Why Is Manufacturing Productivity Growth So Low?

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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 that conventional measures understate manufacturing productivity growth by failing to fully capture quality improvements. To do so, 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.

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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 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.

The leader-follower flip we highlight has not garnered much research attention until recently, and is still not well understood. We examine manufacturing productivity using a price-based dual approach. We infer mismeasurement in TFP by comparing gross output deflators to the prices that consumers face. In industry accounts, gross output deflators deflate nominal gross output and intermediate inputs to real terms. Consumer prices better capture quality gains, so comparing them to producer deflators shows where output growth may be understated.

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 show 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, and 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

[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-`

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, we argue that past assessments may have presented an overly negative depiction of their success.

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

Specific to the manufacturing productivity slowdown, Syverson (2016) documents that the Computer and Electronic Products manufacturing industry was key to the 1995–2004 productivity resurgence and the subsequent productivity slowdown. These results are echoed by Sprague (2021).[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

product/R47523.

[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.

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

Closer to our work, David Byrne and co-authors have examined the performance of producer price indices, focusing on individual 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]

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

where the summation is over all industries within the manufacturing sector and ω_{tj} denotes industry j's share of manufacturing output at time t. Both $\Delta \log A_{t,j}$ and ω_{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 can explain nearly 100% of the trajectory of whole sector since the late 1980s. We make this point by plotting in Figure 2 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

[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.)

[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.

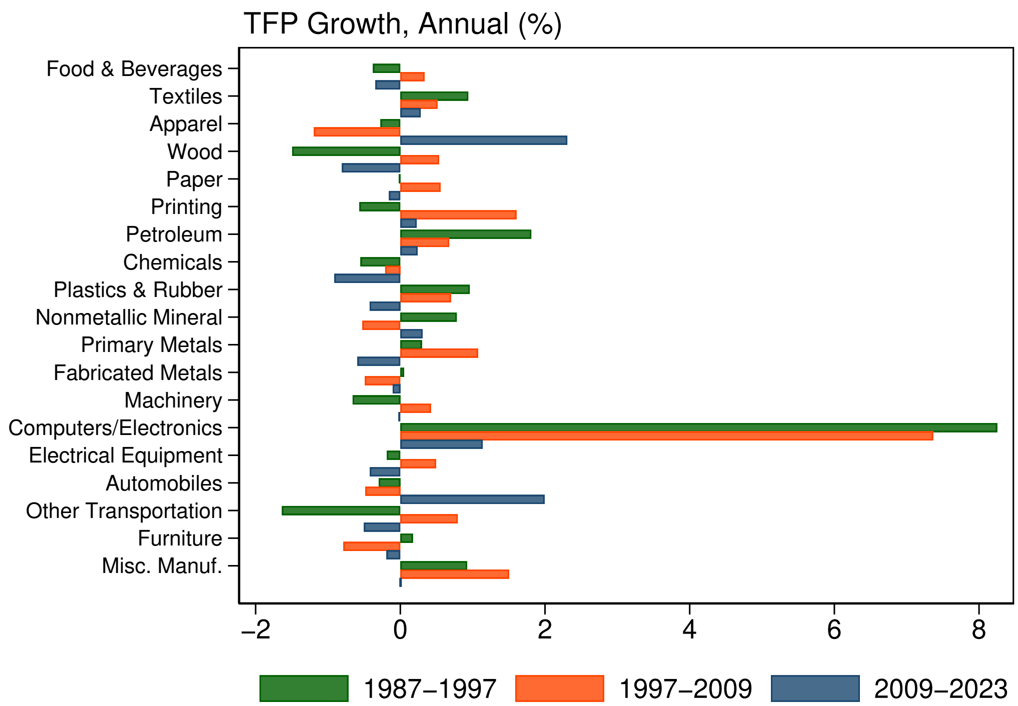

Figure 1: Annual TFP Growth Rate by 3-digit Manufacturing Industry
Notes: "Food & Beverages" is the collection of NAICS 311 and 312. "Textiles" is the collection of NAICS 313 and 314. "Apparel" is the collection of NAICS 315 and 316. "Automobiles" is the collection of NAICS 3361, 3362, and 3363. "Other 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.

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

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 (essentially the entire economy less the government sector).

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

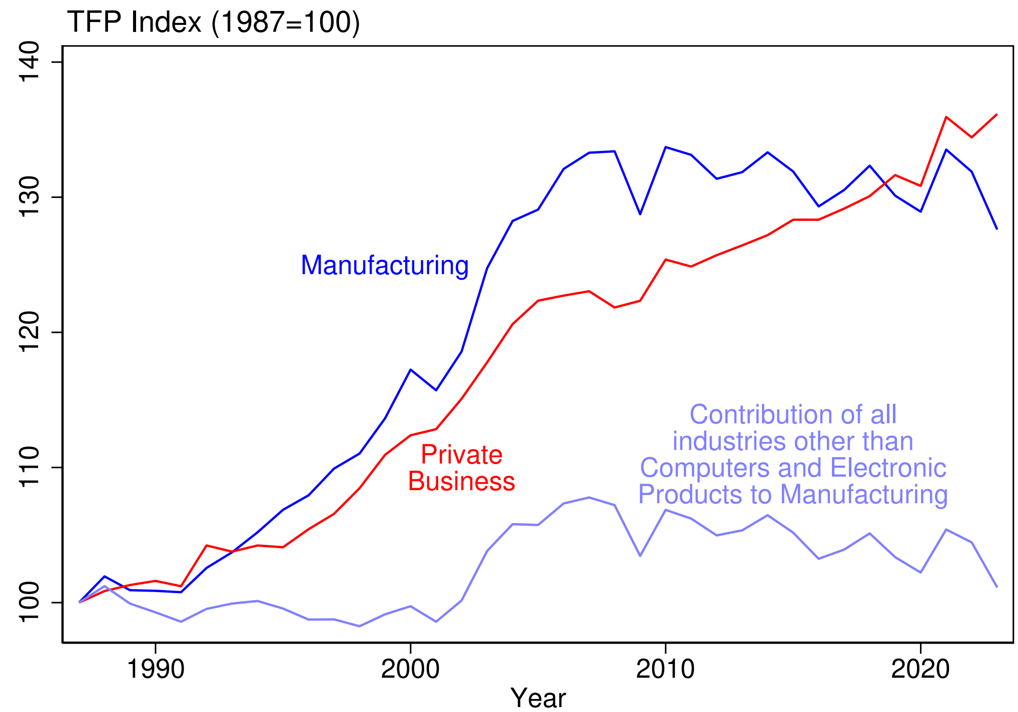

Figure 2: TFP for Manufacturing, Manufacturing excluding Computer and Electronic Products, and the Private Business Sector

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 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 PCE price indices 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]

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

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 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 wholesaling. 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 the latter, the BLS invests significantly—in its survey design, in its data collection efforts, and in its statistical and economic methodology—to ensure *all* of its price measures provide accurate and representative depictions of inflation experienced by households and firms. But, given its finite budget, some prioritization must inevitably be made in where BLS resources are allocated. Given the BLS' frequent reference to the CPI as 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

[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.

[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 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, 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—or inflation measures derived from the CPI, like the PCE—on the one hand and the PPI and Import Price Indices on the other—or inflation measures derived from the PPI and Import Price Indices, such as industry gross output deflators—as suggestive evidence incomplete quality adjustment in the latter price indices, especially so if the differences were concentrated in goods experiencing rapid technological progress.

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 depending on whether one is looking from the consumer's or producer's perspective. 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

[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.

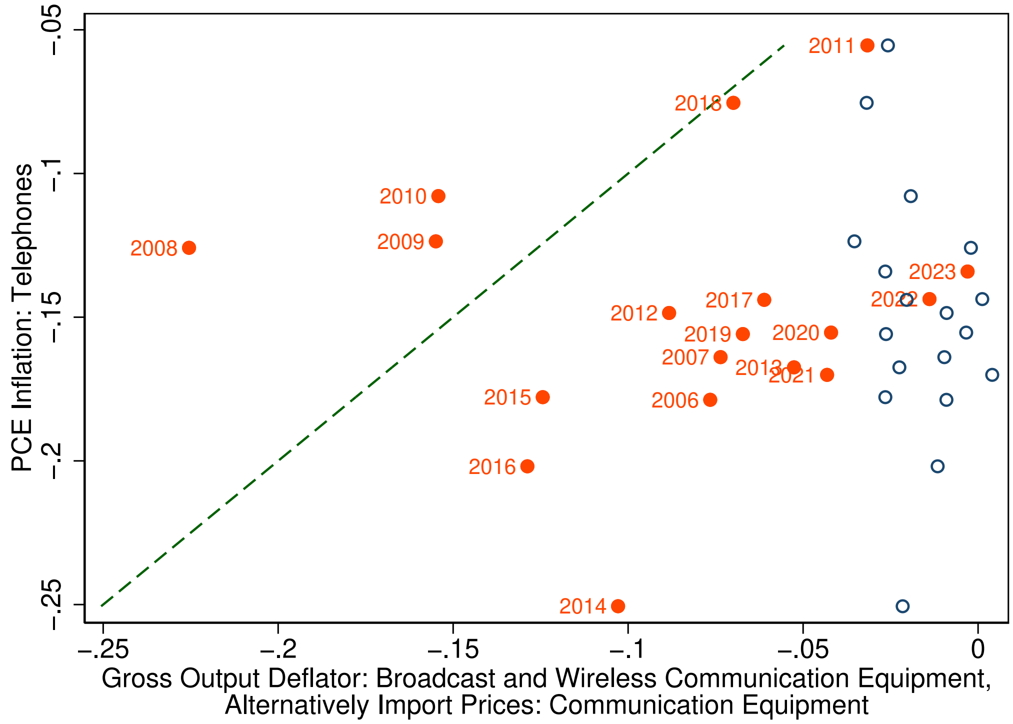

Figure 3: Telephone Apparatus Inflation
Notes: The vertical axis gives Telephone Apparatus inflation according to the PCE price index. The horizontal axis gives two measures of producer inflation. In orange filled circles, we plot changes in the gross output deflator for the Broadcast and Wireless Communications 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.

Communications Equipment Manufacturing (NAICS 3342) fell by 1.6% per year.[13] At least for this one product category, price declines are much greater from the perspective of a consumer than that of a producer.

In Figure 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

[13]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 Broadcast and Wireless Communications Equipment would display greater price declines than what the green 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.

but using gross output deflators and import price indices.[14] As the Telephone Apparatus 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. [15] We use the Input-Output Tables to assign weights for domestic production vs. imports.[16]

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

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

where c indexes a PCE category, j a NAICS commodity, $s_{j\to c}$ gives the share of PCE category c that is made up of commodity j, and $m_{t,j}$ equals the share of personal consumption expenditures of commodity j that comes from imports. For each category, we use the finest level of commodity detail that is available. In some instances—as in the example of the Telephone Apparatuses category, for instance—the level of aggregation is coarser in the import price 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 $\Delta \log P_t^{\text{Producer}}$. The (consumption-weighted) correlation across the two measures is 0.66. Our Producer Inflation measure

[14]For 1997 to 2005, we impute commodities' import price growth using the 2025-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 Producer Inflation — as defined in Equation 1 — as the dependent variable. The two explanatory variables are (i) gross output price growth, $\Delta \log P_{t,j}^{\text{GO}}$, and (ii) the interaction of import price growth and the import share of PCE, $m_{t,j}\Delta \log P_{t,j}^{\text{Import}}$. 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. Given this, for each year between 1997 and 2005, we impute $\Delta \log P_{t,c}^{\text{Producer}}$ as $\Delta \log P_{t,j}^{\text{GO}} - 0.736 \cdot m_{t,j}\Delta \log P_{t,j}^{\text{Import}}$.

[15]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.

[16]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.

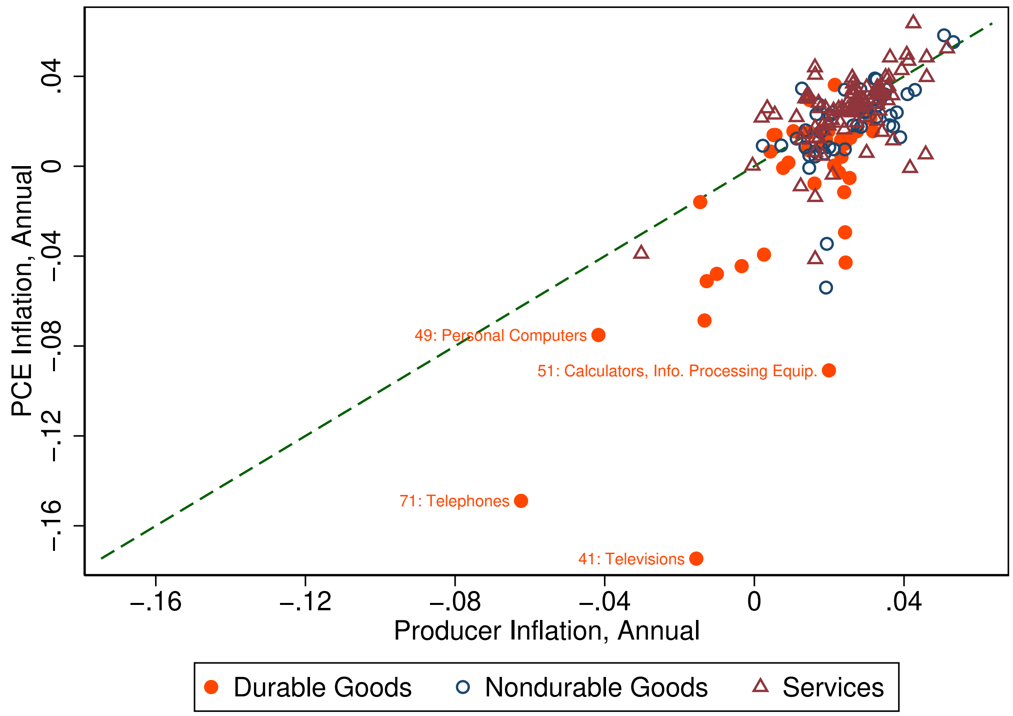

Figure 4: Two Measures of Inflation Across PCE Categories, 1997–2023
Notes: Each point is a single PCE category. The vertical axis gives annual inflation according to the PCE price index between 1997 and 2023. The horizontal axis gives our measure of Producer Inflation (defined by Equation 1) over the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

exceeds PCE by 0.6 percentage point overall, but with much larger gaps in nondurable goods (where the gap is 1.1 percentage points) and durable goods (with a 2.6 percentage point gap.) The difference in inflation rates is exceptionally high for computers and other electronic products. An extreme but instructive example is the Television category. Inflation in televisions averages -17.5% per year between 2005 and 2023 according to the CPI or PCE. The gross output deflator for the more aggregated Audio and Video Manufacturing industry (NAICS 3343) is -0.5% per year. Inflation according to the import price index is -2.9% per year. Given that nearly half (48%) of Audio and Video Manufactured Products that enter personal consumption expenditures are imported, the -0.5% and the -2.9% average out to a -1.6% Producer Inflation rate. Some of the difference between the -17.5% PCE inflation and -1.6% Producer Inflation likely reflects the inclusion of Audio Equipment and Other Video Equipment in our Producer Inflation measure. However, PCE inflation for these other categories were also exceptionally low, -4.8% for Audio Equipment and -6.9% for Other Video Equipment. So, for Televisions and Other Audio and Video Equipment, PCE deflation is vastly greater than deflation according to price indices from the producer perspective.

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

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

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

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

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 as a function of changes in the unit cost of labor, the unit cost of labor, and the price of individual intermediate inputs, i. The final line writes this equation in vector notation. Within this line, the "$\circ$" operator denotes element-wise multiplication.

Below, we use $\tilde{\mathbf{x}}$ to refer to mismeasurement in variable $\mathbf{x}$. Since our preceding analysis did not 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, the log deviation of an observed variable from its "true" value. Equation 2 can be written as:

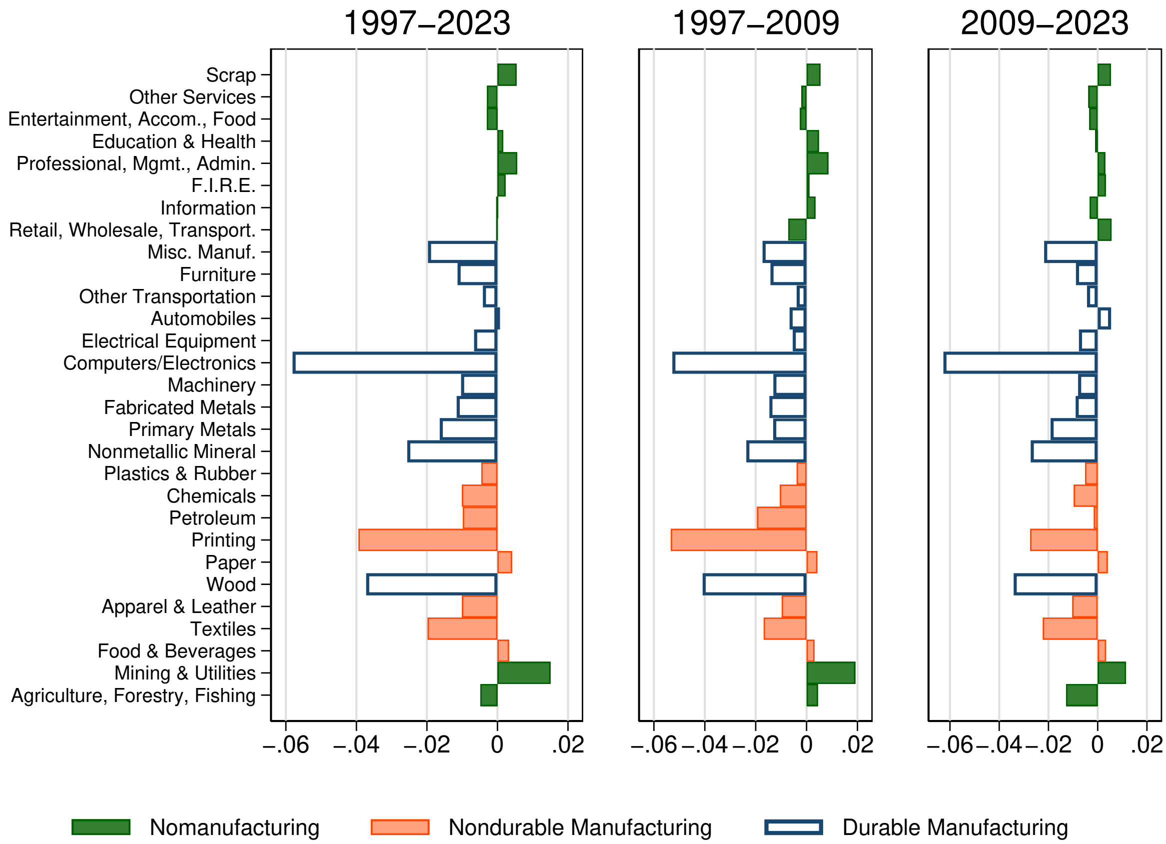

Figure 5: TFP Mismeasurement

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

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

Our second building block comes from comparing Producer Inflation — defined in Section 2 — and PCE inflation. We attribute differences between PCE and Producer Inflation to mismeasurement in import price indices or gross output deflators:

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

We write this equation in matrix form:

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

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

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

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:

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

We apply Equation 7 using data from 1997 to 2023. We highlight four main results. First, within the durable goods manufacturing industry, TFP is most mismeasured for the Computer and Electronic products industry, by roughly 6 percentage points per year. Second, looking across sectors, TFP mismeasurement is greatest in the durable goods manufacturing sector (at -1.7 percentage points per year), much smaller in the nondurable goods manufacturing sector (at -0.4 percentage points per year), and essentially nonexistent in the nonmanufacturing sector (at 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.[17]

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 (1.3%), 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 Section 3.

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 attribute gaps between PCE and "Producer" inflation to inadequate quality adjustment in the latter index. To explore this concern, in Appendix D.4, we progressively restrict the sample to NAICS commodities that have more of their sales sold as final consumption. We find that the patterns given in Figure 5 are robust to this restriction.

In Appendix D.5, 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

[17] For the durable goods sector, the average of $\Delta \log \widetilde{\mathbf{A}}_t$ was -1.8 percentage points between 1997 to 2009 and 1.6 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.

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

We then marshal suggestive evidence that quality improvements and, by implication, productivity growth may be substantially underestimated in durable goods manufacturing, primarily so in the manufacturing of computers and other electronic goods. We estimate that annual TFP growth in durable goods manufacturing may be understated by up to 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,[18] 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.

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

References

Alfaro, L. and D. Chor (2023): "Global Supply Chains: The Looming 'Great Reallocation'," NBER Working Papers 31661.

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

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

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

Byrne, D. M. (2015): "Prices for Data Storage Equipment and the State of IT Innovation," FEDS Notes 2015-07-01, Board of Governors of the Federal Reserve System.

Byrne, D. M. and C. Corrado (2015a): "Prices for Communications Equipment: Rewriting the Record," Finance and Economics Discussion Series 2015-69, Board of Governors of the Federal Reserve System.

——— (2015b): "Recent Trends in Communications Equipment Prices," FEDS Notes 2015-09-29, Board of Governors of the Federal Reserve System.

Byrne, D. M., J. G. Fernald, and M. B. Reinsdorf (2016): "Does the United States Have a Productivity Slowdown or a Measurement Problem?" *Brookings Papers on Economic Activity*, 2016, 109–182.

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

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

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

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

Houseman, S. (2018): "Understanding the Decline of U.S. Manufacturing Employment," Upjohn Working Papers 18-287.

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

KLUMP, R., A. JURKAT, AND F. SCHNEIDER (2021): "Tracking the Rise of Robots: A Survey of the IFR Database and Its Applications," MPRA Paper 110390.

LASHKARI, D. AND J. PEARCE (2024): "The Mysterious Slowdown in U.S. Manufacturing Productivity," Liberty Street Economics 20240711, Federal Reserve Bank of New York.

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

MOULTON, B. (2024): "The Measurement of Output, Prices, and Productivity: What's Changed Since the Boskin Commission?" in *The Measure of Economies: Measuring Productivity in an Age of Technological Change*, ed. by M. B. Reinsdorf and L. Sheiner, 51–88.

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

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

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

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

A Discussion of Underlying Source Data and Quality Adjustment

In this appendix, we discuss the sources of inflation data, both from the household and 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 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 late-2010s, 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 no the BEA index for installation support services.) For service commodities, while the CPI is the primary data source for many components of the PCE price index, a larger set of components draw on the PPI (examples include most financial service charges and fees, air transportation; hospitals, and physician services) and BEA input cost indices (examples include labor organization dues, life insurance, financial services furnished without payment, among others).

Gross Output Deflators

The 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, p. 4-25). There are two sets of exceptions. First, for military equipment, the BEA applies price indices from the Department of Defense ("prices paid for military equipment"). Second, the BEA employs quality-adjusted price indices for computers, photocopying equipment, digital telephone switching equipment, and LAN equipment. Some of these quality-adjusted price indices draw on the BLS PPI. In other cases, where quality adjustment has not been available, the BEA has constructed its own (Bureau of Economic Analysis, 2024, Chapter 4, Page 25). For service industries, the BEA gross output deflators draw on a wider variety of sources. 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
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)	————	————	————

Year	2004	2010	2018
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	———	———
For Farms, Excluding Residential	Trade sources cost index; Census Bureau price deflator for new single family houses under construction	———	———

Year	2004	2010	2018
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
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)	————	————	————

Year	2004	2010	2018
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
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)	————	————	————

Year	2004	2010	2018
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)	————	————	————
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

Year	2004	2010	2018
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
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)	————————	————————	————————

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

Year	2004	2010	2018
Management of Companies and Enterprises (55)	BLS wages and salaries per full-time employee	BLS QCEW	PPI
Administrative and Waste Management Services (56)	For administrative support: BLS wages and salaries per full- time employee; PCE; PPI For waste management: CPI	NIPA PCE based on CPI data; BLS QCEW; PPI	PPI and NIPA PCE
Educational Services (61)	PCE	NIPA PCE based on trade source data for input costs	NIPA PCE
Health Care and Social Assistance (62)	PPI; PCE	———	PPI and NIPA PCE
Ambulatory Health Care Services (621)	PPI; PCE	NIPA PCE based on CPI; PPI	———
Hospital and Nursing and Nursing Care Facilities (622, 623)	PCE	NIPA PCE based on CPI and Centers for Medicare and Medicaid Services	———
Social Assistance (624)	PCE	NIPA PCE based on trade source data on input costs	———
Arts, Entertainment, and Recreation (71)	PCE	NIPA PCE based on CPI.	NIPA PCE
Accommodation and Food Services (72)	———	———	———
Accommodation (721)	For hotels and motels, PPI; PCE price index.	PPI; NIPA PCE based on CPI	PPI and NIPA PCE
Food Services (722)	CPI	Census Bureau ARTS; PPI composite price index.	PPI

Year	2004	2010	2018
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.[19] 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.

[19] 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),[20] land-line telephone services (2019),[21] 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,[22] late 2016,[23] and 2018,[24] 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 2017. We first discuss our estimates at producing $m_{t,j}$— the share of consumption expenditures of detailed commodity j that is imported in year t.

B.1 Import Interpolation Methodology

Crosswalk

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

There are 73 summary import commodities categories; use φ to denote a summary category. Of the 73 of these summary commodities two are "scrap used and secondhand goods and non-comparable imports" and "rest-of-the-world adjustment"; we refer to the remaining

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

[21]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`.

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

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

[24]See Sawyer and So (2018).

71 summary commodities as “normal”. We have data on these commodities from 1997 to 2023.

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

Interpolation

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

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

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

That is: PCE Bridge Imputation Methodology

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Notes on these methods

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

- There are no cases of $m_{\varphi,2007} \neq 0$ and $m_{\varphi,2012} = 0$ (or its 2012-2017 analogue) so we didn't design a method for that scenario.

B.2 PCE Bridge Imputation Methodology

Crosswalk

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

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

Interpolation

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

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

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

That is:

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

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

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

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

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

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

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

Link to the Measures Used in the Body of the Paper The $s_{t,j\to c}$ that appear in Sections 2 and 3 are given byV_{dt} divided by the sum of $V_{d't}$ for which consumption category c is the "destination" category. Remember that d denotes a commodity $\times$ consumption category pair.

B.3 Input-Output Use Table Interpolation Methodology

Crosswalk

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

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

Each intersection of an aggregate commodity category and an aggregate industry category is composed of the intersections of some subset of the detailed commodity and some subset of the detailed industry categories. Each detailed intersection is part of exactly one aggregate intersection. We matched the detailed intersections to their aggregate intersections by comparing the commodity codes and by checking that the sum of the detailed intersections from 2017 matched the value of the aggregate category intersection in 2017.

Interpolation

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

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

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

That is:

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

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

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

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

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

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

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

Thus, the estimation equation becomes:

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

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

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

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

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

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

B.4 PCE Bridge Margin Assignment

The PCE bridge 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 use table (using the interpolated detailed use values). Next, for each commodity - margin combination in the PCE bridge, we multiply the use table shares by the margin value. This gets rid of the margins and leaves all values in the PCE bridge 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. 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 $v_{j\rightarrow c,t}$. 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, $s_{t,j\rightarrow c}$ equals:

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

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 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, $v_{2017,j\rightarrow 88}$ = \$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 $v_{t,\omega;j\rightarrow c}$, $v_{t,\rho;j\rightarrow c}$, and $v_{t,\theta;j\rightarrow c}$ refer to the dollar value of these different margins in the PCE Bridge Table. In the Eggs consumption category, in 2017, transportation accounts for \$509 ($v_{2017,\theta;11230\rightarrow 88}$=\$499; $v_{2017,\theta;31199\rightarrow 88}$=\$60), the wholesale margin accounts for \$727 ($v_{2017,\omega;11230\rightarrow 88}$=\$214; $v_{2017,\omega;31199\rightarrow 88}$=\$513), and the retail margin accounts for \$4055 ($v_{2017,\rho;11230\rightarrow 88}$=\$2807; $v_{2017,\rho;31199\rightarrow 88}$=\$1248).

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.

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 m 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 μ 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:

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

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

$$= \frac{v_{j\to c}}{\sum_{j'}(v_{j'\to c} + \sum_{\mu} v_{\mu;j'\to c})} \text{ if } j \notin \mathcal{M} \; .$$

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 computers and electronics-related consumption categories, 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 -4.1% in Figure 4, it is at -2.3% 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 1.4 percentage points (decreasing by 0.4% annually, instead of by 1.8% annually, as in Figure 4. For Telephones, the difference is 4.9 percentage points (1.3% annual price declines in Figure 4 vs. 6.2% 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 — there impact of including distribution margins in our calculations has minimal impact.

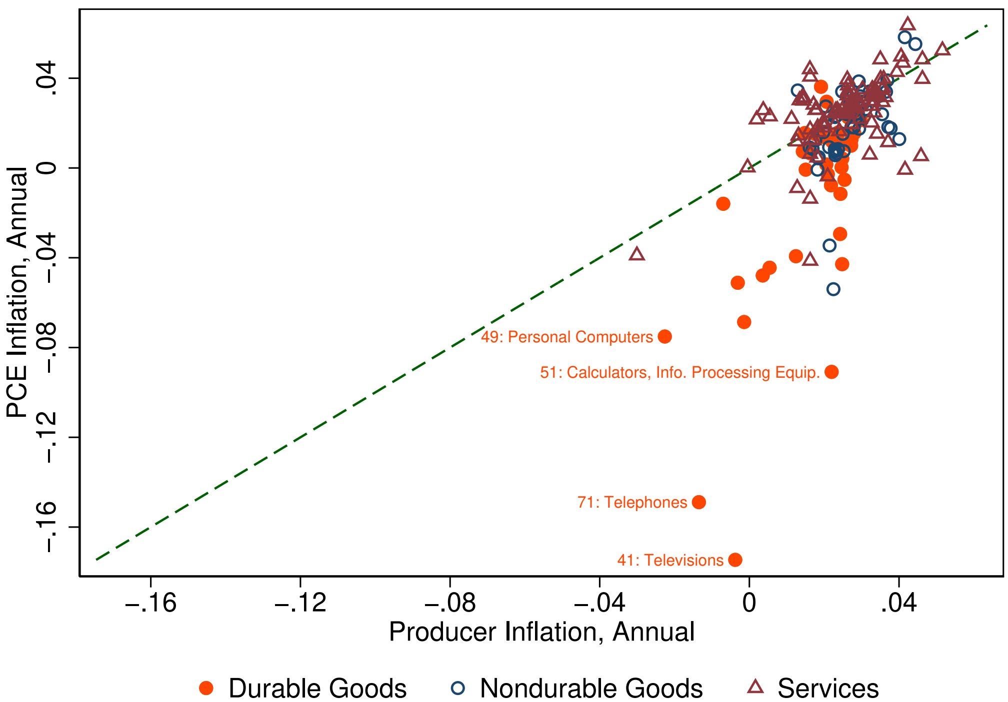

Figure A.1: Two Measures of Inflation Across PCE Categories, 2005–2023
Notes: See the notes for Figure 4. In contrast to that figure, we rely on Producer Inflation measures from Equation 1′.

D Additional Figures and Tables

In this section, we collect figures supplementing those in the body of the paper. Appendix D.1 supplements Section 1. Appendix D.3 evaluates whether our conclusions of TFP mismeasurement in broad sectors are problematic due to the potential non-representativeness of which industries are not observed in the PCE Bridge Table. In Appendix D.4, we assess whether our results are robust to excluding commodities that only enter with small entries in the PCE Bridge Table. In Appendix D.5, 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,

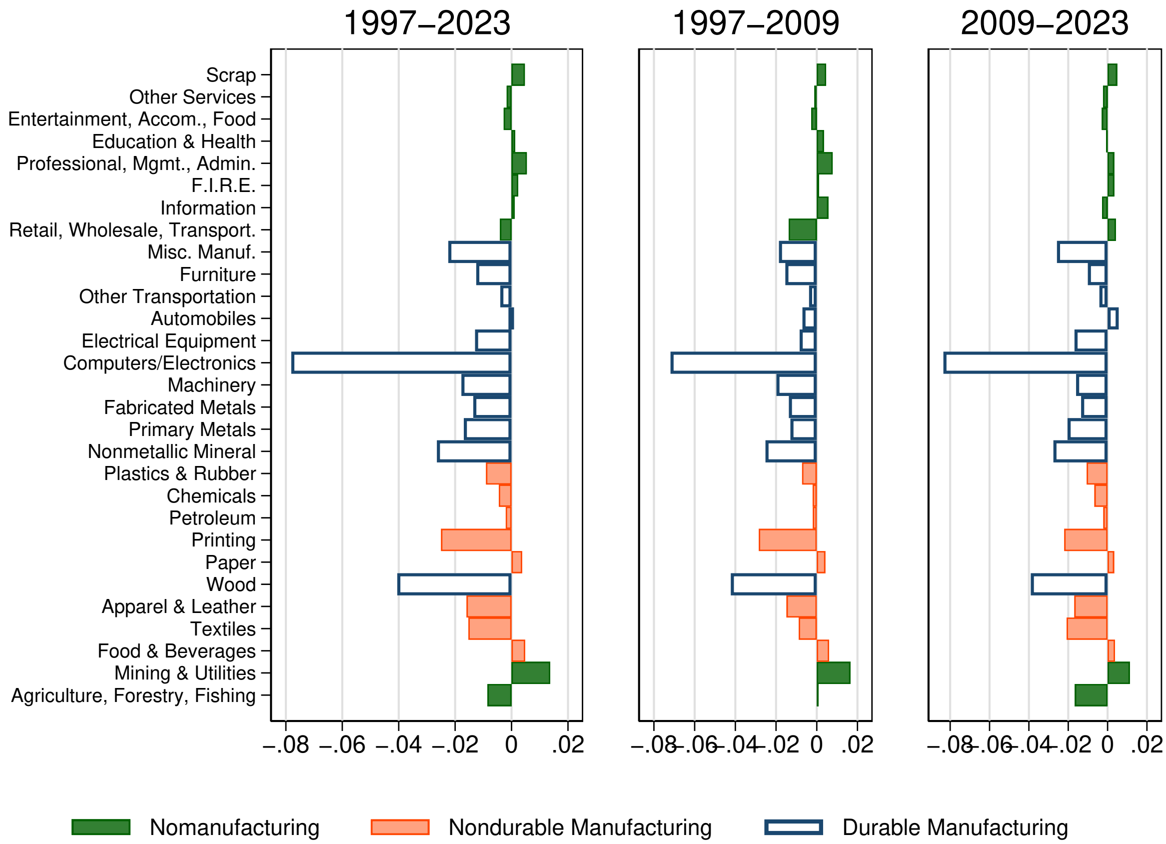

Figure A.2: TFP Mismeasurement
Notes: See the notes for Figure 5. In contrast to that figure, we rely on Producer Inflation measures from Equation 1′.

we compute average TFP growth rates and output shares for three subperiods within our 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.

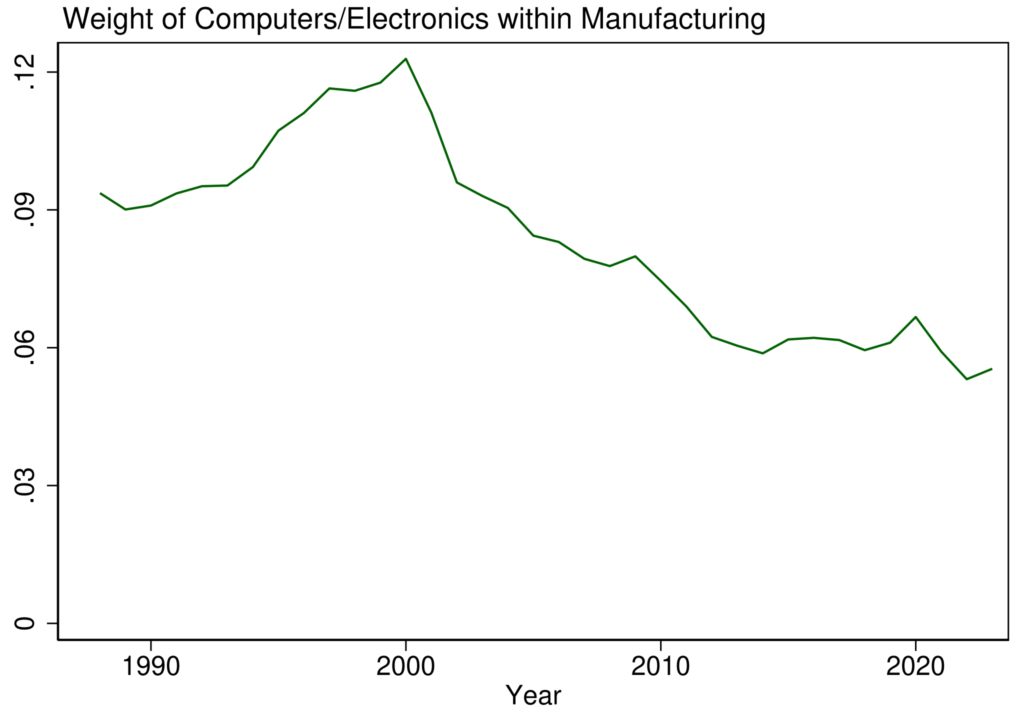

Figure A.3: Share of Sectoral Output of NAICS 334 within Manufacturing

D.2 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.3 Industries Missing in the PCE Bridge Table

To compute TFP mismeasurment 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 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

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

not appear in the PCE Bridge, all of the industries producing Food & Beverages (NAICS 311, 312), Textiles (NAICS 313, 314), Apparel and Leather (NAICS 315, 316), and Entertainment, Accommodation, and Food (NAICS 71, 72) do. Overall, 74% of manufacturing industries and 58% 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 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.7 presents our comparison. Overall, we find no relationship across the two variables. Weighting observations equally, the correlation is -0.01; weighting groups of industries according to their gross output (as of 2017), the correlation is an (insignificant) -0.07.

While Figure A.7 looks across industry groupings, Table A.4 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:

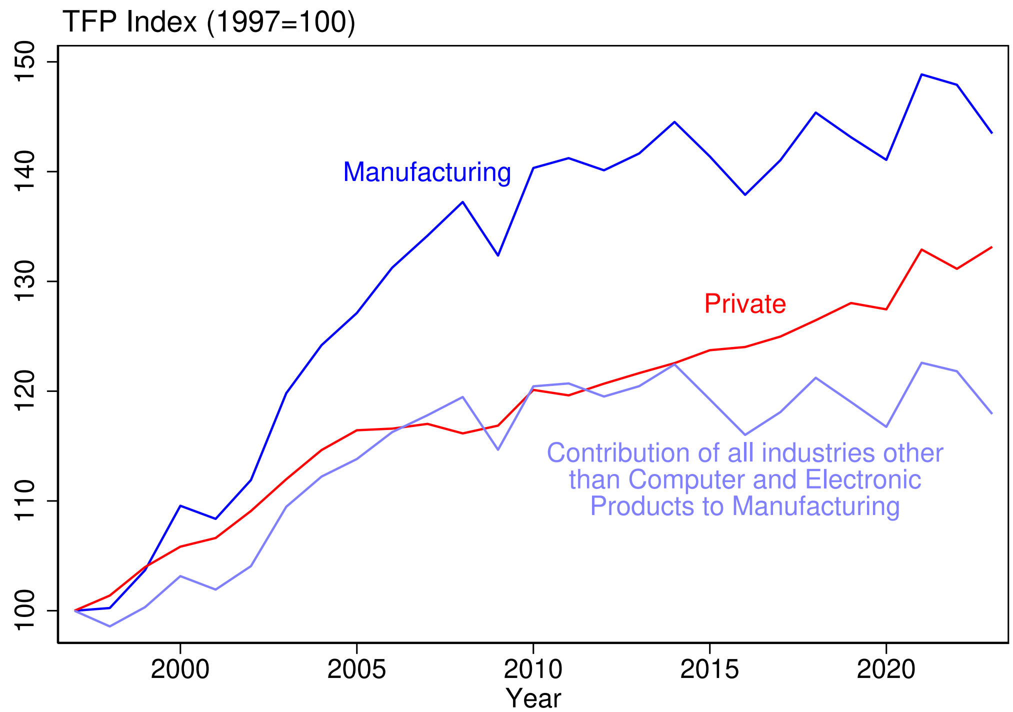

Figure A.4: TFP for Manufacturing, Manufacturing excluding Computer and Electronic Products, and the Private Business Sector

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

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

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.4 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 have systematically faster or slower Producer Inflation rates than those that are not represented.

D.4 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 com-

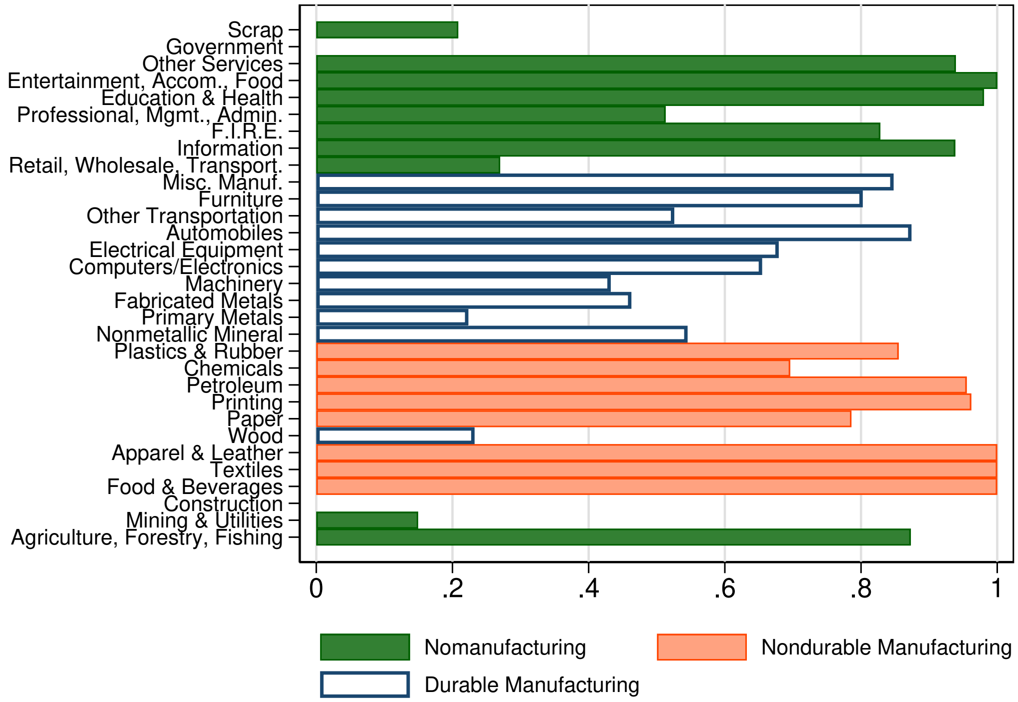

Figure A.5: Share of Industries For Which we Estimate TFP Mismeasurement
Notes: This figure lists the share of grouping of detailed industries for which we can compute TFP mismeasurement. When averaging across industries, we weight according to their gross output in 2017. In computing this figure, we 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 0.27 to 0.80, increasing the private economy average from 0.58 to 0.73.

modity 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 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

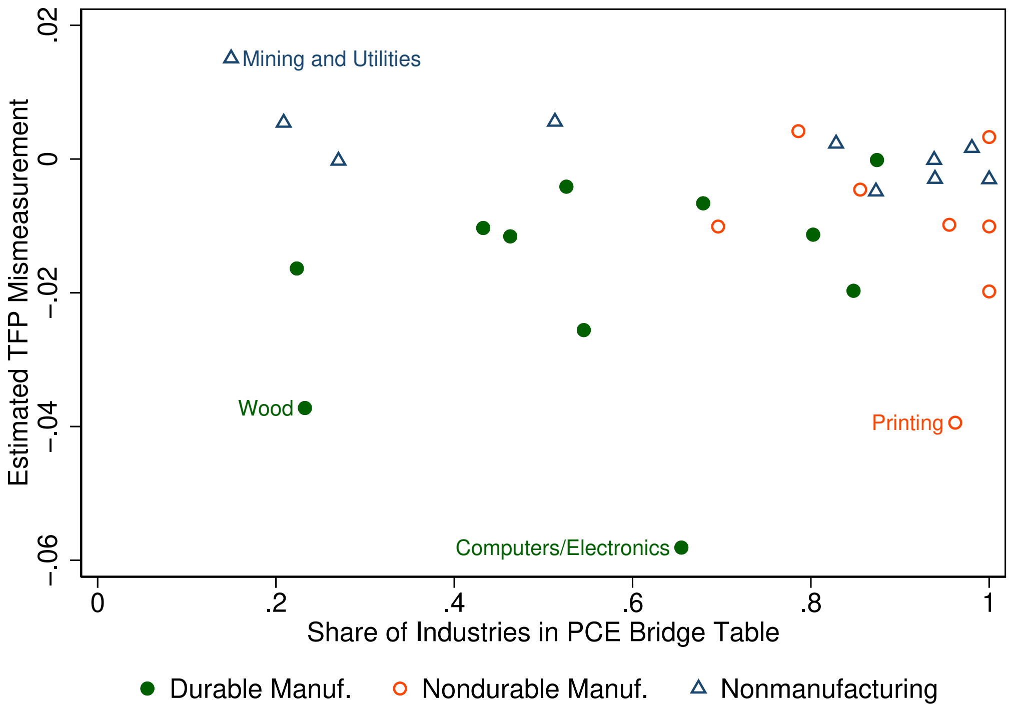

Figure A.6: Share of Industries For Which we Estimate TFP Mismeasurement vs. Average TFP Mismeasurement protect

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.

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 mismeasurement was 1.7% in the durable goods sector, -0.4% in the nondurable goods sector, and 0.1% in nonmanufacutring sectors. In the middle and right panels, TFP mismeasurement in the durable goods manufacturing sector is similar -1.8%. In both the middle and right panels, the nondurable goods manufacturing sector, TFP mismeasurement in -0.4%; in the nonmanufacturing sector it is 0.1%. For the Computer and Electronic Products manufacturing industry, TFP mismeasurement is -5.8% in the left panel, 5.9% in the middle panel, and -6.2% in the right panel.

One noticeable difference across the three panels, increasing the threshold ratio of PCE Bridge Table contributions to gross output results in certain groups of industries altogether. Consider the entry for "Printing" (NAICS 323). Only a single industry — also called Printing (NAICS 32311) — represented in the lef panel. Here, the ratio of this industry's 2017 contributions to the PCE Bridge Table is 10.5% of its gross output. Since this single industry is dropped in the middle and right panels, there are no industries within the "Printing" row for which we can compute TFP mismeasurement.

D.5 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 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, $\mathbf{O_{,jc}}$ would be equal to 1 for the column associated with NIPA Line 7, and 0 otherwise. In essence, we infer price mismeasurement of Automobile Manufacturing from price mismeasurement in New Domestic Autos.

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

Returning to our autos example, for the row associated with NAICS 336111, $\mathbf{O_{,jc}}$ 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. As in Figure 5, annual manufacturing TFP growth is understated by 0.8 percentage points. For durable goods, TFP growth is understated by 1.6 percentage points, only slightly smaller than the 1.7 percentage points in the baseline specification.

Panel A: All Sectors						
Dependent Variable		Producer Inflation			Gross Output Deflator	
In PCE Bridge	-0.003	-0.001	-0.001	0.006***	-0.001	0.006***
	(0.003)	(0.002)	(0.004)	(0.001)	(0.004)	(0.001)
Observations	412	412	412	412	412	412
Adjusted R^2	0.005	0.395	-0.002	0.482	-0.002	0.481
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	0.000	-0.005*	0.002
	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)
Observations	152	152	152	152	152	152
Adjusted R^2	0.049	0.431	0.006	0.460	0.001	0.446
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	0.005*
	(0.003)	(0.002)	(0.004)	(0.002)	(0.005)	(0.002)
Observations	80	80	80	80	80	80
Adjusted R^2	-0.008	0.362	-0.008	0.573	-0.002	0.563
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	0.000	0.008***	-0.002	0.007***	-0.001	0.007***
	(0.005)	(0.002)	(0.005)	(0.001)	(0.005)	(0.001)
Observations	180	180	180	180	180	180
Adjusted R^2	-0.006	0.365	-0.002	0.442	-0.003	0.442
Fixed Effect	None	Industry	None	Industry	None	Industry
Weighted	No	No	Yes	Yes	Yes	Yes

Table A.4: Differences in Output Prices between Industries Present or Absent in 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.)

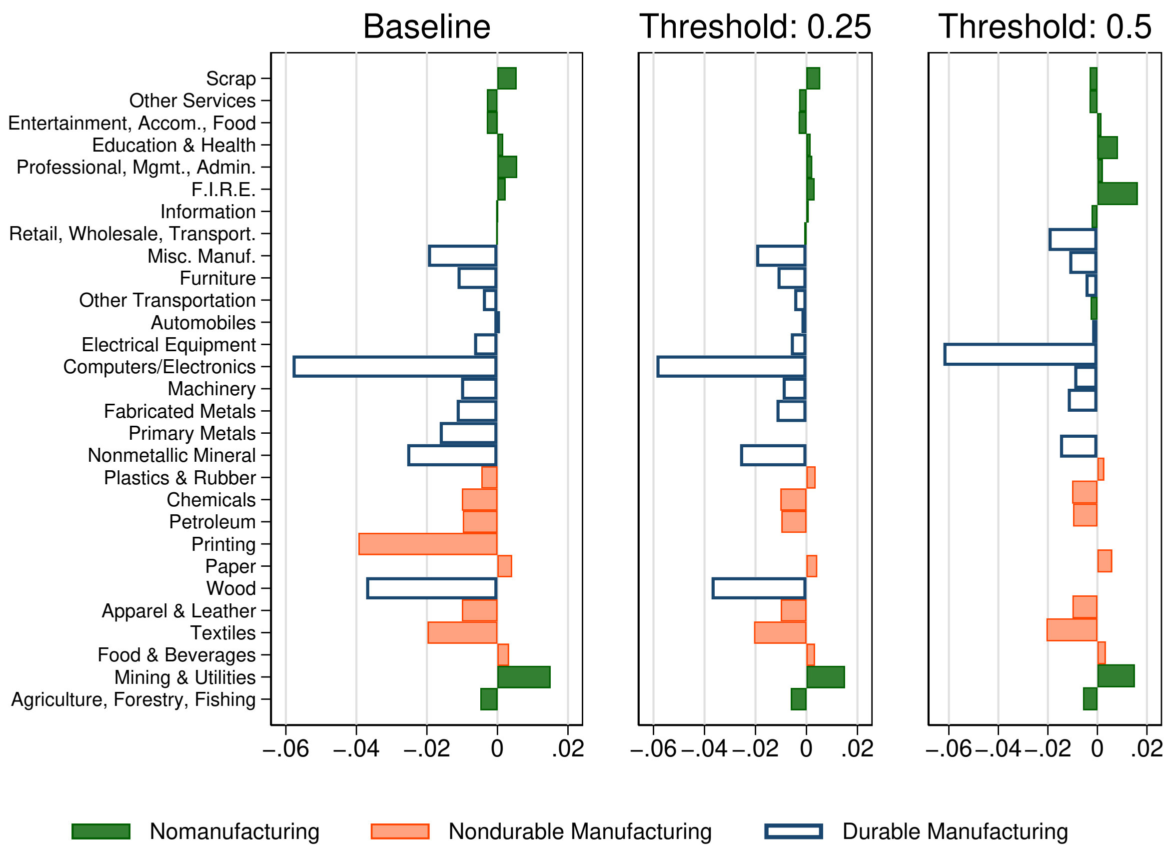

Figure A.7: Sensitivity to Dropping Commodities with Only "Small" Entries in the PCE Bridge Table

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. Entries for "Printing" and "Primary Metals" are missing for this panel, as there are no detailed industries meeting this threshold. 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 "Wood" and "Scrap" are additionally missing for this panel, as there are no detailed industries meeting this threshold. Of the 255 detailed industries represented in the left panel, 158 are included in the middle panel, and 132 in the right panel.

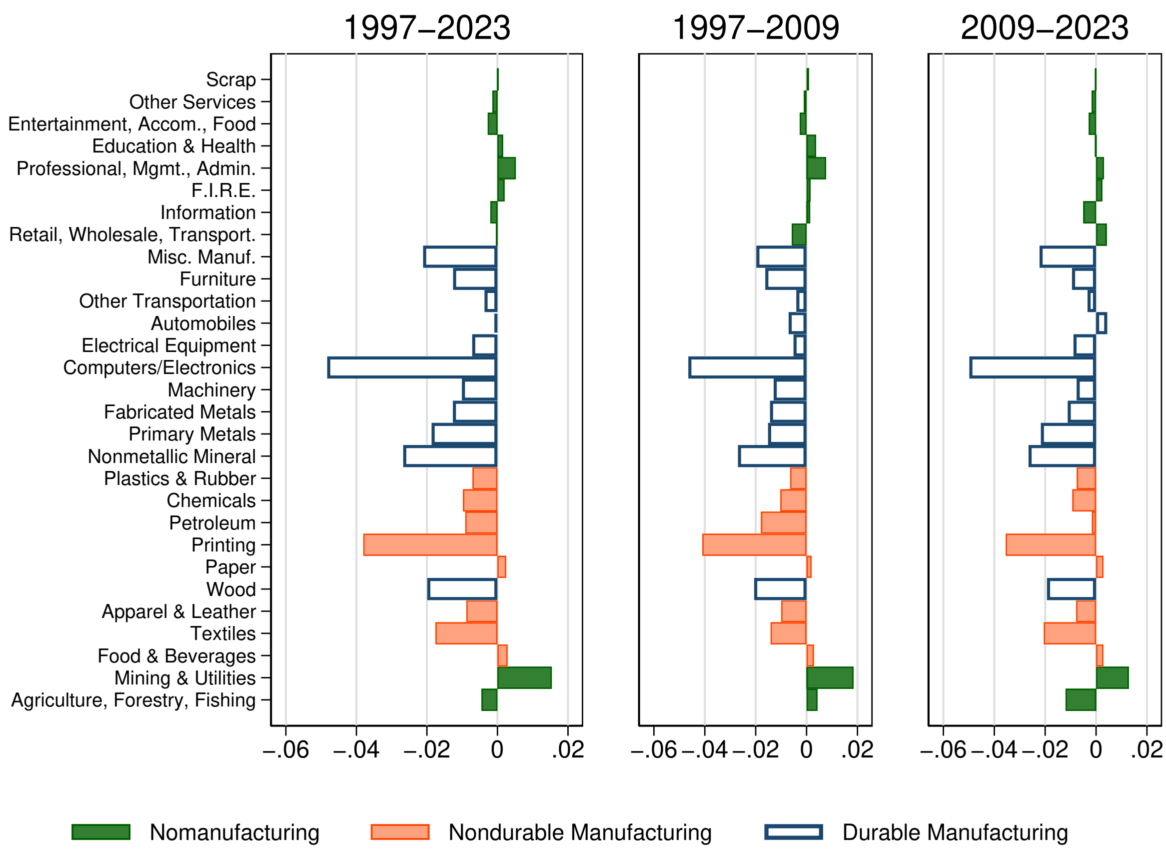

Figure A.8: TFP Mismeasurement

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