Quality Adjustment in Industry Deflators Strengthens Estimated Innovation–Productivity Relationships

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March 17, 2026

How do investments in innovation translate into future productivity growth? Empirically answering this question is challenging. R&D spending 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 forgo patenting to preserve secrecy, while others patent strategically to protect existing products even when their underlying innovations are marginal.

A second challenge is at least as important: accurately measuring real output growth. Innovation often raises quality by introducing new products or improving existing ones, but conventional output deflators may not fully capture these improvements—biasing measured TFP growth downward in innovative industries. As emphasized by Griliches (1979, 1994) and Hall, Mairesse and Mohnen (2010), estimates of the returns to innovation hinge on how well deflators capture quality change.

In this short article, we show in an empirically relevant setting how correcting TFP mismeasurement meaningfully strengthens the estimated relationship between industries' past innovation efforts and their subsequent productivity growth. The TFP corrections come from our recent work arguing that PPI-based deflators miss important quality improvements for high-tech manufactured goods (Atalay et al., 2025). There, we show that replacing producer-facing price indices with

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consumer-facing indices, the latter of which incorporate richer hedonic adjustments, increases implied manufacturing TFP growth by approximately 0.7 percentage points per year, with little impact on TFP growth outside of manufacturing. Using this corrected measure, we find the slope of the relationship between productivity growth and past investments in innovation is roughly twice as large as that obtained using uncorrected TFP. These results are consistent across different measures of innovation, time horizons, and industry definitions.

1 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 producer-facing price indices understate quality improvements for high-tech manufactured goods. As a result, producer price indices used in gross output deflators fall less rapidly than consumer price indices, which incorporate richer hedonic adjustments.

Figure 1 supports this hypothesis. The left panel compares the Bureau of Labor Statistics (BLS) Producer Price Index (PPI) with the BLS Consumer Price Index (CPI) for selected electronic products. Between 1997 and 2023, computer prices declined by 5.0 percent annually according to the PPI, compared with a 12.9 percent annual decline according to the CPI.[1] Similar gaps exist between CPI Telephones (-9.1 percent inflation) and PPI Communications Equipment (-0.5 percent inflation), and across components of Audio and Video Equipment.

The right panel compares industry gross output deflators with components of the personal consumption expenditures (PCE) price index. While gross output deflators, which are used by the Bureau of Economic Analysis (BEA) to construct industry real output series, are based primarily on PPI (especially within manufacturing), the PCE price index draws primarily on the CPI (especially among goods). Once again, consumer-facing price indices exhibit steeper declines, indicating more comprehensive quality adjustments. Although the BEA independently adjusts some of its gross output deflators to account for quality differences (e.g., computers), these are not 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 North American Industry Classification System (NAICS) commodities. For instance, Telephone and Related Communication Equipment (National Income and Product Accounts, NIPA, Line 71) is a composite of the output of Telephone Apparatus Manufac-

[1] In this paragraph and in Figure 1, the average inflation rates refer to compound annual growth rates.

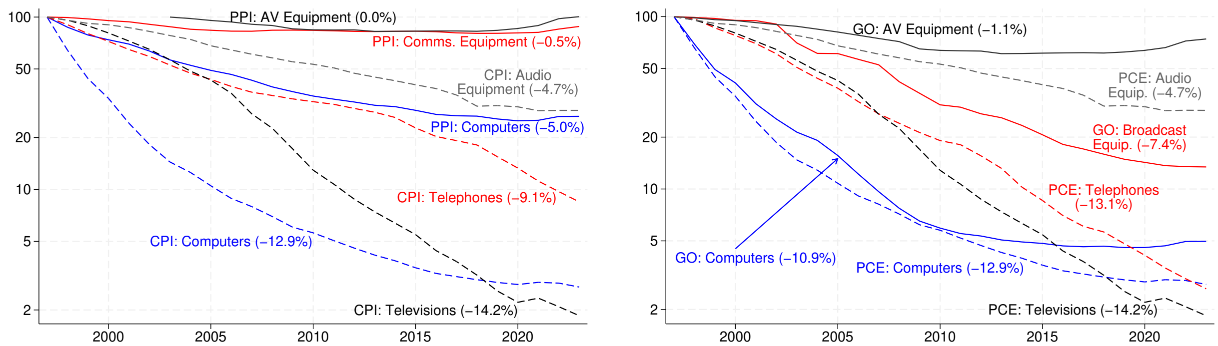

Figure 1: Price Indices for Selected Electronic Goods

Notes: The figure compares price indices across four data sources: the PPI and CPI are in Panel A, and the PCE price index and BEA industry gross output deflators are in Panel B. The CPI and PCE are shown as dashed lines; the PPI and gross output deflators are shown as solid lines. Each series is normalized to 100 in its first year. The PPI for Audio and Video Equipment Manufacturing begins only in December 2003. The y-axes are on a logarithmic scale.

turing (NAICS 33421) and Broadcast and Wireless Communications Equipment Manufacturing (NAICS 33422). Second, commodities in the PCE price index are produced domestically or imported, whereas the gross output deflators measure only changes in the prices of domestically produced commodities.[2]

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

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

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 commodity j; $m_{t,j}$ is the share of personal consumption expenditures of commodity j that comes from imports; and $\Delta \log P_{t,j}^{\text{GO}}$ and $\Delta \log P_{t,j}^{\text{Import}}$ are domestic and import price growth for commodity j. We hypothesize that—since consumer-facing price indices better capture quality improvements—gaps between PCE inflation and the "Producer Inflation" measure we define in Equation 1 signify mismeasurement in gross output deflators and import price indices.

In a final step, we use input–output and capital flows tables to recover TFP mismeasurement from our estimates of mismeasurement in gross output deflators and import price indices. 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

[2]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 has only modest impacts on estimated TFP mismeasurement.

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	-0.7	-0.7	-0.6	1.2	2.0	0.5
Nondurable	0.0	0.4	-0.3	-0.3	-0.4	-0.3	0.3	0.8	-0.0
Durable	1.0	1.9	0.3	-1.4	-1.5	-1.3	2.4	3.3	1.6
Computer & Electronic Products	4.0	7.4	1.2	-5.5	-5.3	-5.7	9.5	12.7	6.9
Nonmanufacturing	1.0	1.1	0.9	0.3	0.4	0.2	0.8	0.7	0.8

Notes: The first three columns present annual TFP growth rates (in percent) according to the BLS Major Sector and Major Industry Total Factor Productivity database. The next three columns present estimates of TFP mismeasurement (in percentage points). Negative values indicate TFP growth is understated, while positive values indicate it is overstated. The final three columns present industries' TFP growth rates (in percent), corrected for the mismeasurement we have estimated.

price and capital rent growth (see Supplemental Appendix A for additional details). As a result, TFP mismeasurement is a linear function of the gap between PCE inflation and producer-side inflation, with weights coming from the BEA Input–Output Tables, investment flows across industries (from Vom Lehn and Winberry, 2022), and the PCE Bridge Table.

Table 1 summarizes the results from this exercise. We highlight three main findings. First, driven by Computer and Electronic Product Manufacturing, measured TFP growth in manufacturing fell from 1.3 percent (1997 to 2009, annually) to -0.1 percent (2009 to 2023, annually). Second, manufacturing TFP growth has been understated by about 0.7 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 Product Manufacturing. Since gaps between consumer-facing and producer-facing price indices are so small outside of manufacturing, we identify little TFP mismeasurement there. Finally, corrected for mismeasurement, annual manufacturing TFP growth has fallen from 2.0 percent in 1997–2009 to 0.5 percent in 2009–2023. From 2009 onward, it has been somewhat below the TFP growth rate for nonmanufacturing industries, but is now meaningfully positive.

2 Implications for the Relationship Between Innovation and TFP Growth

We next examine how correcting for TFP mismeasurement affects inference about the innovation–productivity relationship. We revisit traditional regressions (Griliches, 1979; Scherer, 1982;

Griliches and Lichtenberg, 1984; and Lach, 1995) relating industries' R&D intensity or patenting activity to subsequent productivity growth. Conceptually, R&D captures innovative effort, while patents are a proxy for realized inventive activity; both are leading indicators of productivity growth.

We compare results using measured versus corrected TFP growth 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 most in innovative industries.

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

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

Here, $x \in \{M, C\}$ indexes "measured" versus "corrected" TFP, and $X_{k,i}$ is either industry R&D intensity or patenting per employee in year k. Throughout this paper, we set $l = 5$, so that current TFP growth is related to innovation decisions made roughly five years earlier, reflecting the gradual gestation of R&D and patents. Our main coefficient, β_x, measures the association between industry innovative activity between years $t+1-l$ 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) or across countries (e.g., Griffith, Redding and Van Reenen, 2004), as well as 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 1993 to 2017. We obtain patent records from PatentsView and map Cooperative Patent Classification (CPC) codes to NAICS industries using Goldschlag, Lybbert and Zolas (2020). We count patents by NAICS industry and application year. As an alternate measure, we consider value-weighted patents from Kogan et al. (2017). For both patent measures, we scale counts by industry employment from the BLS Industry Productivity database. R&D intensity comes from Compustat (R&D expenditures-to-sales) and from the BEA-BLS Industry Level Production Account (R&D capital compensation-to-value added).[3] Our baseline specifications use the industry classification from the BLS Major Sector and Major Industry Total Factor Productivity database.[4]

[3] For this one variable, our data begin in 1997. For this reason, our regressions in columns (3) and (4) of panel A of Table 2 begin with $t = 2002$.

[4] In Supplemental Appendix Table 3, we apply a finer industry classification, with 4-digit NAICS codes in man-

Table 2: Estimates of Equation 2

	R&D Expenditures/ Revenues: Compustat		R&D Capital Comp./ Val. Added: BEA-BLS		Patents/ Employment		Patents/Employment (Value-Weighted)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: $\tau = 5$								
β_M	0.0036	0.0041	0.0003	0.0020	0.0036	0.0030	0.0056	0.0051
	(0.0019)	(0.0018)	(0.0014)	(0.0015)	(0.0017)	(0.0018)	(0.0022)	(0.0022)
β_C	0.0084	0.0101	0.0047	0.0081	0.0109	0.0119	0.0134	0.0138
	(0.0032)	(0.0032)	(0.0026)	(0.0028)	(0.0026)	(0.0025)	(0.0028)	(0.0023)
P-Value: $\beta_M = \beta_C$	0.004	0.001	0.011	<0.001	<0.001	<0.001	<0.001	<0.001
N	165	165	136	136	170	170	170	170
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes
Panel B: $\tau = \{12, 13\}$								
β_M	0.0039	0.0040	0.0011	0.0022	0.0039	0.0029	0.0058	0.0047
	(0.0030)	(0.0024)	(0.0020)	(0.0021)	(0.0027)	(0.0024)	(0.0032)	(0.0028)
β_C	0.0087	0.0096	0.0054	0.0079	0.0114	0.0118	0.0138	0.0138
	(0.0050)	(0.0046)	(0.0038)	(0.0041)	(0.0041)	(0.0032)	(0.0042)	(0.0028)
P-Value: $\beta_M = \beta_C$	0.068	0.054	0.067	0.027	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_M	0.0041	0.0050	0.0019	0.0030	0.0042	0.0042	0.0047	0.0046
	(0.0031)	(0.0022)	(0.0029)	(0.0030)	(0.0027)	(0.0021)	(0.0025)	(0.0018)
β_C	0.0089	0.0102	0.0062	0.0084	0.0118	0.0130	0.0130	0.0134
	(0.0065)	(0.0055)	(0.0060)	(0.0061)	(0.0054)	(0.0036)	(0.0046)	(0.0028)
P-Value: $\beta_M = \beta_C$	0.193	0.161	0.194	0.112	0.012	<0.001	0.001	<0.001
N	33	33	34	34	34	34	34	34
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Each column reports coefficients from regressions of annual TFP growth between years t and $t+\tau$ on (5-year) lagged measures of industry innovation activity. Within each column and panel, estimates of β_M 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 from 2009 to 2022 (where $t = 2009$ and $\tau = 13$). In Panel C, we consider TFP growth rates from 1997 to 2022 (where $t = 1997$ and $\tau = 25$). Columns (5) and (6) use raw patent counts; columns (7) and (8) use the sum of patent value (Kogan et al., 2017) among publicly traded firms. Supplemental Appendix A lists the industries in the sample. In the "weighted" columns, we weight observations by labor costs in year $t+\tau$. The Compustat data (used in columns 1 and 2) do not include any firms in Management of Companies and Enterprises (NAICS 55).

ufacturing and 3-digit NAICS codes outside of manufacturing. With this finer industry classification, β_M and β_C are somewhat smaller, with the broad conclusions of this section largely unchanged.

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 increase in R&D intensity is associated with a 0.4 percentage point increase in measured TFP growth, but a 0.8 percentage point increase in corrected TFP growth. The difference between β_M 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 Supplemental Appendix Table 4, these stronger elasticities are driven disproportionately by Computer and Electronic Product Manufacturing (NAICS 334). Excluding this single industry substantially reduces the magnitudes of both coefficients. Here, the estimate of β_M is often statistically insignificant and its point estimate is sometimes negative. On the other hand, estimates of β_C typically remain positive and statistically significant, albeit with coefficients only a quarter of those in Table 2.

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 undercounted quality improvements both raises estimated productivity growth—in the manufacturing sector as a whole, 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 in the manufacturing sector.

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A Additional Description of the Data

A.1 Price Indices Used in Figure 1

The left panel of Figure 1 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 the PPI include Computer and Peripheral Equipment Manufacturing (NAICS 3341), Communications Equipment Manufacturing (NAICS 3342), and Audio and Video Equipment Manufacturing (NAICS 3343).

The right panel of Figure 1 plots industry gross output deflators and components of the PCE price index. Both series come from the Bureau of Economic Analysis. The industry gross output deflators shown are 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 Telephone and Related Communication Equipment (NIPA Line 71).[5]

A.2 Measures of TFP Growth

Our TFP measures come from the Bureau of Labor Statistics.[6]

For our baseline regressions, we take TFP and labor costs from the BLS Major Sector and Major Industry Total Factor Productivity database. These data cover 18 nonmanufacturing industries and 19 manufacturing industries.[7] In Supplemental Appendix Table 3, we apply a finer industry

[5]The industry gross output deflators can be found in worksheet UGO304-A of `https://apps.bea.gov/industry/Release/XLS/UGdpxInd/GrossOutput.xlsx`, while components of the PCE price index come from NIPA Table 2.4.4U.

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

[7]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 Tex-

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 that we can reconstruct by comparing aggregate private sector TFP growth and manufacturing TFP growth. In principle, private sector TFP growth should be a weighted average of manufacturing and nonmanufacturing TFP growth:

$$\Delta \log A_{\text{Private},t} \approx \omega_{\text{Manufacturing},t} \cdot \Delta \log A_{\text{Manufacturing},t} + \sum_{\phi \in \text{Nonmanufacturing}} \omega_{\phi,t} \cdot \Delta \log A_{\phi,t} \ .$$

In this equation, ϕ refers to one of the 18 nonmanufacturing industries listed in footnote 7, $\omega_{\phi,t}$ refers to the sectoral output share of nonmanufacturing industry ϕ (sectoral output of this industry divided by the sum of sectoral output across all 2-digit private industries), and $\omega_{\text{Manufacturing},t}$ refers to the 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, and thus excludes intra-industry sales—sectoral output measures do not "aggregate up": The sum of $\sum_{\phi \in \text{Nonmanufacturing}} \omega_{\phi,t}$ will not equal the sectoral output share of the broader nonmanufacturing sector, for instance. For this reason, we instead solve for nonmanufacturing TFP growth assuming that private-sector TFP growth can be written as:

$$\Delta \log A_{\text{Private},t} = \omega_{\text{Manufacturing},t} \cdot \Delta \log A_{\text{Manufacturing},t} + (1 - \omega_{\text{Manufacturing},t}) \cdot \Delta \log A_{\text{Nonmanufacturing},t} .$$

Using this equation, we can solve for nonmanufacturing TFP growth as:

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

tile 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 2 and Supplemental Appendix B, we omit Construction, Wholesale Trade, and Retail Trade as we cannot compute TFP mismeasurement for these industries.

A.3 Estimation of TFP Mismeasurement

Next, 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 appendix draws from this earlier paper, with some passages reproduced verbatim.

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

$$\begin{aligned}
\Delta \log A_{t,j} &= -\Delta \log P_{t,j}^{\mathrm{GO}} + \gamma_{t,w\to j}\Delta \log w_{t,j} + \gamma_{t,r\to j}\Delta \log r_{t,j} + \gamma_{t,\mathrm{Int.}\to j}\Delta \log P_{t,j}^{\mathrm{Int.}} \qquad (3)\\
&= -\Delta \log P_{t,j}^{\mathrm{GO}} + \gamma_{t,w\to j}\Delta \log w_{t,j}\\
&\quad + \sum_{i=1}^{N} \gamma_{t,i\to j}^{K}\left[(1-m_{t,i})\Delta \log P_{t,i}^{\mathrm{GO}} + m_{t,i}\Delta \log P_{t,i}^{\mathrm{Import}}\right]\\
&\quad + \sum_{i=1}^{N} \gamma_{t,i\to j}\left[(1-m_{t,i})\Delta \log P_{t,i}^{\mathrm{GO}} + m_{t,i}\Delta \log P_{t,i}^{\mathrm{Import}}\right]\\
\Delta \log \mathbf{A}_t &= -\Delta \log \mathbf{P}_t^{\mathrm{GO}} + \boldsymbol{\gamma}_{t,w}\Delta \log \mathbf{w}_t\\
&\quad + \left[\boldsymbol{\Gamma}_t + \boldsymbol{\Gamma}_t^{\mathbf{K}}\right]\left[(\mathbf{I}-\mathbf{M}_t)\Delta \log \mathbf{P}_t^{\mathrm{GO}} + \mathbf{M}_t\Delta \log \mathbf{P}_t^{\mathrm{Import}}\right] .
\end{aligned}$$

According to this equation, industries are more productive when they are able to produce at a lower cost given the price of the inputs that they use. The first line breaks inputs across labor, capital, and intermediate inputs. Here, $\gamma_{t,\iota\to j}$ refers to the cost share of (some generic) input ι for industry j in year t. The second line breaks out changes in industry j's capital input and intermediate input prices according to the prices of different supplying industries. Here, $\gamma_{t,i\to j}^{K}$ and $\gamma_{t,i\to j}$ respectively refer to the cost shares of capital inputs and intermediate inputs from upstream industry i in the production of industry j in year t;[8] $m_{t,i}$ equals the import share of commodity i in year t. The final line writes the TFP growth equation in matrix form.

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 $\Delta \log \widetilde{\mathbf{w}}_t = 0$. With this additional assumption, Equation 3 implies:

$$\begin{aligned}
\Delta \log \widetilde{\mathbf{A}}_t &\equiv \Delta \log \mathbf{A}_t^{M} - \Delta \log \mathbf{A}_t^{C} \qquad (4)\\
&= -\Delta \log \widetilde{\mathbf{P}}_t^{\mathrm{GO}} + \left(\boldsymbol{\Gamma}_t + \boldsymbol{\Gamma}_t^{\mathbf{K}}\right)\left[(\mathbf{I}-\mathbf{M}_t)\Delta \log \widetilde{\mathbf{P}}_t^{\mathrm{GO}} + \mathbf{M}_t\Delta \log \widetilde{\mathbf{P}}_t^{\mathrm{Import}}\right] .
\end{aligned}$$

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

[8] Note that $\gamma_{t,w\to j} + \gamma_{t,r\to j} + \gamma_{t,\mathrm{Int.}\to j} = \gamma_{t,w\to j} + \sum_{i=1}^{N}\left(\gamma_{t,i\to j}^{K} + \gamma_{t,i\to j}\right) = 1$ for all j and t.

measures:

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

We write this equation in matrix form:

$$\Delta \log \mathbf{P}_t^{\text{PCE}} = \mathbf{S}_t\left[\left(\mathbf{I}-\mathbf{M}_t\right)\left(\Delta \log \mathbf{P}_t^{\text{GO}} + \Delta \log \widetilde{\mathbf{P}}_t^{\text{GO}}\right) + \mathbf{M}_t\left(\Delta \log \mathbf{P}_t^{\text{Import}} + \Delta \log \widetilde{\mathbf{P}}_t^{\text{Import}}\right)\right] .$$

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

$$(\mathbf{I}-\mathbf{M}_t)\Delta \log \widetilde{\mathbf{P}}_t^{\text{GO}} + \mathbf{M}_t \Delta \log \widetilde{\mathbf{P}}_t^{\text{Import}} = \mathbf{O}_t\Big[\Delta \log \mathbf{P}_t^{\text{PCE}} - \mathbf{S}_t\big((\mathbf{I}-\mathbf{M}_t)\Delta \log \mathbf{P}_t^{\text{GO}} + \mathbf{M}_t \Delta \log \mathbf{P}_t^{\text{Import}}\big)\Big]. \tag{5}$$

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.

Guided by Errico and Lashkari (2025), we assume that mismeasurement in import price indices is 50 percent greater than that in gross output deflators. With this assumption, we can combine Equations 4 and 5 to infer mismeasurement in productivity:

$$\Delta \log \widetilde{\mathbf{A}}_t = -\left[\left(\mathbf{I}+\frac{1}{2}\mathbf{M}_t\right)^{-1} - \mathbf{\Gamma}_t - \mathbf{\Gamma}_t^{\mathbf{K}}\right]\mathbf{O}_t\left[\Delta \log \mathbf{P}_t^{\text{PCE}} - \mathbf{S}_t\left[(\mathbf{I}-\mathbf{M}_t)\Delta \log \mathbf{P}_t^{\text{GO}} + \mathbf{M}_t \Delta \log \mathbf{P}_t^{\text{Import}}\right]\right] . \tag{6}$$

The left-hand side of Equation 6 collects industries' TFP mismeasurement. The three price indices we draw on are the BEA industry gross output deflators ($\mathbf{P}_t^{\text{GO}}$), the BLS import price index ($\mathbf{P}_t^{\text{Import}}$), and the PCE price index ($\mathbf{P}_t^{\text{PCE}}$). To elicit TFP mismeasurement from these three price indices, we draw on the BEA Input–Output Tables (which are used to compute $\mathbf{\Gamma}_t$ and $\mathbf{M_t}$ and an input to our calibration of $\mathbf{\Gamma}_t^{\mathbf{K}}$), the investment network from Vom Lehn and Winberry (2022) (which is the other main input in calibrating $\mathbf{\Gamma}_t^{\mathbf{K}}$), and the PCE Bridge Table (necessary to compute $\mathbf{O_t}$ and $\mathbf{S_t}$). Atalay et al. (2025) provide additional detail on the data sources and construction of these matrices.

A.4 Constructing R&D Intensity

We consider two measures of industry R&D intensity.

First, from the Compustat Fundamentals Annual file,[9] 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) to sales (measured as the sum of the `sale` variable across firms within the industry-year).

Second, from the BEA-BLS Industry Level Production Accounts file, we compute R&D intensity as the ratio of industry R&D Capital Compensation to industry Value Added.[10] 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.

A.5 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 1993 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 Goldschlag, Lybbert and Zolas's (2020) 'Algorithmic Links with Probabilities' patent crosswalks that convert patent classifications to industry classifications. We choose the crosswalk that converts Cooperative Patent Classification (CPC) subclasses to 4-digit NAICS categories, including services.[11] 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 the year of application for each patent. We drop any duplicate patents in the annualized data and keep only 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.[12] Most patents have multiple subclasses,

[9]These data are from S&P Global Market Intelligence (2025) via Wharton Research Data Services.

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

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

[12]The authors of Kogan et al. (2017) continue to update this dataset. See `https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data`. For our analysis, we take the October 7, 2024 version.

so both of these sets are organized by patent-by-subclass.

There are 25 CPC subclasses that are not included in Nikolas Zolas'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 our dropping 43,316 out of 50.37 million patent-by-subclass observations in the set of successful utility patent applications, and 11,423 out of 16.01 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 1993.

B Additional Tables and Figures

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

First, Supplemental Appendix Table 3 reproduces Table 2 with a finer industry classification. Instead of grouping manufacturing industries by $\sim$3-digit NAICS codes and nonmanufacturing industries by $\sim$2-digit NAICS codes, we group manufacturing industries by 4-digit NAICS codes and nonmanufacturing industries by 3-digit NAICS codes. Applying a finer industry classification leads to smaller coefficients for both β_M and β_C, with little change in the relative magnitudes.

Second, Supplemental Appendix Table 4 presents regression results, estimating Equation 2 while excluding Computer and Electronic Product Manufacturing (NAICS 334) from the sample. Dropping this single 3-digit industry leads to considerably lower estimates of both β_M and β_C. The median estimates of β_M and β_C in Table 2 are 0.0040 and 0.0106, respectively. After dropping Computer and Electronic Product Manufacturing, the median β_M and β_C coefficients are 0.0003 and 0.0028. 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. Dropping this one industry from the sample weakens the positive estimated relationship between proxies for innovation and subsequent productivity growth. In addition, the difference, $\beta_C - \beta_M$, is statistically significant (at the 5 percent significance level) in fewer specifications: 13 out of 24 in Supplemental Appendix Table 4, as opposed to 17 of 24 in Table 2. Nevertheless, the ratio of coefficients, β_C/β_M, is at least as large when we drop the Computer and Electronic Product Manufacturing industry as it is in the full sample.

Table 3: Sensitivity Analysis to Table 2–Alternate Industry Classification

	R&D Expenditures/ Revenues: Compustat		R&D Capital Comp./ Val. Added: BEA-BLS		Patents/ Employment		Patents/Employment (Value-Weighted)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: $\tau = 5$								
β_M	0.0034	0.0027	0.0010	0.0031	0.0012	-0.0014	0.0009	-0.0016
	(0.0015)	(0.0012)	(0.0009)	(0.0009)	(0.0011)	(0.0011)	(0.0012)	(0.0011)
β_C	0.0071	0.0026	0.0053	0.0039	0.0054	0.0014	0.0036	0.0014
	(0.0022)	(0.0013)	(0.0016)	(0.0012)	(0.0019)	(0.0014)	(0.0019)	(0.0013)
P-Value: $\beta_M = \beta_C$	<0.001	0.945	<0.001	0.406	<0.001	0.088	0.019	0.088
N	592	592	488	488	605	605	605	605
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes
Panel B: $\tau = \{12, 13\}$								
β_M	0.0031	0.0015	0.0020	0.0028	0.0012	-0.0015	0.0009	-0.0016
	(0.0021)	(0.0017)	(0.0012)	(0.0009)	(0.0013)	(0.0006)	(0.0016)	(0.0005)
β_C	0.0063	0.0019	0.0060	0.0034	0.0057	0.0016	0.0036	0.0013
	(0.0033)	(0.0016)	(0.0021)	(0.0013)	(0.0025)	(0.0007)	(0.0029)	(0.0007)
P-Value: $\beta_M = \beta_C$	0.025	0.768	0.003	0.573	0.002	<0.001	0.066	<0.001
N	241	241	244	244	242	242	242	242
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes
Panel C: $\tau = 25$								
β_M	0.0025	0.0007	0.0026	0.0025	0.0027	-0.0009	0.0018	-0.0011
	(0.0023)	(0.0017)	(0.0016)	(0.0009)	(0.0026)	(0.0005)	(0.0026)	(0.0003)
β_C	0.0052	0.0013	0.0066	0.0028	0.0073	0.0011	0.0044	0.0008
	(0.0040)	(0.0017)	(0.0029)	(0.0013)	(0.0041)	(0.0006)	(0.0044)	(0.0005)
P-Value: $\beta_M = \beta_C$	0.155	0.434	0.028	0.723	0.013	<0.001	0.214	<0.001
N	122	122	122	122	121	121	121	121
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes

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

Supplemental Appendix Figure 2 presents a visual depiction of the relationship between innovation and TFP mismeasurement in our baseline regression. We focus on the odd-numbered columns in panel A of Table 2. We plot a binscatter of TFP mismeasurement—the difference between measured and corrected five-year TFP growth—against five-year averages of lagged R&D intensity or lagged patents per employee. Innovation is extremely skewed: the Computer and Electronic Product Manufacturing industry has far higher patenting per employee and R&D intensity than other industries, and it exhibits the largest TFP mismeasurement. This industry lies far to

Table 4: Sensitivity Analysis to Table 2–Dropping NAICS 334

	R&D Expenditures/ Revenues: Compustat		R&D Capital Comp./ Val. Added: BEA-BLS		Patents/ Employment		Patents/Employment (Value-Weighted)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: $\tau = 5$								
β_M	0.0003	0.0016	-0.0009	0.0009	0.0003	-0.0005	0.0004	-0.0001
	(0.0010)	(0.0013)	(0.0012)	(0.0014)	(0.0009)	(0.0008)	(0.0008)	(0.0007)
β_C	0.0009	0.0031	0.0007	0.0035	0.0030	0.0027	0.0035	0.0028
	(0.0013)	(0.0018)	(0.0015)	(0.0016)	(0.0012)	(0.0011)	(0.0014)	(0.0010)
P-Value: $\beta_M = \beta_C$	0.463	0.152	0.092	<0.001	0.003	<0.001	0.004	<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_M	0.0004	0.0017	-0.0007	0.0006	0.0005	-0.0005	0.0006	-0.0004
	(0.0011)	(0.0016)	(0.0010)	(0.0015)	(0.0011)	(0.0007)	(0.0010)	(0.0006)
β_C	0.0009	0.0029	0.0009	0.0028	0.0033	0.0028	0.0036	0.0026
	(0.0015)	(0.0023)	(0.0014)	(0.0017)	(0.0016)	(0.0010)	(0.0018)	(0.0010)
P-Value: $\beta_M = \beta_C$	0.705	0.354	0.123	<0.001	0.023	<0.001	0.026	<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_M	0.0007	0.0024	-0.0005	0.0006	0.0000	-0.0005	-0.0002	-0.0004
	(0.0012)	(0.0015)	(0.0009)	(0.0014)	(0.0007)	(0.0006)	(0.0008)	(0.0007)
β_C	0.0012	0.0034	0.0010	0.0024	0.0029	0.0028	0.0029	0.0026
	(0.0019)	(0.0013)	(0.0017)	(0.0014)	(0.0019)	(0.0009)	(0.0020)	(0.0011)
P-Value: $\beta_M = \beta_C$	0.771	0.485	0.262	0.017	0.082	<0.001	0.058	<0.001
N	32	32	33	33	33	33	33	33
Weighted?	No	Yes	No	Yes	No	Yes	No	Yes

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

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 (see Supplemental Appendix Table 4).

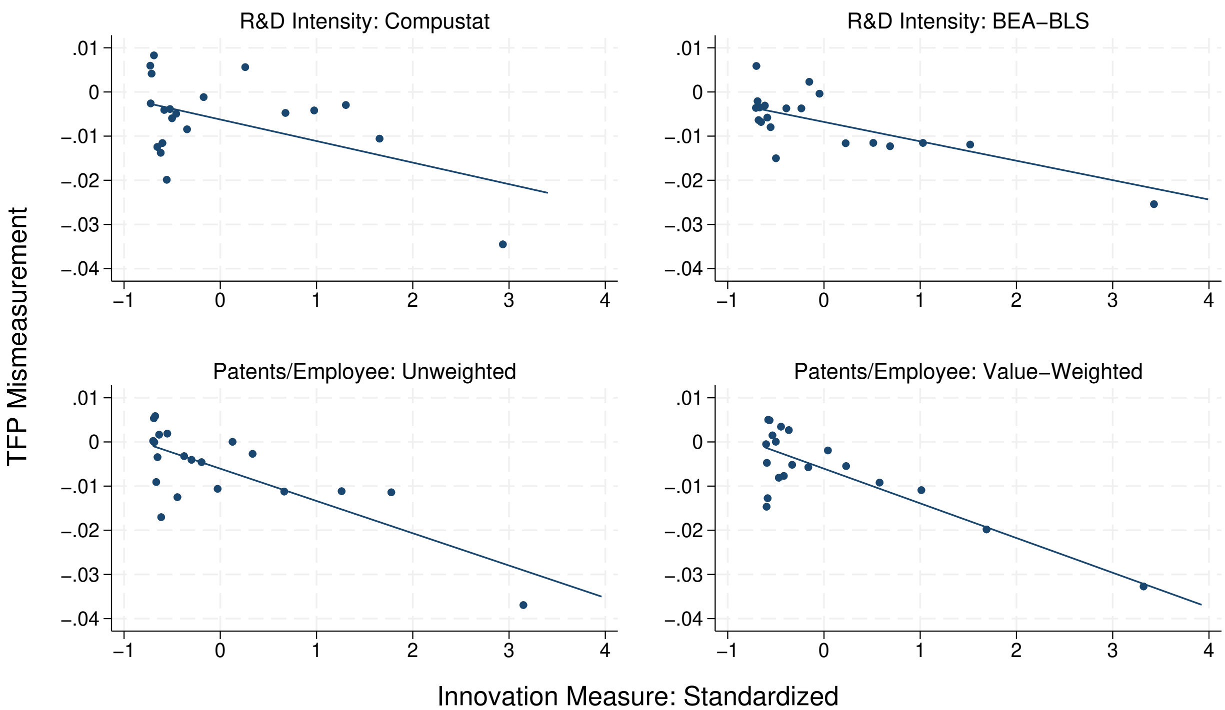

Figure 2: Relationships Between Innovation and TFP Growth Mismeasurement
This figure presents binscatter plots corresponding to columns (1), (3), (5), and (7) of Panel A of Table 2. On the vertical axis of each panel, we plot TFP mismeasurement: the difference between $\frac{1}{5}\Delta \log A^{M}_{i,t,t+5}$ and $\frac{1}{5}\Delta \log A^{C}_{i,t,t+5}$. On the horizontal axis of each panel, we plot $\frac{1}{5}\sum_{k=t-4}^{t} X_{i,k}$. For each panel, the explanatory variable is normalized to have mean 0 and standard deviation 1. 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 package developed by Cattaneo et al. (2025) to construct this binscatter plot.

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