Industry Deflators Understate Quality Growth. Correcting This Strengthens Estimated Innovation–Productivity Relationships.

By ENGHIN ATALAY, ALI HORTAÇSU, NICOLE KIMMEL, AND CHAD SYVERSON*

How do investments in innovation translate into future productivity growth? Economists face many challenges in addressing this question. R&D spending, for example, is an observed input into the innovation process, but mapping it to productivity growth requires assumptions about the depreciation of R&D capital, gestation lags, and how well such expenditures capture true innovative effort (Hall, 2007). Patents, an alternative measure, capture successful innovations but vary widely in novelty (Kelly et al., 2021) and economic value (Kogan et al., 2017). Firms may choose not to patent their inventions to preserve secrecy (Cohen, Nelson and Walsh, 2000), while others patent strategically to protect existing products even if they represent only marginal innovations (Argente et al., 2020).

A second challenge is at least as important: accurately measuring real output growth. Innovation, to the extent that it leads to new products or improved characteristics for its existing products, will lead to quality improvements, but conventional output deflators may not fully account for these improvements. As emphasized in Griliches (1979, 1994) and Hall, Mairesse and Mohnen (2010), estimates of the returns to innovation depend critically on how well deflators capture quality change.

In this short article, we discuss a recent paper (Atalay et al., 2025) arguing that PPI-based deflators miss some portion of quality improvements for high-tech manufactured goods. For every commodity that goes into households' consumption baskets, we compare consumer-facing price indices—which incorporate richer hedonic adjustments—to the producer-facing indices used in deflating industry data. Based on gaps between the two sets of indices, we find that 1997-to-2023 manufacturing TFP growth is understated by approximately 0.8 percentage points per year. (TFP growth in nonmanufacturing industries is ever-so-slightly overstated, by 0.1 percentage points per year.) The adjustment is especially large for durable goods (1.6 percentage points per year) and is overwhelmingly concentrated in Computer and Electronic Products Manufacturing.

We then document that correcting TFP growth for mismeasurement meaningfully strengthens the estimated relationship between industries' past innovation and their subsequent productivity growth. We look across different measures of innovation, time horizons, and industry definitions. Across these specifications, the slope of the relationship between TFP growth and past investment in innovation is roughly twice as large after accounting for mismeasurement due to undercounting quality growth.

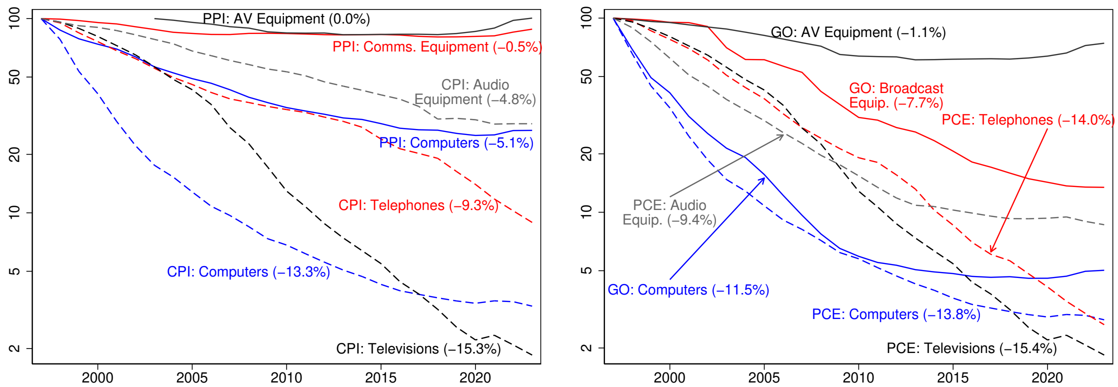
I. Estimating Productivity Mismeasurement Using Producer-Consumer Price Gaps

In this section, We review Atalay et al. (2025), a recent paper estimating mismeasurement in industries' TFP growth rates. We begin with the hypothesis that, for high-tech manufactured products, producer price indices (PPIs), which tend to be the source of industry output deflators but rarely have hedonic adjustments, rise faster than consumer price indices (CPIs), which are not used to deflate output but have more comprehensive quality adjustments.

Figure I supports this hypothesis. The right panel compares PPI and CPI for selected electronic products. For example, computer prices declined by 5.1% annually between 1997 and 2023 according to the PPI, but by 13.3% according to the CPI. Similar gaps exist between CPI Telephones (-9.3%

* Atalay: Research Department, Federal Reserve Bank of Philadelphia, atalayecon@gmail.com; Hortaçsu: Department of Economics, University of Chicago, hortacsu@uchicago.edu; Kimmel: Research Department, Federal Reserve Bank of Philadelphia, nicole.kimmel@phil.frb.org; Syverson: University of Chicago Booth School of Business, chad.syverson@chicagobooth.edu. 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.

FIGURE 1. PRICE INDICES FOR SELECTED ELECTRONIC GOODS



Note: The figure compares price indices across four data sources: the Producer Price Index (PPI) and the Consumer Price Index (CPI) are in Panel A, and the Personal Consumption Expenditures (PCE) deflator and industry gross output deflators are in Panel B. Each series is normalized to 100 in its first year. The PPI for Audio and Video Equipment Manufacturing only begins in December 2003.

inflation) and PPI Communications Equipment (-0.5% inflation), and across components of Audio and Video Equipment.

The right panel compares industry gross output deflators (from the BEA) to components of the PCE price index. While gross output deflators, which are used by the BEA to construct industry real output series, are based primarily on PPI (especially so within manufacturing), the PCE price index draws primarily on the CPI (especially so among goods). Once again, consumer-facing price indices exhibit steeper declines, indicating more comprehensive quality adjustments. Although the BEA makes some adjustments to gross output deflators for certain goods to account for quality differences (e.g., Computers), these adjustments may still not be as comprehensive as those embedded in PCE price indices.

Beyond differences in quality adjustment, gross output deflators and PCE price indices have important conceptual differences. First, the PCE price index for a given consumption category is a composite of many different NAICS commodities. For instance, Computer Software and Accessories (NIPA line 50) is a combination of Software Publishers (NAICS 5112) and Data Processing, Hosting, and Related Services (NAICS 5182). Second, commodities in the PCE price index are produced domestically or imported, whereas the gross output deflator only measures changes in the prices of domestically produced commodities.[1]

To account for these conceptual differences, we use the PCE Bridge Table to construct a producer-side analogue of PCE inflation for each consumption category c:

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

In Equation 1, $s_{t,j\to c}$ refers to the share (as of year t) of consumption category c that is sourced from NAICS industry j; $m_{t,j}$ is the share of personal consumption expenditures of commodity j that comes from imports; and $\log P^{\text{GO}}_{t,j}$ and $\Delta \log P^{\text{Import}}_{t,j}$ are domestic and import price growth for commodity j. We hypothesize that—since producer-facing price indices better capture quality improvements—gaps between PCE inflation and "Producer Inflation" can be used to infer mismeasurement in gross output deflators and import price indices.

[1]Third, the PCE price index includes margins paid to wholesalers, retailers, and distributors, something that the gross output deflator omits. In our baseline calculations, presented below, we abstract from this consideration. In Atalay et al. (2025), we show that accounting for these margins does not materially alter our estimates of TFP mismeasurement.

In a final step, we use input-output tables to recover TFP mismeasurement from our estimates of mismeasurement in gross output deflators. Following a standard growth-accounting identity, and under some additional assumptions, industry TFP growth is inversely related to gross output deflator growth and proportional to intermediate input price growth. As a result, TFP mismeasurement is a linear function of the gap between PCE inflation and producer-side inflation, with weights coming from the input–output matrix and the PCE bridge.

Table 1 summarizes the results from this exercise. We highlight three results from this table.

- Driven by Computer and Electronic Products Manufacturing, measured TFP growth in manufacturing fell from 1.3% in 1997 to 2009 to -0.1% in 2009 to 2023.
- Manufacturing TFP growth has been understated by about 0.8 percentage points per year from 1997 to 2023, slightly more in the first half of the sample than in the second. TFP mismeasurement is especially pronounced in Computer and Electronic Products Manufacturing.
- Corrected for mismeasurement, annual manufacturing TFP growth has fallen from 2.2% in 1997-2009 to 0.6% in 2009-2023. From 2009 onward, it is somewhat below the TFP growth rate for nonmanufacturing industries but now meaningfully positive.

TABLE 1—TFP GROWTH AND ESTIMATES OF TFP MISMEASUREMENT

Industry	Measured TFP Growth			TFP Mismeasurement			Corrected TFP Growth		
Period	’97-’23	’97-’09	’09-’23	’97-’23	’97-’09	’09-’23	’97-’23	’97-’09	’09-’23
Manufacturing	0.6%	1.3%	-0.1%	-0.8%	-0.9%	-0.7%	1.4%	2.2%	0.6%
...Nondurable	0.0%	0.4%	-0.3%	-0.5%	-0.6%	-0.4%	0.5%	1.0%	0.0%
...Durable	1.0%	1.9%	0.3%	-1.6%	-1.7%	-1.6%	2.7%	3.6%	1.9%
......Computer & Electronic Products	4.0%	7.4%	1.1%	-5.7%	-5.2%	-6.2%	9.7%	12.5%	7.3%
Nonmanufacturing	0.7%	0.5%	0.9%	0.1%	0.2%	0.0%	0.6%	0.3%	0.9%

Note: The first three columns present annual TFP growth rates according to the BLS-Major Sector and Major Industry Total Factor Productivity database. The next three columns present estimates of TFP mismeasurement across different groups of industries. The final three columns present industries’ TFP growth rates, corrected for the mismeasurement we have estimated.

II. Implications for the Relationship Between Innovation and TFP Growth

We next examine how correcting for TFP mismeasurement affects inference about the innovation–productivity relationship. In particular, we revisit traditional regressions (Griliches, 1979; Griliches and Lichtenberg, 1984; Scherer, 1982; Griffith, Redding and Van Reenen, 2004) relating industries’ R&D intensity or patenting activity to subsequent productivity growth.

We compare results using measured versus corrected TFP as our dependent variable. Griliches (1979, 1994), among others, elucidates the importance of statistical agencies’ efforts at accounting for quality growth in estimating the returns to R&D spending. Investments in research and development pay off, in part, through new and improved products. To the extent that quality growth is not captured by standard measures, TFP growth will be understated precisely in innovative industries.

To gauge the importance of TFP mismeasurement in estimates of the innovation-productivity growth link, we consider regressions of the form:

$$\frac{1}{\tau}\Delta \log A^x_{t,t+\tau,i} \quad = \quad \beta_t + \beta^x \frac{1}{\tau}\sum_{k=t}^{t+\tau} X_{k-l,i} + \varepsilon^x_{ti} \quad . \tag{2}$$

Here, $x \in M, C$ indexes "measured" versus "corrected" TFP and $X_{t,i}$ is either industry R&D intensity or patenting per employee in year t. Throughout this paper, we set $l = 5$.

TABLE 2—ESTIMATES OF EQUATION 2

	R&D Expenditures/ Revenues: Compustat		R&D Capital Comp./ Value Added: BEA		Patents/Employment		Patents/Employment (Value Weighted)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: $\tau = 5$								
β_A	0.0036	0.0041	0.0003	0.0019	0.0035	0.0030	0.0056	0.0050
	(0.0020)	(0.0019)	(0.0014)	(0.0015)	(0.0017)	(0.0018)	(0.0022)	(0.0022)
β_C	0.0089	0.0106	0.0049	0.0084	0.0110	0.0123	0.0133	0.0140
	(0.0032)	(0.0032)	(0.0028)	(0.0029)	(0.0025)	(0.0024)	(0.0026)	(0.0022)
P-Value: $\beta_A = \beta_C$	0.002	0.001	0.013	0.001	<0.001	<0.001	<0.001	<0.001
N	175	175	144	144	180	180	180	180
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes
Panel B: $\tau = \{12, 13\}$								
β_A	0.0040	0.0040	0.0011	0.0021	0.0039	0.0029	0.0058	0.0047
	(0.0030)	(0.0025)	(0.0019)	(0.0021)	(0.0027)	(0.0024)	(0.0032)	(0.0028)
β_C	0.0092	0.0100	0.0055	0.0082	0.0114	0.0121	0.0138	0.0140
	(0.0050)	(0.0046)	(0.0039)	(0.0042)	(0.0040)	(0.0030)	(0.0041)	(0.0026)
P-Value: $\beta_A = \beta_C$	0.051	0.048	0.074	0.029	0.001	<0.001	<0.001	<0.001
N	66	66	68	68	68	68	68	68
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes
Panel C: $\tau = 25$								
β_A	0.0041	0.0050	0.0018	0.0030	0.0042	0.0042	0.0047	0.0045
	(0.0031)	(0.0023)	(0.0028)	(0.0030)	(0.0027)	(0.0021)	(0.0025)	(0.0018)
β_C	0.0094	0.0106	0.0063	0.0087	0.0118	0.0132	0.0130	0.0135
	(0.0066)	(0.0055)	(0.0060)	(0.0061)	(0.0055)	(0.0035)	(0.0046)	(0.0027)
P-Value: $\beta_A = \beta_C$	0.157	0.141	0.194	0.097	0.015	<0.001	0.001	<0.001
N	33	33	34	34	34	34	34	34
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes

Note: Each column reports coefficients from regressions of average annual TFP growth between years t and $t+\tau$ on (5-year) lagged measures of industry innovation activity. Within each column-by-panel, estimates of β_A and β_C are from separate regressions. For each regression, the explanatory variable is standardized to have mean 0 and standard deviation 1. Robust standard errors are in parentheses. In Panel A, $t \in \{1997, 2002, 2007, 2012, 2017\}$ for columns (1), (2), (5), (6), (7), and (8) and $t \in \{2002, 2007, 2012, 2017\}$ for columns (3) and (4). In Panel B, we consider TFP growth rates from 1997 to 2009 (where $t = 1997$ and $\tau = 12$) and TFP growth rates from 2009 and 2022 (where $t = 2009$ and $\tau = 13$). In Panel C, we consider TFP growth rates from 1997 to 2022 (where $t = 1997$ and $\tau = 25$). Appendix A provides a list of industries in the sample. In the "weighted" columns, we weight observations by year-$t+\tau$ labor costs.

Our main coefficient, β^x, measures the association between industry innovative activity between years $t-l$ and $t+\tau-l$ and TFP growth between years t and $t+\tau$. Papers in the literature have augmented this regression to study spillovers across industries (e.g., Scherer, 1982), spillovers from frontier to other countries (e.g., Griffith, Redding and Van Reenen, 2004), and the capitalization of R&D knowledge (e.g. Hall, 2007). Instead, we intentionally consider the most stripped-down specification to isolate the effect of quality adjustment.

We construct industry-level innovation measures from 1992 to 2017. We download patents by Cooperative Patent Classification (CPC) scheme category and application year from PatentView. We apply the mapping from CPCs to NAICS codes from Goldschlag, Lybbert and Zolas (2019) and consider, as an alternate measure, value-weighted patents from (Kogan et al., 2017). For both patent measures, we divide by employee counts from the BLS Industry Productivity database. R&D intensity comes from Compustat (R&D expenditures-to-sales) and the BEA-BLS Industry Level Production Accounts (R&D capital compensation-to-value added). Our baseline specifications use the industry classification from the BLS Major Sector and Major Industry Total Factor Productivity database.[2]

Table 2 reports estimates of Equation 2. The main takeaway is that the sensitivity of TFP growth to past innovation is stronger after accounting for potential TFP mismeasurement. To consider one example, the first column of panel A indicates that a 1 standard deviation difference in R&D intensity is associated with a 0.5 percentage point increase in measured TFP growth, but a 1.0 percentage point increase in "true" TFP growth. The difference between β_A and β_C is similar across weighting schemes and time horizons, and stronger when using patenting as the measure of innovation. Overall, adjusting for mismeasurement roughly doubles the estimated responsiveness of productivity growth to past innovation. As we show in Appendix Table B2, these stronger elasticities are driven disproportionately by Computer and Electronic Products Manufacturing (NAICS 334). Excluding this single industry substantially reduces both the level of the innovation–TFP link and the gap between measured and corrected TFP.

Taken together, our results highlight that accounting for "missing" quality growth in standard price indices is essential for understanding the link between innovation and productivity growth: Industries that innovate the most tend to experience the greatest quality improvements in their output. These industries are precisely those where price indices embed the largest mismeasurement. Correcting deflators for undercounting of quality improvements both raises estimated productivity growth—in manufacturing, especially in the manufacturing of computers and other electronic products—and reveals a significantly stronger relationship between past innovative activity and subsequent TFP growth. While our analysis is intentionally simple, our findings suggest that widely used measures of productivity understate the payoff from innovative activity, and that re-evaluating real output measurement may be key to reconciling slow measured productivity growth with sustained innovative investment.

REFERENCES

Argente, David, Salomé Baslandze, Douglas Hanley, and Sara Moreira. 2020. "Patents to Products: Product Innovation and Firm Dynamics." CEPR Discussion Paper DP14692.

Atalay, Enghin, Nicole Kimmel, Ali Hortaçsu, and Chad Syverson. 2025. "Why Is Manufacturing Productivity Growth So Low?" NBER Working Paper #34264.

Cohen, Wesley M, Richard R Nelson, and John P Walsh. 2000. "Protecting Their Intellectual Assets: Appropriability Conditions and Why US Manufacturing Firms Patent (or Not)." NBER Working Paper 7552.

Goldschlag, Nathan, Travis Lybbert, and Nikolas Zolas. 2019. "An 'Algorithmic Links with Probabilities' Crosswalk for USPC and CPC Patent Classifications with an Application Towards Industrial Technology Composition." *Economics of Innovation and New Technology*, 1–21.

Griffith, Rachel, Stephen Redding, and John Van Reenen. 2004. "Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries." *Review of Economics and Statistics*, 86(4): 883–895.

Griliches, Zvi. 1979. "Issues in Assessing the Contribution of Research and Development to Productivity Growth." *The Bell Journal of Economics*, 92–116.

Griliches, Zvi. 1994. "Productivity, R&D, and the Data Constraint." *American Economic Review*, 84(1): 1–23.

[2]In Appendix Table B1, we apply a finer industry classification, with 4-digit NAICS codes in manufacturing and 3-digit NAICS codes outside of manufacturing. With this finer industry classification, tends to result in smaller estimates of β_A and β_C, with the broad conclusions of this section largely unchanged.

Griliches, Zvi, and Frank R Lichtenberg. 1984. "R&D and Productivity Growth at the Industry Level: Is There Still a Relationship?" In *R&D, Patents, and Productivity*. 465–502. University of Chicago Press.

Hall, Bronwyn H. 2007. "Measuring the Returns to R&D: The Depreciation Problem." National Bureau of Economic Research NBER Working Paper 13473.

Hall, Bronwyn H, Jacques Mairesse, and Pierre Mohnen. 2010. "Measuring the Returns to R&D." In *Handbook of the Economics of Innovation*. Vol. 2, 1033–1082. Elsevier.

Kelly, Bryan, Dimitris Papanikolaou, Amit Seru, and Matt Taddy. 2021. "Measuring Technological Innovation Over the Long Run." *American Economic Review: Insights*, 3(3): 303–320.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. 2017. "Technological Innovation, Resource Allocation, and Growth." *Quarterly Journal of Economics*, 132(2): 665–712.

Scherer, Frederic M. 1982. "Inter-Industry Technology Flows and Productivity Growth." *The Review of Economics and Statistics*, 64(4): 627–634.

Additional Description of the Data

A1. Price Indices Used In Figure I

The left panel of Figure I plots individual entries of the Consumer Price Index and the Producer Price Index. Both series come from the Bureau of Labor Statistics. The components of the CPI in this panel include: Computers, Peripherals, and Smart Home Assistants (Item SEEE01); Telephone Hardware, Calculators, and Other Consumer Information Items (Item SEEE04); Televisions (Item SERA01); and Audio Equipment (Item SERA05). The components of PPI include Computers and Peripheral Equipment Manufacturing (NAICS 3341), Communications Equipment Manufacturing (NAICS 3342), Audio and Video Equipment Manufacturing (NAICS 3343).

The right panel of Figure I plots industry gross output deflators and components of the PCE price index. Both series come from the Bureau of Economic Analysis. The different industry gross output deflators include those for: Computers and Peripheral Equipment Manufacturing (NAICS 3341), Radio and Television Broadcasting and Wireless Communications Equipment Manufacturing (NAICS 33422), and Audio and Video Equipment Manufacturing (NAICS 3343). The different components of the PCE price index that are plotted include Televisions (NIPA line 41), Audio Equipment (NIPA line 43), Personal Computers/Tablets and Peripheral Equipment (NIPA line 49), and Telephones and Related Communications Equipment (NIPA line 71). The industry output deflators can be found within worksheet UGO304-A `https://apps.bea.gov/industry/Release/XLS/UGdpxInd/GrossOutput.xlsx`, while components of the PCE price index come from National Income and Product Accounts (NIPA) Table 2.4.4U.

A2. Measures of TFP Growth

Our TFP growth measures come from the Bureau of Labor Statistics.[3]

For our baseline regressions, we take TFP and labor costs from the Major Sector and Major Industry Total Factor Productivity database. These data cover 18 nonmanufacturing industries and 19 manufacturing industries.[4] In Appendix Table B1, we apply a finer industry disaggregation within the manufacturing sector. For this table, our TFP measures come from the Detailed Industry Productivity database.

In the final row of Table 1, we present measured TFP growth for nonmanufacturing industries. This is not a variable that exists within the BLS Major Sector and Major Industry Total Factor Productivity database, but one which we can reconstruct by comparing aggregate private sector TFP growth and manufacturing TFP growth. Private sector TFP growth should be a weighted average of manufacturing and nonmanufacturing TFP growth:

$$\Delta \log A_{\text{Private},t} \propto \omega_{\text{Manufacturing},t} \cdot \Delta \log A_{\text{Manufacturing},t} + \sum_{j \in \text{Nonmanufacturing}} \omega_{\phi,t} \cdot \Delta \log A_{\phi_t} \,. \tag{A1}$$

[3]These data can be found at `https://www.bls.gov/productivity/data.htm`.

[4]The nonmanufacturing industries are Agriculture, Forestry, Fishing, and Hunting (NAICS 11); Mining (NAICS 21); Utilities (NAICS 22); Construction (NAICS 23); Wholesale Trade (NAICS 42); Retail trade (NAICS 44,45); Transportation and Warehousing (NAICS 48-49); Information (NAICS 51); Finance and Insurance (NAICS 52); Real Estate and Rental and Leasing (NAICS 53); Professional, Scientific, and Technical Services (NAICS 54); Management of Companies and Enterprises (NAICS 55); Administrative and Waste Management Services (NAICS 56); Educational Services (NAICS 61); Health Care and Social Assistance (NAICS 62); Arts, Entertainment, and Recreation (NAICS 71); Accommodation and Food Services (NAICS 72); and Other Services, Except Government (NAICS 81). The 19 manufacturing industries are Food and Beverage and Tobacco Products (NAICS 311, 312); Textile Mills and Textile Product Mills (NAICS 313, 314); Apparel and Leather and Allied Products (NAICS 315, 316); Wood Products (NAICS 321); Paper Products (NAICS 322); Printing and Related Support Activities (NAICS 323); Petroleum and Coal Products (NAICS 324); Chemical Products (NAICS 325); Plastics and Rubber Products (NAICS 326); Nonmetallic Mineral Products (NAICS 327); Primary Metal Products (NAICS 331); Fabricated Metal Products (NAICS 332); Machinery (NAICS 333); Computer and Electronic Products (NAICS 334); Electrical Equipment, Appliances, and Components (NAICS 335); Motor Vehicles, Bodies and Trailers, and Parts (NAICS 3361-3363); Other Transportation Equipment (NAICS 3364-3369); Furniture and Related Products (NAICS 337); and Miscellaneous Manufacturing (NAICS 339). In Section II, we omit Construction, Wholesale Trade, and Retail Trade as we cannot compute TFP mismeasurement for these industries.

In this equation, j refers to one of the 18 nonmanufacturing industries listed in footnote 4, $\omega_{j,t}$ refers to the sectoral output share of nonmanufacturing industry j (sectoral output of this industry divided by the sum of sectoral output across all 19 2-digit private industries), and $\omega_{\text{Manufacturing},t}$ refers to corresponding sectoral output share of the manufacturing sector. One complication is that—since the BLS measure of sectoral output refers to the value of goods and services produced by that industry and sold to final consumers or firms outside of that industry—sectoral output measures do not "aggregate up": the sum of $\sum_{j\in\text{Nonmanufacturing}}\omega_{\phi,t}$ will not equal the sectoral output share of the broader nonmanufacturing sector, for instance. For this reason, we solve for the κ_t that multiplies $\omega_{\text{Manufacturing},t}$ and $\omega_{\phi,t}$ such that the left- and right-hand sides of Equation A1 are equal. In other words, we choose κ_t so that the weighted sum of 2-digit industries TFP growth exactly matches aggregate private-sector TFP growth in each year, effectively rescaling sectoral output shares so that the decomposition is internally consistent. With this κ_t, we can solve for nonmanufacturing TFP growth as:

$$\frac{\Delta\log A_{\text{Private},t}-\kappa_t\cdot\omega_{\text{Manufacturing},t}\cdot\Delta\log A_{\text{Manufacturing},t}}{1-\kappa_t\cdot\omega_{\text{Manufacturing},t}}\,.$$

A3. Estimation of TFP Mismeasurement

In this appendix, we explain how we estimate TFP mismeasurement by detailed industry and year. We introduce this method in Atalay et al. (2025). The exposition in this section draws from this earlier paper, in parts verbatim.

We begin with the following accounting relationship between gross output prices, input prices, and TFP:

$$\begin{aligned}
\text{(A2)}\qquad \Delta\log A_{t,j} &= -\Delta\log P^{\text{GO}}_{t,j}+\Delta\log P^{\text{Input}}_{t,j}\\
&= -\Delta\log P^{\text{GO}}_{t,j}+\gamma_{t,w\to j}\Delta\log w_{t,j}+\gamma_{t,r\to j}\Delta\log r_{t,j}\\
&\quad +\sum_{i=1}^{N}\gamma_{t,i\to j}\left[\left[(1-m_{t,i})\,\Delta\log P^{\text{GO}}_{t,i}+m_{t,i}\Delta\log P^{\text{Import}}_{t,i}\right]\right]\\
\Delta\log \mathbf{A}_t &= -\Delta\log \mathbf{P}^{\text{GO}}_{t}+\gamma_{t,w}\Delta\log \mathbf{w}_t+\gamma_{t,r}\Delta\log \mathbf{r}_t+\\
&\quad \Gamma_t\left[(\mathbf{1}-\mathbf{m}_t)\circ\Delta\log\mathbf{P}^{\text{GO}}_{t}+\mathbf{m}_t\circ\Delta\log\mathbf{P}^{\text{Import}}_{t}\right].
\end{aligned}$$

According to this equation, industries are more productive when they are able to produce at lower cost given the price of the inputs that they use. The second line breaks out changes in industry j's input price growth into the price growth of labor, capital, and individual intermediate inputs, i. Within this line, $\gamma_{t,\iota\to j}$ refers to the cost share of input ι for industry j in year t, and $m_{t,i}$ equals the import share of commodity i in year t. The final line writes this equation in vector notation. Here, the "$\circ$" operator denotes element-wise multiplication.

Below, we use $\tilde{\mathbf{x}}$ to refer to mismeasurement in variable $\mathbf{x}$. Since our method of comparing producer-facing and consumer-facing price indices does not pertain to mismeasurement in unit labor costs, we assume $\Delta\log\widetilde{\mathbf{w}}_t=0$. In our baseline calculations, we also assume $\Delta\log\widetilde{\mathbf{r}}_t=0$. With these assumptions, Equation A2 implies:

$$\text{(A3)}\quad \Delta\log\widetilde{\mathbf{A}}_t\equiv\Delta\log\mathbf{A}^M_t-\Delta\log\mathbf{A}^C_t=\Delta\log\widetilde{\mathbf{P}}^{\text{GO}}_t+\Gamma_t\left[(\mathbf{1}-\mathbf{m}_t)\circ\Delta\log\widetilde{\mathbf{P}}^{\text{GO}}_t+\mathbf{m}_t\circ\Delta\log\widetilde{\mathbf{P}}^{\text{Import}}_t\right]\,.$$

Our second building block comes from comparing producer-side inflation measures and PCE inflation. We attribute differences between PCE inflation (on the one hand) and import price indices and gross output deflators (on the other) to mismeasurement in the producer-side inflation measures:

$$\Delta \log P^{\text{PCE}}_{t,c} = \sum_j s_{t,j\to c}\Big[(1-m_{t,j})\left(\Delta\log P^{\text{GO}}_{t,j} + \Delta\log \tilde{P}^{\text{GO}}_{t,j}\right) + m_{t,j}\left(\Delta\log P^{\text{Import}}_{t,j} + \Delta\log \widetilde{P}^{\text{Import}}_{t,j}\right)\Big] . \tag{A4}$$

We write this equation in matrix form:

$$\Delta\log \mathbf{P}^{\text{PCE}}_t = \mathbf{S}_t\Big[(\mathbf{1}-\mathbf{m}_t)\circ\left(\Delta\log\mathbf{P}^{\text{GO}}_t + \Delta\log\widetilde{\mathbf{P}}_t^{\text{GO}}\right) + \mathbf{m}_t\circ\left(\Delta\log\mathbf{P}^{\text{Import}}_t + \Delta\log\widetilde{\mathbf{P}}^{\text{Import}}_t\right)\Big] . \tag{A5}$$

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

$$(\mathbf{1}-\mathbf{m}_t)\circ\Delta\log\widetilde{\mathbf{P}}^{\text{GO}}_t + \mathbf{m}_t\circ\Delta\log\widetilde{\mathbf{P}}^{\text{Import}}_t = \mathbf{O}_t\Big[\Delta\log\mathbf{P}^{\text{PCE}}_t - \mathbf{S}_t\big((\mathbf{1}-\mathbf{m}_t)\circ\Delta\log\mathbf{P}^{\text{GO}}_t + \mathbf{m}_t\circ\Delta\log\mathbf{P}^{\text{Import}}_t\big)\Big]. \tag{A6}$$

Above, $\mathbf{O}_t$ is a matrix that transforms mismeasurement in "consumption category" space to "NAICS commodity" space. In our baseline calculations in Atalay et al. (2025), row j and column c elements of $\mathbf{O}_t$ are equal to 1 if PCE category c has the largest value in the PCE Bridge Table for NAICS commodity j.

If we assume that mismeasurement in gross output deflators equals mismeasurement in import price indices, we can combine Equations A3 and A6 to infer mismeasurement in productivity:

$$\Delta\log\widetilde{\mathbf{A}}_t = -[\mathbf{I}-\Gamma_t]\,\mathbf{O}_t\Big[\Delta\log\mathbf{P}^{\text{PCE}}_t - \mathbf{S}_t\left[(\mathbf{1}-\mathbf{m}_t)\circ\Delta\log\mathbf{P}^{\text{GO}}_t + \mathbf{m}_t\circ\Delta\log\mathbf{P}^{\text{Import}}_t\right]\Big] . \tag{A7}$$

The left-hand side of Equation A7 collects industries' TFP mismeasurement. The right-hand side requires data on flows of intermediate inputs across industries (necessary to compute Γ_t), the import share of each commodity (necessary to compute $\mathbf{m_t}$), the share of each detailed PCE consumption category that comes from each NAICS commodity (necessary to compute $\mathbf{O_t}$ and $\mathbf{S_t}$), and components of the PCE price index, industry gross output deflators, and components of the BLS import price index.

A4. Constructing R&D Intensity

We consider two measures of industry R&D intensity.

First, from the Compustat Fundamentals Annual file, we compute R&D intensity by NAICS industry and year as the ratio of research and development expenses (measured as the sum of the `xrd` variable across firms within the industry-year) and sales (measured as the sum of the `sale` variable across firms within the industry-year.)

Second, from the BEA-BLS Industry Level Product Accounts file, we compute R&D intensity as the ratio of industry R&D Capital Compensation to industry Value Added.[5] Note that these data (a) only begin in 1997 and (b) are at a more aggregated industry definition—roughly at the 2-digit level for nonmanufacturing industries and at the 3-digit level for manufacturing industries.

[5]These data can be found at `https://www.bea.gov/sites/default/files/2025-04/BEA-BLS-industry-level-production-account-1997-2023.xlsx`

A5. Constructing the Patent Measures

We construct two measures of patenting intensity by industry. The first is a count of the number of successful patent applications in each year since 1987 by industry. The second is the estimated total value of patents from publicly traded firms by industry. The value of each patent is the stock market response to its announcement, as estimated by Kogan et al. (2017). In both cases, we define industry according to 4-digit NAICS codes.

To construct our two measures of patenting by NAICS code, we rely on Nikolas Zolas's 'Algorithmic Links with Probabilities' patent crosswalks that convert patent classifications to industry classifications Goldschlag, Lybbert and Zolas (2019). We chose the crosswalk that converts Cooperative Patent Classification (CPC) subclasses to 4-digit NAICS categories, including services.[6] We retrieve the CPC classification of each patent from PatentsView's classification of utility patents by current CPC.

To construct the set of utility patents by application year, we combine PatentsView's current CPC classification of utility patents with PatentsView's annualized data tables which include year of application for each patent. We drop any duplicate patents in the annualized data and only keep patents that appear in both data sets.

To construct the set of patents with values by application year we combine the set of patents with estimated values provided by Kogan et al. (2017) with PatentsView's CPC classification dataset, keeping patents that appear in both data sets. Most patents have multiple subclasses, so both of these sets are organized by patent-by-subclass.

There are 25 CPC subclasses that are not included in Nikolas Zola's crosswalk from CPC subclass to NAICS code. Of these, we reclassify 21 to other similar subclasses that exist in the crosswalk. The remaining 4 cases do not have any similar subclasses. For these, we drop all patent-by-subclass observations. This results in us dropping 43,649 out of 55.7 million patent-by-subclass observations in the set of successful utility patent applications, and 11,528 out of 17.87 million patent-by-subclass observations in the set of patents with values.

Each patent may have multiple subclasses associated with it. For each patent, we assign each subclass a weight according to the share of the patent's total subclasses. Summing up these weights by CPC subclass and application year gives us the number (or value) of successful patent applications in each subclass for each year. Applying the CPC to NAICS crosswalk gives us the number (or value) of patents in each NAICS code for each year since 1987.

Additional Tables and Figures

In this section, we present two tables that provide sensitivity analysis for the results in Section II. We also present a binscatter plot, an alternate depiction of the baseline regression results in Panel A of Table 2.

First, Table B1 reproduces Table 2 with a finer industry classification. Instead of grouping manufacturing industries by 3-digit NAICS codes and nonmanufacturing industries by 1/2-digit NAICS codes, we group manufacturing industries by 4-digit NAICS codes and nonmanufacturing industries by 3-digit NAICS codes.[7] Applying a finer industry classification leads to smaller coefficients for both β_A and β_C.

Second, Table B2 presents regression results, estimating Equation 2 while excluding Computer and Electronic Products Manufacturing (NAICS 334) from the sample. Dropping this single 3-digit industry leads to considerably lower estimates of both β_A and β_C. The median estimates of β_A and β_C in Table 2 are, 0.0040 and 0.0108, respectively. After dropping the Computer and Electronic Products Manufacturing industry, the median β_A and β_C coefficients are 0.0014 and 0.0029. Consistent with the experience of Griliches (1994), industries producing high-tech goods have exceptionally fast productivity growth and exceptionally high rates of R&D expenditures and patenting. So, dropping

[6]See `https://sites.google.com/site/nikolaszolas/PatentCrosswalk`.

[7]The exception is apparel manufacturing industries, where we retain a 3-digit NAICS industry-classification.

TABLE B1—SENSITIVITY ANALYSIS TO TABLE 2–ALTERNATE INDUSTRY CLASSIFICATION

	R&D Expenditures/ Revenues: Compustat		R&D Capital Comp./ Value Added: BEA		Patents/Employment		Patents/Employment (Value Weighted)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: $\tau = 5$								
β_A	0.0035	0.0027	0.0009	0.0030	0.0011	-0.0017	0.0009	-0.0019
	(0.0015)	(0.0012)	(0.0009)	(0.0009)	(0.0011)	(0.0013)	(0.0012)	(0.0013)
β_C	0.0067	0.0018	0.0046	0.0025	0.0050	0.0008	0.0033	0.0009
	(0.0022)	(0.0013)	(0.0017)	(0.0011)	(0.0020)	(0.0018)	(0.0019)	(0.0018)
P-Value: $\beta_A = \beta_C$	0.002	0.551	0.002	0.591	0.001	0.213	0.041	0.184
N	569	569	476	476	575	575	575	575
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes
Panel B: $\tau = \{12, 13\}$								
β_A	0.0031	0.0015	0.0021	0.0028	0.0013	-0.0017	0.0009	-0.0019
	(0.0022)	(0.0017)	(0.0012)	(0.0009)	(0.0014)	(0.0007)	(0.0017)	(0.0005)
β_C	0.0060	0.0014	0.0056	0.0024	0.0056	0.0010	0.0035	0.0008
	(0.0033)	(0.0014)	(0.0022)	(0.0011)	(0.0027)	(0.0005)	(0.0028)	(0.0005)
P-Value: $\beta_A = \beta_C$	0.060	0.913	0.019	0.699	0.006	<0.001	0.063	<0.001
N	220	220	226	226	218	218	218	218
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes
Panel C: $\tau = 25$								
β_A	0.0025	0.0007	0.0026	0.0025	0.0027	-0.001	0.0018	-0.0012
	(0.0023)	(0.0018)	(0.0016)	(0.0009)	(0.0027)	(0.0005)	(0.0026)	(0.0003)
β_C	0.0048	0.0008	0.0060	0.0024	0.0068	0.0007	0.0040	0.0005
	(0.0039)	(0.0016)	(0.0030)	(0.0012)	(0.0040)	(0.0006)	(0.0042)	(0.0004)
P-Value: $\beta_A = \beta_C$	0.237	0.904	0.072	0.888	0.023	<0.001	0.227	<0.001
N	117	117	119	119	115	115	115	115
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes

Note: See the notes for Table 2. In contrast with that table, we apply a finer industry classification. Manufacturing industries are defined at using a 4-digit NAICS classification. Elsewhere, industries are grouped according to a 3-digit NAICS classification.

this one industry from the sample weakens the positive estimated relationship between proxies for innovation and subsequent productivity growth. Moreover, the difference between estimates of β_A and β_C is also smaller after dropping NAICS 334. Now only 10 (of the 24) specifications lead to a significant difference between the two coefficients. In Table 2, 17 of the specifications had a significant difference.

Figure B1 presents a visual depiction of these relationships. We plot a binscatter, using five-year TFP growth rates and five-year averages of lagged R&D intensity or lagged patents per employee. Innovation is extremely skewed: the Computer and Electronic Products Manufacturing industry has far higher patenting per employee and R&D intensity than any other sector, and it exhibits the largest TFP mismeasurement. This industry lies far to the right of the distribution and drives much of the steep corrected slope, consistent with quality improvement being a major output of its innovation. Excluding it substantially weakens the Table 2 results (Appendix Table B1).

APPENDIX REFERENCES

Cattaneo, Matias D., Richard K. Crump, Max H. Farrell, and Yingjie Feng. 2025. "Binscatter Regressions." *The Stata Journal*, 25(1): 3–50.

Goldschlag, Nathan, Travis Lybbert, and Nikolas Zolas. 2019. "An 'Algorithmic Links with

TABLE B2—SENSITIVITY ANALYSIS TO TABLE 2–DROPPING NAICS 334

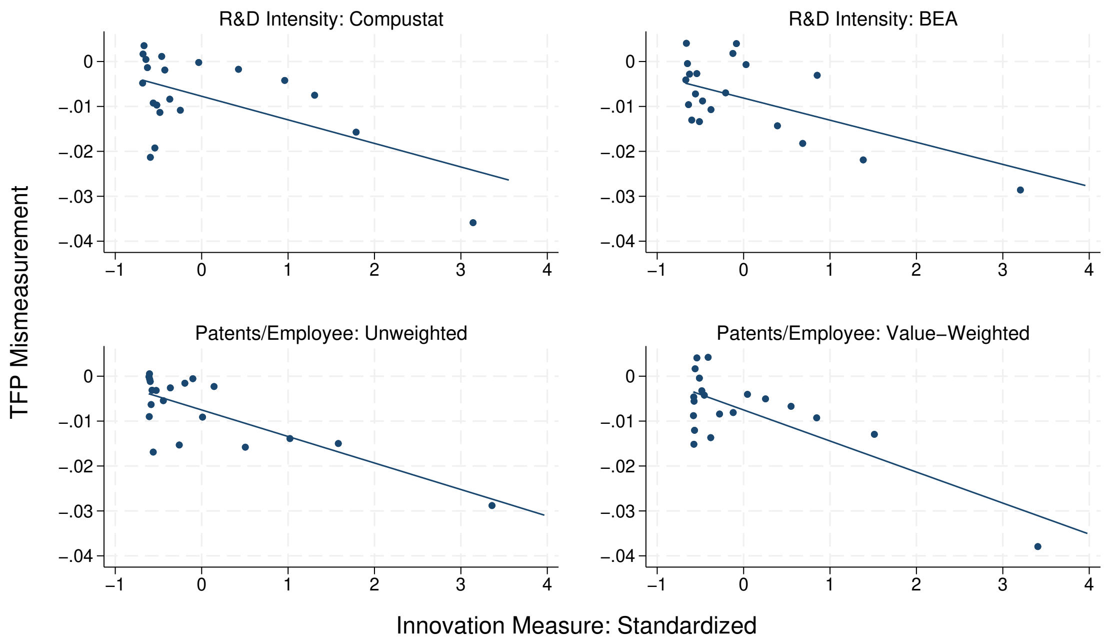
	R&D Expenditures/ Revenues: Compustat		R&D Capital Comp./ Value Added: BEA		Patents/Employment		Patents/Employment (Value Weighted)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: $\tau = 5$								
β_A	0.0002	0.0016	-0.0009	0.0009	0.0003	-0.0005	0.0004	-0.0001
	(0.0010)	(0.0013)	(0.0011)	(0.0014)	(0.0009)	(0.0008)	(0.0008)	(0.0007)
β_C	0.0012	0.0034	0.0007	0.0036	0.0029	0.0028	0.0035	0.0030
	(0.0014)	(0.0018)	(0.0016)	(0.0017)	(0.0013)	(0.0011)	(0.0014)	(0.0010)
P-Value: $\beta_A = \beta_C$	0.260	0.105	0.096	<0.001	0.006	<0.001	0.006	<0.001
N	160	160	132	132	165	165	165	165
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes
Panel B: $\tau = \{12, 13\}$								
β_A	0.0004	0.0017	-0.0007	0.0006	0.0005	-0.0005	0.0006	-0.0004
	(0.0010)	(0.0016)	(0.0010)	(0.0015)	(0.0011)	(0.0007)	(0.0010)	(0.0006)
β_C	0.0012	0.0032	0.0009	0.0029	0.0032	0.0029	0.0036	0.0028
	(0.0016)	(0.0024)	(0.0014)	(0.0017)	(0.0017)	(0.0011)	(0.0018)	(0.0010)
P-Value: $\beta_A = \beta_C$	0.509	0.275	0.133	<0.001	0.033	<0.001	0.031	<0.001
N	64	64	66	66	66	66	66	66
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes
Panel C: $\tau = 25$								
β_A	0.0007	0.0024	-0.0005	0.0006	-0.0001	-0.0005	-0.0002	-0.0004
	(0.0013)	(0.0015)	(0.0009)	(0.0014)	(0.0007)	(0.0006)	(0.0008)	(0.0007)
β_C	0.0015	0.0037	0.0011	0.0027	0.0028	0.0030	0.0028	0.0028
	(0.0020)	(0.0014)	(0.0017)	(0.0015)	(0.0020)	(0.0009)	(0.0021)	(0.0011)
P-Value: $\beta_A = \beta_C$	0.592	0.387	0.265	0.004	0.107	<0.001	0.077	<0.001
N	32	32	33	33	33	33	33	33
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes

Note: See the notes for Table 2. In contrast to that table, our sample excludes the Computer and Electronic Products Manufacturing industry (NAICS 334.)

Probabilities' Crosswalk for USPC and CPC Patent Classifications with an Application Towards Industrial Technology Composition." *Economics of Innovation and New Technology*, 1–21.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. 2017. "Technological Innovation, Resource Allocation, and Growth." *Quarterly Journal of Economics*, 132(2): 665–712.

FIGURE B1. ESTIMATES OF EQUATION 2



Note: This figure presents binscatter plots corresponding to columns (1), (3), (5), and (7) of Panel A of Table 2. On the vertical axis of each panel, we plot TFP mismeasurement: the difference between $\Delta \log A^{C}_{i,t,t+5}$ and $\Delta \log A^{M}_{i,t,t+5}$. On the horizontal axis of each panel we plot, $\frac{1}{\tau}\sum_{k=t}^{t+\tau} X_{i,k-l}$. In the top left, bottom left, and bottom right panels, $t \in \{1997, 2002, 2007, 2012, 2017\}$. In the top right panel, $t \in \{2002, 2007, 2012, 2017\}$. We use the STATA package developed by Cattaneo et al. (2025) to construct this binscatter plot.