Supplemental Appendix

Additional Description of the Data

A1. 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]

A2. 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 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:

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

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

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:

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

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

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

A3. 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:

$$\text{(A1)} \qquad \begin{aligned} \Delta \log A_{t,j} &= -\Delta \log P^{\text{GO}}_{t,j} + \gamma_{t,w\to j} \Delta \log w_{t,j} + \gamma_{t,r\to j} \Delta \log r_{t,j} + \gamma_{t,\text{Int.}\to j} \Delta \log P^{\text{Int.}}_{t,j} \\ &= -\Delta \log P^{\text{GO}}_{t,j} + \gamma_{t,w\to j} \Delta \log w_{t,j} \\ &\quad + \sum_{i=1}^{N} \gamma^{K}_{t,i\to j} \left[\left(1 - m_{t,i}\right) \Delta \log P^{\text{GO}}_{t,i} + m_{t,i} \Delta \log P^{\text{Import}}_{t,i} \right] \\ &\quad + \sum_{i=1}^{N} \gamma_{t,i\to j} \left[\left(1 - m_{t,i}\right) \Delta \log P^{\text{GO}}_{t,i} + m_{t,i} \Delta \log P^{\text{Import}}_{t,i} \right] \\ \Delta \log \mathbf{A}_t &= -\Delta \log \mathbf{P}^{\text{GO}}_t + \boldsymbol{\gamma}_{t,w} \Delta \log \mathbf{w}_t \\ &\quad + \left[\boldsymbol{\Gamma}_t + \boldsymbol{\Gamma}^{\mathbf{K}}_t \right] \left[\left(\mathbf{I} - \mathbf{M}_t\right) \Delta \log \mathbf{P}^{\text{GO}}_t + \mathbf{M}_t \Delta \log \mathbf{P}^{\text{Import}}_t \right] \ . \end{aligned}$$

According to this equation, industries are more productive when they are able to produce at 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, $\gamma^{K}_{t,i\to j}$ 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.

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

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 A1 implies:

$$\text{(A2)} \qquad \begin{aligned} \Delta \log \widetilde{\mathbf{A}}_t &\equiv \Delta \log \mathbf{A}_t^M - \Delta \log \mathbf{A}_t^C \\ &= -\Delta \log \widetilde{\mathbf{P}}_t^{\mathrm{GO}} + \left(\mathbf{\Gamma}_t + \mathbf{\Gamma}_t^{\mathbf{K}}\right)\left[(\mathbf{I} - \mathbf{M}_t)\,\Delta \log \widetilde{\mathbf{P}}_t^{\mathrm{GO}} + \mathbf{M}_t \Delta \log \widetilde{\mathbf{P}}_t^{\mathrm{Import}}\right] . \end{aligned}$$

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 measures:

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

We write this equation in matrix form:

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

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

$$\text{(A3)} \qquad \begin{aligned} (\mathbf{I} - \mathbf{M}_t)\Delta \log \widetilde{\mathbf{P}}_t^{\mathrm{GO}} + \mathbf{M}_t \Delta \log \widetilde{\mathbf{P}}_t^{\mathrm{Import}} = \mathbf{O}_t\Big[\Delta \log \mathbf{P}_t^{\mathrm{PCE}} - \mathbf{S}_t\big((\mathbf{I} - \mathbf{M}_t)\Delta \log \mathbf{P}_t^{\mathrm{GO}} \\ + \mathbf{M}_t \Delta \log \mathbf{P}_t^{\mathrm{Import}}\big)\Big]. \end{aligned}$$

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 A2 and A3 to infer mismeasurement in productivity:

$$\text{(A4)} \qquad \begin{aligned} \Delta \log \widetilde{\mathbf{A}}_t &= -\left[\left(\mathbf{I} + \frac{1}{2}\mathbf{M}_t\right)^{-1} - \mathbf{\Gamma}_t - \mathbf{\Gamma}_t^{\mathbf{K}}\right]\mathbf{O}_t\Big[\Delta \log \mathbf{P}_t^{\mathrm{PCE}} \\ &\qquad - \mathbf{S}_t\left[(\mathbf{I} - \mathbf{M}_t)\,\Delta \log \mathbf{P}_t^{\mathrm{GO}} + \mathbf{M}_t \Delta \log \mathbf{P}_t^{\mathrm{Import}}\right]\Big] . \end{aligned}$$

The left-hand side of Equation A4 collects industries' TFP mismeasurement. The three price indices we draw on are the BEA industry gross output deflators ($\mathbf{P}_t^{\mathrm{GO}}$), the BLS import price index ($\mathbf{P}_t^{\mathrm{Import}}$), and the PCE price index ($\mathbf{P}_t^{\mathrm{PCE}}$). 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.

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) 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.[9] 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.

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 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.[10] 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.[11] 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 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.

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 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 ∼3-digit NAICS codes and nonmanufacturing indus-

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

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

[11]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.

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

Note: 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.

tries by ∼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

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

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

is in the full sample.

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 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).

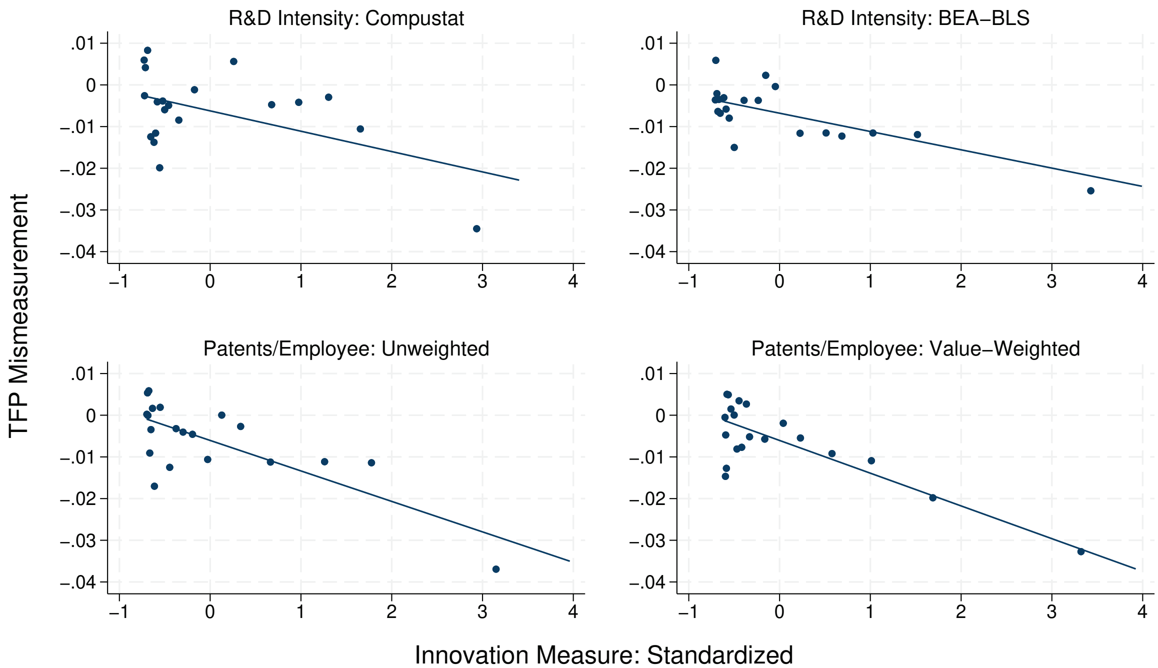

FIGURE 2. RELATIONSHIPS BETWEEN INNOVATION AND TFP GROWTH MISMEASUREMENT

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 $\frac{1}{5}\Delta\log A^M_{i,t,t+5}$ 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.

APPENDIX REFERENCES

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