# Why Is Manufacturing Productivity Growth So Low?

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July 3, 2025

**Abstract**

We examine the recent slow growth in manufacturing productivity. We show that nearly all measured TFP growth since 1987—and its post-2000s decline—comes from a few computer-related industries. We argue conventional measures understate manufacturing productivity growth by failing to fully capture quality improvements. We compare consumer to producer and import price indices. In industries with rapid technological change, consumer price indices indicate less inflation, suggesting mismeasurement in standard industry deflators. Using an input-output framework, we estimate that TFP growth is understated by 1.7 percentage points in durable manufacturing, 0.4 percentage points in nondurable manufacturing, with no mismeasurement in nonmanufacturing industries.

**JEL Codes: C67, D24, E01, E31**

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After outpacing overall U.S. productivity growth for decades, manufacturing productivity growth has collapsed. The Bureau of Labor Statistics (BLS) total factor productivity (TFP) index for the manufacturing sector increased by 1.2% per year between 1987 and 2009, faster than the 0.9% TFP growth rate for the overall private economy. Between 2009 and 2023, manufacturing TFP *fell* ever so slightly, even as private economy TFP maintained a 0.8% annual growth rate.

The leader-follower flip we highlight has not garnered much research attention until recently, and is still not well understood. The manufacturing sector's considerable size makes its productivity performance of inherent interest. The concern raised by this stagnation is heightened by the fact that manufacturing typically punches above its weight in innovative activity, at least by some common metrics (R&D spending and patenting, in particular). This means that there is considerable potential for productivity growth patterns in manufacturing to spill over to other parts of the economy. If the sector's productivity growth slows down, there could be broader implications for economy-wide growth as well.

In this paper, we introduce a price-based dual approach—contrasting consumer-facing and producer-facing price indices—to assess measurement in real output and TFP growth. We begin our analysis by documenting that, while productivity growth slowdowns are observed in multiple manufacturing industries, most of the measured sector-wide stagnation is quantitatively explained by productivity changes in Computer and Electronic Products manufacturing (NAICS 334). In fact, nearly all of the manufacturing sector's productivity growth since 1987—and its deceleration since 2009—can be attributed to this single 3-digit industry.

We then show that consumer price indices for computers and electronic products indicate less inflation than do corresponding producer and import price indices. This pattern is consistent with too little quality improvements being incorporated into producer and import price indices. We demonstrate this pattern holds more broadly. We compare Bureau of Economic Analysis (BEA) industry gross output deflators and BLS import price indices to corresponding category deflators within the personal consumption expenditures (PCE) price index. We find 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 within manufacturing, is concentrated within durable goods manufacturing especially so for durable goods experiencing the greatest quality adjustments. Overall, annual price changes of durable goods are 2.6 percentage points 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, real output growth is likely understated for durable goods manufacturing industries using conventional national accounts data. However, by the same token, intermediate input price growth is also understated for these industries. Using BEA Input-Output matrices to parse these offsetting effects, we find that manufacturing TFP growth (from 1997 to 2023) is understated by 0.8 percentage points: 1.7 percentage points for durable goods industries and 0.4 percentage points for nondurable goods manufacturing industries. By contrast, TFP growth in nonmanufacturing industries is slightly *over*stated, by 0.1 percentage points annually. TFP mismeasurement is slightly larger before 2009 than after.

In sum, correcting for the under-counting of quality improvements implies that manufacturing TFP growth has continued to grow since the late 2000s, even if this growth rate has slowed. Our corrections matter most for ICT-related industries, but are pertinent for the rest of manufacturing as well.

Our results reshape our understanding of research on innovation and on the desirability of public policies targeting the manufacturing sector. In terms of the academic literature, recent research has highlighted the manufacturing sector's over-representation in innovation: It accounts for only one-tenth of aggregate employment, but 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 much of this apparent stagnation can be explained by properly accounting for quality improvements. In terms of policy, over the last several decades, the U.S. federal government has enacted several programs to boost manufacturing productivity growth, spending many billions of dollars annually.[1] 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 policies are judged on the basis of boosting productivity, past assessments may have presented an overly

[1]These programs include SEMATECH (a public-private partnership established in 1987), the Manufacturing Extension Partnership (1988), the Advanced Manufacturing Partnership (initiated in 2011), and Manufacturing USA (formed in 2014). See `https://web.archive.org/web/20130702191328/http://www.sematech.org/corporate/history.htm`, `https://www.nist.gov/mep`, `https://obamawhitehouse.archives.gov/the-press-office/2011/06/24/president-obama-launches-advanced-manufacturing-partnership`, and `https://www.manufacturingusa.com/pages/history` for more details on each program. In addition, the American Recovery and Reinvestment Act of 2009 and the 2022 CHIPS ACT (2022) provided tens of billions for firms for, respectively, energy-related and semiconductor production. See `https://obamawhitehouse.archives.gov/blog/2010/04/21/impact-american-recovery-and-reinvestment-act-clean-energy-transformation`, and `https://www.congress.gov/crs-product/R47523`.

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).[2] 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 1 more closely align with Syverson (2016) and Sprague (2021), though we emphasize the central role of the Computer and Electronic Product Manufacturing even more so than these earlier works. Finally, by showing that manufacturing TFP growth is materially understated, our results in Sections 2 and 3 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 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. 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 in the CPI. Instead, our contribution is to apply consumer price indices—which, to be sure, face challenges in measurement and

[2] Houseman (2018) considers the special role that the Computer and Electronic Products industry played in the decline of the manufacturing sector's employment. She notes that, from the 1980s onward, manufacturing real output and labor productivity growth would have been much weaker without the Computer and Electronic Products industry.

interpretation—to learn about biases in producer price indices (and, in turn, gross output deflators).

Closer to our work, David Byrne and coauthors have examined the performance of producer price indices, focusing on individual information-and-communication technology (ICT) industries. Byrne and Corrado (2015a,b) compute significant biases in conventional producer price indices for communications equipment. 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. Along similar lines, Byrne et al. (2018) argue that the PPI for semiconductors vastly understates price declines—by more than 15 percentage points between 2000 and 2013—in that industry. 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. Unlike these works, we seek to provide comprehensive economy-wide measures of these biases.

Finally, 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 points per year and is concentrated in the Computer and Electronic Products industry.

# 1 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 gains in manufacturing productivity since 1987 *and* the productivity growth stagnation since 2010 are due to a single 3-digit manufacturing industry: Computer and Electronic Products manufacturing (NAICS 334).

To make this point, consider the following equation linking TFP growth in the manufacturing sector ($\Delta \log A_{t,M}$) to TFP growth in each of the sector's constituent industries: ($\Delta \log A_{t,j}$):[3]

[3]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, is more closely linked to its marginal cost of production and, as a result, its output price (though, as noted above, the manufacturing sector's productivity stagnation is also observed in labor productivity.)

$$\Delta \log A_{t,M} = \sum_{j \in \text{Manufacturing}} \omega_{tj} \Delta \log A_{t,j},$$

where $\omega_{tj}$ denotes industry $j$'s share of manufacturing output at time $t$. Both $\Delta \log A_{t,j}$ and $\omega_{tj}$ come from the BLS Major Sector and Major Industry Total Factor Productivity dataset.[4]

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 clear outlier is the Computer and Electronic Products manufacturing industry. Its TFP grew at a 8.3% annual rate from 1987 to 1997. It then decelerated, modestly, to a 7.4% clip between 1997 and 2009. From 2010 on, TFP growth has slowed to 0.8% per year. So, while productivity in the Computer and Electronic Products manufacturing industry is still above average, it has slowed considerably compared to prior decades.[5]

Over the sample period, the Computer and Electronic Products industry's share of manufacturing output has followed an inverted-U shaped trajectory; see Appendix Figure A.3. It rose from 9.4% to 12.3% between 1987 and 2000, but has since fallen to 5.5% in 2023. Some of the slowdown in manufacturing productivity is therefore attributable to this high-productivity-growth industry's declining share of output.

It turns out that the combination of the Computer and Electronic Products industry's TFP growth slowdown and its shrinking size within the manufacturing sector can explain nearly 100% of the trajectory of whole sector since the late 1980s. We make this point in Figure 2 by plotting the cumulative contribution to manufacturing productivity growth for all industries other than Computer and Electronic Products manufacturing. This is defined as the cumulative total of

$$\Delta \log A^{c}_{t,M} = \sum_{\substack{j \in \text{Manufacturing excluding} \\ \text{Computer and Electronic Products}}} \omega_{tj} \Delta \log A_{t,j},$$

from the beginning of the sample to year t. Figure 2 also plots TFP growth (relative to 1987) in both the manufacturing sector and the private economy.

Two patterns stand out in this figure. First, between 1987 and the late 2000s, TFP

[4]See https://www.bls.gov/productivity/data.html ; these data begin in 1987.

[5]In Appendix Table A.3, we consider which 4-digit industries are responsible for the deceleration of TFP growth in Computer and Electronic Products manufacturing. Within this 3-digit industry, annual TFP growth in Computers and Peripheral Equipment (NAICS 3341) fell from 16.2% in 1997 to 2009 to 0.5% in 2009 to 2023. TFP growth in Semiconductors and Other Electronic Components (NAICS 3344) fell from 8.0% to 2.3%. Other 4-digit industries—accounting for roughly half of the output—within NAICS 334 already had TFP growth below 3% in the 1997 to 2009 period.

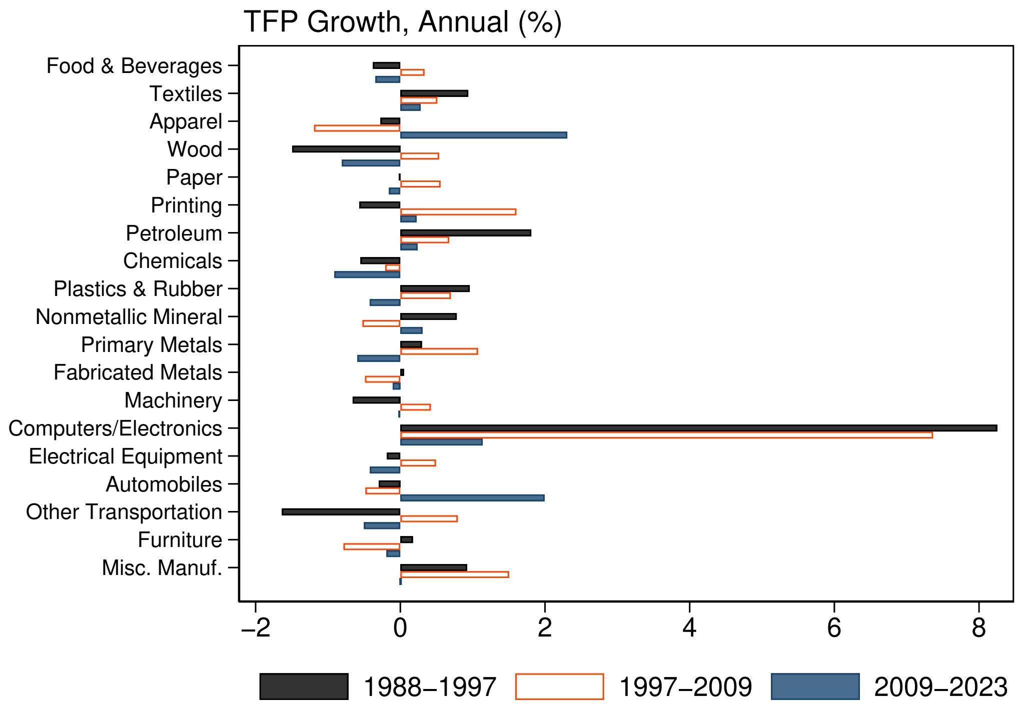


Figure 1: Annual TFP Growth Rate by 3-digit Manufacturing Industry
Notes: "Food & Beverages" is the collection of NAICS 311 and 312. "Textiles" is the collection of NAICS 313 and 314. "Apparel" is the collection of NAICS 315 and 316. "Automobiles" is the collection of NAICS 3361, 3362, and 3363. "Other Transportation" is the collection of NAICS 3364, 3365, 3366, and 3369. All other rows give the TFP growth rates for a single 3-digit NAICS industry.

growth was faster in manufacturing than in the rest of the economy. This flipped in the mid-to-late 2000s, when manufacturing productivity growth collapsed while TFP for the broader private business sector grew by more than 8%. Second, Computer and Electronic Products manufacturing accounted for nearly all of the manufacturing sector's productivity growth between 1987 and 2009. With the exception of a few years of modest TFP growth during the early 2000s, all other manufacturing industries combined saw basically zero TFP growth over the sample.

## 2 For Computer and Electronic Products, Producer and Import Price Indices Suggest Less Quality Growth than Do Consumer Price Indices

In this section, we relate industry gross output deflators and import price indices to components of the PCE price index. We find that, for rapidly innovating durable goods industries, the PCE price index shows much larger price declines than the other two price indices. From this pattern, we infer that gross output deflators understate quality growth within durable

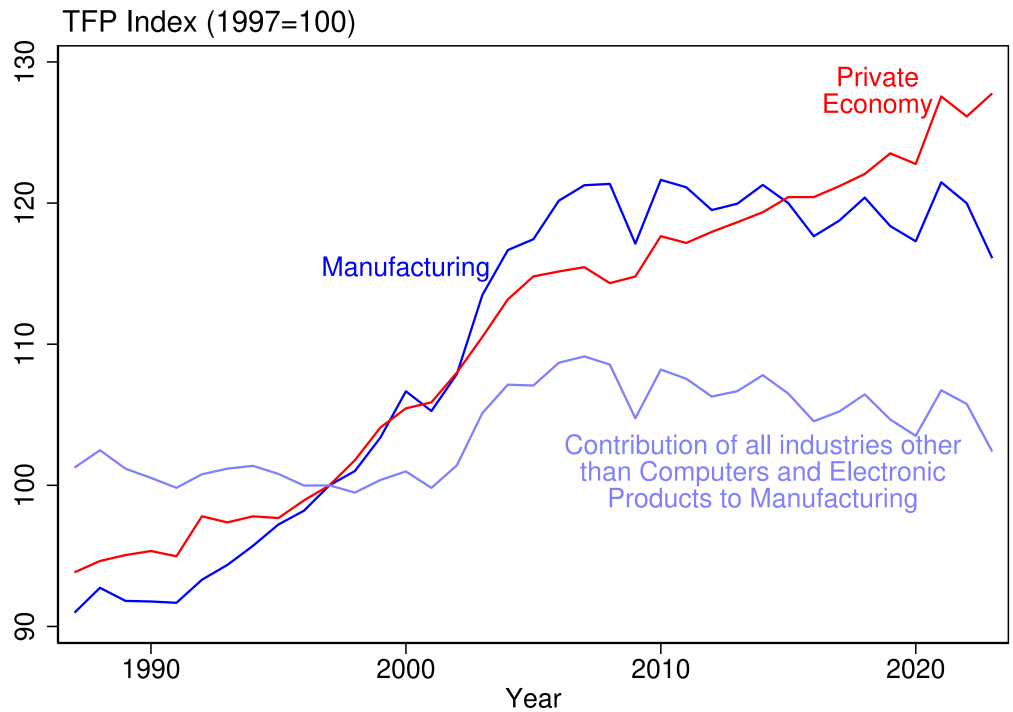


Figure 2: TFP for Manufacturing, Manufacturing excluding Computer and Electronic Products, and the Private Business Sector

goods manufacturing.

Our primary comparison in this section is of the PCE price index against the BEA industry gross output deflators and BLS import price index. The components of the PCE price index come from National Income and Product Accounts (NIPA) Table 2.4.4U (which contain price indices for 212 consumption categories). The gross output deflator, also constructed by the BEA, measures changes in the price of industries' (domestically produced) output.[6] Beginning in 1997, the data cover 414 detailed industries. Finally, we use the BLS import price index to measure changes in the price of imported commodities.[7]

In computing industries' gross output deflators, the BEA uses the PPI (produced by the BLS) for most industries across all sectors, and essentially all industries within the manufacturing sector; see Appendix Table A.1. By contrast, in constructing its PCE price index, the BEA relies on the CPI (also produced by the BLS) for essentially all manufactured goods

[6]See worksheet UGO304-A within `https://apps.bea.gov/industry/Release/XLS/UGdpxInd/GrossOutput.xlsx`.

[7]These indices measure 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 measuring inflation by NAICS commodity. These data begin in 2006 and cover nearly all commodities produced by the manufacturing sector, though only a handful of nonmanufactured products.

and for a majority of all consumption categories. So, methodological differences between the CPI and PPI will be key.

We divide these methodological differences into what the indices aim to measure and how they account for quality improvements over time. Regarding the former, aiming to characterize inflation from the household's perspective, the CPI measures price changes for domestically produced and imported commodities, inclusive of margins paid to wholesalers, retailers, and firms in transportation and warehousing. By contrast, aiming to characterize inflation from the producer's perspective, the PPI measures price changes for only domestically produced commodities, excluding distribution margins.

Regarding differences in quality adjustment procedures, 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's frequent reference to the CPI as the "nation's principal gauge of inflation"[8] 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.[9]

Consistent with this, consider how the BLS measures quality adjustment for commodities with rapid technological change. For these commodities, the BLS preferred method to identify quality changes involves "hedonic quality adjustment". In this method, for a given product category, researchers at the BLS determine the set of relevant product characteristics. They then apply a regression model to estimate consumers' valuation for—or, in the case of the PPI, the additional costs associated with—these characteristics. 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). By contrast,

[8]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` .

[9]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`.

the BLS applies hedonic adjustments to 36 of the 273 entry level items in the CPI.[10,11,12]

For these reasons, we take any differences between the CPI and PPI/import price index as suggestive evidence of incomplete quality adjustment in the latter indices, especially so if these differences are concentrated in goods experiencing rapid technological progress. The same premise will apply to comparisons of indices derived from the CPI and PPI, such as the PCE price index and the BEA's industry gross output deflators.

Having spelled out the different aims and methodological foundations for the various price indices, in Figure 3 we show for a single consumption category—Telephone Apparatuses (NIPA Line 71)—how inflation rates vary between the consumer and producer perspectives.[13] 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 PCE Bridge Table, this one consumption category is a composite of two NAICS Commodities: Radio and Television Broadcasting and Wireless Communications Equipment (NAICS 33422; 90% of the consumption category) and Telephone Apparatuses (NAICS 33421; the remaining 10%). For brevity, below we refer to NAICS 33422 as Broadcast and Wireless Communications Equipment. The gross output deflator for this industry declined by 8.4% per year. The import price index for the broader Communications Equipment Manufacturing (NAICS 3342) fell by 1.6% per year.[14] At least for this one product category,

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[10]See Appendix A for a list of commodities for which the BLS applies hedonic quality adjustment in the PPI and CPI.

[11]Byrne et al. (2016, p.123) note that the hedonic quality adjustments the BLS employs for the PPI may omit design improvements that raise the value of product to consumers that are not clearly tied to costs or not easily identified in technical specifications. As a result, the PPI quality adjustments may be less impactful than those for the CPI.

[12]Another salient difference between the price indices, one which is not necessarily related to quality adjustment, 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.) Dalton et al. (1998) estimates that using a geometric mean formula—instead of an arithmetic mean formula—leads to a 0.2 percentage point reduction in the reported aggregate CPI inflation rate.

[13]Despite the near-total offshoring of telephone processing and assembly since the early 2000s, domestic manufacturing still accounts for a substantial share of personal consumption of phones. Indeed, as of 2017 —the most recent date for which the BEA produced detailed input-output tables—less than half, approximately 40%, of Communications Equipment Manufacturing (NAICS 3342) personal consumption expenditures came from imports. Much of the domestic industry now focuses on engineering, computing, and design, with assembly largely occurring overseas. As of 2023, production occupations account for less than a quarter of Communications Equipment manufacturing employment. See Appendix D.2 for more details.

[14]It is plausible that the prices of imported communications equipment other than Broadcast and Wireless Communications Equipment grew more slowly. To the extent that this is the case, prices for imported

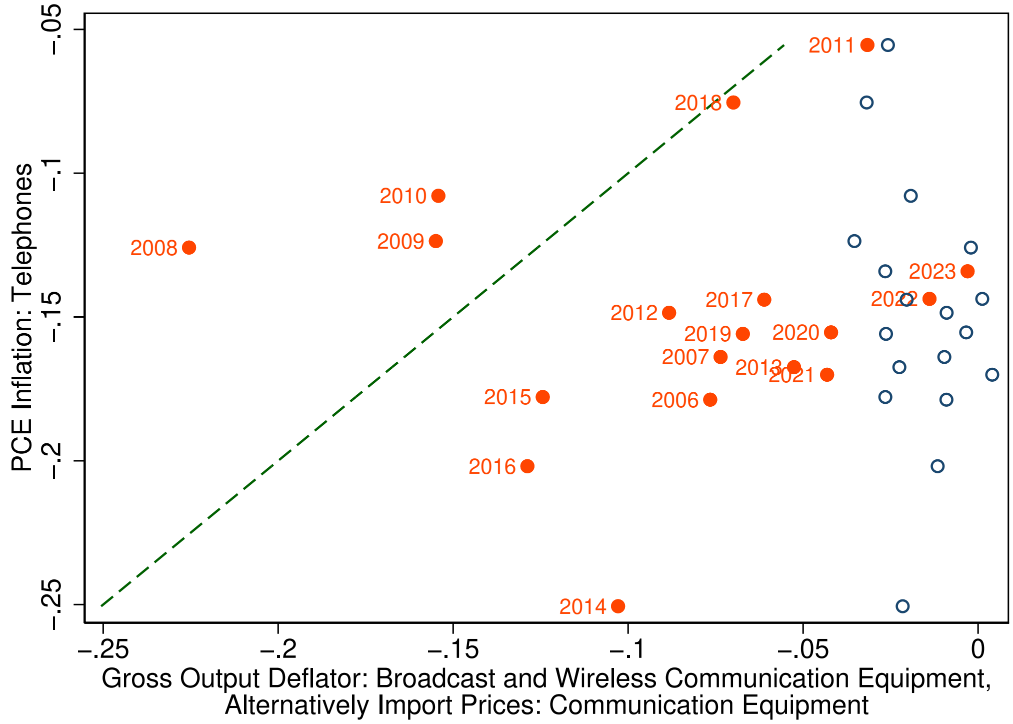


Figure 3: Telephone Apparatus Inflation

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.

price declines are much greater from the perspective of a consumer than that of a producer.

In Figure 4, we expand the scope of analysis beyond telephone equipment. For each PCE category, the vertical axis gives the average annual price growth between 1997 and 2023. The horizontal axis gives our attempt at recreating the corresponding measure of inflation but using gross output deflators and import price indices.[15] As the Telephone Apparatus

Broadcast and Wireless Communications Equipment would display greater price declines than what the orange circles within Figure 3 indicate. In an unreported check, we attempt to impute import prices for the detailed commodity based on (a) the import prices for the broader industry and (b) the difference in gross output deflators for the detailed industry and the broader industry. Our main results are robust to using this alternate import price index.

[15] For 1997 to 2005, we impute commodities' import price growth using the 2005-to-2023 historical relationship between gross output deflator price growth and import price growth. In more detail, for 2005 to 2023, we estimate a regression with the commodity $j$ summand into Equation 1—namely,

example 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. For each component of the PCE price index, the PCE Bridge Table lists the contribution of individual commodities, the latter of which are measured using the NAICS commodity system. This table also lists the contribution of the transportation, wholesale, and retail sectors to the value of each PCE category. [16] We use the Input-Output Tables to assign weights for domestic production vs. imports.[17]

Written out explicitly, we use the term "Producer Inflation" to refer to this weighted average of deflators:

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

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—for example, the Telephone Apparatuses category—the level of aggregation is coarser in the import price index than in the BEA industry gross output deflator.

For the most part, looking across PCE categories and averaging over the 1997–2023 sample, PCE inflation is highly correlated to changes in $\Delta \log P^{\text{Producer}}_t$. The (consumption-weighted) correlation across the two measures is 0.75. Our Producer Inflation measure exceeds PCE by 0.5 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

$(1 - m_{t,j})\Delta \log P^{\text{GO}}_{t,j} + m_{t,j}\Delta \log P^{\text{Import}}_{t,j}$—as the dependent variable. The two explanatory variables are (i) gross output price growth, $\Delta \log P^{\text{GO}}_{t,j}$, and (ii) the interaction of import price growth and the import share of PCE, $m_{t,j}\Delta \log P^{\text{GO}}_{t,j}$. We restrict the intercept of the regression to be equal to 0. The estimated coefficients on the two explanatory variables are 0.998 and -0.736. The R-Squared on the regression is 0.994. If we further restrict the coefficient on $\Delta \log P^{\text{GO}}_{t,j}$ to be equal to 1, the coefficient on the interaction term is -0.743. Given this, for each year between 1997 and 2005, we impute $(1 - m_{t,j})\Delta \log P^{\text{GO}}_{t,j} + m_{t,j}\Delta \log P^{\text{Import}}_{t,j}$ as $\Delta \log P^{\text{GO}}_{t,j} - 0.743 \cdot m_{t,j}\Delta \log P^{\text{GO}}_{t,j}$.

[16] These data are produced at the same level of detail as the data on gross output deflators and PCE inflation for 2007, 2012, and 2017 and at a higher level of aggregation for all years beginning in 1997. In Appendix B, we discuss how we combine detailed and more aggregated PCE Bridge Tables to construct estimates of commodity-to-consumption category linkages for each year at the more detailed 414-commodity-by-212 consumption category level.

[17] See `https://www.bea.gov/industry/input-output-accounts-data` . These tables contain information on total personal consumption expenditures as well as imported personal consumption expenditures—at a 71-industry level of aggregation for each year beginning in 1997 and a more detailed 402-industry level of aggregation for 2007, 2012, and 2017. We, again, combine the two data sets to infer industry-by-commodity measures at the more detailed level of aggregation for all years beginning in 1997. See Appendix B for a discussion of how we do so.

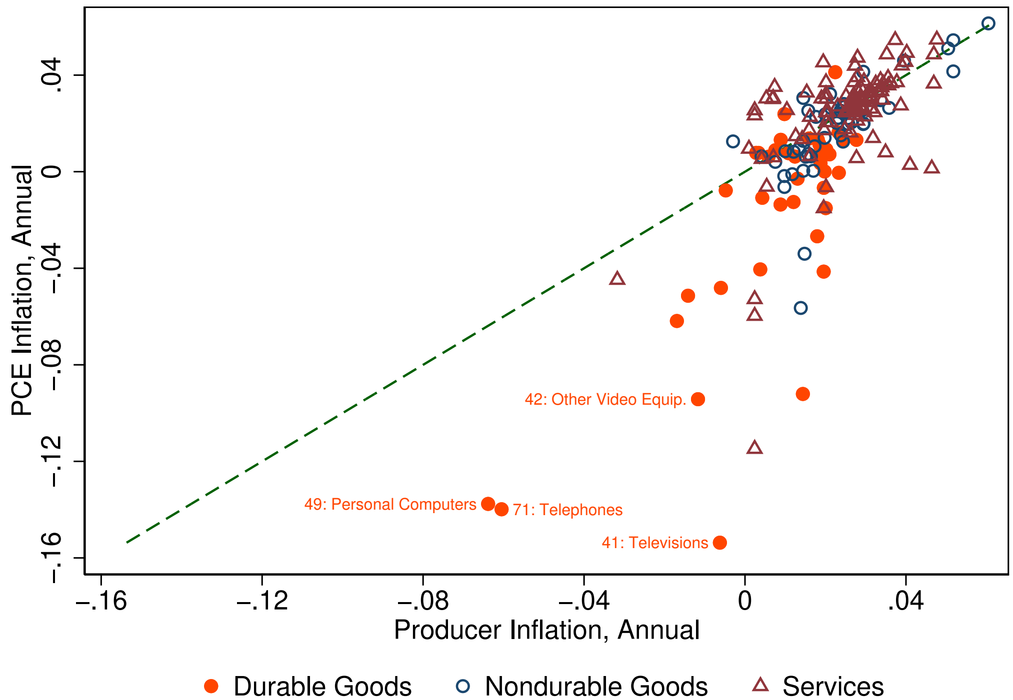


Figure 4: Two Measures of Inflation Across PCE Categories, 1997–2023
Notes: Each point is a single PCE category. The vertical axis gives annual inflation according to the PCE price index between 1997 and 2023. The horizontal axis gives our measure of Producer Inflation (defined by Equation 1) over the same period. For the four data points in the bottom of the figure, the number preceding the colon is the NIPA line number.

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 -15.4% per year between 1997 and 2023 according to the CPI or PCE. The gross output deflator for the more aggregated Audio and Video Equipment manufacturing industry (NAICS 3343) is -1.1% per year. Inflation according to the import price index is -2.0% per year (between 2005 and 2023). Given that roughly half (51%) of Audio and Video Equipment manufacturing that enter personal consumption expenditures are imported, the -1.1% and the -2.0% average out to a -1.7% Producer Inflation rate (given the adjustments described in footnote 15). Some of the difference between the -15.4% 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 -9.4% 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.

## 3 Annual TFP Growth in 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:

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

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 breaks out changes in industry $j$'s input price growth into the price growth of labor, capital, and individual intermediate inputs, $i$. The final line writes this equation in vector notation. Here, 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 pertain to mismeasurement in unit labor costs or the rental price of capital, we assume $\Delta \log \widetilde{\mathbf{r}}_t = \Delta \log \widetilde{\mathbf{w}}_t = 0$. With this assumption, Equation 2 implies:

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

Our second building block comes from comparing Producer Inflation—defined in Section

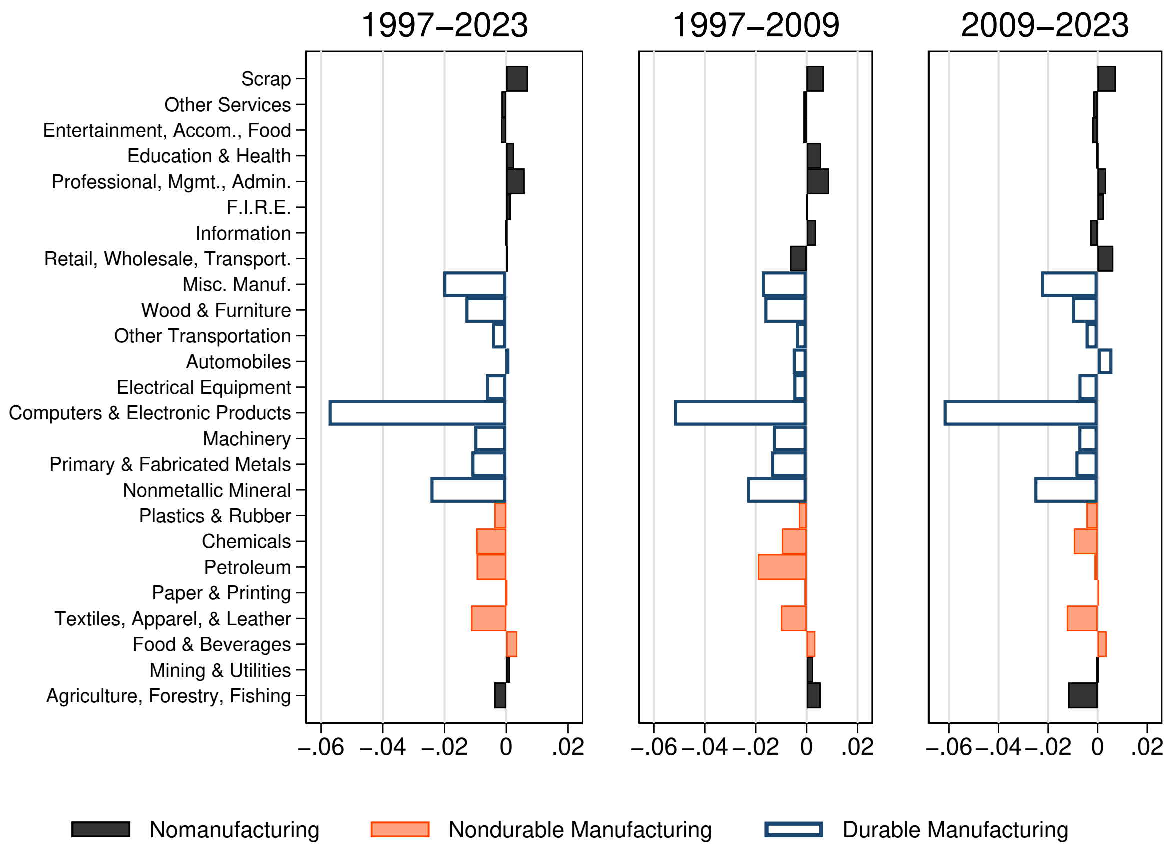


Figure 5: TFP Mismeasurement

Notes: We apply Equation 7 to recover the mismeasurement in TFP by industry and year. We average these variables by broad sector and years, weighting industries according to their gross output within each year. Compared to Figure 2, we combine the following, where at least one of the industries has a small share of its output sold as personal consumption: We combine Wood (NAICS 321) and Lumber (NAICS 337); Textiles (NAICS 313-314) and Clothing and Leather (NAICS 315-316); Paper (NAICS 322) and Printing (NAICS 323); and Primary Metals (NAICS 331) and Fabricated Metals (NAICS 332).

2—and PCE inflation. We attribute differences between PCE and Producer Inflation to mismeasurement in import price indices and gross output deflators:

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

We write this equation in matrix form:

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

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

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

Above, the $\mathbf{O}_t$ is a matrix which transforms mismeasurement in "consumption category" space to "NAICS commodity" space. We consider two $\mathbf{O}_t$ matrices. In our baseline calculations, presented below, row $j$ and column $c$ elements of $\mathbf{O}_t$ are equal to 1 if PCE category $c$ has the largest value in the PCE Bridge Table for NAICS commodity $j$.

If we assume that mismeasurement in gross output deflators equals mismeasurement in import price indices, we can combine Equations 3 and 6 to infer mismeasurement in productivity:

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

We apply Equation 7 using data from 1997 to 2023. We highlight four main results. First, within the durable goods manufacturing industry, TFP is understated for the Computer and Electronic products industry, by 5.8 percentage points per year. Second, looking across sectors, TFP mismeasurement is greatest in the durable goods manufacturing sector (understated by 1.7 percentage points per year), much smaller in the nondurable goods manufacturing sector (understated by 0.4 percentage points per year), and essentially nonexistent in the nonmanufacturing sector (overstated by 0.1 percentage points per year.) Third, even though TFP mismeasurement was most severe in the Computer and Electronic Products industry, it is pervasive throughout manufacturing. Finally, mismeasurement of TFP growth was slightly larger towards the beginning of the sample. So, while our corrections can explain why manufacturing TFP growth is so slow throughout the sample, they cannot explain why TFP growth has slowed down beginning around 2009.[18]

Adding our estimates of TFP mismeasurement in Figure 5 to observed TFP growth rates in Figure 1, we find continued TFP growth for the manufacturing sector since 2009, with a growth rate much closer to that of the rest of the private economy (even if this growth rate is appreciably slower than in early decades); see Figure A.4 for the time series of corrected TFP. Our estimates imply that true TFP growth rate in the manufacturing sector was 0.6% between 2009 and 2023—1.9% in durable goods manufacturing industries and -0.1% in nondurable goods manufacturing industries. This is slower than TFP growth in the manufacturing sector between 1997 and 2009 (2.3%), but much stronger than what the official statistics would suggest.

**Sensitivity Analyses** To close this section, we discuss three sets of sensitivity analyses.

In Equation 1, we have excluded the wholesale, retail, and transport margins when summing over commodities $j$—that is, we include only entries from the "Producers' Value" column of the PCE Bridge Table when computing $s_{t,j\to c}$. Under this (extreme) definition, price increases from distribution margins are excluded from Producer Inflation. In Appendix C, we consider an alternative: including distribution margins in proportion to columns F-H of the PCE Bridge Table. Under this alternate assumption, the gap between PCE inflation and Producer Inflation is at least as large as what is reported in Figure 4, with substantially larger gaps for durable goods industries. This, in turn, implies that TFP is understated for durable goods industries even more than what we report in Figure 5.

A potential concern with our approach is that, even aside from quality measurement issues, within the same detailed NAICS commodity consumer-facing products may have different inflation rates than business-facing products. For instance, it is conceivable that Telephone Equipment (NAICS 33421) sold to consumers (e.g., iPhones) has faster price declines than those sold to businesses (e.g., Cisco). In this scenario, we would erroneously

[18]For the durable goods sector, the average of $\Delta \log \widetilde{\mathbf{A}}_t$ was -1.9 percentage points between 1997 to 2009 and -1.5 percentage points between 2009 and 2023. For nondurable goods, $\Delta \log \widetilde{\mathbf{A}}_t$ was (on average) $-0.6$ percentage points between 1997 and 2009 and -0.3 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 percentage points between 2009 and 2023.

attribute gaps between PCE and "Producer" inflation to inadequate quality adjustment in the latter index. To explore this concern, in Appendix D.5, we progressively restrict the sample to NAICS commodities that have more of their sales sold as personal consumption expenditures. The patterns given in Figure 5 are robust to these restrictions.

In Appendix D.6, we consider an alternate definition for row $j$ and column $c$ of the $\mathbf{O}_t$ matrix: the contribution of NAICS commodity $j$ to consumption category $c$, where each row is normalized to have sum equal to 1. Our results are unchanged with this alternate definition.

## 4 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. The first half of the article documents that these trends can by explained by the resolution of the ICT revolution. Between 1987 and 2009, Computer manufacturing TFP grew by an astronomical 15% per year. Semiconductor manufacturing TFP 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 1.7 percentage points and by 0.4 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 is 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 (Moulton, 2024). It would also contradict 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 and Corrado, 2015a; Byrne et al., 2018.)

The U.S. manufacturing sector has changed profoundly over the last three decades. It has grown more import-reliant, first from China and then from Vietnam and Mexico (Alfaro and Chor, 2023), more capital intensive,[19] and more robot intensive (see Figure 5 of Klump 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.

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

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# A Discussion of Underlying Source Data and Quality Adjustment

In this appendix, we discuss the sources of inflation data, both from the household and producer 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 exclusively has (throughout the sample period) drawn on the CPI. Manufacturing gross output deflators (also throughout the sample period) are derived from the PPI.

In the final portion of this 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, concentrated in service industries; and (b) an increase in the number of commodities for which the BLS applies a hedonic adjustment to account for quality improvements over time. For both price indices, the increasing use of hedonic adjustments have occurred either before 2000 or beginning in the late 2010s. An implication of this discussion is that, since most methodological changes occurred in the service sector (or for service consumption categories), or either took place before the early 2000s or beginning in the late2010s, they are unlikely to explain the deceleration in measured manufacturing productivity growth 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 on 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). For a comprehensive list of the sources used in the construction of the PCE price index, see Bureau of Economic Analysis (2024, Chapter 5).

**Industry Gross Output Deflators**

The BEA 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, Chapter 4). 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). For service industries, the BEA gross output deflators draw on a wider variety of sources. Table A.1 lists the underlying sources of the BEA gross output deflator for a year near the beginning (2004), middle (2010), and end (2018) of the sample.

| 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 |

| Year | 2004 | 2010 | 2018 |
|---|---|---|---|
| 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 |
| 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 | ———— | ———— |

| Year | 2004 | 2010 | 2018 |
|---|---|---|---|
| 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 | ——— | ——— |
| 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 |

| Year | 2004 | 2010 | 2018 |
|---|---|---|---|
| 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 |
| 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 |

| Year | 2004 | 2010 | 2018 |
|---|---|---|---|
| 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 |
| 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) | ———— | ———— | ———— |

| Year | 2004 | 2010 | 2018 |
|---|---|---|---|
| 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 |

| Year | 2004 | 2010 | 2018 |
|---|---|---|---|
| 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 |
| 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 | ——————— |

| Year | 2004 | 2010 | 2018 |
|---|---|---|---|
| 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 |
| 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 |

| Year | 2004 | 2010 | 2018 |
|---|---|---|---|

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: U.S. 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 (2024) 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 the introduction of:

- 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;
- 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 in the CPI.[20] In 1988, it began applying age-bias adjustment factors 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.

[20] 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` .

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),[21] land-line telephone services (2019),[22] internet services (2019), 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,[23] late 2016,[24] and 2018,[25] 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 $c$ 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 2023. We first discuss our estimates at producing $m_{t,j}$—, the share of consumption expenditures of detailed commodity $j$ that is imported in year $t$ (Appendix B.1). In this appendix, we then discuss how we compute $s_{t,j\to c}$ for detailed commodities and consumption categories in each year (Appendix B.2).

When computing TFP mismeasurement, we required information of the use of individual detailed commodities in the production of different downstream industries' otuputs. Again, the "Detailed" versions of the BEA "Use" Tables only exist for 2007, 2012, and 2017, with more aggregated "Summary" data for other years between 1997 and 2023. In Appenidx B.3, we describe our methodology to impute commodity flows for each year between 1997 and 2023.

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

[22]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`.

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

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

[25]See Sawyer and So (2018).

Finally, Appendix B.4 describes how we estimate the contribution of transportation, wholesale, and retail margins in the distribution of each detailed commodity.

## 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 $\varphi$ 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 $\varphi$. We have constructed a mapping between each detailed commodity $j$ and summary commodity $\varphi$ 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.

## B.2 PCE Bridge Imputation Methodology

### Crosswalk

The PCE Bridge Table 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 $V_{d,y+t} = 0$ 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 of the PCE Bridge Table. 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 happened that 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 and use the remainder as the estimate of the detailed bridge pair in these cases. If there happens to be multiple bridge pairs with this issue in the same summary bridge pair we split the remainder between them based on their relative sizes.

**Link to the Measures Used in the Body of the Paper** The $s_{t,j\to c}$ that appear in Sections 2 and 3 are given by $V_{dt}$ 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 $\varphi$ refer to a combination of a detailed (upstream) commodity$\times$detailed (downstream) industry, and $d$ to refer to a combination of a summary (upstream) commodity$\times$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. In these problematic cases we apply one of the two following methods:

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 $U_{\varphi,2012} = 0$, but $U_{d,2007} \neq 0$ and $U_{d,2017} \neq 0$, we estimate $U_{d,2007+t} = 0$ using a modified version Equation 9 with the 2017 values replacing the 2012 values and $t/10$ replacing of $t/5$.

The method also fails if the sign of $\frac{U_{d,2012}}{U_{d,2007}}$ is different then the sign of $\frac{U_{\varphi,2007}}{U_{\varphi,2012}}$. In practice this only occurs for two of the farming-government intersections and in both cases the detailed values are very small so we set $U_{d,2007+t}$ to zero.

**Link to the Measures Used in the Body of the Paper** The $\gamma_{t,i \to j}$ that appear in Section 3 are given by $U_{dt}$ divided by the gross output of industry $j$ in year $t$. Remember that $d$ denotes an upstream commodity $\times$ downstream industry pair.

## B.4 PCE Bridge Margin Assignment

The PCE Bridge Table reports both producer's value and purchaser's value, which adds the transportation, wholesale, and retail costs to the producer's value. We refer to these as the transportation, wholesale, and retail margins. We would like to be able to assign the value in these margins to the commodities they come from, however, each of the three margins is made up of multiple commodities.

We do not have data on what commodities each industry uses only for its finished products, but the the use tables do give each industry's use of the margin commodities as part of their intermediate inputs.

We make the assumption that the relative shares of intermediate inputs in the commodities that make up each margin category is predictive of their relative shares within the margin. For example, Truck Transportation is the majority of the transportation type intermediate inputs for Grain Farming and we expect the same to be true for its share of Grain Farming's transportation margin.

First, we compute the share of each commodity within its margin type in the BEA's Use Table (using the interpolated detailed use values). Next, for each commodity-margin combination in the PCE Bridge Table, we multiply the use table shares by the margin value. This gets rid of the margins and leaves all values in the PCE Bridge Table assigned to some commodity.

Since there generally are multiple commodities in each PCE category, this procedure usually results in there being multiple of each of the margin type commodities in the PCE Bridge Table. Thus, as a final step, we combine the duplicate commodities via summation.

## C Sensitivity to Including Distribution Margins in Equation 1

In this section, we examine the sensitivity of our results in Sections 2 and 3 to our definition of Producer Inflation, where we now include changes in the price of retailing, wholesaling, and transporting goods.

To describe this robustness check, it will be helpful to first describe the structure of the PCE Bridge. Each row within the PCE Bridge Table corresponds to a PCE consumption category ($c$) by NAICS commodity ($j$) pair in year $t$; for future reference call this $v_{j\to c,t}$. For each pair, the Bridge Table lists the dollar value of the contribution of commodity ($j$) to consumption category ($c$).

In Equation 1, in the body of the paper, $s_{t,j\to c}$ equals:

$$\frac{v_{t,j\to c}}{\sum_{j'} v_{t,j'\to c}} \tag{10}$$

Consider, as an example, NIPA Line 88: "Eggs." For a single year (2017), the rows associated with this consumption category are given in Table A.2. There are two NAICS

| Commodity Description | Commodity Code | Producers' Value | Transportation Costs | Wholesale Margin | Retail Margin |
|---|---|---|---|---|---|
| Poultry and Egg Production | 11230 | 5,034 | 499 | 214 | 2,807 |
| All Other Food Manufacturing | 31199 | 2,237 | 60 | 513 | 1,248 |

Table A.2: Excerpt from PCE Bridge Table
Notes: This table lists the rows associated with the consumption category of Eggs (NIPA Line, 81) from the 2017 PCE Bridge Table. The dollar figures in the final four columns are all nominal.

commodities that contribute to the Eggs consumption category: "Poultry and Egg Production" (NAICS 11230) and "All Other Food Manufacturing" (NAICS 31199). In terms of Equation 10, $v_{2017,j \to 88}$ = \$5034 for $j = 11230$ and \$2237 for $j = 31199$. As a result, our Producer Inflation measure for the Eggs consumption category would weight Poultry and Egg Production at roughly 70 percent and All Other Food Manufacturing at roughly 30 percent.

In our robustness check, we allow for price changes in distribution margins to enter the Producer Inflation measure. The PCE Bridge Table includes three additional columns, listing the dollar contribution of wholesale, retail, and transportation margins in commodity $j$ to consumption category $c$. Let $v_{t,\omega;j \to c}$, $v_{t,\rho;j \to c}$, and $v_{t,\theta;j \to c}$ refer to the dollar value of these different margins in the PCE Bridge Table. In the Eggs consumption category, in 2017, transportation accounts for \$559 ($v_{2017,\theta;11230 \to 88}$=\$499; $v_{2017,\theta;31199 \to 88}$=\$60), the wholesale margin accounts for \$727 ($v_{2017,\omega;11230 \to 88}$=\$214; $v_{2017,\omega;31199 \to 88}$=\$513), and the retail margin accounts for \$4055 ($v_{2017,\rho;11230 \to 88}$=\$2807; $v_{2017,\rho;31199 \to 88}$=\$1248).

While the PCE Bridge Table does not have any further detail on the importance of these distribution margins, we employ the Input-Output Table to infer the importance of detailed distribution channels (e.g., inferring the weight of Auto Wholesalers vs. Machinery Wholesalers; Supermarkets vs. Non-Store Retailers; and Air Transport vs. Pipeline Transport). Using $\mu$ to refer to a generic detailed distribution industry and $\mathcal{M}$ the set of detailed distribution industries, let $v_{t,\mu;j \to c}$ refer to the value of distribution margin $\mu$ earned in year $t$ when transporting, wholesaling, or retailing commodity $j$ toward consumption of category $c$.

Returning to our Egg example, according to the 2017 Use Table (Before Redefinitions), Truck Transportation (NAICS 484) accounted for 73 percent (=\$1360 of the \$1858) of the transportation inputs used in the production of Poultry and Egg Production, and 75 percent (=\$970 of the \$1290) of the transportation inputs used in the production of All Other Foods Manufacturing. As a result, we estimate that—toward the Eggs consumption category—$v_{2017,484;11230\to 88} = 0.73 \cdot \$499 = \$365$ and $v_{2017,484;31199\to 88} = 0.73 \cdot \$60 = \$45$. In words, Trucking Transportation contributes \$410 towards the PCE category of Egg consumption, \$365 through the Poultry and Egg Production commodity and \$45 through the All Other Food Manufacturing commodity.

Having laid out our notation, we consider an alternate definition of Producer Inflation:

$$\Delta \log \tilde{P}^{\text{Producer}}_{t,c} = \sum_j \tilde{s}_{t,j\to c} \left[ (1 - m_{t,j}) \, \Delta \log P^{\text{GO}}_{t,j} + m_{t,j} \Delta \log P^{\text{Import}}_{t,j} \right], \text{where} \tag{1'}$$

$$\begin{aligned} \tilde{s}_{j\to c} &= \frac{v_{j\to c} + \sum_{j'} v_{j;j'\to c}}{\sum_{j'}(v_{j'\to c} + \sum_{\mu} v_{\mu;j'\to c})} \text{ if } j \in \mathcal{M} \\ &= \frac{v_{j\to c}}{\sum_{j'}(v_{j'\to c} + \sum_{\mu} v_{\mu;j'\to c})} \text{ if } j \notin \mathcal{M} \; . \end{aligned}$$

In the second line within Equation 1′, the terms in the numerator account for the two ways in which commodity $j$ can contribute to consumption category $c$, the first as a producing industry, the second through distribution margins. For instance, the NAICS commodity of Rail Transportation (NAICS, 482) appears as a producing industry for the Railway Transportation PCE Category (NIPA Line 201) and contributes to the distribution margin of multiple NAICS-Commodity-to-PCE-Category ($j' \to c$) pairs.

Figure A.1 presents the analogue of Figure 4 using this alternate definition of Producer Inflation. The key takeaway from this figure is that for computers and electronics-related consumption categories, their scatter-points fall even farther from the 45-degree line in Figure A.1 than in Figure 4. The Personal Computers (NIPA Line 49) consumption category is again instructive. Whereas Producer Inflation was -6.8% in Figure 4, it is at -4.4% here. For this consumption category, distribution margins account for 35% to 40% (depending on the year) of the weight in Equation 1′. The industries accounting for most of the distribution margins for Personal Computers consumption includes "Professional and Commercial Equipment and Supplies Merchant Wholesalers" (NAICS 4234) and "Motor Vehicle and Parts Dealers" (NAICS 441). Over the 1997 to 2023 period, for these two industries, gross output deflators increased by -0.4% and 2.1%, respectively. Including these terms and those of other distribution industries' in Equation 1′ increases our measure of Producer Inflation up. The same goes for other consumption categories for which Figure 4 indicated deflation. The Producer Inflation measure of Televisions increases by 1.0 percentage points (decreasing by 0.8% annually, instead of by 1.7% annually, as in Figure 4. For Telephones, the difference is 5.1 percentage points (0.8% annual price declines in Figure 4 vs. 6.0% in A.1). Overall, since wholesale, transportation, and retail experienced roughly 2% inflation over the sample period, their inclusion in Producer Inflation will attenuate any observed deflation from non-margin commodities in PCE categories experiencing large price declines.

Figure A.2 next considers the implications of including distribution margins for our estimates of TFP mismeasurement. We follow the same procedure detailed in Section 3 to infer TFP mismeasurement from price gaps between PCE inflation and our Producer Inflation measure. More pronounced output price mismeasurement in Figure A.1 implies greater TFP mismeasurement in Figure A.2. For the 3-digit Computer and Electronic Products manufacturing industry, TFP mismeasurement is 7.8 percentage points, 2 percentage points more than in Figure 5. For other manufacturing industries—where price declines are rarer—including distribution margins in our calculations has minimal impact.

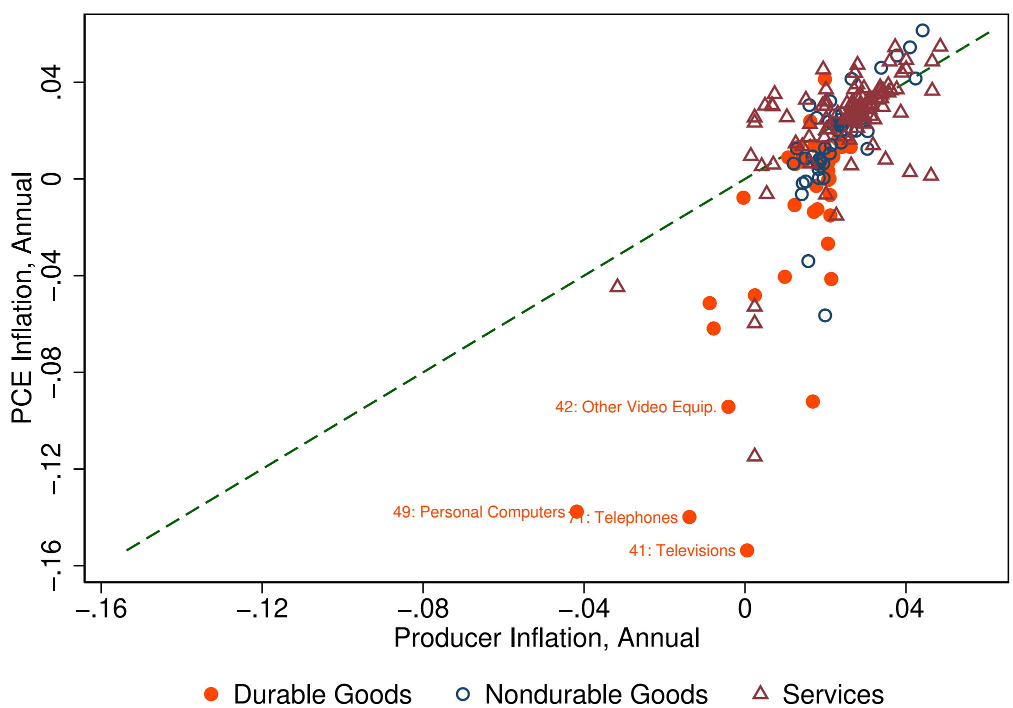


Figure A.1: Two Measures of Inflation Across PCE Categories, 2005–2023
Notes: See the notes for Figure 4. In contrast to that figure, we rely on Producer Inflation measures from Equation 1′.

## D Additional Figures and Tables

In this section, we collect figures supplementing those in the body of the paper. Appendices D.1 and D.3, respectively, supplement Sections 1 and 3. Appendix D.4 evaluates whether our conclusions of TFP mismeasurement in broad sectors are problematic due to the potential

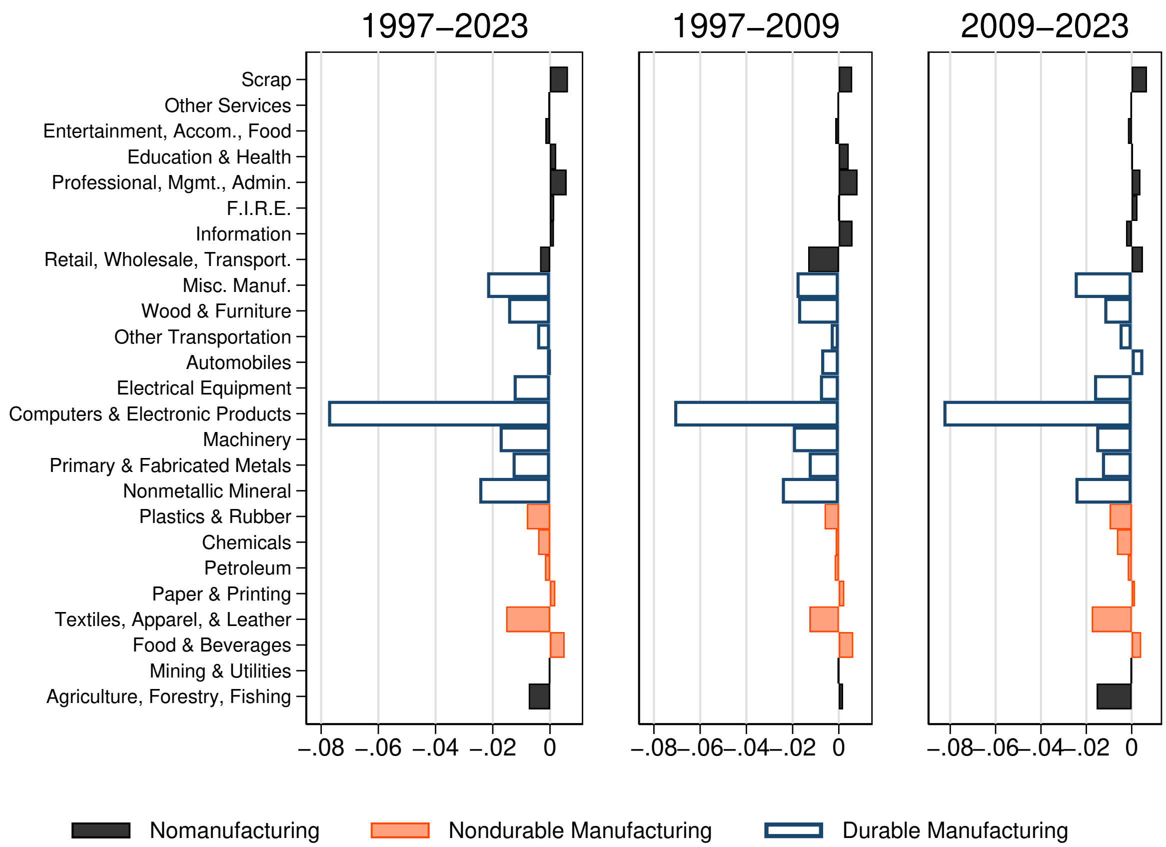


Figure A.2: TFP Mismeasurement
Notes: See the notes for Figure 5. In contrast to that figure, we rely on Producer Inflation measures from Equation 1′.

non-representativeness of which industries are not observed in the PCE Bridge Table. In Appendix D.5, we assess whether our results are robust to excluding commodities that only enter with small entries in the PCE Bridge Table. In Appendix D.6, we consider an alternate definition of $\mathbf{O_t}$ (see Equation 6) when computing TFP mismeasurement.

## D.1 Figures and Tables Supplementing Section 1

Figure A.3 plots the share of manufacturing output attributable to NAICS 334: the Computer and Electronic Products manufacturing industry. In 1987, this was 9.4%, peaked at 12.3%, and fell to 5.5% by the end of the sample.

In Table A.3, we study which 4-digit industries are responsible for the TFP deceleration of the Computer and Electronic Products 3-digit industry. For each of the 4-digit industries, we compute average TFP growth rates and output shares for three subperiods within our

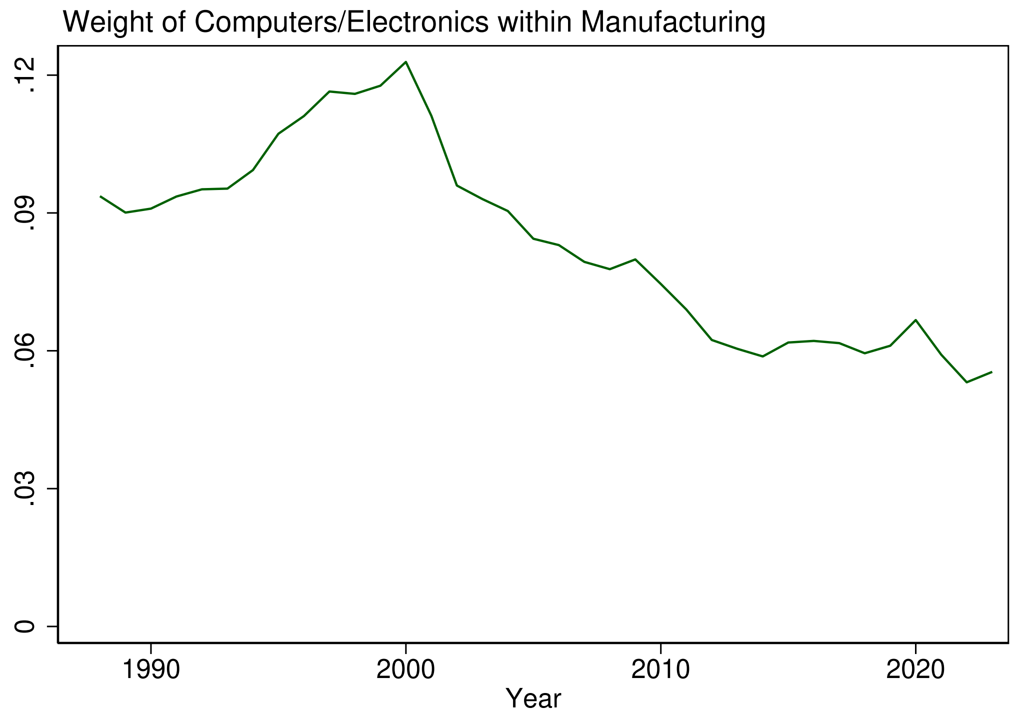


Figure A.3: Share of Sectoral Output of NAICS 334 within Manufacturing

sample: 1987 to 1997, 1997 to 2009, and 2009 to 2023. The outstanding pre-2009 growth of this industry is largely due to two 4-digit industries: Computer and Peripheral Equipment manufacturing (NAICS 3341) and Semiconductors and Other Electronic Compoents manufacturing (NAICS 3344). These two industries had the largest slowdown in TFP growth post 2009. The other large industry—Navigational, Measuring, Electromedical, and Control Instrument manufacturing (NAICS 3345)—had similar TFP growth rates across the three subperiods within the sample. If anything, productivity growth increased for the industries outside of NAICS 3341 and NAICS 3344.

## D.2 Imports and Production Fragmentation of Computer and Electronic Products Manufacturing

In this section, we describe changes in the production process for Computer and Electronic Products Manufacturing—the extent to which final private consumption reflects domestic production, the sets of tasks that have been offshored, and the set of tasks that still take place within domestic manufacturers.

Mass market consumer electronics are almost exclusively assembled outside of the United States. While there are exceptions—such as Apple assembling Mac Pros in Austin, Texas or

| Industries | TFP Growth 87-97 | 97-09 | 09-23 | Output Share 87-97 | 97-10 | 09-23 |
|---|---|---|---|---|---|---|
| 3341: Computer and Peripheral Equip. | 0.142 | 0.163 | 0.005 | 0.229 | 0.184 | 0.082 |
| 3342: Communications Equip. | 0.046 | 0.027 | 0.021 | 0.158 | 0.173 | 0.127 |
| 3343: Audio and Video Equip. | 0.023 | 0.022 | 0.021 | 0.029 | 0.020 | 0.009 |
| 3344: Semiconductors and Other Electronic Components | 0.145 | 0.080 | 0.023 | 0.273 | 0.308 | 0.296 |
| 3345: Navigational, Measuring, Electromedical, and Control Instruments | 0.008 | 0.002 | 0.012 | 0.283 | 0.295 | 0.477 |
| 3346: Magnetic and Optical Media | 0.039 | -0.006 | -0.012 | 0.028 | 0.019 | 0.008 |

Table A.3: TFP Growth and Output Shares of 4-Digit Industries Within NAICS 334

Element Electronics' production of televisions in Winnsboro, South Carolina—nearly all top-selling televisions, stereos, personal computers, and cell phones are processed and assembled abroad.[26]

But domestic manufacturing industries still play an import role in the production of computers and other electronic products that are sold to final consumers. Table A.4 lists the ratio of imports of personal consumption expenditures to total personal consumption expenditures. While this increased over the 2000s, there is still a meaningful share of consumer electronic goods that are produced by domestic manufacturers. By the end of the sample, 46% of Computer and Electronic Products personal consumption expenditures comes from imports. This is substantially higher than at the beginning of the sample (32%) and higher than the import share for the manufacturing sector as a whole (12% in 1997, 16% in 2023). Yet, even Computers and Peripheral Equipment Manufacturing, the 4-digit NAICS industry with the highest import share, had at least two-fifths of its personal consumption expenditures produced domestically throughout the sample.

How can one reconcile the figures in Table A.4 with paucity of processing and assembly of domestic consumer electronics manufacturers? Table A.5 lists the types of occupations employed in different manufacturing industries, using data from the BLS Occupational Employment and Wage Statistics (OEWS) dataset. Panel A lists the share of employment in five of the largest 2-digit SOC (Standard Occupational Classification) occupation codes for 2002. (This is the first year for which the public version of the OEWS used the NAICS classification system.) Slightly more than half of manufacturing employees work in a single 2-digit occupation: Production (SOC 51). By contrast, in Computer and Electronic Prod-

[26]See `https://nr.apple.com/d2s4W269s6` and `https://www.prnewswire.com/news-releases/element-electronics-reinvesting-in-american-jobs-220711711.html`.

| Year | 1997 | 2002 | 2007 | 2012 | 2017 | 2023 |
|---|---|---|---|---|---|---|
| Manufacturing (31-33) | 0.123 | 0.165 | 0.179 | 0.176 | 0.162 | 0.160 |
| Computers and Electronic Products (334) | 0.323 | 0.419 | 0.469 | 0.488 | 0.440 | 0.464 |
| Computer and Peripheral Equip. (3341) | 0.304 | 0.395 | 0.441 | 0.519 | 0.563 | 0.594 |
| Communications Equipment (3342) | 0.183 | 0.238 | 0.266 | 0.352 | 0.369 | 0.389 |
| Audio and Video Equipment (3343) | 0.394 | 0.512 | 0.573 | 0.609 | 0.444 | 0.468 |
| Semiconductors and Other Electronic Components (3344) | 0.232 | 0.301 | 0.337 | 0.302 | 0.218 | 0.230 |
| Navigational, Measuring, Electromedical, and Control Instruments (3345) | 0.229 | 0.298 | 0.333 | 0.290 | 0.244 | 0.258 |
| Magnetic and Optical Media (3346) | 0.350 | 0.454 | 0.508 | 0.297 | 0.122 | 0.129 |

Table A.4: Import Share of Personal Consumption Expenditures

ucts Manufacturing, only one-third of employees work in Production occupations. From 2002 to 2023, the share of production workers declined by about 3 percentage points (from 52% to 49%) for the manufacturing sector and by 6 percentage points for the Computer and Electronic Products Manufacturing industry (from 34% to 28%.) For this industry, Management (SOC 11), Finance (SOC 13), Computer Programming (SOC 15), and Engineering and Architecture (SOC 17) collectively account for more than half of its workers, and nearly double the number of workers in production occupations. For this particular industry, domestic manufacturers add value not through their production and assembly of the goods that are consumed but through researching, designing, prototyping, and testing the manufacturing process. The other components of the manufacturing process—namely production and assembly—occur abroad.

### D.3 Additional Figures Supplementing Section 3

In Figure A.4, we plot the trajectory of corrected TFP for the manufacturing sector, for the private economy, and for the contribution of all manufacturing industries with the exception of the Computer and Electronic Products industry. Corrected for TFP mismeasurement, manufacturing productivity growth is faster than in Figure 2. As in Figure 2, TFP growth is slower after 2009 than before. But unlike Figure 2, industries other than Computer and Electronic products manufacturing contribute to the sector's productivity growth.

### D.4 Industries Missing in the PCE Bridge Table

To compute TFP mismeasurement of a detailed industry ($j$), it must appear in the PCE Bridge Table for at least one consumption category ($c$). For instance, while Vegetable and

| Panel A: 2002 | | | | | | |
|---|---|---|---|---|---|---|
| Occupation | Mgmt. | Finance | Computers | Engineering | Admin. | Production |
| Manufacturing (31-33) | 0.057 | 0.025 | 0.018 | 0.054 | 0.099 | 0.521 |
| Computers and Electronics (334) | 0.091 | 0.053 | 0.093 | 0.198 | 0.112 | 0.341 |
| Computers (3341) | 0.094 | 0.068 | 0.202 | 0.188 | 0.105 | 0.233 |
| Communications Equip. (3342) | 0.100 | 0.059 | 0.082 | 0.186 | 0.147 | 0.314 |
| Audio and Video Equip. (3343) | 0.081 | 0.035 | 0.026 | 0.115 | 0.128 | 0.476 |
| Semiconductors (3344) | 0.079 | 0.039 | 0.059 | 0.201 | 0.085 | 0.443 |
| Navigational, Measuring, Electromedical, and Control Instruments (3345) | 0.102 | 0.063 | 0.079 | 0.232 | 0.122 | 0.295 |
| Magnetic and Optical Media (3346) | 0.071 | 0.022 | 0.137 | 0.045 | 0.181 | 0.232 |
| Panel B: 2023 | | | | | | |
| Occupation | Mgmt. | Finance | Computers | Engineering | Admin. | Production |
| Manufacturing (31-33) | 0.066 | 0.050 | 0.026 | 0.061 | 0.076 | 0.488 |
| Computers and Electronics (334) | 0.122 | 0.092 | 0.142 | 0.179 | 0.070 | 0.281 |
| Computers (3341) | 0.163 | 0.124 | 0.293 | 0.119 | 0.066 | 0.110 |
| Communications Equip. (3342) | 0.142 | 0.100 | 0.169 | 0.154 | 0.082 | 0.222 |
| Audio and Video Equip. (3343) | 0.137 | 0.080 | 0.087 | . | 0.099 | 0.323 |
| Semiconductors (3344) | 0.095 | 0.067 | 0.074 | 0.227 | 0.060 | 0.380 |
| Navigational, Measuring, Electromedical, and Control Instruments (3345) | 0.125 | 0.101 | 0.141 | 0.176 | 0.078 | 0.269 |
| Magnetic and Optical Media (3346) | 0.174 | 0.119 | 0.225 | . | 0.087 | 0.114 |

Table A.5: Share of Employment Across Occupations by Manufacturing Industry
Notes: This table lists the share of employment in various manufacturing industries. The column headers are as follows: Mgmt. refers to Management Occupations (SOC 11). Finance refers to Business and Financial Operations Occupations (SOC 13). Computers refers to Computer and Mathematical Occupations (SOC 15). Engineering refers to Architecture and Engineering Occupations (SOC 17). Admin. refers to Office and Administrative Support Occupations (SOC 43). Production refers to Production Occupations (SOC 51). In Panel B, the share of Engineering occupation workers who are in Audio and Video Equipment Manufacturing and Magnetic and Optical Media Manufacturing was not published.

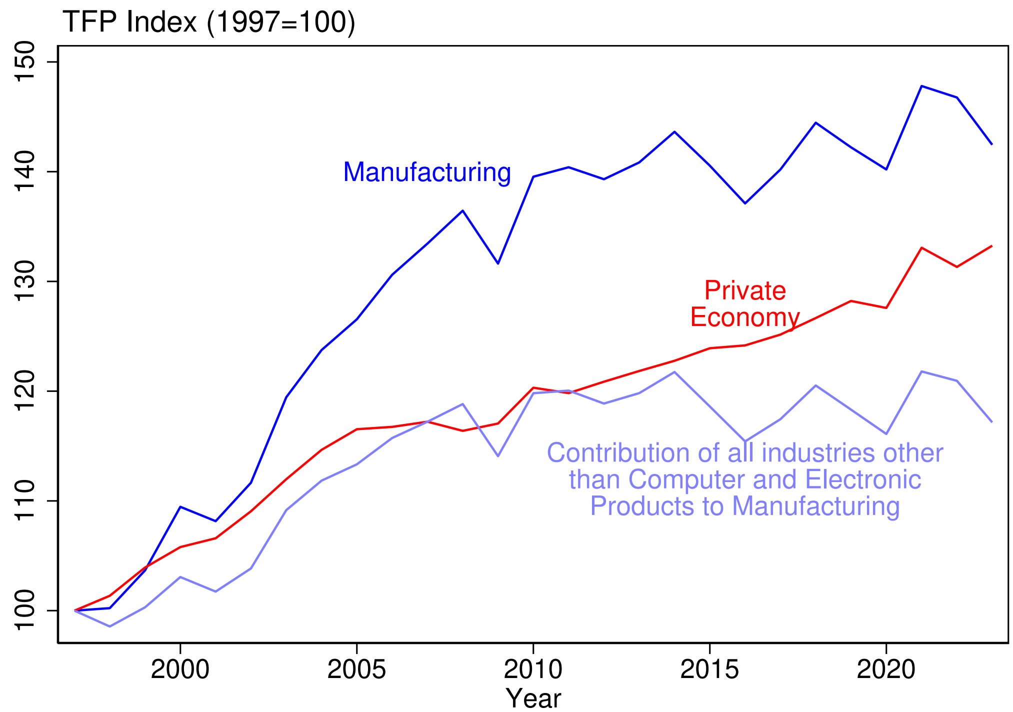


Figure A.4: TFP for Manufacturing, Manufacturing excluding Computer and Electronic Products, and the Private Business Sector

Notes: This figure reproduces Figure 2, but correcting for TFP mismeasurement using the adjustments in Section 3.

Melon Farming (NAICS 1112) appears in the PCE Bridge Table for the Fresh Vegetables consumption category (NIPA Line 92), Oilseed and Grain Farming (NAICS 1111) does not appear in the PCE Bridge Table. This commodity is sold only to other businesses, not to final consumers.

Figure A.5 plots the share of industries which appear in the PCE Bridge Table, for which we can compute TFP mismeasurement. While Government and Construction industries do not appear in the PCE Bridge, all of the industries producing Food & Beverages (NAICS 311, 312), Textiles, Apparel, and Leather (NAICS 313-316), and Entertainment, Accommodation, and Food (NAICS 71, 72) do. Overall, weighting observations by their gross output, 75% of manufacturing industries and 62% of private (non-governmental industries) appear in the PCE Bridge.

In the remainder of this subsection, we investigate whether industries missing in the PCE Bridge Table are likely to have lower (or higher) estimated mismeasurement. We consider two exercises. First, we look across broad groups of industries, comparing TFP mismeasurement (among the set of detailed industries for which we can estimate it) to the

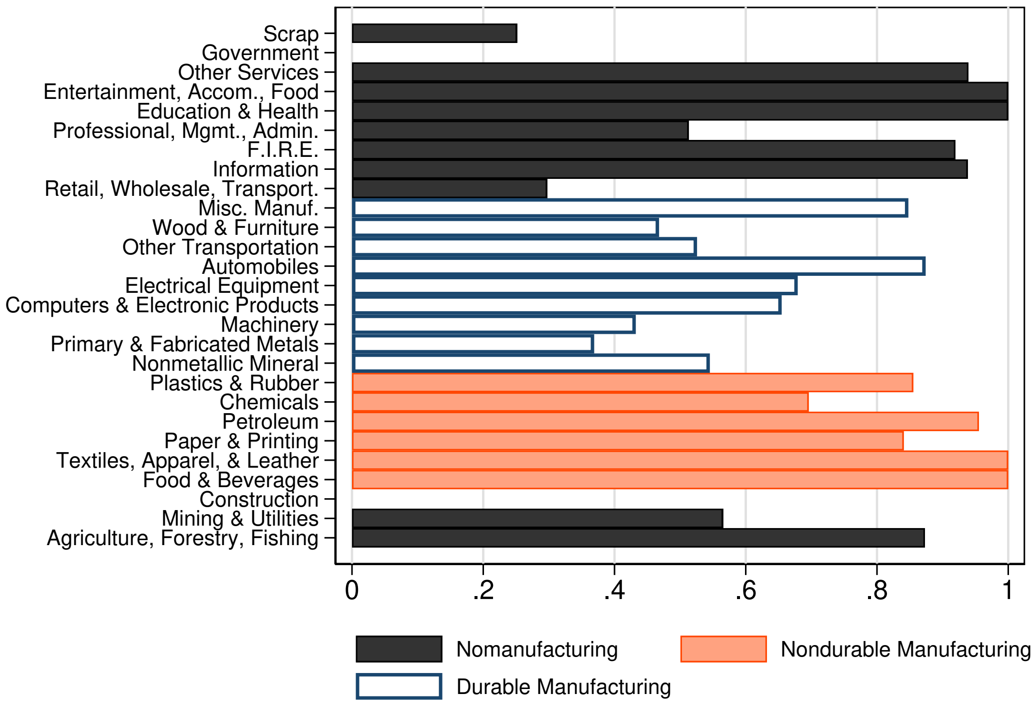


Figure A.5: Share of Industries for Which We Estimate TFP Mismeasurement
Notes: This figure lists the share of grouping of detailed industries for which we can compute TFP mismeasurement. When averaging across industries, we weight according to their gross output in 2017. In computing this figure, we exclude Retail, Wholesale, and Transport industries that appear only through columns D-F of the PCE Bridge Table (see the discussion in Appendix C. Including these industries would increase the entry for the “Retail, Wholesale, and Transport” row from 0.30 to 0.87, increasing the private economy average from 0.62 to 0.78.

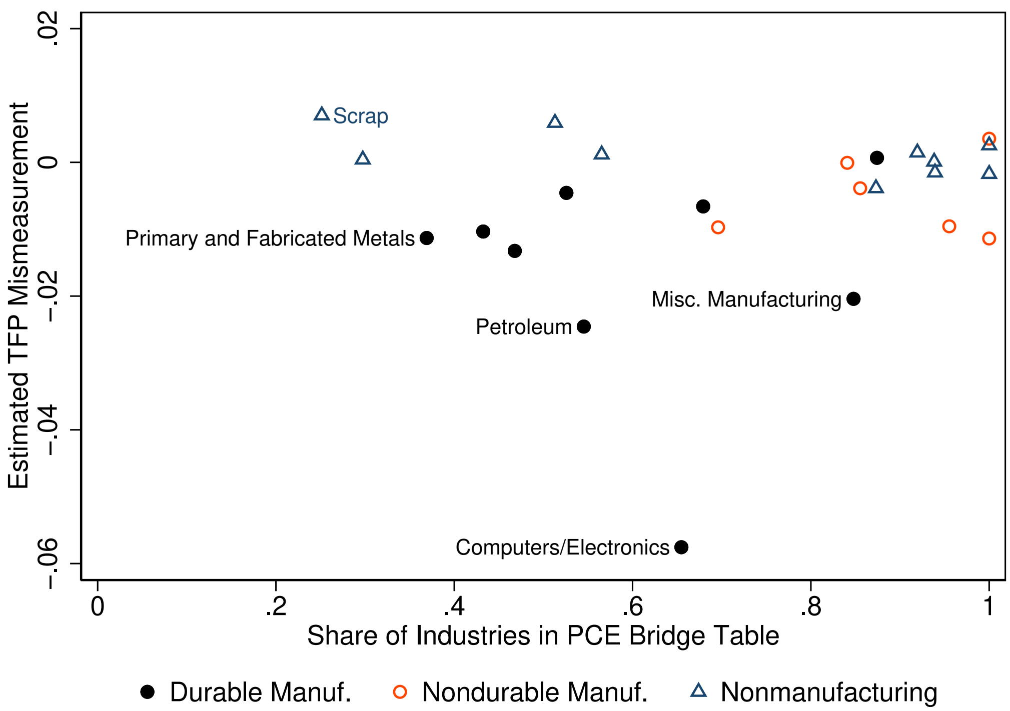


Figure A.6: Share of Industries For Which we Estimate TFP Mismeasurement vs. Average TFP Mismeasurement protect

Notes: For each of the industries appearing in Figure A.5, excluding "Government" and "Construction," we related the share of industries for which we estimate TFP mismeasurement to the average TFP mismeasurement among the industries for which we can compute it.

share of industries appearing in the PCE Bridge Table. The idea behind this exercise is that—if the extent to which gross output deflators understate quality growth is correlated within 2- or 3-digit industries, then we can infer whether we are missing estimates of TFP mismeasurement particularly so in industries where this mismeasurement is likely to be exceptionally high (or exceptionally low.) Figure A.6 presents our comparison. Overall, we find no relationship across the two variables. Weighting observations equally, the correlation is an (insignificant) 0.09; weighting groups of industries according to their gross output (as of 2017), the correlation is 0.03.

While Figure A.6 looks across industry groupings, Table A.6 examines whether there are any differences within industry groupings between those detailed industries that are present or absent in the PCE Bridge Table. We compare industries according to their output prices—either the gross output deflator or our Equation 1 measure of "Producer Inflation." (We cannot compare industries' TFP mismeasurement, as we cannot compute this for detailed industries absent from the PCE Bridge Table.)

In more detail, we estimate the following regression:

$$\Delta \log P_j = \beta_J + \beta_1 \cdot \mathbf{1}_{j \in \text{PCE Bridge}} + \varepsilon_j \tag{11}$$

In some regressions, we include fixed effects for the broad industry grouping (i.e., one of the 29 industries listed in Figure 5.) In others, we do not. Table A.6 lists our estimates from Equation 11. Here, we find some differences, but with the sign and significance varying across groups of industries and empirical specifications. Overall, we do not find that industries in the PCE Bridge Table have systematically faster or slower Producer Inflation rates than those that are not represented.

### D.5 Dropping Industries With Only Small Entries in the PCE Bridge Table

Another concern, which we examine in this section, is that our estimates of TFP mismeasurement may be driven by a NAICS commodities which appear within the PCE Bridge Table, but only marginally so. Consider, as an example of this potential concern, the NAICS commodity 3274: Lime and Gypsum Products Manufacturing. In 2017, domestic gross output of this commodity was \$8.1 billion. This commodity appears in the PCE Bridge Table once, contributing \$71 million towards the consumption category "Clocks, Lamps, Lighting Fixtures, and Other Household Decorative Items" (NIPA Line 26.) (The three most important NAICS Commodities for this consumption category are 33999, S00402, and 335120: "Used and Secondhand Goods," "All Other Miscellaneous Manufacturing," and "Lighting Fixture

| | | | | | | |
|---|---|---|---|---|---|---|
| Panel A: All Sectors | | | | | | |
| Dependent Variable | | Producer Inflation | | | Gross Output Deflator | |
| In PCE Bridge | -0.004 | -0.002 | -0.001 | 0.005*** | -0.001 | 0.005*** |
| | (0.002) | (0.002) | (0.004) | (0.002) | (0.004) | (0.002) |
| Observations | 398 | 398 | 398 | 398 | 398 | 398 |
| Adjusted $R^2$ | 0.009 | 0.421 | -0.001 | 0.480 | -0.002 | 0.478 |
| Fixed Effect | None | Industry | None | Industry | None | Industry |
| Weighted | No | No | Yes | Yes | Yes | Yes |
| Panel B: Durable Manufacturing | | | | | | |
| Dependent Variable | | Producer Inflation | | | Gross Output Deflator | |
| In PCE Bridge | -0.010** | -0.008** | -0.005 | 0.001 | -0.005 | 0.002 |
| | (0.003) | (0.003) | (0.003) | (0.004) | (0.003) | (0.003) |
| Observations | 151 | 151 | 151 | 151 | 151 | 151 |
| Adjusted $R^2$ | 0.050 | 0.437 | 0.006 | 0.466 | 0.001 | 0.453 |
| Fixed Effect | None | Industry | None | Industry | None | Industry |
| Weighted | No | No | Yes | Yes | Yes | Yes |
| Panel C: Nondurable Manufacturing | | | | | | |
| Dependent Variable | | Producer Inflation | | | Gross Output Deflator | |
| In PCE Bridge | -0.002 | 0.003* | 0.003 | 0.002 | 0.004 | 0.004 |
| | (0.003) | (0.001) | (0.004) | (0.002) | (0.005) | (0.003) |
| Observations | 80 | 80 | 80 | 80 | 80 | 80 |
| Adjusted $R^2$ | -0.008 | 0.344 | -0.008 | 0.566 | -0.002 | 0.557 |
| Fixed Effect | None | Industry | None | Industry | None | Industry |
| Weighted | No | No | Yes | Yes | Yes | Yes |
| Panel D: Nonmanufacturing | | | | | | |
| Dependent Variable | | Producer Inflation | | | Gross Output Deflator | |
| In PCE Bridge | -0.002 | 0.006*** | -0.002 | 0.006** | -0.002 | 0.006*** |
| | (0.005) | (0.002) | (0.005) | (0.002) | (0.005) | (0.002) |
| Observations | 167 | 167 | 167 | 167 | 167 | 167 |
| Adjusted $R^2$ | -0.003 | 0.401 | -0.000 | 0.430 | -0.001 | 0.429 |
| Fixed Effect | None | Industry | None | Industry | None | Industry |
| Weighted | No | No | Yes | Yes | Yes | Yes |

Table A.6: Differences in Output Prices between Industries Present or Absent in the PCE Bridge Table

Notes: Each column by panel presents the results from a separate regression. The first four columns have the Producer Inflation measure (defined in Equation 1) as the dependent variable. The final two columns have gross output deflator inflation as the dependent variable. An observation is a detailed industry. The standard errors are clustered at the more aggregated industry level (i.e., each of the clusters is one of the 29 industries listed in Figure 5.)

Manufacturing," respectively.) Our estimate of TFP mismeasurement for this commodity comes from comparing its price index to that in an only loosely related consumption category. More generally, we may doubt our estimates of TFP mismeasurement for commodities which have a small contribution in the PCE Bridge Table, relative to their total gross output.

In the panels of Figure A.7, we consider the impact of removing commodities with small contributions to the PCE Bridge Table. The left panel reproduces our baseline results. The middle panel removes detailed commodities for which the total value in the PCE Bridge Table relative to its gross output is less than 0.25. In the right panel, we increase that threshold to 0.50.

In the main, our conclusions are robust across these three panels. In our baseline specification, TFP growth was understated by 1.7 percentage points in the durable goods sector, understated by 0.4 percentage points in the nondurable goods sector, and overstated by 0.1 percentage points in nonmanufacutring sectors. In the middle and right panels, TFP growth in the durable goods manufacturing sector is understated by 1.8 percentage points. In both the middle and right panels, nondurable goods' TFP growth is understated by 0.4 percentage points and overstated by 0.1 percentage points in nonmanufacturing industries. For the Computer and Electronic Products manufacturing industry, TFP growth is understated by 5.8 percentage points in the left and middle panels and 6.2 percentage points in the right panel.

### D.6 TFP Mismeasurement with Alternate Definition of $\mathbf{O_t}$

In this section, we assess the robustness of our conclusions in Section 3 to our definition of $\mathbf{O_t}$. This matrix was necessary for translating price mismeasurement at the PCE category level to price mismeasurement at the NAICS commodity level.

In the body of the paper, we defined:

$$\begin{aligned} \mathbf{O_{t,jc}} &\equiv 1 \text{ if } v_{t,j\to c} = \max_{c'} v_{t,j\to c'} \text{ and} \\ &\equiv 0 \text{ otherwise .} \end{aligned}$$

In words, for each NAICS commodity ($j$) we searched for the PCE consumption category $c$ that has the largest value in the PCE Bridge Table. As an example, consider NAICS Commodity 336111 (Automobile Manufacturing). This appears twice in the PCE Bridge Table. As of 2017, it contributes \$ 14.87 billion in the consumption of New Domestic Autos (NIPA Line 7) and \$ 5.23 billion in the consumption of New Foreign Autos (NIPA Line 8.) According to this first definition, for the row associated with $j$ =336111, $\mathbf{O_{t,jc}}$ would be equal to 1 for the column associated with NIPA Line 7, and 0 otherwise. In essence,

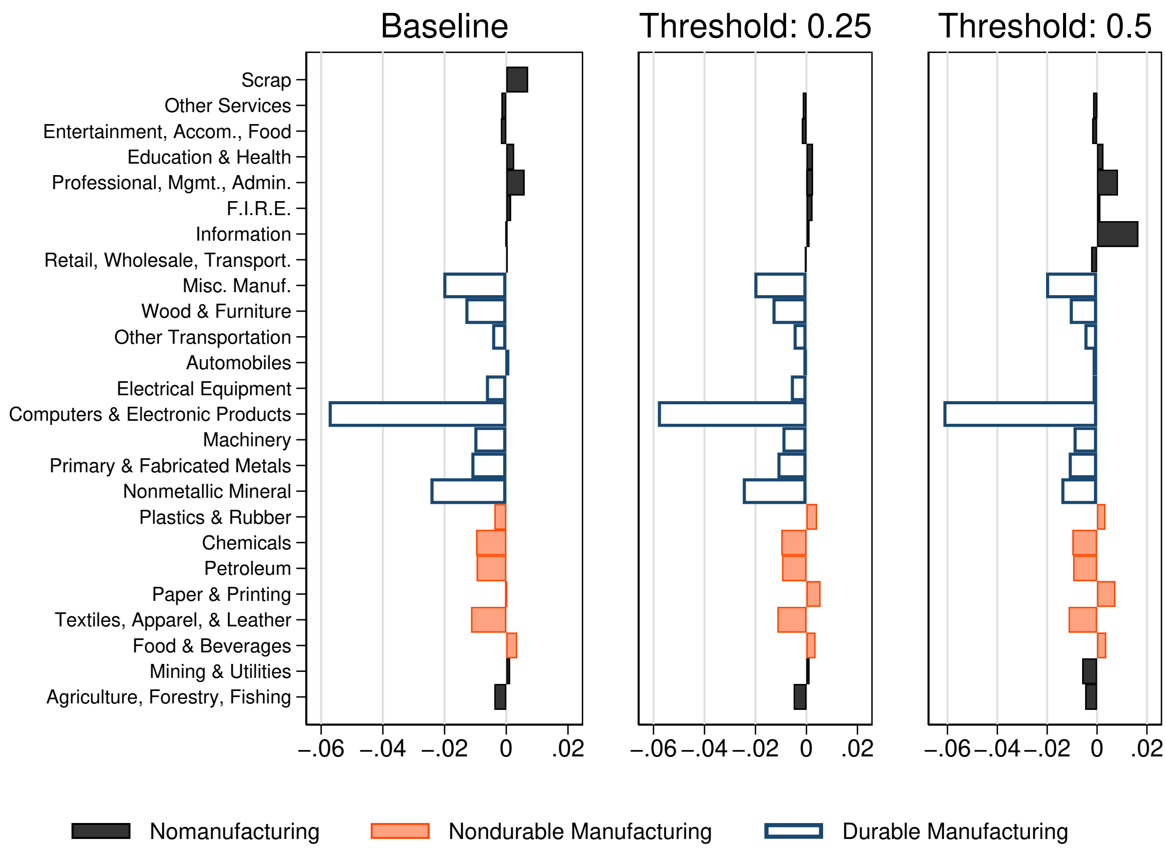


Figure A.7: Sensitivity to Dropping Commodities with Only "Small" Entries in the PCE Bridge Table

Notes: The left panel recapitulates the left panel of Figure 5. The middle panel drops detailed industries for which the sum of its entries in the 2017 PCE Bridge Table is less than 25% of the its gross output in the same year. The right panel drops detailed industries for which the sum of its entries in the 2017 PCE Bridge Table is less than 50% of the its gross output in the same year. Entries for "Scrap" are missing for these panels, as there are no detailed industries meeting this threshold. Of the 255 detailed industries represented in the left panel, 156 are included in the middle panel, and 130 in the right panel.

we infer price mismeasurement of Automobile Manufacturing from price mismeasurement in New Domestic Autos.

In this section, we consider an alternative definition for $\mathbf{O_{t,jc}}$. We set:

$$\mathbf{O_{t,jc}} \equiv \frac{v_{t,j\to c}}{\sum_{c'} v_{t,j\to c'}} \ . \tag{12}$$

Here, we infer an industry's price mismeasurement as a weighted average of the mismeasurement in all of the PCE consumption categories it is linked to. Returning to our autos example, for the row associated with NAICS 336111, $\mathbf{O_{t,jc}}$ would be equal to 0.739$= \frac{14.87}{14.87+5.23}$ for the column associated with NIPA Line 7, 0.261 for the column associated with NIPA Line 8, and 0 elsewhere. Here, we infer price mismeasurement of Automobile Manufacturing from a weighted average of price mismeasurement in New Domestic Autos and New Foreign Autos.

Figure A.8 presents our alternate results. TFP mismeasurement is similar to what we had presented in Figure 5. In Figure 5, annual manufacturing TFP growth is understated by 0.7 percentage points. For durable goods, TFP growth is understated by 1.6 percentage points. Both figures are 0.1 percentage points less than the, respectively, 0.8 percentage points and 1.7 percentage points in the baseline specification.

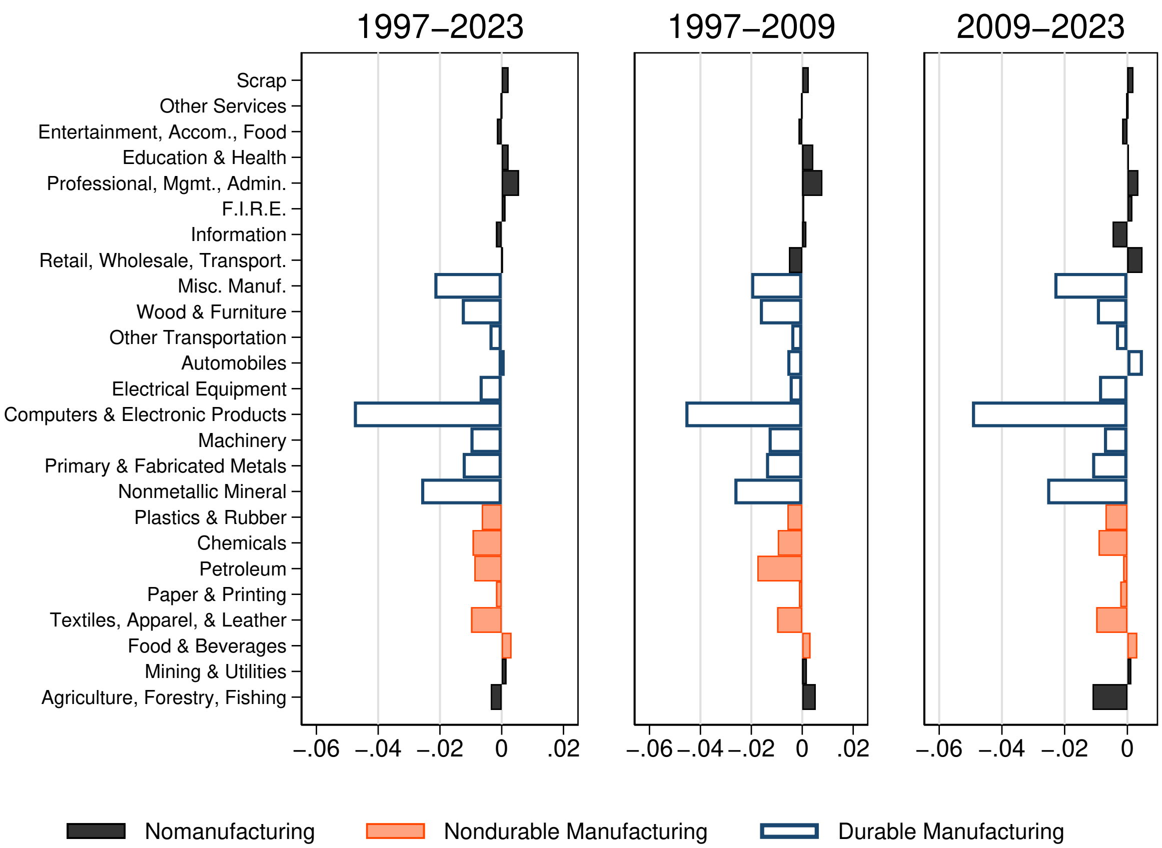


Figure A.8: TFP Mismeasurement

Notes: See the notes for Figure 5. In contrast to that figure, we apply Equation 12 to compute $\mathbf{O_t}$.