

Tradability and Goods' Prices: A Tale of Two Regions

Germán Gutiérrez* Joseba Martinez† Thomas Philippon‡ Sophie Piton§

June 2026

Abstract:

We provide new evidence on manufacturing price inflation and the allocation of productivity gains by comparing US and EU industries from 1992 to 2017. Two patterns emerge. In tradable industries, where global competition is strong, prices have moved in lockstep across the Atlantic. In non-tradable industries, relatively sheltered from foreign competition, prices in the US have risen about four times faster than in Europe despite similar wages and industry compositions. The inflation differential is unrelated to compositional shifts, and evident in narrowly defined product categories where unobserved quality differences are unlikely to matter. A decomposition attributes most of the differential to rising market power in US non-tradable manufacturing industries, a pattern absent in tradable ones. Using variation in import penetration, we find that greater trade exposure lowers prices and profit shares, while competition policy remains crucial in non-tradable industries.

JEL: E24, E25, E31, F62, L16, L60.

Keywords: Price, Manufacturing, Nontradable, Labor share, Markup.

*UW Foster School of Business.

†London Business School & CEPR.

‡NYU Stern, NBER & CEPR.

§Bank of England & Centre for Macroeconomics. Email: sophie.piton@bankofengland.co.uk.

The views expressed in this paper are those of the authors and not necessarily those of the Bank of England and its committees. We are grateful to seminar participants at the UW Foster School of Business, the Bank of England, and the University of Bristol for useful comments and discussions.

1 Introduction

Between 1992 and 2017, producer prices in US non-tradable manufacturing goods rose by about 60%, compared to only 10% in comparable European industries. Over the same period, tradable manufacturing prices followed nearly identical trends across the two regions. This pattern, shown in Figure 1 using harmonized US–EU industry data, is the empirical puzzle at the center of this paper. It is not an artifact of aggregation or quality adjustment: across 97 matched homogeneous nontradable products, including ready-mix concrete, frozen vegetables, and shipping containers, where scope for quality change is minimal, prices in the US rose roughly twice as fast as in Europe.

The first explanation that comes to mind when presented with this fact is of course the Balassa-Samuelson effect. If the US experiences faster tradable productivity growth than Europe, the stronger labor demand would bid up wages economy-wide, raising marginal costs and thus prices in all sectors where productivity growth lags in relative terms.

Yet the data do not support this interpretation. As we show below, wage growth in US and EU manufacturing has been strikingly similar, both in tradable and non-tradable industries. The wage channel through which Balassa-Samuelson should operate does not appear to be active.

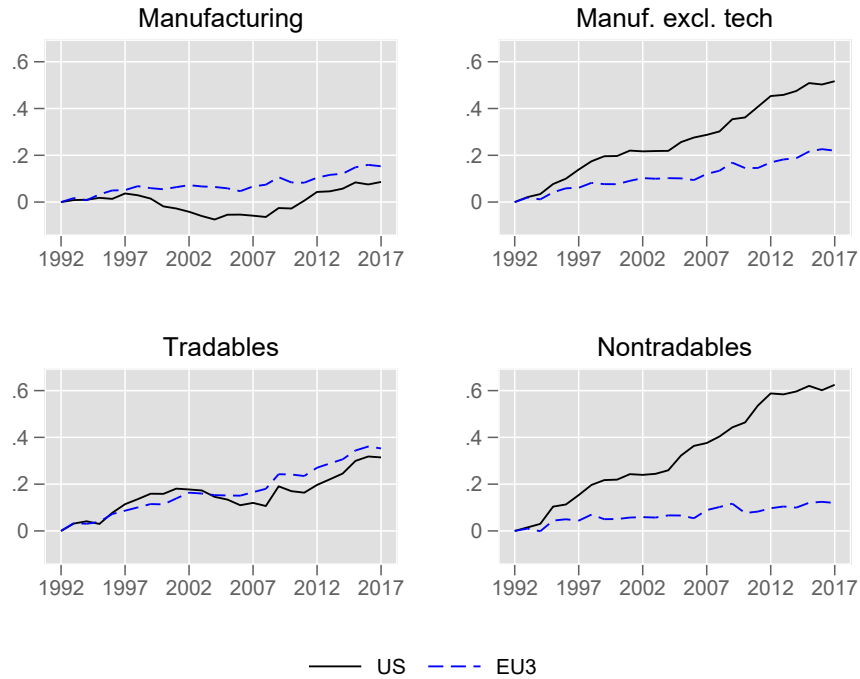
Moreover, the apparent US productivity advantage in the tradable sector is almost entirely driven by a single industry: computers, electronics, and related technology goods, where measured prices decline dramatically because of large hedonic quality adjustments. These generate very large theoretical productivity gains. Excluding this sector, US tradable productivity grew only slightly faster than in Europe, while US non tradable productivity grew somewhat *more slowly*.

If not differential productivity growth, what explains the sharp divergence in non-tradable prices? Using a decomposition that links value-added prices to wages, productivity, cost shares, and markups net of returns to scale (μ/γ), we show that the US–EU inflation differential in non tradable prices is accounted for by two forces: modestly slower US productivity growth and, more importantly, a sustained increase in μ/γ , the component that captures firms' ability to set prices above costs, beyond what can be attributed to economies of scale. In tradable industries, where global competition disciplines pricing, μ/γ evolves almost identically in the US and Europe. The divergence is concentrated precisely where foreign rivals are absent.

This paper develops and applies this framework in four steps. We first present a transparent accounting decomposition that extends the standard unit labor cost framework to incorporate changes in factor cost shares and markups net of returns to scale, enabling us to separate technology-driven from market-power-driven price changes within a single identity. Second, we apply the decomposition to harmonized US–EU data, showing that the sharp nontradable price divergence reflects rising μ/γ in the US, a pattern absent in tradables, where both regions exhibit parallel trends in costs, productivity, and markups. Third, we embed the decomposition in a CES production model to connect the accounting to economic primitives, recovering technology and market-power parameters in a unified structural framework. Fourth, we provide causal US evi-

Figure 1: The Divergence in US vs. EU Manufacturing Goods Producer Prices

GVA deflators, 1992–2017, 1992=0



Source: authors' calculations using OECD STAN. EU3 = France, Germany, Italy. See Table ?? in Appendix for industry definitions.

dence that trade exposure disciplines pricing: using variation in import penetration instrumented with PNTR-related tariff changes following China's WTO accession, we show that greater trade exposure reduces prices and profit shares.

The cross-country comparison is central to our identification strategy. By using the EU as a counterfactual for the US, we compare how similar manufacturing industries evolve under different institutional environments, particularly with respect to competition and trade policy. The tradable–nontradable distinction sharpens the comparison further: tradable industries face global competition and often share production technologies across borders (Covarrubias et al., 2019, Amiti and Heise, 2024), while nontradables are shaped more by domestic market structure and regulation (Besley et al., 2021). The fact that tradable sectors track each other closely across the Atlantic, while nontradable sectors diverge sharply, points to domestic market power, not technology or wages, as the key driver.

Our results also speak to a broader puzzle in the market power literature. Several studies have documented rising firm-level markups in the US but found little connection between markups and prices (Ganapati, 2021, Conlon et al., 2023). We show that this disconnect arises because gross markups do not control for simultaneous changes in technology and scale. The relevant object is

μ/γ , markups net of returns to scale, which we link directly to prices through our decomposition. Measured this way, rising market power maps clearly into higher nontradable prices, reconciling the firm-level evidence with aggregate price dynamics.

Related Literature. This paper contributes to a growing literature on the relationship between market structure, trade exposure, and pricing dynamics, particularly in the context of rising concentration and markups in advanced economies.

A first strand examines the disconnect between rising markups and stable or falling prices. This literature is often motivated by [Syverson \(2019\)](#), which presents a simple decomposition of prices. [Ganapati \(2021\)](#) finds that more concentrated industries often exhibit falling prices, rising productivity and falling labor shares. He interprets the latter as evidence of technological change rather than rising market power. [Conlon et al. \(2023\)](#) show that firm-level markup growth is not correlated with industry-level price increases, casting doubt on the idea that rising markups necessarily harm consumers. Relative to [Ganapati \(2021\)](#), we show that changes in labor shares depend on capital and profit shares, and may therefore be driven by either technology or market power. Relative to [Conlon et al. \(2023\)](#), we show that markups alone need not be related to prices: the relevant measure is markups net of returns to scale, controlling for technology, rather than gross markups relative to prices. Using this extended decomposition, we show that price growth in US goods is closely linked to rising profit shares, particularly in markets with limited trade exposure.

A second strand studies how international trade disciplines firm behavior. [Covarrubias et al. \(2019\)](#) show that foreign competition explains substantial increases in concentration. [Amiti and Heise \(2024\)](#) shows that import competition reduces markups and raises pass-through, particularly in manufacturing sectors exposed to foreign rivals. [Besley et al. \(2021\)](#) provides cross-country evidence that openness to trade correlates with stronger antitrust enforcement, especially in markets less exposed to global competition. These findings suggest that trade exposure plays a central role in shaping pricing behavior, especially in domestically oriented sectors. We build on this insight by showing that US–EU price divergence is concentrated in nontradable manufacturing, where US firms appear to exert growing market power.

A third strand studies factor shares and income distribution. [Barkai \(2020\)](#) documents a decline in both labor and capital shares in US industries, implying a rising profit share. We link these profit share dynamics directly to value-added price growth, using a structural decomposition that accounts for wages, productivity, and capital costs. Whereas Barkai focuses on income levels, our analysis emphasizes price changes—the key channel through which market power affects consumers—and compares their evolution across countries.

Finally, we relate to recent debates over international price divergence and the role of measurement error. Studies such as [Byrne et al. \(2016\)](#) and [Atalay et al. \(2025\)](#) highlight concerns about deflator quality, particularly in technology-intensive sectors. We address this by excluding such

sectors from our core analysis and focusing on comparably measured manufacturing industries, where price differences are more likely to reflect economic forces rather than statistical noise.

Taken together, this paper unifies these strands—on markup dynamics, trade and competition, and factor shares—through a single decomposition framework applied to harmonized US–EU data. By combining cross-country price evidence, a welfare-relevant measure of market power, and sector-level trade variation, we provide the first systematic explanation for why nontradable manufacturing prices have diverged between the US and Europe.

The remainder of the paper is organized as follows. Section 2 develops the price decomposition. Section 3 applies it to US–EU manufacturing. Section 4 connects the results to economic primitives in a CES model. Section ?? complements the cross-country evidence with causal US industry evidence. Section 6 concludes.

2 Decomposition Framework

To understand the forces behind the US–EU nontradables price divergence documented above, we begin by decomposing changes in nominal gross value-added prices, P , at the industry level as:

$$\Delta \log P = \underbrace{\Delta \log W - \Delta \log \frac{Y}{N}}_{\Delta \log \text{ULC}} - \underbrace{\Delta \log s^L}_{\text{Change in Labor Share}}, \quad (1)$$

where W denotes average nominal wages, $\frac{Y}{N}$ is real output per hour, and $s^L \equiv \frac{WN}{PY}$ is the labor share of value added. The first term captures changes in unit labor costs (ULC), while the second term reflects shifts in the distribution of value added away from labor.

From labor share to profit share to prices. The labor share can fall because of either a decrease in the labor cost share or an increase in the profit share:

$$\Delta \log s^L = \underbrace{\Delta \log c_L}_{\text{Labor Cost Share}} + \underbrace{\Delta \log(1 - s^\pi)}_{1 - \text{Profit Share}}.$$

The labor cost share may decline due to capital-biased technical change, automation, or declines in the relative price of capital if the elasticity of substitution is high (Karabarbounis and Neiman, 2014). The profit share, in turn, reflects changes in markups net of returns to scale. Following Syverson (2019):

$$\frac{\mu}{\gamma} = \frac{1}{1 - s^\pi},$$

where μ denotes the markup and γ the degree of returns to scale. Profit shares rise when markup growth exceeds the cost-reducing effects of increased scale. Combining these relationships yields:

$$\Delta \log P = \Delta \log W - \Delta \log \frac{Y}{N} - \Delta \log c_L + \Delta \log \frac{\mu}{\gamma}, \quad (2)$$

where $c_L \equiv \frac{WN}{WN+RK}$ is labor's share of total cost and $\frac{\mu}{\gamma}$ is the markup net of returns to scale.

Accounting Decomposition. Equation (2) shows that prices rise when: (i) unit labor costs increase (wages grow faster than productivity); (ii) labor's share of total costs decreases for a given ULC; (iii) profit shares rise, implying higher markups net of returns to scale. Equation (2) thus provides a transparent decomposition of changes in prices into unit labor costs, cost structure, and profits.¹

Economic Decomposition: Technology and market power. Of course technology and market power are likely to operate simultaneously. Technological progress typically reduces unit labor costs by raising productivity, lowering prices. If capital-biased, it may also reduce the labor cost share and increase the capital share, raising prices relative to unit labor costs. When technological change enhances scale economies—as in models with fixed costs or intangible capital ([Ganapati, 2021](#), [Crouzet and Eberly, 2023](#))—prices may fall further unless markups rise commensurately. In some cases, the same innovation can drive both higher productivity and higher markups: [Miller et al. \(2025\)](#) shows that in the cement industry, technological change increased scale economies and markups; prices fell, but not enough to pass through the full productivity gains to consumers.

Relation to existing work. Our approach builds directly on and extends two strands of the literature. Relative to [Ganapati \(2021\)](#), we show that changes in producer prices depend not only on productivity and the labor share, but also on whether the decline in labor share reflects higher capital shares or higher profit shares—a distinction that allows us to identify technology-versus market-power-driven price changes. Relative to [Conlon et al. \(2023\)](#), who compare firm-level markups from [De-Loecker et al. \(2019\)](#) to narrow industry-level price indices and find little correlation, we focus on markups net of returns to scale, controlling for technology and capital intensity. This provides a more welfare-relevant link between profits and prices and clarifies why rising gross markups may not always translate into higher consumer prices.

¹Our decomposition focuses on value-added prices and speaks directly to the factor shares in gross value added most referred to in the literature. In equation ?? and Figure ?? in Appendix, we extend the discussion and demonstrate that our main findings hold using a decomposition in gross output space.

Measurement. Our central object is the markup net of returns to scale. Empirically we measure

$$m_{jct}^{obs} \equiv \log \left(\frac{\mu}{\gamma} \right)_{jct}^{obs} = \log (P_{jct} Y_{jct}) - \log (W_{jct} N_{jct} + R_{jct} K_{jct}),$$

where j indexes industries, c regions, and t years. Because m^{obs} is a ratio of nominal magnitudes, price deflators do not enter it directly. Because it is a residual, it inherits any error in the measurement of nominal value added or factor costs (Karabarbounis and Neiman, 2018, Basu, 2019).

Write $m_{jct}^{obs} = m_{jct} + \eta_{jct}$, where m_{jct} is the true markup net of scale and η_{jct} is measurement error. Our evidence is a triple difference: measured markups rose more in US nontradables than in European nontradables, with no comparable gap in tradables. The identifying restriction is

$$(\Delta \eta_{US}^{NT} - \Delta \eta_{EU}^{NT}) - (\Delta \eta_{US}^T - \Delta \eta_{EU}^T) = 0, \quad (3)$$

the analogue of a parallel-trends assumption, with European industries serving as cross-country controls and tradable industries as within-country controls. Restriction (3) allows level differences in accounting systems, capital measurement, compensation practices, and industry composition, which difference out, and error that trends over time, provided the trend is common to a country's manufacturing sector or to an industry group across countries. It fails only if error trends differentially across the tradability boundary in one region but not the other. We consider the main candidates in turn.

The largest constructed, as opposed to reported, cost component is capital. The stock K_{jct} is built by statistical offices from investment flows, depreciation rates, asset lives, and retirements, and we build the rental rate R_{jct} from investment prices, interest rates, depreciation, and expected capital gains. If measured capital costs are too low, measured total costs are too low and m_{jct}^{obs} is too high; profit residuals of this kind are sensitive to exactly these choices (Karabarbounis and Neiman, 2018). Within each statistical system, however, the same investment surveys and asset deflators generate the tradable and the nontradable series, so an artifact of capital cost construction would move measured markups across manufacturing as a whole rather than in sheltered industries alone. Consistent with this, measured markups in US tradables track their European counterparts (Figure 3), and the decomposition is robust to alternative user-cost calibrations (Appendix ??).

A second concern is uncaptured intangible capital. If true costs include an intangible service flow that the accounts omit, measured costs are understated and the omission appears as profit; because intangible investment has grown faster in the US (Corrado et al., 2009, Haskel and Westlake, 2017), this error can trend. National accounts capitalize software and R&D, so the omitted flow consists largely of economic competencies: branding, organizational capital, and training (Bontadini et al., 2023). The industry footprint of these investments points away from

our result. Intangible intensity is highest in the technology industries the core analysis excludes, while the divergence we document is largest in food and in wood and paper products, where US prices rose about 50 points more than in Europe (Figure 4).

Labor costs are reported rather than constructed, but coverage differs across systems. The labor term is the nominal wage bill $W_{jct}N_{jct}$ adjusted for self-employed (see [Gutiérrez and Piton, 2020](#), for a discussion on the adjustment), not a quality-adjusted input index, so changes in skill composition are reflected in compensation and do not bias the profit share. The relevant threats are omitted forms of pay: employer benefits, payroll taxes, pensions, stock-based pay, and contract labor ([Elsby et al., 2013](#), [Smith et al., 2022](#)). Across countries these differences are persistent features of institutions and accounting systems, and persistent differences cancel in changes. To bias the triple difference, omitted compensation would have to grow specifically in US nontradable manufacturing. Stock-based pay, the fastest-growing omitted component in the US, is concentrated in the technology and health industries ([Eisfeldt et al., 2023](#)); the former are excluded from the core analysis, and the robustness excluding pharmaceuticals proposed above addresses the latter.

Industry boundaries and accounting conventions pose a similar threat. Outsourcing, contract manufacturing, and purchased services move costs between labor, intermediates, and value added, and production taxes, subsidies, and the distinction between basic and producer prices affect nominal value added. Reclassification biases the result only if it shifts measured costs relative to value added in US nontradables while leaving European nontradables and US tradables unaffected. Domestic outsourcing in the US has instead grown across industries rather than in sheltered manufacturing specifically ([Dorn et al., 2018](#)), and the decomposition in gross-output space in Appendix Figure ??, which does not depend on the split between intermediates and value added, yields the same conclusions.

The residual is profit, not necessarily monopoly profit. It can contain rents to scarce factors, quasi-rents on fixed capital, risk premia, and returns to unmeasured assets ([Barkai, 2020](#), [Karabarbounis and Neiman, 2018](#)), which is why we interpret the object as μ/γ rather than as a pure markup. These components are economics rather than error, but they face the same restriction: a rise in risk premia or in fixed-factor rents common to US manufacturing would move tradables and nontradables alike, so any alternative reading of the residual must explain why it rose where foreign competition is weakest.

Price deflators matter for the split of nominal growth between prices and real productivity, not for m_{jct}^{obs} itself, which is a ratio of nominal magnitudes. Differences in quality adjustment across statistical agencies are largest for the technology goods the core analysis excludes (Table ??); in tradables, where the same methodological differences apply, prices, cost shares, and μ/γ show no divergence.

The US–EU comparison therefore does not eliminate measurement error; it restricts its form. To overturn the markup interpretation, error would have to be large, grow over time, and be

specific to US nontradable manufacturing, while absent both from the same industries in Europe and from the tradable industries measured by the same statistical systems.

3 Cross-Country Application: US–EU Manufacturing

We now apply the decomposition in Equation 2 to quantify the drivers of inflation in US and EU manufacturing, distinguishing between tradable and non-tradable industries. We begin with aggregate results and then examine patterns by broad national account industry.

3.1 Data and Sample

Data Sources. We compile industry accounts in a harmonized ISIC Rev. 4 classification for OECD countries from the [OECD Structural Analysis Database](#) (STAN). These data are sourced from National Accounts and include industry-level measures of average wages, prices, output, employment, and capital stock. Our baseline sample covers the US and the three largest euro area economies—France, Germany, and Italy (“EU3”) — from 1992–2017, the period with continuous coverage. As a robustness check, we also use an unbalanced panel of up to 33 OECD economies (Appendix Figure ??).

Data robustness. While the OECD STAN harmonization reduces cross-country comparability issues, several sources of measurement error remain. Most importantly, price indices may differ in their treatment of quality change (see Table ?? in Appendix). For example, the US applies hedonic adjustments for high-technology goods and a production-cost approach for other products, which involves asking firms about the production cost of a given item, and quality adjusts the price of a good when its price changes as a result of a feature change that also changes the production cost. Some European countries, like Germany, use option-cost adjustments, valuing additional product features at their observable marginal cost. These methodological differences are most pronounced in technology-intensive sectors, which we exclude from our core analysis. In our robustness analyses, we restrict the comparison set to countries using similar price index construction methodologies.

Classification changes and historical revisions to national accounts can also introduce breaks in the series. STAN applies backward concordances to mitigate this, and our analysis uses broad industry aggregates to further reduce sensitivity to classification shifts.

Sample coverage. We focus on manufacturing for three reasons. First, manufacturing prices are more reliably measured than service-sector prices,² which is critical for cross-country comparisons. Second, although manufacturing represents only 10–20% of GDP, it plays a central role in

²See the [OECD Methodological Guide for Developing Producer Price Indices for Services](#) for a discussion.

macroeconomic trends, including the decline in the labor share (Gutiérrez and Piton, 2020) and the post-2000 productivity slowdown (Syverson, 2016). Third, it is important for cost-of-living and inflation dynamics, given its large weight in household consumption (e.g., food manufacturing accounts for roughly 30% of household spending) and its role as a supplier to downstream sectors.

Tradability classification. We classify manufacturing industries as tradable or nontradable based on their trade openness, measured by the ratio of exports plus imports to total production in the US (similarly to Piton, 2021). Industries above the manufacturing-wide average are classified as tradable; the rest are nontradable. In our data, tradables account for about 45% of gross value added and include textiles, machinery, and transport equipment. Nontradables include food, wood, paper, chemicals, pharmaceuticals, and basic metals. The industry coverage and categorization is listed in Table ??.

Capital Costs. To recover capital's share in total production cost — a necessary input in the decomposition — we follow a standard user-cost approach (Hall and Jorgenson, 1967, Barkai, 2020). Specifically, capital cost for industry i , country c and year t is defined as the product of $K_{i,t}$, the constant price capital stock from STAN, and $R_{i,c,t}$, its implicit rental rate given by:

$$R_{i,c,t} = p_{i,c,t-1}^K [r_{c,t} + \delta_{i,c,t}(1 + \pi_{i,c,t}^K) - \pi_{i,c,t}^K] ,$$

with $r_{c,t}$ the opportunity cost of capital (long-term risk-free bond yields), $\delta_{i,c,t}$ the (country, industry and time-varying) depreciation rate³ and $\pi_{i,c,t}^K$ expected capital gains (moving average of realized investment price growth). These inputs are sourced from national accounts and the OECD. In Appendix A, we test alternative calibrations—e.g., with no capital gains/losses and a fixed opportunity cost of capital, and find that price decomposition results remain highly robust to these changes.

3.2 Contribution of Technology

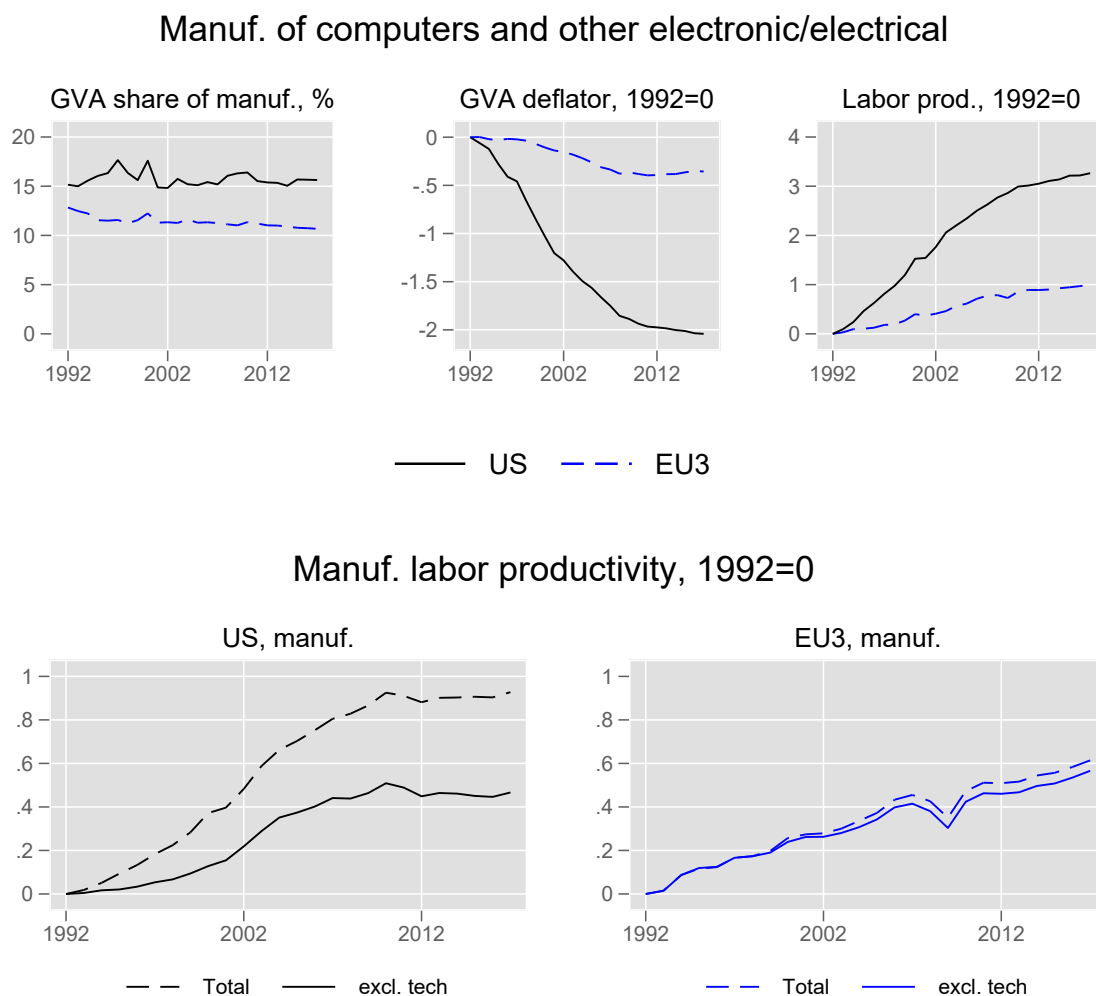
Technology-intensive manufacturing—computers, electronics, optical products, and electrical equipment—differs from the rest of manufacturing in three ways: rapid innovation, steep price declines, and extensive quality adjustments (Atalay et al., 2025). These features make it a major driver of measured productivity growth but also a challenge for cross-country price comparisons.

Figure 2 illustrates these dynamics.⁴ The top panel shows that technology manufacturing's

³We recover "implicit" depreciation rates from capital stock and investment data for each country, industry and year assuming geometric depreciation.

⁴We use here historical data which means we lose some industry granularity and cannot identify precisely the role of computer manufacturing. We focus here on C26-C27 that corresponds to "computers, electronics, optical products, and electrical equipment". The results carry through if using data for C26 (Manufacture of computer, electronic and optical products) available since 2000 only. We also have data for the gross output deflator for ICT

Figure 2: The Role of Technology Manufacturing in US–EU Price and Productivity Gaps



Notes: Technology manufacturing ("tech.") includes computers, electronics, optical products, and electrical equipment (ISIC Rev. 4 industries C26–C27). The figure shows the level of the share of tech. in total GVA and log changes of the GVA deflator and labor productivity. US prices fall much faster than EU prices, inflating the measured US productivity advantage. Source: authors' calculations using OECD STAN; EU3 = France, Germany, Italy.

value-added share is larger in the US than in the EU but stable over time. Price trends, however, diverge sharply: US technology prices fell by nearly 200% between 1992 and 2018, compared to only 40% in the EU. This differential drives a large transatlantic productivity gap: US technology labor productivity rose by a factor of 3, while in the EU it rose by a factor of 1. The bottom panel

manufacturing in the US since 2000 –a subset of C26– and find that this sector is driving the fall in the C26 sector output deflator.

shows the aggregate implications. Including technology, US manufacturing productivity rose by about 90%; excluding it, growth was only 45%. In the EU, the difference is much smaller (60% vs. 50%), implying faster non-technology productivity growth than in the US.

The US lead in technology manufacturing is well documented (e.g., the [Draghi Report, 2024](#)) and reflects both real innovation and sectoral composition. But differences in price deflation methods—especially the US reliance on hedonic adjustments for high-tech goods—likely account for part of the transatlantic gap in measured prices and productivity.⁵

To focus on underlying cost dynamics and market structure, we exclude technology manufacturing from our core analysis. This avoids confounding our results with sector-specific innovation and measurement practices. While this choice removes one source of transatlantic price divergence, it sharpens the comparison for the rest of manufacturing, where methodological differences are smaller and price trends more likely reflect genuine economic forces.

3.3 Tradable vs. Nontradable Manufacturing (Excluding Technology)

We next apply the decomposition to non-technology manufacturing, splitting industries into tradable and nontradable sectors. Figure 3 shows the evolution of prices, wages, productivity, and labor shares in the US and EU3 from 1992–2017. The main analysis uses nominal value-added prices; Appendix ?? reports analogous results for gross output prices.

Tradable manufacturing. In tradable industries, trends are strikingly similar across the US and EU3. Prices, wages, productivity, and cost shares move in parallel, consistent with common global technologies, intense cross-border competition, and similar quality adjustments in price measurement. Between 1992 and 2017, labor productivity increased by roughly 60% in both regions, while wages rose by about 80%, leading to a 20% rise in unit labor costs. The labor cost share fell by about 10% in the US and remained essentially flat in the EU, while markups net of returns to scale (μ/γ) increased by roughly 15% in both. These changes offset each other, leaving price growth at about 30% in both regions.

Nontradable manufacturing. In contrast, nontradable industries display a large and persistent divergence. US nontradable manufacturing prices rose by 62%, compared to only 12% in the EU. This gap reflects two main forces: US labor productivity grew about 20p.p. less than in the EU, and the labor share fell a little less than 30p.p. more. Breaking this down, the labor cost share fell by about 10% in the US but increased by about 5% in the EU, while μ/γ rose by 23% in the US versus 10% in the EU. Wage growth was similar in both regions, ruling it out as the primary driver.

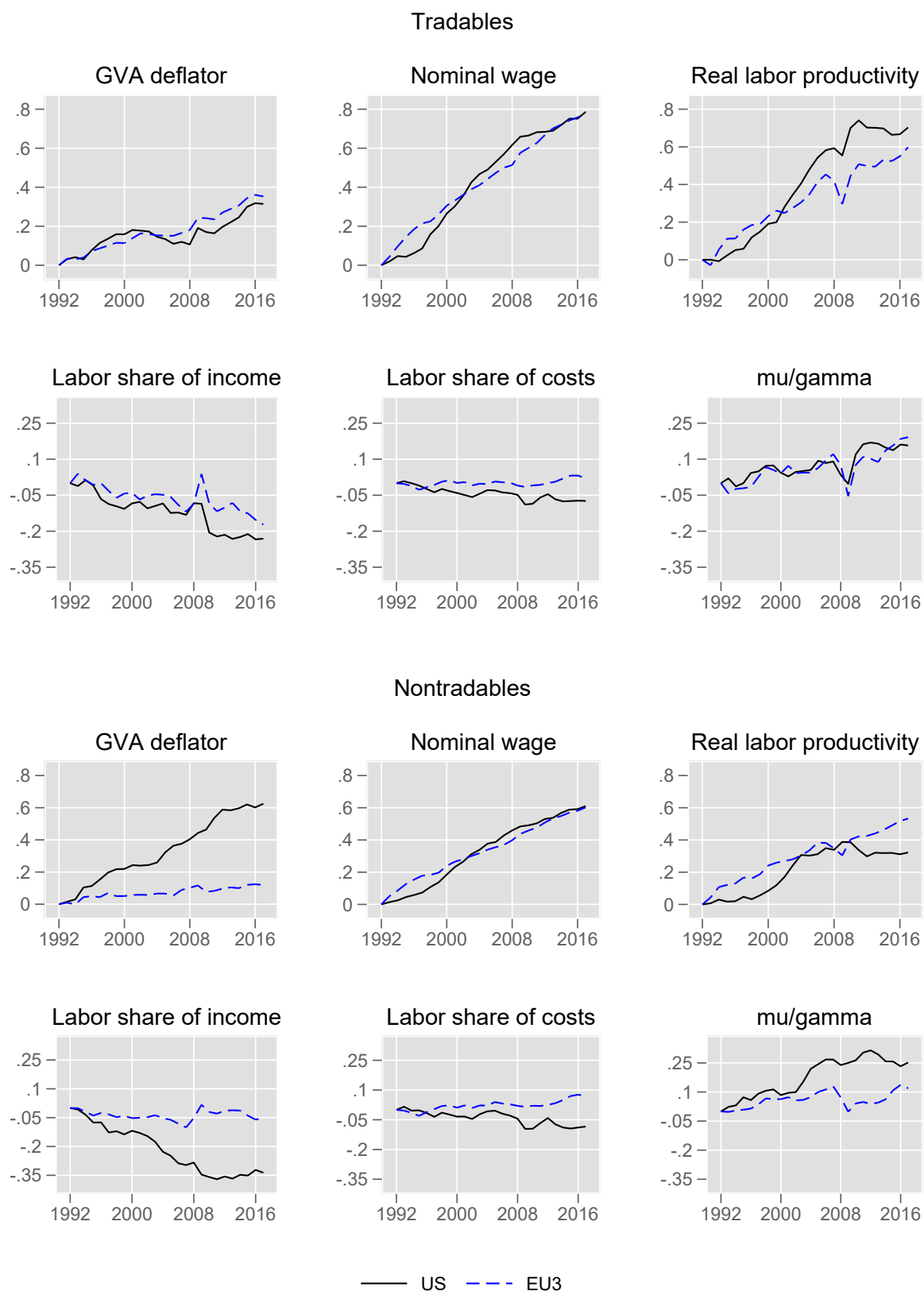
⁵See, e.g., [Byrne and Corrado \(2017\)](#) on how hedonic deflation and statistical practices can materially affect measured prices and productivity.

The combination of weaker productivity growth, a sharper labor cost share decline, and faster growth in μ/γ in the US points to a rising profit share—rather than capital deepening alone—as a key contributor to the price gap: if capital intensity had risen substantially, we would expect stronger, not weaker, measured productivity growth.

One alternative explanation is systematic under-measurement of quality in US nontradables—due, for example, to branding, customization, or advertising—that is not mirrored in the EU. Such mis-measurement would not only overstate price growth but also understate measured productivity, since higher-quality output would be partly unaccounted for in real terms. However, for this explanation to account for the observed gap, mismeasurement would need to be both large and heavily concentrated in US nontradable manufacturing—an asymmetry that seems unlikely given the effort to harmonize statistical methods across sectors and countries.

To increase comparability between US and EU3, we exclude ICT manufacturing from our analysis. Including ICT manufacturing, as we show in Figure 2, US tradable productivity increased significantly faster in the US than EU3 over our sample period, which leaves open the possibility that our finding of faster relative nontradable price growth in the US is due to the Balassa-Samuelson effect. Contrary to the Balassa-Samuelson prediction, however, real wage growth in US nontradable was *lower* than in the EU3 nontradable sector (see Figure ?? in Appendix presenting the decomposition with nominal objects deflated by CPI).

Figure 3: Tradable and Nontradable Manufacturing, log deviation from 1992



Notes: EU3 = France, Germany, Italy. See Table ?? in Appendix for industry definitions, and Section 3.1 for a description of variables. Source: authors' calculations using OECD STAN.

3.4 National Account Industries

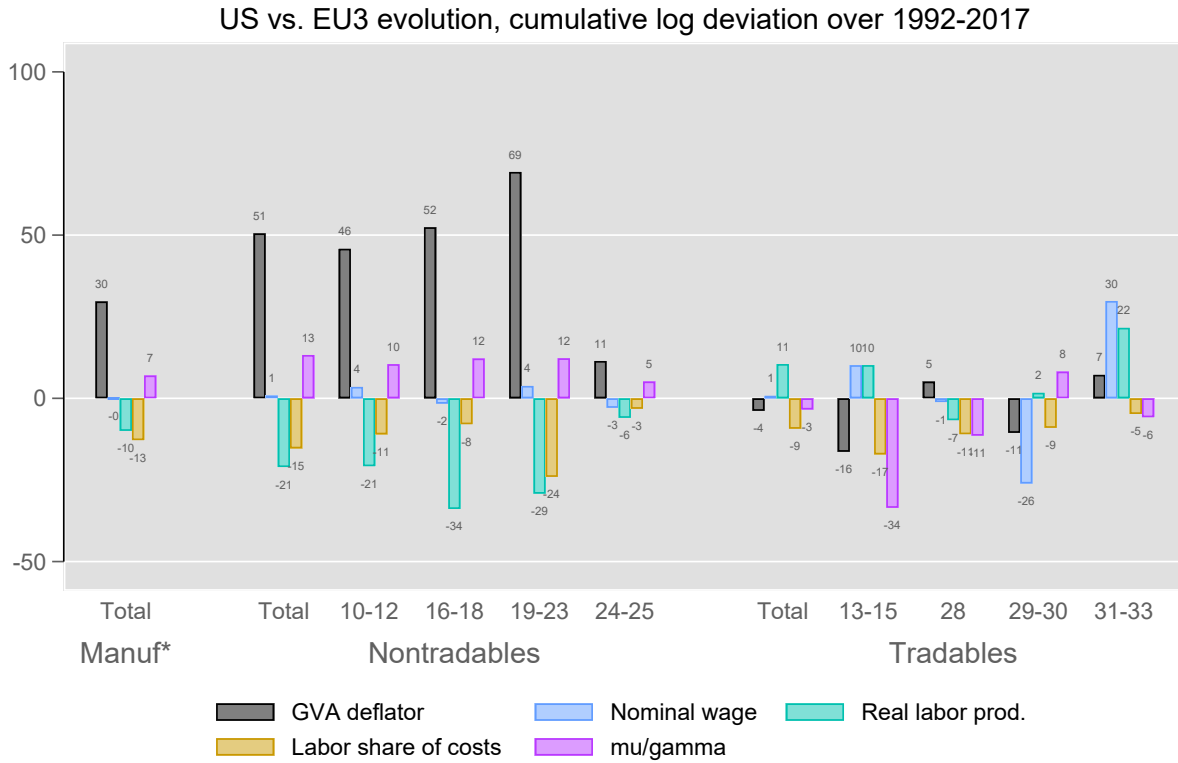
We further disaggregate manufacturing into the broad industry groups reported in STAN, focusing on non-technology manufacturing. Figure 4 shows the relative changes in prices, productivity, wages, labor cost shares, and markups net of returns to scale for the US versus the EU3, separately for all manufacturing excluding technology, for nontradables, and for tradables.

Price divergence is concentrated in nontradable industries and is generally associated with both slower productivity growth and faster increases in μ/γ in the US. In food manufacturing (ISIC 10–12) and wood and paper products (ISIC 16–18), US prices rose about 50p.p. more than in the EU3. In both cases, US labor productivity grew markedly slower, the labor cost share fell by around 10p.p. more in the US than in the EU, and μ/γ increased by 10p.p. more in the US. In chemicals and pharmaceuticals (ISIC 19–23), the divergence is even starker: US prices rose about 70p.p. more than in the EU, productivity growth lagged by 30p.p., the labor cost share fell by roughly 25p.p., and μ/γ grew by 10p.p. more. The only nontradable industry without a pronounced divergence is basic metals (ISIC 24–25), where productivity and cost shares evolved similarly across regions and μ/γ growth was modest in both.

By contrast, tradable industries—including textiles (13–15), machinery (28), transport equipment (29–30), and furniture (31–33)—show broadly parallel trends across regions in prices, productivity, and cost shares. In most tradable sectors, labor cost shares changed little in the EU and declined slightly in the US. These similarities reinforce the interpretation that shared technologies and competitive pressures limit sustained price divergence in tradables.

In Appendix Figure ??, we show relative US prices and labor shares against trade intensity for an unbalanced panel of up to 33 OECD countries (US, 27 EU member states, UK, Canada, Turkey, Japan, South Korea). This suggests the divergence between the US and the median OECD country in nontradable manufacturing mirrors our baseline EU3 comparison, so the result is not driven by the specific choice of France, Germany, and Italy.

Figure 4: Industry-Level Divergence in Prices, Productivity, Labor Cost Shares, and Markups



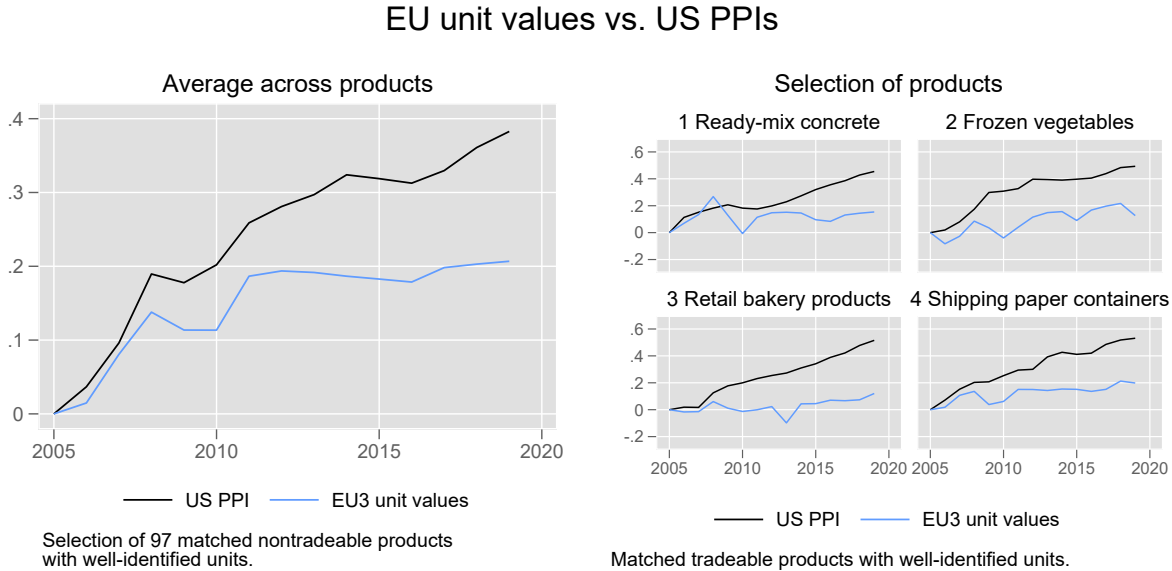
Notes: “Manuf*” excludes technology industries (ISIC 26–27). Industry definitions and tradability classifications follow Appendix ???. Labor cost share and μ/γ changes are computed from the decomposition in Equation 2. The change in the GVA deflator is the sum of the changes in: nominal wage - real labor prod. - labor share of costs + μ/γ . Source: authors’ calculations using OECD STAN.

3.5 Product-level Prices

A potential limitation of the preceding analyses is their reliance on industry-level price indices, which may embed measurement error—particularly from differences in quality adjustment practices across countries. In Appendix Figure ??, we show the results still hold when looking at a restricted sample of countries sharing similar PPI construction methodologies. To further assess whether such differences could drive our results, we then turn to narrowly defined, homogeneous products: goods with standardized units, consistent production methods, and minimal scope for quality change.

For the US, we compile product-level Producer Price Indices (PPIs) from the Bureau of Labor Statistics. For the EU, comparable product-level PPIs are not available. Instead, we draw on two sources: (i) EU Prodcom, which reports annual revenues and physical quantities at the product level, and (ii) the EU Short-Term Business Statistics (STS), which provides granular industry-level

Figure 5: Evolution of Prices for Homogeneous Nontradable Products: EU Prodcom Unit Values vs. US PPIs, log deviation from 2005



Notes: Sample includes 97 homogeneous nontradable products harmonized between US BLS PPI data and EU Prodcom unit values. EU Prodcom prices are not quality-adjusted. Source: authors' calculations.

PPIs at the NACE 4-digit level. To obtain prices in Prodcom, we compute unit values (revenues over quantities) for goods with consistent and homogeneous quantities across time and countries. Our main results are based on Prodcom, with STS-based results reported in Appendix ???. Prodcom unit values are not quality-adjusted, so price increases are likely overestimated relative to US data for PPI categories in which quality adjustment is applied.

We match our selected products from Prodcom to US PPI by applying a two-stage LLM-based matching procedure to category names. First, we create sentence embeddings for each category name and compute pair-wise cosine similarities across the two lists. Then, we find the nearest match from Prodcom to US PPI by matching each Prodcom category to the closest US PPI by cosine similarity. As a second filter, we use a chat completion algorithm, which we ask to assign a production cost similarity score (0-10) for each pair of matched category names.⁶ We keep all product categories with a cosine similarity greater than 0.9 and a cost similarity score above 8.

⁶We use the OpenAI text-embedding-ada-002 model to create the embeddings and gpt-3.5-turbo with the query "For this pair of product descriptions separated by ||, assign a score from 0-10 to two decimal places, that measures how likely it is that they have the same production costs. For example, if two products use raw materials with the same cost, but employ different production processes, the score would be somewhere in between 0 and 10; if two products use identical raw materials and production processes, the score should be 10. Please output the score, and a very concise (one sentence maximum) explanation for how you chose the score. Please return the output as a tab-separated file, with the score in one column and the explanation in the next." to obtain the cost similarity score.

Furthermore, we filter out product categories associated with tradable industry codes. Our final sample includes 97 nontradable products (out of approximately 1,700 total categories), which include, for example, homogeneous products such as Ready-mix Concrete and Frozen Vegetables.

Figure 5 shows the average price index across all products in the sample, as well as selected examples. Although the comparison period is limited to 2005–2018, the results align closely with our aggregate findings: US prices for these homogeneous nontradable products rose more than their EU counterparts, despite the absence of quality adjustment in the EU data. Price growth is slightly higher in this product-level sample than in the aggregate series. Still, the US–EU gap persists, suggesting that measurement differences alone cannot explain the divergence in nontradable manufacturing prices.

Summary. Taken together, the cross-country evidence paints a consistent picture. In tradable manufacturing, prices, productivity, labor cost shares, and μ/γ have evolved in near parallel across the US and EU, consistent with common global technologies and competitive pressures. In nontradable manufacturing, by contrast, US prices have risen far faster, driven by both slower productivity growth and a sharper decline in the labor cost share—accompanied by a much larger increase in μ/γ than in the EU. These patterns persist across industry definitions, product-level data, alternative price measures, and all robustness checks, and are not explained by wage growth or plausible measurement differences (see Appendix ?? for a detailed discussion of the different robustness analyses). The stability of tradable sectors suggests that the divergence in nontradables reflects differences in domestic market structure and exposure to competition.

4 Technology or Market Power?

The decomposition in Section 2 links the US–EU nontradable price gap to weaker US productivity growth, a sharper decline in labor cost shares, and a larger increase in μ/γ . This raises a natural question. Could the rise in μ/γ be a disguised form of technology change, or a change in returns to scale, rather than an increase in market power? We use a simple CES production framework to discipline that question. The exercise asks whether the technology and input-bias terms implied by measured inputs, factor prices, and output have the same region-by-sector pattern as the price divergence. If technology were the main force, it should show up most strongly in US nontradables. If instead the distinctive movement is in revenues relative to factor costs, the evidence points to markups net of scale.

4.1 Framework

Production function. We model industry output using a CES production function with increasing returns to scale:

$$Y^{\frac{1}{\gamma}} = z \left[a_k K^{\frac{\epsilon-1}{\epsilon}} + L^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}}, \quad (4)$$

where $\gamma \geq 1$ is the degree of returns to scale and ϵ is the elasticity of substitution between capital and labor. This is a reparameterization of the standard CES production function

$$Y^{1/\gamma} = Z \left[\alpha (A_k K)^{\frac{\epsilon-1}{\epsilon}} + (1-\alpha) (A_l L)^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}},$$

after factoring out labor-augmenting technology and the distribution parameters.⁷ Thus a_k can capture capital-biased technical change, automation, or changes in the relative weight of capital in the CES bundle, while z captures factor-neutral productivity relative to labor-augmenting change.

Cost minimization and measurement equations. Denote the input bundle by

$$X \equiv \left[a_k K^{\frac{\epsilon-1}{\epsilon}} + L^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}},$$

so that $Y^{1/\gamma} = zX$. Solving the cost-minimization problem $\min_{K,L} R_k K + W L$ subject to a given X yields the first-order condition

$$\frac{R_k}{W} = a_k \left(\frac{K}{L} \right)^{-1/\epsilon}.$$

Together with the production function and the revenue-to-cost ratio, this gives three measurement equations:

$$\ln z = \frac{1}{\gamma} \ln Y - \ln X \quad (5)$$

$$\ln a_k = \frac{1}{\epsilon} \ln \left(\frac{K}{L} \right) - \ln \left(\frac{W}{R_k} \right) \quad (6)$$

$$\ln \frac{\mu}{\gamma} = \ln \left(\frac{PY}{WL + R_k K} \right) \quad (7)$$

Equation (6) determines the relative CES input-bias term from observed factor ratios and factor prices. Equation (5) then recovers factor-neutral technology as a residual, conditional on γ . Equation (7) is the key market-power object. Under cost minimization, total cost is $C = WL + R_k K$ and marginal cost is $MC = C/(\gamma Y)$, so $P/MC = \mu$ implies $PY/C = \mu/\gamma$.

⁷Specifically, a_k is a composite of α , A_k , and A_l , while z absorbs Z , A_l , α , and $(1-\alpha)$. Since A_l is not separately identified, a_k should be interpreted as a normalized CES input-bias term rather than a direct measure of capital efficiency.

Thus, under the maintained cost-minimization and user-cost assumptions, revenues relative to measured factor costs recover markups net of scale.

This distinction matters for measurement. Labor quality is important for productivity accounting, but it is not the central issue in measuring μ/γ : the labor term is the total nominal wage bill, WL , not a headcount measure. The main measurement risks instead concern the split of value added into labor costs, capital costs, and profits; the user cost of capital; and the consistency between the capital quantity and the rental price. These errors matter because they enter the denominator of (7). The US–EU comparison helps by asking whether such errors would have to appear only in US nontradables, while leaving tradables and European nontradables largely unaffected. The tradable sectors provide a useful check: they draw on OECD-harmonized accounts, are processed with the same user-cost construction, and yet show little US–EU divergence in μ/γ .

Parameter recovery. Table 1 summarizes the recovery chain. We measure the user cost of capital R_k following the approach in Section 3. This is enough to recover μ/γ from revenues and factor costs. We then treat ϵ as fixed and use industry-level estimates from Oberfield and Raval (2021), reported in Appendix Table ??; this pins down the normalized input-bias term a_k . To recover z and gross markups μ , we also need γ . In the baseline we set $\gamma = 1.05$, consistent with estimates in Basu and Fernald (1997), Covarrubias et al. (2019), and De-Loecker et al. (2019). We assess how much this assumption would have to change below.

Table 1: Recoverable parameters under different assumptions

Assumptions	Recoverable Parameters
R_k	$\frac{\mu}{\gamma}$
+ ϵ	$\frac{\mu}{\gamma}, a_k$
+ γ	μ, a_k, z

4.2 Model-implied technology and markups

Figure 6 presents the recovered market-power, input-bias, and technology terms for tradable and nontradable manufacturing in the US and EU3, expressed as value-added-weighted log deviations from 1992 values. The first three rows show μ/γ , a_k , and z ; the last two rows show the factor-price and factor-quantity ratios that discipline the recovery of a_k . The figure delivers two messages.

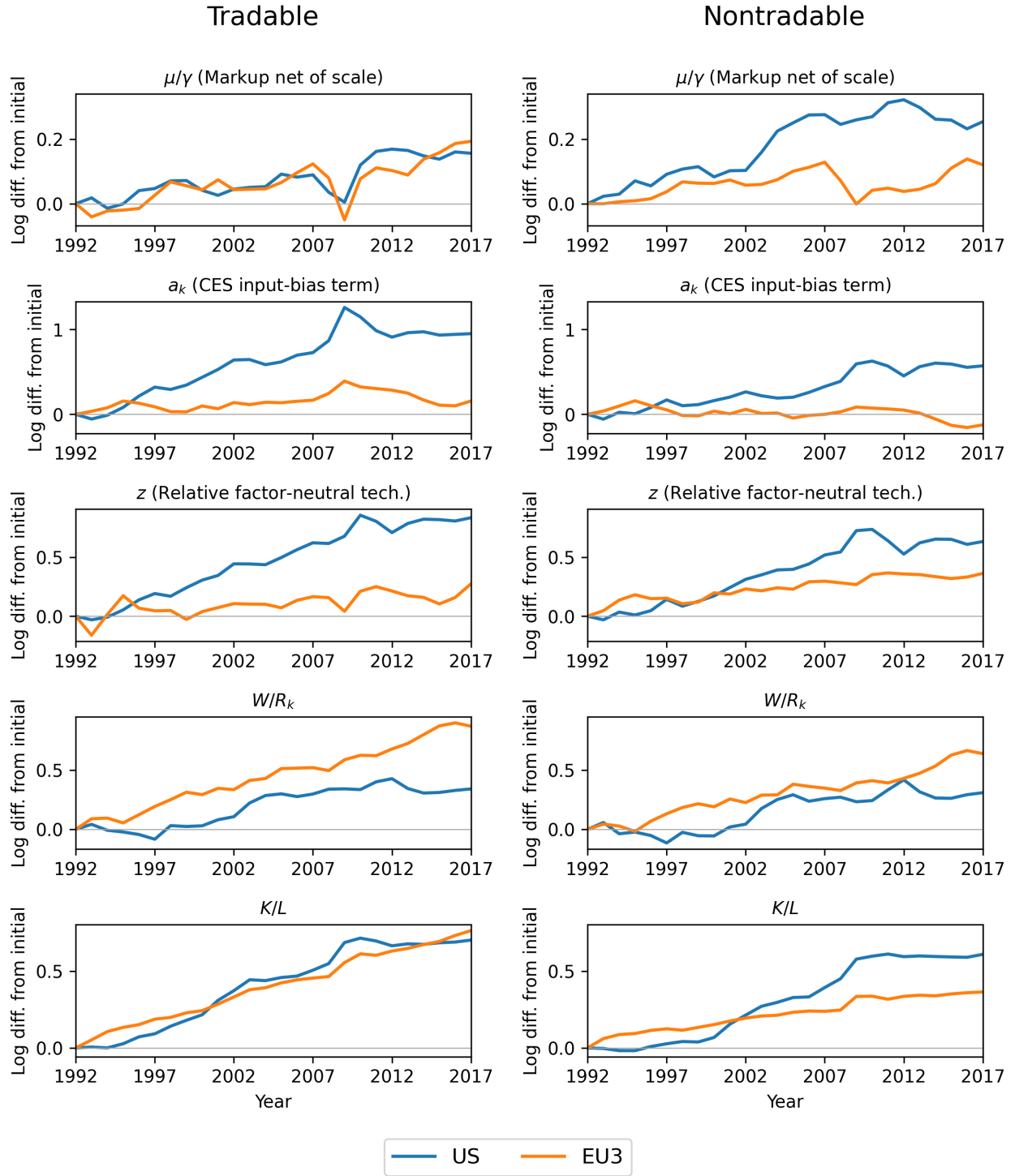
Factor-neutral technology (z). The US has faster growth in recovered factor-neutral technology than the EU3 in both tradable and nontradable sectors. This is an important correction to a simple reading of productivity growth: once factor substitution and capital-biased change are accounted for, the model does imply stronger US residual technology growth. But the pattern is

not the one needed to explain the nontradable price divergence. The US–EU gap in z is larger in tradables, where prices move in parallel across the Atlantic, than in nontradables, where prices diverge sharply. Differential factor-neutral technology therefore cannot explain why the price gap appears specifically in nontradables.

CES input-bias term (a_k). The normalized input-bias term a_k also grows faster in the US than in the EU3 in both sectors. This reflects the joint movement of K/L and W/R_k in (6): relative to Europe, the US combines lower growth in the wage-rental ratio with comparable or stronger growth in capital intensity. This pattern is consistent with capital-biased technical change, but it should not be read as a direct index of automation or capital efficiency. What matters for our argument is that it is a broad US pattern, not a nontradable-specific one. It appears in tradables as well as nontradables, so it cannot by itself explain why nontradable prices diverged while tradable prices did not.

Markups net of returns to scale (μ/γ). μ/γ is the object with the clearest region-by-sector pattern. In tradable manufacturing, the US increase is slightly smaller than the EU3 increase. In nontradable manufacturing, the US increase is about 13 log points larger. Equivalently, the US–EU gap in μ/γ rises in nontradables but not in tradables. This is the same pattern as the price facts in Section 3: the divergence appears where foreign competition is weak and not where tradable competition is strong.

Figure 6: Model-implied input bias, technology, and markups net of scale



Notes: Series are value-added-weighted log deviations from 1992. EU3 is France, Germany, and Italy. The figure excludes computers and electronics. The baseline sets $\gamma = 1.05$ and uses industry elasticities from [Oberfield and Raval \(2021\)](#).

Returns to scale. A remaining concern is that the rise in μ/γ could reflect declining returns to scale rather than rising markups. The scope for this explanation is limited. Since

$$\ln \mu = \ln(\mu/\gamma) + \ln \gamma,$$

holding μ fixed would require a fall in $\ln \gamma$ equal to the rise in $\ln(\mu/\gamma)$. In US nontradables, the cumulative increase in $\ln(\mu/\gamma)$ is about 0.25 log points. To explain this entirely through scale, γ would need to start near $e^{0.25} \simeq 1.28$ and fall all the way to constant returns. This is much larger than standard manufacturing estimates, which cluster close to 1.0–1.1 (Basu and Fernald, 1997, Covarrubias et al., 2019, De-Loecker et al., 2019). More importantly, the cross-region comparison requires an even stronger claim: returns to scale would need to fall differentially in US nontradables, but not in US tradables or EU nontradables. That pattern is hard to reconcile with the broad technology movements in Figure 6.

Interpretation. The CES exercise does not say that technology is irrelevant. The US shows faster recovered factor-neutral productivity growth than the EU3, especially in the tradable sector, and faster growth in the CES input-bias term. The point is sharper: these terms do not have the same nontradable-specific pattern as prices. By contrast, μ/γ rises differentially in US nontradables and not in US tradables. The model therefore reinforces the interpretation from the accounting decomposition. The distinctive change is not labor quality, broad productivity growth, or a broad shift in the relative role of capital. It is revenues rising relative to measured factor costs in the industries least exposed to foreign competition.

Summary. Taken together, the accounting evidence and the CES recovery make technology and scale explanations less plausible. Wage growth, broad productivity growth, the CES input-bias term, and plausible changes in returns to scale do not have the region-by-sector pattern needed to explain the US nontradable price divergence. The object that does is μ/γ : markups net of scale rose in US nontradable manufacturing in a way that has no counterpart in tradables or in the EU. Interpreting this as a rise in gross markups requires ruling out a large and differential fall in γ , which is not supported by existing estimates. This conclusion motivates the causal analysis in Section ??, which uses variation in trade exposure to identify the competitive forces behind these markup dynamics.

5 Causal Evidence from US Industries

The cross-country patterns in Section 3 suggest that the divergence in nontradable manufacturing prices between the US and the EU reflects domestic factors — particularly differences in market structure and exposure to competition — rather than global technology trends. To investigate

these mechanisms directly, we turn to US industry-level data, which allow for richer controls, causal identification, and a closer link to the forces shaping μ/γ .

Data. We build an annual panel of NAICS-6 manufacturing industries from the NBER–CES Manufacturing Industry Database (2018 vintage), which provides shipments, prices, wages, employment, intermediate inputs, and capital stocks. We combine these with import and export data from [Schott \(2008\)](#) and the permanent normal trade relations (PNTR) measure of trade liberalization from [Pierce and Schott \(2018\)](#). Import penetration is defined as $IP_{it} = M_{it}/(Y_{it} + M_{it})$, imports over domestic shipments plus imports. Labor shares are payroll over shipments. Profit shares are shipments net of payroll, materials, energy, and capital costs, relative to shipments, where capital costs apply the same annual user cost of capital as in Section 3. The baseline sample covers 1990–2017 and excludes computers, electronics, and electrical equipment (NAICS 334–335), consistent with the cross-country analysis; results are nearly identical in five-year-window panels matching the prior literature.

Trade exposure differs sharply across the tradability boundary: shipment-weighted import penetration in nontradable manufacturing was 10.4% in 2000 and 12.9% in 2017, against 23.8% and 23.1% in tradables — a two-to-one gap in levels, with tradables’ penetration plateauing after China’s WTO accession ran its course. The variation we exploit below is therefore concentrated precisely where the cross-country evidence locates the pricing discipline.

5.1 Import Penetration and Industry Outcomes: Binned Scatterplots

We begin with the unconditional relationships. Figure 7 groups industries into 25 equal-sized bins by their five-year change in import penetration, nets out year fixed effects, and plots the average change in prices, labor shares, and profit shares against the average change in import penetration within each bin. Industries experiencing larger increases in import penetration see slower price growth, rising labor shares, and falling profit shares — weaker growth in μ/γ .

5.2 Regression Estimates with the PNTR Instrument

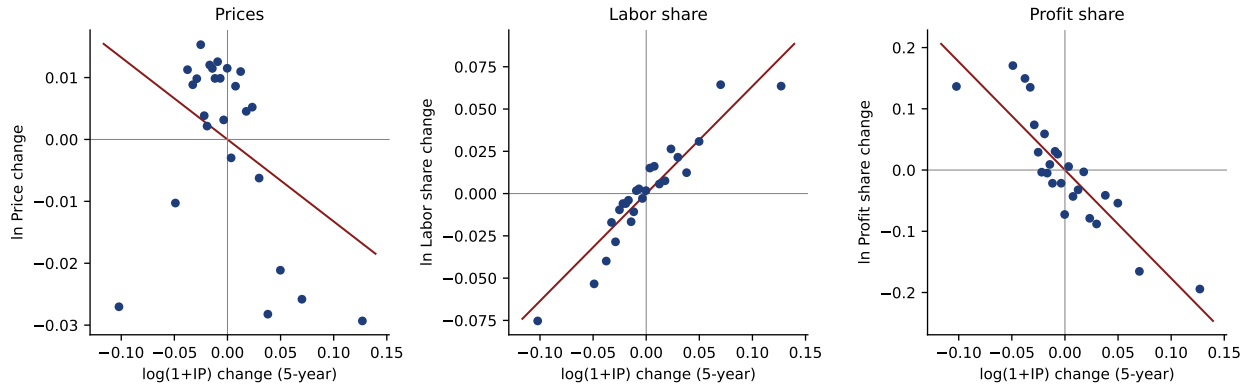
We quantify these relationships with panel regressions of the form

$$\log y_{it} = \beta \log(1 + IP_{it}) + \alpha_i + \delta_t + \theta' X_{it} + \varepsilon_{it}, \quad (8)$$

where y_{it} denotes producer prices, labor shares, or profit shares in industry i and year t ; α_i and δ_t are industry and year fixed effects; and X_{it} is a vector of controls. Standard errors are clustered by industry.

Table 2 presents the results. A ten-percentage-point increase in import penetration is associated with roughly 2.5% lower prices (columns 1–2), a 4.5% higher labor share (column 3), and

Figure 7: Binned scatterplots: changes in outcomes vs. changes in import penetration



Notes: Each dot is an equally sized bin of NAICS-6 industries sorted by their five-year change in $\log(1 + IP)$. Axes plot changes net of year fixed effects; the line is the OLS fit on the underlying industry-year observations ($N = 6,493$). Sources: NBER-CES, [Schott \(2008\)](#).

a 13% lower profit share (column 4). These magnitudes are economically large relative to the exposure gap documented above: nontradable industries' import penetration is not only half the tradables' level but rose by a fraction of it over the sample.

To address endogeneity — reverse causality from domestic price changes to imports, and measurement error in import penetration — column (5) instruments $\log(1 + IP_{it})$ with the PNTR-based measure of tariff-uncertainty reduction from [Pierce and Schott \(2018\)](#), interacting the pre-PNTR NTR gap with a post-2001 indicator. The instrument is strong (first-stage $F = 34.7$), and the reduced forms are themselves informative: industries with larger NTR gaps saw prices fall by 13.5% (4.9) and profit shares by 62% (15) relative to unexposed industries after 2001. The IV estimate for profit shares is roughly twice the OLS estimate, consistent with attenuation from measurement error in import penetration and with the instrument isolating industries where the China shock bit hardest.

Combined, these results reinforce the cross-country evidence: exposure to trade disciplines prices and profit shares within the US, through the same margin — trade openness — that organizes the US–EU divergence across industries and products in Section 3. Industries sheltered from that discipline are precisely where markups net of scale, and prices, pulled away from their European counterparts.

6 Conclusion

This paper has examined the joint evolution of prices, productivity, and income shares in US and EU manufacturing using a transparent decomposition of value-added prices into unit labor costs, labor cost shares, and markups net of returns to scale.

Our central finding is that the sharp rise in US nontradable manufacturing prices over the

Table 2: Import penetration, prices, and factor shares

	$\log P_{it}$		$\log LS_{it}$	$\log PS_{it}$	
	(1)	(2)	(3)	(4) OLS	(5) IV
$\log(1 + IP_{it})$	-0.28** (0.08)	-0.28** (0.05)	0.54** (0.09)	-1.58** (0.23)	-3.81** (1.00)
$\log LP_{it}$		-0.28** (0.03)			
$\log w_{it}$		+0.38** (0.05)			
$\log P_{it}^{mat}$		+0.64** (0.05)			
$\log P_{it}^{ene}$		+0.05 (0.04)			
Industry FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Within R^2	0.02	0.43	0.03	0.03	—
First-stage F					34.7
Observations	8,861	8,861	8,861	8,331	8,250

Notes: Annual NAICS-6 panel, 1990–2017, manufacturing excluding NAICS 334–335. All regressions include industry and year fixed effects; standard errors clustered by industry ($^+ p < 0.1$, $^* p < 0.05$, $^{**} p < 0.01$). Column (5) instruments $\log(1 + IP_{it})$ with the NTR gap $\times$ post-2001 (Pierce and Schott, 2018). Results are essentially unchanged in five-year-window panels (1997–2012: -0.27 , -0.19 , $+0.57$, -1.66 , -4.00), and controlling for industry regulatory restrictions (RegData) leaves all coefficients unaffected on the available subsample. Sources: NBER–CES, Schott (2008), Pierce and Schott (2018).

past 25 years is not explained by wage growth, productivity trends, or capital deepening, but by a sustained increase in markups net of scale effects. Tradable manufacturing, by contrast, shows parallel trends in prices, productivity, and markups across the US and EU, consistent with common global technology shocks and competitive discipline from trade.

Within the US, industry-level evidence confirms that greater import penetration—especially from China following PNTR—lowers prices, raises labor cost shares, and reduces profit shares. Moreover, when we measure market power using profit shares rather than gross markups, firm-level increases in profitability align closely with rising industry-level markups, reconciling earlier findings that gross markups alone are weakly correlated with prices.

These results underscore three broader points. First, prices provide a direct welfare-relevant measure of market power’s impact—one that incorporates both cost pressures and pass-through. Second, separating tradable from nontradable sectors is essential: the forces shaping each are distinct, and policy aimed at one will not necessarily affect the other. Third, measurement choices matter—differences in quality adjustment and index construction can shift levels, but the US–EU nontradables divergence persists across robust specifications.

A natural interpretation of our findings is that, while global competition keeps tradable prices in check, non-tradable manufacturing remains vulnerable to weak competitive pressure. Strength-

ening antitrust enforcement, targeting regulation in concentrated supply chains, and improving the measurement of subtle quality changes are essential steps to ensure that productivity gains are passed through to consumers.

References

- AMITI, M. AND S. HEISE (2024): “U.S. Market Concentration and Import Competition,” *The Review of Economic Studies*.
- ATALAY, E., A. HORTACSU, N. KIMMEL, AND C. SYVERSON (2025): “Why Is Manufacturing Productivity Growth So Low?” Tech. rep., 2025 NBER Sl.
- BARKAI, S. (2020): “Declining Labor and Capital Shares,” *The Journal of Finance*, 75, 2421–2463.
- BASU, S. (2019): “Are Price-Cost Mark-ups Rising in the United States? A Discussion of the Evidence,” .
- BASU, S. AND J. G. FERNALD (1997): “Returns to Scale in U.S. Production: Estimates and Implications,” *Journal of Political Economy*, 105, 249–283.
- BESLEY, T., N. FONTANA, AND N. LIMODIO (2021): “Antitrust Policies and Profitability in Nontradable Sectors,” *American Economic Review: Insights*, 3, 251–65.
- BONTADINI, F., C. CORRADO, J. HASKEL, M. IOMMI, AND C. JONA-LASINIO (2023): “EUKLEMS & INTANProd: Industry Productivity Accounts with Intangibles. Sources of Growth and Productivity Trends: Methods and Main Measurement Challenges,” Deliverable D2.3.1, LUISS Lab of European Economics.
- BYRNE, D. AND C. CORRADO (2017): “ICT Services and their Prices: What do they tell us about Productivity and Technology?” Finance and Economics Discussion Series (FEDS) 2017-015r1, Board of Governors of the Federal Reserve System, revised October 2017.
- BYRNE, D. M., J. G. FERNALD, AND M. B. REINSDORF (2016): “Does the United States Have a Productivity Slowdown or a Measurement Problem?” *Brookings Papers on Economic Activity*, 47, 109–182.
- CONLON, C., N. H. MILLER, T. OTGON, AND Y. YAO (2023): “Rising Markups, Rising Prices?” *AEA Papers and Proceedings*, 113, 279–83.
- CORRADO, C., C. HULTEN, AND D. SICHEL (2009): “Intangible Capital and U.S. Economic Growth,” *Review of Income and Wealth*, 55, 661–685.
- COVARRUBIAS, M., G. GUTIÉRREZ, AND T. PHILIPPON (2019): “From Good to Bad Concentration? U.S. Industries over the past 30 years,” *NBER Macroannuals*.
- CROUZET, N. AND J. EBERLY (2023): “Rents and Intangible Capital: A Q+ Framework,” *The Journal of Finance*, 78, 1873–1916.

- DE-LOECKER, J., J. EECKHOUT, AND G. UNGER (2019): “The Rise of Market Power and the Macroeconomic Implications,” .
- DORN, D., J. F. SCHMIEDER, AND J. R. SPLETZER (2018): “Domestic Outsourcing in the United States,” .
- DRAGHI REPORT (2024): “Report on the Future of the EU Economy,” Mario Draghi and Others.
- EISFELDT, A. L., A. FALATO, AND M. Z. XIAOLAN (2023): “Human Capitalists,” in *NBER Macroeconomics Annual 2022, volume 37*, University of Chicago Press, 1–61.
- ELSBY, M., B. HOBIJN, AND A. SAHIN (2013): “The Decline of the U.S. Labor Share,” *Brookings Papers on Economic Activity*, 44, 1–63.
- GANAPATI, S. (2021): “Growing Oligopolies, Prices, Output, and Productivity,” *American Economic Journal: Microeconomics*, 13, 309–27.
- GUTIÉRREZ, G. AND S. PITON (2020): “Revisiting the Global Decline of the (Non-housing) Labor Share,” *American Economic Review: Insights*, 2, 321–38.
- HALL, R. AND D. JORGENSON (1967): “Tax Policy and Investment Behavior,” *American Economic Review*, 57, 391–414, reprinted in Bobbs-Merrill Reprint Series in Economics , Econ-130. Investment 2, ch. 1, pp 1-26.
- HASKEL, J. AND S. WESTLAKE (2017): *Capitalism without Capital*, Princeton University Press.
- KARABARBOUNIS, L. AND B. NEIMAN (2014): “The Global Decline of the Labor Share,” *Quarterly Journal of Economics*, 129, 61–103.
- (2018): “Accounting for factorless income,” in *NBER Macroeconomics Annual 2018, volume 33*, University of Chicago Press.
- MILLER, N., M. OSBORNE, G. SHEU, AND G. SILEO (2025): “Technology and Market Power in the Cement Industry,” .
- OBERFIELD, E. AND D. RAVAL (2021): “Micro Data and Macro Technology,” *Econometrica*, 89, 703–732.
- PIERCE, J. R. AND P. K. SCHOTT (2018): “Investment responses to trade liberalization: Evidence from U.S. industries and establishments,” *Journal of International Economics*, 115, 203 – 222.
- PITON, S. (2021): “Economic integration and unit labour costs,” *European Economic Review*, 136.

- SCHOTT, P. K. (2008): "The Relative Sophistication of Chinese Exports," *Economic Policy*, 23, 5–49.
- SMITH, M., D. YAGAN, O. ZIDAR, AND E. ZWICK (2022): "The Rise of Pass-Throughs and the Decline of the Labor Share," *American Economic Review: Insights*, 4, 323–40.
- SYVERSON, C. (2016): "The slowdown in manufacturing productivity growth," *Brookings Briefs*.
- (2019): "Macroeconomics and Market Power: Facts, Potential Explanations, and Open Questions," Tech. rep., Brookings Economic Studies.