactions, foreign investment, and technology transfer.
- Production subsidies inferred from the model show that almost all countries subsidise manufacturing relative to Taiwan. Europe and the United States focus more on research support than production.

Figure 7: Estimated Country Fixed Effects
(Relative to Taiwan)



Interpretation

The findings imply that semiconductor industrial policy is a global norm rather than an exception. Learning spillovers across borders mean that subsidies can lower costs internationally. At the same time, subsidies can also shift market share between countries. Whether a global subsidy race is harmful or beneficial depends on the balance between learning effects, spillovers, and market concentration. The paper shows that the structure of semiconductor production makes cross-country policy interactions especially important.

2.9 Exporting and Plant-Level Efficiency Gains: It's in the Measure

Overview

This paper examines whether plants become more efficient after they begin exporting. Earlier studies found almost no within-plant productivity gains, which led to the belief that gains from trade come mainly from reallocation between plants. The authors show that this conclusion is driven by the use of revenue productivity, which combines physical productivity with prices. When plants gain efficiency and cut prices, revenue productivity does not rise.

The paper uses plant-product level marginal cost as an efficiency measure that is not affected by price changes.

Data and Empirical Approach

The analysis uses the Chilean annual manufacturing census from 1996 to 2005, which reports plant-product revenues, quantities, costs and export shares. Export entry is defined at the plant-product level. The empirical approach combines three elements: First, the authors run an event-study around the year in which a plant exports a specific product for the first time. Second, they use a propensity score matching strategy to compare new exporters with domestic sellers that looked similar before entry. Third, they validate the main results using self-reported product-level cost information and evidence on investment timing. Marginal cost is constructed by estimating markups from the production approach, using materials as the flexible input, and dividing prices by markups.

Main Findings

The results show within-plant efficiency gains once products begin to be exported. Marginal cost falls sharply, by roughly 15 to 25 percent in the first three years after entry. Prices decline by a similar amount and quantities rise. Revenue productivity does not change during this period, which explains why earlier research did not detect these efficiency gains, since TFPR adjusts downward when firms pass efficiency improvements on to buyers. Markups remain roughly constant in the first years after entry and start to increase only once plants become more established exporters.

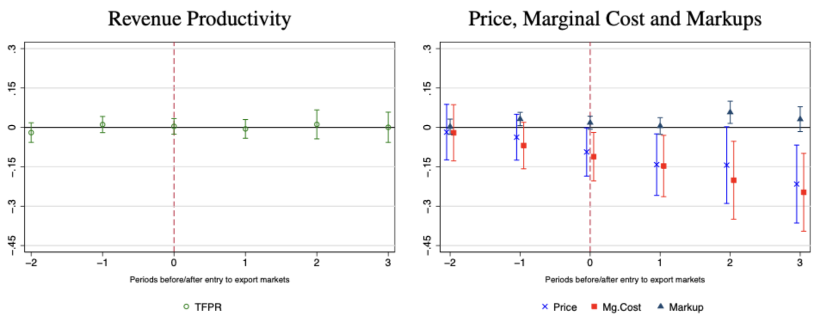


Figure 1: Price, Marginal Cost and TFPR Trajectories for New Exported Products

Notes: The left panel shows the estimated within plant trajectory for revenue productivity, and the right panel, for price, marginal cost and markup before and after export entry. Period $t = 0$ corresponds to the export entry year. For each plant-product, export entry occurs at period $t = 0$. The trajectories correspond to the estimated coefficients of equation (5), as reported in Table 2. A product is defined as an entrant if it is the first product exported by a plant and is sold domestically for at least one period before entry into the export market. Section 4.1 provides further detail.

Mechanisms

The findings do not fit a pure demand story, because greater demand would raise markups rather than leave them unchanged. The evidence is more consistent with supply-side channels. Plants appear to invest in better technologies once they have access to larger markets, and they become more efficient as they accumulate export experience. The largest marginal-cost reductions are observed in plants that were less productive before exporting, which supports the idea that exporting and investment complement each other.

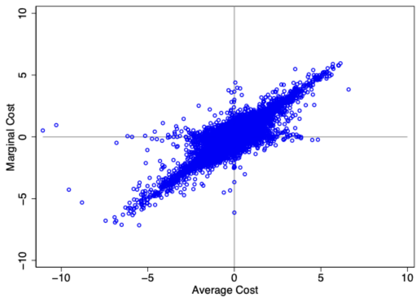


Figure 2: Estimated Marginal Cost and Reported Average Cost

Notes: The figure plots plant-product level marginal costs computed using the methodology described in Section 2 against plant-product level average costs reported in the Chilean ENIA panel (see Section 3 for a detailed description). The underlying data include both exported and domestically sold products, altogether 98,688 observations. The figure shows the relationship between the two cost measures after controlling for plant-product fixed effects (with products defined at the 7-digit level) and 4-digit sector-year fixed effects. The strong correlation thus indicates that changes in computed marginal cost at the plant-product level are a good proxy for actual variable costs.

Robustness and Additional Evidence

The results hold when using matched control groups of similar domestic sellers. They also hold in a balanced panel of successful export entrants. Marginal cost estimates closely match self-reported cost measures, confirming that the efficiency measure is reliable.

Interpretation

Export entry is linked to meaningful efficiency gains within plants. These gains are hidden when using revenue productivity because exporters pass the gains to customers in the form of lower prices. The efficiency improvements are large enough to be comparable to the usual cross-sectional productivity premium of exporters. This suggests that within-plant gains are an important part of the total gains from trade.

2.10 Industrial Policy and Downstream Export Performance (Blonigen, 2013)

Motivation and Research Question

Industrial policies in upstream sectors can raise or lower the cost of inputs for the rest of the economy. This paper examines whether steel-sector industrial policies reduce the export performance of downstream manufacturing sectors that use steel intensively. The main question is whether greater policy intervention in steel harms the export competitiveness of sectors that depend on steel as an input, and whether the effects differ across policy types and across countries.

Data and Empirical Approach

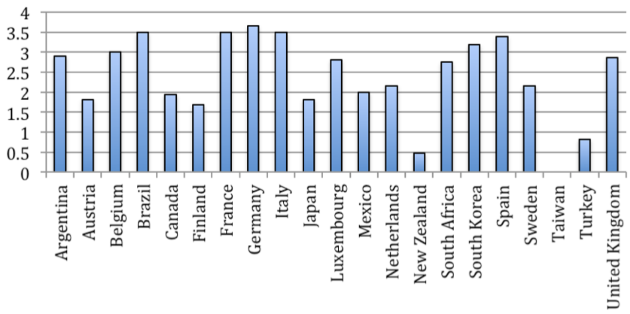
The study uses a hand-collected panel of annual steel-sector industrial policies for 21 major steel-producing countries from 1975 to 2000. These policies include export subsidies, production subsidies or grants, government ownership, cartel arrangements, and non-tariff barriers. Export data come from UN COMTRADE at the five-digit SITC level. Steel input shares by sector come from OECD STAN input–output tables and are fixed at the year 2000 values within each country.

The key variable of interest is the interaction of a country–year policy measure with a sector's steel input share:

$$\log X_{cit} = \beta\,(\text{IP}_{ct} \times \text{SteelShare}_{ci}) + \eta_{ct} + \eta_{ci} + \varepsilon_{cit}.$$

Country–time effects absorb macroeconomic shocks, exchange rates, and any direct impact of policy presence. Country–sector effects capture baseline comparative advantage. Steel shares are technological and measured before the decline in policies, which reduces endogeneity concerns.

Figure 2: Average number of steel IP types by country over 1975-2000 period



Main Findings

Stronger steel-sector industrial policies reduce downstream export performance. For an average sector, a one-standard-deviation rise in policy presence lowers export value by about **3.6%**. For highly steel-intensive sectors the reduction can approach **50%**. Similar results appear when exports are measured in quantities, indicating both prices and volumes adjust. The evidence shows that cost increases created by upstream intervention are transmitted downstream.

Heterogeneity

The negative effect is concentrated in less-developed countries in the sample. Developed economies show near-zero average effects. Asian producers (Japan, South Korea, Taiwan) exhibit negative effects similar to the less-developed group. Country-by-country estimates also show that most countries have negative coefficients, many statistically significant.

Prices Versus Quantities

Quantity-based regressions give slightly smaller negative coefficients, while value-based regressions reflect larger adjustments due to price reductions. This pattern suggests downstream firms respond to higher steel prices by cutting prices or quality while also reducing output.

Policy Channels

Different policy types have different effects. Export subsidies and non-tariff barriers show the largest negative impacts on downstream export competitiveness, particularly in less-developed countries. Government production subsidies or grants have a small positive effect, but it is much smaller than the negative effects of export subsidies and non-tariff barriers. Government ownership is weakly negative on average. Cartel arrangements show no clear pattern.

Robustness

The main results hold across functional forms, time splits, and specifications with lags. The effects appear immediate and are present even in sectors with below-average steel intensity. The impact is stronger in the years before 1990, when policy use was more common.

Implications

Steel-sector industrial policies often raise domestic steel prices, which can weaken the export capability of downstream industries. These effects are largest in less-developed countries and where policy mixes rely heavily on protection and export subsidies. The results imply that upstream support in core input sectors can impose substantial hidden costs on the broader manufacturing base. Policies that directly lower marginal costs, are temporary, and are paired with credible phase-outs are less likely to depress downstream competitiveness.

3 Replication Exercise

3.1 Introduction

Multiproduct firms and product turnover in the developing world: Evidence from India, a paper written by Pinelopi Goldberg, Amit Khandelwal, Nina Pavcnik and Petia Topalova studied the the patterns and characteristics of multiproduct firms(in comparison with their singleproduct counterparts) in India. They further hypothesize that the restrictive nature of firms, with respect to menu changes, was due to India's high tariffs and licensing raj. They set out to study creative destruction in India by understanding the portfolio of company's as well as product additions and drops. Before we move on to understanding the data, we'd like to give a brief around the data and how we come to create variables of interest in our dataset. There are four main aspects to this replication:

- Understanding output and overall statistics of single vs multi-product firms
- Revenue share of ranked products within firms
- Decomposing growth driven by portfolio changes and within portfolio growth (or shrinkage)
- How likely are firms to keep the their product portfolios constant?

3.2 Background on the Data

We use the Prowess dataset provided by CMIE which collects data from a total of 110,390 companies. Our dataset has data from the years 1988-2024. Our study is concerned from the timeline of 2010-2025 so we can exaggerate these results to the overall behaviour of firms. It's a very rich firm level dataset that provides information on a firm's products over time, their sales contribution and which industry it belongs to. Each product of each firm is characterised by a *product code* which is allocated by CMIE. On further studying the product code, we subdivided the code to classify product, sector and industry. Codes that are distinguished by 6 digits are different products, those distinguished by 4 digits are different industry and those characterised by 2 digits are different sectors. Using this approach we filtered out all non-manufacturing and service firms. A detailed breakdown of the products code can be found on the prowess CMIE website. A similar classification was provided in the initial paper, however, CMIE did not have it's own classification system, hence a HS code classification was used. We attribute some level of difference between the two datasets because of this reason.

3.2.1 Understanding Product Mixes

The main objective of the paper is to understand creative destruction and firm dynamism through product additions and drop in two consecutive years. Hence, the creation of three key variables is key to our analysis: *products added*, *products dropped*, *number of products*. The original paper used only one existing variable to determine the aforementioned: number of products. The approach we take is by creating a list of products and using a series of if conditions to find these variables. Essentially, we compare the two lists in t and $t+1$, and even if the number of observations in the list is the same, however the list is of different variables, it will yield a combination of product additions and equal number of products dropped.

We then classify firms as *Single Product* if the number of products(6 digit product codes) is equal to 1, and *Multiple Product* otherwise. The same approach is used for *Single Industry* and *Single Sector* at 4 digit and 2 digit product code levels.

3.3 Tariffs and their impact

The original paper had also included a regression analysis that looked at the impact of tariffs on number of products, and also had a binary for pre and post liberalisation. In our replication exercise, this was one analysis we did not recreate because of two reasons. Firstly, the motivation of the authors was to understand business dynamism and creative destruction through the lens of liberalization. They wanted to attribute firm behaviour to pre-liberalization regimes, which came as a shock at that time and provided a perfect timeline for an intervention led regression analysis. We do not share the same motivation since India hasn't seen any abrupt changes in its outlook on trade policy since. Secondly, the data we are dealing with classifies products through a code generated and tabulated by CMIE(called NIC code). The authors manually cross-referenced with HS level codes to merge tariff data. This exercise was virtually impossible with the new update of CMIE product codes that are far more extensive.

3.4 Summary Statistics

We start by understanding the number of single product, industry and sector firms from 2010-2024 as well as just in 2024. We also look at their respective contribution to total sales. All are in proportions and in relation to total firms(or sales).

Type of Firm	Share of firms (2010–2024)	Share of Output (2010–2024)	Mean Number of Products/Industries/Sectors (2010–2024)
Single Product	0.772	0.770	1.00
Multiple product	0.228	0.230	2.63
Multiple industry	0.177	0.196	2.41
Multiple sector	0.121	0.143	2.20

Table 1: Summary statistics by firm type, 2010–2024.

Type of Firm	Share of Firms–2024	Share of output–2024	Mean Number of Products/Industries/Sectors (2024)
Single Product	0.767	0.813	1.00
Multiple product	0.233	0.187	2.63
Multiple industry	0.183	0.162	2.43
Multiple sector	0.129	0.111	2.19

Table 2: Summary statistics by firm type, 2024.

3.4.1 Output and Number of Firms

The lion's share of firms are single product- as an average since 2010 as well as in 2024. Undeniably, the proportions of single industry and sector firms is larger. In terms of output as well, single product firms contribute 77% of the total output in the time period 2010-2024 and 81.3% in 2024. Multiple product/industry or sector firms are also not heavily diversified as seen by the average number of products, industries and sectors they produce are not very high- averages of product/industry/sector offerings are all under 3.

A static look at the numbers would not provide much insight, as even the original paper compared these characteristics with United States counterparts, however we have the privilege of a temporally wide enough dataset to look at a dynamic evolution. We go on to chart similar numbers across time from 2010.

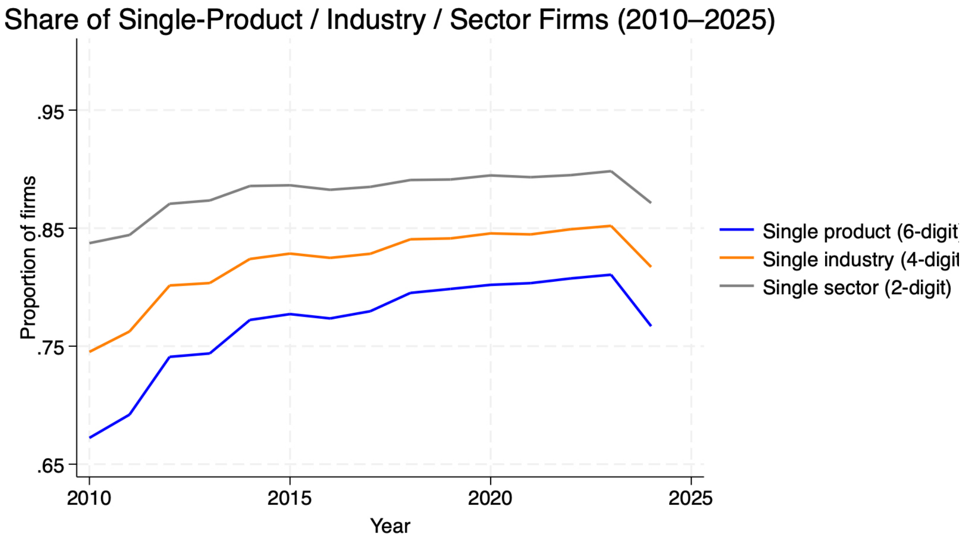


Figure 4: Share of Single Product/Industry/Sector Firms

The above figure clearly shows that the number of single product firms as a total of all firms have been on an increasing trend, and steadily that too. There could be two main reasons behind why the number of single-product, single-industry and single-sector firms have been on the rise:

1. Higher proportion of single product firms in the new samples over the years
2. Multiple product firms dropping enough products to become single product firms

The second reason is something we study later in this exercise when we try to answer the question how likely are firms to retain the number of products. However, the first question is an interesting one. It could mean two things- newly incorporated firms have increasingly been single product firms or unfortunately the sampling is skewed to a higher density of single product firms. The latter is something we cannot say with absolute certainty, but if we assume robust random sampling techniques by CMIE, then we can reach the conclusion that *newly incorporated firms are increasingly single product* and continue to be so. There is a sudden drop in the share of single product firms towards 2024, which we show with a shorter time period on the x-axis.

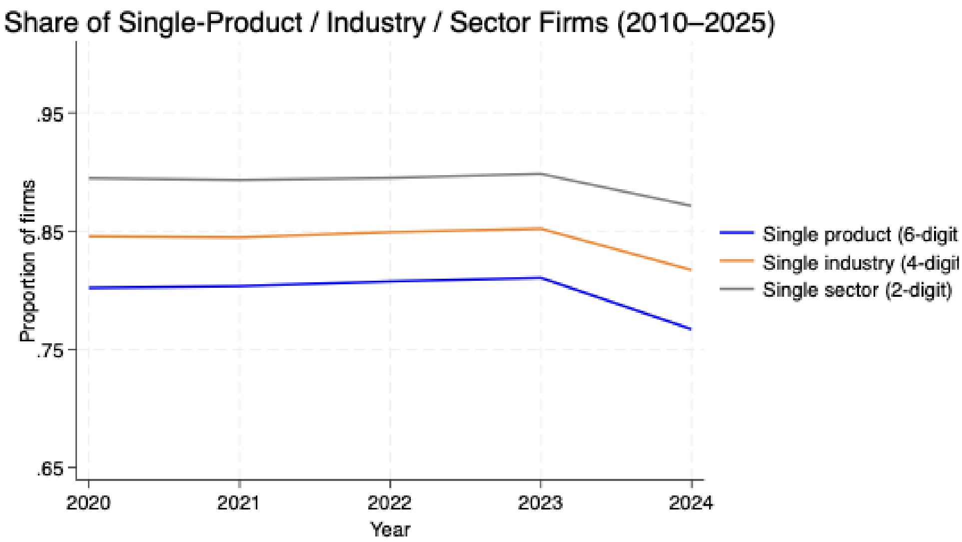


Figure 5: Looking at the drop

There is no explicable reason for this sharp and sudden drop, it is however interesting given the otherwise stable and increasing trend.

3.4.2 Dynamic look at the share of output

We also look at the progression of the share of output of single product/industry and sector firms over time. As was consistent with the previous data, the share of output to total output is also increasing. This increase can be broken down into- the increase in number of single product firms, and the increase in the scale of single product firms. There was drop around 2018, but that recovered quickly to return to it's original increasing trend. It has started to decrease since 2021 which is also consistent with the previous data of a reduction in share of single-product/industry and sector firms(in number).

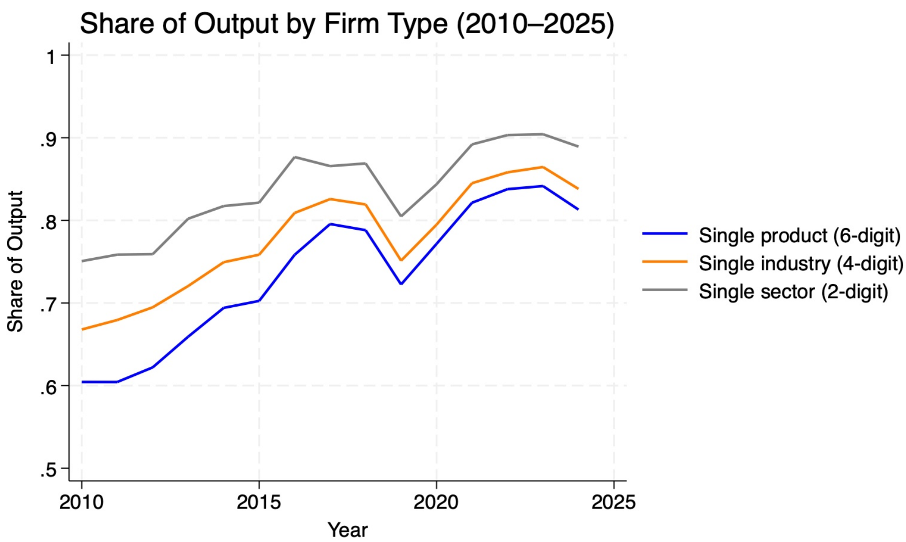


Figure 6: Share of Output- Single Product/Industry and Sector Firms

3.4.3 Trends behind products added and dropped

We now go back to using two of the other variables we created- products added and dropped. We look at the average number of products added and dropped over time, which would simply be the total number of products added or dropped divided number of firms. Since this is concerned only with products, it's analysed at the 6 digit product code level.

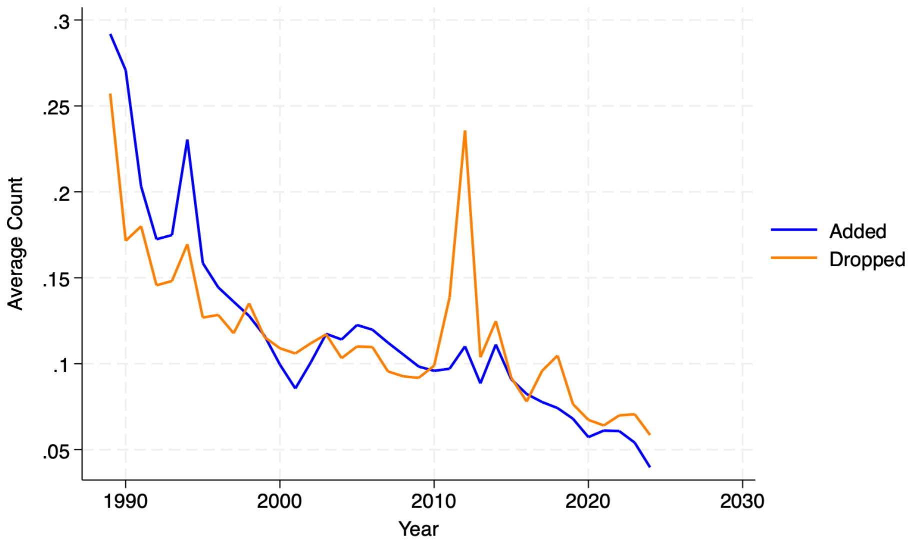


Figure 7: Average Products Added and Dropped

The trend is very clear in this graph- the average number of products added and dropped has seen a very steep decline. Products added or dropped or both would be indicative of product mix churning which would hint at business dynamism and the after effects of creative destruction. While the paper effectively concluded that the lack of bysiness dynamism and creative destruction in Indian manufacturing firms had nothing to do with the relatively closed off, tariff heavy and license driven economy- the novel data we present just validates this idea. Business dynamism and creative destruction would see an increase in average products added and dropped. The first graph we show is over a long time horizon from 1988, and now we show it for the newer more relevant data- from 2010.

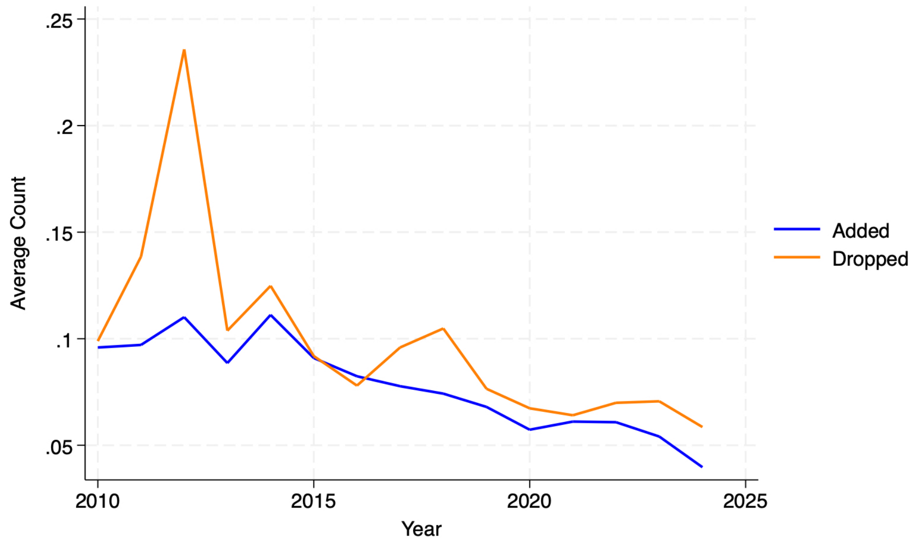


Figure 8: Average Products Added and Dropped 2010-2024

There's a very sharp blip in the products dropped around 2011-2013, and an equally steep drop. This would show a consolidation in the product mix. Such an outlier would require a detailed study on the history of any regulations introduced then. There could be several reasons behind this- the euro area's recession could drive down demand, a 2% increase in excise taxes or the taper tantrum could be some plausible reasons. Regresssions and difference-in-difference analyses could back these hypotheses, however, that remains beyond the scope of the study. Adjacently, we also want to study average portfolio sizes of firms.

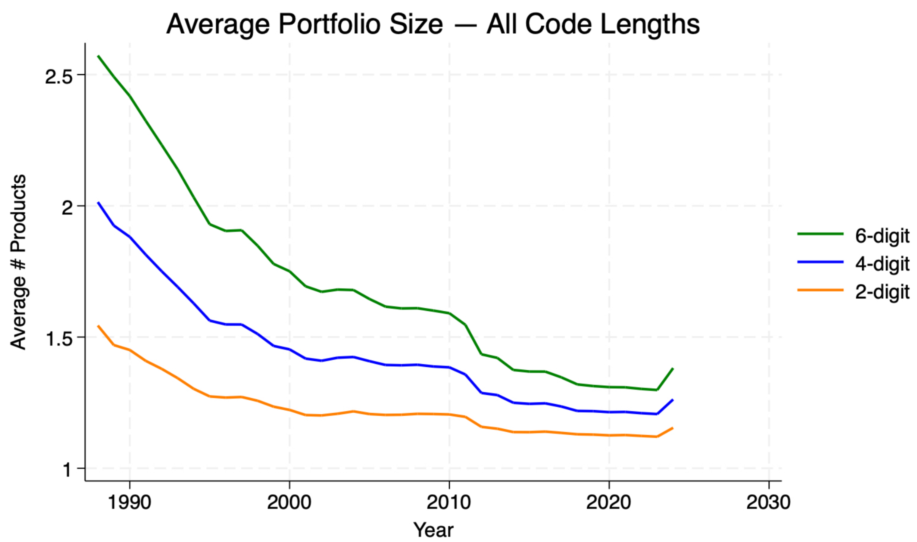


Figure 9: Average Portfolio Sizes- Products, Industries and Sector

Again, the average portfolio sizes have steeply dropped since 1988, which remains consistent with previous data- the increase in share of single product firms, increase in share of output of single product firms as well as the reduction in portfolio churning. Again, if we look at a detailed look at the time period in question of 2010-2024, we see:

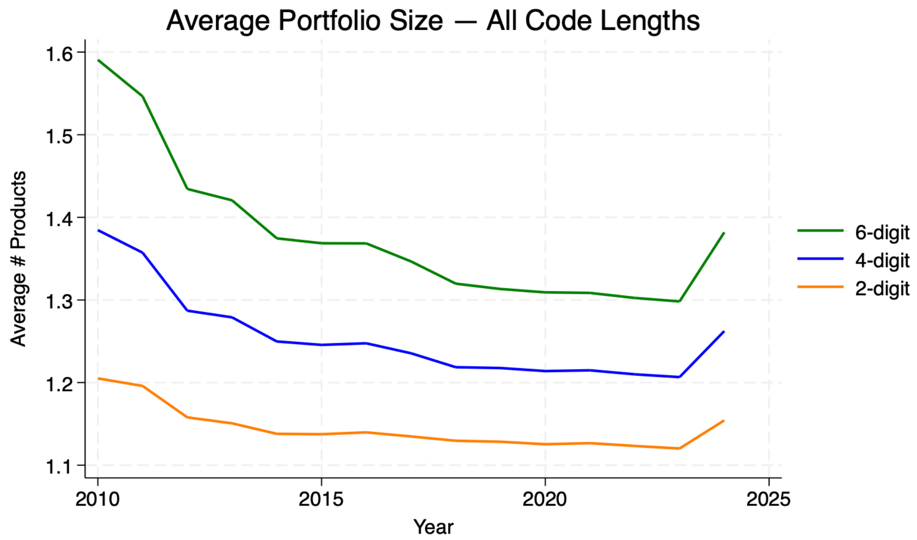


Figure 10: Average Portfolio Sizes- Products, Industries and Sector Post 2010

There are two characteristics amongst this data that stand out- the sudden drop around 2011-2013 which was consistent with a sharp increase in average number of products dropped, as well as an increasing trend from 2023 which was consistent with a reduction in the share of single product firms as seen in the beginning.

3.4.4 Concluding Summary Characteristics

Before we move on to the rest of the replication which talks about decomposing sales growth, contribution of sales by ranked products as well as behaviour of product addition and drops in consecutive years, there are some conclusions we arrive from all the data presented above.

1. A lion's share of the number of firms as well as output contribution accrues to single product firms. More importantly, it's an increasing trend since 2010(except from 2023 to 2024).

2. Product churning and dynamism which proxy by average products added and dropped have been on the decline. There was a short time period of extraordinarily high product drops around 2011-2013.

3. Average portfolio sizes of firms have also been on the decline.

3.5 Understanding Product Contributions to Revenue

Here, what we want to understand is whether the multiproduct firms are truly multiproduct i.e; are the revenue contributions of their non-main products significant. To prepare the data, we rank the products offered by firms by their contribution to revenue. Then, we go on to see their overall contribution to revenue as a percentage of total sales. We present two tables- one shows the status quo at 2023 and the other at 2010 to see the evolution of the share of the k-th product in firm revenue.

Table 3: Product Revenue Share by Rank (Year: 2024)

No of Products by Firm	Share of k-th Product in Firm Revenue (%)									
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10+
1	100	–	–	–	–	–	–	–	–	–
2	91	9	–	–	–	–	–	–	–	–
3	88	10	2	–	–	–	–	–	–	–
4	85	11	3	1	–	–	–	–	–	–
5	82	13	4	1	0	–	–	–	–	–
6	80	14	4	1	1	0	–	–	–	–
7	77	14	5	2	1	0	0	–	–	–
8	71	17	7	3	1	1	0	0	–	–
9	70	16	7	3	2	1	0	0	0	–
10	59	20	9	5	3	2	1	1	0	0

Notes: "10+" denotes the combined share of the 10th product and any additional products. Dashes indicate not applicable.

For the most recent full financial year, 2024, we see the concentration of revenue of multi-product firms highly skewed to the highest ranked product(by revenue). In fact, up till firms that have five products in their portfolio, the first ranked product contributes more than 80% of it's total revenue. This is an incredibly important indicator of the lack of creative destruction. It's fair to say that non main products, i.e; products which are not the highest contributors to revenue, are not that significant. Yet, firms continue to keep them. And, this is shown not only in the insignificant contributions of non-main products, but also previously when we saw a sharp decline in the average number of products dropped. What we would assume, and what the initial authors of the paper did as well, is that with the introduction of trade reforms that open up the economy, less productive products exit and all firms reduce scope. Although all firms have reduced scope- it is our understanding that that's due to an increasing number of newly incorporated firms which are single product. We can also look at the data for the year 2010:

Table 4: Product Revenue Share by Rank (Year: 2010)

No of Products by Firm	Share of k-th Product in Firm Revenue (%)									
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10+
1	100	–	–	–	–	–	–	–	–	–
2	87	13	–	–	–	–	–	–	–	–
3	81	16	3	–	–	–	–	–	–	–
4	76	17	5	1	–	–	–	–	–	–
5	71	18	7	3	1	–	–	–	–	–
6	67	20	8	4	2	1	–	–	–	–
7	62	21	9	5	2	1	0	–	–	–
8	57	21	11	5	3	2	1	0	–	–
9	55	21	11	6	4	2	1	1	0	–
10	50	20	11	7	4	3	2	1	1	1

Notes: "10+" denotes the combined share of the 10th product and any additional products. Dashes indicate not applicable.

Here, the concentration of revenue, although high, is far lesser towards the main product. So, the significance of non-main products has vastly reduced, on an aggregate level, when we look at revenue contribution and at the same time the average number of products dropped has also fallen. It points to a larger characteristic of Indian firms- their reluctant nature to withdraw establish product lines. One could argue that the sunk costs of withdrawal is very high, but we would only expect this pre-liberalization. A micro level study about such a behaviour would be incredibly useful in understanding why firms behave in such a manner.

3.6 Decomposing Growth

Let y_{ijt} denote (real) sales of product i produced by firm j in year t. For any adjacent years $t-1$ and t, define the product sets for each continuing firm j:

$$C_{jt} = \{i : \ i \text{ is produced in both } t-1 \text{ and } t\} \quad \text{(“continuing” products),}$$

$$E_{jt} = \{i : \ i \text{ is produced in exactly one of } t-1 \text{ or } t\} \quad \text{(“extensive” products).}$$

Firm j's change in total output between $t-1$ and t can then be written as

$$\Delta Y_{jt} \ = \sum_{i \in C_{jt}} \Delta y_{ijt} \ + \sum_{i \in E_{jt}} \Delta y_{ijt},$$

where $\Delta y_{ijt} \equiv y_{ijt} - y_{ijt-1}$ with the convention that the missing side of a product that appears or disappears is zero.

We further split the extensive part into product additions (newly produced in t) and product droppings (no longer produced in t):

$$A_{jt} = \{i \in E_{jt} : y_{ijt-1} = 0, \ y_{ijt} > 0\}, \qquad D_{jt} = \{i \in E_{jt} : y_{ijt-1} > 0, \ y_{ijt} = 0\}.$$

Similarly, we split the intensive part (products that continue) into those whose sales grow and those whose sales shrink:

$$G_{jt} = \{i \in C_{jt} : \Delta y_{ijt} > 0\}, \qquad S_{jt} = \{i \in C_{jt} : \Delta y_{ijt} < 0\}.$$

Aggregating across continuing firms gives the decomposition of aggregate real-sales growth:

$$\boxed{\Delta Y_t \ = \sum_j \Bigg[\underbrace{\sum_{i \in A_{jt}} \Delta y_{ijt} + \sum_{i \in D_{jt}} \Delta y_{ijt}}_{\text{Extensive margin } (A+D)} \ + \underbrace{\sum_{i \in G_{jt}} \Delta y_{ijt} + \sum_{i \in S_{jt}} \Delta y_{ijt}}_{\text{Intensive margin } (G+S)} \Bigg]}.$$

3.6.1 Reported columns and identities.

Let Gross Sales (Net) $\equiv \Delta Y_t$ be scaled to percentage points (e.g., divide by Y_{t-1} and multiply by 100). The table components satisfy:

$$\text{Extensive Net} = \text{Product Entry} + \text{Product Exit}, \tag{1}$$

$$\text{Product Entry} \equiv \sum_j \sum_{i \in A_{jt}} \Delta y_{ijt}, \qquad \text{Product Exit} \equiv \sum_j \sum_{i \in D_{jt}} \Delta y_{ijt}, \tag{2}$$

$$\text{Intensive Net} = \text{Growing Products} + \text{Shrinking Products}, \tag{3}$$

$$\text{Growing Products} \equiv \sum_j \sum_{i \in G_{jt}} \Delta y_{ijt}, \qquad \text{Shrinking Products} \equiv \sum_j \sum_{i \in S_{jt}} \Delta y_{ijt}, \tag{4}$$

$$\text{Gross Sales (Net)} = \text{Extensive Net} + \text{Intensive Net}. \tag{5}$$

This is a replication of Goldberg–Khandelwal–Pavcnik–Topalova(GKPT from now on) applied from 2010-2024 data. GKPT had come to the conclusion that over the long run, there was a 75/25 split between intensive and extensive growth(net). This is validated, and more pronounced from this data as well. In fact, in most cases wherein extensive net has a positive contribution, net intensive growth is about 82.7%. This is calculated by Intensive Net/(Gross Net) if Extensive Net is positive. The mysterious blip in previous data characterized by unusually high average products dropped and a steeper decline in average portfolio sizes can be seen here as well- 2012 shows a large product exit of -5.6. This pattern—India's adjustment working mostly through growth/shrinkage of continuing products—matches GKPT's broader finding that the intensive margin does the heavy lifting. To conclude, extensive margin contributions are small on net, and their gross pieces are dominated by additions, not droppings, exactly as GKPT emphasized for India

Year	Extensive Margin				Intensive Margin		
	Gross Sales (Net)	Product Entry	Product Exit	Extensive Net	Intensive Net	Growing Products	Shrinking Products
2010	9.7	2.1	-1.0	1.1	8.6	17.3	-8.7
2011	20.9	2.5	-2.4	0.2	20.7	25.3	-4.5
2012	19.8	3.3	-5.6	-2.3	22.1	26.9	-4.8
2013	10.9	2.4	-2.6	-0.2	11.1	17.9	-6.8
2014	9.6	2.7	-1.6	1.1	8.4	14.7	-6.3
2015	6.1	3.3	-2.3	1.0	5.1	12.7	-7.6
2016	2.9	2.7	-1.9	0.9	2.0	11.9	-9.9
2017	7.7	2.9	-3.4	-0.6	8.2	15.1	-6.9
2018	9.9	2.3	-2.6	-0.3	10.1	16.1	-6.0
2019	13.9	1.6	-1.4	0.2	13.7	19.0	-5.2
2020	0.8	1.4	-2.2	-0.8	1.6	10.3	-8.7
2021	0.4	1.3	-1.0	0.4	0.1	11.0	-10.9
2022	27.3	1.4	-1.3	0.1	27.2	30.5	-3.4
2023	18.5	1.9	-1.3	0.5	18.0	23.2	-5.2
2024	7.0	0.4	-0.5	-0.1	7.2	12.5	-5.3

Notes: Gross Sales (Net) is total net growth of continuing firms. Extensive margin columns report contributions from product entry and exit (Extensive Net = entry + exit). Intensive margin columns report the net effect (Intensive Net) and the contributions from growing and shrinking products among incumbents. All values are percentage points.

3.7 How likely are firms to maintain portfolio sizes?

The last piece of our data replication is an addition we introduced that looks at aggregate firm behaviour for portfolio sizes. We look at firms over a three year time period, so it must be firms that have been in the sample of data for three years. First, we have the transition probabilities as a heat map:

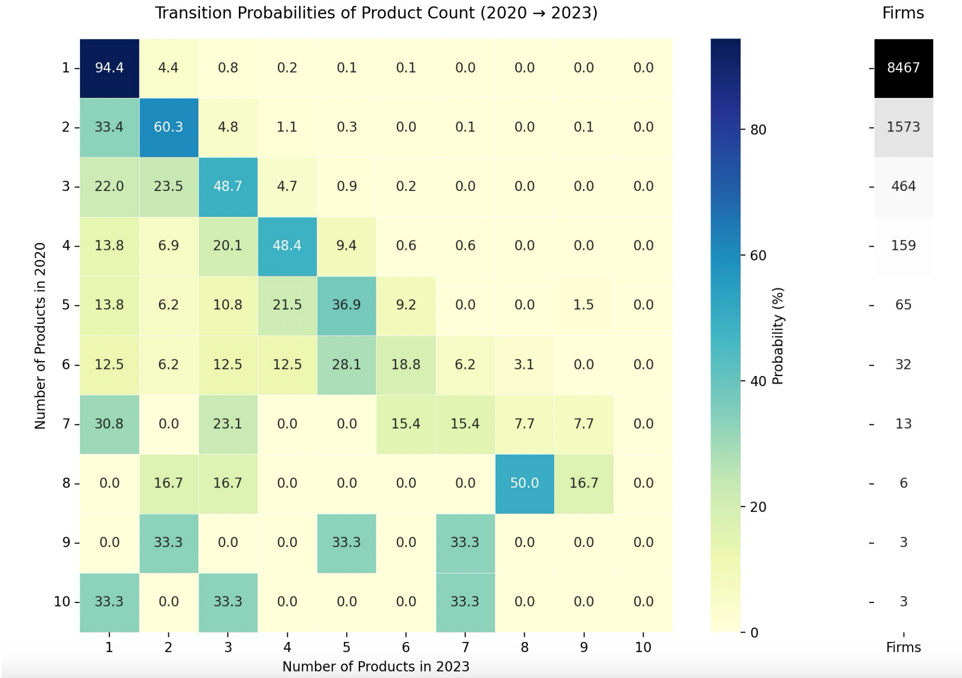


Figure 11: Transition Probabilities

How do we read the data? If we look at the first row and first column

$$94.4\% = \frac{Number\ of\ Firms\ with\ 1\ product\ in\ 2020\ and\ 2023}{Number\ of\ Firms\ with\ 1\ product\ in\ 2020}$$

Or, if we look at row 2 and column 1,

$$33.4\% = \frac{Number\ of\ Firms\ with\ 2\ products\ in\ 2020\ and\ 1\ in\ 2023}{Number\ of\ Firms\ with\ 1\ product\ in\ 2020}$$

Hence higher values in the bottom left would indicate overall products being dropped. And, a concentration along the diagnol center would mean firms stick with the same number of products in the three year time-frame. We can look at the same data in the beginning of our concerned time period.

Although there's enough variation for ambiguity, we can see that compared to 2010-2012, the most recent transition plots see lesser products being dropped- again consistent with our above conclusions. The probabilities are highest in the diagonal center, which is maintains the fact that firms, on an average, maintain their portfolio sizes. We can effectively conclude, that they mostly stay the same portfolio sizes, rarely increase, and often reduce.

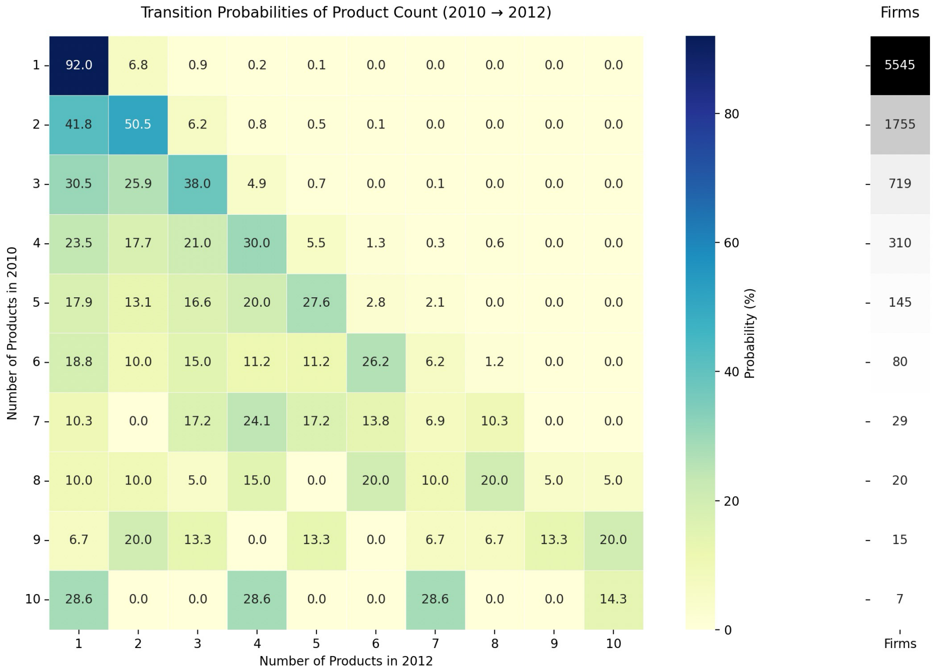


Figure 12: Transition Probabilities 2010

3.8 Conclusion

From our exercise of recreating GKPT's analysis for newer data we come to some pretty interesting conclusions that validate and exaggerate their findings. It's an important exercise to understand how Indian manufacturing firms behave when it comes to product mix. It also allows us to understand business dynamism and creative destruction better. A drawback is of course that on an aggregate level, we cannot explain exactly why the firms behave the way they do. But, if we were to characterize Indian firms of this behaviour, it's very different from what models of growth would predict. We learn that:

1. Indian manufacturing firms have become far less dynamic. Product additions and product drops are a good way to proxy for this quality. It's also worsening over time. It calls on the government to allow for easier withdrawal of product lines by minimizing sunk costs. But, why does this matter? Entry costs are exit costs. The manufacturing firms in our data are clearly characterized by a long tail of inefficient firms (Hsieh and Klenow 2009, Padmakumar 2022). A paper by Chatterjee et al, 2025 argues that there are several structural reasons behind having unnecessarily high exit costs- they include lengthy bankruptcy processes, burdensome administrative clearances, and strict labour laws that raise the costs of firing what are termed regular workers for firms

2. Single product firms clearly dominate in number as well as output. But, what is surprising is that even multi-product firms are not that diversified. They derive most of their revenue from their main products. Is this really multi-product or multi-sector? It adds to the above point of the long tail of inefficiency even within firms. The product lines continue to exist not adding much value to the overall revenue, but sucking in unnecessary costs.

3. Sales growth is driven mainly by products already in the product mix. This shows a lack of experimentation to add new products, but also shows failure of firms to successfully launch new

products. It paints a dismal picture for the already anxious firms waiting to launch a new product. And, creates a self-sustaining cycle of growth driven by status quo that makes firms risk averse to try and churn businesses.

4. We can finally also conclude with data that looks at the same firms over a three period horizon, that they're most likely to stick with the same number of products. Often, they do drop, but without any aggregate signs of product addition. What it leads to is highly concentrated portfolios of firms that stifles innovation.

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5 Data Guide

All the data we have used has been uploaded in the shared drive. Here's a brief guide to the data:

- The most minimally cleaned dataset from CMIE is *products_new.dta*. This has product level, firm level and year level data from 1988 to 2024. It also has industry classfications.
- There are three datasets which have the variables *Number of Products*, *Products Added* and *Products Dropped- 6digit.dta*, *4digit.dta* and *2digit.dta*. The naming convention is so that the three variables are product, industry and sector wise accordingly. This is not product level data-it just shows the three variables in a given year for a given firm.
- The codes folder contains Python codes for the if statements to arrive at the products added and dropped, as well as number of products. It also has some do files for other data.

Please find the link here: Link