Non-Neutral Technology and Monopsony Power in Foreign Input Markets

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Abstract

This paper investigates monopsony power in foreign-input markets—the ability of downstream firms to pay prices below the marginal revenue product of imported intermediates. We develop a structural estimator that incorporates factor-biased (non-Hicks-neutral) technical change to recover firm-level markdowns. Using matched Chinese industrial firm and customs data from 2000–2007, we document economically large and persistent foreign-input markdowns. Over the same period, non-neutral technology expanded rapidly, reshaping effective input productivity. Ignoring this channel generates substantial bias in markdown estimates—overstating buyer power when technology is labor- or material-augmenting, and understating it when input-saving forces dominate. Monte Carlo simulations confirm that the proposed estimator performs well in finite samples. Empirically, we find that the median firm-level markdown corresponds to a market power measure of about 2.81, while the average growth rate of factor-biased technology is approximately 1.40. These results underscore the importance of incorporating non-neutral technical change in measuring input-market monopsony and provide a tractable empirical framework for its identification.

Keywords: Monosony Power,Non-Hicks Neutral Technology, Foreign Input Market, nested CES demand,Production Function Estimation

JEL Codes: L13, F14, D24, O33, C15

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1 Introduction

Over the past four decades, China' s manufacturing sector has become deeply integrated into the world economy, as evidenced by the rapid expansion of exports and imports and the tightening of links within global value chains.

Large buyers occupy a prominent position in many modern industries. Their ability to secure supplier prices below competitive benchmarks is particularly salient in international trade, where high entry costs deter rivalry and activity is concentrated among a small set of large or highly productive firms. In such environments, dispersion in the prices of imported intermediates is systematically related to market concentration and to the demand systems of individual importers. Transactions along global value chains therefore often occur in buyer-concentrated markets in which purchasers possess nontrivial market power. These features make concerns about dominant buyers especially salient in international input trade (Antras et al. (2017); Bernard et al. (2007)). Yet our understanding of the size and implications of importers' buyer power remains limited, because canonical analyses of input trade typically treat buyers as price takers.

A central implication of open-economy models is that importer market power operates like an implicit tariff. It distorts production and trade volumes yet improves the terms of trade by shifting rents away from foreign suppliers. The net welfare effect is theoretically ambiguous: output contractions and higher prices reduce consumer surplus, whereas profit increases—reflecting the transfer of foreign rents—raise producer surplus. Countries that wield import market power may thus exploit it in the design of trade policy; even in the absence of statutory tariffs, large importers can secure terms-of-trade gains when they possess buyer power in input trade.

In China, the post-WTO expansion in firm scale endowed a subset of manufacturers with unprecedented purchasing leverage. Following China' s WTO entry, tariff reductions were accompanied by strong import growth: between 2000 and 2006, the value of intermediate imports rose by roughly 256 percent, and by 2007 about 7.1 percent of manufacturing firms used imported intermediates, which accounted for approximately 7.5 percent of total inputs in ordinary trade (Brandt et al. (2017)). Ignoring this heterogeneity when formulating policy can lead to biased predictions for pass-through, quantities, and welfare. Consequently, credible measurement of market power in imported-intermediate markets is essential, with careful separation of buyer-power wedges from technology-driven changes in input demand.

We document two facts for Chinese manufacturing in the 2000s. First, there is substantial cross-sectional heterogeneity in the foreign-input cost share across firms and within industries. Second, despite import liberalization, the sales-weighted foreign-input cost share **de-**

clines in several major sectors over 2000–2007. The magnitude and timing of these changes differ across industries and across firms, indicating nontrivial within-industry adjustment and composition effects.

This paper provides micro evidence that buyer power in foreign-input markets and non-Hicks-neutral technology, including its evolution over time, help explain both the dispersion and the decline of within-industry foreign-input cost shares. To our knowledge, this is the first study in a developing-country setting to document the downward trend in imported-input expenditure shares while jointly assessing the roles of buyer power (monopsony) and non-Hicks-neutral, input-biased technological change.

This study examines the role of non-Hicks-neutral, input-biased technology in driving the decline of imported-input cost shares and shaping the cross-sectional dispersion of imported-input shares across firms in Chinese manufacturing. When technology raises the effective productivity of imported intermediates, firms require fewer physical units per unit of output; with gross substitutability between domestic and foreign materials, the expenditure share on imported inputs can decline even as their efficiency rises. Concurrent developments—upgrading of domestic substitutes, movements in relative prices, and shifts in the composition of production toward firms or products less reliant on imports—reinforce this pattern. Hence, foreign-biased efficiency gains can coexist with, and in some cases contribute to, a declining imported-input cost share.

I estimate firm–time–specific foreign-input markdowns and non-Hicks-neutral technology using firm-level production data and variation in input prices. Firms minimize costs by choosing domestic and foreign materials conditional on technology and market conditions. Our approach focuses on variation in cost shares, which can be induced either by changes in markdowns or by factor-augmenting productivity. Because foreign-input–biased technology and buyer power both move cost shares, prices and quantities alone do not separately identify the two. To achieve identification, I combine a final-goods demand relationship, a production function that allows factor bias, and controls for the foreign-input supply curve.

The empirical procedure proceeds in three steps. First, I construct a markdown-adjusted foreign-input expenditure share using the firms' first-order conditions. Second, I estimate a production function that allows factor bias by two-step GMM, following Ackerberg et al. (2015) and Doraszelski and Jaumandreu (2018), which delivers output elasticities while disciplining timing and functional-dependence assumptions. Third, I adapt the double-ratio approach of Brooks et al. (2021a) to separate the foreign-input markdown from non-Hicks-neutral, input-biased technology by exploiting relative elasticities and relative cost shares for foreign versus domestic materials.

Buyer power (markdowns). We find economically large markdowns with substantial heterogeneity both across and within sectors. Distributions are right-skewed and heavy-tailed: means typically exceed medians and dispersion is sizable, indicating that a small set of firms with strong buyer power drives sectoral averages. Over 2000–2007, the revenue-weighted mean foreign-input markdown rises markedly—from about 4.0 to about 6.8 (roughly a 70 percent increase)—while the median increases more modestly, from roughly 2.2 to 3.1 (about 41 percent). The widening gap between the weighted mean and the median (from 1.8 to 3.7) shows that growth in markdowns is concentrated among larger firms rather than reflecting a uniform shift of the entire distribution.

Non-Hicks-neutral technology. By construction, the level of our estimated foreign-input–augmenting technology is not intrinsically interpretable, as it depends on normalization and units; what is informative is its trajectory over time. Our estimates show that the log of the foreign-input–augmenting technology rises from –3.86 in 2000 to –3.34 in 2007, implying roughly a 67 percent increase in the effective productivity embodied in imported intermediates—about 7.6 percent per year. This pattern documents pronounced foreign-biased technical change. The concurrent decline in the expenditure share of imported inputs does not contradict this result: as imported intermediates became more efficient, firms required fewer units for a given output, while rapid upgrading among Chinese suppliers compressed quality gaps and encouraged substitution toward domestic inputs. Taken together, these forces align with China's 2000s structural transformation—deepening integration into global value chains, absorption of embodied foreign know-how, and the rise of competitive domestic producers—so that growth in the estimated foreign-input–augmenting technology captures technological upgrading associated with globalization even amid falling import cost shares.

Interpretation and link to misallocation. Our markdown measure can be understood as a relative wedge on foreign materials. In the spirit of the misallocation literature (e.g., (Hsieh and Klenow, 2009)), it captures distortions on imported inputs relative to domestic materials. Following the standard assumption that domestic materials are flexibly chosen at market prices, the recovered wedge is interpretable as a foreign-input-specific distortion. Importantly, allowing for non-Hicks-neutral technology shows that part of what would otherwise be attributed to distortions is in fact technology-driven variation in input requirements. In this sense, incorporating input-biased technology mitigates overstatement of misallocation that would arise from attributing all movements in expenditure shares to buyer power alone.

The rest of the paper is organized as follows. Section 2 reviews the related literature on production-based measures of market power, input-market wedges, and non-neutral technical change. Section 3 describes the data, industry background, and stylized facts. Section 4 develops the empirical framework and identification strategy. Section 5 reports the estimation results. Section 6 presents Monte Carlo simulations assessing finite-sample performance and robustness. Section 7 concludes.

2 Literature Review

A large empirical literature uses micro production data to infer firm-level market power from first-order conditions that relate observed expenditure shares to marginal products. In product markets, markups capture the wedge between prices and marginal costs; under cost minimization, they can be recovered by combining an estimate of a flexible input' s output elasticity with that input' s revenue share. Modern implementations pair this accounting identity with production-function methods that identify input elasticities in the presence of unobserved productivity (Hall, 1988; Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015; De Loecker and Warzynski, 2012; De Loecker et al., 2016a, 2020). A complementary literature studies factor-market power through markdowns, defined as the ratio of an input' s marginal revenue product to its purchase price. In labor markets, wage markdowns map to firm-specific labor supply elasticities under standard monopsony-based environments, providing a tractable link between wage-setting and observed employment and pay outcomes (Manning, 2003; Dobbelaere and Mairesse, 2013; Brooks et al., 2021b; Yeh et al., 2022). Taken together, production-based markups and markdowns summarize product- and factor-market wedges and inform a broad set of questions in industrial organization, trade, and macroeconomics—including pass-through, factor income shares, misallocation, and welfare (Restuccia and Rogerson, 2017).

Under the production approach, the marginal revenue product of a variable input equals its price scaled by the markup; rearrangement yields the ratio of output elasticity to revenue share as the empirical object (De Loecker and Warzynski, 2012). Applications document substantial dispersion and nontrivial aggregate movements in markups in trade-exposed settings (De Loecker et al., 2016a, 2020). Two identification caveats recur. First, the estimator presumes *competitive input markets*; if firms exert buyer power, the statistic conflates output- and input-side wedges (Dobbelaere and Mairesse, 2013). Second, most implementations treat technology as *Hicks-neutral*, implying proportional movements of elasticities and cost shares across inputs. In practice, markups computed from different flexible inputs, notably labor versus materials, often diverge in levels and trends, consistent with input-market imperfections and non-neutral technology (Raval, 2019). Moreover, with sunk costs and irreversibility, persistently low or even sub-unity price–cost margins can be optimal because of option value (Dixit and Pindyck, 1994).

Markdowns capture buyer power by comparing marginal revenue products with observed input prices. In labor applications, markdowns map to the inverse of the firm-specific labor-supply elasticity under standard assumptions; large-sample evidence for China and India indicates economically meaningful wedges that depress wages and reduce the labor share (Manning, 2003; Brooks et al., 2021b; Rubens et al., 2024). Recent work extends the same logic to materials and imported intermediates. Using customs microdata and firm accounts, researchers construct *importer-level markdowns* by pairing revenue elasticities of imported inputs with their revenue shares, while allowing input prices to result from bargaining rather than perfect competition (Morlacco, 2020). Plant-level evidence that jointly estimates output markups and input markdowns shows that policy shocks, such as subsidies or movements in world prices, are partly absorbed through markdown adjustments, which limits pass-through to targeted agents (Avignon and Guigue, 2023). The open-economy implication is distinctive: buyer power over foreign inputs carries terms-of-trade content akin to an implicit tariff (Morlacco, 2020; Avignon and Guigue, 2023).

Both strands inherit identification frictions from production-function estimation. The proxy-variable literature addressed simultaneity using investment or intermediate inputs (Olley and Pakes, 1996; Levinsohn and Petrin, 2003), and clarified timing and functional dependence conditions for identification (Ackerberg et al., 2015). Unobserved input-price dispersion contaminates deflated expenditures; recovering quality-adjusted quantities using first-order conditions mitigates this bias (Grieco et al., 2016). General conditions for identifying heterogeneous productivity in flexible environments are now well understood (Gandhi et al., 2020). These pillars are preconditions for credible wedge measurement, particularly when wedges are constructed from imported-input data with quality, variety, and bilateral price dispersion.

Under Hicks neutrality, productivity scales output proportionally across inputs, leaving factor shares unchanged. If technology is factor-augmenting, cost shares and elasticities move even when wedges are stable. This generates attribution problems: a decline in the labor share may reflect labor-saving technical change rather than stronger monopsony; shifts in material shares may arise from input-augmenting efficiency rather than buyer power (Doraszelski and Jaumandreu, 2018; Raval, 2018). Evidence from U.S. manufacturing rejects Cobb–Douglas and neutrality, with the micro elasticity of substitution well below one and persistent dispersion in factor shares (Raval, 2018; Oberfield and Raval, 2014). Macro patterns further underscore the need to separate technology from wedges (Karabarbounis and Neiman, 2014; De Loecker et al., 2020).

Most empirical analyses focus on labor- and capital-augmenting components. For foreign-input buyer power, the relevant margin is materials-augmenting efficiency. Using Chinese steel, Zhang (2019) estimates a CES technology with three factor-specific efficiencies—labor, capital, and materials—finding $\sigma < 1$ (gross complementarity), rapidly rising labor-augmenting efficiency, more modest capital efficiency, and lagging materials efficiency; counterfactuals attribute a sizable share of the decline in labor's revenue share to non-neutrality. Because materials efficiency is distinct from capital efficiency and exhibits its own dispersion and dynamics, input-side bias is economically meaningful rather than a residual of labor and capital trends (Zhang, 2019). Two identification consequences follow for importer markdowns: revenue elasticities of imported inputs respond to movements in materials efficiency, and expenditure shares shift with input-augmenting progress even when wedges are unchanged (Raval, 2018; Doraszelski and Jaumandreu, 2018; Raval, 2019).

Three points follow. First, wedge estimation should be joint: markups, markdowns, and factor-biased productivity ought to be identified within a unified framework rather than sequentially under neutrality (Doraszelski and Jaumandreu, 2018; Brooks et al., 2021b). Second, measurement must confront input-price heterogeneity and variety and quality composition; treating deflated expenditures as quantities biases elasticities and shares (Grieco et al., 2016). Third, welfare analysis must be open-economy: importer buyer power resembles an implicit tariff, so incidence and welfare depend on demand curvature, foreign supply elasticities, and pass-through; wedges net of factor bias provide appropriate inputs for policy evaluation (Morlacco, 2020; Avignon and Guigue, 2023; De Loecker et al., 2016a). Overall, production-based methods enable measurement of product-side markups and factor-side markdowns at scale, and extensions to imported intermediates document economically large importer buyer power with distinctive open-economy implications (Morlacco, 2020; Avignon and Guigue, 2023). At the same time, robust evidence shows that productivity is non-neutral, with factor-augmenting components—including materials—that move elasticities and shares even when wedges are unchanged (Doraszelski and Jaumandreu, 2018; Raval, 2018). Credible measurement in foreign input markets therefore requires joint estimation of wedges and factor-biased technology under production-function identification that corrects for input-price heterogeneity (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015; Grieco et al., 2016; Gandhi et al., 2020).

3 Data and Empirical Facts

3.1 Data

We construct the analysis sample by linking two longitudinal micro datasets: (i) the National Bureau of Statistics (NBS) Annual Survey of Industrial Firms (ASIF) and (ii) transaction-level customs records compiled by the General Administration of Customs of China. The resulting panel is unbalanced.

The ASIF covers manufacturing enterprises that fall into two groups: state-owned enterprises and non-state firms that satisfy the "above-scale" eligibility threshold (annual sales of at least RMB 5 million, about US$650,000, in the corresponding year). This sampling rule is economically consequential: the ASIF is not a census of all manufacturers and systematically under-represents smaller private firms. Throughout, our statements and inference therefore pertain to the above-scale manufacturing population rather than the universe of firms (see Brandt et al., 2014).

The ASIF reports firm-year outcomes needed for production-based wedge measurement: revenues and intermediate expenditures, employment and payroll (hence average wages), capital proxies, and a rich set of covariates (age, ownership, location, and balance-sheet items). These variables support production-function estimation with firm heterogeneity and allow us to construct the revenue and cost shares that enter first-order-condition (FOC) based measures of markups and markdowns (e.g., Hall, 1988; De Loecker and Warzynski, 2012; Dobbelaere and Mairesse, 2013).

Customs records are reported at the Harmonized System eight-digit (HS8) level and contain, for each firm-product shipment, the trade direction (imports/exports), values, quantities, and implied unit values. A key strength for our purposes is that these data provide firm-level, product-level price information for imported intermediates, which is otherwise unobserved in the ASIF. Because deflated expenditures confound physical quantities with unobserved input-price heterogeneity, the customs unit values are essential for mitigating the classical "quantity proxy" problem emphasized in production-function and wedge estimation (see De Loecker et al., 2016b; Grieco et al., 2016).

The customs files also classify processing-trade regimes (e.g., processing with imported materials versus processing with supplied materials). This institutional detail matters for measurement: processing regimes induce systematic differences in the composition and pricing of imported intermediates and in firms' exposure to tariff and duty-drawback policies. We exploit these classifications to characterize firms' sourcing modes and to motivate controls for foreign-input supply-side conditions.

We focus on six CIC two-digit manufacturing industries: textiles (17), textiles and textile products (18), leather and leather products (19), electrical machinery and equipment (39), communications/computers and related electronics (40), and measuring instruments and office machinery (41). The choice is deliberate rather than exhaustive.

First, these sectors are import- and processing-trade intensive, which increases the signal-to-noise ratio in the key objects we need to identify: (i) the foreign-input expenditure share and (ii) dispersion in foreign-input unit values. Both are prerequisites for recovering importer-side wedges from first-order conditions, because buyer power is only visible through systematic comovement between quantities, prices, and expenditure shares.

Second, the 2000–2007 window spans China's WTO accession and the associated liberalization episode. Tariff reductions and trade-regime instruments (e.g., duty-drawback and VAT rebate policies) changed firms' incentives to source abroad and to select into processing versus ordinary trade. We do *not* treat these policy shifts as clean instruments by themselves; instead, they motivate rich controls for time, industry, and firm characteristics and help explain why the period contains substantial variation in foreign-input prices, quantities, and sourcing modes.

Third, these industries generate dense customs transactions with reliable value-and-quantity reporting. This matters because unit values allow us to address a central measurement problem in production-based IO: deflating expenditures with an industry deflator does not deliver physical quantities when input prices are firm-specific (De Loecker et al., 2016b; Grieco et al., 2016). Our customs-based unit values therefore discipline the construction of foreign-input quantities and reduce spurious dispersion in inferred wedges.

We build a firm-year panel for 2000–2007 by linking ASIF records to customs transactions and harmonizing firm identifiers and CIC industry codes. Nominal outcomes are deflated using industry-specific price indices. For imported intermediates, we compute unit values from HS8 transactions and then aggregate them to the HS6 level for consistency with standard concordances and to reduce noise from within-HS8 reporting idiosyncrasies. We exclude observations with missing core variables or missing lags required by the dynamic production-function estimator (Ackerberg et al., 2015) and trim extreme values that are mechanically inconsistent with cost-minimization accounting (e.g., implausible ratios driven by recording errors). The resulting working sample is an unbalanced panel and contains 58,520 firm-year observations across the six industries. Appendix A.1 defines all variables; Table 1 reports summary statistics.

Table 1: Descriptive Statistics

(1) Variable	(2) Mean	(3) SD	(4) P25	(5) P50	(6) P75	(7) Min	(8) Max	(9) N
Capital stock (K)	55041.30	236033.42	3146.08	10076.76	34670.16	30.00	14809013.65	58520
Employment (L)	651.96	1673.19	144.00	296.00	629.00	8.00	188151.00	58520
Domestic input cost	17110605.75	1.22e+08	974354.72	2668856.63	8178027.50	2173.75	7.39e+09	58520
Foreign input cost	10656224.11	1.16e+08	312281.50	982999.50	3518031.50	531.00	1.61e+10	58520
Revenue (R)	34413670.41	2.43e+08	2282619.25	5656501.98	16643492.18	16793.93	2.45e+10	58520
Foreign input quantity (M^F)	16517494.66	1.49e+08	85902.50	421716.50	2126632.50	1.00	1.54e+10	58520
Wage (WL)	2374.20	13280.50	1254.42	1794.83	2626.10	0.00	3174890.00	58520
Labor cost	2374.20	13280.50	1254.42	1794.83	2626.10	0.00	3174890.00	58520
Gross fixed asset	6546691.00	28364486.32	371796.42	1193967.78	4111052.42	3624.50	1.78e+09	58520
Management fees	1246634.02	11559751.24	147641.60	328259.06	819948.82	120.82	1.73e+09	58520

Notes: Columns (1)–(9) report summary statistics for each variable: (1) variable name; (2) mean (sample mean); (3) SD (sample standard deviation); (4) P25 (25th percentile); (5) P50 (median/50th percentile); (6) P75 (75th percentile); (7) min (sample minimum); (8) max (sample maximum); (9) N (number of observations). The sample is restricted to CIC-2 industries 17, 18, 19, 39, 40, and 41. All monetary variables are in levels and measured in USD. Wage equals labor cost divided by employment. Statistics are computed variable-by-variable using available observations.

3.2 Heterogeneity and Declining of Foreign Input Share

We measure firm-level foreign-input intensity using the expenditure share of imported intermediates in total intermediate spending. For firm f in sector s and year t, define [1] This definition keeps the object of interest aligned with the first-order-condition approach used later: expenditure shares are the observable statistics that map into wedges once elasticities are identified (e.g., De Loecker and Warzynski, 2012; Dobbelaere and Mairesse, 2013).

[1]Formally, $e^F_{fst} \equiv$ (expenditure on imported intermediates)/(total intermediate expenditure). We aggregate to the sector-year level using sales weights:

$$E^F_{st} = \sum_{f \in s} \left(\frac{\text{sales}_{fst}}{\sum_{j \in s} \text{sales}_{jst}} \right) e^F_{fst},$$

so that larger firms receive greater weight in the sector-level series. Sales-weighting is natural in the ASIF context because the sample represents above-scale firms and aggregate outcomes are mechanically dominated by high-revenue producers.

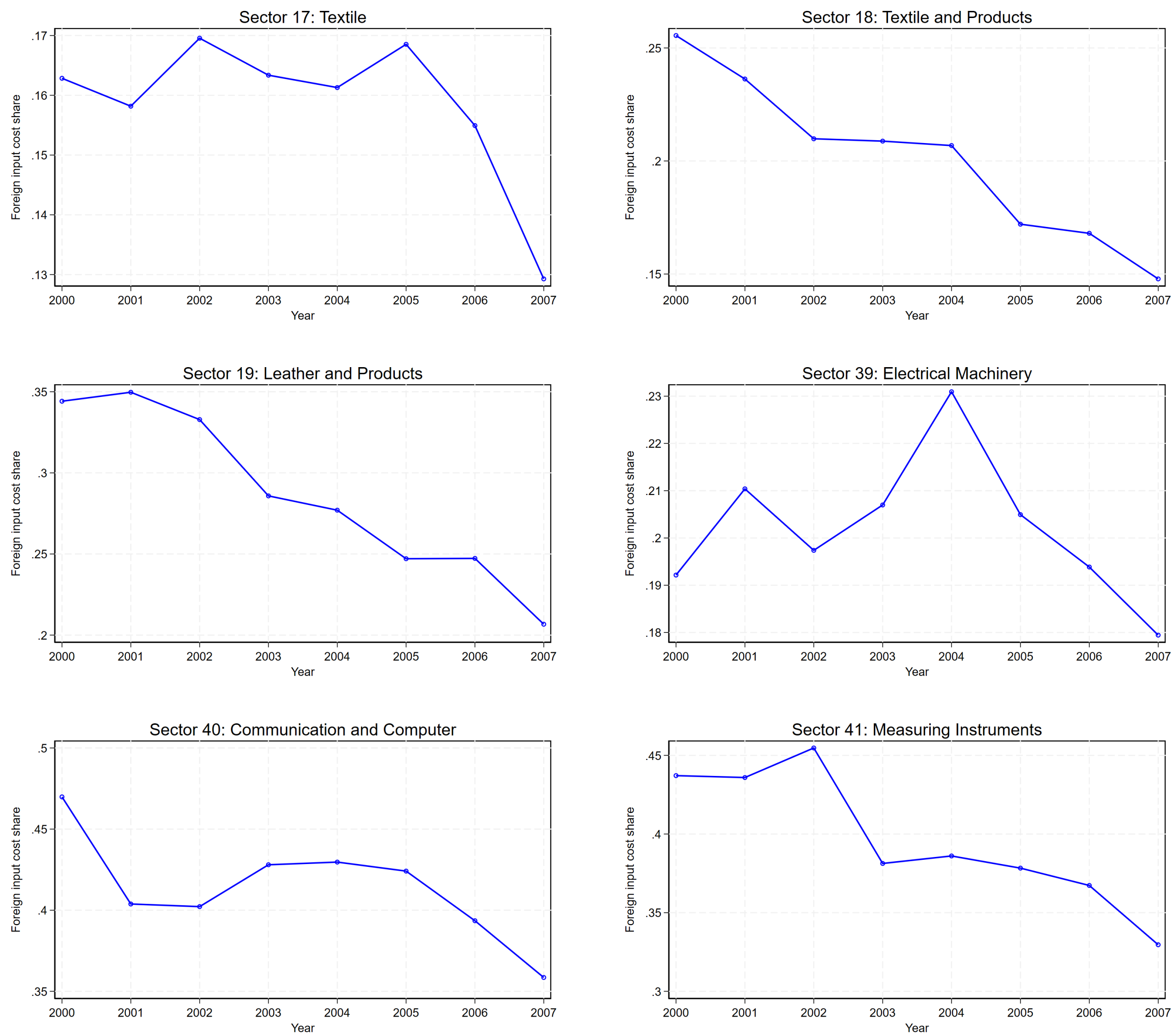

Figure 1: Change of Foreign Cost Share across Sectors

Figure 1 reports sales-weighted foreign-input expenditure shares for 2000–2007. The dominant empirical pattern is a decline in foreign-input intensity across all six sectors, but the time profile differs sharply by industry. Textiles (17) declines gradually and then drops late; textiles and products (18) falls steadily; leather (19) falls early and then flattens. Among the more technology-intensive sectors, electrical machinery (39) is hump-shaped; communications/computers (40) is roughly flat early and then declines; measuring instruments (41) declines modestly.

Two implications follow. First, levels differ: sectors 17–19 exhibit lower import intensity than sectors 39–41. Second, the time-series decline in E^F_{st} is *not* identified with a change in buyer power. Expenditure shares are equilibrium objects that mix firm-specific input prices, physical quantities, and endogenous quality/variety choice; the same decline in E^F_{st} is consistent with (i) larger foreign-input markdowns, (ii) foreign-input–augmenting technical change that lowers physical input requirements at a given output, and/or (iii) selection and composition effects (entry/exit and reallocation toward firms with lower import dependence).

These identification issues are standard in production-based IO: mapping observed cost shares into wedges requires disciplined measurement of quantities and elasticities, and fails when deflated expenditures are contaminated by unobserved input-price heterogeneity (De Loecker and Warzynski, 2012; Dobbelaere and Mairesse, 2013; De Loecker et al., 2016b; Grieco et al., 2016; Doraszelski and Jaumandreu, 2018). Section 4 therefore develops a framework that jointly accommodates buyer power and non-Hicks-neutral technology and uses customs unit values to discipline the price/quantity decomposition.

4 Empirical Model

Consider a firm f that produces output Q using labor L, domestic intermediate input M^D_{ft}, foreign intermediate input M^F_{ft}[2], and capital K at time t according to a production function $G(\cdot)$. We allow firm-specific productivity to have a Hicks-neutral component Ω_{ft} and a foreign-input–augmenting component A_{ft}, and let ϵ_{ft} denote measurement error in log output. The production function coefficients β are assumed to be common across firms:

$$Q_{ft} = G(L_{ft}, M^D_{ft}, A_{ft}M^F_{ft}, K_{ft}; \beta)\Omega_{ft} \exp(\epsilon_{ft}) \tag{1}$$

Output and intermediate inputs can be traded across borders. We defer the specification of the final-good demand system to Section 4.4 and focus here on the production side. We assume the production function $G(\cdot)$ is twice differentiable in all variable inputs. Specifically, we treat domestic and foreign intermediate inputs as variable inputs and define their output elasticities as θ^F_{ft} and θ^D_{ft}, respectively:

$$\theta^F_{ft} \equiv \frac{\partial G(\cdot)}{\partial M^F_{ft}} \frac{M^F_{ft}}{G(\cdot)} \qquad \theta^D_{ft} \equiv \frac{\partial G(\cdot)}{\partial M^D_{ft}} \frac{M^D_{ft}}{G(\cdot)} \tag{2}$$

Firms pay variable input prices W^F_{ft} and W^D_{ft} and face input supply curves with inverse supply elasticities $\psi^F_{ft} - 1$ and $\psi^D_{ft} - 1$, such that

$$\psi^F_{ft} \equiv \frac{\partial W^F_{ft}}{\partial M^F_{ft}} \frac{M^F_{ft}}{W^F_{ft}} + 1 \qquad \psi^D_{ft} \equiv \frac{\partial W^D_{ft}}{\partial M^D_{ft}} \frac{M^D_{ft}}{W^D_{ft}} + 1 \tag{3}$$

[2]In terms of notations, superscript F denotes foreign inputs, D denotes domestic inputs, subscript f denotes firm.

4.1 Firm Behavior

Because we assume that domestic and foreign intermediate inputs are variable inputs, they are chosen in every period by the producer to minimize current variable costs. We denote marginal costs as λ_{ft}, and the cost minimization problem is given by the following equation:

$$\min_{\{M_{ft}^F, M_{ft}^D\}} \left[W_{ft}^D M_{ft}^D + W_{ft}^F M_{ft}^F - \lambda_{ft}(Q_{ft} - G(\cdot))\right] \tag{4}$$

From F.O.C. w.r.t. M_{ft}^F, we can get

$$W_{ft}^F + M_{ft}^F \frac{\partial W_{ft}^F}{\partial M_{ft}^F} = \lambda_{ft} \frac{\partial Q_{ft}}{\partial M_{ft}^F} \tag{5}$$

Multiply both sides by $\frac{M_{ft}^F}{Q_{ft}}$

$$W_{ft}^F \psi_{ft}^F \frac{M_{ft}^F}{Q_{ft}} = \lambda_{ft} \frac{\partial Q_{ft}}{\partial M_{ft}^F} \frac{M_{ft}^F}{Q_{ft}} = \lambda_{ft} \theta_{ft}^F \tag{6}$$

$$\frac{1}{\lambda_{ft}} = \frac{\theta_{ft}^F Q_{ft}}{W_{ft}^F M_{ft}^F \psi_{ft}^F} \tag{7}$$

As shown in De Loecker et al. (2016b), the markup of the final goods P_{ft} over marginal costs λ_{ft}, $\mu_{ft}^P \equiv P_{ft}/\lambda_{ft}$, is defined in the following equation:

$$\mu_{ft}^P = \frac{\theta_{ft}^F}{\gamma_{ft}^F \psi_{ft}^F} \tag{8}$$

From F.O.C. w.r.t. M_{ft}^D, we can get

$$\mu_{ft}^P = \frac{\theta_{ft}^D}{\gamma_{ft}^D \psi_{ft}^D} \tag{9}$$

where γ_{ft}^j denotes the cost of input j ($j = D, F$) as a share of gross revenues of firm f in year t, such that $\gamma_{ft}^F = \frac{W_{ft}^F M_{ft}^F}{P_{ft} Q_{ft}}$ and $\gamma_{ft}^D = \frac{W_{ft}^D M_{ft}^D}{P_{ft} Q_{ft}}$. Following Morlacco (2019) and Brooks et al. (2021a), from Eq. (8) and Eq. (9) , the ratio of ψ_{ft}^F to ψ_{ft}^D equals the ratio of γ_{ft}^D to γ_{ft}^F multiplied by the ratio of their output elasticities (i.e., $\frac{\theta_{ft}^F}{\theta_{ft}^D}$). And because we assume firms are price takers in domestic input market (i.e.,$\psi_{ft}^D = 1$), we can get the following equation:

$$\psi_{ft}^F = \frac{\theta_{ft}^F}{\gamma_{ft}^F}\frac{\gamma_{ft}^D}{\theta_{ft}^D}\psi_{ft}^D = \frac{\theta_{ft}^F}{\gamma_{ft}^F}\frac{\gamma_{ft}^D}{\theta_{ft}^D} \tag{10}$$

Thus, the inverse supply elasticity of foreign intermediate inputs is the ratio of the foreign input's output elasticity to the domestic input's output elasticity, multiplied by the ratio of the domestic to foreign input expenditure shares. By definition, the foreign intermediate-input markdown is the ratio of the marginal revenue product to the input price, $\mu_{ft}^F \equiv \frac{MRPM_{ft}^F}{W_{ft}^F}$. Therefore, from the FOC, the foreign-input markdown can be expressed as a function of the inverse foreign-input supply elasticity:

$$\mu_{ft}^F = \frac{\theta_{ft}^F}{\gamma_{ft}^F}\frac{\gamma_{ft}^D}{\theta_{ft}^D} = \psi_{ft}^F \tag{11}$$

where the marginal revenue product of foreign input is defined as:

$$MRPM_{ft}^F = P_{ft}\frac{\partial Q_{ft}}{\partial M_{ft}^F} \tag{12}$$

We interpret ψ_{ft}^F as the foreign-input markdown, i.e., the wedge between the marginal revenue product of imported intermediates and their purchase price. Recovering ψ_{ft}^F therefore requires both (i) the relevant revenue/cost shares and (ii) the output elasticities of foreign and domestic intermediate inputs.

The key "double-ratio" logic (Brooks et al., 2021a) is that taking the ratio of the two first-order conditions (foreign vs. domestic materials) eliminates the unobserved marginal cost (and hence any product-market markup), so that buyer power is pinned down by a ratio of *ratios*: combining $\mu_{ft}^P = \theta_{ft}^F/(\gamma_{ft}^F\psi_{ft}^F)$ and $\mu_{ft}^P = \theta_{ft}^D/(\gamma_{ft}^D\psi_{ft}^D)$ yields $\psi_{ft}^F/\psi_{ft}^D = (\theta_{ft}^F/\theta_{ft}^D)\,(\gamma_{ft}^D/\gamma_{ft}^F)$. Under the maintained assumption that domestic-input markets are competitive ($\psi_{ft}^D = 1$), this delivers equation (11): $\psi_{ft}^F = (\theta_{ft}^F/\theta_{ft}^D)\,(\gamma_{ft}^D/\gamma_{ft}^F)$.

Econometrically, the "double-ratio" estimator therefore maps observables into the markdown by (a) computing γ_{ft}^F and γ_{ft}^D from firm accounts and (b) estimating θ_{ft}^F and θ_{ft}^D from the production function. This construction clarifies why foreign-input markdowns are not identified from prices and quantities alone: changes in cost shares can be generated either by wedges (markdowns) or by factor-biased technology that shifts elasticities, motivating the joint identification strategy in Rubens et al. (2024).

4.2 Identification Challenge

A central challenge is that the same movements in foreign-input expenditure shares are consistent with two distinct mechanisms. The first is an *input-market wedge*: buyer power over imported intermediates implies a foreign-input markdown that creates a gap between the marginal revenue product and the purchase price (Dobbelaere and Mairesse, 2013; Brooks et al., 2021a). The second is *non-neutral, input-augmenting technical change*: foreign-input–augmenting productivity A_{ft} enters the production function as $A_{ft}M_{ft}^F$ and changes the effective services of imported intermediates, thereby shifting the relevant (local) output elasticities and, in turn, equilibrium cost shares (Doraszelski and Jaumandreu, 2018). Because our markdown estimator maps relative elasticities and relative cost shares into ψ_{ft}^F, a production specification that rules out augmentation would mechanically attribute technology-driven movements in shares to changes in buyer power. We therefore discipline wedges and augmentation jointly using a translog-type (second-order) representation of the materials aggregator and standard timing restrictions for production-function identification (Ackerberg et al., 2015).

Formally, from (1) we can rewrite the FOC for foreign materials as

$$W_{ft}^F + M_{ft}^F \frac{\partial W_{ft}^F}{\partial M_{ft}^F} = \lambda_{ft} \frac{\partial G(L_{ft}, M_{ft}^D, A_{ft}M_{ft}^F, K_{ft}; \beta)}{\partial M_{ft}^F} \Omega_{ft} A_{ft} \tag{13}$$

and the FOC for domestic materials as

$$W_{ft}^D = \lambda_{ft} \frac{\partial G(L_{ft}, M_{ft}^D, A_{ft}M_{ft}^F, K_{ft}; \beta)}{\partial M_{ft}^D} \Omega_{ft}. \tag{14}$$

Taking the ratio of (13) and (14) eliminates the unobserved marginal cost λ_{ft} and Hicks-neutral productivity Ω_{ft}, yielding

$$\frac{W_{ft}^F + M_{ft}^F \frac{\partial W_{ft}^F}{\partial M_{ft}^F}}{W_{ft}^D} = \frac{\frac{\partial G(L_{ft}, M_{ft}^D, A_{ft}M_{ft}^F, K_{ft}; \beta)}{\partial M_{ft}^F}}{\frac{\partial G(L_{ft}, M_{ft}^D, A_{ft}M_{ft}^F, K_{ft}; \beta)}{\partial M_{ft}^D}} A_{ft}. \tag{15}$$

Equation (15) makes the identification problem transparent. If the foreign input market were competitive (so that $\partial W_{ft}^F / \partial M_{ft}^F = 0$ and hence $\psi_{ft}^F = 1$), then relative prices would directly identify A_{ft} through relative marginal products. Once firms have buyer power, however, the term $M_{ft}^F(\partial W_{ft}^F / \partial M_{ft}^F)$ enters the left-hand side, so the data confound a markdown channel (variation in ψ_{ft}^F) with a technology channel (variation in A_{ft}).

This confounding is not a nuisance but a structural identification issue: with factor-augmenting (non-neutral) technology, productivity is effectively multidimensional and cannot be reduced to a single Hicks-neutral scalar without loss (Doraszelski and Jaumandreu, 2018). Likewise, in monopsony environments the same first-order conditions that identify markdowns under exogenous technology cease to be sufficient when the firm endogenously (or differentially) augments inputs, so wedges and augmentation must be jointly disciplined by the production model and the timing/variation restrictions used for identification (Rubens et al., 2024; see also Dobbelaere and Mairesse, 2013).

Our empirical strategy proceeds by estimating a production function that accommodates foreign-input augmentation and delivers state-dependent output elasticities, and then mapping those elasticities and observed cost shares into firm-year foreign-input markdowns via the double-ratio restriction (Brooks et al., 2021a). This sequencing separates the role of non-neutral technology in shaping elasticities from the input-market wedge embodied in ψ^F_{ft} (Doraszelski and Jaumandreu, 2018; Rubens et al., 2024).[3]

4.3 Production Function

We discipline the wedge decomposition using a production structure that allows for non-neutral (factor-augmenting) technical change. Consistent with Doraszelski and Jaumandreu (2018) and equation (1), we model productivity as the vector (Ω_{ft}, A_{ft}), where A_{ft} enters as an input-augmenting term so that imported intermediates appear as $A_{ft}M^F_{ft}$.

On the estimation side, the key object for recovering markdowns is the pair of output elasticities $\{\theta^F_{ft}, \theta^D_{ft}\}$. Treating these elasticities as fixed can make the production-approach mapping from observed cost shares to wedges fragile and can introduce a circularity between wedge measurement and elasticity estimation.[4]

We therefore adopt a translog-type (second-order) representation—i.e., a second-order polynomial in log inputs—which provides a local second-order approximation to an unknown twice-differentiable technology and nests Cobb–Douglas as a special case. Crucially for our application, this specification implies state-dependent (local) elasticities that can vary with the state variables (including input-augmenting productivity), which helps reduce the risk

[3]Closely related production-approach arguments have recently been applied to firm-to-firm trade and two-sided market power; see, e.g., Alviarez et al. (2023) and the survey in Syverson (2024).

[4]Intuitively, wedges (markdowns) are identified by mapping observed expenditure shares into first-order conditions using output elasticities. When technology is non-neutral and/or input markets are imperfectly competitive, relative shares can move because elasticities move (through augmentation or state dependence) even if wedges do not; imposing fixed elasticities risks misattributing technology-driven variation in shares to market-power wedges. Moreover, because markdowns are computed using estimated elasticities while the production-function estimates can themselves depend on how one treats wedges and price/quantity measurement, sequentially fixing one object and then the other can create a “self-referential” (circular) estimation problem.

of mechanically attributing technology-driven movements in observed relative cost shares to changes in market power (e.g., Raval, 2023; Doraszelski and Jaumandreu, 2018).[5]

We denote ω_{ft} and a_{ft} as the logarithms of Hicks-neutral (Ω_{ft}) and foreign-input–augmenting productivity (A_{ft}), respectively. Hicks-neutral and foreign-input–augmenting productivity are $\Omega_{ft} = e^{\omega_{ft}}$ and $A_{ft} = e^{a_{ft}}$.

$$Q_{ft} = e^{(\omega_{ft}+\varepsilon_{ft})}\, K_{ft}^{\beta_k}\, L_{ft}^{\beta_l}\, M_{ft}^{\beta_m} \tag{16}$$

$$M_{ft} = \left[(M_{ft}^D)^{\frac{\gamma-1}{\gamma}} + (A_{ft} M_{ft}^F)^{\frac{\gamma-1}{\gamma}} \right]^{\frac{\gamma}{\gamma-1}} \tag{17}$$

Taking logs on both sides of equation (16), and applying a second-order Taylor expansion of equation (17) around $\gamma = 1$ and denoting ω_{ft} and a_{ft} as the logarithms of Hicks-neutral, foreign intermediate inputs augmenting productivity, respectively, one can write the firm's production function as

$$q_{ft} = \beta_k k_{ft} + \beta_l l_{ft} + \beta_F (m_{ft}^F + a_{ft}) + \beta_D m_{ft}^D + \frac{1}{2}\beta_{FF}(m_{ft}^F + a_{ft})^2 + \frac{1}{2}\beta_{DD}(m_{ft}^D)^2 + \beta_{FD}(m_{ft}^F + a_{ft}) m_{ft}^D + \omega_{ft} + \varepsilon_{ft} \tag{18}$$

We define $m_{ft}^F + a_{ft} = m_{ft}^{F*}$ and impose homogeneity of degree $\beta_F + \beta_D$ in M_{ft}^F and M_{ft}^D by setting $-\beta_{FF} = -\beta_{DD} = \beta_{FD} \equiv \beta$. Then the production function becomes

$$q_{ft} = \beta_k k_{ft} + \beta_l l_{ft} + \beta_F m_{ft}^{F*} + \beta_D m_{ft}^D - \frac{1}{2}\beta (m_{ft}^D - m_{ft}^{F*})^2 + \omega_{ft} + \varepsilon_{ft} \tag{19}$$

Therefore, the output elasticity of foreign input can be expressed as:

$$\theta_{ft}^F = \frac{\partial Q_{ft}}{\partial M_{ft}^F}\frac{\partial M_{ft}^F}{\partial Q_{ft}} = \frac{\partial q_{ft}}{\partial m_{ft}^F} = \beta_F + \beta(m_{ft}^D - m_{ft}^{F*}) = \beta_F + \beta(m_{ft}^D - m_{ft}^F - a_{ft}) \tag{20}$$

Similarly, the output elasticity of domestic input can be expressed as:

$$\theta_{ft}^D = \frac{\partial Q_{ft}}{\partial M_{ft}^D}\frac{\partial M_{ft}^D}{\partial Q_{ft}} = \frac{\partial q_{ft}}{\partial m_{ft}^D} = \beta_D - \beta(m_{ft}^D - m_{ft}^{F*}) = \beta_D - \beta(m_{ft}^D - m_{ft}^F - a_{ft}) \tag{21}$$

Using the definition of m_{ft}^{F*}, we can then express the ratio of output elasticity between

[5] We state this point conservatively because the empirical "shares–elasticities" mismatch can reflect multiple mechanisms—including measurement error, unobserved input-price dispersion, and imperfect competition—so a flexible translog-type specification is best viewed as providing an empirically tractable channel for state-dependent elasticities rather than as a full resolution of all sources of mismatch.

foreign input and domestic input as:

$$\frac{\theta^F_{ft}}{\theta^D_{ft}} = \frac{\beta_F + \beta(m^D_{ft} - m^{F*}_{ft})}{\beta_D - \beta(m^D_{ft} - m^{F*}_{ft})} \tag{22}$$

From the F.O.C. of firm's cost minimization problem, we have the following conditions:

$$\frac{\partial Q_{ft}}{\partial M^F_{ft}} = \psi^F_{ft}\frac{W^F_{ft}}{\lambda_{ft}}, \qquad\qquad \frac{\partial Q_{ft}}{\partial M^D_{ft}} = \frac{W^D_{ft}}{\lambda_{ft}}$$

Using the definition of output elasticity and rearrange the first-order conditions for foreign and domestic inputs, we can get

$$\frac{\partial Q_{ft}}{\partial M^D_{ft}} = \frac{\partial q_{ft}}{\partial m^D_{ft}}\frac{Q_{ft}}{M^D_{ft}} = \frac{W^D_{ft}}{\lambda_{ft}} = \left[\beta_D - \beta(m^D_{ft} - m^{F*}_{ft})\right]\frac{Q_{ft}}{M^D_{ft}}$$

$$\frac{\partial Q_{ft}}{\partial M^F_{ft}} = \frac{\partial q_{ft}}{\partial m^F_{ft}}\frac{Q_{ft}}{M^F_{ft}} = \psi^F_{ft}\frac{W^F_{ft}}{\lambda_{ft}} = \left[\beta_F + \beta(m^D_{ft} - m^{F*}_{ft})\right]\frac{Q_{ft}}{M^F_{ft}}$$

Using the definition of foreign input inverse supply elasticity ψ_{ft}, we can then express the ratio of output elasticity between foreign input and domestic input as a function of ψ^F_{ft} and input expenditures:

$$\frac{\theta^F_{ft}}{\theta^D_{ft}} = \frac{\beta_F + \beta(m^D_{ft} - m^{F*}_{ft})}{\beta_D - \beta(m^D_{ft} - m^{F*}_{ft})} = \frac{\psi^F_{ft}W^F_{ft}M^F_{ft}}{W^D_{ft}M^D_{ft}} \tag{23}$$

We can define the markdown-adjusted foreign input expenditure share S^{FD}_{ft} as the fraction of a firm's total variable input spending that goes to foreign inputs after those foreign-input expenditures have been adjusted by the markdown:

$$S^{FD}_{ft} \equiv \frac{\psi^F_{ft}W^F_{ft}M^F_{ft}}{\psi^F_{ft}W^F_{ft}M^F_{ft} + W^D_{ft}M^D_{ft}} \tag{24}$$

From (20) and (24), we can get

$$m^D_{ft} - m^{F*}_{ft} = -\frac{\beta_F}{\beta} + \frac{\beta_F + \beta_D}{\beta}S^{FD}_{ft}$$

From (21) and (24), we can get

$$m^F_{ft} + a_{ft} = \frac{\beta_F}{\beta} - \frac{\beta_F + \beta_D}{\beta}S^{FD}_{ft} + m^D_{ft} \tag{25}$$

We can then express the output elasticity of foreign and domestic inputs as a function of S_{ft}^{FD}, β_F and β_D:

$$\theta_{ft}^F = \beta_F + \beta(m_{ft}^D - m_{ft}^{F*}) = (\beta_F + \beta_D)S_{ft}^{FD} \tag{26}$$

$$\theta_{ft}^D = \beta_D - \beta(m_{ft}^D - m_{ft}^{F*}) = (\beta_F + \beta_D)(1 - S_{ft}^{FD}) \tag{27}$$

Using (26) and (27), we can get the sum of the output elasticity of the foreign and domestic input as:

$$\theta_{ft}^F + \theta_{ft}^D = \beta_F + \beta_D$$

From (26),(27) and (18), we can rewrite the production function as:

$$q_{ft} = \beta_k k_{ft} + \beta_l l_{ft} + \beta_D m_{ft}^D + \beta_F\big(\frac{\beta_F}{\beta} - \frac{\beta_F + \beta_D}{\beta} S_{ft}^{FD} + m_{ft}^D\big) - \frac{1}{2}\beta\big(\frac{\beta_F}{\beta} + \frac{\beta_F + \beta_D}{\beta} S_{ft}^{FD}\big)^2 + \omega_{ft} + \varepsilon_{ft} \tag{28}$$

Further simplifying the above equation, we can get

$$q_{ft} = \beta_k k_{ft} + \beta_l l_{ft} + (\beta_D + \beta_F)m_{ft}^D + \frac{1}{2}\frac{(\beta_F)^2}{\beta} - \frac{1}{2}\frac{(\beta_D + \beta_F)^2}{\beta}(S_{ft}^{FD})^2 + \omega_{ft} + \varepsilon_{ft} \tag{29}$$

4.4 Final Good Market

Regarding the final good market, we follow Zhang (2019) and assume the monopolistic competition (Morlacco, 2019).

$$Q_{ft} = \Delta_{ft} P_{ft}^{-\eta} \tag{30}$$

Where P_{ft} is the output price endogenously chosen by the firm, and η is the constant demand elasticity. Δ_{ft} is a time-specific demand shifter observed by the firm before choosing domestic and foreign inputs in each period. Δ_{ft} is further decomposed to be a time dummy Δ_t common to all firms, an unexpected i.i.d. shock ξ_{ft}^D, and the effects of other observed firm characteristics, such as firm size, age, and ownership. Assume that Δ_{ft} can be written in the following form:

$$\ln \Delta_{ft} = \Delta_t + \alpha_{\text{size}} \cdot \text{firm size}_{ft} + \alpha_{\text{age}} \cdot \text{firm age}_{ft} + \alpha_{\text{own}} \cdot \text{firm ownership}_{ft} + \xi_{ft}^D.$$

Consider the firm's profit maximization problem:

$$\pi_{ft} = \max_{P_{ft}} \{\, P_{ft} Q_{ft}(P_{ft}) - C_{ft}(Q_{ft}(P_{ft}))\,\}$$

From the F.O.C., we can get

$$MR_{ft} = MC_{ft}$$

From final good demand function (30), we can have

$$MR_{ft} = P_{ft} + Q_{ft}\frac{dP_{ft}}{dQ_{ft}} = P_{ft} + Q_{ft}\left(-\frac{1}{\eta}\frac{P_{ft}}{Q_{ft}}\right) = P_{ft}\frac{\eta-1}{\eta} = MC_{ft}$$

Then the final good markup μ^P_{ft} can be expressed as

$$\mu^P_{ft} = \frac{P_{ft}}{MC_{ft}} = \frac{\eta}{\eta-1} \tag{31}$$

4.5 Foreign Input Markdown Calculation

In this section we show that identifying the foreign-input markdown is equivalent to identifying S^{FD}_{ft}. Identification is achieved by combining the final-good demand function and the production function with appropriate controls for the foreign-input supply side. We then identify non-neutral technology.

Taking natural log of the demand function, we can get

$$p_{ft} = \frac{1}{\eta}\ln(\Delta_{ft}) - \frac{1}{\eta}q_{ft} \tag{32}$$

From the cost minimization problem and $\lambda_{ft} = MC_{ft}$, we can get

$$W^F_{ft}\psi^F_{ft} = \lambda_{ft}\frac{\partial Q_{ft}}{\partial M^F_{ft}} = MC_{ft}\frac{\partial Q_{ft}}{\partial M^F_{ft}} \tag{33}$$

Using the output elasticity of foreign input, we have

$$W^F_{ft}\psi^F_{ft} = MC_{ft}\frac{\partial q_{ft}}{\partial m^F_{ft}}\frac{Q_{ft}}{M^F_{ft}} \tag{34}$$

Using the final good markup (31), we can express the F.O.C of foreign input as:

$$W^F_{ft}\psi^F_{ft} = \frac{\eta-1}{\eta}P_{ft}\theta^F_{ft}\frac{Q_{ft}}{M^F_{ft}} \tag{35}$$

Similarly, we can express the F.O.C of domestic input as:

$$W_{ft}^D = \frac{\eta - 1}{\eta} P_{ft} \theta_{ft}^D \frac{Q_{ft}}{M_{ft}^D} \tag{36}$$

From (35) and (36) and using the double-ratio approach, we can express foreign input markdown as:

$$\psi_{ft}^F = \frac{W_{ft}^D M_{ft}^D}{W_{ft}^F M_{ft}^F} \frac{S_{ft}^{FD}}{1 - S_{ft}^{FD}} \tag{37}$$

From (37), we show that calculate markdown is equal to identifying S_{ft}^{FD} as $\frac{W_{ft}^D M_{ft}^D}{W_{ft}^F M_{ft}^F}$ can be observed from data.

4.5.1 Identify Markdown-Adjusted Foreign Input Expenditure Share

Building on Rubens et al. (2024), we recover firm-year foreign-input markdowns using the double-ratio restriction while allowing A_{ft} to shift relative elasticities, so that wedges and augmentation are jointly disciplined by relative shares, relative elasticities, and the timing/variation restrictions in the structural estimation. Building on Rubens et al. (2024), we recover firm-year foreign-input markdowns using the double-ratio restriction while allowing A_{ft} to shift relative elasticities, so that wedges and augmentation are jointly disciplined by relative shares, relative elasticities, and the timing/variation restrictions in the structural estimation. To identify S_{ft}^{FD}, we first rearrange (36) and from (27), we can get

$$\frac{P_{ft} Q_{ft}}{W_{ft}^D M_{ft}^D} = \frac{\frac{\eta}{\eta - 1}}{(\beta_D + \beta_F)(1 - S_{ft}^{FD})} \tag{38}$$

From the cost minimization problem, one can use (38) and the definition of revenue $R_{ft} = P_{ft} Q_{ft}$ to identify S_{ft}^{FD}. Specifically, we can get:

$$\ln\left(\frac{R_{ft}}{W_{ft}^D M_{ft}^D}\right) = \ln \frac{\eta}{\eta - 1} - \ln(\beta_D + \beta_F) - \ln\big(1 - S_{ft}^{FD}\big) + \varepsilon_{ft} \tag{39}$$

where ε_{ft} is the pure disturbance term at the production end of the firm. In order to identify S^{FD}, we can run the following regression:

$$\ln\left(\frac{R_{ft}}{W_{ft}^D M_{ft}^D}\right) = \alpha_0 + X_{ft}\,\sigma + \varepsilon_{ft} \tag{40}$$

Here, the control variable X_{ft} is used to absorb heterogeneity on the foreign input-supply side and the combined effects of demand price elasticity and variable-input output elasticities. Specifically, X_{ft} includes firm capital, labor and domestic inputs, firm age, management cost, firm location, ownership type, year and industry dummy variables. After removing the stochastic disturbance ε_{ft}, the expression becomes:

$$\ln\left(\frac{\widehat{R_{ft}}}{W_{ft}^D M_{ft}^D}\right) = \hat{\alpha_0} + X_{ft}\,\hat{\sigma} \tag{41}$$

We let $\widehat{s}_{ft}^R$ be the fitted value of the dependent variable from the regression equation $\ln\left(\frac{\widehat{R_{ft}}}{W_{ft}^D M_{ft}^D}\right)$. We use this expression as a constraint in the production-function estimation. After removing ϵ_{ft}, S_{ft}^{FD} can be expressed as:

$$S_{ft}^{FD} = 1 - \frac{\eta}{\eta-1}\frac{1}{\beta_D+\beta_F}e^{-\widehat{s}_{ft}^R} \tag{42}$$

Equation (42) shows that the estimated adjusted foreign–domestic input share S_{ft}^{FD} is a function of the ratio of sales revenue to domestic input cost $\widehat{s}_{ft}^R = \frac{\widehat{R_{ft}}}{W_{ft}^D M_{ft}^D}$

4.5.2 Production Function Estimation

After we identify S_{ft}^{FD}, the production function (29) can be rewritten as:

$$q_{ft} = \beta_k k_{ft} + \beta_l l_f + (\beta_D+\beta_F)m_{ft}^D + \tfrac{1}{2}\frac{\beta_F^2}{\beta} - \tfrac{1}{2}\frac{(\beta_D+\beta_F)^2}{\beta}\left(1 - \frac{\eta}{(\eta-1)(\beta_D+\beta_F)}e^{-\widehat{s}_{ft}^R}\right)^2 + \omega_{ft} + \varepsilon_{ft} \tag{43}$$

We know revenue (in natural log) can be expressed as $r_{ft} = p_{ft} + q_{ft}$ and substitute the expressions of p_{ft} (32) and q_{ft} (43) into r_{ft}, we can get

$$\begin{aligned} r_{ft} = p_{ft} + q_{ft} = \frac{1}{\eta}\ln(\Delta_{ft}) + \frac{\eta-1}{\eta}\beta_k k_{ft} + \frac{\eta-1}{\eta}\beta_l l_{ft} + \frac{\eta-1}{\eta}(\beta_D+\beta_F)m_{ft}^D - \frac{\eta-1}{\eta}\frac{\beta_D^2+2\beta_D\beta_F}{2\beta} \\ + \frac{\eta-1}{\eta}\frac{(\beta_D+\beta_F)\eta}{\beta(\eta-1)}e^{-\widehat{s}_{ft}^R} - \frac{\eta-1}{\eta}\frac{\eta^2}{2\beta(\eta-1)^2}e^{-2\widehat{s}_{ft}^R} + \frac{\eta-1}{\eta}\omega_{ft} + \frac{\eta-1}{\eta}\varepsilon_{ft} \end{aligned} \tag{44}$$

Substitute the expression of $\ln(\Delta_{ft})$ into (44) and if we assume $\epsilon_{ft} \equiv \frac{1}{\eta}\xi_{ft}^D + \frac{\eta-1}{\eta}\varepsilon_{ft}$, we can get

$$r_{ft} = p_{ft} + q_{ft} = \frac{\eta-1}{\eta}\beta_k k_{ft} + \frac{\eta-1}{\eta}\beta_l l_{ft} + \frac{\eta-1}{\eta}(\beta_D+\beta_F)m_{ft}^D - \frac{\eta-1}{\eta}\frac{\beta_D^2+2\beta_D\beta_F}{2\beta}$$
$$+\frac{\eta-1}{\eta}\frac{(\beta_D+\beta_F)\eta}{\beta(\eta-1)}e^{-\hat{s}_{ft}^R} - \frac{\eta-1}{\eta}\frac{\eta^2}{2\beta(\eta-1)^2}e^{-2\hat{s}_{ft}^R} + \frac{\eta-1}{\eta}\omega_{ft}$$
$$+\frac{1}{\eta}\big(\Delta_t + \alpha_{\text{size}}\cdot\text{firm size}_{ft} + \alpha_{\text{age}}\cdot\text{firm age}_{ft} + \alpha_{\text{own}}\cdot\text{firm ownership}_{ft}\big) + \epsilon_{ft} \quad (45)$$

Following Ackerberg et al. (2015); Doraszelski and Jaumandreu (2018), we use two-stage approach to estimate the above production function. At first stage, we estimate

$$r_{ft} = h\big(l_{ft}, k_{ft}, m_{ft}^D, m_{ft}^F, w_{ft}^l, w_{ft}^F, e^{-\hat{s}_{ft}^R}, p_{ft}\big) + \nu_{ft},$$

via OLS with $h(\cdot)$ as a third-order polynomial, yielding $\hat{r}_{ft}$.

$$\frac{\eta-1}{\eta}\omega_{ft} = \hat{r}_{ft} - \frac{\eta-1}{\eta}\beta_k k_{ft} - \frac{\eta-1}{\eta}\beta_l l_{ft} - \frac{\eta-1}{\eta}(\beta_D+\beta_F)m_{ft}^D + \frac{\eta-1}{\eta}\frac{\beta_D^2+2\beta_D\beta_F}{2\beta}$$
$$-\frac{\eta-1}{\eta}\frac{(\beta_D+\beta_F)\eta}{\beta(\eta-1)}e^{-\hat{s}_{ft}^R} + \frac{\eta-1}{\eta}\frac{\eta^2}{2\beta(\eta-1)^2}e^{-2\hat{s}_{ft}^R}$$
$$-\frac{1}{\eta}\big(\Delta_t + \alpha_{\text{size}}\cdot\text{firm size}_{ft} + \alpha_{\text{age}}\cdot\text{firm age}_{ft} + \alpha_{\text{own}}\cdot\text{firm ownership}_{ft}\big)$$

We define the above parameters as: $\frac{\eta-1}{\eta}\frac{\beta_D^2+2\beta_D\beta_F}{2\beta} \equiv \alpha_0$, $\frac{\eta-1}{\eta}\beta_k \equiv \alpha_k$, $\frac{\eta-1}{\eta}\beta_l \equiv \alpha_l$, $\frac{\eta-1}{\eta}(\beta_D+\beta_F) \equiv \alpha_m^D$, $\frac{\eta-1}{\eta}\frac{(\beta_D+\beta_F)\eta}{\beta(\eta-1)} \equiv \alpha_{s1}$, $\frac{\eta-1}{\eta}\frac{\eta^2}{2\beta(\eta-1)^2} \equiv \alpha_{s2}$ and we can get

$$\frac{\eta-1}{\eta}\omega_{ft} = r_{ft} + \alpha_0 - \alpha_k k_{ft} - \alpha_l l_{ft} - \alpha_m^D m_{ft}^D - \alpha_{s1}e^{-\hat{s}_{ft}^R} - \alpha_{s2}e^{-2\hat{s}_{ft}^R}$$
$$-\frac{1}{\eta}\big(\Delta_t + \alpha_{\text{size}}\cdot\text{firm size}_{ft} + \alpha_{\text{age}}\cdot\text{firm age}_{ft} + \alpha_{\text{own}}\cdot\text{firm ownership}_{ft}\big)$$

At second stage, we introduce law of motion of the Hicks-neutral productivity,

$$\frac{\eta-1}{\eta}\omega_{ft} = g\Big(\frac{\eta-1}{\eta}\omega_{ft-1}\Big) + \mu_{ft} \quad (46)$$

, where we approximate $g(\cdot)$ as a first order polynomial in all its argument. Then the innovation $\mu_{ft} = \frac{\eta-1}{\eta}\omega_{ft} - \frac{\eta-1}{\eta}\omega_{ft-1}$ depends only on observables and all parameters to be estimated, and we use the GMM method proposed by Ackerberg et al. (2015) to estimate vector of parameter α from the following moment condition:

$$\mathbb{E}\big[\mu_{ft}(\alpha)\ Z_{ft}\big] = 0, \tag{47}$$

where instrument variable vector Z_{ft} contains lags of domestic input, labor, markdown-adjusted cost share $e^{-\widehat{s}_{ft}^{R}}$ and current capital as well as their interaction terms.

4.5.3 Foreign Input Markdown and Non-Neutral Technology Calculation

After identifying $\widehat{s}_{ft}^{R}$, from (42), we can get

$$S_{ft}^{FD} = 1 - \frac{1}{\hat{\alpha}_m^D} e^{-\widehat{s}_{ft}^{R}}$$

From (37), foreign input markdown can be expressed as:

$$\psi_{ft}^{F} = \frac{W_{ft}^{D} M_{ft}^{D}}{W_{ft}^{F} M_{ft}^{F}} \frac{\left(1 - \frac{1}{\hat{\alpha}_m^D} e^{-\widehat{s}_{ft}^{R}}\right)}{\frac{1}{\hat{\alpha}_m^D} e^{-\widehat{s}_{ft}^{R}}} \tag{48}$$

From (25), the foreign input-biased technology can be expressed as

$$a_{ft} = \frac{\beta_F}{\beta} - \frac{\beta_F + \beta_D}{\beta} S_{ft}^{FD} + m_{ft}^{D} - m_{ft}^{F}$$

After removing the mean, we obtain an estimate of foreign input-augmenting productivity

$$\hat{a}_{ft} = -\frac{(\hat{\alpha}_{s1})^2}{2\hat{\alpha}_{s2}\hat{\alpha}_m^D} S_{ft}^{FD} + m_{ft}^{D} - m_{ft}^{F}$$

where $-\frac{(\hat{\alpha}_{s1})^2}{2\hat{\alpha}_{s2}\hat{\alpha}_m^D} \equiv -\frac{\hat{\beta}_F + \hat{\beta}_D}{\hat{\beta}}$

5 Estimation Results

The estimation results for the non-neutral production functions are reported in the table 2.

The table 2 reports the estimated results for the main parameters. Among these, the production-side parameters are the ones this paper cares about most. Therefore, although some of the parameters do not have an immediate, intuitive economic interpretation, the short-run returns-to-scale parameter α_m^D represents their short-run revenue scale returns. Table 2 shows α_m^D ranges from 0.79 to 0.99, and the industry average of the short-run scale parameter is 0.89. These findings are very close to estimates reported in the existing literature. In addition, based on the parameter estimates, the average income elasticities for labor and capital are 0.07 and 0.01, respectively. The above estimates closely match existing results and lie within a reasonable range.

To show the relationship between estimated parameters and short-run returns-to-scale as well as revenue elasticity of different inputs, we can show the following:

$$\begin{aligned}
\theta_{ft}^{RF} &= \frac{\partial R_{ft}}{\partial M_{ft}^F}\frac{M_{ft}^F}{R_{ft}} = \frac{\partial (P_{ft}Q_{ft})}{\partial M_{ft}^F}\frac{M_{ft}^F}{P_{ft}Q_{ft}} \\
&= \left[Q_{ft}\frac{\partial P_{ft}}{\partial Q_{ft}} + P_{ft}\right]\frac{\partial Q_{ft}}{\partial M_{ft}^F}\frac{M_{ft}^F}{P_{ft}Q_{ft}} \\
&= \left[\frac{Q_{ft}}{P_{ft}}\frac{\partial P_{ft}}{\partial Q_{ft}} + 1\right]\frac{M_{ft}^F}{Q_{ft}}\frac{\partial Q_{ft}}{\partial M_{ft}^F} = \frac{\theta_{ft}^F}{\mu_{ft}^P} \\
&= \frac{(\beta_F + \beta_D)\, S_{ft}^{FD}}{\mu_{ft}^P} = \alpha_M^D\, S_{ft}^{FD}
\end{aligned}$$

$$\theta_{ft}^{RD} = \frac{\partial R_{ft}}{\partial M_{ft}^D}\frac{M_{ft}^D}{R_{ft}} = \frac{\partial (P_{ft}Q_{ft})}{\partial M_{ft}^D}\frac{M_{ft}^D}{P_{ft}Q_{ft}} = \alpha_M^D(1 - S_{ft}^{FD})$$

$$\theta_{ft}^{RL} = \frac{\partial R_{ft}}{\partial L_{ft}}\frac{L_{ft}}{R_{ft}} = \frac{\partial (P_{ft}Q_{ft})}{\partial L_{ft}}\frac{L_{ft}}{P_{ft}Q_{ft}} = \alpha_l$$

$$\theta_{ft}^{RK} = \frac{\partial R_{ft}}{\partial K_{ft}}\frac{K_{ft}}{R_{ft}} = \frac{\partial (P_{ft}Q_{ft})}{\partial K_{ft}}\frac{K_{ft}}{P_{ft}Q_{ft}} = \alpha_k$$

If we only consider domestic intermediate input and foreign intermediate input as variable inputs, then the short-run revenue scale returns can be expressed as $\theta_{ft}^{RD} + \theta_{ft}^{RF} = \alpha_M^D$.

Table 2: Non-Neutral Production Function Estimates

(1) Code	(2) Industry	(3) α_l	(4) α_k	(5) α_m^D	(6) α_{s1}	(7) α_{s2}	(8) N
17	Textile	0.0757	0.0169	0.8565	-1.7785	0.4586	3423
		(0.3337)	(0.0848)	(0.3143)	(3.9825)	(3.3273)	
18	Textile and Products	0.0833	0.0220	0.8033	-9.9465	8.3320	4015
		(0.0383)	(0.0159)	(0.1227)	(3.6977)	(3.7560)	
19	Leather and Products	0.0895	-0.0279	0.9458	-10.0451	8.3571	2416
		(0.0481)	(0.0197)	(0.0773)	(4.6588)	(4.4319)	
39	Electrical Machinery	0.0569	-0.0137	0.9878	-1.3100	-0.3096	3706
		(0.0997)	(0.0406)	(0.3360)	(6.6030)	(6.0578)	
40	Communication and Computer	0.0795	0.0028	0.9706	-0.6182	-0.8466	6067
		(0.1405)	(0.0249)	(0.3029)	(8.2199)	(8.1785)	
41	Measuring Instruments	0.0575	-0.0239	0.7935	-11.3693	9.8667	1396
		(0.0795)	(0.0273)	(0.1789)	(5.5840)	(5.7113)	

Note: Standard errors are shown in parentheses on the line below each estimate; they were calculated from 200 bootstrap replications.

From Eq. (48), the foreign input markdown under non-neutral technology are reported in table 3.

Table 3: Sector-Level Buyer Power, Non-Neutral, by CIC-2 Sector

(1) Code	(2) Industry	(3) N	(4) Mean	(5) Median	(6) SD
17	Textile	9590	5.61	3.05	6.94
18	Textile and Products	12293	5.57	2.62	7.21
19	Leather and Products	6460	6.67	3.10	9.11
39	Electrical Machinery	9992	6.51	3.50	8.19
40	Communication and Computer	16277	5.65	2.60	8.41
41	Measuring Instruments	3842	4.03	1.94	5.94
Total		58454	5.78	2.81	7.87

Notes: Col. (3) gives the number of observations (N); Cols. (4)–(6) report mean, median, and standard deviation (SD) of firm-level buyer power.

The table 3 shows that markdowns exist and that substantial heterogeneity is present both across sectors and within sectors. The frequent occurrence of means exceeding medians and the sizable standard deviations point to right-skewed, heavy-tailed distributions—a small subset of firms with very large buyer power drives sectoral averages.

Furthermore, we also illustrate the change of markdown under non-neutral technology over sample period 2000-2007.

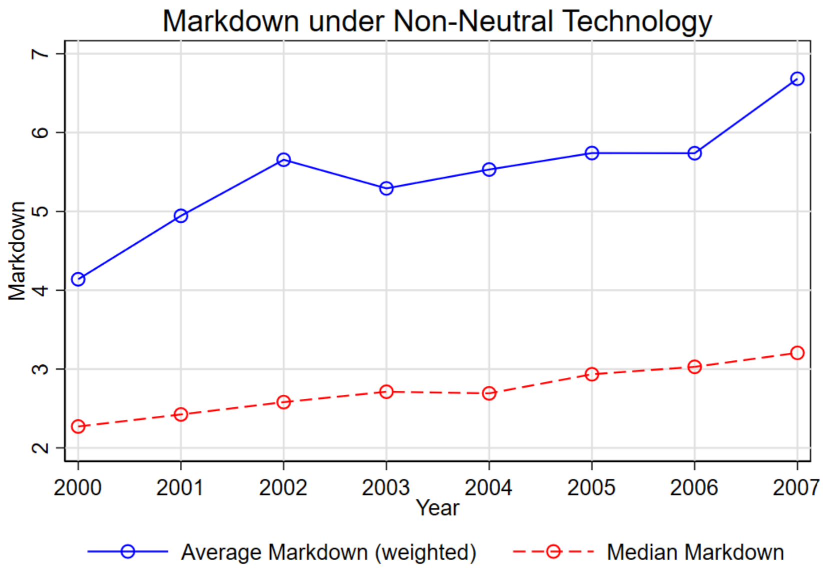

Figure 2: Change of Markdown over Time under Non-Neutral Technology

Across the selected sectors from 2000 to 2007 the revenue-weighted ("average") foreign-input markdown rises substantially while the median markdown increases more slowly. The weighted average climbs from approximately 4.0 in 2000 to about 6.8 in 2007 (an increase of $6.8 - 4.0 = 2.8$, i.e. a 70% increase), whereas the median moves from roughly 2.2 to 3.1 (an increase of 0.9, i.e. $\approx 40.9\%$). Because the weighted mean is consistently and increasingly larger than the median (the gap widens from 1.8 to 3.7, an absolute rise of 1.9, or $\approx 105.6\%$), the pattern indicates that the growth in markdowns is driven disproportionately by larger firms (or higher-revenue observations) rather than a uniform shift across the firm distribution.

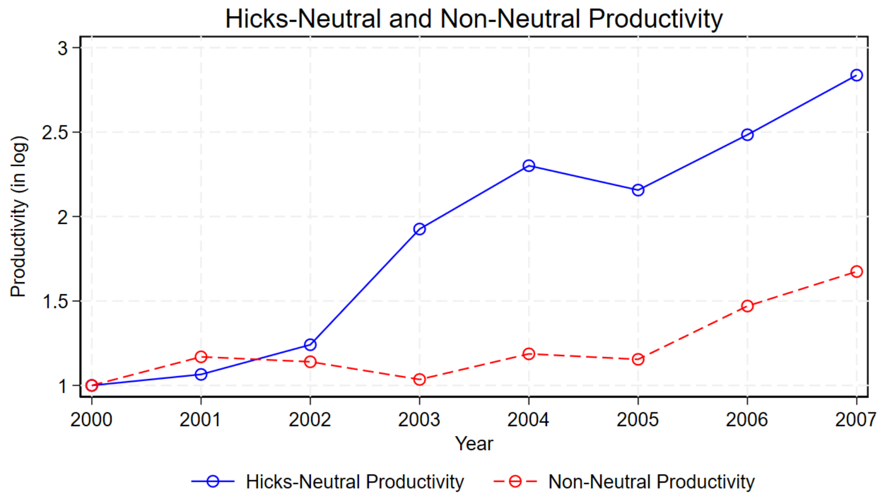

Figure 3: Dynamics of Hicks-neutral and non-Hicks technology

Furthermore, Figure 3 demonstrates the dynamics of sector-level Hicks-neutral technology and non-neutral technology from 2000 to 2007. Solid blue line represents revenue-weighted Hicks-neutral (total factor) productivity, normalized to 1 in 2000. Dashed red line represents revenue-weighted non-neutral productivity, normalized to 1 in 2000.

The non-neutral productivity rises relatively quickly in the early 2000s technology (blue) remains close to 1 through 2002, accelerates after 2002–2003, overtakes the non-neutral measure following the 2004 peak, and reaches roughly 1.33 by 2007.

Because these are revenue-weighted series, the plotted movements primarily reflect changes among higher-revenue firms. Descriptively, non-neutral (foreign input biased) productivity gains appear earlier in the sample while Hicks-neutral gains are more sustained later; this description is intended as a factual summary of the plotted trends rather than a causal claim.

One plausible interpretation is that initial adoption of foreign input biased technologies or improved sourcing raised the marginal productivity of foreign inputs first (captured by red line), and these gains later diffused into wider productivity-enhancing adjustments.

And the Table 4 shows the Hicks-neutral and non-neutral technology growth rate for each selected sector.

Table 4: Growth Rate of Hicks-neutral and Non-Neutral Productivity

Code	Industry	Hicks-neutral (%)	Non-neutral (%)
17	Textile	2.97	0.92
18	Textile and Products	2.87	7.48
19	Leather and Products	-0.68	8.72
39	Electrical Machinery	-1.44	10.90
40	Communication and Computer	-3.56	4.97
41	Measuring Instruments	-2.17	2.52

Across the sectors shown, non-neutral (foreign input-biased) productivity growth exceeds Hicks-neutral (TFP) growth in five sectors (18, 19, 39, 40, 41). The largest non-neutral gains are concentrated in electrical machinery (39, 10.90%) and leather and related products (19, 8.72%), while the Hicks-neutral growth rate is positive and comparatively larger only in the Textile sector (17, 2.97% vs 0.92%). Several sectors (19, 39, 40, 41) display negative Hicks-neutral productivity growth alongside positive non-neutral technology growth, indicating that measured improvements in productivity tied to imported intermediates can be large even when aggregate (Hicks-neutral) TFP is flat or declining.

This pattern is descriptive: revenue-weighted growth rates emphasize outcomes for higher-revenue firms, so the reported magnitudes primarily reflect what happens at larger firms within each sector. A cautious interpretation is that input-specific (non-neutral) productivity improvements are an important component of measured productivity dynamics in these sectors, particularly in machinery and leather-related manufacturing, while broad-based Hicks-neutral gains are modest and concentrated in textiles.

We also examine three determinants of firm-level foreign-input markdown: size, foreign-input–biased technology, and ownership. Size is proxied by the firm's revenue. Foreign-input–biased technology is represented by a_{ft} and used in natural-log form, $\ln a_{ft}$. Ownership is captured by a dummy variable FOE that equals 1 if the firm has any positive foreign ownership share (majority or minority) and 0 otherwise.

We then run the following regression:

$$\ln \psi_{ft}^{F} = \alpha + \beta_1 \,\mathrm{size} + \beta_2 \,\ln \mathrm{a}_{ft} + \beta_3 \,\ln \mathrm{FOE} + \mathrm{FE}_{ft} + \varepsilon_{ft}$$

Table 5: Impact of Firm Size on Firm's Buyer Power

	(1)	(2)	(3)
Dependent Variable		$\ln \psi_{ft}^{F}$	
ln(size)	0.290^{***}	0.167^{***}	0.167^{***}
	(0.009)	(0.007)	(0.007)
a_{ft}		0.458^{***}	0.458^{***}
		(0.003)	(0.003)
FOE			0.462^{***}
			(0.110)
Observations	51,997	51,997	51,997
FE	FY	FY	FY
Adj. R^2	0.66	0.79	0.79

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. FY denote firm and year fixed effects. Size is measured as firm's total revenue and results are robust if we use total employment as an alternative measure. Standard errors are reported in parentheses.

The table reports OLS estimates where the dependent variable is the natural log of the firm-level foreign-input markdown (log buyer power), $\ln \psi_{ft}^{F}$. Model (1) reports the baseline association between firm size (logged revenue) and markdown; Model (2) adds the foreign-input–biased technology measure a_{ft}; Model (3) further adds the FOE ownership dummy. All specifications include firm and year fixed effects (FY). Standard errors are shown in parentheses and significance stars indicate conventional p-value thresholds.

Firm size is positively and highly significantly associated with larger markdowns: the coefficient on ln(size) falls from 0.29 in (1) to 0.17 in (2)–(3) after adding technology and ownership controls, indicating that a 1% increase in revenue is associated with roughly a 0.17–0.29% higher markdown, conditional on fixed effects. The foreign-input–biased technology coefficient is 0.458 and precisely estimated; if a_{ft} is entered in natural-log form, this is interpreted as an elasticity (a 1% increase in the input-biased productivity measure corresponds to 0.46% higher markdown). The FOE dummy in (3) is positive and significant: FOE firms have substantially larger markdowns, about $\exp(0.462) - 1 \approx 0.59$ (59%) higher on average relative to purely domestic firms, conditional on the included controls.

Model fit improves when adding the technology and ownership variables (adjusted R^2 rises from 0.66 to 0.79). The sample covers 51,997 firm–year observations. Results are reported with standard errors in parentheses and are robust to using employment instead of revenue as the size measure (see notes). These estimates are descriptive associations conditional on fixed effects and covariates; they document that larger firms, firms with higher measured foreign-input–biased productivity, and foreign-owned firms tend to exhibit systematically larger buyer power as measured by the log markdown.

5.1 Application

We also estimate production function (19) when $\psi_{ft}^F = 1$, (i.e. under competitive foreign input market) From (23), we can get

$$\frac{\theta_{ft}^F}{\theta_{ft}^D} = \frac{\beta_F + \beta(m_{ft}^D - m_{ft}^{F*})}{\beta_D - \beta(m_{ft}^D - m_{ft}^{F*})} = \frac{W_{ft}^F M_{ft}^F}{W_{ft}^D M_{ft}^D} \tag{49}$$

We then define

$$S_{ft}^{NM} \equiv \frac{W_{ft}^F M_{ft}^F}{W_{ft}^F M_{ft}^F + W_{ft}^D M_{ft}^D} \tag{50}$$

From (20) and (24), we can get

$$m_{ft}^D - m_{ft}^{F*} = -\frac{\beta_F}{\beta} + \frac{\beta_F + \beta_D}{\beta} S_{ft}^{NM}$$

From (21) and (24), we can get

$$m_{ft}^F + a_{ft} = \frac{\beta_F}{\beta} - \frac{\beta_F + \beta_D}{\beta} S_{ft}^{NM} + m_{ft}^D \tag{51}$$

$$q_{ft} = \beta_k k_{ft} + \beta_l l_{ft} + (\beta_D + \beta_F) m_{ft}^D + \frac{1}{2}\frac{(\beta_F)^2}{\beta} - \frac{1}{2}\frac{(\beta_D + \beta_F)^2}{\beta}(S_{ft}^{NM})^2 + \omega_{ft} + \varepsilon_{ft} \tag{52}$$

$$\begin{aligned} r_{ft} = p_{ft} + q_{ft} = \frac{1}{\eta}\ln(\Delta_{ft}) + \frac{\eta-1}{\eta}\beta_k k_{ft} + \frac{\eta-1}{\eta}\beta_l l_{ft} + \frac{\eta-1}{\eta}(\beta_D + \beta_F) m_{ft}^D + \frac{1}{2}\frac{\eta-1}{\eta}\frac{(\beta_F)^2}{\beta} \\ -\frac{1}{2}\frac{\eta-1}{\eta}\frac{(\beta_D+\beta_F)^2}{\beta}(S_{ft}^{NM})^2 + \frac{\eta-1}{\eta}\omega_{ft} + \frac{\eta-1}{\eta}\varepsilon_{ft} \end{aligned} \tag{53}$$

Following Ackerberg et al. (2015); Doraszelski and Jaumandreu (2018), we use two-stage approach to estimate the above production function. At first stage, we estimate

$$r_{ft} = h\big(l_{ft}, k_{ft}, m_{ft}^D, m_{ft}^F, w_{ft}^l, w_{ft}^F, (S_{ft}^{NM})^2, p_{ft}\big) + \nu_{ft},$$

via OLS with $h(\cdot)$ as a third-order polynomial, yielding $\hat{r}_{ft}$.

$$\frac{\eta-1}{\eta}\,\omega_{ft} = \hat{r}_{ft} - \frac{\eta-1}{\eta}\,\beta_k k_{ft} - \frac{\eta-1}{\eta}\,\beta_l l_{ft} - \frac{\eta-1}{\eta}\,(\beta_D+\beta_F)\,m_{ft}^D - \frac{1}{2}\frac{\eta-1}{\eta}\frac{(\beta_F)^2}{\beta}$$
$$+\frac{1}{2}\frac{\eta-1}{\eta}\frac{(\beta_D+\beta_F)^2}{\beta}(S_{ft}^{NM})^2 - \frac{1}{\eta}\big(\Delta_t + \alpha_{\text{size}}\cdot \text{firm size}_{ft} + \alpha_{\text{age}}\cdot \text{firm age}_{ft} + \alpha_{\text{own}}\cdot \text{firm ownership}_{ft}\big)$$

We define the above parameters as: $\frac{1}{2}\frac{\eta-1}{\eta}\frac{(\beta_F)^2}{\beta} \equiv \alpha_0$, $\frac{\eta-1}{\eta}\beta_k \equiv \alpha_k$, $\frac{\eta-1}{\eta}\beta_l \equiv \alpha_l$, $\frac{\eta-1}{\eta}(\beta_D+\beta_F) \equiv \alpha_m^D$ and $-\frac{1}{2}\frac{\eta-1}{\eta}\frac{(\beta_D+\beta_F)^2}{\beta} \equiv \alpha_s$ and we can get

$$\frac{\eta-1}{\eta}\,\omega_{ft} = \hat{r}_{ft} + \alpha_0 - \alpha_k k_{ft} - \alpha_l l_{ft} - \alpha_m^D\,m_{ft}^D - \alpha_s\,(S_{ft}^{NM})^2$$
$$-\frac{1}{\eta}\big(\Delta_t + \alpha_{\text{size}}\cdot \text{firm size}_{ft} + \alpha_{\text{age}}\cdot \text{firm age}_{ft} + \alpha_{\text{own}}\cdot \text{firm ownership}_{ft}\big)$$

At second stage, we introduce law of motion of the Hicks-neutral productivity,

$$\frac{\eta-1}{\eta}\,\omega_{ft} = g\left(\frac{\eta-1}{\eta}\,\omega_{ft-1}\right) + \mu_{ft} \tag{54}$$

The estimation results are shown in the table below.

Table 6: Non-Neutral Production Function Estimates

(1) Code	(2) Industry	(3) α_l	(4) α_k	(5) α_m^D	(6) α_{S2q}	(7) N
17	Textile	0.0397	0.0242	0.8994	2.1593	3424
		(0.0059)	(0.0049)	(0.0070)	(0.0492)	
18	Textile and Products	0.0368	0.0199	0.9260	2.2141	4020
		(0.0075)	(0.0043)	(0.0145)	(0.1128)	
19	Leather and Products	0.0555	0.0061	0.9380	2.1646	2419
		(0.0063)	(0.0038)	(0.0079)	(0.0505)	
39	Electrical Machinery	0.0224	0.0141	0.9345	2.4185	3708
		(0.0042)	(0.0027)	(0.0064)	(0.0418)	
40	Communication and Computer	0.0316	0.0253	0.9338	2.2399	6071
		(0.0042)	(0.0029)	(0.0045)	(0.0348)	
41	Measuring Instruments	0.0168	0.0188	0.9080	2.4105	1398
		(0.0488)	(0.0172)	(0.1182)	(0.4318)	

After remove the mean, we can get

$$\hat{a}_{ft} = \frac{2\hat{\alpha}_s}{\hat{\alpha}_m^D} S_{ft}^{NM} + m_{ft}^D - m_{ft}^F$$

And we plot the change of non-neutral technology over time.

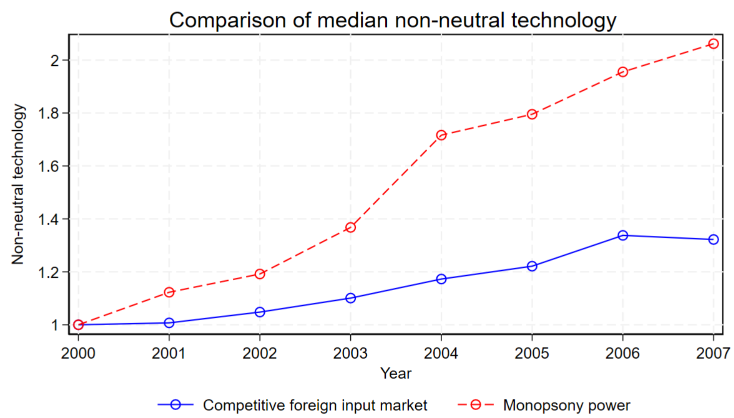

Figure 4: Change of Non-Neutral Technology over Time

Figure 4 plots the median foreign-input-biased (non-neutral) technology across sectors 17–19 (textiles/leather) and 39–41 (electrical, communication, instruments), rebased so 2000 equals 1. We take the monopsony-power specification as the benchmark; the competitive case lies lower and rises more slowly, and the gap widens over time—consistent with stronger non-neutral technical change when buyer power is allowed.

Moreover, Figure 4 indicates that omitting buyer power understates non-neutral technology growth. These medians pool all six sectors; the Figure 5 below shows heterogeneity across sectors.

Furthermore, Figure 5 plots normalized paths of non-neutral technology from 2000–2007 under two foreign-input market regimes: blue is the competitive benchmark (technology without monopsony power), red incorporates monopsony power in foreign-input markets. Across sectors the two lines co-move and trend upward, while the red series typically sits above and often pulls away from the blue, indicating an incremental lift in effective technology associated with buyer power. Short-lived pauses or dips do not alter the general pattern over 2000–2007.

In the first three panels (17 Textile, 18 Textile & Products, 19 Leather & Products), which are less import-intensive, the red–blue gap is modest and often temporary, suggesting technology is the main driver with monopsony adding a smaller premium. In the last three panels (39 Electrical Machinery, 40 Communication & Computer, 41 Measuring Instruments), which are more import- and technology-intensive, the red–blue gap is wider and more persistent—especially from the mid-2000s onward—consistent with a stronger interaction between monopsony power and non-neutral technological change.

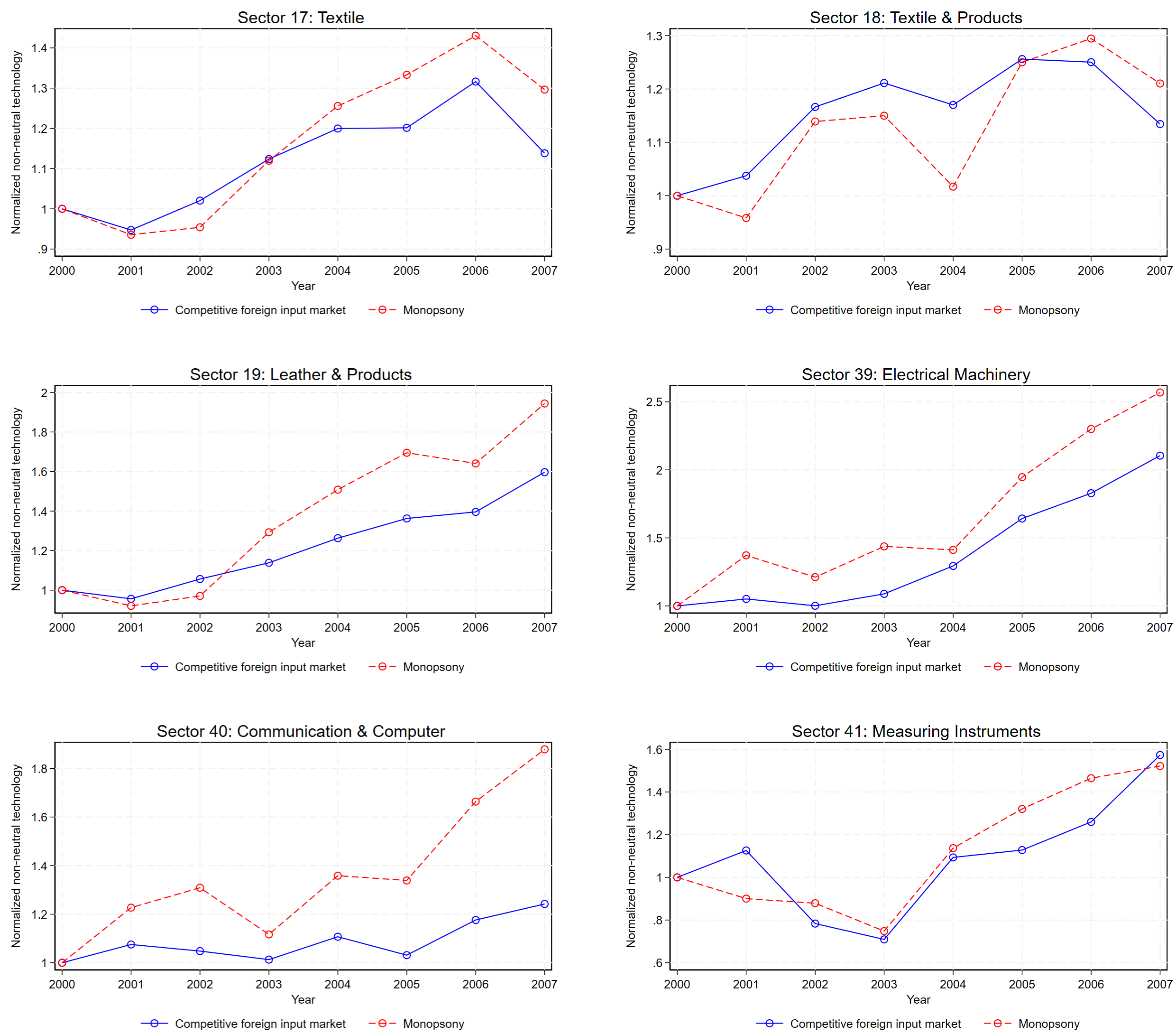

Figure 5: Change of Non-Neutral Technology across Sectors

5.2 Decomposing the Cost Share of Foreign Input

To quantify the contributions of foreign input -augmenting technological change and changing labor market competition to the aggregate labor cost share, we recompute two counterfactual changes in the labor cost share. From (27) and (26),

$$\frac{W^F_{ft}M^F_{ft}}{W^F_{ft}M^F_{ft}+W^D_{ft}M^D_{ft}} = \frac{\theta^F_{ft}}{\theta^F_{ft}+\theta^D_{ft}\psi^F_{ft}} = \frac{(\beta_F+\beta_D)S^{FD}_{ft}}{(\beta_F+\beta_D)S^{FD}_{ft}\psi^F_{ft}+(\beta_F+\beta_D)(1-S^{FD}_{ft})\psi^F_{ft}} \tag{55}$$

$$\frac{W^F_{ft}M^F_{ft}}{W^F_{ft}M^F_{ft}+W^D_{ft}M^D_{ft}} = \frac{\theta^F_{ft}}{\theta^F_{ft}+\theta^D_{ft}\psi^F_{ft}} = \frac{1-\frac{1}{\hat{\alpha}^D_m}e^{-\hat{s}^R_{ft}}}{\left(1-\frac{1}{\hat{\alpha}^D_m}e^{-\hat{s}^R_{ft}}\right)+\frac{1}{\hat{\alpha}^D_m}e^{-\hat{s}^R_{ft}}\psi^F_{ft}} \tag{56}$$

Taking the weighted average of both sides of (56), we can get

$$\frac{W_t^F M_t^F}{W_t^F M_t^F + W_t^D M_t^D} = \frac{\theta_t^F}{\theta_t^F + \theta_t^D \psi_t^F} = \frac{1 - \frac{1}{\hat{\alpha}_m^D} e^{-\widehat{s}_t^R}}{\left(1 - \frac{1}{\hat{\alpha}_m^D} e^{-\widehat{s}_t^R}\right) + \frac{1}{\hat{\alpha}_m^D} e^{-\widehat{s}_t^R} \psi_t^F} \tag{57}$$

The left-hand side of (57) is the foreign input cost share in total variable expenditure. θ_t^F denotes the weighted average (aggregate) output elasticity of foreign intermediate inputs, θ_{ft}^D denotes the weighted average output elasticity of domestic inputs, and ψ_t^F denotes the weighted average foreign-input markdown parameter. To examine the contributions of non-Hicks neutral technology and foreign input markdown to the change of foreign input cost share, we perform the following counterfactual experiments.

Counterfactual 1: the impact of non–Hicks-neutral technology on foreign-input cost share. Hold the aggregate foreign-input markdown fixed at its year-2000 level and let aggregate output elasticities vary over time; that is, set $\psi_t^F = \psi_{2000}^F$ while allowing θ_t^F and θ_t^D to change. The counterfactual foreign input cost share is

$$s_t^{\text{Non-neutral}} = \frac{1 - \frac{1}{\hat{\alpha}_m^D} e^{-\widehat{s}_t^R}}{\left(1 - \frac{1}{\hat{\alpha}_m^D} e^{-\widehat{s}_t^R}\right) + \frac{1}{\hat{\alpha}_m^D} e^{-\widehat{s}_t^R} \psi_{2000}^F}. \tag{58}$$

Counterfactual 2: the impact of foreign-input markdown on foreign-input cost share. Hold the aggregate output elasticities of foreign and domestic inputs fixed at its year-2000 level and let the markdown vary over time; that is, set $\theta_t^D = \theta_{2000}^D$, $\theta_t^F = \theta_{2000}^F$ and allow ψ_t^F to change with t. The counterfactual foreign input cost share is

$$s_t^{\text{Markdown}} = \frac{1 - \frac{1}{\hat{\alpha}_m^D} e^{-\widehat{s}_{2000}^R}}{(1 - \frac{1}{\hat{\alpha}_m^D} e^{-\widehat{s}_{2000}^R}) + \frac{1}{\hat{\alpha}_m^D} e^{-\widehat{s}_{2000}^R} \psi_t^F} \tag{59}$$

These two paths separately attribute movements in the foreign input cost share to changes in non–neutral technology and to time-variation in the foreign-input markdown, respectively, while holding the other channel fixed at its initial level (year-2000 benchmark).

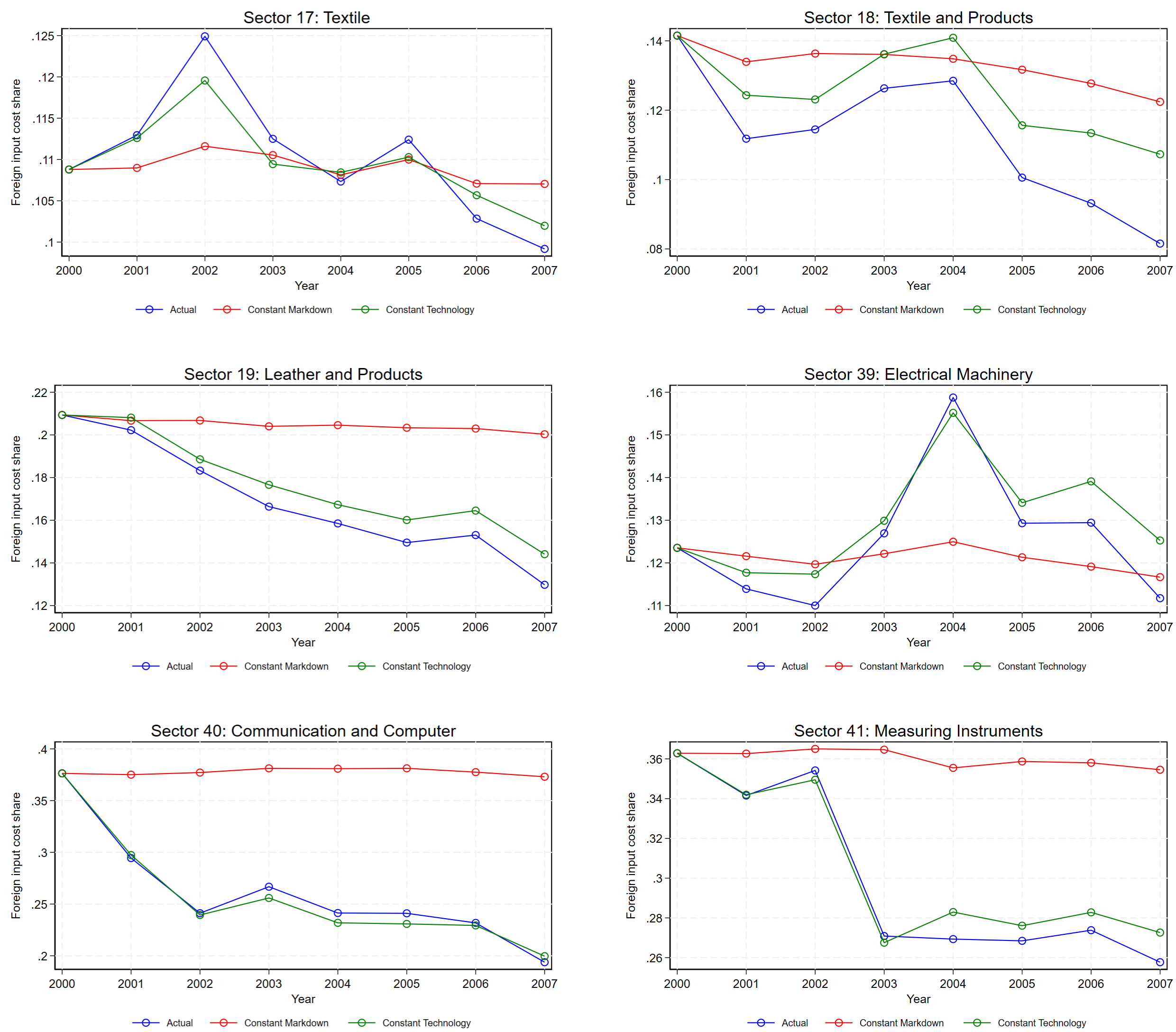

Figure 6: Change of Foreign Input Cost Share across Sectors

From Figure 6, we can observe that first three sectors (17–19: Textile; Textile and Products; Leather and Products). These less import-intensive industries show a decline in the foreign-input cost share that is still largely driven by monopsony power in foreign-input markets, accounting for roughly 50–60% of the drop on average (with non-neutral, factor-biased technology explaining the remaining 40–50%). In practice, Textile and Products is close to a half-and-half split, while Textile and Leather and Products still exhibit a sizable monopsony component alongside a meaningful technology role. The constant-markdown counterfactual closely mimics the observed foreign-input cost share decline in Figure 2 for these sectors, confirming that technology helps but does not dominate.

Last three sectors (39–41: Electrical Machinery; Communication and Computer; Measuring Instruments). These are more import- and technology-intensive. The decline is primarily technology-driven, with Communication and Computer and Measuring Instruments showing technology explaining the large majority (roughly 80–95%), while Electrical Machinery is the key exception where monopsony power explains almost all of the decline. Overall, these counterfactual paths mimic the actual foreign-input cost share decline in Figure 2: the constant-markdown line tracks the observed fall in the technology-intensive pair, whereas the constant-technology line highlights the monopsony-led pattern in Electrical Machinery.

We also estimate Hicks-neutral production function to calculate markdown as robustness check. To do it, we take logs on both sides of equation (16), and use a second-order Taylor expansion of equation (17) around $\gamma = 1$. One can write the firm's production function as

$$q_{ft} = \beta_k k_{ft} + \beta_l \ell_f + \beta_F m_{ft}^F + \beta_D m_{ft}^D + \beta_{FF}(m_{ft}^F)^2 + \beta_{DD}(m_{ft}^D)^2 + \beta_{FD} m_{ft}^F m_{ft}^D + \omega_{ft} + \varepsilon_{ft}, \quad (60)$$

Therefore, the output elasticity of foreign input can be expressed as:

$$\theta_{ft}^F = \beta_F + 2\beta_{FF} m_{ft}^F + \beta_{FD} m_{ft}^D$$

Similarly, the output elasticity of domestic input can be expressed as:

$$\theta_{ft}^D = \beta_D + 2\beta_{DD} m_{ft}^D + \beta_{FD} m_{ft}^F$$

And we can also get:

$$\frac{\theta_{ft}^F}{\theta_{ft}^D} = \frac{\beta_F + 2\beta_{FF} m_{ft}^F + \beta_{FD} m_{ft}^D}{\beta_D + 2\beta_{DD} m_{ft}^D + \beta_{FD} m_{ft}^F}$$

We first do the input-demand inversion. From the first-order conditions of cost minimization, foreign and domestic intermediate input quantities satisfy

$$M_{ft}^F = \delta\big(W_{ft},\, V_{ft}/M_{ft}^F,\, K_{ft},\, P_{ft},\, e^{\omega_{ft}}\big), \quad (61)$$

$$M_{ft}^D = \mu\big(W_{ft},\, V_{ft}/M_{ft}^D,\, K_{ft},\, P_{ft},\, e^{\omega_{ft}}\big). \quad (62)$$

Here W_{ft} is the vector of input prices, V_{ft} the vector of input quantities, P_{ft} the output price, and $e^{\omega_{ft}}$ productivity. Monotonicity in prices allows us to invert (62):

$$W_{ft}^D \;=\; \mu^{-1}\big(W_{ft}/W_{ft}^D,\, V_{ft},\, K_{ft},\, P_{ft},\, e^{\omega_{ft}}\big) \quad (63)$$

Substituting (63) into (61) yields

$$M_{ft}^F \;=\; \widetilde{\delta}\big(W_{ft}/W_{ft}^D,\, V_{ft}/M_{ft}^F,\, K_{ft},\, P_{ft},\, e^{\omega_{ft}}\big), \tag{64}$$

which in turn can be inverted for productivity:

$$e^{\omega_{ft}} \;=\; \widetilde{\delta}^{-1}\big(V_{ft},\, K_{ft},\, W_{ft}/W_{ft}^D,\, P_{ft}\big). \tag{65}$$

Although P_{ft} is unobserved, we proxy it with firm-level output deflators $\tilde{P}_{ft}$. The above production function becomes

$$\begin{aligned}\tilde{q}_{ft} = \beta_k k_{ft} + \beta_l l_{ft} + \beta_F m_{ft}^F + \beta_D \bar{m}_{ft}^D + \beta_{FF}(m_{ft}^F)^2 + \beta_{DD}(\bar{m}_{ft}^D)^2 + \beta_{FD} m_{ft}^F \bar{m}_{ft}^D \\ + \widetilde{\delta}^{-1}\big(\ell_{ft}, k_{ft}, \bar{m}_{ft}^{D\,6}, m_{ft}^F, w_{ft}^F, w_{ft}^\ell, p_{ft}\big) + u_{ft}\end{aligned} \tag{66}$$

where $u_{ft} = \varepsilon_{ft} + \beta^{\mathbf{D}} h(w_{st}^D - w_{ft}^D)$

We use two-stage approach to estimate the above production function. At first stage, we estimate

$$q_{ft} = \phi\big(l_{ft}, k_{ft}, m_{ft}^D, m_{ft}^F, w_{ft}^F, w_{ft}^l, p_{ft}\big) + \varepsilon_{ft},$$

via OLS with $\phi(\cdot)$ as a third-order polynomial, yielding $\hat{q}_{ft}$. At Second stage, we introduce a law of motion for productivity:

$$\omega_{ft} = \rho(\omega_{ft-1}) + \xi_{ft}, \quad \rho(\cdot) \text{ is a first-order polynomial,} \tag{67}$$

[7] and we can get

$$\omega_{ft}(\beta) = \hat{q}_{ft} - \big(\beta_k k_{ft} + \beta_l l_{ft} + \beta_F m_{ft}^F + \beta_D \bar{m}_{ft}^D + \beta_{FF}(m_{ft}^F)^2 + \beta_{DD}(\bar{m}_{ft}^D)^2 + \beta_{FD} m_{ft}^F \bar{m}_{ft}^D\big) \tag{68}$$

Then we can get

$$\xi_{ft}(\beta) = \omega_{ft}(\beta) - \rho\big(\omega_{ft-1}(\beta)\big)$$

Then the innovation ξ_{ft} depends only on observables and parameter vector β, and we estimate β from the following moment condition:

$$\mathbb{E}\big[\xi_{ft}(\beta)\; Z_{ft}\big] = 0, \tag{69}$$

where instrument variable vector Z_{ft} contains lags of domestic and foreign input, current capital and labor, and their interaction terms.

[7] Results are robust if we assume $\rho(\cdot)$ is a second-order polynomial in all its arguments.

Using double-ratio approach, we can derive the foreign input markdown under Hicks-neutral productivity $\psi_{ft}^{FHN} = \frac{\beta_F + 2\beta_{FF} m_{ft}^F + \beta_{FD} m_{ft}^D}{\beta_D + 2\beta_{DD} m_{ft}^D + \beta_{FD} m_{ft}^F} \cdot \frac{W_{ft}^D M_{ft}^D}{W_{ft}^F M_{ft}^F}$

Under Hicks-neutral production function, we estimate production function using 2-step GMM methods proposed by Ackerberg et al. (2015). Table 3 reports the estimated parameters. The output elasticity of labor and capital is defined as β_k and β_l respectively. And output elasticity for foreign input and domestic input are given as following $\theta_{ft}^F = \beta_F + 2\beta_{FF} m_{ft}^F + \beta_{FD} m_{ft}^D$ and $\theta_{ft}^D = \beta_D + 2\beta_{DD} m_{ft}^D + \beta_{FD} m_{ft}^F$, repspectively.

The median output elasticity of foreign input across sectors is 0.30 whereas median output elasticity of domestic input is 0.38. The median output elasticity of labor is 0.12 and output elasticity of capital is 0.06. The full estimation results are reported in table 3.

Table 7: Estimation Results for Hicks-neutral Production Function

(1) Code	(2) Industry	(3) β_k	(4) β_l	(5) β_D	(6) β_F	(7) β_{DD}	(8) β_{FF}	(9) β_{FD}	(10) N
17	Textile	0.0439	0.0693	-0.0333	0.1731	0.0637	0.0225	-0.0544	8579
		(0.0197)	(0.0402)	(0.0583)	(0.0642)	(0.0141)	(0.0044)	(0.0127)	
18	Textile and Products	-0.0569	-0.1048	-0.0123	0.2539	0.1027	0.0221	-0.0724	9871
		(0.0231)	(0.0459)	(0.0812)	(0.0564)	(0.0105)	(0.0057)	(0.0107)	
19	Leather and Products	0.0380	0.1189	0.0183	0.1937	0.0364	0.0225	-0.0379	5032
		(0.0209)	(0.0271)	(0.0983)	(0.0369)	(0.0158)	(0.0033)	(0.0111)	
39	Electrical Machinery	0.0774	0.1110	0.0364	0.1742	0.0328	0.0121	-0.2464	8106
		(0.0245)	(0.0412)	(0.0749)	(0.0410)	(0.0117)	(0.0040)	(0.1143)	
40	Communication and Computer	0.0803	0.1789	-0.0360	0.1453	0.0284	0.0149	-0.2262	11559
		(0.0178)	(0.0330)	(0.0546)	(0.0326)	(0.0210)	(0.0062)	(0.0209)	
41	Measuring Instruments	0.0109	0.0456	-0.3106	0.1648	0.0621	-0.0023	-0.0082	2975
		(0.0233)	(0.0644)	(0.1039)	(0.0547)	(0.0180)	(0.0103)	(0.2152)	

Note: Standard errors are shown in parentheses on the line below each estimate; they were calculated from 200 bootstrap replications.

Using the double-ratio approach, the foreign input markdown under Hicks-neutral technology are reported in the table 8.

Table 8 indicates that foreign-input markdowns under a Hicks-neutral technology are present: the economy-wide mean buyer power is 3.98 (median 2.22), implying that firms on average obtain non-negligible markdowns on foreign intermediates. There is clear sectoral heterogeneity. Textile and related sectors (CIC-2 codes 17–19) display substantially higher buyer power (means: 3.32, 6.50, 4.58; medians: 2.38, 4.10, 2.59) and larger dispersion (SDs up to 8.87) than machinery and electronics sectors (codes 39–41), which show lower means (3.1, 2.95, 3.10) and lower medians (1.5–1.7).

Table 8: Sector-Level Buyer Power, Hicks-Neutral, by CIC-2 Sector

(1) Code	(2) Industry	(3) N	(4) Mean	(5) Median	(6) SD
17	Textile	9612	3.32	2.38	8.53
18	Textile and Products	12360	6.50	4.10	8.87
19	Leather and Products	6504	4.58	2.59	6.76
39	Electrical Machinery	10015	3.13	1.71	3.87
40	Communication and Computer	16347	2.95	1.48	6.75
41	Measuring Instruments	3852	3.10	1.63	5.75
Total		58690	3.98	2.22	7.27

Notes: Col. (3) gives the number of observations (N); Cols. (4)–(6) report mean, median, and standard deviation (SD) of firm-level buyer power.

5.3 Change of Buyer Power over Time

This section analyzes the markdowns on foreign intermediate inputs across selected Chinese manufacturing sectors between 2000 and 2007. Figure 7 demonstrates the six panels plot the median firm-level buyer power over time under two specifications: the blue lines representing the Hicks-neutral specification and the red dashed lines representing the Non-Hicks specification. A clear, general pattern is that the Non-Hicks estimates are typically larger and show stronger upward trends over 2000–2007 than the Hicks-neutral estimates. This visual gap indicates that the assumed technology (Hicks-neutral vs. non-Hicks) materially affects the level and time path of inferred buyer power.

Within the textile and leather group (CIC 17–19) the dynamics are heterogeneous. Sector 17 (Textile) shows a widening gap with Non-Hicks medians substantially above the Taylor medians and increasing more rapidly. Sector 18 (Textile and Products) is the notable exception: the Hicks-neutral lies above the Non-Hicks series and rises toward the end of the sample, suggesting that Hicks-neutral assumptions allocate relatively more buyer power to this sub-sector. Sector 19 (Leather and Products) exhibits rising buyer power in both specifications, but much more sharply under Non-Hicks. In short, the textile cluster (sectors 17-19) shows within-group reallocation when technology assumptions change —one sub-sector (18) moves opposite to the other two.

The other cluster (CIC 39–41: Electrical Machinery; Communication and Computer; Measuring Instruments) presents a more uniform story. For these sectors the Non-Hicks medians are consistently higher and generally increasing, while the Taylor medians remain low and roughly flat (or slightly rising). Sector 39 and 40 show especially persistent gaps, and sector 41 has a sharp early spike in the Non-Hicks series before stabilizing. That uniform

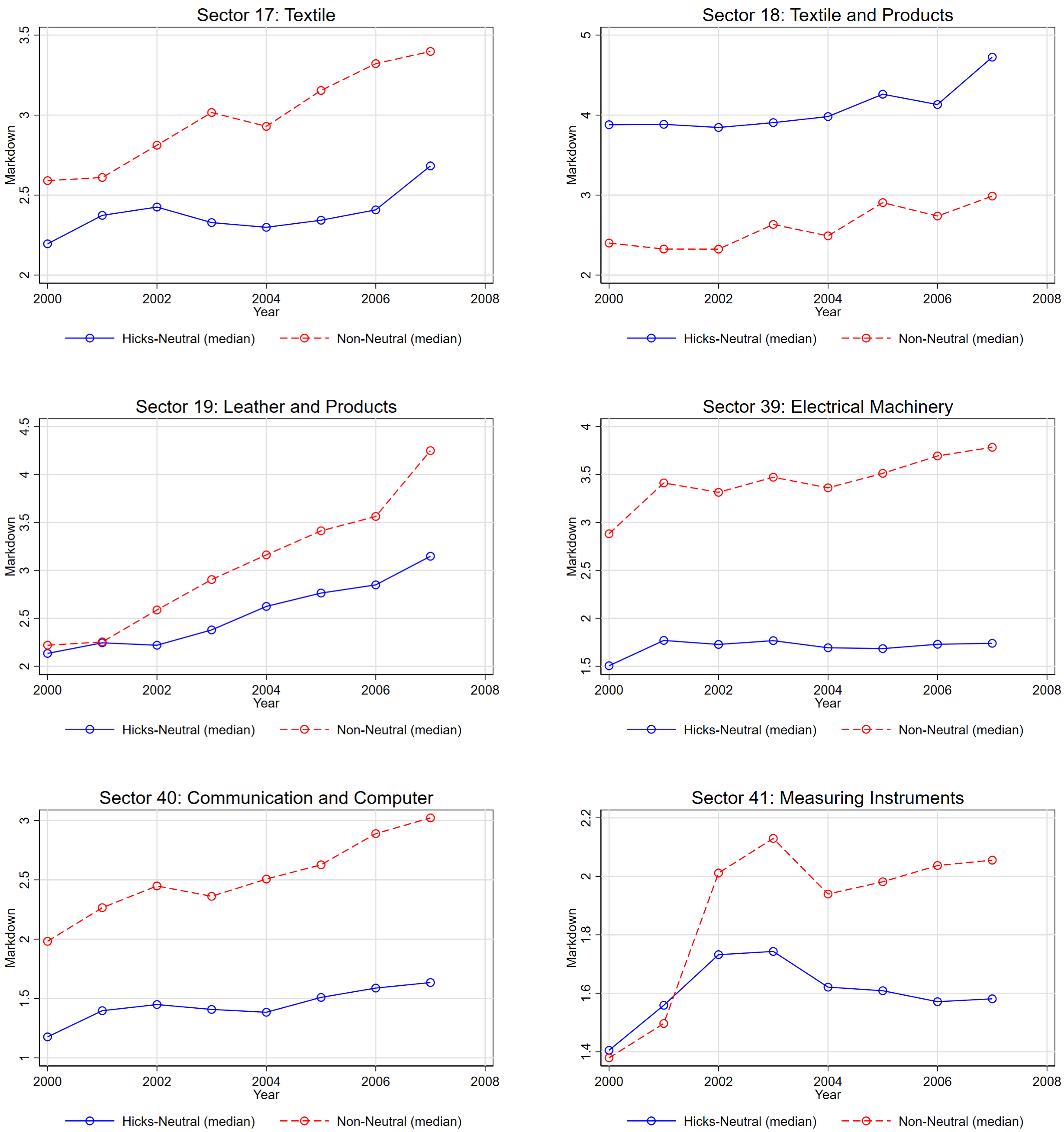

Figure 7: Median buyer power under non-neutral and Hicks-neutral technology

downward shift under Hicks-neutral assumptions suggests the Hicks-neutral technology restriction underestimated buyer power across these capital- and technology-intensive industries.

These patterns imply that estimated foreign-input buyer power is sensitive to the production-technology assumption. Non-Hicks specifications tend to deliver higher and more volatile buyer-power medians, whereas Hicks-neutral specifications often yield lower and smoother medians —though the effect is heterogeneous across sub-sectors. Because multiple channels (e.g., input substitution patterns) can produce these differences.

6 Monte Carlo Simulation

6.1 Non-Neutral Technology

We conduct a Monte Carlo experiment to evaluate the performance of our estimation method described in Section 4. The data-generating process (DGP) is based on Equation (44). Specifically, we simulate a panel dataset of 30 independent markets, each containing 50 firms observed over 10 years. Thus, the simulated dataset contains 1,500 firms and 15,000 firm-year observations in total.

The true structural parameters are set to $\alpha_0 = 7$, $\alpha_l = 0.07$, $\alpha_k = 0.02$, $\alpha_m^D = 0.9$, $\alpha_{s1} = -6$, and $\alpha_{s2} = 4$. The logarithms of labor input l_{ft}, capital input k_{ft}, and domestic intermediate input m_{ft}^D are independently drawn from normal distributions with means 10, 5, 3, respectively, and unit variance. The exponential form of domestic input cost $e^{-s_{ft}}$ is drawn from a normal distribution: $e^{-s_{ft}} \sim N(2.5, 1)$. After that, we generate the quadratic term of $e^{-s_{ft}}$. We simulate the logarithms of Hicks-neutral ω_{ft} be normally distributed: $\omega_{ft} \sim N(0, 0.5)$. The logarithms of Hicks-neutral also follows an AR(1) process with serial correlation parameter $\rho = 0.9$. Measurement error ε_{ft} is drawn from a normal distribution $N(0, 0.1)$.

6.2 Estimation

For estimation, we implement a two-step GMM procedure to estimate the vector of parameters

$$\theta = (\alpha_0, \alpha_l, \alpha_k, \alpha_m^D, \alpha_{s1}, \alpha_{s2}, \rho)$$

from the moment condition Equation (69). We use the same set of instruments contains lags of domestic and foreign input, and current capital and labor as in our empirical analysis.

We conduct $R = 200$ Monte Carlo replications and summarize the distribution of estimates by their mean, standard deviation, finite-sample bias, and root mean squared error (RMSE).

6.3 Results

Table 9 presents the Monte Carlo results for non-neutral technology productivity. We find that the non-neutral technology estimator yields precise and consistent estimates. As summarized in table 9, the parameter of α_l, α_k, α_m^D, α_{s1}, α_{s2} are estimated at their true values 0.07, 0.02 0.9, -6, and 4, with the standard deviation of these estimates across 200 replications being very small, at 0.0011, 0.0008, 0.0015, 0.0220 and 0.0044. The estimator successfully recovers the true parameter values with high accuracy. Both bias and RMSE remain negligible across all coefficients.

To illustrate the finite-sample distribution of the estimates, Figure 8 plots their distribution. Red dashed lines indicate the true parameter values, while blue dotted lines indicate the Monte Carlo means. The distributions are tightly centered around the truth, suggesting that the estimator performs well in finite samples.

These findings demonstrate that our non-neutral technology estimator is consistent and reliable under the DGP we consider. In particular, the inclusion of lagged instruments effectively addresses endogeneity stemming from the autoregressive error component.

6.4 Cobb-Douglas Production and Hicks-neutral Technology

As a robustness check, we also conduct Monte Carlo simulations under a Cobb–Douglas production function and under Hicks-neutral technology. In both cases, we simulate panel dataset of 30 markets with 50 firms observed over 10 years, and conduct 200 replications.

For the Cobb–Douglas specification, we follow the estimation method outlined in the Appendix, with the data-generating process defined by Equation (70). The true structural parameters are set to $\beta_l = 0.01$, $\beta_k = 0.01$, $\beta_D = 0.91$ and $\beta_F = 0.07$. The logarithms of labor input l_{ft}, capital input k_{ft}, domestic intermediate input m_{ft}^D and foreign intermediate input m_{ft}^D are independently drawn from normal distributions with means 10, 5, 3, 2, respectively, and unit variance. We simulate a Hicks-neutral productivity shock ω_{ft} be normally distributed: $\omega_{ft} \sim N(0, 0.5)$. The logarithms of production function follows an AR(1) process with serial correlation parameter $\rho = 0.9$. Measurement error ε_{ft} is drawn from a normal distribution $N(0, 0.1)$. Table 10 summarizes the Monte Carlo results while Figure 8 plots their distribution.

For Hicks-neutral specification, DGP follows Equation (60). The true structural parameters are set to $\beta_l = 0.13$, $\beta_k = 0.06$, $\beta_D = 0.14$, $\beta_F = 0.12$, $\beta_{DD} = 0.04$, $\beta_{FF} = 0.03$ and $\beta_{FD} = -0.05$. The logarithms of labor input l_{ft}, capital input k_{ft}, domestic intermediate input m^D_{ft} and foreign intermediate input m^F_{ft} are independently drawn from normal distributions with means 10, 5, 3, 2, respectively, and unit variance. After that, we generate the quadratic term of domestic intermediate input m^D_{ft} and foreign intermediate input m^D_{ft}, as well as their interaction term. We simulate a Hicks-neutral productivity shock ω_{ft} be normally distributed: $\omega_{ft} \sim N(0, 0.5)$. The logarithms of production function follows an AR(1) process with serial correlation parameter $\rho = 0.9$. Measurement error ε_{ft} is drawn from a normal distribution $N(0, 0.1)$. The corresponding results are reported in Table 11 and Figure 10.

In both the Cobb–Douglas and Hicks-neutral specifications, the estimated means are close to the true values, with small standard deviations, bias, and RMSE. The distributions are tightly centered around the truth. These findings confirm that our estimation method performs well in finite samples and remains consistent and reliable under alternative production function specifications.

Table 9: Monte Carlo Simulation: Non-neutral Technology Estimates

Parameter	True	Mean Estimate	Std. Dev.	Bias	RMSE
a_l	0.060	0.0639	0.0087	0.0039	0.0096
a_{l^2}	0.002	0.0016	0.0008	-0.0003	0.0009
a_k	0.090	0.0897	0.0079	-0.0002	0.0079
a_{k^2}	-0.003	-0.0029	0.0004	-0.0000	0.0004
a_m^D	0.870	0.8692	0.0047	-0.0007	0.0047
a_{es}	-3.500	-3.5020	0.0113	-0.0020	0.0115
a_{es^2}	1.800	1.8003	0.0023	0.0003	0.0024

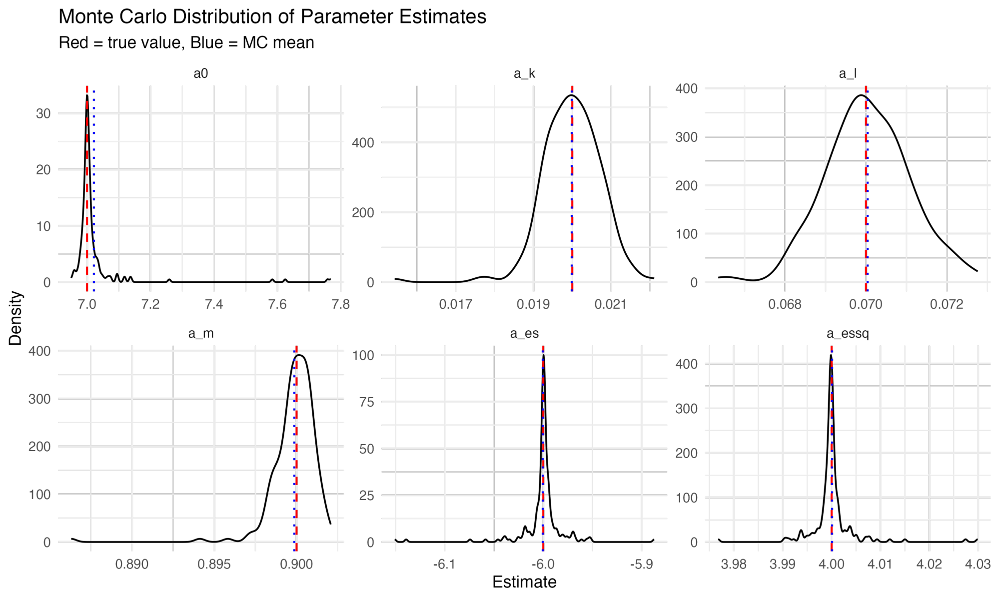

Figure 8: Monte Carlo Simulation: Non-neutral Technology Estimates

Table 10: Monte Carlo Simulation: Cobb-Douglas Production Estimates

Parameter	True	Mean Estimate	Std. Dev.	Bias	RMSE
β_l	0.01	0.010125	0.002055	0.000125	0.001843
β_k	0.01	0.010173	0.001519	0.000173	0.001369
β_D	0.91	0.910015	0.001212	0.000015	0.001084
β_F	0.07	0.069724	0.001468	-0.000276	0.001342

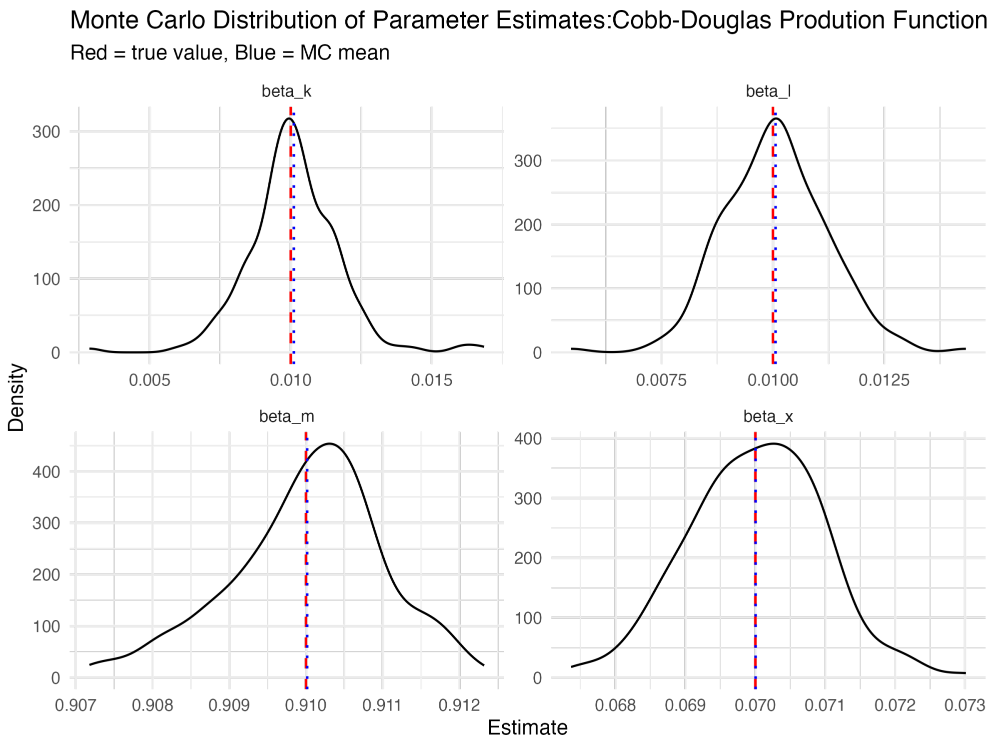

Figure 9: Monte Carlo Simulation: Cobb-Douglas Production Estimates

Table 11: Monte Carlo Simulation: Hicks-neutral Technology Estimates

Parameter	True	Mean Estimate	Std. Dev.	Bias	RMSE
β_k	0.06	0.060083	0.000669	0.000083	0.000673
β_l	0.13	0.130055	0.001256	0.000055	0.001254
β_D	0.14	0.143041	0.024295	0.003041	0.024424
β_F	0.12	0.124258	0.027972	0.004258	0.028225
β_{DD}	0.04	0.039068	0.008718	-0.000932	0.008746
β_{FF}	0.03	0.029202	0.005954	-0.000798	0.005992
β_{FD}	-0.05	-0.049758	0.004549	0.000242	0.004544

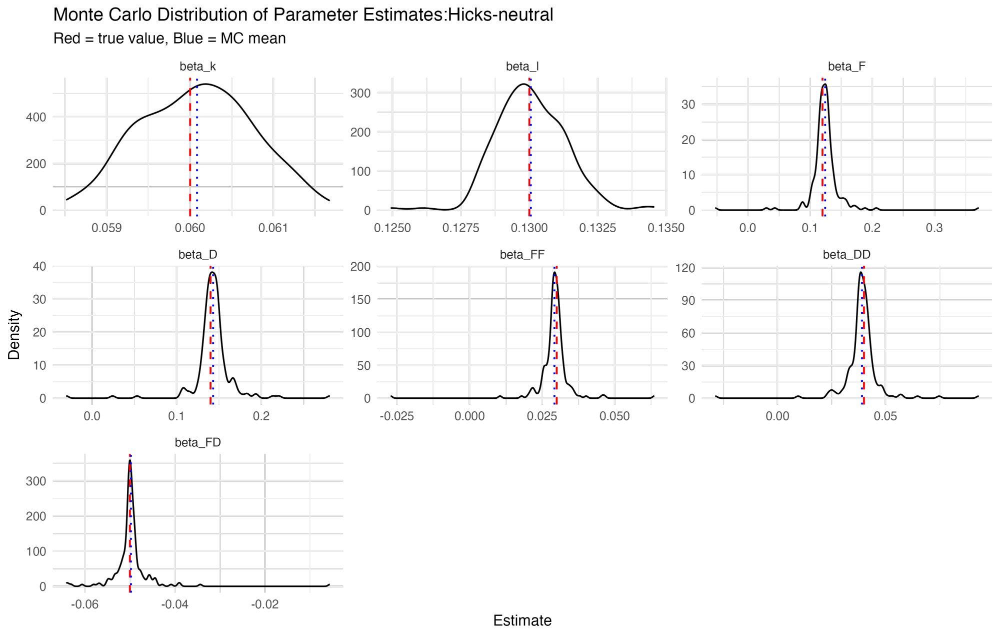

Figure 10: Monte Carlo Simulation: Hicks-neutral Technology Estimates

7 Conclusion

we begin by documenting the declining trend in selected Chinese manufacturing sectors' foreign-input cost share (CIC 17–19 and 39–41) over 2000–2007. This paper provides empirical evidence of buyer power in the foreign-input market and quantifies the buyer power of these sectors using firm-level data for 2000–2007 while allowing production technology to be foreign-input-biased rather than Hicks-neutral. By explicitly incorporating factor-biased technology, the analysis recovers firm-level foreign-input markdowns and compares them to Hicks-neutral benchmarks, showing that treating technology as Hicks-neutral when it is not leads to biased estimates of buyer power.

Specifically, we develop a framework to identify a firm's foreign input buyer power by jointly conditioning on determinants of foreign-input supply, final-good demand, and production-side technology. Under the factor-biased technology assumption, markdowns are pinned down by the equilibrium relationships among supply, demand, and production. Using this approach, we find that Revenue-weighted average markdowns rise over the sample period under both the Hicks-neutral and foreign-input-biased productivity specifications, and that the foreign-input-biased interpretation systematically affects both the level and the evolution of measured markdowns.

However, the empirical implementation controls for exporter responses rather than fully parametrizing an exporter-side supply function; consequently, foreign-input supply elasticities are not structurally recovered.

These limitations suggest straightforward extensions to strengthen identification and policy relevance. Access to foreign-input supplier price and quantity data would allow joint estimation of foreign-input supply elasticities, which, combined with an explicit model of downstream bargaining, would recover supply elasticities and welfare shares and would enable credible structural counterfactuals that decompose the contributions of factor-biased technology and firm buyer power to the decline in foreign-input cost shares. Implementing decomposition exercises and counterfactual reweighting that hold firm composition fixed would clarify the mechanisms driving aggregate markdown and cost-share dynamics. Expanding sectoral, cross-country, and temporal coverage beyond the six sectors and the 2000–2007 window would test the generality of the findings and their relevance for current policy debates about global value chains and buyer power. A natural future direction is to undertake a welfare analysis of markdowns and factor-biased technology change on the economy.

A Appendix

A.1 Cobb-Douglas Production Function

Because we do not observe firm-level output prices P_{ft} directly, we construct a proxy firm-level output deflator $\tilde{P}_{ft}$ by combining the two-digit industry output deflator P_{st} with a firm-specific deviation $\hat{P}_{ft}$. Following Morlacco (2019), we define the firm-level output deflator

$$\tilde{P}_{ft} = P_{st}\hat{P}_{ft}$$

If we denote each variable's logarithm by its corresponding lowercase letter, then we can get

$$\hat{p}_{ft} = \ln \tilde{P}_{ft} - \ln P_{st} = \tilde{p}_{ft} - p_{st}.$$

Here, $\hat{p}_{ft}$ represents the unobserved firm-level deviation from the industry average output price. Since $\hat{p}_{ft}$ is not directly observable, we infer it from firm-level export prices. For each destination market c, we observe

$$\hat{p}_{fct} = p_{fct} - p_{Ict},$$

where p_{fct} is the log export price of firm f in market c, and p_{Ict} is the corresponding industry-level export price to country c (industries defined at the two-digit level).

Let X_{fct} be the export value of firm f to country c and $X_{ft} = \sum_c X_{fct}$ be its total export value. Define weights

$$w_{fct} = \frac{X_{fct}}{X_{ft}},$$

i.e., the share of firm f's export value to country c relative to its total export value. Aggregating across destinations with these weights, we obtain

$$\hat{p}_{ft} = \sum_c w_{fct}\,\hat{p}_{fct}.$$

Substituting back gives the firm-level output price deflator in logs,

$$\tilde{p}_{ft} = p_{st} + \hat{p}_{ft},$$

which we use to deflate revenue and thereby control for firm-level output price bias in our estimations.

We apply an analogous procedure to construct a firm-specific foreign input deflator for imported inputs. Let W^F_{st} denote the 2-digit sector input deflator for foreign intermediate inputs. First, we define firm-level foreign input deflator as:

$$\tilde{W}^F_{ft} = W^F_{st}\hat{W}^F_{ft},$$

and if we take logs of both sides, we can get:

$$\hat{w}^F_{ft} = \ln \tilde{W}^F_{ft} - \ln W^F_{st} = \tilde{w}^F_{ft} - w^F_{st}.$$

Here, $\hat{w}^F_{ft}$ represents the firm-level deviation from the industry average imported-input price. For each destination c, let W^F_{fct} and W^F_{Ict} be firm-level and industry-level imported-input prices, respectively, and define

$$\hat{w}^F_{fct} = w^F_{fct} - w^F_{Ict}.$$

Similarly, let Y_{fct} be the import value of firm f from country c and $Y_{ft} = \sum_c Y_{fct}$ be its total import value. Define weights

$$\eta_{fct} = \frac{Y_{fct}}{Y_{ft}},$$

i.e., the share of firm f's import value from country c relative to its total import value. Aggregating with weights η_{fct} as above, we can get

$$\hat{w}^F_{ft} = \sum_c \eta_{fct}\, \hat{w}^F_{fct},$$

we construct the firm-level foreign input price deflator (in natural log)

$$\tilde{w}^F_{ft} = w^F_{st} + \hat{w}^F_{ft}.$$

To estimate the Cobb–Douglas production function under non-competitive foreign-input markets, we follow the two-step GMM procedure of Ackerberg et al. (2015) as implemented by Morlacco (2019). Moreover, since we do not have firm-level price data for output and domestic input, we use price bias control approach following De Loecker (2011). Following Morlacco (2019), we use the following log-linear production function for firm f at time t:

$$q_{ft} \;=\; f\big(l_{ft},\, k_{ft},\, m^D_{ft},\, m^F_{ft};\, \beta\big) \;+\; \omega_{ft} \;+\; \varepsilon_{ft}, \tag{70}$$

where lower-case denotes natural logs, ω_{ft} is a Hicks-neutral productivity shock, and ε_{ft}

denotes measurement error. The parameter vector β is constant within each two-digit manufacturing sector over our sample. Lowercase letters (e.g., l, k, m, w) denote input quantities or prices in natural logarithms; for example, l_{ft} is the natural logarithm of firm f's total employment in year t and w^l_{ft} is the natural logarithm of firm f's wage in year t. We treat capital and labor as dynamic inputs subject to adjustment frictions.

We first do the input-demand inversion. From the first-order conditions, foreign and domestic intermediate input quantities satisfy

$$M^F_{ft} = \delta\big(W_{ft},\, V_{ft}/M^F_{ft},\, K_{ft},\, P_{ft},\, e^{\omega_{ft}}\big), \tag{71}$$

$$M^D_{ft} = \mu\big(W_{ft},\, V_{ft}/M^D_{ft},\, K_{ft},\, P_{ft},\, e^{\omega_{ft}}\big). \tag{72}$$

Here W_{ft} is the vector of input prices, V_{ft} the vector of input quantities, P_{ft} the output price, and $e^{\omega_{ft}}$ productivity. Monotonicity in prices allows us to invert (45):

$$W^D_{ft} \;=\; \mu^{-1}\big(W_{ft}/W^D_{ft},\, V_{ft},\, K_{ft},\, P_{ft},\, e^{\omega_{ft}}\big). \tag{73}$$

Substituting this into (44) yields

$$M^F_{ft} \;=\; \widetilde{\delta}\big(W_{ft}/W^D_{ft},\, V_{ft}/M^F_{ft},\, K_{ft},\, P_{ft},\, e^{\omega_{ft}}\big), \tag{74}$$

which in turn can be inverted for productivity:

$$e^{\omega_{ft}} \;=\; \widetilde{\delta}^{-1}\big(V_{ft},\, K_{ft},\, W_{ft}/W^D_{ft},\, P_{ft}\big). \tag{75}$$

Although P_{ft} is unobserved, we proxy it with firm-level output deflators $\tilde{P}_{ft}$.

In particular, we outline the procedure of estimating Cobb–Douglas production function. Combining these steps, the Cobb–Douglas specification becomes

$$q_{ft} = \beta_l\, l_{ft} + \beta_k\, k_{ft} + \beta_D\, \bar{m}^D_{ft} + \beta_F\, m^F_{ft} + \widetilde{\delta}^{-1}\big(l_{ft}, k_{ft}, \bar{m}^{D\,[8]}_{ft}, m^F_{ft}, w^F_{ft}, w^l_{ft}, p_{ft}\big) + u_{ft}, \tag{76}$$

where $u_{ft} = \varepsilon_{ft} + \beta_D(w^D_{st} - w^D_{ft})$.

We use two-stage approach to estimate Cobb-Douglas production function. At first stage, we estimate

$$q_{ft} = \phi\big(l_{ft}, k_{ft}, m^F_{ft}, m^D_{ft}, w^F_{ft}, w^l_{ft}, p_{ft}\big) + \varepsilon_{ft},$$

via OLS with $\phi(\cdot)$ as a third-order polynomial, yielding $\hat{q}_{ft}$. At Second stage, we introduce

[8] $\bar{m}^D_{ft}$ is the natural logarithm of the deflated domestic quantity, where the deflator is the two-digit sector-specific input deflator.

a law of motion for productivity:

$$\omega_{ft} = \rho(\omega_{ft-1}) + \xi_{ft}, \quad \rho(\cdot) \text{ is a first-order polynomial,} \tag{77}$$

[9] and we can get

$$\omega_{ft}(\beta) = \hat{q}_{ft} - \big(\beta_l\, l_{ft} + \beta_k\, k_{ft} + \beta_D\, \bar{m}_{ft}^D + \beta_F\, m_{ft}^F\big) \tag{78}$$

Then we can get

$$\xi_{ft}(\beta) = \omega_{ft}(\beta) - \rho\big(\omega_{ft-1}(\beta)\big)$$

Then the innovation ξ_{ft} depends only on observables and β, and we estimate β from the following moment condition:

$$\mathbb{E}\big[\xi_{ft}(\beta)\ Z_{ft}\big] = 0, \tag{79}$$

where Z_{ft} contains lags of domestic and foreign input, and current capital and labor. We therefore report sector-level estimates of β and use the double-ratio approach to estimate firm-level foreign intermediate input markdown under the Cobb-Douglas specification:

$$\psi_{ft}^F = \frac{\theta_{fg}^F}{\gamma_{fg}^F} \frac{\gamma_{ft}^D}{\theta_{ft}^D}$$

where γ_{ft}^F denotes the cost of foreign input bundle F as a share of gross revenues of firm f in year t, such that $\gamma_{ft}^F = \frac{W_{ft}^F M_{ft}^F}{P_{ft} Q_{ft}}$. θ_f^F denotes the output elasticity of foreign input bundles. Since we already estimated the output elasticity (β vector), then the firm-level markdown under Cobb-Douglas production function can be expressed as

$$\psi_{ft}^{FCD} = \frac{\beta_F}{\gamma_f^F} \frac{\gamma_{ft}^D}{\beta_D}$$

The estimated output elasticity under Cobb-Douglas and resulting sector-level foreign input markdown are reported in table 12 and table 13.

[9] Results are robust if we assume $\rho(\cdot)$ is a second-order polynomial in all its arguments.

Table 12: Non-Neutral Production Function Estimates

(1) Code	(2) Industry	(3) β_l	(4) β_k	(5) β_D	(6) β_F	(7) N
17	Textile	0.0020	-0.0025	0.8418	0.1260	5574
		(0.0159)	(0.0106)	(0.0235)	(0.0093)	
18	Textile and Products	-0.0100	0.0278	0.8484	0.1699	6865
		(0.0174)	(0.0092)	(0.0208)	(0.0098)	
19	Leather and Products	0.0329	0.0203	0.8635	0.0707	3880
		(0.0223)	(0.0134)	(0.0296)	(0.0112)	
39	Electrical Machinery	0.0444	0.0051	0.9968	0.0256	5989
		(0.0195)	(0.0128)	(0.0233)	(0.0071)	
40	Communication and Computer	0.0254	0.0327	0.9294	0.0350	9887
		(0.0149)	(0.0085)	(0.0149)	(0.0053)	
41	Measuring Instruments	0.0244	-0.0186	1.0078	0.0210	2278
		(0.0277)	(0.0188)	(0.0261)	(0.0108)	

Note: Standard errors are shown in parentheses on the line below each estimate; they were calculated from bootstrap replications.

Table 13: Sector-Level Buyer Power, Cobb-Douglas, by CIC-2 Sector

(1) Code	(2) Industry	(3) N	(4) Mean	(5) Median	(6) SD
17	Textile	10690	1.61	0.57	2.27
18	Textile and Products	13593	1.67	0.47	2.60
19	Leather and Products	6980	1.14	0.32	1.94
39	Electrical Machinery	10893	0.55	0.18	0.85
40	Communication and Computer	17109	0.58	0.15	1.13
41	Measuring Instruments	4148	0.86	0.21	1.52
Total		63413	1.06	0.37	1.90

Notes: Col. (3) gives the number of observations (N); Cols. (4)–(6) report mean, median, and standard deviation (SD) of firm-level buyer power under Cobb-Douglas production.

A.2 Variable Definitions

Unless otherwise specified, all variables are measured at the plant–year level in the merged production–customs dataset. Output is proxied by nominal value of industrial output of each firm. Total intermediate expenditures capture total intermediate inputs for production, while domestic intermediate inputs are defined as total intermediate expenditures minus the value of imported intermediates. Imported intermediates are constructed from customs records as the sum of shipments not classified as "final consumption" or "capital goods" under the Broad Economic Classification (BEC); our findings remain robust when foreign intermediates are alternatively defined using only those BEC-coded as intermediate goods[10]. Labor input is measured by full-time-equivalent employment, and the implied average wage is computed by dividing total salary costs by total employment. Capital stock is proxied by the gross book value of fixed assets, including both movable and immovable assets. Following Morlacco (2019), we infer a date of purchase from the installment quota given a proxy lifetime duration of equipment (20 years) to obtain the current value of capital stock. We deflate theinitial nominal capital stock with the investment deflator from Perkins and Rawski (2008). This deflator is a chain-linked price de ator based on separate price indices for equipment, machinery, and building structures.[11] We construct this alternative series via $K_t = \left(1 - \delta_s\right) K_{t-1} + I_t$, where I take the book value of capital in the firm's first year of activity as the initial level, and set the depreciation rate δ_s (which may vary by sector s). All nominal variables (domestic inputs, foreign inputs, and nominal output), except nominal capital, are deflated using four-digit industry price deflators[12] from Brandt et al. (2012): output deflators rely on "reference price" series from the China Statistical Yearbooks, and input deflators are derived by combining these output deflators with the 2002 national input–output table. We derive two-digit industry price deflators as a weighted average of the corresponding four-digit industry deflators, where the weights are given by each four-digit industry's output share within the corresponding two-digit industry. Firm age: the difference between the data year and the year in which the firm started up.

A.3 Dynamics of Import Value

During the sample period 2000–2007 we observe a general upward trend in total imported intermediates across Chinese manufacturing sectors.

[10]To isolate intermediate inputs, we then apply the United Nations' Broad Economic Categories (BEC) Revision 4 specification—also defined on the 1996 HS6 basis—thereby yielding a consistent and reproducible set of intermediate-goods codes for our analysis. Results are robust if use this narrow definition of intermediate goods

[11]Results are robust to using an alternative measure of capital, which we construct using a perpetual-inventory method.

[12]The four-digit output and input deflator values are aggregated to the two-digit sector level.

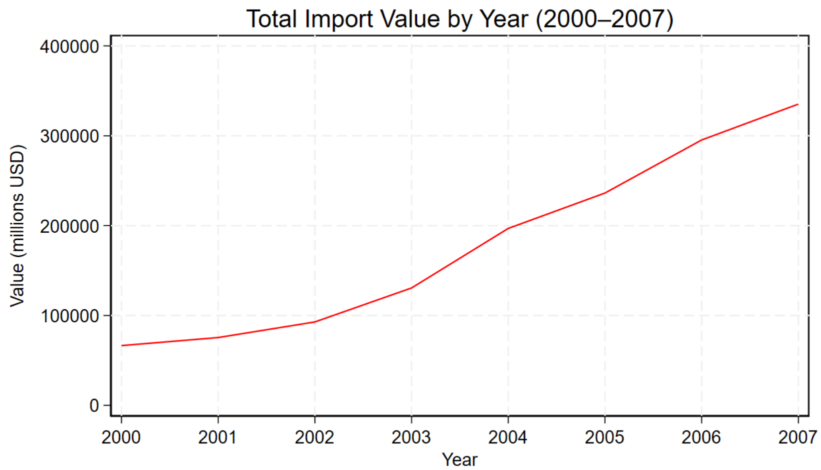

Figure 11: Total value of foreign inputs

Specifically, figure 11 plots total import value of Chinese intermediate inputs aggregated across CIC 2-digit sectors 13–42 for 2000–2007 and shows a clear upward trend: imports rise modestly from roughly 65,000 million USD in 2000 to about 90,000 million USD by 2002, then increase sharply after 2003 to approximately 340,000 million USD by 2007, indicating sustained and accelerating growth in imported intermediates over the period.

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