Why Is Manufacturing Productivity Growth So Low?

Enghin Atalay Ali Hortaçsu Nicole Kimmel Chad Syverson*

March 20, 2025

Abstract

We examine the recent slow growth of manufacturing productivity. We document that a handful of industries producing computers and electronics accounts for nearly all of measured TFP growth since 1987 as well the slowdown since the late 2000s. We then argue that conventional industry accounts perennially understate U.S. manufacturing productivity growth. To show this, we compare consumer, producer, and import price indices. Beyond measuring different concepts, these indices vary in how comprehensively they account for quality improvements, especially for rapidly innovating goods. We interpret the gap between the consumer price index and the producer and import price indices as evidence of under-accounting for quality improvements. Using an input-output accounting framework, we estimate that these gaps imply an understatement of manufacturing TFP growth by 2.3 percentage points for durable goods manufacturing, 0.7 percentage points for nondurable goods manufacturing, but no difference for nonmanufacturing industries.

JEL Codes: D24, E01, E31

*Atalay: Research Department, Federal Reserve Bank of Philadelphia, atalayecon@gmail.com; Hortaçsu: Department of Economics, University of Chicago, hortacsu@uchicago.edu; Kimmel: Federal Reserve Bank of Philadelphia, nicole.kimmel@phil.frb.org; Syverson: University of Chicago Booth School of Business, chad.syverson@chicagobooth.edu. This Philadelphia Fed working paper represents preliminary research that is being circulated for discussion purposes. The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. Any errors or omissions are the responsibility of the authors.

This paper re-considers the special role that manufacturing plays within the economy. It examines the sources of the manufacturing productivity slowdown, then explores how differences in productivity growth between manufacturing and nonmanufacturing sectors translates to the relative prices of goods and services in the personal consumption expenditures (PCE) price index.

Up to the 2010s, the conventional wisdom held that:

- Relative to other sectors in the economy, manufacturing has exceptional productivity growth.
- The price of goods—which are produced primarily within the manufacturing sector—tends to grow more slowly than the price of services—which are produced primarily outside of the manufacturing sector.

These two empirical patterns are linked by the fact that productivity growth in an industry allows that industry to produce its output at lower marginal cost. This tends to lead to lower price growth for related consumption categories. Herrendorf et al. (2015) exemplifies this conventional wisdom. Examining data from 1947 and 2010 for the United States, they document that (i) total factor productivity (TFP) growth in the manufacturing sector was roughly half a percentage point per year faster than in the service sector, and (ii) the relative price of services to manufactured products nearly doubled. These trends have been observed in other developed economies (Duarte and Restuccia, 2010) and are the foundation of the literature on structural transformation.

Recent data are at odds with this conventional wisdom. Since 2009, manufacturing productivity growth has stagnated, falling by 0.1% annually to 2023. To understand this weak productivity growth, we decompose manufacturing TFP growth by industry. We find that nearly all of the sector's productivity growth since 1987—and its deceleration since 2009—can be attributed to a single 3-digit industry: Computer and Electronic Products Manufacturing.

We then examine the measurement of industry TFP growth, with a focus on industries in the manufacturing sector. In measures of industries' productivity growth, a key underlying ingredient is the output price index of each industry's (gross) output. In computing industries' gross output, the Bureau of Economic Analysis (BEA) uses the Bureau of Labor Statistics (BLS) producer price index (PPI) for most industries across all sectors, and essentially all industries within the manufacturing sector; see Table 1 in Appendix A. By contrast, in constructing its PCE price index, the BEA relies on the BLS Consumer Price Index (CPI) for essentially all manufactured goods and for a majority of all consumption categories. While the CPI and PPI are conceptually distinct from one another, attempting to measure inflation from different perspectives (see the discussion in Section 3), they also differ in the extent to which they capture quality improvements over time.

The BLS invests significantly—in its survey design, in its data collection efforts, and in its statistical and economic methodology—to ensure all of its price measures provide accurate and

representative depictions of inflation experienced by households and firms. But, given its finite budget, some prioritization must inevitably be made in where BLS resources are allocated. Given the BLS' frequent reference to the CPI as "nation's principal gauge of inflation" [1] as well as the many government programs whose parameters are directly tied to the CPI, we hypothesize that the CPI may better confront the perennially challenging task of adjusting for quality improvements over time.[2] We take any differences between the CPI (or inflation measures derived from the CPI) on the one hand and the PPI and Import Price Indices on the other (or inflation measures derived from the PPI and Import Price Indices) as suggestive evidence for lack of quality adjustment in the latter price indices, especially so if the differences were concentrated in goods experiencing rapid technological progress.

With this perspective in mind, we compare BEA industry gross output deflators to categories within the PCE price index. For each category of goods or services within the PCE, we produce a corresponding measure of inflation using gross output deflators and import price indices. The main conclusion of this exercise is that inflation according to PCE price indices is substantially less than what gross output deflators and import price indices would indicate. This difference exists only for durable goods and is strongest for goods experiencing the greatest quality adjustments. Overall, durable goods' price changes are 2.4 percentage points (per year) greater when using gross output deflators and import price indices than when using PCE price indices.

In a final step of our analysis, we consider the implications of these differences for mismeasurement in productivity. Under the interpretation that price indices measuring consumers' experiences of inflation more comprehensively measure quality improvements than price indices measuring producers' experiences of inflation (at least for durable goods, and particularly so for durable goods experiencing rapid technological change), real output growth is likely understated for durable goods manufacturing industries using conventional national accounts data. At the same time real durable goods intermediate input purchases are likely understating. Using BEA Input-Output matrices we estimate the extent to which mismeasured real output and intermediate input growth translates to mismeasured TFP growth. We find annual TFP growth (between 1997 and 2019) is understated by 2.3 percentage points in durable goods manufacturing industries, 0.7 percentage points for nondurable goods manufacturing industries, and -0.1 percentage points for nonmanufacturing industries. In sum, despite slowing down since the late 2000s, the manufacturing sector may still be the locus of aggregate productivity growth.

[1] See page 47 of the most recent Annual Performance Report of the Department of Labor—`https://www.dol.gov/sites/dolgov/files/general/budget/2024/FY2024APR.pdf`—or page 39 of the most recent budget request for the Department of Labor—`https://www.dol.gov/sites/dolgov/files/general/budget/2025/CBJ-2025-V3-01.pdf` .

[2] Among other things, the CPI helps determine IRS federal income tax brackets, eligibility thresholds for the Earned Income Tax Credit, and social security benefits to retirees; see `https://www.dol.gov/sites/dolgov/files/general/budget/2024/CBJ-2024-V3-01.pdf`.

Our results reshape our understanding of research on innovation and on the desirability of public policies targeting the manufacturing sector. In terms of the former, recent research has highlighted the manufacturing sector's over-representation in innovation: Despite accounting for only one-tenth of aggregate employment, the manufacturing sector accounts for more than two-thirds of corporate patents and R&D spending (Autor et al., 2020; Fort et al., 2020). Given this, stagnant manufacturing productivity presents something of a puzzle (Lashkari and Pearce, 2024, 2025). We argue that slow productivity growth in the manufacturing sector is illusory. In terms of policy, over the last several decades, the U.S. federal government has enacted several programs to boost manufacturing productivity growth, spending multiple billions of dollars annually.[3] These programs are premised on the pivotal role that the manufacturing sector plays in national security, in global trade, and in generating high-quality jobs for people without a college degree. To the extent that these polices are judged on the basis of boosting productivity, we argue that past assessments may have presented an overly negative depiction of their success.

Related Literature This paper builds on a literature interrogating the measurement of real output growth and a related literature on the manufacturing productivity slowdown.

Specific to the manufacturing productivity slowdown, Syverson (2016) documents that the Computer and Electronic Products Manufacturing industry was key to the 1995–2004 productivity resurgence and the subsequent productivity slowdown. These results are echoed by Sprague (2021). By contrast, Lashkari and Pearce (2024; 2025) consider the slowdown in productivity growth, but argue that it is "broad based." They find that the contrast between the high (and increasing) R&D intensity and the slow productivity growth of the manufacturing sector is "puzzling". Our results in Section 2 more closely align with Syverson (2016) and Sprague (2021), though emphasize the central role of the Computer and Electronic products

[3]These programs include SEMATECH, a public-private consortium of the U.S. government and semiconductor manufacturers, which was formed in 1987 and aimed at boosting productivity by funding collaborative R&D in advanced chip fabrication; see `https://web.archive.org/web/20130702191328/http://www.sematech.org/corporate/history.htm`. Following up from this program, the CHIPS Act of 2022 provided $52.7 billion in subsidies related to semiconductor production and innovation; see `https://www.congress.gov/crs-product/R47523`. Beyond semiconductors, Manufacturing USA, established in 2014, funded 16 institutes with the aim of "closing the gap between research and development activities and the deployment of technological innovations in domestic production of goods"; see `https://web.archive.org/web/20130213203428/http://www.manufacturing.gov/nnmi_overview.html`. The Advanced Manufacturing Partnership, initiated in 2011, provided government funds to invest in "innovative technologies that will jumpstart domestic manufacturing;" see `https://obamawhitehouse.archives.gov/the-press-office/2011/06/24/president-obama-launches-advanced-manufacturing-partnership`. The American Recovery and Reinvestment Act of 2009 included $90 billion for clean energy manufacturing, accelerating productivity improvements in battery and solar panel production; see `https://obamawhitehouse.archives.gov/blog/2010/04/21/impact-american-recovery-and-reinvestment-act-clean-energy-transformation`. Finally, the Manufacturing Extension Partnership, created in 1988, has enhanced small and mid-sized manufacturers' productivity by providing technical assistance in lean manufacturing, automation, and other process improvements; see `https://www.nist.gov/mep`.

even more so than these earlier works. Our results in Sections Section 3 and 4 provide one resolution to the puzzle proposed in Lashkari and Pearce (2025).

Second, our work contributes to the literature assessing biases in government-produced price indices and in applying these indices to measure economic and improving living standards. Groshen et al. (2017) provides a recent overview of efforts at the BEA and BLS toward measuring quality improvements and the contribution of new products to real output growth. Byrne et al. (2016) and Syverson (2017) examine the "mismeasurement hypothesis" —the idea that aggregate growth is increasingly mismeasured either due to price deflators that (increasingly) do not properly reflect quality growth or due to the proliferation of goods and services that are sold for free and thus do not enter in the measurement of real output. They present a sequence of empirical patterns to argue that the mismeasurement hypothesis cannot fully (or even mostly) explain the aggregate productivity slowdown beginning in the mid-2000s. While not seeking to explain the aggregate slowdown, Brynjolfsson et al. (2025) estimate substantial consumer welfare gains from the introduction of Facebook and the development of smartphone cameras, above and beyond what is captured by the consumer price index. We share with these articles the idea that price indices may understate quality improvements, especially for goods and services linked to information and communication technologies. Distinct from Byrne et al. (2016) and Syverson (2017), we do not seek to measure why productivity growth has slowed down. Rather, we attempt to estimate mismeasurement in productivity growth that differs between the manufacturing and nonmanufacturing sectors. Distinct from all of these studies, we do not seek to estimate mismeasurement on consumer price indices.

Closer to our work, several others have examined the performance of producer price indices: Byrne et al. (2018) argue that the BLS PPI for semiconductors vastly understates price declines in that industry. Whereas the PPI declined by 28% per year between 2000 and 2013, their estimate of price declines was 44% per year. They argue that the difference is primarily due to the lack of hedonic quality adjustment in the PPI. Partially in response to the publication of Byrne et al. (2018), the BLS has adopted hedonic quality adjustments in their PPI for semiconductors.[4] Byrne (2015) argues that BLS PPI may understate price declines in data storage equipment, potentially because of unmeasured increases in storage *within* a product's life cycle. Our contribution is to apply consumer price indices—which, to be sure, face challenges in measurement and interpretation—to learn about biases in producer price indices (and, in turn, gross output deflators). Unlike studies like Byrne (2015) or Byrne et al.

[4]Over this period, Intel, the primary supplier of chips, would keep the price of their existing products flat, introducing newer products at lower (quality-adjusted) prices. The matched-model methodology that the BLS was adopting at the time missed any of the overall reduction in prices due to the introduction of new chips. (Essentially, this methodology employs only price changes of existing products— or pairs of products that are close enough substitutes.) Of course, the "true" decline in prices will depend on how one adjusts for quality. Byrne et al. (2018) use semiconductor performance benchmarks as the main characteristic of chip quality. While adopting Byrne et al.'s (2018) general framework, BLS economists Sawyer and So (2018) include more product characteristics in their identification of chip quality and find a much more modest rate of price declines.

(2018), we seek to provide comprehensive economy-wide measures of these biases.[5]

1 We Combine Standard Data Sources from the BEA and BLS

We employ data collected by the Bureau of Labor Statistics and the Bureau of Economic Analysis.

Data on industry productivity come from the BEA/BLS Integrated Industry-Level Production Accounts. From this dataset, we take the data series on TFP and sectoral output.[6] We use the sectoral output data as weights to compute weighted averages of industries' productivity growth rates. These data begin in 1987.[7]

We use these the BEA Input-Output Accounts data to measure (i) the composition of PCE of different commodities, (ii) the use of different commodities by each industry, (iii) imports of different commodities for PCE, and (iv) the use of different imported commodities by each industry. We use the 71-industry summary tables, which begin in 1997, as well as the 402-industry detail tables, which cover 2007, 2012, and 2017.[8] In Appendix B, we discuss how we combine detail and summary tables to construct estimates of commodity-to-industry linkages for each year at the more detailed 402-industry level.

We consider three sets of price indices:

The BEA PCE price indices come from National Income and Product Accounts (NIPA) Table 2.4.4 (which cover 113 commodities) and NIPA Table 2.4.4U (which contain price indices at a finer level of disaggregation, with 368 commodities). We use NIPA Tables 2.4.5 and 2.4.5U— information on expenditures by commodity—to assign weights when computing weighted averages of inflation across categories.[9]

In addition to the PCE price index (which measures inflation from the consumer's perspective), we employ industry gross output deflators and import price indices (which measure inflation from the producer's perspective). The gross output deflator, constructed by the BEA, measures changes in the price of industries' (domestically produced) output.[10] We employ two versions of this dataset. The first is at the same 71-industry level of aggregation as the BEA

[5] Also with an aggregate focus, Houseman et al. (2011) argue that an "offshoring bias" may lead official statistics to overstate manufacturing productivity growth. In the 1990s and 2000s, U.S. manufacturers substituted away from (relatively expensive) domestically sourced intermediate inputs to (relatively inexpensive) imported intermediate inputs. This substitution is not picked up in conventional input price indices, leading one to understate real purchases of the inputs that manufacturers use and, in turn, overstate productivity growth. In practice, Houseman et al. (2011) argue that this bias is on the order of 0.1 to 0.2 percentage point per year and is concentrated in the Computer and Electronic Products industry.

[6] Throughout this paper, we focus on TFP as opposed to labor productivity or other possible productivity measures. This choice is motivated by the fact that an industry's TFP—at least when compared to labor productivity—is more closely linked to its marginal cost of production and, as a result, its output price.

[7] See `https://www.bls.gov/productivity/` .

[8] See `https://www.bea.gov/industry/input-output-accounts-data` .

[9] See `https://apps.bea.gov/iTable/?reqid=19&step=2&isuri=1&categories=survey` and `https://apps.bea.gov/iTable/?reqid=19&step=2&isuri=1&categories=underlying`.

[10] See `https://www.bea.gov/data/industries/gross-output-by-industry` .

Summary Input-Output Tables. The second is at a finer level of detail, with 414 industries. Both versions contain data beginning in 1997. We use the BLS Import Price Index to measure changes in the price of imported commodities. Their dataset measures price changes using various industry and commodity categorizations. To provide the cleanest match to other data series used in this paper, we apply the version of the dataset that measures inflation by North American Industry Classification (NAICS) commodity. These data begin in 2006 and cover nearly all commodities produced by the manufacturing sector but only a handful of nonmanufactured products.

Finally, we use the PCE Bridge, which in principle allows one to "bridge" the consumer and producer perspectives on commodities' price changes. For each component of the PCE price index, the PCE Bridge lists the contribution of individual commodities, the latter of which are measured using the NAICS. The table lists, as well, the contribution of the transportation, wholesale, and retail sectors to the value of each PCE category.

2 A Handful of Industries are Responsible for Nearly All of the Manufacturing Sector's TFP Trajectory

In this section, we argue that essentially all of the (a) gains in manufacturing productivity since 1987 and (b) deceleration in productivity growth since 2009 is due to a single 3-digit manufacturing industry: Computer and Electronic Products Manufacturing.

To make this point, consider the following equation linking productivity growth in the manufacturing sector ($\Delta \log A_{t,M}$) to productivity growth in each of the constituent industries within the sector ($\Delta \log A_{t,j}$):

$$\Delta \log A_{t,M} = \sum_j \omega_{tj} \Delta \log A_{t,j},$$

where the summation is over all industries within the manufacturing sector and ω_{tj} denotes the industry j's share of manufacturing sectoral output as of time t.

Figure 1 plots the average $\Delta \log A_{t,j}$ for each manufacturing industry j for each of three subperiods within the 1987 to 2023 sample. The outlier industry is the Computer and Electronic Products Manufacturing industry (NAICS=334). TFP grew at a 8.3% annual rate in the first decade of the sample, from 1987 to 1997. It then decelerated, modestly, to a 7.4% clip between 1997 and 2009. Since 2009, TFP growth has slowed to 1.1%. So, while productivity in the Computer and Electronic Products Manufacturing industry is still above average, it has slowed considerably compared to prior decades.

Figure 2 plots the share of manufacturing sectoral output for the Computer and Electronic Products industry. From 1987 to 2000, this industry's share of the manufacturing industry rose from 9% to 12%. It has since fallen steadily to 6% as of 2023. A lower weight assigned to

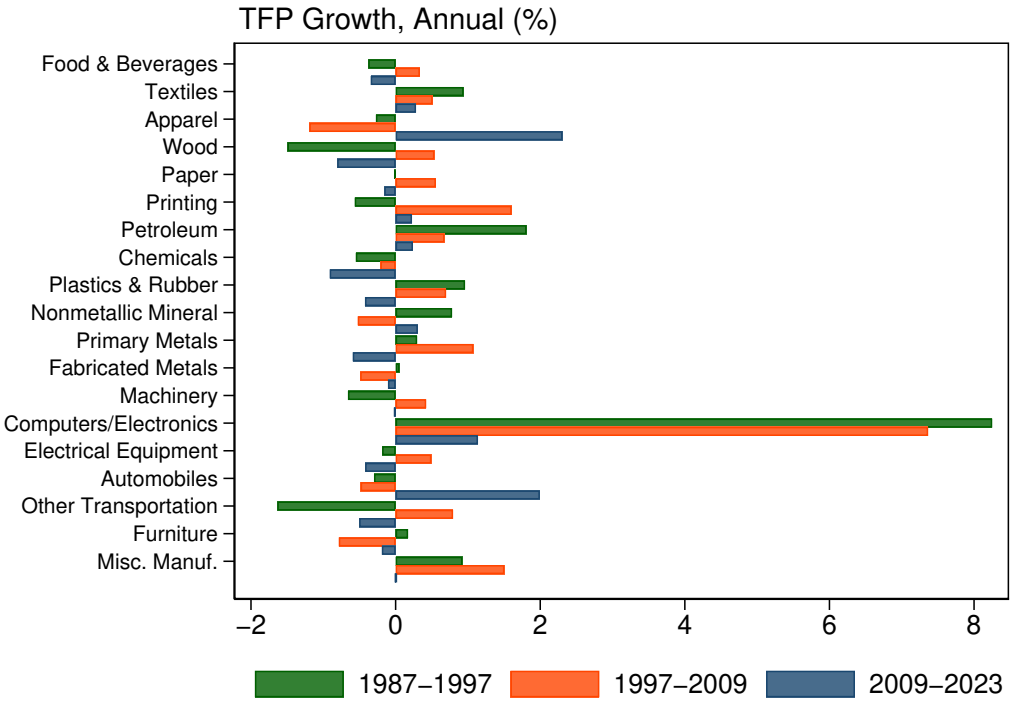


Figure 1: Annual TFP Growth Rate by 3-digit Manufacturing Industry

this still relatively fast-growing industry accounts for an additional portion of the slowdown in manufacturing productivity.

The evolution of productivity growth and size of the Computer and Electronic Products industry explains nearly 100% of the trajectory of manufacturing productivity since the late 1980s. To make this point, we plot (in Figure 3) the cumulative contribution to manufacturing productivity growth for all industries other than Computer and Electronic Products Manufacturing. This variable is defined as the cumulative total of

$$\Delta \log A^{c}_{t,M} \quad = \sum_{j \neq \text{Computers and Electronic Products}} \omega_{tj} \Delta \log A_{t,j},$$

from the beginning of the sample to year t. In addition, Figure 3 plots TFP growth in the manufacturing sector (relative to 1987) as well as TFP growth in the private business sector (which is essentially the entire economy less the government sector).

Two patterns stand out within this figure. First, between 1987 and the late 2000s TFP growth was faster in manufacturing than in the rest of the economy. In the 2010s, manufacturing productivity was flat while TFP for the broader private business sector grew by more than 7%. Second, a single 3-digit industry—Computer and Electronic Products Manufactur-

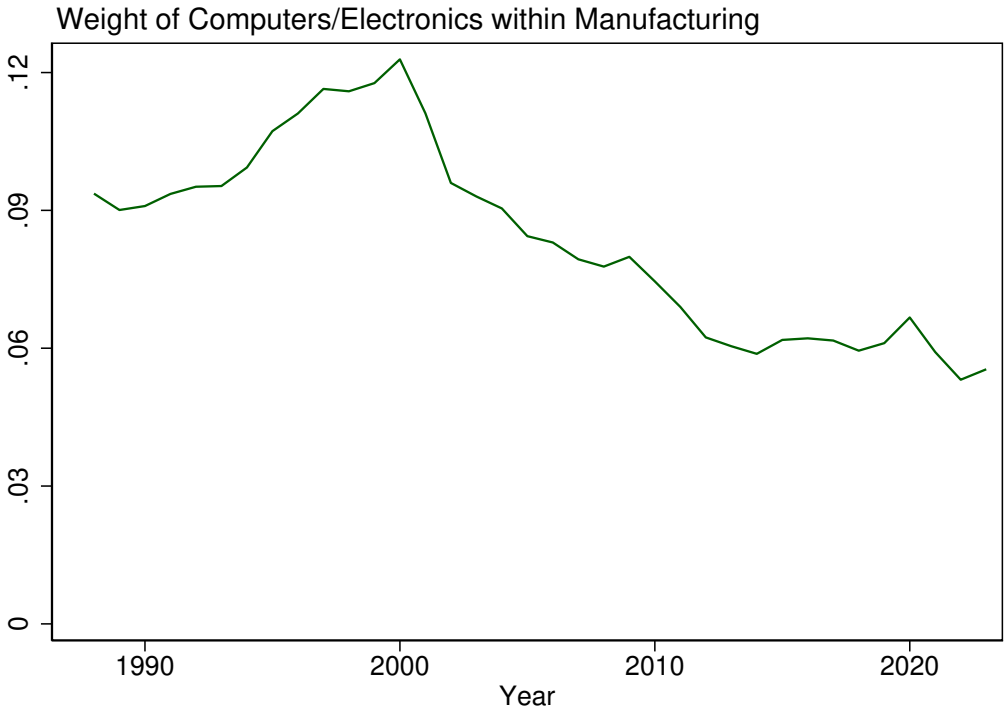


Figure 2: Share of Sectoral Output of NAICS 334 within Manufacturing

ing—accounts for nearly all of the manufacturing sector's productivity growth between 1987 and 2009.

3 For Computers and Electronic Goods, Producer and Import Price Indices Suggest Less Quality Growth than do Consumer Price Indices

In this section, we relate industry gross output deflators to components of the PCE price index. In considering differences in inflation trajectories between the two price indices, there are (at least) three differences to be mindful of in what each index is attempting to measure:

- First, each commodity entering the PCE price index may reflect the output of multiple industries. For instance, consider the PCE category "Video Cassettes and Discs, Blank and Prerecorded." This reflects a combination of two NAICS commodities—Manufacturing and Reproducing Magnetic Optical Media (NAICS 334610) and Motion Picture and Video Industries (NAICS 512100).

- Second, the PCE price index reflects not only changes in the costs of producing each commodity, buy also changes in distribution costs paid to transport, wholesale, and retail that commodity. The gross output deflator only captures changes to the prices paid to the producing industry.

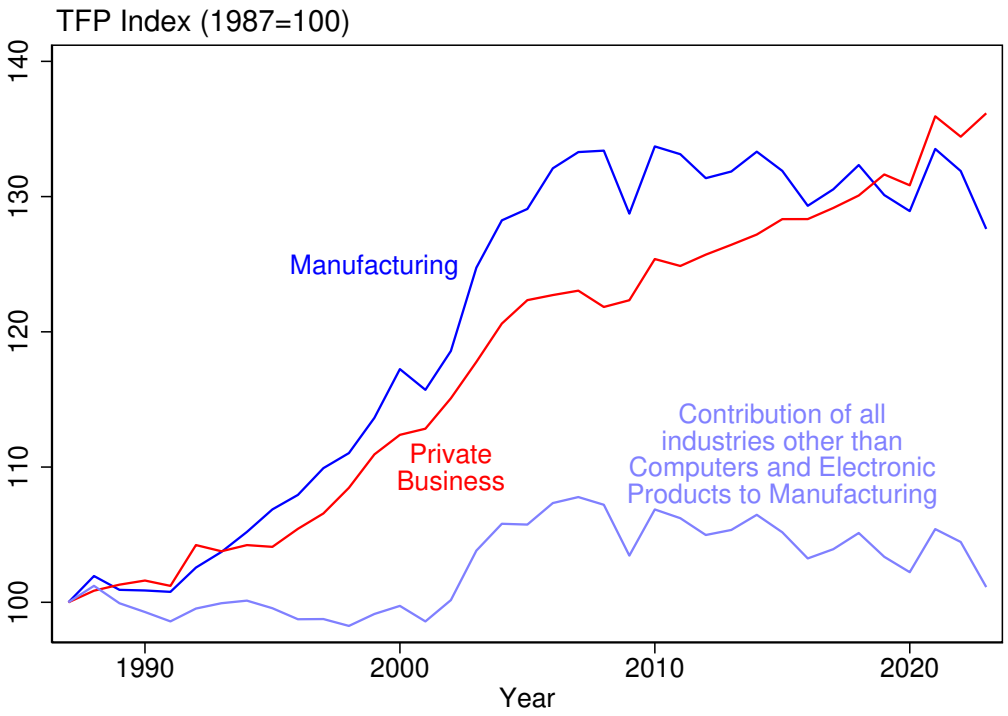


Figure 3: TFP for Manufacturing, Manufacturing excluding Computer and Electronic Products, and the Private Business Sector

- Finally, the gross output deflator reflects goods and services produced in the United States, while the consumption categories measured within the PCE price index are produced both domestically and abroad.

Beyond these differences in what the two sets of deflators are attempting to measure, another distinction lies in how the statistical agencies that produce these deflators deal with quality improvements and the introduction of new goods and services. In principle, both output price indices (e.g., the PPI or BEA industry gross output deflators) and consumer price indices (e.g., the CPI or the PCE price indices) should measure price changes for a fixed-quality basket of goods and services. But the methodology with which statistical agencies measure quality improvements over time varies across the different price indices they produce. Compare, for instance, how the BLS applies "hedonic quality adjustment" when producing the PPI and CPI. Quoting from the BLS Q&A website for the consumer price index:

> *"Hedonic quality adjustment refers to a method of adjusting prices whenever the characteristics of the products included in the CPI change due to innovation or the introduction of completely new products."*

In this method, for a given product category, researchers at the BLS determine the set of characteristics that are relevant for consumers. They then apply a regression model to esti-

mate consumers' valuation for these characteristics. For instance, in considering consumers' valuation for different televisions, BLS researchers estimate the relationship between the price of different televisions and the inclusion of various features—screen size, display type, whether the TV has a built-in DVD player, whether the TV has picture-in-picture—and so on. This procedure allows the BLS to consider the counterfactual price of a product even in periods before it was introduced to the market.[11]

The BLS applies this hedonic quality adjustment to multiple CPI product categories—in various apparel, electronics, and housing categories—but in only three narrow PPI product categories: computers (NAICS 334111), microprocessors (NAICS 334413), and broadband internet access (517311) with the latter two only introduced in 2016 and 2018 (Sawyer and So, 2018). To be clear, hedonic quality adjustment is just one of the potential methods by which it attempts to control for quality changes over time. The point is that—for the same type of product—the methods differ across producer and consumer price indices.[12]

Do these methodological differences matter? To begin answering this question, in Figure 4 we compare price changes for a single commodity: Telephone Apparatuses. For each year between 2005 and 2023, the vertical axis plots the change in prices according to the PCE price index. (Here, we choose 2005 as this is the first year with import price data for NAICS commodities.) Over this 18-year period, the average price change was -14.9% per year. On the horizontal axis, we present the gross output deflator (orange filled circles with the year listed) and the import price index (blue hollow circles without the year). According to the BEA Gross Output Deflator for Broadcast and Wireless Communications Equipment Manufacturing (NAICS 33422), prices fell by 8.4% per year. (According to the PCE bridge, this NAICS commodity comprises approximately 90% of the Telephone Apparatus PCE category. Telephone Apparatuses—NAICS 33421—account for the remaining 10%.) The import price index for the broader Communications Equipment Manufacturing (NAICS 3342) fell by 1.6% per year.[13] At least for this one product category, price declines are much greater from the perspective of a consumer than that of a producer.

In Figure 5, we expand the scope of analysis beyond telephone equipment. For each PCE category, the vertical axis gives the average annual price growth between 2005 and 2023. The horizontal axis gives our attempt at recreating the corresponding measure of inflation but using gross output deflators and import price indices. As the Telephone Apparatus example

[11] See `https://www.bls.gov/cpi/quality-adjustment/questions-and-answers.htm` .

[12] Another difference between the PPI and CPI is that the CPI applies a geometric mean formula when combining price changes of individual products within a product category whereas the PPI applies a Laspeyres formula (an arithmetic mean.) Directly before introducing this change, in 1999, BLS economists Dalton et al. (1998) estimated that this change would reduce aggregate CPI inflation by 0.2 percentage points per year.

[13] It is plausible that the prices of imported communications equipment other than broadcast and wireless communications equipment —primarily radio and television broadcasting equipment—grew more slowly. To the extent that this is the case, prices for imported broadcast and wireless communications equipment would display greater price declines than what the green circles within Figure 4 indicate. In future versions of the paper, we will try to account for these differences.

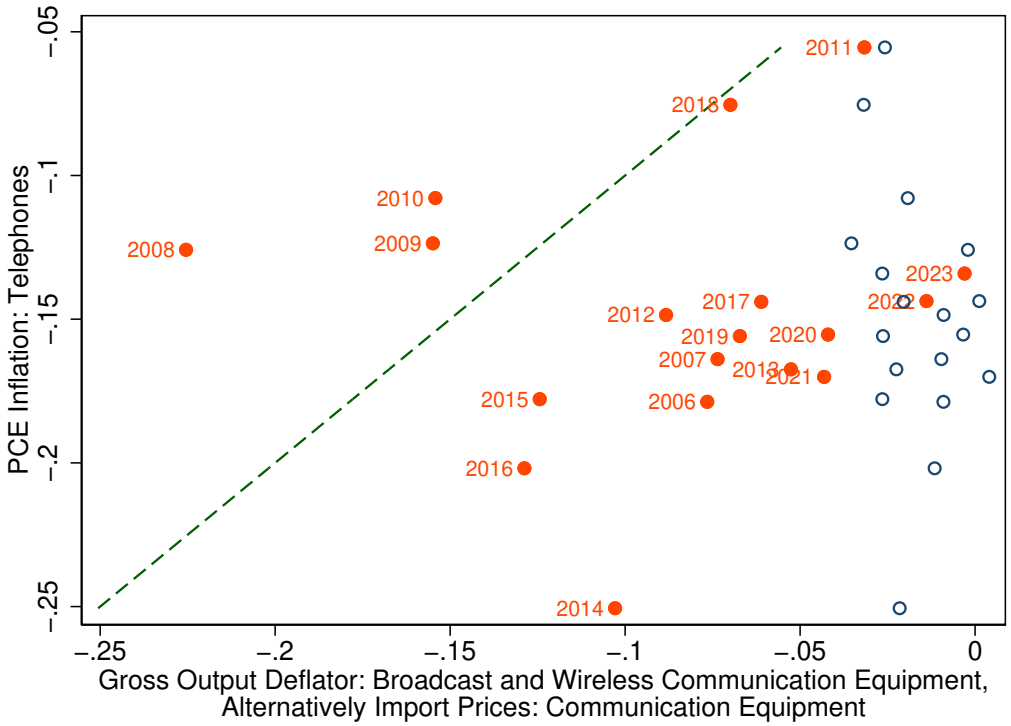


Figure 4: Telephone Apparatus Inflation

Notes: The vertical axis gives Telephone Apparatus inflation according to the PCE price index. The horizontal axis gives two measures of producer inflation. In orange filled circles, we plot changes in the gross output deflator for the Broadcast and Wireless Communications Equipment Manufacturing industry (NAICS 33422). For this data series, we write out the corresponding year as well. The listed year, t, refers to the price growth between years $t-1$ and t (e.g., the point for 2014 refers to price growth between 2013 and 2014). The import price index for the broader Communications Equipment Manufacturing industry (NAICS 3342) is plotted using hollow blue circles without listing the year.

indicates, each PCE category may comprise multiple distinct commodities, and each commodity may be produced domestically or imported. We use the PCE Bridge to assign weights to each commodity, and the Input-Output Tables to assign weights for domestic production vs. imports. Written out explicitly, we use the term "Producer Inflation" to refer to this weighted average of deflators:

$$\Delta \log P_{t,c}^{\text{Producer}} = \sum_j s_{t,j\to c} \left[(1 - m_{t,j})\, \Delta \log P_{t,j}^{\text{GO}} + m_{t,j} \Delta \log P_{t,j}^{\text{Import}} \right], \tag{1}$$

where c indexes a PCE category, j a NAICS commodity, $s_{j\to c}$ gives the share of PCE category c that is made up of commodity j, and $m_{t,j}$ equals the share of personal consumption expenditures of commodity j that comes from imports. For each category, we use the finest level of commodity detail that is available. In some instances—as in the example of the Telephone Apparatuses category, for instance—the level of aggregation is coarser in the import price

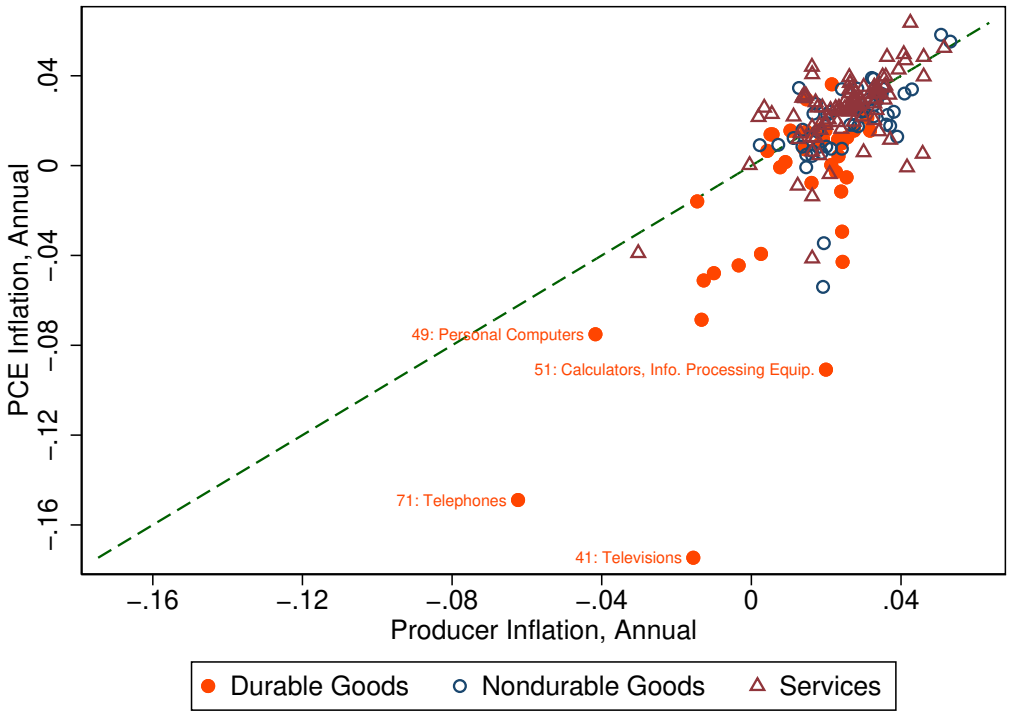


Figure 5: Two Measures of Inflation Across PCE Categories, 2005–2023

Notes: Each point is a single PCE category. The vertical axis gives annual inflation according to the PCE price index between 2005 and 2023. The horizontal axis gives our measure of Producer Inflation (defined by Equation 1) over the same period.

index than in the BEA industry gross output deflator.

For the most part, looking across PCE categories and averaging over the 2005–2023 sample, PCE inflation is highly correlated to changes in $\Delta \log P_t^{\text{Producer}}$. The (consumption-weighted) correlation across the two measures is 0.66. Our Producer Inflation measure exceeds PCE by 0.6 percentage point overall, but with much larger gaps in nondurable goods (where the gap is 1.1 percentage points) and durable goods (with a 2.6 percentage point gap.) The difference in inflation rates is exceptionally high for computers and other electronic products. An extreme but instructive example is the Television category. Inflation in televisions averages -17.5% per year between 2005 and 2023 according to the CPI or PCE. The gross output deflator for the more aggregated Audio and Video Manufacturing industry (NAICS 3343) is -0.5% per year. Inflation according to the import price index is -2.9% per year. Given that nearly half (48%) of Audio and Video Manufactured Products that enter personal consumption expenditures are imported, the -0.5% and the -2.9% average out to a -1.6% Producer Inflation rate. Some of the difference between the -17.5% PCE inflation and -1.6% Producer Inflation likely reflects the inclusion of Audio Equipment and Other Video Equipment in our Producer Inflation measure. However, PCE inflation for these other categories were also exceptionally low, -4.8% for Audio

Equipment and -6.9% for Other Video Equipment. So, for Televisions and Other Audio and Video Equipment, PCE deflation is vastly greater than deflation according to price indices from the producer perspective.

Our preferred interpretation of these patterns is that output price indices—like the BEA's gross output deflator —insufficiently account for quality improvements in high-tech products. As a result, growth in real output and productivity growth in these industries may be understated. Even if gross output deflators overstate durable goods inflation by 2.6 percentage points, we do not believe that TFP growth is understated by this amount. After all, similar considerations would imply that durable goods input price growth is understated. Accounting for this would partially offset the 2.6 percentage point gap that we have highlighted. In the next section, using the BEA's input-output tables we estimate the extent to which TFP growth may be overstated for goods-manufacturing industries.

4 Annual TFP Growth in the Durable Goods Manufacturing May be Understated by Up to Two Percentage Points

In the final step of our analysis, we consider the implications of mismeasured gross output deflators for TFP growth. We apply the following accounting relationship between gross output prices, input prices, and TFP:

$$\begin{aligned}
\Delta \log A_{t,j} &= -\Delta \log P^{\text{GO}}_{t,j} + \Delta \log P^{\text{Input}}_{t,j} \qquad (2)\\
&= -\Delta \log P^{\text{GO}}_{t,j} + \gamma_{w\to j,t}\Delta \log w_{t,j} + \gamma_{r\to j,t}\Delta \log r_{t,j}\\
&\quad + \sum_{i=1}^{N} \gamma_{t,i\to j}\left[\left[(1-m_{t,i})\,\Delta \log P^{\text{GO}}_{t,i} + m_{t,i}\Delta \log P^{\text{Import}}_{t,i}\right]\right]\\
\Delta \log \mathbf{A}_t &= -\Delta \log \mathbf{P}^{\text{GO}}_t + \boldsymbol{\gamma}_{w,t}\Delta \log \mathbf{w}_t + \boldsymbol{\gamma}_{r,t}\Delta \log \mathbf{r}_t +\\
&\quad \boldsymbol{\Gamma}_{\mathbf{t}}\left[(1-\mathbf{m}_t)\circ \Delta \log \mathbf{P}^{\text{GO}}_t + \mathbf{m}_t \circ \Delta \log \mathbf{P}^{\text{Import}}_t\right].
\end{aligned}$$

According to this equation, industries are more productive when they are able to produce at lower cost given the price of the inputs that they use. The second line lists the components of changes in industry j's input price index: changes in the unit cost of labor, changes in the unit cost of capital, and changes in the cost of different commodities, i. The final line writes this equation in vector notation. Within this line, the "$\circ$" operator denotes element-wise multiplication.

Below, we use $\tilde{\mathbf{x}}$ to refer to mismeasurement in variable $\mathbf{x}$. Since our preceding analysis did not having anything to say about mismeasurement in unit labor costs or the rental price of capital, we omit expressions for $\Delta \log \tilde{\mathbf{r}}_t$ or $\Delta \log \tilde{\mathbf{w}}_t$. With this assumption, the log deviation of an observed variable from its "true" value. Equation 2 can be written as:

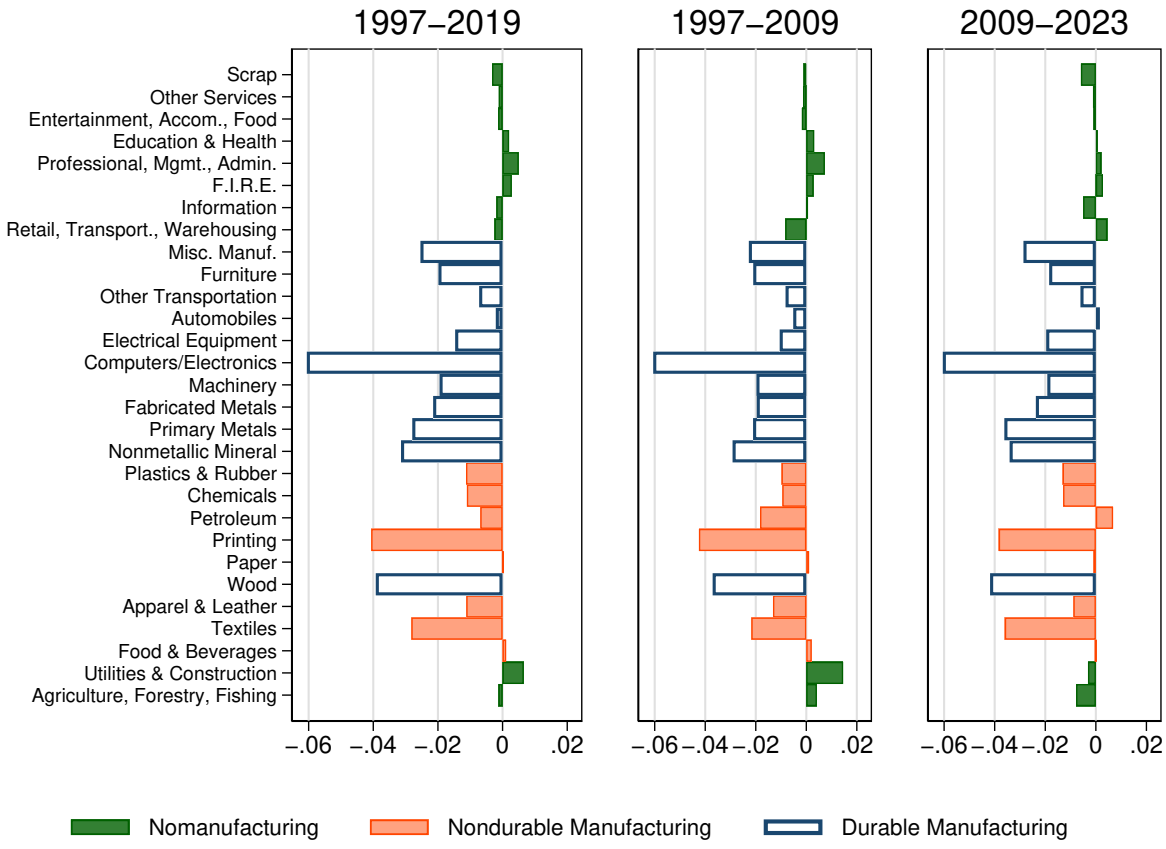


Figure 6: TFP Mismeasurement

Notes: We apply Equation 7 to recover the mismeasurement in TFP by industry (j) and year (t). We average these variables by broad sector and years, weighting industries according to their gross output within each year.

$$\Delta \log \widetilde{\mathbf{A}}_t = -\Delta \log \widetilde{\mathbf{P}}_t^{\text{GO}} + \mathbf{\Gamma_t} \left[(1 - \mathbf{m}_t) \circ \Delta \log \widetilde{\mathbf{P}}_t^{\text{GO}} + \mathbf{m}_t \circ \Delta \log \widetilde{\mathbf{P}}_t^{\text{Import}} \right] . \tag{3}$$

Our second building block comes from comparing Producer Inflation — defined in Section 3 — and PCE inflation. We consider any deviation between producer and consumer inflation as indicative of mismeasured import price indices or gross output deflators.[14]

$$\begin{aligned} \Delta \log P_{t,c}^{\text{PCE}} \quad = \quad & \sum_j s_{t,j \to c} \Big[(1 - m_{t,j}) \left(\Delta \log P_{t,j}^{\text{GO}} + \Delta \log \tilde{P}_{t,j}^{\text{GO}} \right) \\ & + m_{t,j} \left(\Delta \log P_{t,j}^{\text{Import}} + \Delta \log \tilde{P}_{t,j}^{\text{Import}} \right) \Big] . \end{aligned} \tag{4}$$

We write this equation in matrix form:

[14] In a future version of this paper, we will additionally consider the possibility that gaps between the two sets of variables may reflect changes in the costs of transporting, wholesaling, or retailing commodity j.

$$\begin{aligned}\Delta \log \mathbf{P}_t^{\text{PCE}} &= \mathbf{S_t}\left[(\mathbf{1}-\mathbf{m_t})\circ\left(\mathbf{\Delta}\log \mathbf{P_t^{GO}}+\mathbf{\Delta}\log \widetilde{\mathbf{P}}_\mathbf{t}^{\text{GO}}\right)\right. \\ &\quad \left.\mathbf{m}_t\circ\left(\Delta\log P_t^{\text{Import}}+\Delta\log\widetilde{\mathbf{P}}_t^{\text{Import}}\right)\right]\ . \end{aligned} \tag{5}$$

This implies that we can write mismeasurement in output deflators and import price indices as:

$$\begin{aligned}(1-\mathbf{m}_t)\circ\Delta\log\widetilde{\mathbf{P}}_t^{\text{GO}}+\mathbf{m}_t\circ\Delta\log\widetilde{\mathbf{P}}_t^{\text{Import}} &= \mathbf{O}_t\left[\Delta\log\mathbf{P}_t^{\text{PCE}}\right. \\ &\quad \left.-\mathbf{S}_t\left[(1-\mathbf{m}_t)\circ\Delta\log\mathbf{P}_t^{\text{GO}}+\mathbf{m}_t\circ\Delta\log\mathbf{P}_t^{\text{Import}}\right]\right]\ . \end{aligned} \tag{6}$$

Above, the $\mathbf{O}_t$ is a matrix which transforms mismeasurement in "consumption category" space to "NAICS commodity" space.

If we assume that mismeasurement in the gross output is equal to mismeasurement in the import price index, we can combine Equations 3 and 6 to infer mismeasurement in productivity:

$$\begin{aligned}\Delta\log\widetilde{\mathbf{A}}_t &= -\left[\mathbf{I}-\mathbf{\Gamma_t}\right]\mathbf{O}_t\left[\Delta\log\mathbf{P}_t^{\text{PCE}}\right. \\ &\quad \left.-\mathbf{S}_t\left[(1-\mathbf{m}_t)\circ\Delta\log\mathbf{P}_t^{\text{GO}}+\mathbf{m}_t\circ\Delta\log\mathbf{P}_t^{\text{Import}}\right]\right]\ . \end{aligned} \tag{7}$$

We apply Equation 7 using data from 1997 to 2023. We highlight three main results. First, within the durable goods manufacturing industry, TFP is most mismeasured for the Computer and Electronic products industry, by roughly 6 percentage points per year. Second, looking across sectors, TFP mismeasurement is greatest in durable goods manufacturing sector (at 2.2 percentage points per year), smaller in nondurable goods manufacturing sector (at 0.6 percentage points per year), and essentially nonexistent in the nonmanufacturing sector (at -0.1 percentage points per year.) Finally, the mismeasurement of TFP growth has stayed roughly constant over the sample period.[15]

Adding our estimates of TFP mismeasurement in Figure 6 to observed TFP growth rates in Figure 1, we find that "true" TFP growth in the manufacturing sector has not fallen below that of the rest of the economy, even into the 2010s (even if this growth rate is appreciably slower than in early decades). Our estimates imply that true TFP growth in the manufacturing sector was 0.8%, annually, between 2009 and 2023—2.5% in durable goods manufacturing industries and 0.1% in nondurable goods manufacturing industries. This equals the 0.8% TFP growth

[15]For the durable goods sector, the average of $\Delta\log\widetilde{\mathbf{A}}_t$ was -2.2 percentage points in both halves of the sample. For nondurable goods, $\Delta\log\widetilde{\mathbf{A}}_t$ was (on average) -0.7 percentage points between 1997 and 2009 and -0.4 percentage points between 2009 and 2023. For the nonmanufacturing sector, the average of $\Delta\log\widetilde{\mathbf{A}}_t$ was 0.2 percentage points between 1997 and 2009 and 0.0 between 2009 and 2023.

rate for the private economy as a whole.

5 Conclusion

In contrast to decades prior, beginning in the late 2000s manufacturing productivity growth started to fall behind productivity growth elsewhere. This article investigates the sources of this pattern from two angles. In the first half of the article, we show that these trends can largely be accounted for by the resolution of the ICT revolution. Between 1987 and 2009, total factor productivity in Computer Manufacturing grew by an astronomical 15% per year. Semiconductor Manufacturing productivity grew by more than 11% per year. By the early 2010s, productivity growth in these industries had decelerated substantially. Were it not for the Computer and Electronic Products Manufacturing industry, productivity growth in the manufacturing sector would have been measured to be sluggish throughout the late 1980s, the 1990s, and the 2000s.

We then marshal suggestive evidence that quality improvements and, by implication, productivity growth may be substantially underestimated in durable goods manufacturing, primarily so in the manufacturing of computers and other electronic goods. We estimate that annual TFP growth in durable goods manufacturing may be understated by up to 2.2 percentage points and by 0.6 percentage points in nondurable goods manufacturing industries.

In interpreting these results, we sound a point of caution. Our "dual" approach to inferring quality growth mismeasurement is, by its nature, indirect: Rather than applying more comprehensive measures of product characteristics, we infer quality growth from discrepancies across price indices. We use household price indices—in particular the PCE—as a benchmark against which to infer quality mismeasurement. It's entirely conceivable that published producer price indices (and hence gross output deflators) provide the correct measure of real output growth and that consumer price indices *overstate* quality improvements in computers and other electronic goods. While possible, such a scenario would conflict with economists' general presumption on the direction of quality biases. It would also run counter to the conclusions of the few studies which have detailed micro data on product characteristics and prices to measure biases in producer price indices (e.g., Byrne, 2015; Byrne et al., 2018.)

The U.S. manufacturing sector has changed profoundly over the last three decades. It has become more reliant on imported intermediate inputs, first from China and then from Vietnam and Mexico (Alfaro and Chor, 2023). Its production has become more capital intensive,[16] more robot intensive (see Figure 5 of Jurkat et al., 2021). Assessments of these particular changes—and on the evolution of the manufacturing sector, more generally—hinge on properly measuring manufacturing real output and productivity. If quality improvements (and, hence, TFP) in goods manufacturing are understated, as our findings suggest, then conventional data sources may distort our understanding of the forces reshaping the manufacturing sector.

[16] See `https://fred.stlouisfed.org/series/MPU9900082` .

References

Alfaro, L. and D. Chor (2023): "Global Supply Chains: The Looming 'Great Reallocation'," Tech. rep., National Bureau of Economic Research.

Autor, D., D. Dorn, G. H. Hanson, G. Pisano, and P. Shu (2020): "Foreign Competition and Domestic Innovation: Evidence from US Patents," *American Economic Review: Insights*, 2, 357–74.

Brynjolfsson, E., A. Collis, W. E. Diewert, and K. J. Fox (2025): "GDP-B: Accounting for the Value of New and Free Goods in the Digital Economy," *American Economic Journal: Macroeconomics*, forthcoming.

Bureau of Economic Analysis (2024): "NIPA Handbook: Concepts and Methods of the U.S. National Income and Product Accounts," .

Byrne, D. M. (2015): "Prices for Data Storage Equipment and the State of IT Innovation," .

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*, 2016, 109–182.

Byrne, D. M., S. D. Oliner, and D. E. Sichel (2018): "How Fast are Semiconductor Prices Falling?" *Review of Income and Wealth*, 64, 679–702.

Dalton, K. V., J. S. Greenlees, and K. J. Stewart (1998): "Incorporating A Geometric Mean Formula into the CPI," *BLS Monthly Labor Review*, 3–7.

Duarte, M. and D. Restuccia (2010): "The Role of Structural Transformation in Aggregate Productivity," *Quarterly Journal of Economics*, 125, 129–173.

Fort, T. C., W. Keller, P. K. Schott, S. Yeaple, and N. Zolas (2020): "Colocation of Production and Innovation: Evidence from the United States," .

Groshen, E. L., B. C. Moyer, A. M. Aizcorbe, R. Bradley, and D. M. Friedman (2017): "How Government Statistics Adjust for Potential Biases from Quality Change and New Goods in an Age of Digital Technologies: A View from the Trenches," *Journal of Economic Perspectives*, 31, 187–210.

Herrendorf, B., C. Herrington, and A. Valentinyi (2015): "Sectoral Technology and Structural Transformation," *American Economic Journal: Macroeconomics*, 7, 104–133.

Houseman, S., C. Kurz, P. Lengermann, and B. Mandel (2011): "Offshoring Bias in U.S. Manufacturing," *Journal of Economic Perspectives*, 25, 111–132.

Jurkat, A., R. Klump, and F. Schneider (2021): "Tracking the Rise of Robots: A Survey of the IFR Database and Its Applications," .

Lashkari, D. and J. Pearce (2024): "The Mysterious Slowdown in US Manufacturing Productivity," Liberty Street Economics 20240711, Federal Reserve Bank of New York.

——— (2025): "The R&D Puzzle in US Manufacturing Productivity Growth," Liberty Street Economics 20250106, Federal Reserve Bank of New York.

Moulton, B. (2018): "The Measurement of Output, Prices, and Productivity: What's Changed Since the Boskin Commission?" .

Sawyer, S. D. and A. So (2018): "A New Approach for Quality-Adjusting PPI Microprocessors," *BLS Monthly Labor Review*, 1–15.

Sprague, S. (2021): "The U.S. Productivity Slowdown: An Economy-wide and Industry-level Analysis," *BLS Monthly Labor Review*, 1–45.

Syverson, C. (2016): "The Slowdown in Manufacturing Productivity Growth," Brookings Briefs.

——— (2017): "Challenges to Mismeasurement Explanations for the US Productivity Slowdown," *Journal of Economic Perspectives*, 31, 165–86.

A Discussion of Underlying Source Data and Quality Adjustment

In this appendix, we discuss the sources of inflation data, both from the household and consumer perspectives. We first discuss the data sources that the BEA draws on when constructing the individual components of the PCE price index. We then discuss the data sources that the BEA draws on when constructing its industry gross output deflators. Each BEA dataset draws on multiple sources, and the data sources employed have changed somewhat since 1997. However, the PCE price index for goods almost has (throughout the sample period) drawn on the CPI. Goods output deflators (also throughout the sample period) are derived from the PPI.

In the final subsection of the appendix, we discuss changes in the methodology that the BLS has employed to produce its PPI and CPI. The two most important changes were (a) a steady expansion in the set of commodities covered in the PPI. But this expansion in scope is concentrated in services; (b) an increase in the number of commodities for which the BLS applied a hedonic adjustment. For both price indices, these increases occurred either in the 1990s or the late 2010s and early 2020s.

An implication of this discussion is that, since most methodological changes occurred in the service sector (or for service consumption categories) or took place before the early 2000s or beginning in the early 2010s, they are unlikely to explain the deceleration in measured manufacturing productivity that occurred in the late 2000s.

Components of the PCE Price Index

For goods commodities, components of the PCE price index draw almost exclusively on the CPI. The three exceptions include Food produced and consumed on farms (which draws on USDA prices received by farmers); Standard Clothing Issued to military personnel (which draws on the PPI line for Apparel); and Expenditures on goods by U.S. residents who are abroad (which draw no the BEA index for installation support services. For service commodities, while the CPI is the primary data source for many components of the PCE price index, a larger set of components draw on the PPI (examples include most financial service charges and fees; air transportation; hospitals; and physician services) and BEA input cost indices (examples include labor organization dues; life insurance; financial services furnished without payment; among others).

Gross Output Deflators

The industry gross output deflators draw on a mix of data from the PPI, CPI, and other sources. For manufacturing industries, the BEA relies primarily on the PPI to construct its gross output deflators (Bureau of Economic Analysis, 2024, p. 4-25). There are two sets of exceptions. First, for military equipment, the BEA applies price indices from the Department of Defense ("prices paid for military equipment"). Second, the BEA employs quality-adjusted

price indices for computers, photocopying equipment, digital telephone switching equipment, and LAN equipment. Some of these quality-adjusted price indices draw on the BLS PPI. In other cases, where quality adjustment has not been available, the BEA has constructed its own (Bureau of Economic Analysis, 2024, Chapter 4, Page 25). For service industries, the BEA gross output deflators draw on a wider variety of sources.

Year	2004	2010	2018
Agriculture, Forestry, Fishing, and Hunting (11)	———	———	———
Farms (111, 112)	USDA prices received by farmers; PPI	USDA prices received by farmers; PPI	NIPA prices based on USDA price indexes
Forestry, Fishing, and Related Activities (113, 114)	PPI; NOAA; NIPA deflator.	USDA; PPI; NIPA PCE; for fisheries for aquaculture, NOAA	PPI, NIPA PCE, USDA National Agricultural Statistics Service unit prices
Mining (21)	———	———	———
Oil and Gas Extraction (211)	For crude petroleum and natural gas, IPD from DOE; for natural gas liquids, PPI	PPI; EIA	PPI and EIA
Mining, Except Oil and Gas (212)	IPD from DOE and USGS.	EIA, USGS, and PPI	EIA, USGS, and PPI
Support Activities for Mining (213)	IPD from DOE, USGS and trade sources; for exploration, PPI	EIA, USGS, PPI, and trade sources	EIA, USGS, PPI, and trade sources
Utilities (22)	PPI for Electric Utilities and Natural Gas, CPI for Water, Sewage, and Other Systems	CPI and PPI; EIA	CPI and PPI
Construction (23)	———	———	———
Residential (2361)	Census Bureau price index for new single-family houses under construction; BEA price index for multifamily construction.	Census Bureau price deflator for new single-family houses under construction; NIPA price index for multifamily home construction.	Census Bureau price deflator for new single-family houses under construction and BEA prices for multifamily home construction

Year	2004	2010	2018
Nonresidential (2362, 237, 238)	———	NIPA composite price indexes based on cost per square foot; cost indexes from trade source data; for single family houses under construction, Census Bureau price deflator; PPI	PPI and BEA composite prices based on trade source data and on the Census Bureau price deflator for single-family houses under construction
For the Department of Defense	DOD prices for military construction; cost indexes from trade sources and government agencies for other construction.	———	———
For State and Local Highways (2373)	Cost indexes from government agencies	———	———
For Private Electric and Gas Utilities (2371)	Cost indexes from trade sources and government agencies	———	———
For Farms, Excluding Residential	Trade sources cost index; Census Bureau price deflator for new single family houses under construction	———	———
For Other Nonresidential	Trade sources and government agency cost indexes; Census Bureau price index for new single-family houses under construction; BEA quality-adjusted price indexes for factories, office buildings, warehouses, and schools	———	———

Year	2004	2010	2018
Manufacturing (31, 32, 33)	PPI; quality adjusted price indexes for computers, photocopying equipment, digital telephone switching equipment, and LAN equipment; BEA price indexes based on DOD prices paid for military equipment.	PPI; NIPA price indexes based on DOD prices paid for military equipment; NIPA hedonic price indexes.	PPI and NIPA prices based on DOD prices paid for military equipment, and NIPA hedonic prices
Wholesale Trade (42)	Sales price by kind-of-business computed from PPI	Census Bureau AWTR and MWTR data to derive margin rates; IRS Statistics of Income (SOI); NIPA sales prices and import prices; IRS SOI commodity taxes.	PPI and NIPA sales deflators
Retail Trade (44, 45)	Sales price by kind-of-business computed from CPI	PPI; NIPA retails sales prices; Census Bureau ARTS and MRTS; IRS SOI	PPI and NIPA sales deflators
Transportation and Warehousing (48, 49)	_____	_____	_____
Air Transportation (481)	IPD for total passenger-related revenues and passenger miles from DOT; IPD for total freight-, mail-, and express-related revenues and ton miles from DOT; wages and salaries per employee from BLS.	PPI; BTS prices.	PPI
Rail Transportation (482)	PPI	For rail passengers, CPI; for freight, PPI	PPI
Water Transportation (483)	PPI for freight; for passengers, CPI.	PPI and CPI; trade source data	For freight, PPI; for passenger, CPI

Year	2004	2010	2018
Truck Transportation (484)	PPI	PPI	PPI
Transit and Ground Passenger Transportation (485)	For taxicabs, intercity buses, and other local transit, PCE price index; for school buses, BLS data on wages and salaries per employee.	NIPA PCE; BLS QCEW.	NIPA PCE
Pipeline Transportation (486)	PPI	PPI	PPI
Other Transportation and Support Activities (488)	For sightseeing, PCE price index; for other transportation and support activities, PCE and PPI	NIPA PCE; PPI	PPI and NIPA PCE
Warehousing and Storage (493)	PPI	PPI	PPI
Information (51)	———	———	———
Publishing Industries, Except Internet (Includes Software) (511)	BEA price indexes for prepackaged and custom software for software publishers; for all other publishing industries, PPI	PPI	PPI and BEA price indexes for software
Motion Picture and Sound Recording Industries (512)	PCE	CPI; NIPA PCE	NIPA PCE
Broadcasting and Telecommunications (515, 517)	For cable networks, programming, and telecommunications, PPI; for radio and television broadcasting, network receipts, and all other telecommunications, composite price index of PPIs.	PPI; for radio and TV broadcasting, NIPA PCE based on PPI	PPI

Year	2004	2010	2018
Data processing, Internet Publishing, and Other Information Services (518, 519)	For information services, PCE; for data processing services, PPI	CPI and PPI; for publishing and broadcasting content on the Internet, NIPA PCE	PPI and NIPA PCE
Finance and Insurance (52)			
Federal Reserve Banks, Credit Intermediation, and Related Activities (521, 522)	PCE; other government data	For financial services, NIPA PCE based on BLS quantity output indexes for commercial banks and employee hours for other depository institutions; PPI and CPI	FRB-priced services and NIPA PCE
Securities, Commodity Contracts, and Investments (523)	PCE	PPI and CPI; NIPA PCE	PPI and NIPA PCE
Insurance Carriers and Related Activities (524)	For health and life insurance, PCE; for property and casualty insurance, PPI; for agents, brokers, and services, composite price index based on trade sources data and PCE	For life insurance, NIPA PCE data on input prices; for health insurance, quantity extrapolations of premiums and benefits deflated with PPI; for all other property and casualty insurance, PPI; for agents, brokers, and services, composite indexes based on trade source data and NIPA PCE	PPI and NIPA PCE

Year	2004	2010	2018
Funds, Trusts, and Other Financial Vehicles (525)	IPD from NIPA imputed service charges; composite price index based on PCE; PPI data; BLS data on wages and salaries per fulltime employee.	CPI; NIPA PCE	NIPA PCE
Real Estate and Rental and Leasing (53)	———	———	———
Real Estate (531, 532)	For nonfarm residential dwellings, NIPA price index; for nonresidential dwellings, PPI; for real estate managers and agents, PPI and trade sources; IPD for nonprofit and farm residential dwellings.	For residential dwellings, CPI; for nonresidential dwellings, PPI; for real estate managers and agents, PPI and trade source data.	For residential dwellings, NIPA PCE and NIPA implicit price deflators for farm rents paid; for nonresidential structures, PPI; for real estate managers and agents, PPI and trade source data
Rental and Leasing Services and Lessors of Intangible Assets (533)	For automotive equipment rental, PPI; for other rental services, PCE; for royalties, PCE price index and IPD from DOE and PPI	PPI	NIPA PCE and implicit price deflators, PPI, BTS, EIA crude oil receipts, and trade source data
Professional, Scientific, and Technical Services (54)	———	———	———
Legal Services (5411)	PPI	PPI	PPI and NIPA PCE
Computer Systems Design and Related Services (5415)	BEA price indexes for prepackaged and custom software.	NIPA price indexes for prepackaged, custom, and own-account software	BEA price indexes for software

Year	2004	2010	2018
Miscellaneous Professional, Scientific and Technical Services (5412, 5413, 5414, 5416, 5417, 5418, 5419)	PPI; BLS wages and salaries per full-time employee.	PPI and QCEW	PPI, NIPA PCE, and BEA price indexes for R&D
Management of Companies and Enterprises (55)	BLS wages and salaries per full-time employee	BLS QCEW	PPI
Administrative and Waste Management Services (56)	For administrative support: BLS wages and salaries per full- time employee; PCE; PPI For waste management: CPI	NIPA PCE based on CPI data; BLS QCEW; PPI	PPI and NIPA PCE
Educational Services (61)	PCE	NIPA PCE based on trade source data for input costs	NIPA PCE
Health Care and Social Assistance (62)	PPI; PCE	———	PPI and NIPA PCE
Ambulatory Health Care Services (621)	PPI; PCE	NIPA PCE based on CPI; PPI	———
Hospital and Nursing and Nursing Care Facilities (622, 623)	PCE	NIPA PCE based on CPI and Centers for Medicare and Medicaid Services	———
Social Assistance (624)	PCE	NIPA PCE based on trade source data on input costs	———
Arts, Entertainment, and Recreation (71)	PCE	NIPA PCE based on CPI.	NIPA PCE
Accommodation and Food Services (72)	———	———	———
Accommodation (721)	For hotels and motels, PPI; PCE price index.	PPI; NIPA PCE based on CPI	PPI and NIPA PCE

Year	2004	2010	2018
Food Services (722)	CPI	Census Bureau ARTS; PPI composite price index.	PPI
Other services, except government (81)	CPI; BLS data on wages and salaries per full-time employee; PCE	CPI; NIPA PCE based on CPI.	PPI and NIPA PCE
Government (92)	———	———	———
Federal	———	———	———
General Government	NIPA price indexes	NIPA price index based on PPI and CPI; for military facilities, DOD data on employment, prices for military construction; construction cost indexes from trade sources.	NIPA prices based on PPI and CPI; for military facilities, DOD data on employment, prices for military construction, and construction cost indexes from trade source data
Government Enterprises	For USPS and electric utilities, PPI; for all others, PCE price index and NIPA price indexes	PPI; NIPA PCE based on PPI and agency data	PPI
State and Local	———	———	———
General Government	NIPA price indexes	PPI; NIPA PCE based on CPI.	PPI and NIPA PCE
Government Enterprises	PPI	PPI	PPI

Notes: The acronyms mentioned within this table are as follows: ARTS: Annual Retail Trade Survey; AWTR: Annual Wholesale Trade Report; DOD: Department of Defense; DOE: Department of Energy; DOT: Department of Transportation; EIA: Energy Information Administration; FRB: Federal Reserve Board; IPD: Industrial Demonstrations Program; IRS SOI: IRS Statistics of Income; LAN: Local Area Network; MRTS: Monthly Retail Trade Survey; MWTR: Monthly Wholesale Trade Report; QCEW: Quarterly Census of Employment and Wages; USDA: United States Department of Agriculture; USGS: United States Geological Survey; USPS: US Postal Service. The sources for this table are Table D of `https://apps.bea.gov/scb/pdf/2004/03March/0304IndustryAcctsV3.pdf`, Table C of `https://apps.bea.gov/scb/pdf/2010/03`, and Table A of `https://apps.bea.gov/scb/issues/2018/08-august/pdf/0818-industry-tables.pdf`. In the first column, the numbers in parentheses give the applicable NAICS commodity code.

Expansion of the PPI; Incorporation of Hedonic Quality Adjustment to the CPI and PPI

Moulton (2018) summarizes changes to BLS consumer and producer price indices in the two decades following the Boskin commission.

Over this period, the producer price index increased the set of commodities in its sample. These changes include:

- In 1997: PPIs for home health care services; legal services; engineering services; and architectural services;
- In 1998: PPIs for prepackaged software; and property and casualty insurance were introduced;
- In 1999: PPIs for life insurance; wireless telecommunications; and physicians;
- In 2000: PPIs for grocery stores; meat and fish markets; fruit and vegetable markets; candy, nut, and confectionery markets; retail bakeries; miscellaneous food stores; and new car dealers;
- In 2001: PPIs for 17 retail industries (the largest being drug stores and proprietary stores); security brokers, dealers, and investment banking; and data processing services;
- In 2002: PPIs for additional retail industries (including gasoline service stations, boat dealers, and recreational vehicle dealers); and television broadcasting;
- In 2003: PPIs for investment advice; and insurance agencies and brokerages;
- In 2004: PPIs for the remaining retail industries; electric power generation; electric bulk power transmission and control; and direct health and medical insurance carriers;
- In 2005: PPIs for commercial banking; savings institutions; construction, mining, forestry machinery, and equipment rental and leasing; nonresidential building construction; wholesale trade; internet service providers; web search portals; security guards and patrol services; and fitness and recreational sports centers;
- In 2006: PPIs for nonresidential building construction for schools; amusement and theme parks; and golf courses and country clubs;
- In 2007: PPIs for nonresidential building construction for offices; management consulting services; blood and organ banks; computer training; commercial and industrial machinery and equipment (except automotive and electronic) repair and maintenance;
- In 2008: PPIs for nonresidential building construction for industrial buildings; and nonresidential building construction for contractors performing poured concrete, roofing, electrical, and plumbing/HVAC work;

- In 2010: PPIs for internet publishing and web search portals;
- In 2011: PPIs for dentists;
- In 2013: PPIs for nonresidential building construction for health care buildings;
- In 2014: PPIs for health care services by payer type; and
- In 2022: PPIs for pipeline transportation for natural gas.

The BLS applies a hedonic adjustment to a large set of commodities to the CPI.[17] In 1988, it began applying age-bias adjustment factors began in for housing. Beginning in 1992, the CPI applied hedonic adjustments to an increasing set of apparel categories: The first set of apparel categories were women's coats, women's suits, women's dresses, women's footwear, men's suits, men's shirts, men's pants, and men's footwear. In 1995, the BLS applied hedonic adjustment to women's tops, girl's tops, men's athletic footwear, and women's athletic footwear. In 1997, hedonic adjustment was added to women's outerwear. In 2004, boy's shirts and sweaters were added to the list of apparel categories with a hedonic adjustment. In 2023, men's underwear and women's bras were added. The remaining categories with a hedonic adjustment include personal computers and peripheral equipment (1998), televisions (1999), audio equipment (2000), other video equipment (2000), refrigerators and freezers (2000), washers and dryers (2000), microwaves (2000), washers and dryers (2000), educational books and supplies (2000), wireless telephone services (2017), smartphones (2018),[18] land-line telephone services (2019),[19] internet services (2019), and cable and satellite television (2019), watches (2022), ranges and cooktops (unknown date), and photographic equipment (unknown date).

By contrast, the PPI uses hedonic models for quality adjustment for computers (NAICS 334111), microprocessors (NAICS 334413), and broadband internet access (NAICS 517311). These were introduced in 1991,[20] late 2016,[21] and 2018,[22] respectively.

B Interpolation Methodology

Equation 1 links the two perspectives of price growth. In the right-hand side of Equation 1, we require (a) import shares for each commodity j and (b) the share of each consumption category

[17] See `https://www.bls.gov/cpi/quality-adjustment/` , the links therein, and `https://www.bls.gov/cpi/white-papers/hedonic-quality-adjustments-statistical-agency-perspective.pdf` .

[18] Smartphones belong to the "telephone, hardware, calculators, and other consumer information items" consumption category.

[19] See `https://www.bls.gov/advisory/tac/review-of-hedonic-price-adjustment-techniques-for-products-experiencing-rapid-and-complex-quality-change-11-20-2020.pdf`.

[20] See `https://fraser.stlouisfed.org/files/docs/publications/cpidr/cpi_199707.pdf`.

[21] See `https://www.bls.gov/ppi/quality-adjustment/ppi-introduces-hedonic-quality-adjustment-for-internet-access-indexes.htm`

[22] See Sawyer and So (2018).

c that comes from NAICS commodity j. Equation (1) applies detailed PCE categories and detailed NAICS commodities. Unfortunately, the "Detailed" data are present only in certain years—2007, 2012, and 2017— with more aggregated "Summary" data for other years between 1997 and 2017. We first discuss our estimates at producing $m_{t,j}$— the share of consumption expenditures of detailed commodity j that is imported in year t.

B.1 Import Interpolation Methodology

Crosswalk

There are 402 detailed import categories; use j to denote a detailed commodity. For these commodities we have data from 2007, 2012, and 2017 but no other years.

There are 73 summary import commodities categories; use φ to denote a summary category. Of the 73 of these summary commodities two are "scrap used and secondhand goods and non-comparable imports" and "rest-of-the-world adjustment"; we refer to the remaining 71 summary commodities as "normal". We have data on these commodities from 1997 to 2023.

Each detailed commodity j is part of exactly one aggregate commodity φ. We have constructed a mapping between each detailed commodity j and summary commodity φ by comparing the commodity codes and by checking that the sum of the import volumes of the detailed commodity values from 2017 matched the import volume of the aggregate commodity in 2017.

Interpolation

For $t \notin \{2007, 2012, 2017\}$, we estimate detailed categories' import shares based on the detailed data that was closest in time to the year being estimated.

- 1997-2006 is estimated using the detailed data from 2007;
- 2008-2011 is estimated using the data from 2007 and 2012;
- 2013-2016 is estimated using the detailed data from 2012 and 2017; and
- 2018-2023 is estimated using the detailed data from 2017.

1997-2006 and 2018-2023 If we had only one year of detailed data, we assume that the import proportion of the detailed category changed by the same amount as the import proportion of the aggregate commodity in the same time frame.

That is: PCE Bridge Imputation Methodology

$$m_{j,y+t} = m_{jy} \frac{m_{\varphi,y+t}}{m_{\varphi,y}} \ ,$$

where, m_{jy} is the import proportion of the detailed commodity in year y and $m_{\varphi,y}$ is the import share of the aggregate commodity in year y.

To find the data for 2018-2023, we used $y = 2017$ and $t \in \{1, 2, \ldots, 6\}$.

To find the data for 1997-2006, we used $y = 2007$ and $t \in \{-1, -2, \ldots, -10\}$.

2008-2011 and 2013-2016 Here, we explain the method used for 2008-2011. The equivalent method is used for 2013-2016.

If, as we assumed above, the import proportion of a detailed category changes by the same amount as the import proportion of its aggregate category in the same time frame, then it should be the case that

$$\frac{m_{j,2012}}{m_{j,2007}} = \frac{m_{\varphi,2012}}{m_{\varphi,2007}} \ .$$

Since we have the detailed data for 2007 and 2012, we can compare $\frac{m_{j,2012}}{m_{j,2007}}$ and $\frac{m_{\varphi,2012}}{m_{\varphi,2007}}$.

If they are not the same, then we assume that for each year since 2007, one-fifth of the divergence in amount of change happens that year. Thus, the estimation equation becomes

$$m_{j,2007+t} = m_{j,2007} \frac{m_{\varphi,2007+t}}{m_{\varphi,2007}} \left(\frac{m_{j,2012}}{m_{j,2007}} \frac{m_{\varphi,2007}}{m_{\varphi,2012}} \right)^{t/5}$$

for each $t \in \{1, ..., 4\}$.

This method fails if $m_{\varphi,2007}$, $m_{\varphi,2012}$, or $m_{j,2007}$ is zero.

In those cases we go through the following methods, in the given order, stopping at the first one that fits:

1. If $m_{\varphi,2007} = 0$, then functionally we don't have two import share ratios to compare anymore, so we go back to the one import share ratio method explained above, using the share ratio from 2012.

2. If both $m_{\varphi,2007}$ and $m_{\varphi,2012}$ are zero, then assume that every $m_{j,t}$ from 2008 to 2011 is zero.

3. If $m_{\varphi,2012} \neq 0$ and $m_{j,2007} = 0$ we know that the import proportions were calculated using import volumes (in millions) that were rounded to the nearest integer. So we assume that an import volume of zero has a true import value in $(0, 0.5)$. We set the detailed 2007 import volume to 0.25 to approximate this and recalculate the 2007 detailed import proportion.

Notes on these methods

- There are no cases (excluding rounding error) of $m_{\varphi,2007} = m_{\varphi,2012} = 0$ and the aggregate imports in the years in between being positive. Thus, method 1 does not account for that.

- There are no cases of $m_{\varphi,2007} \neq 0$ and $m_{\varphi,2012} = 0$ (or its 2012-2017 analogue) so we didn't design a method for that scenario.
- The order of the methods above matters. For example, method 3 implicitly assumes $m_{j,2012} \neq 0$ because otherwise the case would have been caught by method 2.

B.2 PCE Bridge Imputation Methodology

Crosswalk

The PCE bridge combines PCE categories and NAICS commodity codes. We will refer to such combinations as *bridge pairs*. There are 704 detailed bridge pairs and 402 summary bridge pairs. For the detailed bridge pairs, we have data from 2007, 2012, and 2017 but no other years. We have data on the summary bridge pairs for each year from 1997 to 2023.

Each summary bridge pair is composed of some subset of the detailed bridge pairs. Each detailed bridge pair is part of exactly one summary bridge pair. We match the detailed bridge pairs to summary bridge pairs by checking that the sum of the detailed bridge pairs in 2017 exactly matches the value of the summary bridge pair in 2017.

Interpolation

We chose to make the estimations based only on the detailed data that was closest in time to the year being estimated:

- 1997-2006 is estimated using the detailed data from 2007;
- 2008-2011 is estimated using the data from 2007 and 2012;
- 2013-2016 is estimated using the detailed data from 2012 and 2017; and
- 2018-2023 is estimated using the detailed data from 2017.

1997-2006 and 2018-2023 If we have only one year of detailed data, we assume that the value of the detailed bridge pair changes by the same amount as the value of the summary bridge pair in the same time frame.

That is:

$$V_{d,y+t} = V_{d,y} \cdot \frac{V_{\varphi,y+t}}{V_{\varphi,y}} \ ,$$

where, $V_{d,y}$ is the value of the detailed bridge pair in year y and $V_{\varphi,y}$ is the value of the summary bridge pair in year y.

To impute $V_{d,y+t}$ for $y + t \in \{2018,...,2023\}$, we use $y = 2017$ and $t \in \{1, 2, \ldots, 6\}$.

To impute $V_{d,y+t}$ for $y + t \in \{1997,...,2006\}$ we used $y = 2007$ and $t \in \{-1, -2, \ldots, -10\}$.

Technically, this method does not work if $V_{\varphi,y} = 0$. In this case, we assume that a value of zero in 2007 implies a value of zero for each preceding year. (Or a value of zero in 2017 implies a value of zero in each succeeding year.) Thus if $V_{\varphi,y} = 0$ we set $V_{\varphi,y+t} = 0$ as well.

2008-2011 and 2013-2016 Here, we explain the method use for $y + t \in \{2008, ..., 2011\}$. An equivalent method is used for 2013-2016.

For these years, we have detailed data from both before and after the year for which we are trying to impute the entry for the PCE bridge. Since we have both $\frac{V_{d,2012}}{V_{\varphi,2012}}$ and $\frac{V_{d,2007}}{V_{\varphi,2007}}$, we want to use both fractions to provide the best estimate $\frac{V_{d,2007+t}}{V_{\varphi,2007+t}}$. We want $\frac{V_{d,2012}}{V_{\varphi,2012}}$ to play a larger role for years that are closer to 2012 and $\frac{V_{d,2007}}{V_{\varphi,2007}}$ to be more important for years closer to 2007. We do this by assuming that for each year since 2007, one-fifth of the divergence happens ear year.

Thus, the estimation equation becomes:

$$V_{d,2007+t} = V_{d,2007} \cdot \frac{V_{\varphi,2007+t}}{V_{\varphi,2007}} \cdot \left(\frac{V_{d,2012}}{V_{d,2007}} \cdot \frac{V_{\varphi,2007}}{V_{\varphi,2012}} \right)^{t/5} \tag{8}$$

for each $t \in \{1, ..., 4\}$.

This method fails if $V_{\varphi,2007}$, $V_{\varphi,2012}$, or $V_{d,2007}$ is zero or if if the sign of $\frac{V_{d,2012}}{V_{d,2012}}$ is different then the sign of $\frac{V_{\varphi,2007}}{V_{\varphi,2007}}$. In practice, only the sign changes are a problem. This issue occurs very rarely, so when it does it is usually the only case with an issue in its summary bridge pair. Thus, we estimate every other detailed bridge pair in the summary bridge pair. We then subtract their sum from the value of the summary bridge pair to get the estimate of the detailed bridge pair in these cases.

Link to the Measures Used in the Body of the Paper The $s_{t,j\to c}$ that appear in Sections 3 and 4 are given byV_{dt} divided by the sum of $V_{d't}$ for which consumption category c is the "destination" category. Remember that d denotes a commodity $\times$ consumption category pair.

B.3 Input-Output Use Table Interpolation Methodology

Crosswalk

There are 402 detailed commodity IO codes and 403 detailed distinct industry IO codes. For these categories, we have data from 2007, 2012, and 2017 but no other years.

There are 73 aggregate commodity IO codes and 73 aggregate industry IO codes. We have data on these categories from 1997 to 2023.

Each intersection of an aggregate commodity category and an aggregate industry category is composed of the intersections of some subset of the detailed commodity and some subset of the detailed industry categories. Each detailed intersection is part of exactly one aggregate

intersection. We matched the detailed intersections to their aggregate intersections by comparing the commodity codes and by checking that the sum of the detailed intersections from 2017 matched the value of the aggregate category intersection in 2017.

Interpolation

We chose to make the estimations based only on the detailed data that was closest in time to the year being estimated:

- 1997-2006 is estimated using the detailed data from 2007;
- 2008-2011 is estimated using the data from 2007 and 2012;
- 2013-2016 is estimated using the detailed data from 2012 and 2017; and
- 2018-2023 is estimated using the detailed data from 2017

1997-2006 and 2018-2023 If we had only one year of detailed data, we assumed that the use value of the detailed intersection changed by the same amount as the use value of the aggregate intersection in the same time frame. Let φ refer to a combination of a detailed (upstream) commodity×detailed (downstream) industry, and d to refer to a combination of a summary (upstream) commodity×summary (downstream) industry.

That is:

$$U_{d,y+t} = U_{d,y} \cdot \frac{U_{\varphi,y+t}}{U_{\varphi,y}},$$

where $U_{d,y}$ is the use value of the detailed intersection in year y and $U_{\varphi,y}$ is the use value of the aggregate intersection in year y.

To impute use values for 2018-2023, we let $y = 2017$ and $t \in \{1, 2, \ldots, 6\}$.

To impute use values for 1997-2006, we let $y = 2007$ and $t \in \{-1, -2, \ldots, -10\}$.

Technically, this method does not work if $U_{\varphi,y} = 0$. In this case, we assume that a use value of zero in 2007 means a use value of zero for every earlier year. Thus, if $U_{\varphi,y} = 0$ we set $U_{d,y+t} = 0$ as well.

2008-2011 and 2013-2016 Here, we explain the method used for 2008-2011. The equivalent method is used for 2013-2016.

For these years, we have detailed data from both before and after the year for which we are trying to impute the use value. Since we have both $\frac{U_{d,2012}}{U_{\varphi,2012}}$ and $\frac{U_{d,2007}}{U_{\varphi,2007}}$, we want to use both fractions to provide the best estimate $\frac{U_{d,2007+t}}{U_{\varphi,2007+t}}$. We want $\frac{U_{d,2012}}{U_{\varphi,2012}}$ to play a larger role for years that are closer to 2012 and $\frac{U_{d,2007}}{U_{\varphi,2007}}$ to be more important for years closer to 2007. We do this by assuming that for each year since 2007, one-fifth of the divergence happens ear year.

Thus, the estimation equation becomes:

$$U_{d,2007+t} = U_{d,2007} \cdot \frac{U_{\varphi,2007+t}}{U_{\varphi,2007}} \cdot \left(\frac{U_{d,2012}}{U_{d,2007}} \cdot \frac{U_{\varphi,2007}}{U_{\varphi,2012}} \right)^{t/5} \tag{9}$$

for each $t \in \{1, ..., 4\}$.

This method fails if $U_{\varphi,2007}$, $U_{\varphi,2012}$, or $U_{d,2007}$ is zero. It would also fail if the sign of $\frac{U_{d,2012}}{U_{d,2007}}$ is different then the sign of $\frac{U_{\varphi,2007}}{U_{\varphi,2012}}$, but in practice this is not a relevant concern.

In the aforementioned problematic cases, we apply the following methods, in order, stopping at the first one that is relevant:

1. If $U_{\varphi,2007} = 0$ or $U_{d,2007} = 0$, we set $U_{d,2007+t} = 0$ for each $t \in \{1, ..., 4\}$.
2. If $U_{\varphi,2007} = 0$, but $U_{\varphi,2012} \neq 0$, we set $U_{\varphi,2007}$ to be a small number (0.25 million dollars), and apply Equation 9 using that value.

Link to the Measures Used in the Body of the Paper The $\gamma_{t,i \to j}$ that appear in Section 4 are given byU_{dt} divided by the gross output of industry j in year t. Remember that d denotes an upstream commodity $\times$ downstream industry pair.