Why Is Manufacturing Productivity Growth So Low?

Enghin Atalay   Ali Hortaçsu   Nicole Kimmel   Chad Syverson*

January 25, 2026

Abstract

We examine the recent slow growth in manufacturing productivity. We show that nearly all measured TFP growth since 1987—and its post-2000s decline—comes from a few computer-related industries. We argue conventional measures understate manufacturing productivity growth by failing to fully capture quality improvements. We compare consumer to producer and import price indices. In rapidly changing industries, 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 1.4 percentage points in durable manufacturing and 0.4 percentage points in nondurable manufacturing, and is slightly overstated in nonmanufacturing industries.

JEL Codes: C67, D24, E01, E31

*Atalay: Research Department, Federal Reserve Bank of Philadelphia, atalayecon@gmail.com; Hortaçsu: Department of Economics, University of Chicago, hortacsu@uchicago.edu; Kimmel: Federal Reserve Bank of Philadelphia, nicole.kimmel@phil.frb.org; Syverson: University of Chicago Booth School of Business, chad.syverson@chicagobooth.edu. We thank David Byrne for constructive feedback on an earlier draft and Dominic Smith for help understanding BLS quality adjustment methods. The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. Any errors or omissions are the responsibility of the authors. Syverson gratefully acknowledges support from Smith Richardson Foundation grant 20233172.

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

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

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

We then show that consumer price indices for computers and electronic products indicate less inflation than do corresponding producer and import price indices. This pattern is consistent with too little quality improvement being incorporated into producer and import price indices. We demonstrate that 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 and is concentrated within durable goods manufacturing, especially so for durable goods experiencing the greatest quality adjustments. Overall, annual price changes of durable goods are 2.6 percentage points greater when using gross output deflators and import price indices than when using PCE price indices.

In a final step of our analysis, we consider the implications of these differences for mismeasurement in productivity. Under the interpretation that consumer-facing price indices more comprehensively measure quality improvements than producer-facing indices, conventional national accounts likely understate real output growth in durable goods industries. However, by the same token, intermediate input price growth is also understated for these industries. Using input-output and capital flows matrices to parse these offsetting effects, we find that manufacturing TFP growth (from 1997 to 2023) is understated by 0.66 percentage points: 1.38 percentage points for durable goods industries and 0.35 percentage points for nondurable goods industries. By contrast, TFP growth in nonmanufacturing industries is slightly *over*stated, by 0.25 percentage points annually. Mismeasurement is slightly larger before 2009 than after.

In sum, correcting for the undercounting 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.[1]

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 US federal government has enacted several programs to boost manufacturing productivity growth, spending many billions of dollars annually.[2] These programs are premised on the pivotal role that the manufacturing sector plays in national security, in global trade, and in generating

[1]In the appendix, we explore whether any ICT-related nonmanufacturing industries share the distinctive features of Computer and Electronic Product Manufacturing—its steep productivity decline, its large producer-vs.-consumer price gaps, and its employment of a substantial share of production workers. While Software Publishing and ICT-related wholesale industries share one or two of these features, none match Computer and Electronic Product Manufacturing on all three dimensions. See Appendix E.

[2]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 and Science Act provided tens of billions of dollars for firms in, respectively, energy-related and semiconductor production. See `https://obamawhitehouse.archives.gov/blog/2010/04/21/impact-american-recovery-and-reinvestment-act-clean-energy-transformation` and `https://www.congress.gov/crs-product/R47523`.

high-quality jobs for people without a college degree. To the extent that these policies are judged on the basis of boosting productivity, past assessments may have presented an overly 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 Product Manufacturing industry was key to the 1995–2004 productivity resurgence and the subsequent productivity slowdown. These results are echoed by Sprague (2021).[3] By contrast, Lashkari and Pearce (2024; 2025) consider the slowdown in productivity growth, but argue that it is broad based. They call the contrast between the high (and increasing) R&D intensity and the slow productivity growth of the manufacturing sector puzzling. Our results in Section 1 more closely align with Syverson (2016) and Sprague (2021), though we emphasize the central role of 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) provide a recent overview of efforts at the BEA and BLS toward measuring quality improvements and the contribution of new products to real output growth. Byrne et al. (2016) and Syverson (2017) examine the "mismeasurement hypothesis"—the idea that aggregate growth is increasingly mismeasured either due to price deflators that (increasingly) do not properly reflect quality growth or due to the proliferation of goods and services that are sold for free and thus do not enter in the measurement of real output. While not seeking to explain the aggregate slowdown, Brynjolfsson et al. (2025) estimate substantial consumer welfare gains from the introduction of Facebook and the development of smartphone cameras, above and beyond what is captured by the consumer price index. We share with these articles the idea that price indices may understate quality improvements, especially for goods and services linked to information and communication technologies. Distinct from Byrne et al. (2016) and Syverson (2017), we do not seek to measure why productivity growth has slowed down. Rather, we attempt to estimate mismeasurement in productivity growth that differs between the manufacturing and nonmanufacturing sectors. Distinct from all of these

[3] Houseman (2018) considers the special role that the Computer and Electronic Product Manufacturing 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 Computer and Electronic Product Manufacturing.

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 coauthors have examined the performance of producer price indices, focusing on individual information-and-communication technology (ICT) industries. Byrne and Corrado (2015a,b) compute significant biases in conventional producer price indices for communications equipment. Byrne (2015b) 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.[4]

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, US 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) calculate that this bias is on the order of 0.1 to 0.2 percentage points per year. Finally, Aghion et al. (2019) develop a growth model in which statistical agencies impute price changes for disappearing items from surviving items, and argue that such imputation may lead official statistics to understate true productivity growth.

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 measured gains in manufacturing productivity since 1987 *and* the productivity growth stagnation since 2009 are due to a single 3-digit manufacturing industry: Computer and Electronic Product Manufacturing (NAICS

[4]Earlier, Gordon (1990) carefully constructs multiple durable goods price indices—from 1947 to 1983—from the Sears Catalogs, Consumers Reports publications, and other non-standard data sources. The indices Gordon constructs have substantially slower price growth relative to corresponding indices in the PPI, indicating lack of quality adjustment in the latter.

334).

To make this point, consider the following equation linking measured TFP growth in the manufacturing sector ($\Delta \log A_{t,M}$) to measured TFP growth in each of the sector's constituent industries ($\Delta \log A_{t,j}$):[5]

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

where 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.[6]

Figure 1 plots the average of $\Delta \log A_{t,j}$ for each manufacturing industry j over three subperiods within the 1987 to 2023 sample. The clear outlier is Computer and Electronic Product Manufacturing. Its TFP grew at an 8.3% annual rate from 1987 to 1997 and 7.4% per year between 1997 and 2009. From 2009 on, TFP growth has slowed to 1.2% per year. So, while productivity growth in Computer and Electronic Product Manufacturing is still above average, it has slowed considerably compared to prior decades.[7]

Over the sample period, the Computer and Electronic Product Manufacturing 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% by 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 Product Manufacturing industry's TFP growth slowdown and its shrinking size within the manufacturing sector can explain nearly all of the trajectory of the whole sector since the late 1980s. We make this point in Figure 2 by plotting the cumulative contribution to manufacturing productivity growth for all industries other than Computer and Electronic Product Manufacturing. This

[5]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 the manufacturing sector's productivity stagnation is also observed in labor productivity).

[6]See `https://www.bls.gov/productivity/data.htm`; accessed December 4, 2025. These data begin in 1987.

[7]In Appendix Table A.3, we show that two 4-digit industries—Computers and Peripheral Equipment (NAICS 3341) and Semiconductors and Other Electronic Components (NAICS 3344)—are responsible for the deceleration of TFP growth in Computer and Electronic Product Manufacturing. Between 1987 and 2009, Computers and Peripheral Equipment manufacturing TFP grew by an astronomical 15% per year. TFP in Semiconductors and Other Electronic Components grew by more than 11% per year. By the early 2010s, productivity growth in these industries had decelerated substantially.

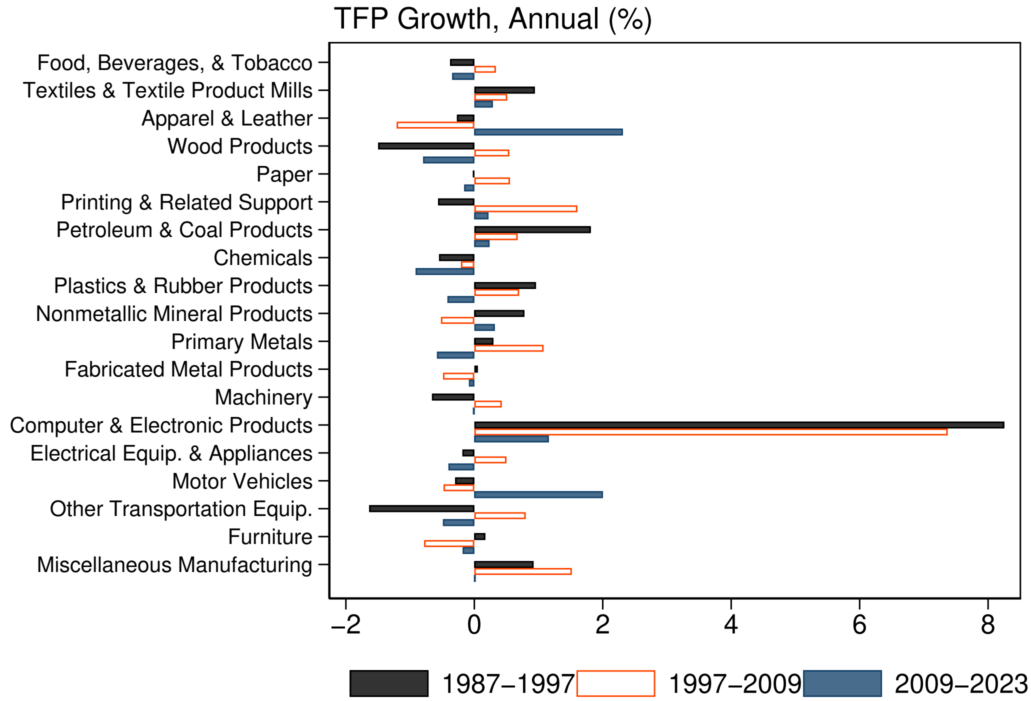

Figure 1: Annual TFP Growth Rate by 3-digit Manufacturing Industry
Notes: Food & Beverages is the collection of NAICS 311 and 312. Textiles & Textile Products is the collection of NAICS 313 and 314. Apparel & Leather is the collection of NAICS 315 and 316. Motor Vehicles is the collection of NAICS 3361,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

is defined as the cumulative total of:

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

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

Two patterns stand out in this figure. First, between 1987 and the late 2000s, TFP 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 0.8% (annually, from 2009 to 2023). Second, Computer and Electronic Product 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 close

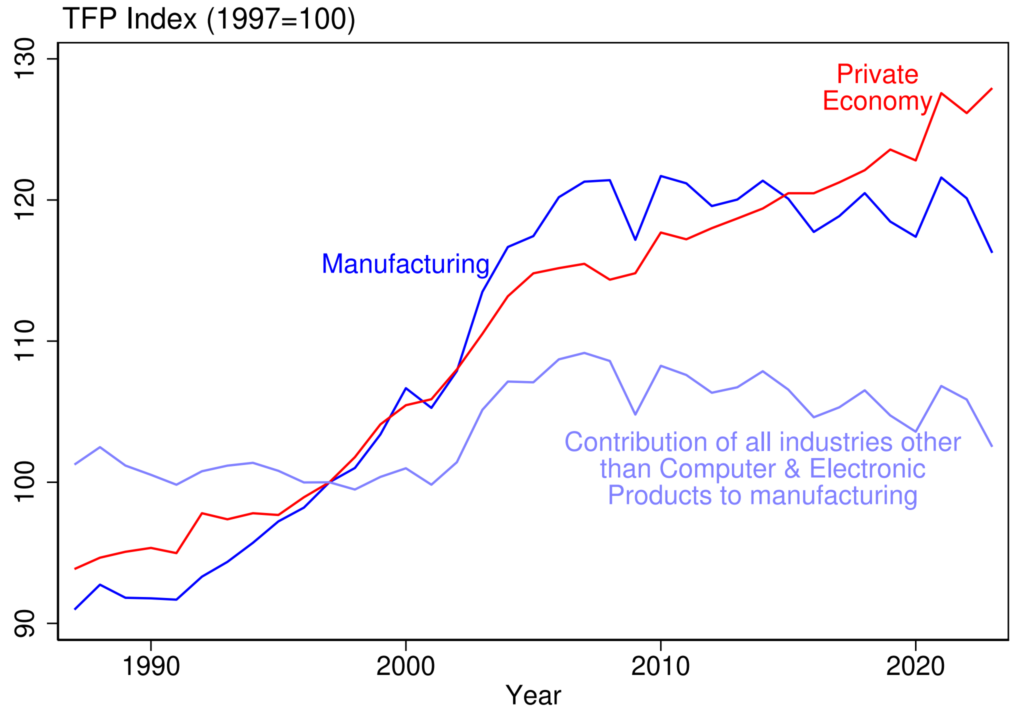

Figure 2: TFP for Manufacturing, Manufacturing excluding Computer and Electronic Product Manufacturing, and the Private Business Sector

to zero TFP growth over the sample.

2 For Computers 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 components of the PCE price index come from National Income and Product Accounts (NIPA) Table 2.4.4U (which contains 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.[8] Beginning in 1997, the data cover 414 detailed industries. Finally, we use the BLS

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

import price index to measure changes in the price of imported commodities.[9]

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 warehousing. By contrast, aiming to characterize inflation from the producer's perspective, the PPI measures price changes for only domestically produced commodities, excluding distribution margins.[10]

Regarding differences in quality adjustment procedures, the BLS invests significantly—in its survey design, in its data collection efforts, and in its statistical and economic methodology—to ensure *all* of its price measures provide accurate and representative depictions of inflation experienced by households and firms. But, given its finite budget, some prioritization must inevitably be made in where BLS resources are allocated. Given the BLS's frequent reference to the CPI as the "nation's principal gauge of inflation"[11] 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.[12]

Consistent with this, consider how the BLS measures quality adjustment for commodities

---

`GrossOutput.xlsx`; accessed December 4, 2025.

[9]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.

[10]The PPI collects prices from *factoryless goods producers*—establishments that perform manufacturing design domestically while contracting out physical production and assembly abroad—in some manufacturing industries (Bayard et al., 2015). In this way, the sample frames of the CPI and PPI are closer to one another than one would infer from domestic assembly shares alone.

[11]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` .

[12]The CPI helps determine IRS federal income tax brackets, eligibility thresholds for the Earned Income Tax Credit, and Social Security benefits; see `https://www.dol.gov/sites/dolgov/files/general/budget/2024/CBJ-2024-V3-01.pdf`.

with rapid technological change. For these commodities, the BLS's preferred method to identify quality changes involves "hedonic quality adjustment." In this method, for a given product category, researchers at the BLS determine the set of relevant product characteristics. They then apply a regression model to estimate consumers' valuation for—or, in the case of the PPI, the additional costs associated with—these characteristics. The BLS applies this hedonic quality adjustment in only three narrow PPI product categories: computers (NAICS 334111), microprocessors (NAICS 334413), and broadband internet access (517311) with the latter two introduced only 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, with the vast majority of these adopted by 2000.[13,14,15]

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

Having spelled out the different aims and methodological foundations for the various price indices, in Figure 3 we show for a single consumption category—Televisions (NIPA Line 41)—how inflation rates vary between the consumer and producer perspectives.[16] For

[13]See Appendix A for a list of commodities for which the BLS applies hedonic quality adjustment in the PPI and CPI. When the BLS introduces hedonic quality adjustment into a particular PPI or CPI category, it does not revise the price series for preceding years. Accordingly, from 1997 through 2016, hedonic quality adjustment is reflected only in the PPI series for computers.

[14]Even for computers, the BLS applies different quality-adjustment methods in the PPI and CPI. The PPI uses a time-dummy hedonic regression; the CPI uses a component-price approach based on component price-aggregator websites. See `https://www.bls.gov/ppi/quality-adjustment/ppi-introduces-hedonic-price-estimation-for-notebook-computers.htm` and `https://www.bls.gov/cpi/factsheets/personal-computers.htm`; accessed January 23, 2026. Note that our analysis compares BEA PCE price indexes to industry gross output deflators. For computers, the PCE and CPI components align, while the BEA applies its own hedonic methods for the computer-industry gross output deflator, distinct from the PPI.

[15]Another salient difference between the price indices, not directly related to quality adjustment, is that the CPI applies a geometric mean formula when combining price changes of individual products within a product category whereas the PPI applies a Laspeyres formula (an arithmetic mean). Existing estimates suggest that moving from arithmetic to geometric averaging would lower stated inflation by a few tenths of a percentage point (Dalton et al., 1998; Boppart et al., 2023).

[16]Despite the near-total offshoring of mass-market television production and assembly since the early 2000s, domestic manufacturing still accounts for a substantial share of personal consumption of TVs. Indeed, as of 2017—the most recent date for which the BEA produced detailed input-output tables—less than half, approximately 44%, of Audio and Video Equipment Manufacturing (NAICS 3343) personal consumption expenditures came from imports. Much of the domestic Computer and Electronic Product Manufacturing industry now focuses on engineering, computing, and design, with assembly largely occurring overseas. As of 2023, production occupations account for roughly a quarter of Computer and Electronic Product Manufacturing employment. See Appendix D.2 for more details.

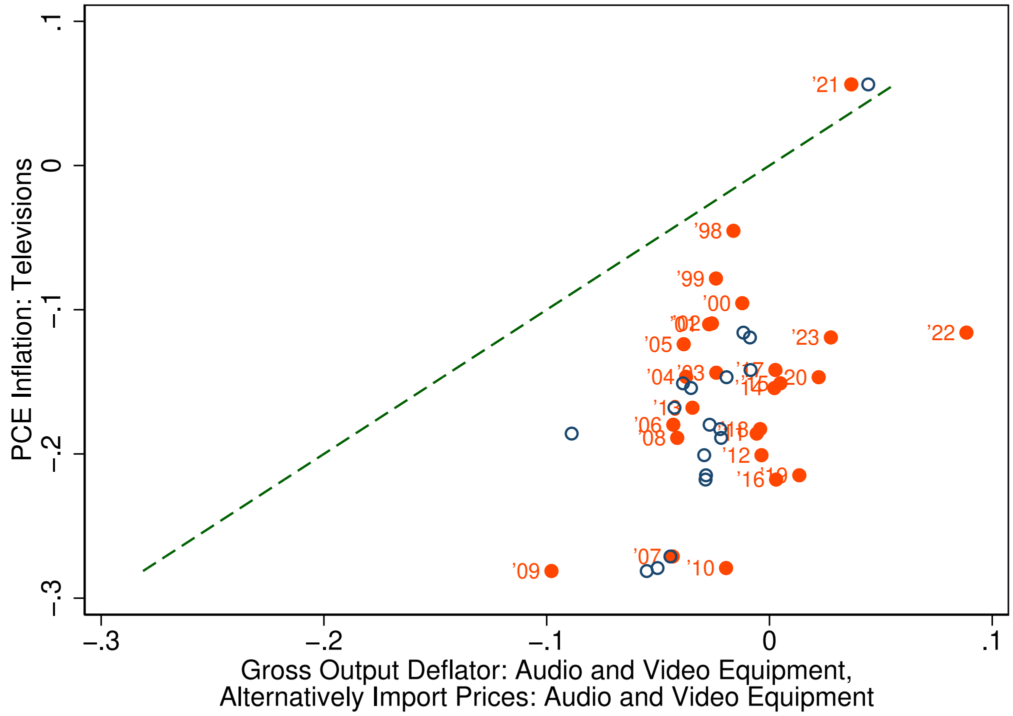

Figure 3: Television Inflation
Notes: The vertical axis gives Television inflation according to the PCE price index. The horizontal axis gives two measures of producer inflation. In orange filled circles, we plot changes in the gross output deflator for the Audio and Video Equipment Manufacturing industry (NAICS 3343). 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 '14 refers to price growth between 2013 and 2014). The import price index for Audio and Video Equipment Manufacturing is plotted using hollow blue circles without listing the year. This latter data series begins in 2006 only.

each year between 1997 and 2023, the vertical axis plots the change in prices according to the PCE price index. Over this 26-year period, the average price change was −15.4% 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), with the latter first published in 2006. The gross output deflator for the corresponding industry—Audio and Video Equipment Manufacturing, NAICS 3343—fell by only 1.1% per year between 1997 and 2023, while the import price index fell by 2.9% per year since 2005. Some of the difference between PCE inflation and gross output or import price inflation likely reflects the inclusion of Audio Equipment and Other Video Equipment in the latter two measures. However, PCE inflation for these other categories were also exceptionally low: −4.8% for Audio Equipment and −9.4% for Other Video Equipment. So, for Televisions and Other Audio and Video Equipment, PCE deflation is vastly greater than deflation according to price indices from the producer perspective.

In Figure 4, we expand the scope of analysis beyond Televisions. For each PCE category, the vertical axis gives the average annual price growth between 1997 and 2023. The horizontal axis gives our attempt at re-creating the corresponding measure of inflation but using gross output deflators and import price indices.[17] Each PCE category may comprise multiple distinct commodities, and each commodity may be produced domestically or imported. We use the PCE Bridge Table 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.[18] We use the input-output tables to assign weights for domestic production vs. imports.[19]

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

[17]For 1997 to 2005, we impute commodities' import price growth using the 2006-to-2023 historical relationship between gross output deflator price growth and import price growth. In more detail, for 2006 to 2023, we estimate a regression with the commodity j summand in Equation 1—namely, $(1 - m_{t,j})\Delta \log P_{t,j}^{\text{GO}} + m_{t,j}\Delta \log P_{t,j}^{\text{Import}}$—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 gross output price growth and the import share of PCE, $m_{t,j}\Delta \log P_{t,j}^{\text{GO}}$. We restrict the intercept of the regression to be equal to 0. The estimated coefficients on the two explanatory variables are 1.007 and -0.777. The R^2 on the regression is 0.996. If we further restrict the coefficient on $\Delta \log P_{t,j}^{\text{GO}}$ to be equal to 1, the coefficient on the interaction term is -0.745. Given this, for each year between 1997 and 2005, we impute $(1-m_{t,j})\Delta \log P_{t,j}^{\text{GO}} + m_{t,j}\Delta \log P_{t,j}^{\text{Import}}$ as $\Delta \log P_{t,j}^{\text{GO}} - 0.745 \cdot m_{t,j}\Delta \log P_{t,j}^{\text{GO}}$.

[18]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. Appendix B describes how we combine detailed and more aggregated PCE Bridge Tables to estimate commodity-to-consumption category linkages for each year at the more detailed 414-commodity-by-212 consumption category level.

[19]See `https://www.bea.gov/industry/input-output-accounts-data`; accessed December 4, 2025. 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.

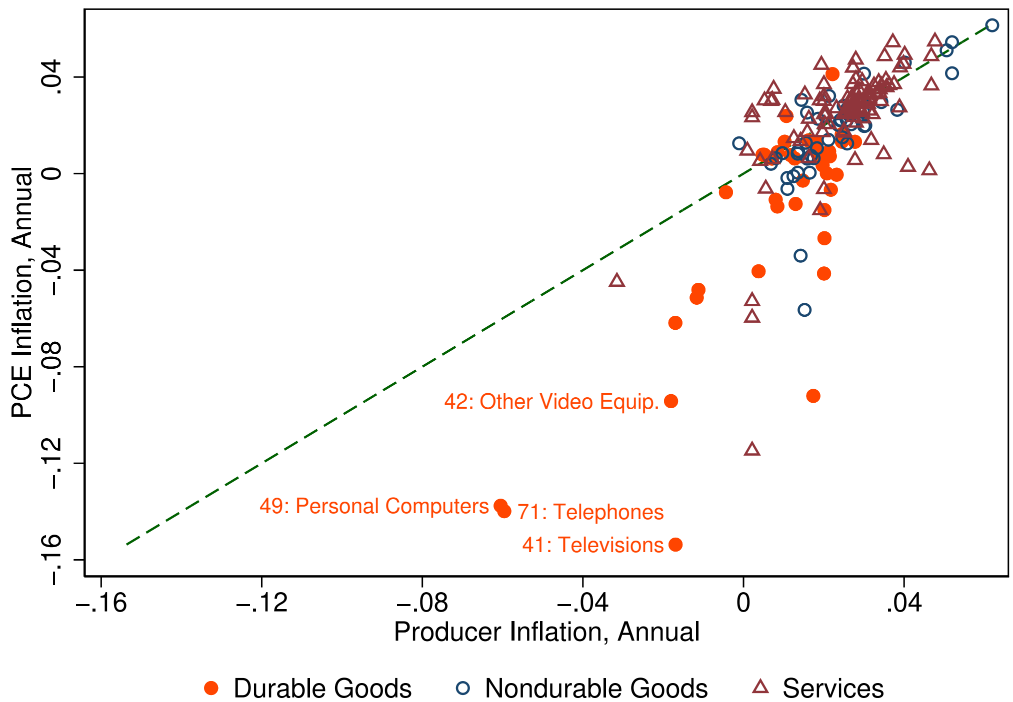

Figure 4: Two Measures of Inflation Across PCE Categories, 1997–2023
Notes: Each point is a single PCE category. The vertical axis gives annual inflation according to the PCE price index between 1997 and 2023. The horizontal axis gives our measure of Producer Inflation (defined by Equation 1) over the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

the Telephone Apparatuses category—the level of aggregation is coarser in the import price index (where it is defined only at the 4-digit NAICS level) than in the BEA industry gross output deflator (where information at the 5-digit NAICS is available).

For the most part, looking across PCE categories and averaging over the 1997–2023 sample, PCE inflation is highly correlated with changes in $\Delta \log P_t^{\text{Producer}}$. The (consumption-weighted) correlation across the two measures is 0.75. Our Producer Inflation measure exceeds PCE by 0.5 percentage points overall, but with much larger gaps in durable goods (where the gap is 2.6 percentage points) and nondurable goods (with a 1.1 percentage-point gap). We see the largest gaps in computers and other consumer electronics. Between 1997 and 2023, PCE inflation ranges between −15.4% and −9.4% for Televisions, Other Video Equipment, Personal Computers, and Telephones. By contrast, our "Producer Inflation" measure for these four consumption categories shows much more modest price declines, ranging from −6.0% for Personal Computers to −1.7% for Televisions.

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 understated for goods-manufacturing industries.[20]

3 Manufacturing TFP Growth Is Understated by Two-Thirds of a Percentage Point

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

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

According to Equation 2, industries are more productive when they are able to produce at lower cost given the price of the inputs that they use. The first line writes input prices as a linear combination of unit labor costs $\Delta \log w_{t,j}$, capital rental costs $\Delta \log r_{t,j}$, and intermediate input costs, $\Delta \log P^{\mathrm{Int.}}_{t,j}$; the weight on a generic input x is given by $\gamma_{t,x\to j}$, with $\gamma_{t,w\to j}+\gamma_{t,r\to j}+\gamma_{t,\mathrm{Int.}\to j} = 1$. The second line breaks out changes in industry j's capital rental price growth and intermediate input price growth into changes in domestically sourced or imported upstream commodities, with $\sum_{i=1}^{N}\gamma^{K}_{t,i\to j} = \gamma_{t,r\to j}$ and $\sum_{i=1}^{N}\gamma_{t,i\to j} = \gamma_{t,\mathrm{Int.}\to j}$. The final line writes this equation in vector notation. Here, $\boldsymbol{\Gamma}^{\mathbf{K}}_t$ and $\boldsymbol{\Gamma}_t$, respectively, collect

[20] An alternative interpretation might have been that producer-consumer price gaps reflect falling retail markups, particularly in electronics. However, data from the Annual Retail Trade Survey indicate that retailers' gross margins *increased* (albeit modestly, by 0.16 percentage points per year between 1997 and 2022), with a similar increase in Electronics and Appliance Stores and the broader retail sector. See `https://www2.census.gov/programs-surveys/arts/tables/2022restated/gmper.xlsx`; accessed September 4, 2025. Consistent with this, Bridgman (2026) estimates that markups in the manufacturing sector are unchanged between 1997 to 2010 vs. 2011 to 2023.

coefficients of capital services and intermediate inputs across pairs of industries; $\mathbf{M_t}$ is a matrix with the import share of each commodity on the diagonal (with zeros in off-diagonal entries). We construct $\mathbf{M}_t$ and $\mathbf{\Gamma}_t$ from the BEA Use Tables and $\mathbf{\Gamma}_t^{\mathbf{K}}$ from the BEA Use Tables and the investment network produced by Vom Lehn and Winberry (2022). See Appendices B.3 and B.4 for details on how we impute these parameters by detailed-industry and year from more aggregated measures.

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, we assume $\Delta \log \widetilde{\mathbf{w}}_t = 0$. With this assumption, Equation 2 implies:

$$\Delta \log \widetilde{\mathbf{A}}_t = -\Delta \log \widetilde{\mathbf{P}}_t^{\mathrm{GO}} + \left[\mathbf{\Gamma}_t^{\mathbf{K}} + \mathbf{\Gamma}_t\right] \left[(\mathbf{I} - \mathbf{M}_t)\, \Delta \log \widetilde{\mathbf{P}}_t^{\mathrm{GO}} + \mathbf{M}_t \Delta \log \widetilde{\mathbf{P}}_t^{\mathrm{Import}}\right] . \tag{3}$$

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

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

We write this equation in matrix form:

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

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

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

Above, $\mathbf{S}_t$ collects terms from the PCE Bridge Table, $\mathbf{O}_t$ is a matrix that transforms mismeasurement in "consumption category" space to "NAICS commodity" space. 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.

To make further progress, we assume that mismeasurement in the import price index is proportionate to mismeasurement in the gross output deflator. That is, we suppose that

$\Delta \log \widetilde{\mathbf{P}}_t^{\text{Import}} = \xi \Delta \log \widetilde{\mathbf{P}}_t^{\text{GO}}$. With this assumption, Equation 6 implies:

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

Together with our assumption on the relative mismeasurement of gross output deflators and import price indices, Equations 3 and 7 imply:

$$\begin{aligned}\Delta \log \widetilde{\mathbf{A}}_t \quad = \quad & -\left[(\mathbf{I} - (1-\xi)\mathbf{M}_t)^{-1} - \mathbf{\Gamma}_t - \mathbf{\Gamma}_\mathbf{t}^\mathbf{K}\right] \mathbf{O}_t \left[\Delta \log \mathbf{P}_t^{\text{PCE}}\right. \\ & \left. -\mathbf{S}_t \left[(\mathbf{1} - \mathbf{M}_t)\, \Delta \log \mathbf{P}_t^{\text{GO}} + \mathbf{M}_t \Delta \log \mathbf{P}_t^{\text{Import}}\right]\right] \ . \end{aligned} \tag{8}$$

We apply Equation 8 using data from 1997 to 2023.[21] Guided by Errico and Lashkari (2025), we choose 1.5 as our baseline value of ξ, but describe sensitivity around this parameter value, below.[22]

Figure 5 presents TFP mismeasurement by industry groups. We highlight four main results: First, within the durable goods manufacturing sector, TFP growth is understated most severely for Computer and Electronic Product Manufacturing, by 5.51 percentage points per year. Within this industry, mismeasurement is greatest in Communications Equipment Manufacturing (NAICS 3342) and Audio and Video Equipment Manufacturing (NAICS 3343)—where quality adjustment methods diverges most between household-facing and producer-facing price indices—and is relatively more modest in Computer and Peripheral Equipment Manufacturing (NAICS 3341); see Appendix Table A.4. Second, looking across sectors, TFP mismeasurement is greatest in the durable goods manufacturing sector (understated by 1.38 percentage points per year), much smaller in the nondurable goods manufacturing sector (understated by 0.35 percentage points per year), and smaller still in

[21]Consider a detailed (upstream) industry that produces only intermediate and investment inputs, where we (consequently) cannot estimate output price mismeasurement. For the purposes of accounting for downstream industries' TFP mismeasurement, we plug in price mismeasurement in that broader (summary) industry. For instance, the detailed Oilseed Farming industry (NAICS 1111A0) produces no output directly to final consumers. But other Farming Industries (e.g., Grain Farming; Vegetable and Melon Farming) do. For industries using Oilseed Farming as an input, we take each year's average—weighted-by-intermediate-input-sales—price mismeasurement of the other industries within the broader Farming Industry.

[22]Errico and Lashkari (2025) argue that quality undercounting is more severe in import price indices than in domestic producer price indices. They estimate that import price indices overstate inflation by 0.7 percentage points *more* than producer price indices. Since (a) approximately 85% of goods consumption is produced domestically and (b) the gap between goods' "Producer Inflation" and PCE inflation is roughly 1.4 percentage points, the 0.7 percentage point gap that Errico and Lashkari (2025) estimate implies a value of $\xi = 1.5$. (Using $\tilde{\mathbf{P}}^{\text{GO}}$ to refer to the mean mismeasurement in the gross output deflator, the relevant calculations are
$[0.85 \cdot \tilde{\mathbf{P}}^{\text{GO}} + 0.15 \cdot (0.7 + \tilde{\mathbf{P}}^{\text{GO}})] \approx 1.4 \Rightarrow \tilde{\mathbf{P}}^{\text{GO}} \approx 1.3$ and $\frac{\tilde{\mathbf{P}}^{\text{GO}} + 0.7}{\tilde{\mathbf{P}}^{\text{GO}}} = \frac{1.3+0.7}{1.3} \approx 1.5$.)

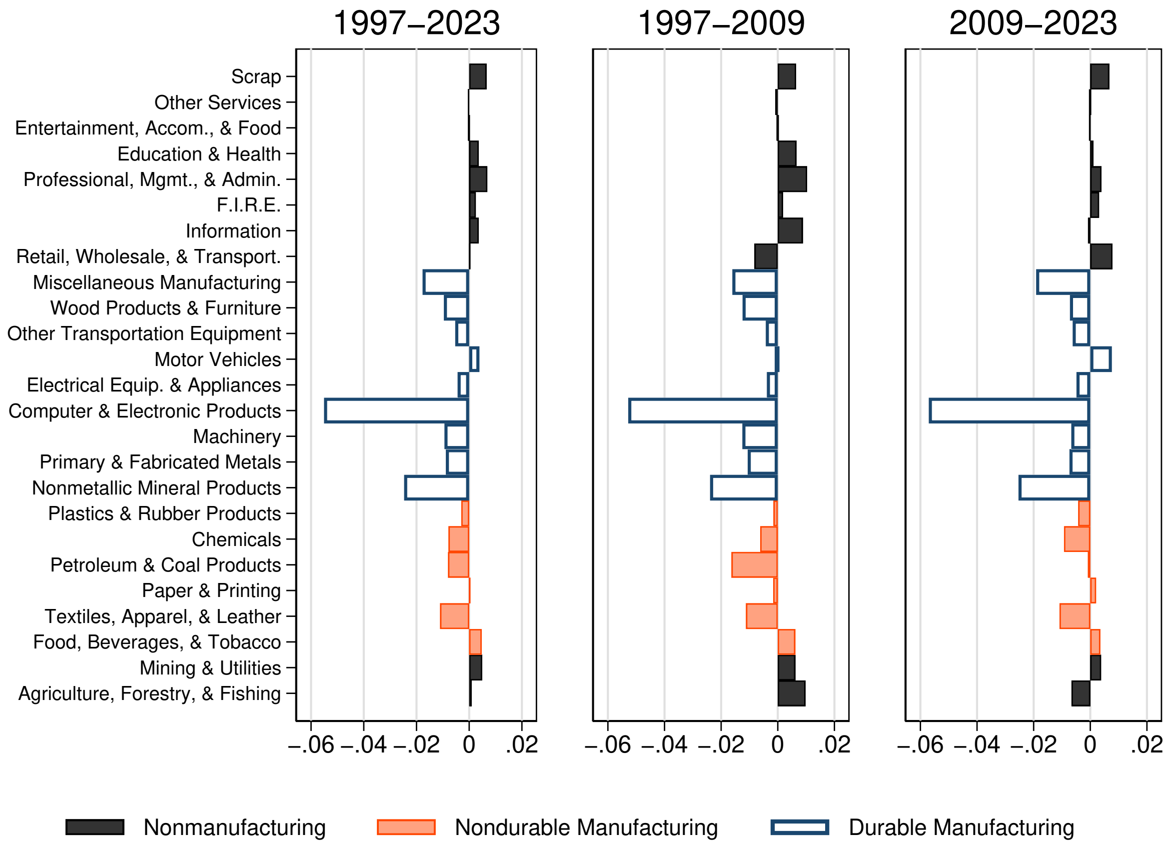

Figure 5: TFP Mismeasurement

Notes: We apply Equation 8 to recover the mismeasurement in TFP by industry and year. We average these variables by broad sector and years, weighting industries according to their personal consumption expenditures within each year. Compared with Figure 2, we combine the following, where at least one of the industries has a small share of its output sold as personal consumption: We combine Wood Products (NAICS 321) and Furniture (NAICS 337); Textiles & Textile Product Mills (NAICS 313-314) and Apparel & Leather (NAICS 315-316); Paper (NAICS 322) and Printing & Related Support (NAICS 323); and Primary Metals (NAICS 331) and Fabricated Metal Products (NAICS 332).

the nonmanufacturing sector (overstated by 0.25 percentage points per year). Third, even though TFP mismeasurement is most severe in Computer and Electronic Product Manufacturing, it is pervasive throughout manufacturing. Finally, mismeasurement of TFP growth is 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.[23]

[23]For the durable goods sector, the average of $\Delta \log \widetilde{\mathbf{A}}_t$ was -1.45 percentage points between 1997 to 2009 and -1.31 percentage points between 2009 and 2023. For nondurable goods, $\Delta \log \widetilde{\mathbf{A}}_t$ was (on average)

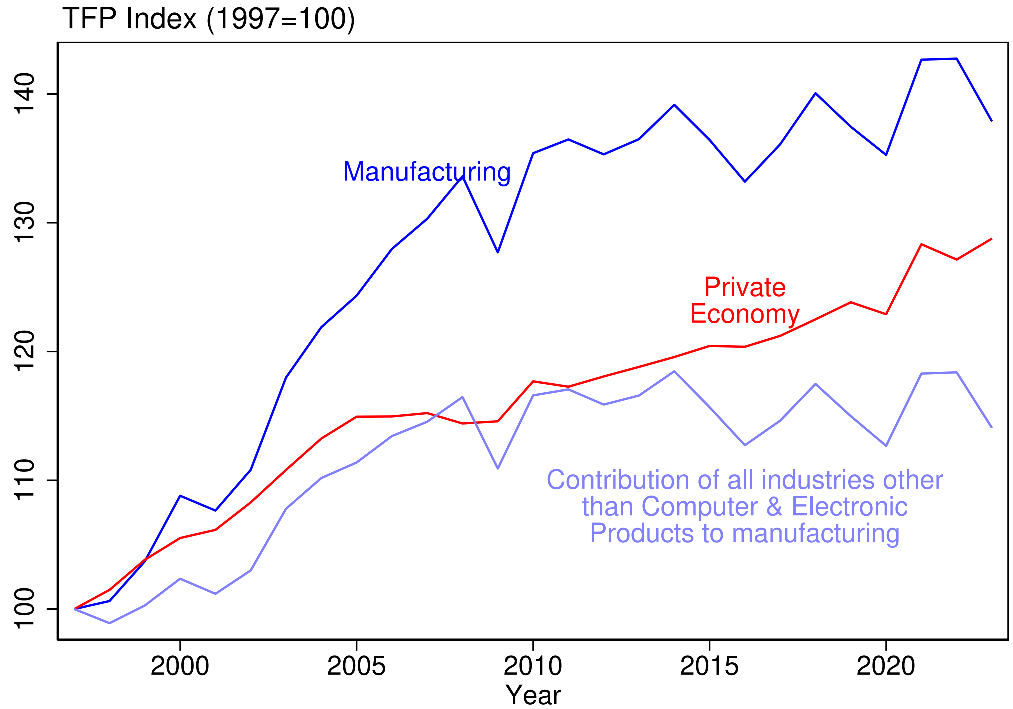

Figure 6: TFP for Manufacturing, Manufacturing excluding Computer and Electronic Product Manufacturing, and the Private Business Sector
Notes: This figure reproduces Figure 2, correcting for TFP mismeasurement using the adjustments in this section.

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 6 for the time series of corrected TFP. Our estimates imply that true TFP growth rate in the manufacturing sector was 0.5% between 2009 and 2023: 1.6% in durable goods manufacturing industries and −0.0% in nondurable goods manufacturing industries. This is slower than TFP growth in the manufacturing sector between 1997 and 2009 (2.0%), but much stronger than what the official statistics would suggest.

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

First, 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"

−0.39 percentage points between 1997 and 2009 and −0.32 percentage points between 2009 and 2023. For the nonmanufacturing sector, the average of $\Delta \log \widetilde{\mathbf{A}}_t$ was 0.35 percentage points between 1997 and 2009 and 0.17 percentage points between 2009 and 2023.

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 as large as what is reported in Figure 4, with substantially larger gaps for ICT-related manufacturing industries. This, in turn, implies that TFP is understated for Computer and Electronic Product Manufacturing even more than what we report in Figure 5. On the other hand, we estimate smaller TFP mismeasurement for nondurable manufacturing industries, and, on balance, slightly more modest TFP mismeasurement for the broader manufacturing sector.

Second, 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 Broadcasting and Wireless Communications Equipment Manufacturing Equipment (NAICS 33422) sold to consumers (e.g., iPhones) had 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 personal consumption expenditures. In a related robustness check, in Appendix D.7 we restrict our sample to industries producing "mass market" goods, dropping industries primarily producing "niche" products. The patterns given in Figure 5 are robust to these different restrictions.

Third, 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 row is normalized to have sum equal to 1. Our results are unchanged with this alternate definition.

Fourth, in Appendix D.6 we re-compute $\Delta \log \tilde{\mathbf{A}}_t$ under different assumptions on the relative mismeasurement of gross output deflator growth and import price growth. We re-compute TFP mismeasurement assuming import price indices contain 100% more (or, alternatively, 150% more) quality undercounting than gross output deflators (relative to the benchmark of the PCE price index). Relative to our benchmark $\xi = 1.5$, raising ξ to 2.0 or 2.5 lowers our estimated manufacturing TFP-growth mismeasurement by roughly 10 and 20 basis points, respectively (to 0.54 and 0.44 percentage points). We view $\xi = 2.5$ as an intentionally extreme calibration, well beyond what Errico and Lashkari (2025) would suggest.

Fifth, in Appendix D.8 we re-compute TFP mismeasurement with $\mathbf{\Gamma^K} = \mathbf{0}$. In our baseline calculations, we use the Vom Lehn and Winberry (2022) investment network to construct $\mathbf{\Gamma^K}$, but in estimating capital rental price mismeasurement we inevitably make two compromises: First, because output of the Construction sector does not directly enter PCE, we cannot estimate mismeasurement for this sector. We thus only account for quality undercounting in equipment and intellectual property products. Second, we equate the Vom Lehn and Winberry (2022) investment network—which describes flows of goods and services in the production of each downstream industry's single capital stock—with the conceptually distinct $\mathbf{\Gamma^K}$ matrix, which captures how important different capital stocks are in downstream industries' production. Investment and capital flows are equal only under restrictive conditions.[24] To gauge sensitivity to these issues, we consider an extreme case in which we shut down the impact of capital rental price mismeasurement by setting $\mathbf{\Gamma^K} = 0$. This extreme assumption lowers our estimates of TFP growth mismeasurement by about 10 basis points, with a slightly larger impact outside of manufacturing.

Finally, in our baseline calculations, we have estimated TFP mismeasurement only for industries with at least some personal consumption expenditures. Consistent with this, and guided by the idea that small-PCE detailed industries may have more noisy estimates of TFP mismeasurement, we produce aggregate and sector averages weighting detailed industries by their PCE. In Appendix D.9, we reproduce our main results weighting by detailed industry gross output. In a second set of calculations, we weight by gross output *and*, "fill in" estimates of TFP mismeasurement using averages from broader summary industries to impute TFP mismeasurement for detailed industries with missing values. Across these two sensitivity analyses, manufacturing TFP growth is understated by 0.60 percentage points (when weighting by gross output) and 0.85 percentage points (when weighting by gross output and imputing missing detailed industries' TFP mismeasurement).

Appendix Table A.9 in Appendix D.10 collects estimates of TFP mismeasurement in each of these sensitivity analyses.

4 Conclusion

In contrast to decades prior, measured manufacturing productivity has stagnated since the late 2000s. This article investigates this pattern from two angles. The first half of the article documents that the end of the ICT revolution can account for the deceleration of manufacturing productivity. We then marshal suggestive evidence that quality improvements and, by implication, productivity growth are substantially underestimated in durable goods

[24]The online appendix of Foerster et al. (2022) contrasts these two specifications. They then show that the two specifications are equivalent if industry capital stocks have a common depreciation rate and industry output prices have a common trend. In practice, neither condition holds in the data.

manufacturing, primarily so in the manufacturing of computers and other electronic goods. Correcting for the mismeasurement we identify, manufacturing productivity is still growing, albeit at a slower rate than before, and is not so concentrated in Computer and Electronic Product Manufacturing.

In interpreting these results, we sound a point of caution. Our 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 that have detailed micro data on product characteristics and prices to measure biases in producer price indices (e.g., Byrne, 2015b; Byrne and Corrado, 2015a; Byrne et al., 2018).

The US manufacturing sector has changed profoundly over the last quarter century. Its employment has collapsed, declining by more than one-quarter (even as private nonfarm employment has grown by more than one-quarter) since 1997.[25] It has grown more import-reliant, first from China and then from Vietnam and Mexico (Alfaro and Chor, 2023), more capital intensive,[26] and more robot intensive (see Figure 5 of Klump et al., 2021). Assessments of these particular changes—and of 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.

[25]See `https://fred.stlouisfed.org/series/MANEMP` and `https://fred.stlouisfed.org/series/PAYEMS`; accessed September 4, 2025.

[26]See `https://fred.stlouisfed.org/series/MPU9900082`; accessed September 4, 2025.

References

Aghion, P., A. Bergeaud, T. Boppart, P. J. Klenow, and H. Li (2019): "Missing Growth from Creative Destruction," *American Economic Review*, 109, 2795–2822.

Alfaro, L. and D. Chor (2023): "Global Supply Chains: The Looming 'Great Reallocation'," NBER Working Paper 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, 357–374.

Bayard, K., D. Byrne, and D. Smith (2015): "The Scope of U.S. 'Factoryless Manufacturing'," in *Measuring Globalization: Better Trade Statistics for Better Policy, Volume 2: Factoryless Manufacturing, Global Supply Chains, and Trade in Intangibles and Data*, ed. by S. N. Houseman and M. Mandel, W.E. Upjohn Institute for Employment Research, 81–120.

Boppart, T., M. Carlsson, M. Kondziella, and M. Peters (2023): "Micro PPI-Based Real Output Forensics," Tech. rep.

Bridgman, B. (2026): "Markups and the Manufacturing Slowdown," *American Economic Association: Papers & Proceedings*, forthcoming.

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. (2015a): "Domestic Electronics Manufacturing: Medical, Military, and Aerospace Equipment and What We Don't Know about High-Tech Productivity," FEDS Notes 2015-06-02, Board of Governors of the Federal Reserve System.

——— (2015b): "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," FEDS Working Paper 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.

Ding, X., T. C. Fort, S. J. Redding, and P. K. Schott (2022): "Structural Change Within Versus Across Firms: Evidence from the United States," NBER Working Paper 30127.

Errico, M. and D. Lashkari (2025): "Aggregation and the Estimation of Quality Change: Application to US Import Prices," *Quarterly Journal of Economics*, 140, 3283–3335.

Foerster, A. T., A. Hornstein, P.-D. G. Sarte, and M. W. Watson (2022): "Aggregate Implications of Changing Sectoral Trends," *Journal of Political Economy*, 130, 3286–3333.

Fort, T. C. (2023): "The Changing Firm and Country Boundaries of US Manufacturers in Global Value Chains," *Journal of Economic Perspectives*, 37, 31–58.

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

Gordon, R. J. (1990): *The Measurement of Durable Goods Prices*, University of Chicago Press.

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, 165–186.

Vom Lehn, C. and T. Winberry (2022): "The Investment Network, Sectoral Comovement, and the Changing US Business Cycle," *Quarterly Journal of Economics*, 137, 387–433.

A Discussion of Underlying Source Data and Quality Adjustment

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

In the final portion of this appendix, we discuss changes in the methodology that the BLS has employed to produce its PPI and CPI. The two most important changes were (a) a steady expansion in the set of commodities covered in the PPI, concentrated in service industries; and (b) an increase in the number of commodities for which the BLS applies a hedonic adjustment to account for quality improvements over time. For both price indices, the increasing use of hedonic adjustments have occurred either before 2000 or beginning in the late 2010s. An implication of this discussion is that, since most methodological changes occurred in the service sector (or for service consumption categories), or either took place before the early 2000s or beginning in the 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 are 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 US Residents Who are Abroad (which draw on the BEA index for installation support services). For service commodities, while the CPI is the primary data source for many components of the PCE price index, a larger set of components draw on the PPI (examples include most financial service charges and fees, air transportation, hospitals, and physician services) and BEA input cost indices (examples include labor organization dues, life insurance, financial services furnished without payment, among others). For a comprehensive list of the sources used in the construction of the PCE price index, see Bureau of Economic Analysis (2024, Chapter 5).

Industry Gross Output Deflators

The BEA industry gross output deflators draw on a mix of data from the PPI, CPI, and other sources. For manufacturing industries, the BEA relies primarily on the PPI to construct its gross output deflators (Bureau of Economic Analysis, 2024, Chapter 4). There are two sets of exceptions. First, for military equipment, the BEA applies price indices from the Department of Defense ("prices paid for military equipment"). Second, the BEA employs quality-adjusted price indices for computers, photocopying equipment, digital telephone switching equipment, and LAN equipment. Some of these quality-adjusted price indices draw on the BLS PPI. In other cases, where quality adjustment has not been available, the BEA has constructed its own (Bureau of Economic Analysis, 2024, Chapter 4). For service industries, the BEA gross output deflators draw on a wider variety of sources. Table A.1 lists the underlying sources of the BEA gross output deflator for a year near the beginning (2004), middle (2010), and end (2018) of the sample.

Year	2004	2010	2018
Agriculture, Forestry, Fishing, and Hunting (11)	——————	——————	——————
Farms (111, 112)	USDA prices received by farmers; PPI	USDA prices received by farmers; PPI	NIPA prices based on USDA price indexes
Forestry, Fishing, and Related Activities (113, 114)	PPI; NOAA; NIPA deflator.	USDA; PPI; NIPA PCE; for fisheries for aquaculture, NOAA	PPI, NIPA PCE, USDA National Agricultural Statistics Service unit prices
Mining (21)	——————	——————	——————
Oil and Gas Extraction (211)	For crude petroleum and natural gas, IPD from DOE; for natural gas liquids, PPI	PPI; EIA	PPI and EIA
Mining, Except Oil and Gas (212)	IPD from DOE and USGS.	EIA, USGS, and PPI	EIA, USGS, and PPI
Support Activities for Mining (213)	IPD from DOE, USGS and trade sources; for exploration, PPI	EIA, USGS, PPI, and trade sources	EIA, USGS, PPI, and trade sources

Year	2004	2010	2018
Utilities (22)	PPI for Electric Utilities and Natural Gas, CPI for Water, Sewage, and Other Systems	CPI and PPI; EIA	CPI and PPI
Construction (23)	————	————	————
Residential (2361)	Census Bureau price index for new single-family houses under construction; BEA price index for multifamily construction.	Census Bureau price deflator for new single-family houses under construction; NIPA price index for multifamily home construction.	Census Bureau price deflator for new single-family houses under construction and BEA prices for multifamily home construction
Nonresidential (2362, 237, 238)	————	NIPA composite price indexes based on cost per square foot; cost indexes from trade source data; for single family houses under construction, Census Bureau price deflator; PPI	PPI and BEA composite prices based on trade source data and on the Census Bureau price deflator for single-family houses under construction
For the Department of Defense	DOD prices for military construction; cost indexes from trade sources and government agencies for other construction.	————	————
For State and Local Highways (2373)	Cost indexes from government agencies	————	————
For Private Electric and Gas Utilities (2371)	Cost indexes from trade sources and government agencies	————	————

Year	2004	2010	2018
For Farms, Excluding Residential	Trade sources cost index; Census Bureau price deflator for new single family houses under construction	————	————
For Other Nonresidential	Trade sources and government agency cost indexes; Census Bureau price index for new single-family houses under construction; BEA quality-adjusted price indexes for factories, office buildings, warehouses, and schools	————	————
Manufacturing (31, 32, 33)	PPI; quality adjusted price indexes for computers, photocopying equipment, digital telephone switching equipment, and LAN equipment; BEA price indexes based on DOD prices paid for military equipment.	PPI; NIPA price indexes based on DOD prices paid for military equipment; NIPA hedonic price indexes.	PPI and NIPA prices based on DOD prices paid for military equipment, and NIPA hedonic prices
Wholesale Trade (42)	Sales price by kind-of-business computed from PPI	Census Bureau AWTR and MWTR data to derive margin rates; IRS Statistics of Income (SOI); NIPA sales prices and import prices; IRS SOI commodity taxes.	PPI and NIPA sales deflators

Year	2004	2010	2018
Retail Trade (44, 45)	Sales price by kind-of-business computed from CPI	PPI; NIPA retail sales prices; Census Bureau ARTS and MRTS; IRS SOI	PPI and NIPA sales deflators
Transportation and Warehousing (48, 49)	___________	___________	___________
Air Transportation (481)	IPD for total passenger-related revenues and passenger miles from DOT; IPD for total freight-, mail-, and express-related revenues and ton miles from DOT; wages and salaries per employee from BLS.	PPI; BTS prices.	PPI
Rail Transportation (482)	PPI	For rail passengers, CPI; for freight, PPI	PPI
Water Transportation (483)	PPI for freight; for passengers, CPI.	PPI and CPI; trade source data	For freight, PPI; for passenger, CPI
Truck Transportation (484)	PPI	PPI	PPI
Transit and Ground Passenger Transportation (485)	For taxicabs, intercity buses, and other local transit, PCE price index; for school buses, BLS data on wages and salaries per employee.	NIPA PCE; BLS QCEW.	NIPA PCE
Pipeline Transportation (486)	PPI	PPI	PPI
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

Year	2004	2010	2018
Warehousing and Storage (493)	PPI	PPI	PPI
Information (51)	———	———	———
Publishing Industries, Except Internet (Includes Software) (511)	BEA price indexes for prepackaged and custom software for software publishers; for all other publishing industries, PPI	PPI	PPI and BEA price indexes for software
Motion Picture and Sound Recording Industries (512)	PCE	CPI; NIPA PCE	NIPA PCE
Broadcasting and Telecommunications (515, 517)	For cable networks, programming, and telecommunications, PPI; for radio and television broadcasting, network receipts, and all other telecommunications, composite price index of PPIs.	PPI; for radio and TV broadcasting, NIPA PCE based on PPI	PPI
Data processing, Internet Publishing, and Other Information Services (518, 519)	For information services, PCE; for data processing services, PPI	CPI and PPI; for publishing and broadcasting content on the Internet, NIPA PCE	PPI and NIPA PCE
Finance and Insurance (52)	———	———	———
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 full-time 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	———
Hospitals and Nursing and Residential 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
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)	———	———	———

Year	2004	2010	2018
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

Table A.1: Sources of the BEA Gross Output Deflators for Selected Years

Notes: The acronyms mentioned within this table are as follows: ARTS: Annual Retail Trade Survey; AWTR: Annual Wholesale Trade Report; BTS: Bureau of Transportation Statistics; DOD: Department of Defense; DOE: Department of Energy; DOT: Department of Transportation; EIA: Energy Information Administration; FRB: Federal Reserve Board; IPD: Implicit Price Deflator; IRS SOI: IRS Statistics of Income; LAN: Local Area Network; MRTS: Monthly Retail Trade Survey; MWTR: Monthly Wholesale Trade Report; NOAA: National Oceanic and Atmospheric Administration; QCEW: Quarterly Census of Employment and Wages; USDA: United States Department of Agriculture; USGS: United States Geological Survey; USPS: US Postal Service. The sources for this table are Table D of `https://apps.bea.gov/scb/pdf/2004/03March/0304IndustryAcctsV3.pdf`, Table C of `https://apps.bea.gov/scb/pdf/2010/03%20March/0310_indy_accts.pdf`, 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. Dashes signify that the industry was not explicitly mentioned in the year's source data documentation.

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. We first describe the expansion of the PPI, then describe expansions in the set of commodities for which the BLS applies a hedonic adjustment to the CPI or PPI. Any expansion of hedonic adjustment in the PPI or CPI matters for the PCE price index and industry gross output deflators only to the extent that the BEA uses those BLS series in constructing its price measures. For example, because the BEA applies its own hedonic adjustment to computers, hedonic adjustment in the BLS PPI for computers does not affect the Computer and Peripheral Equipment Manufacturing industry's gross output deflator.

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; and 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.[27] 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, Girls' Tops, Men's Athletic Footwear, and women's athletic footwear. In 1997, hedonic adjustment was added to Women's Outerwear. In 2004, Boys' Shirts and Sweaters were added to the list of apparel categories with a hedonic adjustment. In 2023, Men's Underwear and Women's Bras were added. The remaining categories with a hedonic adjustment include Personal Computers and Peripheral Equipment (1998), Televisions (1999), Audio Equipment (2000), Other Video Equipment (2000), Refrigerators and Freezers (2000), Washers and Dryers (2000), Microwaves (2000), Educational Books and Supplies (2000), Wireless Telephone Services (2017), Smartphones (2018),[28] Land-Line

[27] 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`.

[28] Smartphones belong to the Telephone, Hardware, Calculators, and Other Consumer Information item's consumption category.

Telephone Services (2019),[29] 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,[30] late 2016,[31] and 2018,[32] respectively.

B Data Construction

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 to detailed PCE categories and detailed NAICS commodities. Unfortunately, the detailed data are present only in certain years—2007, 2012, and 2017—with more aggregated summary data for other years between 1997 and 2023. We first discuss our estimates for producing $m_{t,j}$, the share of consumption expenditures of detailed commodity j that is imported in year t (Appendix B.1).

We then discuss how we compute $s_{t,j\to c}$ for detailed commodities and consumption categories in each year (Appendix B.2).

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

In Appendix B.4, we describe how we apply Vom Lehn and Winberry (2022) to calibrate the importance of individual upstream industries in the production of downstream industries' capital services.

Finally, Appendix B.5 describes how we estimate the contribution of transportation, wholesale, and retail margins in the distribution of each detailed commodity.

[29]See https://www.bls.gov/cpi/quality-adjustment/hedonic-price-adjustment-techniques.htm.

[30]See page 42 of https://fraser.stlouisfed.org/files/docs/publications/cpidr/cpi_199707.pdf.

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

[32]See Sawyer and So (2018).

B.1 Import Interpolation Methodology

Crosswalk

Use j to denote a detailed commodity. We have detailed data from 2007, 2012, and 2017 but no other years. Use φ to denote a summary commodity. We have data on summary commodities from 1997 to 2023. Each detailed commodity j is part of exactly one summary commodity φ. We check that the sum of the import volumes of the detailed commodity in 2017 exactly matches the import volume of the summary commodity in that year.

Interpolation

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

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

1997 to 2006 and 2018 to 2023 If we have only one year of detailed data, we assume that the import proportion of the detailed category changes by the same amount as the import proportion of the summary commodity in the same time frame.

That is:

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

where $\lambda_{y,j}$ is the import proportion of the detailed commodity in year y and $\lambda_{y,\varphi}$ is the import share of the summary commodity in year y. For 2018 to 2023, we use $y = 2017$ and $t \in \{1, 2, \ldots, 6\}$. For 1997 to 2006, we use $y = 2007$ and $t \in \{-1, -2, \ldots, -10\}$.

2008 to 2011 and 2013 to 2016 Here, we explain the method used for 2008 to 2011. We apply an equivalent method for 2013 to 2016.

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

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

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

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

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

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

This method fails if $\lambda_{2007,\varphi}$, $\lambda_{2012,\varphi}$, or $\lambda_{2007,j}$ is zero. In those cases, we go through the following methods, in the given order, stopping at the first one that fits:

1. If $\lambda_{2007,\varphi} = 0$, 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 $\lambda_{2007,j}$ and $\lambda_{2012,j}$ are zero, then we assume that every $\lambda_{t,j}$ from 2008 to 2011 is zero.

3. If $\lambda_{2012,\varphi} \neq 0$ and $\lambda_{2007,j} = 0$ or $\lambda_{2012,j} = 0$ and $\lambda_{2007,j} \neq 0$, then we replace the detailed import volume that is zero with 0.25, recalculate the detailed import proportion, and apply the estimation equation.

Notes on these methods

- There are no cases (excluding rounding error) where $m_{2007,\varphi} = m_{2012,\varphi} = 0$ and the summary imports in the years in between are positive. For this reason, we do not need to design a method for this scenario.

- There are no cases where $\lambda_{2007,\varphi} \neq 0$ and $\lambda_{2012,\varphi} = 0$ (or its 2012 to 2017 analogue). For this reason, we do not need to design a method for this scenario.

- The import proportions were calculated using import volumes (in millions) that were rounded to the nearest integer. For the method in point (3) we assume that an import volume of zero has a true import value in $(0, 0.5)$, which we approximate by 0.25 (million).

Link to the Measures Used in the Body of the Paper In Sections 2 and 3, we use $m_{t,j}$. This is the year-t shares of detailed commodity j's PCE that is imported. This $m_{t,j}$ is computed by dividing $\lambda_{t,j}$ by the sum of PCE for commodity j in year t. We obtain total PCE for commodity j in year t by using the same interpolation methods as in this subsection.

B.2 PCE Bridge Table Imputation Methodology

Crosswalk

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

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

Interpolation

We estimate based only on detailed data in the year closest to what is being estimated:

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

1997 to 2006 and 2018 to 2023 If we have only one year of data with detailed industries, 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:

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

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

To impute $V_{y+t,d}$ for $y + t \in \{2018, ..., 2023\}$, we use $y = 2017$ and $t \in \{1, 2, \ldots, 6\}$. To impute $V_{y+t,d}$ for $y + t \in \{1997,...,2006\}$ we use $y = 2007$ and $t \in \{-1, -2, \ldots, -10\}$.

Technically, this method does not work if $V_{y,\varphi} = 0$. 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 $V_{y,\varphi} = 0$ we set $V_{y+t,d} = 0$ as well.

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

For these years, we have detailed data from both before and after the year for which we are trying to impute the entry of the PCE Bridge Table. Since we have both $\frac{V_{2012,d}}{V_{2012,\varphi}}$ and $\frac{V_{2007,d}}{V_{2007,\varphi}}$, we use both fractions to provide the best estimate of $V_{2007+t,d}$. We want $\frac{V_{2012,d}}{V_{2012,\varphi}}$ to play a larger role for years that are closer to 2012 and $\frac{V_{2007,d}}{V_{2007,\varphi}}$ to be more important for years closer to 2007. Here, we set:

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

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

This method fails if $V_{2007,\varphi}$, $V_{2012,\varphi}$, or $V_{2007,d}$ is zero or if the sign of $\frac{V_{2012,d}}{V_{2007,d}}$ is different than the sign of $\frac{V_{2007,\varphi}}{V_{2012,\varphi}}$. In practice, only the sign changes are problematic. This issue occurs very rarely, so when it does it is usually the only case with an issue in its summary bridge pair. Thus, we estimate every other detailed bridge pair in the summary bridge pair. We then subtract their sum from the value of the summary bridge pair and use the remainder as the estimate of the detailed bridge pair. If there happens to be multiple bridge pairs with this issue in the same summary bridge pair we split the remainder between them based on their relative sizes.

Link to the Measures Used in the Body of the Paper In Sections 2 and 3, we use $s_{y,j\to c}$. These are the year-y shares of detailed consumption category c's PCE that is sourced from detailed commodity j. This $s_{y,j\to c}$ is computed by dividing $V_{y,d}$ by the sum of the V's for which consumption category c is the "destination" category in the year y. Remember that d denotes a commodity (j) $\times$ consumption category (c) pair.

B.3 Input-Output Use Table Interpolation Methodology

Crosswalk

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

There are 73 commodity codes and 73 industry codes in the summary Use Table. We have data on these categories from 1997 to 2023.

Each intersection of a summary commodity category and a summary industry category is composed of the intersections of some subset of detailed commodities and some subset of detailed industry categories. Each detailed intersection corresponds to exactly one summary intersection.

Interpolation

We estimate use values based only on the detailed data that is closest in time to the year being estimated:

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

1997 to 2006 and 2018 to 2023 In these instances, we assume that the use value of the detailed intersection changes by the same amount as the use value of the summary intersection in the same time frame. Let d refer to a combination of a detailed upstream commodity×detailed downstream industry, and φ to refer to a combination of a summary upstream commodity×summary downstream industry. That is:

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

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

To impute use values for 2018 to 2023, we let $y = 2017$ and $t \in \{1, 2, \ldots, 6\}$. To impute use values for 1997 to 2006, we let $y = 2007$ and $t \in \{-1, -2, \ldots, -10\}$.

Technically, this method does not work if $U_{y,\varphi} = 0$. 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 $U_{y,\varphi} = 0$, we set $U_{y+t,d} = 0$ as well. We apply an analogous assumption for values of zero occurring in 2017.

2008 to 2011 and 2013 to 2016 Here, we explain the method used for 2008 to 2011. The equivalent method is used for 2013 to 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 $\frac{U_{2012,d}}{U_{2012,\varphi}}$ and $\frac{U_{2007,d}}{U_{2007,\varphi}}$, we can apply both fractions to estimate $\frac{U_{2007+t,d}}{U_{2007+t,\varphi}}$. Intuitively, $\frac{U_{2012,d}}{U_{2012,\varphi}}$ should play a larger role for years that are closer to 2012 and $\frac{U_{2007,d}}{U_{2007,\varphi}}$ should play a larger role for years closer to 2007. Here, we impute the use value of an intersection as:

$$U_{2007+t,d} = U_{2007,d} \cdot \frac{U_{2007+t,\varphi}}{U_{2007,\varphi}} \cdot \left(\frac{U_{2012,d}}{U_{2007,d}} \cdot \frac{U_{2007,\varphi}}{U_{2012,\varphi}} \right)^{t/5} \tag{10}$$

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

This method fails if $U_{2007,\varphi}$, $U_{2012,\varphi}$, or $U_{2007,d}$ is zero. In these problematic cases, we apply one of the two following methods:

1. If $U_{2007,\varphi} = 0$ or $U_{2007,d} = 0$, we set $U_{2007+t,d} = 0$ for each $t \in \{1, ..., 4\}$.
2. If $U_{2012,\varphi} = 0$, but $U_{2007,d} \neq 0$ and $U_{2017,d} \neq 0$, we estimate $U_{2007+t,d} = 0$ using a modified version of Equation 10 with the 2017 values replacing the 2012 values and $t/10$ replacing of $t/5$.

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

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

B.4 Calibrating the $\Gamma_t^{\mathbf{K}}$ Matrix

In this appendix, we describe how we calibrate the importance of different upstream industries in the capital services for different downstream industries' production. We need this *capital flows table* to link mismeasurement in upstream industries' gross output deflators to mismeasurement in downstream industries' rental price of capital.

Our starting point is the 43-by-43 investment network produced by Vom Lehn and Winberry (2022).[33] Vom Lehn and Winberry (2022) model capital investment in downstream industry j as a Cobb-Douglas composite of different upstream industries i, with the coefficients on the Cobb-Douglas production function allowed to vary year-by-year.[34]

[33] The benchmark investment network from Vom Lehn and Winberry (2022) has 37 industries, excludes the government, excludes the agricultural sector, has all of the Utilities sector in a single category, and has all of the Real Estate and Rental and Leasing Services industry in a single category. We apply the 43-category version to capture the agricultural sector and the government.

[34] Vom Lehn and Winberry (2022) calibrate investment flows across sectors using annual information on (a) total investment expenditures for each sector, (b) total production of investment goods—by type: residential and non-residential structures, equipment, and intellectual property—by each sector, and (c) sector-level investment expenditures by detailed asset types, from the NIPA Fixed Assets by Industry Table. Part of the

We construct a correspondence between the 43 sectors in Vom Lehn and Winberry (2022) and the 402 detailed industries in our analysis. Let d (or d') denote a detailed industry and j (or j') denote one of the 43 sectors in Vom Lehn and Winberry (2022). And let $j(d)$ denote the broad sector corresponding to a particular detailed industry and $\mathcal{D}(j)$ the set of detailed industries corresponding to a particular broad sector j. For instance, there are two detailed industries—Printing (NAICS 32311) and Support Activities for Printing (NAICS 32312)—associated with a single broader industry, NAICS 323 (Printing and Related Support Activities). In this example, $j(d = 32311) = 323$ and $\mathcal{D}(j = 323) = \{d = 32311 \cup d = 32312\}$.

The Vom Lehn and Winberry (2022) investment network contains measures $\iota_{t,j' \to j}$, the share of industry j's investment flows that are sourced from upstream industry j'. The data run from 1947 to 2018. Our goal is to calibrate $\gamma^K_{t,d' \to d}$, the share of detailed industry d inputs that are sourced as capital from upstream industry d'. Note that $\sum_{j'} \iota_{t,j' \to j} = 1$, while $\sum_{d'} \gamma_{t,d' \to d} = \gamma_{t,r \to d}$: While the sum of the entries in the Vom Lehn and Winberry (2022) investment network equals 1, the sum of the γ^Ks that we wish to compute equals the capital share of downstream industry d.

To compute $\mathbf{\Gamma}^K$, we make three assumptions. First, we assume that the investment network is unchanged over the last six years of the sample: $\iota_{\tau,j' \to j} = \iota_{2018,j' \to j}$ for $\tau \in \{2019, 2020, 2021, 2022, 2023\}$. Second, for each d', t pair, we assume that $\iota_{t,d' \to d} = \iota_{t,d' \to d''}$ if d and d'' both correspond to the same broader industry j. Third, the contribution of detailed upstream industries sums up to that of the broader j' sector, with the relative importance of individual detailed upstream industries proportional to its total gross output (which we estimated by detailed industry and year in Appendix B.3). We multiply this ratio by the industry's capital share (which we take as the ratio of gross operating surplus to gross output, also from the BEA Input-Output Table) to arrive at $\gamma^K_{t,d' \to d.}$. That is, we compute:

$$\gamma^K_{t,d' \to d.} = \frac{\text{Gross Operating Surplus}_{t,d}}{\text{Gross Output}_{t,d}} \cdot \frac{\text{Gross Output}_{t,d'}}{\sum_{d'' \in \mathcal{D}(j(d'))} \text{Gross Output}_{t,d''}} \cdot \iota_{t,j(d') \to j(d)}. \tag{11}$$

B.5 PCE Bridge Margin Assignment

The PCE Bridge Table reports both producer's value and purchaser's value, which adds the transportation, wholesale, and retail costs to the producer's value. We refer to these as the transportation, wholesale, and retail margins. We would like to be able to assign the value

calibration also imposes assumptions about the sets of industries that are likely to produce different capital types. For example, non-residential structures are assumed to be produced either by the Construction industry—or, for mining structures, in the Mining industry—while software and R&D investment are produced by the Professional and Technical Services industry, and so on.

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 use tables do give each industry's use of the margin commodities as part of their intermediate inputs.

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

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

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

C Sensitivity to Including Distribution Margins in Equation 1

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

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

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

$$\frac{v_{t,j\to c}}{\sum_{j'} v_{t,j'\to c}} \tag{12}$$

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

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 88) from the 2017 PCE Bridge Table. The dollar figures in the final four columns are all nominal.

(NAICS 11230) and All Other Food Manufacturing (NAICS 31199). In terms of Equation 12, $v_{2017,j\to 88}$ = \$5034 for $j = 11230$ and \$2237 for $j = 31199$. As a result, our Producer Inflation measure for the Eggs consumption category would weight Poultry and Egg Production at roughly 70 percent and All Other Food Manufacturing at roughly 30 percent.

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

While the PCE Bridge Table does not have any further detail on the importance of these distribution margins, we employ the input-output table to infer the importance of detailed distribution channels (e.g., inferring the weight of Auto Wholesalers vs. Machinery Wholesalers; Supermarkets vs. Non-Store Retailers; and Air Transportation vs. Pipeline Transportation). Using μ to refer to a generic detailed distribution industry and $\mathcal{M}$ the set of detailed distribution industries, let $\nu_{t,\mu;j\to c}$ 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 Eggs 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—$\nu_{2017,484;11230\to 88} = 0.73 \cdot \$499 = \$365$ and $\nu_{2017,484;31199\to 88} = 0.75 \cdot \$60 = \$45$. In words, Truck Transportation contributes \$410 towards the PCE category of Egg consumption, \$365 through the Poultry and Egg Production commodity and $45 through the All Other Food Manufacturing commodity.

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

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

$$\begin{aligned} \tilde{s}_{t,j\to c} &= \frac{v_{t,j\to c} + \sum_{j'} \nu_{t,j;j'\to c}}{\sum_{j'} (v_{t,j'\to c} + \sum_{\mu\in\mathcal{M}} \nu_{t,\mu;j'\to c})} \text{ if } j \in \mathcal{M} \\ &= \frac{v_{t,j\to c}}{\sum_{j'} (v_{t,j'\to c} + \sum_{\mu\in\mathcal{M}} \nu_{t,\mu;j'\to c})} \text{ if } j \notin \mathcal{M} \,. \end{aligned}$$

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

Figure A.1 presents the analogue of Figure 4 using this alternate definition of Producer Inflation. The key takeaway from this figure is that for computers and electronics-related consumption categories, their scatter-points fall even farther from the 45-degree line in Figure A.1 than in Figure 4. The Personal Computers (NIPA Line 49) consumption category is again instructive. Whereas Producer Inflation was −6.0% in Figure 4, it is at −4.1% 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 include 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 for Personal Computers. The same goes for other consumption categories for which Figure 4 indicated deflation. The Producer Inflation measure for Other Video Equipment, now accounting for distribution margins, increases by 0.9 percentage points (decreasing by 0.9% annually, instead of by 1.8% annually, as in Figure 4). For Telephones, the difference is 5.1 percentage points (6.0% annual price declines in Figure 4 vs. 0.8% in Figure 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

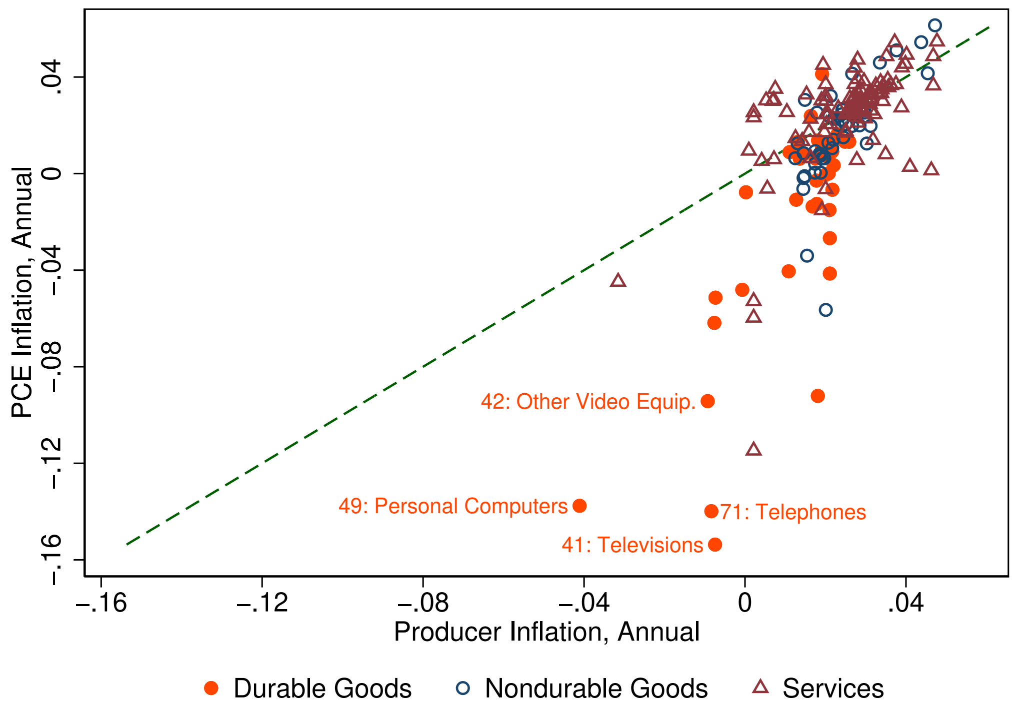

Figure A.1: Two Measures of Inflation Across PCE Categories, 2005–2023
Notes: See the notes for Figure 4. In contrast to that figure, we rely on Producer Inflation measures from Equation 1′.

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 Product Manufacturing industry, TFP mismeasurement is 7.0 percentage points, roughly 1.5 percentage points more than in Figure 5. For other manufacturing industries—where price declines are rarer—including distribution margins in our calculations has either a minimal impact or (for Petroleum and Coal Products Manufacturing and Chemical Manufacturing) leads to smaller estimates of TFP mismeasurement. For the manufacturing sector as a whole, including distribution margins leads to a slightly smaller estimate of TFP mismeasurement: 0.58 percentage points vs. 0.66 percentage points in the baseline specification.

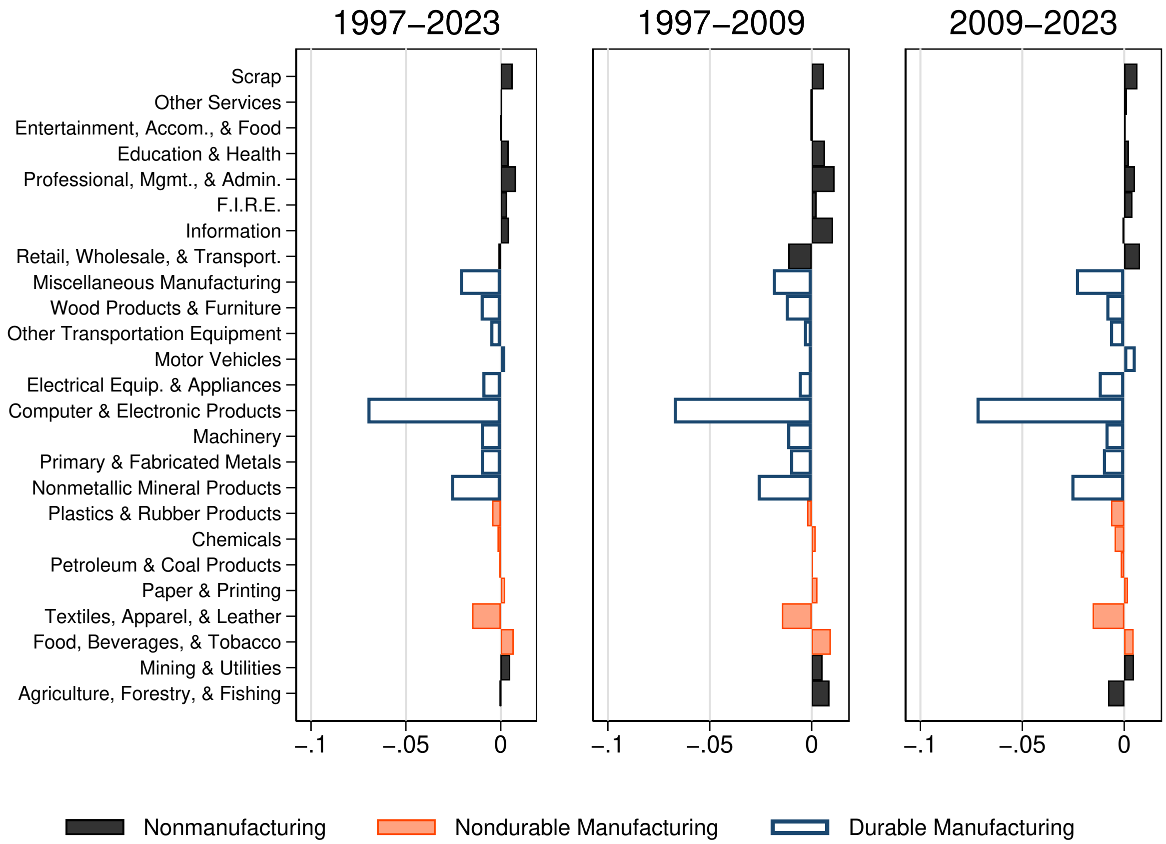

Figure A.2: TFP Mismeasurement
Notes: See the notes for Figure 5. In contrast to that figure, we rely on Producer Inflation measures from Equation $1'$.

D Additional Figures and Tables

In this section, we collect figures and tables supplementing those in the body of the paper. Appendix D.1 collects a figure two tables providing additional detail about the size, productivity growth, and productivity mismeasurement of Computer and Electronic Product Manufacturing. Appendix D.2 digs deeper into offshoring and production fragmentation in the manufacturing sector. 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 enter only 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. In Appendix D.6, we examine the sensitivity of our results to assumptions on the relative mismeasurement in gross output deflators and

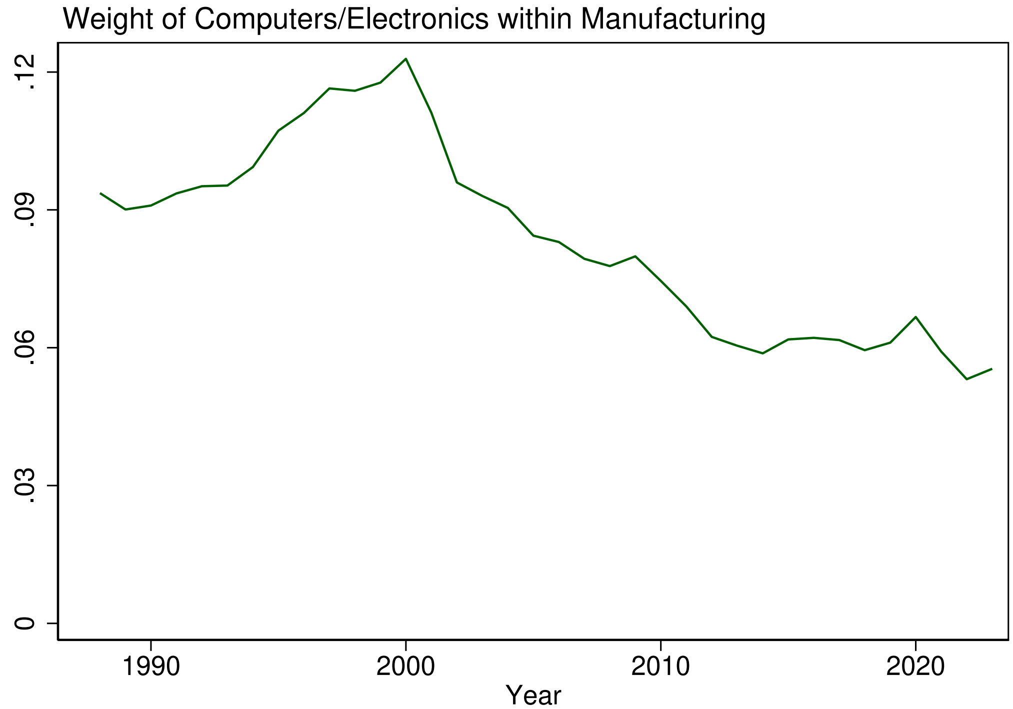

Figure A.3: Share of Sectoral Output of NAICS 334 within Manufacturing

import price indices. In Appendix D.7, we discuss the hypothesis that the domestic manufacturing sector increasingly specializes in "niche" products, with mass-market products being produced elsewhere. We then examine whether TFP mismeasurement differs across industries producing "niche" vs. "mass market" products. In Appendix D.8, we discuss the importance of accounting for capital rent mismeasurement. In Appendix D.9, we attempt to expand the set of detailed industries for which we estimate TFP mismeasurement, essentially drawing on estimates from "nearby" detailed industries. For this broader set of industries, we consider whether our results differ when weighting detailed industries according to their gross output. Finally, in Appendix D.10 we summarize the different robustness checks in Appendix C and Appendices D.4 through D.9.

D.1 Additional Figures and Tables Relating to Computer and Electronic Products Manufacturing

Figure A.3 plots the share of manufacturing output attributable to NAICS 334: the Computer and Electronic Product 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

Industries	TFP Growth '87-'97	TFP Growth '97-'09	TFP Growth '09-'23	Output Share '87-'97	Output Share '98-'09	Output Share '10-'23
Computer and Peripheral Equip. (3341)	0.137	0.163	0.012	0.229	0.184	0.075
Communications Equipment (3342)	0.045	0.027	0.019	0.158	0.173	0.122
Audio and Video Equipment (3343)	0.028	0.022	0.030	0.029	0.020	0.011
Semiconductors and Other Electronic Components (3344)	0.139	0.080	0.034	0.273	0.308	0.296
Navigational, Measuring, Electromedical, and Control Instruments (3345)	0.010	0.002	0.012	0.283	0.295	0.488
Magnetic and Optical Media (3346)	0.032	-0.006	-0.005	0.028	0.019	0.007

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

of the 3-digit Computer and Electronic Product Manufacturing industry. For each of the 4-digit industries, 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 Components Manufacturing (NAICS 3344). These two industries had the largest slowdown in post-2009 TFP growth. 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.

Finally, Table A.4 lists estimated TFP mismeasurement for each 4-digit NAICS industry within Computer and Electronic Product Manufacturing. TFP growth is understated most in Audio and Video Equipment Manufacturing (NAICS 3343) and second most in Communications Equipment Manufacturing (NAICS 3342). These are the two 4-digit industries where quality adjustment methods between consumer-facing and producer-facing price indices differ most. For both industries, none of the relevant PPI components use hedonic quality adjustment. In the CPI, by contrast, BLS introduced hedonic adjustment for multiple audio and video equipment items between 1998 and 2000, and for multiple communications equipment items between 2017 and 2019. For Computer and Peripheral Equipment Manufacturing (NAICS 3341) and Semiconductors and Other Electronic Components (NAICS 3344), estimated TFP mismeasurement is below the average for Computer and Electronic Product Manufacturing.

Industry	'97-'23	'97-'09	'09-'23
Computer and Electronic Products (334)	-5.51	-5.28	-5.70
Computer and Peripheral Equip. (3341)	-4.22	-5.24	-3.39
Communications Equipment (3342)	-5.94	-2.98	-7.22
Audio and Video Equipment (3343)	-8.74	-7.25	-10.46
Semiconductors and Other Electronic Components (3344)	-3.49	-3.72	-2.77
Navigational, Measuring, Electromedical, and Control Instruments (3345)	0.58	0.11	0.89
Magnetic and Optical Media (3346)	-2.16	-2.30	-1.33

Table A.4: TFP Growth Mismeasurement of 4-Digit Industries Within NAICS 334

D.2 Imports and Production Fragmentation of Computer and Electronic Product Manufacturing

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

Mass market consumer electronics are almost exclusively assembled outside of the United States. While there are exceptions—such as Apple assembling Mac Pros in Austin, Texas, or Element Electronics' production of televisions in Winnsboro, South Carolina—nearly all top-selling televisions, stereos, personal computers, and cell phones are assembled abroad.[35]

But domestic manufacturing industries still play an important role in the production of computers and other electronic products that are sold to final consumers. Table A.5 lists the ratio of imports of personal consumption expenditures to total personal consumption expenditures. While this increased over the 2000s, there is still a meaningful share of consumer electronics that are produced domestically. By the end of the sample, 46% of Computer and Electronic Product Manufacturing personal consumption expenditures come from imports. This is substantially higher than at the beginning of the sample (32%) and higher than the import share for the manufacturing sector as a whole (12% in 1997 and 16% in 2023). Yet, even Computers and Peripheral Equipment Manufacturing, the 4-digit NAICS industry with the highest import share, had at least two-fifths of its personal consumption expenditures produced domestically throughout the sample.

How can one reconcile the figures in Table A.5 with the paucity of processing and assem-

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

Industry	1997	2002	2007	2012	2017	2023
Manufacturing (31-33)	0.123	0.165	0.179	0.176	0.162	0.160
Computer and Electronic Products (334)	0.323	0.419	0.469	0.488	0.440	0.462
Computer and Peripheral Equip. (3341)	0.304	0.395	0.441	0.519	0.563	0.591
Communications Equipment (3342)	0.183	0.238	0.266	0.352	0.369	0.388
Audio and Video Equipment (3343)	0.394	0.512	0.573	0.609	0.444	0.466
Semiconductors and Other Electronic Components (3344)	0.232	0.301	0.337	0.302	0.218	0.229
Navigational, Measuring, Electromedical, and Control Instruments (3345)	0.229	0.298	0.333	0.290	0.244	0.257
Magnetic and Optical Media (3346)	0.350	0.454	0.508	0.297	0.122	0.128

Table A.5: Import Share of Personal Consumption Expenditures

bly of domestic consumer electronics manufacturers? Table A.6 lists the types of occupations employed in different manufacturing industries, using data from the BLS Occupational Employment and Wage Statistics (OEWS) dataset. Panel A lists the share of employment in five of the largest 2-digit SOC (Standard Occupational Classification) occupation codes for 2002. (This is the first year for which the public version of the OEWS used the NAICS classification system.) Slightly more than half of manufacturing employees work in a single 2-digit occupation: Production (SOC 51). By contrast, in Computer and Electronic Product Manufacturing, only one-third of employees work in Production occupations. From 2002 to 2023, the share of production workers declined by about 3 percentage points (from 52% to 49%) for the manufacturing sector and by 6 percentage points for Computer and Electronic Product Manufacturing (from 34% to 28%). For this industry, Management (SOC 11), Finance (SOC 13), Computer and Mat (SOC 15), and Engineering and Architecture (SOC 17) collectively account for more than half of its workers, and nearly double the number of workers in production occupations. For this particular industry, domestic manufacturers add value not through their production and assembly of the goods that are consumed but through researching, designing, prototyping, and testing the manufacturing process. The other components of the manufacturing process—namely production and assembly—occur abroad.[36]

[36] These results align with, but are slightly different from, those in Ding et al. (2022) and Fort (2023): These articles document within-firm shifts by which "manufacturing firms" increasingly specialize in establishments performing research and design. Since the OEWS samples establishments, the trends that we document in Table A.6 occur within establishments.

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

Table A.6: Share of Employment Across Occupations by Manufacturing Industry
Notes: This table lists the share of employment in various manufacturing industries. The column headers are as follows: Mgmt. refers to Management Occupations (SOC 11). Finance refers to Business and Financial Operations Occupations (SOC 13). Computers refers to Computer and Mathematical Occupations (SOC 15). Engineer. refers to Architecture and Engineering Occupations (SOC 17). Admin. refers to Office and Administrative Support Occupations (SOC 43). Prod'n refers to Production Occupations (SOC 51). In Panel B, the share of Engineering occupation workers that are in Audio and Video Equipment Manufacturing and Magnetic and Optical Media Manufacturing was not published.

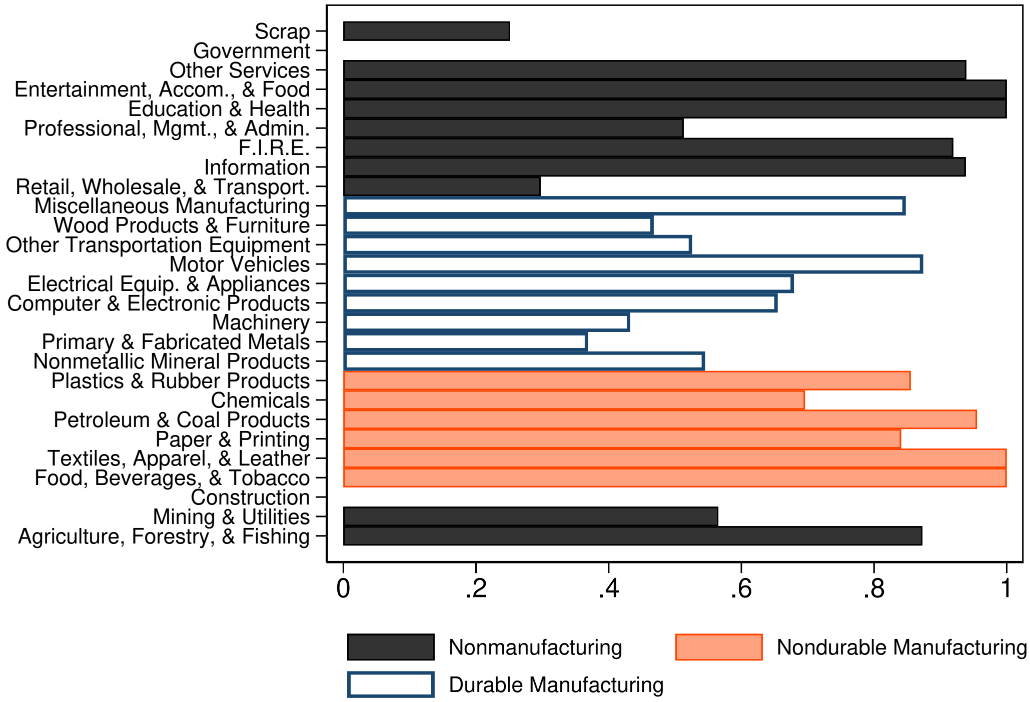

Figure A.4: Share of Industries for Which We Estimate TFP Mismeasurement
Notes: This figure lists the share of groupings of detailed industries for which we can compute TFP mismeasurement. When averaging across industries, we weight according to their gross output in 2017. In computing this figure, we exclude retail, wholesale, and transport industries that appear only through columns D-F of the PCE Bridge Table (see the discussion in Appendix C. Including these industries would increase the entry for the Retail, Wholesale, and Transport row from 0.30 to 0.87, increasing the private economy average from 0.62 to 0.77.

D.3 Industries Missing in the PCE Bridge Table

To compute TFP mismeasurement of a detailed industry (j), it must appear in the PCE Bridge Table for at least one consumption category (c). For instance, while Grain Farming (NAICS 1111B0) contributes to several consumption categories in the PCE Bridge Table, such as Cereals (NIPA Line 77), Oilseed Farming (NAICS 1111A0) does not appear in the PCE Bridge Table. This commodity is sold only to other businesses, not to final consumers.

Figure A.4 plots the share of industries that appear in the PCE Bridge Table, for which we can compute TFP mismeasurement. While Government and Construction industries do not appear in the PCE Bridge Table, all of the industries producing Food & Beverages (NAICS 311, 312), Textiles, Apparel, and Leather (NAICS 313-316), and Entertainment, Accommodation, and Food (NAICS 71, 72) do. Overall, weighting observations by their gross output, 71% of manufacturing industries and 62% of private (non-governmental industries)

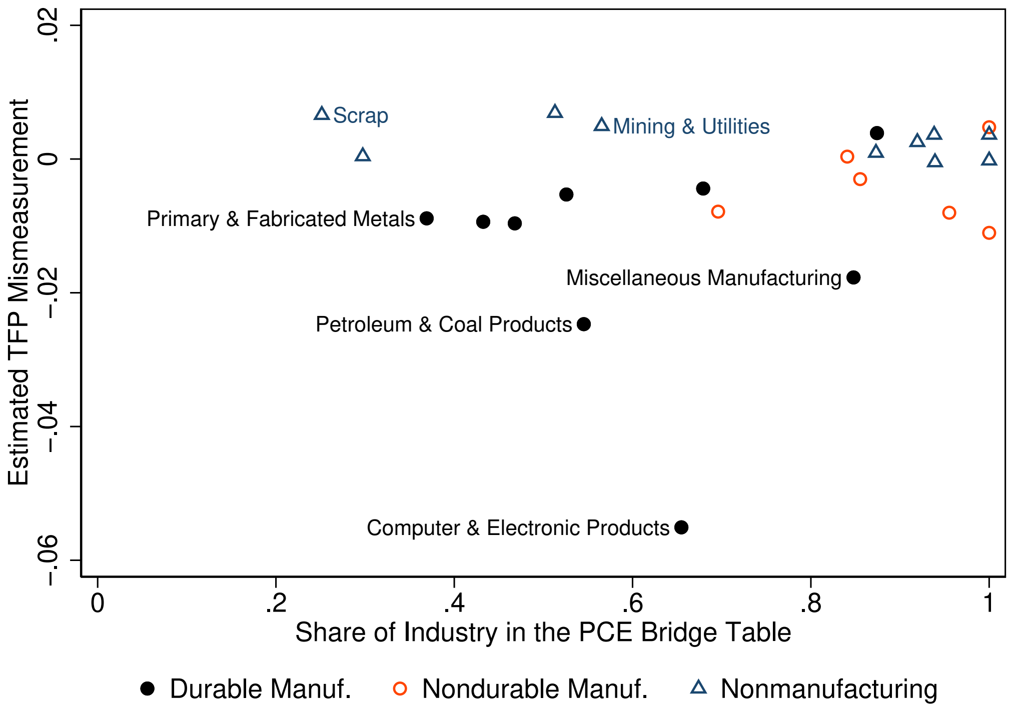

Figure A.5: Share of Industries for Which We Estimate TFP Mismeasurement vs. Average TFP Mismeasurement

Notes: For each of the industries appearing in Figure A.4, excluding the Government and Construction sectors, we relate the share of industries for which we estimate TFP mismeasurement to the average TFP mismeasurement among the industries for which we can compute it.

appear in the PCE Bridge Table.

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.5 presents our comparison. Overall, we find no relationship across the two variables. Weighting observations equally, the correlation is an (insignificant) 0.12; weighting groups of industries according to their gross output (as of 2017), the correlation is (an also insignificant) 0.10.

While Figure A.5 looks across industry groupings, Table A.7 examines whether there are any differences within industry groupings between those detailed industries that are present or absent in the PCE Bridge Table. We compare industries according to their output prices—either the gross output deflator or our Equation 1 measure of "Producer Inflation." (We cannot compare industries' TFP mismeasurement, as we cannot compute this for detailed industries absent from the PCE Bridge Table.)

In more detail, we estimate the following regression:

$$\Delta \log P_j = \beta_J + \beta_1 \cdot \mathbf{1}_{j \in \text{PCE Bridge}} + \varepsilon_j \ . \tag{13}$$

In some regressions, we include fixed effects for the broad industry grouping (i.e., one of the 25 industries listed in Figure 5). In others, we do not. Table A.7 lists our estimates from Equation 13. Here, we find some differences, but with the sign and significance varying across groups of industries and empirical specifications. Overall, we do not find that industries in the PCE Bridge Table have systematically faster or slower Producer Inflation rates than those that are not represented.

D.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 NAICS commodities that appear within the PCE Bridge Table, but only marginally so. Consider, as an example of this potential concern, the NAICS commodity 3274: Lime and Gypsum Products Manufacturing. In 2017, domestic gross output of this commodity was \$8.1 billion. This commodity appears in the PCE Bridge Table once, contributing \$71 million towards the consumption category Clocks, Lamps, Lighting Fixtures, and Other Household Decorative Items (NIPA Line 26). (The three most important NAICS Commodities for this consumption category are 33999, S00402, and 335120: Used and Secondhand Goods, All Other Miscellaneous Manufacturing, and Lighting Fixture 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 that have a small contribution in the PCE Bridge Table, relative to their total gross output.

In the panels of Figure A.6, we consider the impact of removing commodities with small contributions to the PCE Bridge Table. The left panel reproduces our baseline results. The middle panel removes detailed commodities for which the total value in the PCE Bridge Table relative to its gross output is less than 0.25. In the right panel, we increase that threshold to 0.50.

In the main, our conclusions are robust across these three panels. In our baseline specifi-

Panel A: All Sectors						
Dependent Variable	——— Producer Inflation ———				Gross Output Deflator	
In PCE Bridge	-0.003	-0.001	-0.001	0.005***	-0.001	0.005***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)
Observations	398	398	398	398	398	398
Adjusted R^2	0.008	0.411	-0.001	0.479	-0.002	0.478
Fixed Effect	None	Industry	None	Industry	None	Industry
Weighted	No	No	Yes	Yes	Yes	Yes
Panel B: Durable Manufacturing						
Dependent Variable	——— Producer Inflation ———				Gross Output Deflator	
In PCE Bridge	-0.009**	-0.007**	-0.005	0.001	-0.005	0.002
	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
Observations	151	151	151	151	151	151
Adjusted R^2	0.046	0.422	0.005	0.465	0.001	0.453
Fixed Effect	None	Industry	None	Industry	None	Industry
Weighted	No	No	Yes	Yes	Yes	Yes
Panel C: Nondurable Manufacturing						
Dependent Variable	——— Producer Inflation ———				Gross Output Deflator	
In PCE Bridge	-0.002	0.003*	0.003	0.002	0.004	0.004
	(0.003)	(0.001)	(0.004)	(0.003)	(0.005)	(0.003)
Observations	80	80	80	80	80	80
Adjusted R^2	-0.008	0.339	-0.007	0.554	-0.002	0.545
Fixed Effect	None	Industry	None	Industry	None	Industry
Weighted	No	No	Yes	Yes	Yes	Yes
Panel D: Nonmanufacturing						
Dependent Variable	——— Producer Inflation ———				Gross Output Deflator	
In PCE Bridge	-0.002	0.006***	-0.002	0.006**	-0.002	0.006***
	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)
Observations	167	167	167	167	167	167
Adjusted R^2	-0.003	0.403	0.000	0.430	-0.001	0.429
Fixed Effect	None	Industry	None	Industry	None	Industry
Weighted	No	No	Yes	Yes	Yes	Yes

Table A.7: Differences in Output Prices Between Industries Present or Absent in the PCE Bridge Table

Notes: Each column by panel presents the results from a separate regression. The first four columns have the Producer Inflation measure (defined in Equation 1) as the dependent variable. The final two columns have gross output deflator inflation as the dependent variable. An observation is a detailed industry. The standard errors are clustered at the more aggregated industry level (i.e., each of the clusters is one of the 29 industries listed in Figure 5). * denotes significance at the 10% level, ** significance at the 5% level, and *** significance at the 1% level.

cation, TFP growth was understated by 1.38 percentage points in the durable goods sector, understated by 0.35 percentage points in the nondurable goods sector, and overstated by 0.25 percentage points in nonmanufacturing sectors. In the middle and right panels TFP growth is understated by, respectively, 1.46 and 1.44 percentage points in durable goods manufacturing, 0.33 and 0.33 percentage points in nondurable goods manufacturing, and is overstated by 0.27 and 0.26 percentage points outside of manufacturing. For Computer and Electronic Product Manufacturing, TFP growth is understated by 5.5 percentage points in the left panel, 5.6 percentage points in the middle panel, and 5.8 percentage points in the right panel.

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

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

$$\mathbf{O_{t,jc}} \equiv \frac{v_{t,j\to c}}{\sum_{c'} v_{t,j\to c'}} \ . \tag{14}$$

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

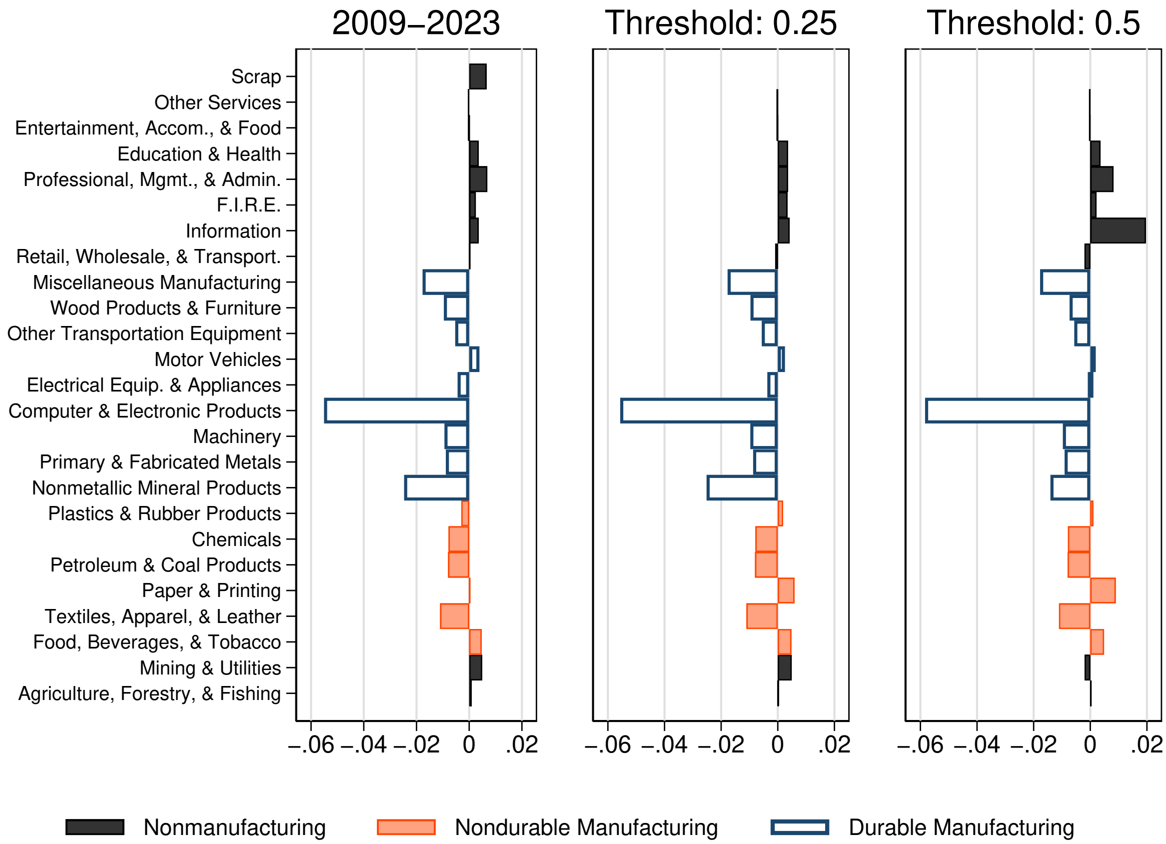

Figure A.6: Sensitivity to Dropping Commodities with Only "Small" Entries in the PCE Bridge Table

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

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.7 presents our alternate results. TFP mismeasurement is similar to what we had presented in Figure 5. In Figure A.7, annual manufacturing TFP growth is understated by 0.63 percentage points. For durable goods, TFP growth is understated by 1.31 percentage points. These figures are in line with the 0.66 percentage points and 1.38 percentage points in the baseline specification.

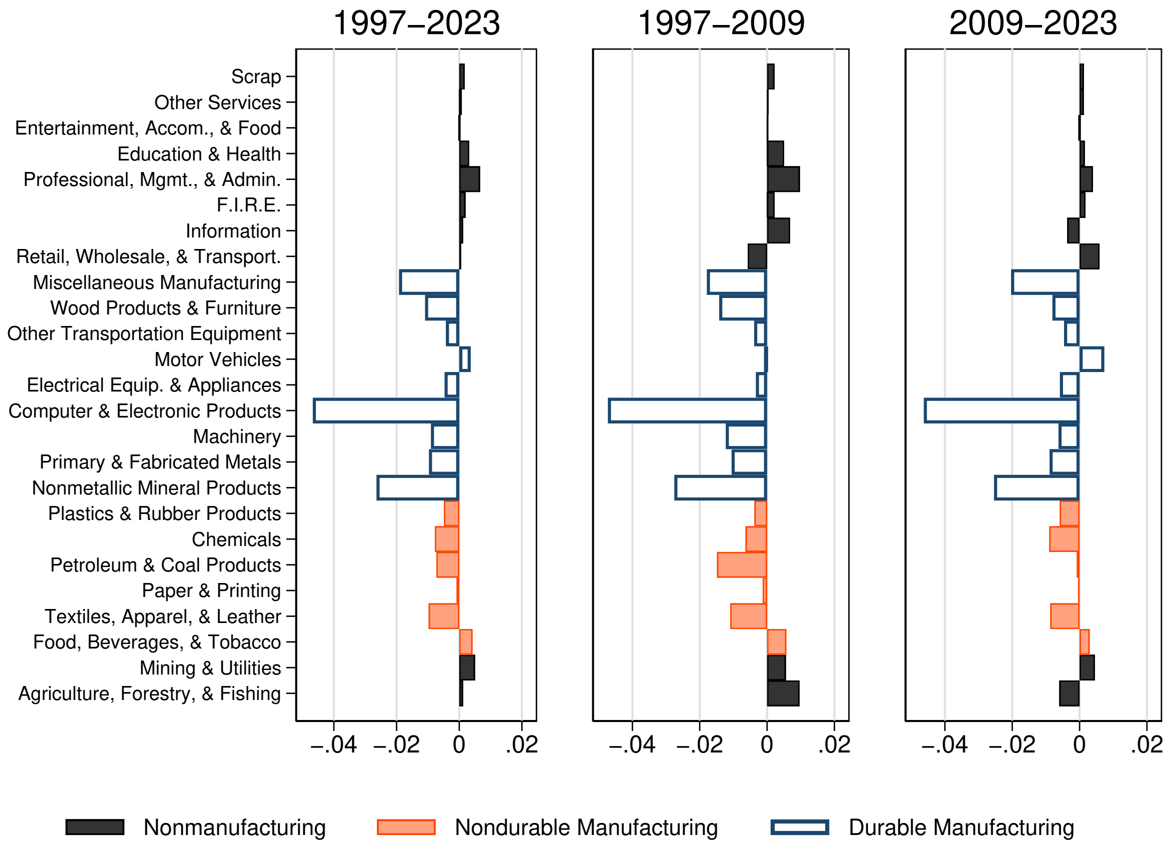

Figure A.7: TFP Mismeasurement
Notes: See the notes for Figure 5. In contrast to that figure, we apply Equation 14 to compute $\mathbf{O}_t$.

D.6 Sensitivity to Assumptions on the Mismeasurement in Import Price Growth and Relative to Mismeasurement in Gross Output Deflator Growth

In this appendix, we consider how our results from Figure 5 would change if the relative mismeasurement of import price indices were higher than in benchmark assumption (of $\xi = 1.5$), with either $\xi = 2.0$ or $\xi = 2.5$. In the first sensitivity analysis, we assume that mismeasurement in import price indices is double that of mismeasurement in gross output deflators ($\xi = 2.0$). In the second, import price indices' mismeasurement is 150% greater than in gross output deflators ($\xi = 2.5$).

In Figure A.8, we plot our estimates of TFP mismeasurement by industry groups for $\xi \in \{1.5, 2, 2.5\}$. Overall, higher values of ξ lead to smaller estimates of TFP mismeasurement in the manufacturing sector: For $\xi = 2.0$, manufacturing TFP growth in this sector is understated by 0.54 percentage points. For $\xi = 2.5$, manufacturing TFP growth is understated by 0.44 percentage points. Computer and Electronic Product Manufacturing has

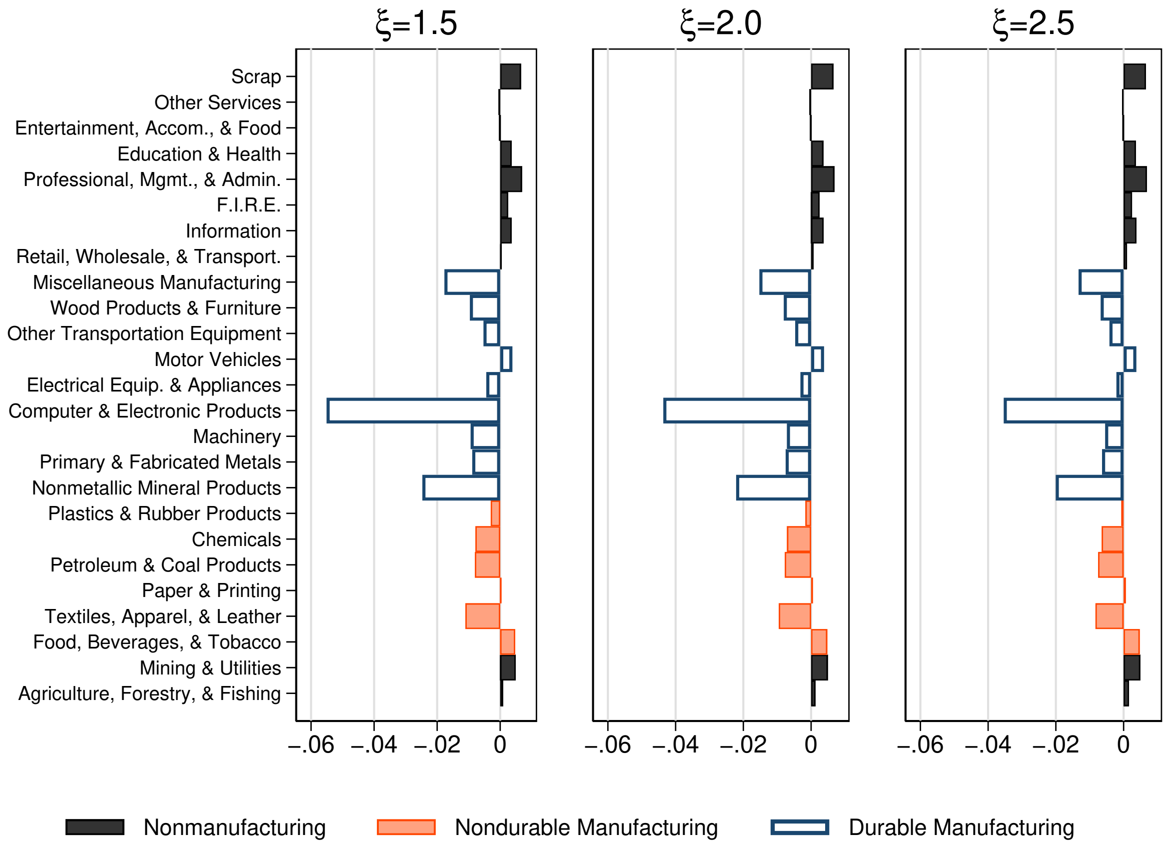

Figure A.8: TFP Mismeasurement

Notes: See the notes for Figure 5. In contrast to that figure, the middle and right panels apply higher values of ξ to compute $\Delta \log \tilde{\mathbf{A}}_{\mathbf{t}}$.

relatively high import penetration. Accordingly, estimated TFP growth mismeasurement is more sensitive to the choice of ξ in this industry than for other industries. Assuming $\xi = 2.5$, we estimate that Computer and Electronic Product Manufacturing TFP growth is understated by 3.5 percentage points (as opposed to 5.5 percentage points when $\xi = 1.5$).

In sum, when identifying TFP mismeasurement from producer-consumer price gaps, we need to make some assumption about the relative mismeasurement of the import price indices and gross output deflators. As our baseline, we adopt what we view as the most credible, state-of-the-art evidence currently available: Following Errico and Lashkari (2025), our baseline calculation assumes that import price indices are 50% more mismeasured (relative to a benchmark of no-mismeasurement in components of the PCE price index) than gross output deflators. The sensitivity exercises in Figure A.8 indicate that our main conclusions are not especially sensitive to this assumption within a plausible range. In particular, setting $\xi = 2.0$ yields only a modest attenuation of our manufacturing TFP-mismeasurement estimates relative to the baseline. By contrast, $\xi = 2.5$ implies an implausibly large wedge between import-price and producer-price mismeasurement. While it mechanically further reduces our estimated TFP mismeasurement, we view this parameterization as an upper-bound stress test rather than a realistic alternative. Overall, the core qualitative pattern—which is substantial understatement of manufacturing TFP growth, concentrated in import-intensive high-tech industries—remains intact across these scenarios.

D.7 Dropping Industries that Manufacture Primarily "Niche" Products

Byrne (2015a) notes that Computer and Electronic Product Manufacturing has, in the first decades of the twenty-first century, shifted from (what he calls) general-purpose to special-purpose electronic equipment. The mass-market personal computers, televisions, and telephones that were once assembled in the United States are now mostly produced abroad. According to Byrne (2015a), what remains of domestic assembly of computers and other electronic products is largely high-end, specialized products, perhaps customized to the needs of the military or some other enterprise customer. This raises the possibility that—at least for computers and electronics—the specific types of products that enter consumer-facing price indices are fundamentally different from those in the gross output deflator. The former would include general-purpose (imported) products; the latter would not. This difference in composition would be an alternate explanation for the gap between consumer-facing and producer-facing price indices, beyond the difference in quality adjustment we have focused on.

We have examined this issue, albeit indirectly, in two preceding sections of the appendix. In Appendix D.4, we drop industries with only small entries in the PCE Bridge Table. The industries that remain are those that tend to produce commodities geared towards household consumption, less so towards the government or enterprise customers. There, we report that manufacturing TFP growth is robust to the exclusion of industries that supplied little to final consumers. Furthermore, in Appendix D.6 we examine the sensitivity of our results to alternate assumptions on the relative mismeasurement of gross output deflators to import price indices. This robustness check is related, as the mismatch between what enters the PCE price index compared with what enters gross output deflators is relevant insofar as mismeasurement in gross output deflators differs from mismeasurement in import price indices.

In this appendix, we present another angle towards examining the concern that domestic manufacturers in general, and domestic Computer and Electronic Product Manufacturing establishments in particular, concentrate on specialized niche goods that may not enter many households' consumption baskets. In brief, our approach is to employ a supervised machine learning model to label the "nicheness" of products produced by each detailed manufacturing industry, and then estimate manufacturing TFP mismeasurement after excluding industries that tend to produce "niche" products.

To begin, we download detailed data from the 2002, 2007, 2012, 2017, and 2022 economic censuses on the sets of products associated with each 6-digit NAICS industry.[37] In 2002 and 2007, products are recorded using a 7-digit NAICS industry classification (e.g., Dog Food and Cat Food are separate 7-digit products within the 6-digit Dog and Cat Food Manufacturing industry). In 2012, 2017, and 2022, products are categorized using the North American Product Classification System (NAPCS). Each dataset contains the dollar value of each detailed (7-digit NAICS or 10-digit NAPCS) product produced by each 6-digit NAICS industry.

For each 7-digit NAICS product or 10-digit NAPCS product, we assign a "nicheness" score using a supervised machine learning model. We begin by hand-labeling nicheness scores for 360 products: 180 products from 2002 and 180 products from 2022. These labels are numbers between 0 and 1, where 0 indicates minimal and 1 indicates maximal nicheness. In assigning nicheness scores, we are guided by the following principles:

- We start by drawing on Byrne (2015a). Within Computer and Electronic Product Manufacturing, Byrne distinguishes between "general purpose equipment" and "special purpose equipment."[38] We assign low nicheness scores for general purpose equipment and high nicheness scores for special purpose equipment.

- We assign low values to mass market consumer goods, standardized products, basically anything one could imagine seeing on the shelf of a supermarket or in a (non-boutique) retailer. We assign high values to "specialty," "specialized," or "customized" products, or to products sold specifically to the military.

- If a product is a direct input into a niche product, we assign it a high value as well.

[37]The data can be found at the following websites:
`https://www2.census.gov/programs-surveys/economic-census/data/2002/sector31/EC0231SX12.zip`, `https://www2.census.gov/programs-surveys/economic-census/data/2007/sector31/EC0731SX12.zip`, `https://www2.census.gov/programs-surveys/economic-census/data/2012/sector31/EC1231SX2.zip`, `https://www2.census.gov/programs-surveys/economic-census/data/2017/sector00/EC1700NAPCSPRDIND.zip`, and `https://www2.census.gov/programs-surveys/economic-census/data/2022/sector00/EC2200NAPCSPRDIND.zip`. The data for 2017 and 2022 contain data products produced by nonmanufacturing establishments. For these years, we keep only observations associated with manufacturers.

[38]The former includes personal computers, computer workstations, computer servers, data storage equipment, wireless communications equipment, wireline communications equipment, and other communications equipment. The latter includes defense and aerospace equipment; medical and laboratory equipment; and monitoring, process control, and testing equipment.

(For example, the components of a military jet should also have a high nicheness score; dairy cattle feed—a key input into the beef we eat—should get a low score even though it is not a mass market consumer good.)

Two of the researchers on the team, Atalay and Kimmel, assigned nicheness scores. Of the 360 labeled products, 120 were labeled by both co-authors, 120 were labeled only by Atalay, and 120 were labeled only by Kimmel. For the 120 products hand-labeled by both researchers, the correlation in assigned nicheness scores was 0.77.

For each product, labeled or unlabeled, we apply a TF-IDF vectorization of the products' names.[39] For the 360 labeled products, we then estimate a penalized (Ridge) regression, where the dependent variable is the assigned niche score for the product and the explanatory variables are the elements of the product's TF-IDF vector representation. We consider three possible values for the penalty parameter—0.1, 1, or 10—which we choose via efficient leave-one-out cross validation. We use the predicted values from the Ridge regression to assign nicheness scores for all products in 2002, 2007, 2012, 2017, and 2022.[40]

Table A.8 presents nicheness scores for 15 of the 7-digit NAICS products from the 2002 Census of Manufactures.[41] We order products according to the predicted niche scores from the Ridge regression. Eight of the 15 products were hand-labeled by both Atalay and Kimmel. We highlight two results from this table. First, consistent with the correlation we reported earlier, the two researchers' hand-labels are strongly related to one another. Second, our algorithm—both in the hand-labels and the resulting predicted values from the Ridge regression—assigns low niche scores to manufactured food products, fabrics, and clothing, relatively high values to military parts, non-consumer electronic products, and detection and monitoring equipment.

The 2002 through 2022 economic censuses list the dollar value of each 7- or 10-digit product manufactured by each 6-digit industry. We construct a mapping between 6-digit NAICS industries and the slightly-more-aggregated detailed industries that form our baseline

[39] TF-IDF, or *term frequency-inverse document frequency*, is a method of assigning the weight of a word in a document's vector representation. In the *term frequency* component of TF-IDF, the weight of a word is proportional to the number of times it appears within the document. In the *inverse document frequency* component, the weight on a given word is inversely proportional to the share of documents in which it appears in the whole corpus. In our application of this concept, a document refers to a given product name. The corpus is the set of all product labels in 2002, 2007, 2012, 2017, and 2022. For each product, we construct a vector with elements corresponding to the TF-IDF statistic for each word in the corpus.

[40] We apply 5-fold cross-validation to assess the performance of our Ridge regression model. Keeping in mind that the niche scores run from 0 to 1, with a standard deviation in the hand labels of 0.294, the RMSE from the Ridge regression is 0.170, meaning the regression's predictions explain 67% ($\approx 1 - \frac{0.170^2}{0.294^2}$) of the variance in the hand labels).

[41] Scores for all products can be found at `https://enghinatalay.github.io/product_niche_scores.xlsx`.

NAICS	Product Name	Atalay	Kimmel	Ridge
3121114	Wheat mill products, except flour	0	0	0.000
3131111	Yarns, carded, cotton	0.1	0	0.083
3152993	Team sport uniforms, women's and girls'	0.1	0.2	0.110
3273904	Prestressed concrete products			0.201
3343101	Automotive audio equipment (excluding speakers)	0.2	0.4	0.301
3341121	Computer storage devices (excl. parts/attachments/accessories)	0.2	0.4	0.301
3272130	Glass containers			0.400
3221105	Woodpulp, sulfite and other types			0.401
3333157	Motion picture equipment	0.5	0.6	0.530
3363121	Gasoline engine and engine parts, motor vehicles, new			0.601
3364113	Aircraft, civilian	0.6	0.8	0.694
3342104	Carrier line equipment (including local loop and long haul transmission) and non-consumer modems			0.800
3364157	Missile/space vehicle engine/propulsion parts/accessories	1	0.9	0.939
3345195	Nuclear radiation detection and monitoring instruments			0.997
3364151	Complete missiles, space vehicle engines, and propulsion units			1.000

Table A.8: Niche Scores for Selected Products

Notes: The first two columns give the 7-digit NAICS code and associated product label for 15 of the products in the 2002 economic census. The third and fourth columns give the hand-labeled niche scores. Empty cells in these columns occur when these products were not hand-labeled. The final column presents the niche score, given by the predicted value from the Ridge regression.

sample. For each detailed industry, we compute the weighted average of its products' niche scores.

Figure A.9 studies how sensitive our conclusions over TFP mismeasurement are to dropping industries concentrating on niche products. After dropping industries with average niche scores above 0.6, TFP growth is understated by 6.0 percentage points in Computer and Electronic Product Manufacturing, 1.38 percentage points in durable manufacturing, and 0.36 percentage points in nondurable manufacturing. Reducing the threshold by dropping industries with average niche scores above 0.4 results in a more noticeable—but still modest—difference. With this additional restriction in the sample, TFP growth is understated by 7.4 percentage points in Computer and Electronic Product Manufacturing, 1.60 percentage points in durable manufacturing, and 0.36 percentage points in nondurable manufacturing. So, removing niche products from the sample leads to larger estimates of mismeasurement for Computer and Electronic Product Manufacturing, but leaves our main conclusions about

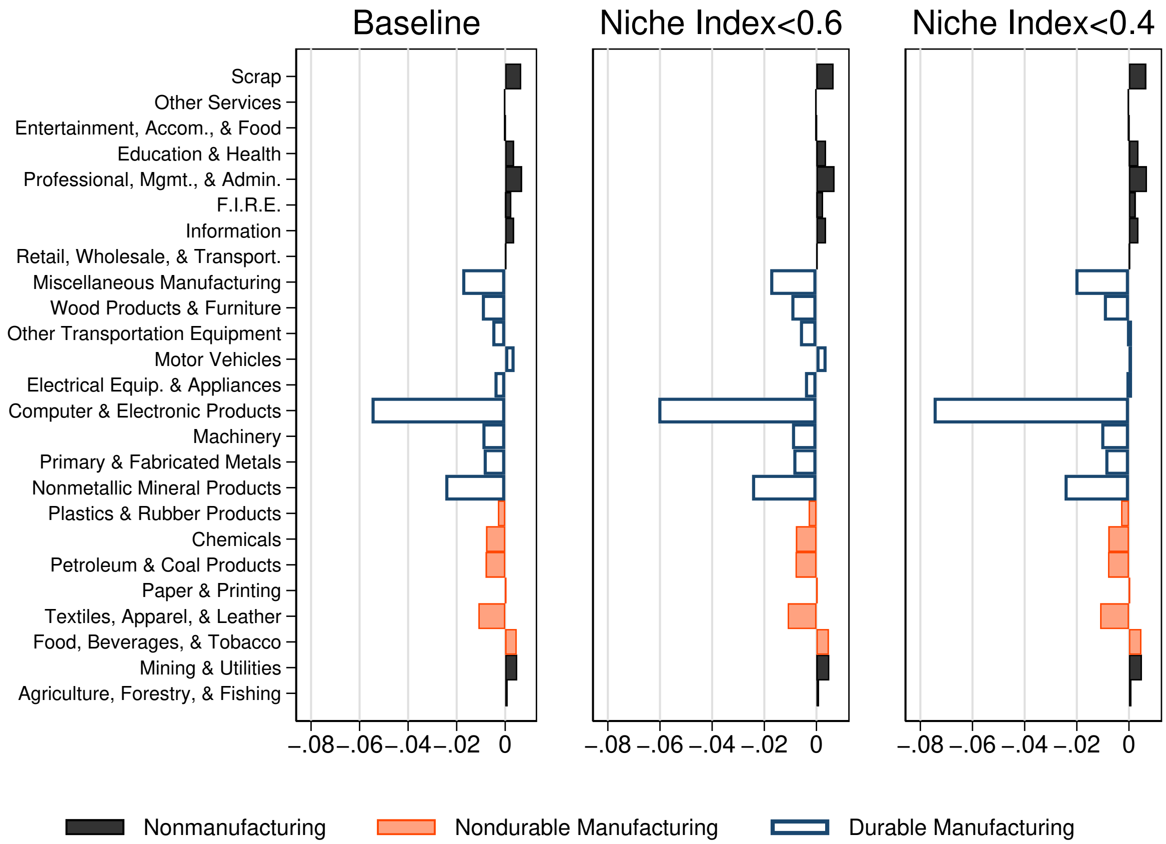

Figure A.9: TFP Mismeasurement
Notes: See the notes for Figure 5. In contrast to that figure, in the middle and right panels, we consider the whole sample period but drop detailed industries with high "niche" scores. The middle panel drops detailed manufacturing industries with average "niche" scores above 0.6. The right panel drops detailed manufacturing industries with average "niche" scores above 0.4. Throughout, we keep all nonmanufacturing industries.

the broader manufacturing sector essentially unchanged.

D.8 TFP Mismeasurement with $\mathbf{\Gamma^K} = 0$

In this appendix, we re-compute our estimates of TFP mismeasurement, imposing $\mathbf{\Gamma^K} = 0$ when applying Equation 8. To the extent that capital equipment prices are overstated, such a calibration would clearly lead us to overstate TFP growth. Nevertheless, we view this calibration as instructive as it allows us to gauge how sensitive our baseline results may be to choices we made when computing $\mathbf{\Gamma^K} = 0$.

Figure A.10 summarizes the results from this exercise. Overall, abstracting from capital rent inflation subtracts 10 to 15 basis points from our estimates of $\Delta \log \tilde{\mathbf{A}}_t$, with a slightly

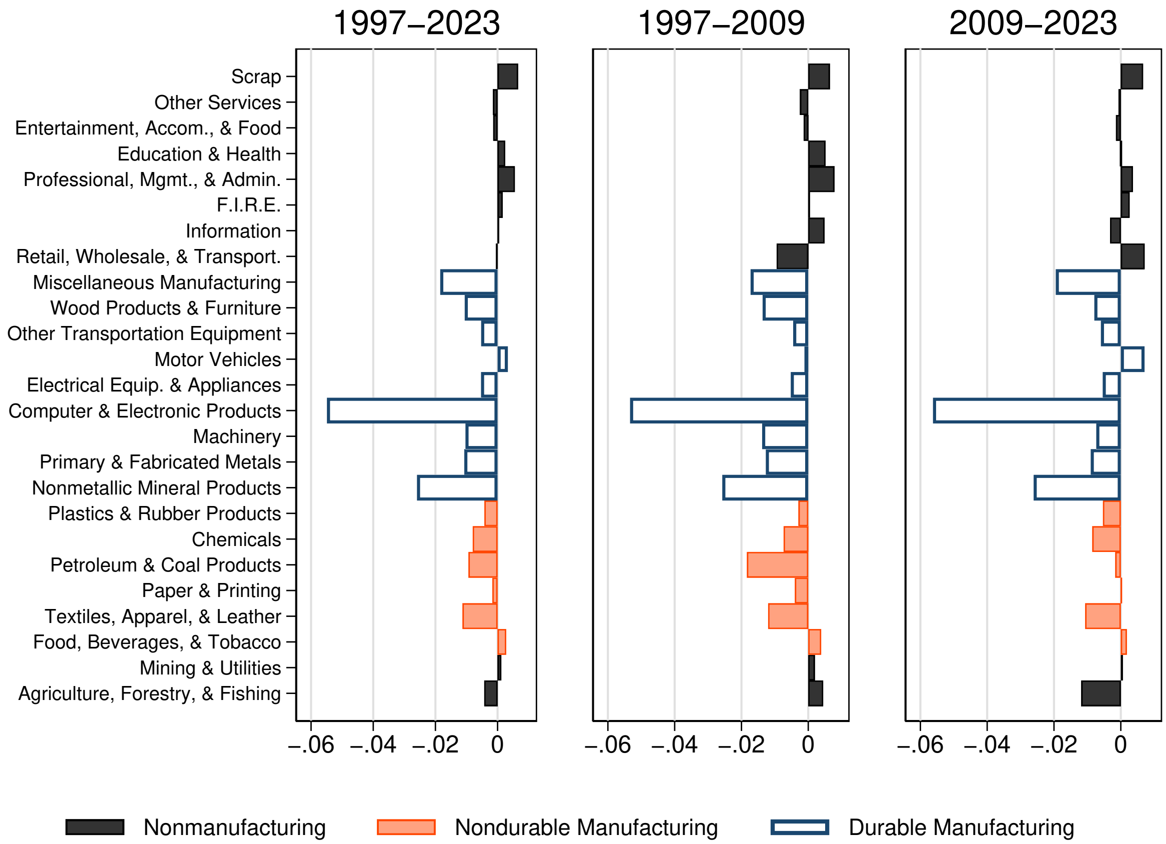

Figure A.10: TFP Mismeasurement
Notes: See the notes for Figure 5. In contrast to that figure, we set $\mathbf{\Gamma^K} = 0$ when applying Equation 8.

larger impact outside of manufacturing than within it. Whereas nonmanufacturing TFP growth is overstated by 0.25 percentage points, annually, according to Figure 5, in Figure A.10 it is overstated by 0.12 percentage points. The slightly larger impact outside of manufacturing reflects the larger role that ICT equipment plays in nonmanufacturing than in manufacturing industries' production.

D.9 Industries' Mismeasurement and Weighting by Gross Output

In producing sectoral or aggregate statistics on TFP mismeasurement, we face a choice of how to weight detailed industries. In our baseline specification, we weighted detailed industries by their personal consumption expenditures. This decision was motivated by the fact that our identification of TFP mismeasurement rested on comparing PCE inflation to corresponding concept measures from producer-side data. Industries with no PCE receive, mechanically,

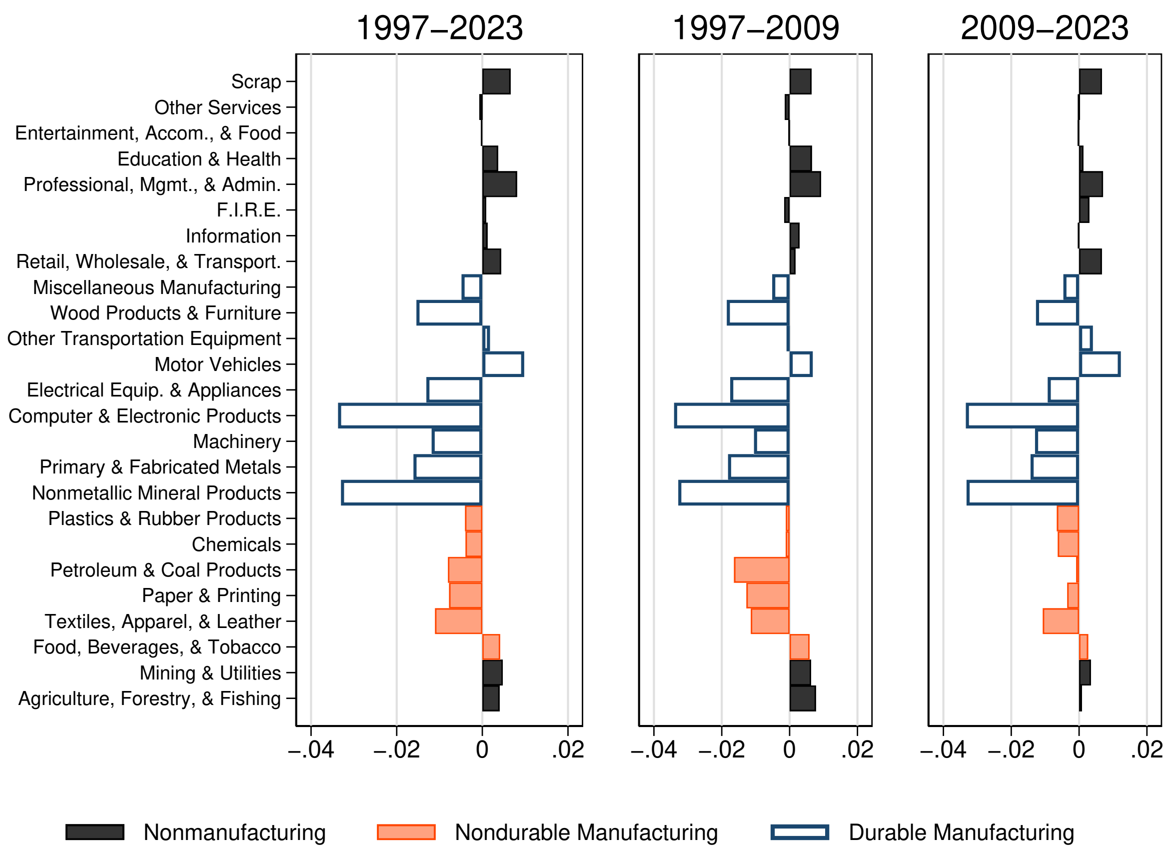

Figure A.11: TFP Mismeasurement
Notes: See the notes for Figure 5. In contrast to that figure, we use detailed industries' gross output to compute weighted averages within each broader industry.

no weight in our mismeasurement calculations. Correspondingly, industries with little PCE have very low signal-to-noise in the extent to which their TFP is mismeasured.

On the other hand, gross output weights may be more appropriate for aggregating TFP from detailed to more aggregated industries. Given this, in this appendix, we consider two final sensitivity analyses. First, we recompute TFP mismeasurement weighting detailed industries by their gross output. Second, we re-weight industries by gross output while also attempting to impute TFP mismeasurement for which our baseline methodology could not do so.

Figure A.11 displays the results of the first of these two exercises. Most of our main results are robust to the choice of how to weight detailed industries: We now estimate that annual manufacturing TFP growth is understated by 0.60 percentage points (as opposed to 0.66 percentage points in Figure 5). Nonmanufacturing TFP growth is overstated by 0.26 percentage points, also nearly identical to our baseline results. Within manufacturing, there are two notable differences. First, mismeasurement in durable goods manufacturing and, especially, Computer and Electronic Product Manufacturing is now more modest than in our baseline specification. For Computer and Electronic Product Manufacturing, this difference has to do with the larger weight now assigned to Navigational, Measuring, Electromedical, and Control Instruments Manufacturing (NAICS 3345), an industry with less severe mismeasurement than other industries within NAICS 334. Second, countervailing this first effect, durable manufacturing comprises a larger share of the manufacturing sector when weighting according to gross output than according to PCE. This second force leads to larger estimated manufacturing TFP growth mismeasurement.

Building off of this exercise, we next try to expand the set of detailed industries with estimates of TFP mismeasurement. In our baseline calculations, we could estimate TFP mismeasurement only for industries with at least some sales as personal consumption expenditures. This yields estimates for 255 out of a possible 402 detailed industries. We hypothesize that quality undercounting in industry deflators is correlated across detailed industries within summary industries. Consider a detailed industry d belonging to a summary industry s. For an industry with missing values, we impute missing TFP mismeasurement as:

$$\Delta \log \hat{A}_{td} = \sum_{\substack{d' \in s \\ \Delta \log \tilde{A}_{td'} \neq \text{missing}}} \omega_{td'} \Delta \log \tilde{A}_{td'} \ , \tag{15}$$

where ω_{td} is the gross output share of detailed industry d among the set of industries within s for which TFP growth mismeasurement is not missing. Equation 15 states that we estimate a missing industry's TFP growth mismeasurement using a weighted average among the industries for which our baseline methodology yields estimates of TFP growth mismeasurement. While this procedure expands our sample, there are still detailed industries for which we cannot compute $\Delta \log \hat{A}_{td}$. These are detailed industries where the entire summary industry has no sales as personal consumption expenditures. Out of the 66 private summary industries there are 10 with no sales as PCE (representing 34 out of a total 392 detailed industries): Oil and Gas Extraction (NAICS 211), Support Activities for Mining (NAICS 213), Construction (NAICS 23), Wholesale (NAICS 42), Motor Vehicle and Parts Dealers (NAICS 441), Food and Beverage Retailers (NAICS 445), General Merchandise Stores (NAICS 452), Pipeline Transportation (NAICS 486), Computer Systems Design and Related Services (NAICS 5415), and Management of Companies and Enterprises (NAICS 55).

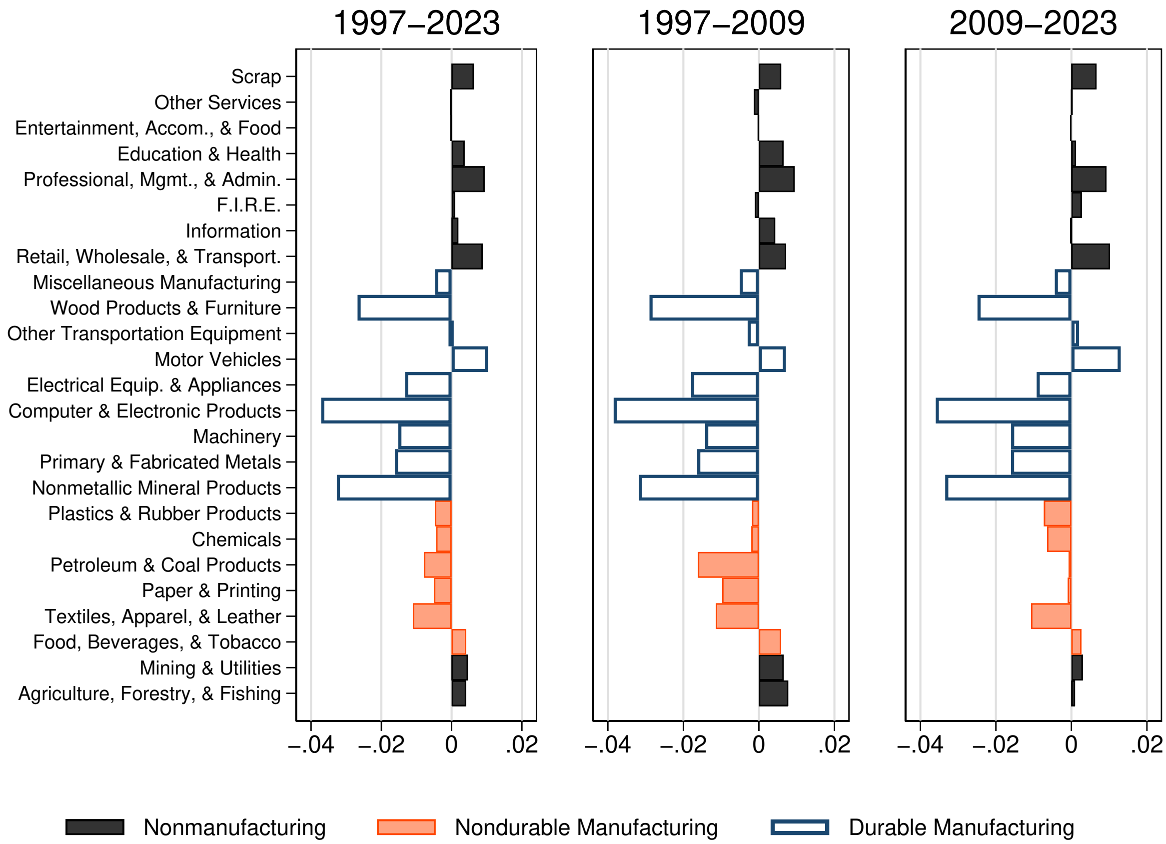

Figure A.12: TFP Mismeasurement

Notes: See the notes for Figure 5. In contrast to that figure, we use detailed industries' gross output to compute weighted averages within each broader industry. In addition, we attempt to impute detailed industries' TFP mismeasurement using mismeasurement we identify from broader summary industries.

Figure A.12 displays results for our expanded sample. Here, manufacturing TFP growth is understated by 0.85 percentage points. Looking within the manufacturing sector, durable TFP growth is understated by 1.29 percentage points, while nondurable manufacturing TFP growth is understated by 0.36 percentage points.

While these are similar to those in our baseline specification, there are important differences within the durable manufacturing sector. Compared to Figure 5, we estimate substantially more modest TFP mismeasurement within the Computer and Electronic Product Manufacturing industry and more severe mismeasurement within the Wood Product Manufacturing, Furniture, and Nonmetallic Mineral Product Manufacturing industries. These disaggregated results should be interpreted with some caution, as gross output weighting makes some of these industries' estimates of TFP mismeasurement sensitive to certain detailed in-

Description	Figure	Manufacturing	Durable Manuf.	Nondurable Manuf.	Computers & Electronics	Nonmanufacturing
Baseline	5	-0.66	-1.38	-0.35	-5.51	0.25
Account for Distribution Margins	A.2	-0.58	-1.81	-0.04	-7.03	0.31
Include if $\frac{\text{PCE}_{2017,i}}{\text{GO}_{2017,i}} \geq \frac{1}{4}$	A.6	-0.66	-1.46	-0.33	-5.57	0.27
Include if $\frac{\text{PCE}_{2017,i}}{\text{GO}_{2017,i}} \geq \frac{1}{2}$	A.6	-0.65	-1.44	-0.33	-5.83	0.26
Alternate $\mathbf{O}_t$ matrix	A.7	-0.63	-1.31	-0.34	-4.67	0.21
$\xi = 2.0$	A.8	-0.54	-1.11	-0.30	-4.36	0.25
$\xi = 2.5$	A.8	-0.44	-0.90	-0.25	-3.54	0.26
Niche Index< 0.6	A.9	-0.67	-1.38	-0.36	-6.03	0.25
Niche Index< 0.4	A.9	-0.66	-1.60	-0.36	-7.35	0.25
Set $\mathbf{\Gamma}_t^{\mathbf{K}} = 0$	A.10	-0.76	-1.44	-0.47	-5.49	0.12
Gross Output Weights	A.11	-0.60	-0.91	-0.36	-3.37	0.26
Impute Detailed Industries if Possible, Gross Output Weights	A.12	-0.85	-1.29	-0.36	-3.71	0.37

Table A.9: Review of Sensitivity Analyses

dustries with very small PCE shares, where our underlying price-gap-based identification is less precise. Consistent with this, we find in Appendix D.5 that dropping detailed industries with small PCE shares reduces estimated TFP mismeasurement in the Wood, Furniture, and Nonmetallic Mineral Product Manufacturing industries.

D.10 Summary of Sensitivity Analyses

In Table A.9, we collect the results discussed in Section 3, Appendix C, and Appendices D.4 through D.9. Each row lists a different specification, the figure associated with it, and our estimates of TFP mismeasurement for (a) the manufacturing sector, (b) durable manufacturing industries, (c) nondurable manufacturing industries, (d) the Computer and Electronic Product Manufacturing industry, and (e) nonmanufacturing industries. With the exception of the robustness check imposing values of ξ higher than what the literature would prescribe, annual manufacturing TFP growth is understated by at least half a percentage point. TFP growth for the durable manufacturing sector is understated by at least 0.9 percentage points across these different specifications.

E Contrasting ICT Industries to All Others

Throughout the paper, our focus has been on the productivity of the manufacturing sector. We have argued that measured productivity growth in manufacturing was considerably higher than in other industries up to the late 2000s and considerably slower since then. We have also argued that productivity growth is mismeasured specifically in manufacturing. Our choice to focus on the manufacturing sector, and the special role that Computer and Electronic Product Manufacturing played within it, is premised on standard industry classifications, which group industries according to their production processes. In this appendix, we consider an alternate perspective of grouping industries: We contrast industries related to information and communication technologies—irrespective of the sectors to which they are apportioned—to all other industries.

In the body of the paper and in the appendix, we have highlighted three distinctive features of Computer and Electronic Product Manufacturing. First, Section 1 and Appendix D.1 documents that two four-digit industries—Computer and Peripheral Equipment Manufacturing (NAICS 3341) and Semiconductor and Other Electronic Component Manufacturing (NAICS 3344)—account for the remarkable growth of the manufacturing sector between 1987 and 2009 and the deceleration since. Furthermore, Sections 2 and 3 illustrate that TFP growth in Computer and Electronic Product Manufacturing (NAICS 334) is understated by five and a half percentage points. Finally, in Appendix D.2 we have highlighted that production occupations make up a meaningful share of workers in all manufacturing industries (albeit with a lower share in Computer and Electronic Product Manufacturing).

In this appendix, we examine ICT-related industries outside of manufacturing. We ask three questions:

- Which industries have production processes, as measured by the occupations of the workers they employ, similar to those within Computer and Electronic Product Manufacturing?
- Which industries, akin to Computer and Electronic Product Manufacturing, play an outsize role in their sectors' productivity growth trajectory?
- Which industries, if any, have their TFP growth understated due to undercounted quality growth?

In addition to in the manufacturing sector, ICT-related industries reside in the wholesale, retail, information, and professional service sectors. In wholesale, the two related industries are Professional and Commercial Equipment and Supplies Merchant Wholesalers (NAICS

4234, hereafter Professional and Commercial Equipment Wholesalers) and Household Appliances and Electrical and Electronic Goods Merchant Wholesalers (NAICS 4236, hereafter Household Appliances and Electronics Wholesaling). In retail, the single related industry is Electronics and Appliance Stores (NAICS 4431). Within the information sector, several industries provide services related to information and communications technologies: Software Publishers (NAICS 5112), Data Processing, Hosting, and Related Services (NAICS 5182), Wired and Wireless Telecommunications Carriers (NAICS 5171), Wireless Telecommunications (NAICS 5172), Satellite, Telecommunications Resellers, and All Other Telecommunications (NAICS 5174, 5179), Internet Publishing and Broadcasting and Web Search Portals (NAICS 51913).[42] Finally, we include Computer Systems Design and Related Services (NAICS 5415), an industry in the professional, scientific, and technical services sector.

Table A.10 presents occupation profiles for ICT-related industries outside of manufacturing. The only industries with any meaningful share of production workers are those in the wholesaling sector. Similar to Computer and Electronic Product Manufacturing, these industries had their employees relatively evenly spread across management, finance, computer, engineering, and transportation-and-material-moving occupations. These industries have occupation profiles most similar to Computer and Electronic Product Manufacturing. By contrast, Electronics and Appliance stores had none of their workers in these occupations. Industries in the information and professional services sectors had a plurality of their workers either in computer occupations or in repair/maintenance occupations, and less than one percent of their workers in production occupations.

Figure A.13 presents the productivity growth rates for all 4-digit wholesale industries in addition to Electronics and Appliance Stores (in retail), Software Publishers (in information), Telecommunications Carriers (in information), Data Processing and Internet Publishing (in information), and Computer Systems Design and Related Services (in professional services). Unfortunately, the BLS Productivity dataset does not contain TFP measures for most of these industries. We plot labor productivity instead. Similar to Computer and Electronic Product Manufacturing, both of the ICT-related wholesale industries have a late-2000s productivity deceleration. Software Publishers' labor productivity follows an even more extreme deceleration, but one which occurred earlier. The other retail, information, and professional service industries followed a different pattern: Labor productivity first increases then decreases in the first three industries and is essentially unchanged in Computer Systems Design.

[42] The codes, here, refer to the 2017 vintage of the NAICS industry definitions. In the information sector in particular, NAICS industry definitions have changed considerably over the last two decades. As an example, the 2002 vintage of the NAICS has 16 (4-digit) information industries, of which 10 are ICT-related, while the 2022 vintage has 10 information industries, of which six are ICT-related. Out of necessity, we apply whatever industry classification appears in the original data.

Panel A: 2002						
Industry	Mgmt.	Computers	Sales	Admin.	Maint.	Prod.
Prof. & Commercial Equipment (4234)	0.078	0.145	0.241	0.227	0.112	0.050
Household Appliances & Electronics (4236)	0.100	0.029	0.265	0.270	0.074	0.063
Electronics & Appliance Stores (4431)	0.053	0.061	0.477	0.167	0.133	0.014
Software Publishers (5112)	0.132	0.501	0.088	0.124	0.005	0.003
Wired Telecommunications (5171)	0.076	0.077	0.103	0.277	0.293	0.003
Wireless Telecommunications (5172)	0.088	0.079	0.268	0.359	0.082	0.006
Telecommunications Resellers (5173)	0.077	0.079	0.156	0.298	0.267	0.001
Cable & Other Program Distrib. (5175)	0.056	0.032	0.086	0.362	0.362	0.002
Other Telecommunications (5179)	0.125	0.106	0.077	0.190	0.220	0.007
Internet Service Providers (5181)	0.138	0.378	0.076	0.249	0.022	.
Data Processing & Hosting (5182)	0.095	0.297	0.049	0.379	0.012	0.015
Other Information Services (5191)	0.056	0.049	0.018	0.415	0.017	.
Computer Systems Design (5415)	0.111	0.532	0.058	0.142	0.018	0.008
Panel B: 2023						
Industry	Mgmt.	Computers	Sales	Admin.	Maint.	Prod.
Other Durable Goods Wholesalers (4230A1)	0.100	0.023	0.221	0.153	0.049	0.080
Professional & Commercial Equip. (4234)	0.122	0.129	0.218	0.162	0.089	0.038
Electronics & Appliance Stores (4492)	0.048	0.020	0.615	0.118	0.123	0.003
Software Publishers (5132)	0.170	0.456	0.104	0.079	0.002	0.002
Telecommunications (5170)	0.073	0.160	0.178	0.149	0.297	0.001
Computing Infrastructure Providers (5182)	0.153	0.393	0.100	0.153	0.004	0.006
Web Search Portals (5192)	0.149	0.365	0.115	0.108	0.002	.
Computer Systems Design (5415)	0.148	0.506	0.070	0.073	0.008	0.003

Table A.10: Share of Employment Across Occupations in Selected Wholesale, Retail, and Information Industries

Notes: This table lists the share of employment in various nonmanufacturing industries. The column headers are as follows: Mgmt. refers to Management Occupations (SOC 11). Computers refers to Computer and Mathematical Occupations (SOC 15). Sales refers to Sales and Related Occupations (SOC 41). Admin. refers to Office and Administrative Support Occupations (SOC 43). Maint. refers to Installation, Maintenance, and Repair Occupations (SOC 49). Prod. refers to Production Occupations (SOC 51). In Panel A, the shares of Production occupation workers that are in the Internet Service Providers and Other Information Services industries was not published. In Panel B the share of Production occupation workers that are in the Web Search Portals industry was not published.

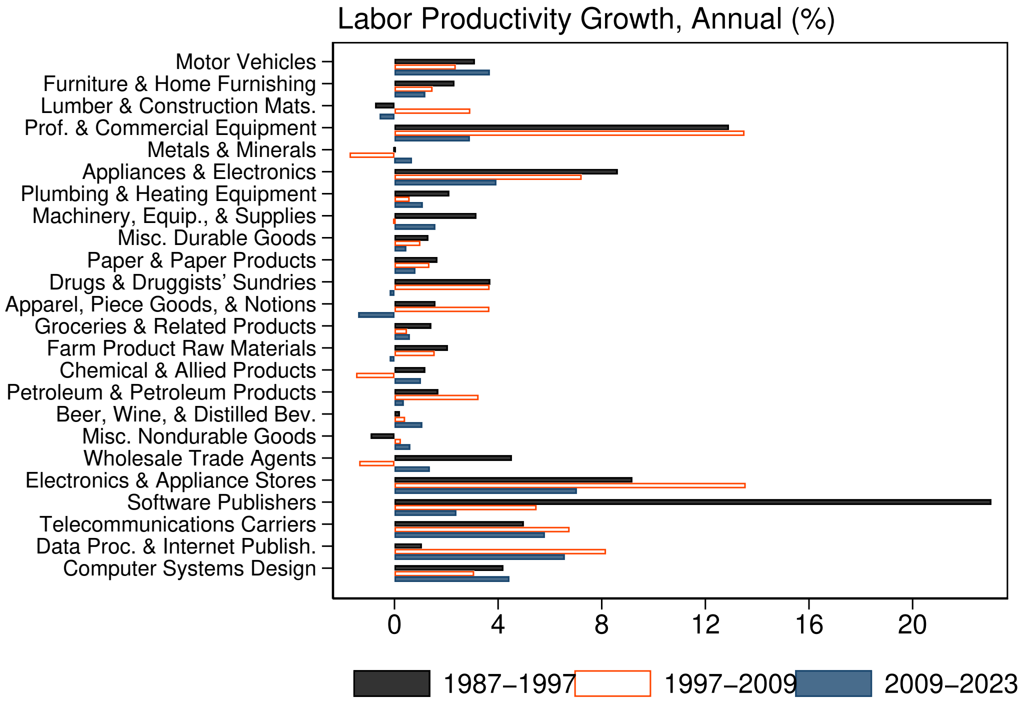

Figure A.13: Annual Labor Productivity Growth Rate for Selected Nonmanufacturing Industries

Notes: This figure plots labor productivity growth for each of the 19 4-digit industries within the wholesale sector. Additionally it plots labor productivity growth for Electronics & Appliance Stores (NAICS 4431, in retail), Software Publishers (NAICS 5112, in information), Telecommunications Carriers (NAICS 517, in information), Data Processing, Internet Publishing, & Related Services (NAICS 5182, in information), and Computer Systems Design Services (NAICS 5415, in professional services).

In sum, the industries with productivity declines most similar to Computer and Electronic Product Manufacturing are those wholesaling ICT goods.

These two industries, by themselves, account for much of the wholesale sector's productivity growth since 1987. To show this, in Figure A.14 we plot labor productivity for the wholesale sector as well as the contribution of all wholesale industries with the exception of the two ICT-related industries. To ease comparison, we also plot labor productivity in the manufacturing sector. Akin to Figure 2, Professional and Commercial Equipment Wholesaling and Household Appliances and Electronics Wholesaling represent the majority of the sector's productivity trajectory. By contrast to manufacturing, the wholesale sector's productivity continued to grow in the 2010s. Also in contrast to Figure 2, industries in wholesale outside of NAICS 4234 and NAICS 4236 had positive productivity growth throughout the

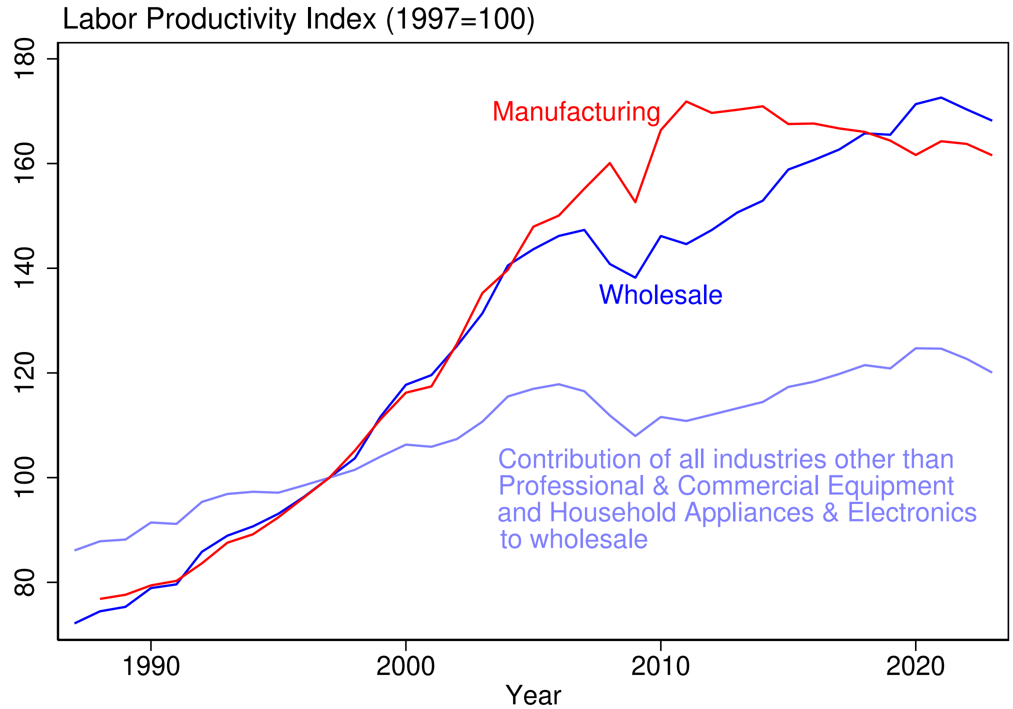

Figure A.14: Labor Productivity for Manufacturing, Wholesale, and Wholesale Excluding Professional & Commercial Equipment and Household Appliances & Electronics

sample.[43]

In a final exercise, we report TFP mismeasurement for ICT-related industries. For our benchmark exercise (described in Figure 5), we cannot identify mismeasurement for ICT-related wholesale, retail, and professional service industries. While TFP mismeasurement for the broader information sector is close to zero (see Figure 5), this sector includes industries like Motion Picture and Video Industries; Newspaper, Periodical, Book, and Directory Publishers; and others that have no connection to information-and-communication technologies. Instead, we consider the specific industries related to ICT information services. Within the information sector, Software Publishers' TFP growth is understated by 3.6 percentage points. Satellite, Telecommunications Resellers, and All Other Telecommunications' TFP growth is understated by 3.1 percentage points. But other ICT industries have much smaller TFP mismeasurement: 1.0 percentage points for Wireless Telecommunication Carriers and overstated by 0.2 percentage points for Data Processing. It is *over*stated for Internet Publishing and Broadcasting (1.8 percentage points) and Wired Telecommunications Carriers (3.0 per-

[43]Part of the difference, here, has to do with the fact that we are considering a different productivity measure-labor productivity instead of TFP. Between 1987 and 2023, manufacturing labor productivity growth exceeds TFP growth by 1.4 percentage points. For wholesale, the difference is 2.3 percentage points.

centage points). Summing up these seven detailed commodities, ICT-related information industries' TFP growth is understated, but by less than half a percentage point.

In sum, in this appendix, we have searched for industries that resemble the distinctive features of Computer and Electronic Product Manufacturing that we highlight in the paper. We search for industries that have (a) at least some production occupation workers, (b) productivity decelerating in the late 2000s, and (c) TFP mismeasurement. Two industries in the wholesale sector—Professional and Commercial Equipment Wholesalers (NAICS 4234) and Household Appliances and Electronics Wholesaling (NAICS 4236)—match the first two criteria. We cannot, unfortunately, estimate TFP mismeasurement for these industries. Software Publishers also had a deceleration in productivity, but one which occurred earlier than for industries that manufactured or wholesaled ICT goods. Our framework suggests that Software Publishers' TFP growth is understated, but is less than the mismeasurement for Computer and Electronic Product Manufacturers' TFP growth. In conclusion, looking across the nonmanufacturing industries we have studied in this appendix, none match the three distinctive characteristics of Computer and Electronic Product Manufacturing.