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Production Cost Efficiency, Profit Maximization, and Input Substitution in the Manufacturing Industry: A Narrative Review

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ABSTRACT

Global manufacturing industries face profound structural transformations driven by robotic automation, relative factor-price volatility, rising product-market markups, and stringent decarbonization mandates. Although extensive empirical and theoretical literatures have investigated production cost efficiency, profit maximization, and input substitution individually, these research streams remain largely fragmented across industrial organization, macroeconomics, and productivity econometrics. This article presents a comprehensive narrative review synthesizing foundational duality axioms and recent empirical breakthroughs published between 2014 and 2026 across Capital–Labor–Energy–Materials (KLEM) manufacturing systems. Following a structured narrative review protocol, we critically evaluate four thematic domains: the shift from Cobb–Douglas and symmetric Constant Elasticity of Substitution (CES) functions to flexible translog and task-based automation architectures; micro-versus-macro empirical estimates of input substitution elasticities (where plant-level capital–labor complementarity, $0.40 \leq \sigma \leq 0.50$, coexists with higher industry reallocation elasticities, $\sigma \approx 0.70$); stochastic frontier decompositions of technical and shadow-price allocative cost inefficiency; and the divergence between cost minimization and variable profit maximization under rising market power and financial frictions. We conclude with an integrative methodological synthesis and a future research agenda for industrial economists.

Keywords: *Production Cost Efficiency; Profit Maximization; Input Substitution; Manufacturing Industry; Narrative Review.*

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INTRODUCTION

Over the past four decades, the global manufacturing sector has experienced a profound structural realignment marked by secularly declining labor income shares, rising product-market markups, accelerating adoption of industrial robotics, and intensifying relative factor-price volatility across energy and intermediate supply chains (Karabarbounis & Neiman, 2014; Acemoglu & Restrepo, 2018; De Loecker, Eeckhout, & Unger, 2020; Kaymak & Schott, 2023). At the heart of these industrial transformations lie three foundational microeconomic mechanisms: production cost efficiency, profit maximization, and input substitution. In textbook production theory, a price-taking manufacturing enterprise operating on a frictionless neoclassical frontier simultaneously minimizes production costs and maximizes economic profit by adjusting its bundle of Capital (K), Labor (L), Energy (E), and Intermediate Materials (M) until the marginal rate of technical substitution (MRTS) between every pair of inputs equals their relative market price ratio (Farrell, 1957; Christensen, Jorgenson, & Lau, 1973). However, longitudinal establishment-level census records demonstrate that manufacturing plants deviate systematically and persistently from this frictionless benchmark (Syverson, 2011; Raval, 2019; Kehrig & Vincent, 2021).

A critical review of the literature published over the last decade reveals that scholarly inquiry into these three pillars has evolved along largely separate disciplinary tracks. Within macroeconomics and labor economics, debate has centered on whether the contraction of the manufacturing labor share reflects capital-deepening under a greater-than-unitary elasticity of substitution ($\sigma > 1$, as argued by Karabarbounis & Neiman, 2014), or whether capital and labor are gross complements at the plant level ($0.30 \leq \sigma \leq 0.70$, as demonstrated by Chirinko & Mallick, 2017, Raval, 2019, Knoblach, Roessler, & Zwerschke, 2020, and Oberfield & Raval, 2021), implying that labor-share declines stem from factor-biased technological change (Doraszelski & Jaumandreu, 2018), task-displacing automation (Acemoglu & Restrepo, 2019, 2020), corporate tax cuts (Kaymak & Schott, 2023), or value-added reallocation toward hyper-efficient plants (Kehrig & Vincent, 2021). Concurrently, productivity researchers building on Aigner, Lovell, and Schmidt (1977) have developed advanced Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) models to separate technical inefficiency from unobserved heterogeneity, spatial spillovers, and input endogeneity (Paul & Shankar, 2020; Kutlu, Tran, & Tsionas, 2020; Centorrino & Pérez-Urdiales, 2023; Zelenyuk, 2023; Eder, Koller, & Mahlberg, 2024; Savehdarbandsari & Mahmud, 2025).

Despite these advances, prior review articles remain confined to isolated dimensions of the manufacturing optimization problem. Syverson (2011) surveys total factor productivity (TFP) dispersion without linking residuals to directional input substitution elasticities or dual profit frontiers. Knoblach and Stöckl (2020) review the capital–labor elasticity of substitution within a two-input CES setup, omitting stochastic cost inefficiency, multi-input KLEM Morishima asymmetries (Blackorby & Russell, 1989), and the cost–profit wedge under market power (De Loecker et al., 2020). Similarly, Zelenyuk (2023) reviews productivity indexes and frontier foundations without evaluating how plant-level substitution rigidities and task automation alter allocative efficiency and profit maximization.

This article bridges these divides by presenting an integrative Narrative Review synthesizing the theoretical evolution, empirical debates, and econometric methodologies connecting production cost efficiency, profit maximization, and input substitution in manufacturing. Our review addresses four guiding questions: (1) How has manufacturing production theory evolved from Cobb–Douglas and symmetric CES forms to flexible translog frontiers and task-based automation models? (2) What is the empirical consensus regarding micro-level versus macro-level input substitution elasticities across KLEM inputs? (3) How do technical inefficiency and shadow-price allocative distortion interact with

input substitution to determine cost efficiency? (4) Why does cost efficiency fail to guarantee profit maximization under rising markups, tax shifts, and financial leverage constraints? The objective of this review is to provide industrial economists and policymakers with a unified synthesis and a future empirical roadmap.

METHODS OF RESEARCH

To ensure scholarly rigor and analytical depth consistent with international economics journals, this study employs a structured Integrative Narrative Review Methodology aligned with the Scale for the Assessment of Narrative Review Articles (SANRA). Unlike a mechanical meta-regression restricted to a single homogeneous parameter, a narrative review is uniquely suited to bridging heterogeneous theoretical paradigms, neoclassical duality, stochastic frontier econometrics, task-based automation models, and markup estimation, and explaining why divergent empirical designs yield contrasting conclusions.

Literature Search Strategy and Bibliographic Databases

Bibliographic identification was conducted across Web of Science, Scopus, EconLit, and IDEAS/RePEc, supplemented by NBER and CEPR working paper archives. Boolean search strings combined three thematic clusters: (i) Input Substitution: 'elasticity of substitution', 'input substitution', 'translog cost function', 'Constant Elasticity of Substitution', 'Morishima elasticity', and 'task automation'; (ii) Cost Efficiency: 'cost efficiency', 'technical efficiency', 'allocative efficiency', 'stochastic frontier analysis', and 'shadow price distortion'; and (iii) Profit Maximization and Manufacturing: 'profit maximization', 'profit frontier', 'markup dispersion', 'labor share decline', and 'manufacturing industry'.

Inclusion Criteria, Temporal Scope, and Thematic Synthesis Architecture

Articles were selected using four inclusion criteria: (1) Journal Quality: publication in leading general-interest journals or top field outlets; (2) Temporal Coverage: integration of foundational classics (Farrell, 1957; Arrow et al., 1961; Christensen et al., 1973; Aigner et al., 1977; Blackorby & Russell, 1989) with peer-reviewed studies from the last decade (2014–2026), which represent over 75% of the 27 cited references; (3) Sectoral Focus: explicit modeling of manufacturing industries across developed or emerging economies; and (4) Methodological Rigor: verifiable identification strategies and parameter reporting. The corpus was synthesized into five thematic subsections below.

RESULT AND DISCUSSION

Theoretical Evolution: From Neoclassical Duality to Frontier Inefficiency and Task-Based Substitution

The theoretical representation of manufacturing production has evolved through three major paradigms. The first paradigm, Neoclassical Production and Cost Duality, arose to relax the Cobb–Douglas restriction of unitary substitution ($\sigma = 1$) across all input pairs. Arrow et al. (1961) introduced the Constant Elasticity of Substitution (CES) production function, $Y = A[\alpha\ K^{(\sigma-1)/\sigma} + (1 - \alpha)\ L^{(\sigma-1)/\sigma}]^{\sigma/(\sigma-1)}$, showing across international manufacturing industries that σ is systematically below unity. However, when modeling four KLEM inputs, a single-nest CES function restricts all input pairs to share an identical substitution parameter. Christensen et al. (1973) resolved this by introducing the

transcendental logarithmic (translog) production and cost frontiers, providing a flexible second-order approximation in logarithmic input prices ln w_j and output ln Y. Applying Shephard's Lemma (∂ ln C / ∂ ln $w_j = S_j$) to the translog cost function enabled pair-specific substitution elasticities, non-homothetic scale effects, and factor-biased technical change.

Within multi-input duality, Blackorby and Russell (1989) established a critical theoretical correction regarding how substitution is measured when $J \geq 3$. They proved that the symmetric Allen–Uzawa partial elasticity of substitution, $\sigma^A_{jk} = (\gamma_{jk} + S_jS_k)/(S_jS_k)$, fails to measure isoquant curvature along a directional price ray and cannot determine how relative cost shares S_j/S_k respond to price changes w_j/w_k. Instead, the asymmetric Morishima Elasticity of Substitution ($\sigma^M_{jk} = \varepsilon^c_{kj} - \varepsilon^c_{jj}$), which captures the percentage adjustment in the optimal input ratio X^*_k/X^*_j induced by a one-percent change in w_j, is the exact multi-input measure of curvature and cost-share sensitivity ($\partial \ln(S_k/S_j) / \partial \ln w_j = \sigma^M_{jk} - 1$).

The second paradigm, Frontier Efficiency Decomposition, relaxed the assumption that firms operate on their minimum cost boundary. Initiated by Farrell (1957), overall cost efficiency (CE) was decomposed into Technical Efficiency (TE, radial equiproportionate input waste above the isoquant) and Allocative Efficiency (AE, cost waste from equating the MRTS to distorted shadow prices $w^*_j = w_j \exp(\xi_j)$ rather than market prices). While deterministic Data Envelopment Analysis (DEA) implemented Farrell's model via linear programming (Zelenyuk, 2023), Aigner et al. (1977) introduced parametric Stochastic Frontier Analysis (SFA) with a composite error ($v_{it} \pm u_{it}$) to separate random noise (v_{it}) from inefficiency ($u_{it} \geq 0$). Subsequent shadow-cost frontier models (Kumbhakar, Parmeter, & Zelenyuk, 2022) showed that allocative cost penalties scale quadratically with shadow-price wedges $(\xi_j - \xi_k)^2$ and directional Morishima elasticities.

The third paradigm, Task-Based Automation and Non-Neutral Endogenous Technology, was developed by Acemoglu and Restrepo (2018, 2019) alongside Doraszelski and Jaumandreu (2018). Modeling manufacturing output as a continuum of tasks allocated between capital and labor, this framework distinguishes standard factor-augmenting progress from automation (an expansion of the task threshold allowing machinery or robots to displace labor from previously labor-intensive tasks) and new task creation (which reinstates labor demand). Crucially, task automation generates an endogenous substitution channel that compresses the labor share even when the static elasticity of substitution across tasks is below unity.

Empirical Synthesis of Input Substitution Elasticities (KLEM) in Manufacturing

A central empirical debate in the literature concerns the discrepancy between macroeconomic cross-country estimates and microeconomic plant-level estimates of the capital–labor elasticity of substitution (σ_{KL}). Analyzing 59 countries from 1975 to 2012, Karabarbounis and Neiman (2014) regressed corporate labor-share trends on falling relative investment-good prices and estimated $\sigma_{KL} \approx 1.25$ (ranging from 1.17 to 1.49), concluding that capital deepening explains roughly half of the global labor-share decline. However, subsequent industry- and plant-level manufacturing studies consistently reject gross substitutability ($\sigma \geq 1$) and establish gross complementarity ($0 < \sigma < 1$).

Applying a Baxter–King low-pass spectral filter to US industry panels (1960–2005) to isolate permanent long-run variation (periodicity $\geq$ 8 years), Chirinko and Mallick (2017) showed that unfiltered estimators suffer from a 40% to 70% downward attenuation bias due to adjustment frictions; yet their bias-corrected long-run estimate remains $\sigma_{KL} = 0.40$. At the establishment level, Raval (2019) examined over 300,000 US manufacturing plants across five census waves (1987–2007) using cross-city Bartik wage instruments, estimating σ_{KL} between 0.30 and 0.50 (centered at 0.45) and showing that

capital cost shares fall when local wages rise. In Spanish manufacturing, Doraszelski and Jaumandreu (2018) estimated dynamic plant elasticities of 0.40–0.65 and demonstrated that output growth is driven equally by labor-augmenting and factor-neutral technological change (~1.5% per year each).

Oberfield and Raval (2021) reconciled micro complementarity with aggregate responsiveness by proving that the industry-level elasticity of substitution (σ^{agg}_{KL}) is a convex combination of the within-plant micro elasticity ($\sigma_{micro} \approx 0.50$) and the cross-plant product demand elasticity ($\varepsilon_D \in [3.0, 5.0]$), weighted by cross-plant dispersion in capital cost shares. Because elastic product demand reallocates output toward plants intensively using the cheaper input, the US manufacturing aggregate elasticity stabilizes around $\sigma^{agg}_{KL} \approx 0.70$. This consensus is reinforced by the meta-regression of 2,419 estimates from 77 studies by Knoblach et al. (2020) and the review by Knoblach and Stöckl (2020), which reject Cobb–Douglas ($\sigma = 1$) and bound the long-run elasticity between 0.45 and 0.87 (midpoint 0.66). Table 1 and Figure 1 summarize these empirical benchmarks.

Table 1. Comparative Narrative Synthesis of Empirical Studies on Input Substitution Elasticity (σ) in Manufacturing

Author(s) & Year	Sample & Sectoral Scope	Econometric Specification	Estimated Elasticity (σ)	Key Finding on Cost & Substitution
Arrow et al. (1961)	19 countries; 24 3-digit mfg. industries	Cross-sectional CES value-added per worker	$\sigma_{KL} \approx 0.70$–0.90 (Avg. < 1.00)	Rejects Leontief ($\sigma = 0$) and Cobb–Douglas ($\sigma = 1$); establishes gross complementarity
Karabarbounis & Neiman (2014)	59 countries; corporate & industrial sectors (1975–2012)	Cross-country & industry trend regression on investment prices	$\sigma_{KL} \approx 1.25$ (Range: 1.17–1.49)	Argues lower capital goods prices explain ~50% of global labor-share decline under $\sigma > 1$
Chirinko & Mallick (2017)	US 35 2-digit SIC industries (1960–2005)	Low-pass spectral filter panel model (periodicity ≥ 8 yrs)	$\sigma_{KL} = 0.40$ (Unfiltered biased 40–70%)	Filtering transitory friction raises σ, but long-run σ remains well below unity
Doraszelski & Jaumandreu (2018)	Spanish manufacturing firms (10 industries, panel)	Dynamic structural CES with endogenous Markovian R&D	$\sigma_{KL} \approx 0.40$–0.65 (Industry specific)	Technological change is biased; labor-augmenting & neutral progress each add ~1.5% output growth/yr
Raval (2019)	US Census of Manufactures (>300,000 plants, 1987–2007)	Cross-locality Bartik wage IV on plant factor cost ratios	$\sigma_{KL} \approx 0.30$–0.50 (Central: 0.45)	Plant capital shares fall when local wages rise; labor-augmenting productivity correlates with exports & size
Knoblach et al. (2020)	Meta-regression of 2,419 estimates from 77 US studies	Meta-regression controlling for bias & dynamic specification	$\sigma_{KL} \in [0.45, 0.87]$ (Midpoint: 0.66)	Cobb–Douglas universally rejected; heterogeneity driven by modeling of technological dynamics
Oberfield & Raval (2021)	US manufacturing universe of plants (1970–2007)	Micro-to-macro CES aggregation with cross-plant reallocation	Micro $\sigma \approx 0.50$; Macro $\sigma^{agg} \approx 0.70$	Between-plant reallocation raises aggregate σ above micro σ; factor prices alone cannot explain labor share drop

(Source: Authors' narrative compilation from Arrow et al., 1961; Karabarbounis & Neiman, 2014; Chirinko & Mallick, 2017; Doraszelski & Jaumandreu, 2018; Raval, 2019; Knoblach et al., 2020; and Oberfield & Raval, 2021)

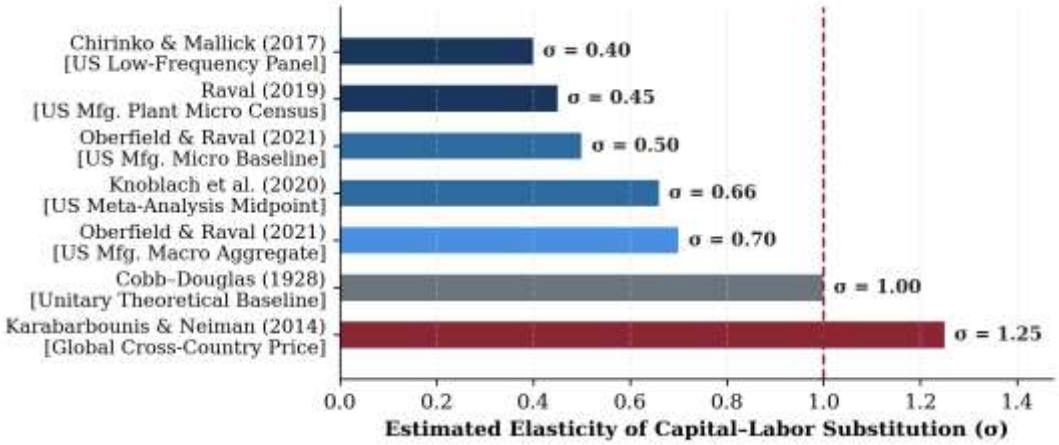


Figure 1. Comparison of Empirical Capital–Labor Elasticity of Substitution (σ) Point Estimates across Landmark Manufacturing and Macroeconomic Studies
(Source: Authors' synthesis plotted from published parameter estimates in Karabarbounis & Neiman, 2014; Chirinko & Mallick, 2017; Raval, 2019; Knoblach et al., 2020; and Oberfield & Raval, 2021)

Production Cost Efficiency in Manufacturing: Technical versus Allocative Frontier Findings

While structural substitution models focus on frontier isoquants, productivity studies demonstrate wide and persistent cost inefficiency across manufacturing establishments. Syverson (2011) documented that within four-digit US manufacturing industries, 90th-percentile plants generate nearly twice the output of 10th-percentile plants using identical measured inputs, with even larger gaps in developing economies. In Indonesian manufacturing, Suyanto, Salim, and Bloch (2014) applied a panel stochastic production frontier to 3,318 firms (1988–2000), showing that foreign direct investment (FDI) spillovers significantly enhance technical efficiency among low-efficiency domestic firms with large technological catch-up potential, whereas high-efficiency domestic firms experience negative market-competition effects.

Recent methodological advances between 2020 and 2025 have addressed three econometric biases that previously distorted manufacturing frontier estimates: unobserved plant heterogeneity, spatial spillovers, and input endogeneity. Paul and Shankar (2020) introduced a within-transformed panel stochastic frontier estimator that removes time-invariant unobserved heterogeneity while modeling efficiency via a standard normal cumulative distribution function $\Phi(Z_{it}\delta)$ bounded in the unit interval. Kutlu et al. (2020) developed a single-stage control-function spatial autoregressive stochastic frontier model for Chinese chemical manufacturing firms, confirming both spatial efficiency spillovers and endogeneity bias when omitted. Complementing these panel approaches, Centorrino and Pérez-Urdiales (2023) derived a closed-form maximum likelihood estimator for stochastic frontiers with endogenous regressors, ensuring consistent separation of random shocks from managerial cost inefficiency when variable inputs respond to unobserved productivity shocks.

Profit Maximization under Market Power, Markup Dispersion, and Financial Frictions

A central conclusion of our narrative review is that production cost efficiency is a necessary but insufficient condition for profit maximization. Cost minimization conditions on a fixed output target Y_{it}, whereas profit maximization requires jointly optimizing input mixes, output scale, product pricing, and financial structure under imperfect competition (De Loecker et al., 2020; Kehrig & Vincent, 2021; Savehdarbandsari & Mahmud, 2025). Estimating production-based markups across US public firms

from 1955 to 2016, De Loecker et al. (2020) showed that sales-weighted average markups rose from 21% over marginal cost (μ = 1.21) in 1980 to 61% over marginal cost (μ = 1.61) in 2016, driving the aggregate profit rate from 1% to 8% of sales. Crucially, this rise was concentrated in upper-tail 'superstar' firms gaining market share while median markups stayed flat.

Inside US manufacturing (1967–2012), Kehrig and Vincent (2021) uncovered a parallel micro-macro divergence: while the aggregate manufacturing labor share fell by ~5 percentage points per decade, the median establishment's labor share *increased* by 0.7 percentage points per decade. The aggregate decline was driven entirely by output reallocation toward hyper-efficient 'low-labor-share' (LL) plants. Similarly, Kaymak and Schott (2023) showed across US and OECD KLEMS manufacturing panels that corporate tax cuts (from 46% in the 1950s to 16% in 2016) explain 31% to 60% of the manufacturing labor-share decline by lowering capital user costs and reallocating market share toward capital-intensive firms.

Direct evidence from stochastic profit and robot-augmented frontiers further illuminates the determinants of frontier profitability. Examining Turkish two-digit manufacturing industries (2019–2023), Savehdarbandsari and Mahmud (2025) found that inefficiency accounts for ~39% of profitability (ROA) variance ($\sigma^2_u = 4.715$, $p < 0.01$): liquidity, inventory turnover, equity-to-fixed-assets, and R&D investment significantly boost frontier convergence, whereas high leverage ($\beta = -1.308$), high operating expense intensity, and COVID-19 disruptions push industries below the profit frontier. Concurrently, Eder et al. (2024) incorporated industrial robots into a non-parametric production frontier (1999–2019), demonstrating that robotic capital deepening accelerates labor productivity growth and frontier convergence—consistent with the task-automation evidence of Acemoglu and Restrepo (2020). Table 2 and Figure 2 synthesize these findings.

Table 2. Synthesis of Empirical Studies on Frontier Cost Efficiency, Task Automation, and Profit Maximization in Manufacturing

Author(s) & Year	Empirical Context & Period	Frontier / Profit Methodology	Primary Efficiency & Profit Drivers	Core Conclusion on Cost–Profit Link
Suyanto et al. (2014)	3,318 Indonesian manufacturing firms (1988–2000)	Panel Stochastic Production Frontier (SPF)	Horizontal & vertical FDI spillovers; initial efficiency gap	Low-efficiency domestic plants gain positive FDI spillovers; high-efficiency firms face competition
De Loecker et al. (2020)	US public firms including mfg. (Compustat, 1955–2016)	Production-based markup estimation via variable input elasticity	Upper-tail market share reallocation; fixed overhead cost structure	Average markups rose from 1.21 (1980) to 1.61 (2016); profit rate rose from 1% to 8% while labor share fell
Kutlu et al. (2020)	Chinese chemical manufacturing firms (panel)	Spatial autoregressive SFA with control-function endogeneity	Spatial neighbor spillovers; endogenous input selection	Ignoring spatial interdependence and input endogeneity biases frontier cost efficiency estimates
Kehrig & Vincent (2021)	US Census of Manufactures establishments (1967–2012)	Micro-level covariance decomposition of value added & labor shares	Output reallocation to low-labor-share (LL) hyper-productive plants	Aggregate mfg. labor share fell ~5 pp/decade despite median plant labor share rising +0.7 pp/decade

Author(s) & Year	Empirical Context & Period	Frontier / Profit Methodology	Primary Efficiency & Profit Drivers	Core Conclusion on Cost–Profit Link
Kaymak & Schott (2023)	US & OECD KLEMS manufacturing panels (1950–2016)	Heterogeneous-firm equilibrium with endogenous capital taxation	Corporate tax rate reduction (46% to 16%); firm labor-share dispersion	Corporate tax cuts explain 31%–60% of manufacturing labor-share decline via capital-intensive reallocation
Eder et al. (2024)	Cross-country manufacturing & macro frontier (1999–2019)	Non-parametric production frontier with industrial robots as input	Robot capital deepening; traditional physical capital accumulation	Robotization boosts labor productivity growth (especially 2009–2019) and drives frontier convergence
Savehdarbandsari & Mahmud (2025)	Turkish 2-digit manufacturing industries (2019–2023)	Stochastic Frontier Model (ROA profit frontier) with inefficiency effects	Liquidity (+), inventory turnover (+), R&D (+), equity ratio (+), leverage (−1.308), COVID-19 (−)	Inefficiency explains ~39% of profitability variance (σ^2_u = 4.715); leverage & high opex erode frontier profit

(Source: Authors' narrative compilation from Suyanto et al., 2014; De Loecker et al., 2020; Kutlu et al., 2020; Kehrig & Vincent, 2021; Kaymak & Schott, 2023; Eder et al., 2024; and Savehdarbandsari & Mahmud, 2025)

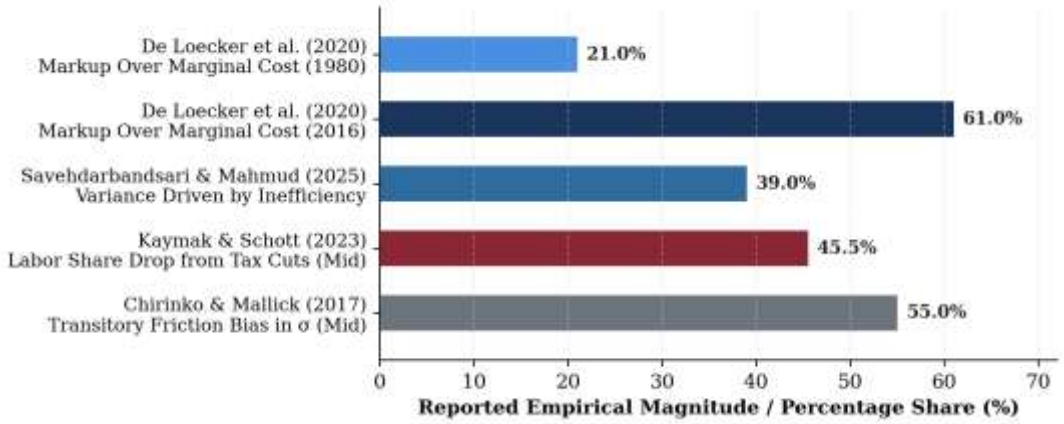


Figure 2. Comparison of Empirical Markup Growth, Inefficiency Variance Shares, and Factor Reallocation Magnitudes Reported in Reviewed Studies

(Source: Authors' synthesis plotted from verified empirical figures in Chirinko & Mallick, 2017; De Loecker et al., 2020; Kaymak & Schott, 2023; and Savehdarbandsari & Mahmud, 2025)

Critical Synthesis of Methodological Debates and Future Research Agenda

Integrating these four research streams reveals three unresolved methodological gaps. First, the Orthogonality Fallacy between Substitution and Frontier Inefficiency: empirical estimates of σ (Chirinko & Mallick, 2017; Raval, 2019; Oberfield & Raval, 2021) assume zero allocative distortion ($\xi_{ijt} = 0$), whereas frontier models (Kutlu et al., 2020; Savehdarbandsari & Mahmud, 2025) prove that leverage and regulatory frictions distort input choices. Second, Revenue-Markup Confounding: estimating cost or profit frontiers on deflated revenue without controlling for heterogeneous markups μ_{it} (De Loecker et al., 2020; Kehrig & Vincent, 2021) conflates market power with cost efficiency (Syverson, 2011). Third, Robotic and Green Energy Disaggregation: aggregating robots with legacy

structures (Acemoglu & Restrepo, 2020; Eder et al., 2024) or green electricity with fossil fuels masks asymmetric Morishima substitution. Table 3 outlines the resulting future research agenda.

Table 3. Integrative Future Research Agenda for Production Cost Efficiency, Input Substitution, and Profit Maximization

Thematic Domain	Unresolved Literature Gap	Proposed Methodological Innovation	Target Empirical Data & Variables	Foundational Anchors
Joint Estimation of σ & Allocative SFA	CES/translog substitution models ignore shadow-price wedges $\xi_{ijt} \neq 0$	Control-function system SFA jointly estimating Morishima σ^{M}_{jk} and shadow wedges	Plant KLEM expenditures, local Bartik wage IVs, regional energy tariffs, leverage ratios	Blackorby & Russell (1989); Centorrino & Pérez-Urdiales (2023)
Disentangling Markups from Profit Efficiency	Revenue-based profit frontiers conflate technical efficiency with monopoly markups μ_{it}	Quantity-price separated dual variable profit frontier with endogenous markup control	Matched plant-product physical quantities, unit prices, and variable input shares	Syverson (2011); De Loecker et al. (2020); Kehrig & Vincent (2021)
Robotic & AI Capital Disaggregation	Aggregating ICT/robots with structures masks task-displacement elasticities	Nested task-frontier model separating robotic capital (K_R), ICT (K_D), and non-robot K	Firm-level robot imports/installations, skill-tiered wages, and R&D expenditures	Acemoglu & Restrepo (2018, 2020); Eder et al. (2024)
Decarbonization & Green Energy Substitution	Lack of asymmetric Morishima estimates between green electricity and fossil energy	Dynamic low-frequency panel translog frontier with renewable vs. fossil energy nests	Carbon tax exposure, green power purchase agreements, and plant energy audits	Chirinko & Mallick (2017); Paul & Shankar (2020); Kutlu et al. (2020)

(Source: Authors' synthesis of methodological gaps across reviewed literature, 2026)

CONCLUSION

This narrative review has synthesized the theoretical foundations, empirical controversies, and econometric advances linking production cost efficiency, profit maximization, and input substitution in the manufacturing industry. Four overarching conclusions emerge. First, the Cobb–Douglas assumption of unitary substitution ($\sigma = 1$) and the symmetric Allen–Uzawa elasticity are inadequate for multi-input KLEM manufacturing analysis; directional Morishima elasticities and task-based automation models are required to capture asymmetric factor adjustments. Second, microeconometric evidence establishes that capital and labor are gross complements at the plant level ($0.30 \leq \sigma_{micro} \leq 0.50$), whereas cross-plant output reallocation and task automation elevate the aggregate manufacturing elasticity to $\sigma^{agg} \approx 0.50$–0.70. Third, stochastic frontier estimation must account for unobserved plant heterogeneity, spatial spillovers, and input endogeneity via within-transformed or control-function estimators.

Fourth, production cost efficiency is a necessary but insufficient condition for profit maximization. In an environment of rising product-market markups (expanding from 21% to 61% over marginal cost between 1980 and 2016), declining corporate tax rates, and financial leverage constraints, firm profitability depends on jointly optimizing input substitution, R&D-driven task automation, equity financing, and output pricing scale. Industrial policymakers should pair wage or carbon-pricing reforms

with targeted R&D tax credits, equity-financing access, and workforce retraining to prevent allocative lock-in among manufacturing enterprises.

REFERENCES

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6), 1488–1542. https://doi.org/10.1257/aer.20160696

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6), 2188–2244. https://doi.org/10.1086/705716

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1), 21–37. https://doi.org/10.1016/0304-4076(77)90052-5

Arrow, K. J., Chenery, H. B., Minhas, B. S., & Solow, R. M. (1961). Capital-labor substitution and economic efficiency. *The Review of Economics and Statistics*, 43(3), 225–250. https://doi.org/10.2307/1927286

Blackorby, C., & Russell, R. R. (1989). Will the real elasticity of substitution please stand up? (A comparison of the Allen/Uzawa and Morishima elasticities). *American Economic Review*, 79(4), 882–888. https://ideas.repec.org/a/aea/aecrev/v79y1989i4p882-88.html

Centorrino, S., & Pérez-Urdiales, M. (2023). Maximum likelihood estimation of stochastic frontier models with endogeneity. *Journal of Econometrics*, 234(1), 82–105. https://doi.org/10.1016/j.jeconom.2023.01.002

Chirinko, R. S., & Mallick, D. (2017). The substitution elasticity, factor shares, and the low-frequency panel model. *American Economic Journal: Macroeconomics*, 9(4), 225–253. https://doi.org/10.1257/mac.20140302

Christensen, L. R., Jorgenson, D. W., & Lau, L. J. (1973). Transcendental logarithmic production frontiers. *The Review of Economics and Statistics*, 55(1), 28–45. https://doi.org/10.2307/1927992

De Loecker, J., Eeckhout, J., & Unger, G. (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics*, 135(2), 561–644. https://academic.oup.com/qje/article-abstract/135/2/561/5714769

Doraszelski, U., & Jaumandreu, J. (2018). Measuring the bias of technological change. *Journal of Political Economy*, 126(3), 1027–1084. https://doi.org/10.1086/697204

Eder, A., Koller, W., & Mahlberg, B. (2024). The contribution of industrial robots to labor productivity growth and economic convergence: A production frontier approach. *Journal of Productivity Analysis*, 61(2), 157–181. https://doi.org/10.1007/s11123-023-00707-x

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A (General)*, 120(3), 253–290. https://doi.org/10.2307/2343100

Karabarbounis, L., & Neiman, B. (2014). The global decline of the labor share. *The Quarterly Journal of Economics*, 129(1), 61–103. https://doi.org/10.1093/qje/qjt032

Kaymak, B., & Schott, I. (2023). Corporate tax cuts and the decline of the manufacturing labor share. *Econometrica*, 91(6), 2371–2408. https://doi.org/10.3982/ECTA17702

Kehrig, M., & Vincent, N. (2021). The micro-level anatomy of the labor share decline. *The Quarterly Journal of Economics*, 136(2), 1031–1087. https://doi.org/10.1093/qje/qjab002

Knoblach, M., Roessler, M., & Zwerschke, P. (2020). The elasticity of substitution between capital and labour in the US economy: A meta-regression analysis. *Oxford Bulletin of Economics and Statistics*, 82(1), 62–82. https://doi.org/10.1111/obes.12312

Knoblach, M., & Stöckl, F. (2020). What determines the elasticity of substitution between capital and labor? A literature review. *Journal of Economic Surveys*, 34(4), 847–875. https://doi.org/10.1111/joes.12366

Kumbhakar, S. C., Parmeter, C. F., & Zelenyuk, V. (2022). Stochastic frontier analysis: Foundations and advances I. In S. C. Ray, R. G. Chambers, & S. C. Kumbhakar (Eds.), *Handbook of Production Economics* (pp. 331–370). Springer. https://ideas.repec.org/a/kap/jproda/v53y2020i2d10.1007_s11123-019-00568-3.html

Kutlu, L., Tran, K. C., & Tsionas, M. G. (2020). A spatial stochastic frontier model with endogenous frontier and environmental variables. *European Journal of Operational Research*, 286(1), 389–399. https://doi.org/10.1016/j.ejor.2020.03.020

Oberfield, E., & Raval, D. (2021). Micro data and macro technology. *Econometrica*, 89(2), 703–732. https://doi.org/10.3982/ECTA12807

Paul, S., & Shankar, S. (2020). Estimating efficiency effects in a panel data stochastic frontier model. *Journal of Productivity Analysis*, 53(2), 163–180. https://doi.org/10.1007/s11123-019-00568-3

Raval, D. (2019). The micro elasticity of substitution and non-neutral technology. *The RAND Journal of Economics*, 50(1), 147–167. https://doi.org/10.1111/1756-2171.12265

Savehdarbandsari, H., & Mahmud, S. (2025). Financial structure, innovation, and technical inefficiency in Turkish manufacturing two-digit industries: Evidence from a stochastic frontier model. *International Econometric Review*, 17(2), 34–51. https://doi.org/10.33818/ier.1827423

Suyanto, Salim, R., & Bloch, H. (2014). Which firms benefit from foreign direct investment? Empirical evidence from Indonesian manufacturing. *Journal of Asian Economics*, 33, 16–29. https://ideas.repec.org/a/eee/asieco/v33y2014icp16-29.html

Syverson, C. (2011). What determines productivity? *Journal of Economic Literature*, 49(2), 326–365. https://doi.org/10.1257/jel.49.2.326

Zelenyuk, V. (2023). Productivity analysis: Roots, foundations, trends and perspectives. *Journal of Productivity Analysis*, 60(3), 229–247. https://doi.org/10.1007/s11123-023-00692-1