# Regulatory Shocks and Inventive Reallocation

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*How portable is specialized human capital when the value of that expertise falls? We study this question using a Medicare price reform that sharply reduced expected returns to innovation in 13 medical device categories. Using linked Census employer–employee records matched to patent data and a difference-in-differences design, we follow inventors whose pre-reform portfolios were concentrated in affected technologies. Exposed inventors sharply reduce patenting in affected device categories but do not significantly reduce their overall probability of patenting. Instead, they redirect inventive activity toward other technologies, especially outside medical devices. This reallocation is costly: their subsequent patents receive fewer normalized citations, and they increasingly work in larger teams, consistent with a need for complementary expertise when moving into unfamiliar domains. We find little evidence of changes in employment, earnings, or job mobility. These results suggest that specialized inventive human capital is redeployable across domains, but not without productivity losses.*

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When the expected returns to a technology decrease, inventors with accumulated expertise in that technology must decide whether to continue building on now devalued knowledge, redirect effort toward nearby or distant fields, or exit inventive work altogether. The consequences depend on how portable specialized knowledge is across domains. If expertise transfers across technologies, inventors can redirect effort while remaining productive. If, instead, expertise is embedded in particular technologies, firms, or teams, shocks to one technology may generate persistent declines in innovation. Understanding this adjustment is important for assessing how shocks to specialized expertise shape the allocation and productivity of innovators.

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This paper studies how inventors respond when regulation sharply lowers the expected returns to technologies in which they have specialized. We examine a Medicare reimbursement reform that reduced prices by 61% for 13 durable medical equipment (DME) categories, lowering returns to innovation across the affected technologies. Inventors' exposure to the reform varied according the pre-reform composition of their patent portfolios. We use this variation to compare more- and less-exposed inventors and examine whether the shock reduced productivity, redirected inventive activity toward other technologies, or led to broader labor-market disruption.

Our analysis combines patent records with linked employer–employee data from the U.S. Census Bureau, allowing us to track inventors' employment, earnings, and patenting activities over time. This linkage enables us to distinguish changes in the direction of invention from exits out of inventive work or the labor market. We find that inventors respond primarily by redirecting their inventive activity. Treated inventors sharply reduce patenting in affected technologies: the probability of patenting in an affected device category falls by 13.3 percentage points after the reform. Yet their overall probability of patenting does not decline significantly. Instead, treated inventors become more likely to patent outside affected technologies, especially in non-device fields. We find little evidence of corresponding labor-market disruption: effects on employment, earnings, and job mobility are small and statistically insignificant. However, this reallocation is not frictionless. Patents produced by treated inventors receive fewer normalized citations after the reform, and treated inventors increasingly work in larger inventor teams. These results suggest that specialized knowledge is portable enough to preserve inventive participation, but that adjustment changes the direction, organization, and measured impact of subsequent invention.

This paper first contributes to work on the portability of specialized knowledge. A growing literature shows that research direction and skill portfolios are sticky. Targeted NIH funding can move scientists toward funded topics, but at high switching costs (Myers, 2020); pivots away from prior work are associated with lower research impact (Hill et al., 2025); and skill mismatch after displacement can generate persistent earnings losses (Neffke, Nedelkoska and Wiederhold, 2024). Related work on skill obsolescence makes a similar point in settings ranging from technology-specific human capital (MacDonald and Weisbach, 2004) to software and sports (Horton and Tambe, 2025; Fillmore and Hall, 2021). Closest to our focus on inventors, McFarland (2025) studies how regulatory burden affects inventor mobility and productivity. We contribute by studying a product-market shock that lowers the value of particular technologies, measuring both the technological direction of subsequent invention and inventors' labor-market adjustment. Our linked inventor–patent–employer data allow us to observe these margins in the same population, combining patenting, the direction of inventive output, citations, team composition, employment, earnings, and job mobility. The results show partial portability: specialized inventive human capital is portable enough

to sustain patenting and labor-market attachment, but not enough to preserve the original direction, organization, or measured impact of invention.

Second, the paper contributes to research on how public policy shapes the supply of innovation. A growing literature studies how insurance and coverage, reimbursement rules (Acemoglu and Linn 2004, Finkelstein 2004, Blume-Kohout and Sood 2013, Agha, Kim and Li 2022), regulation (Grennan and Town 2020, Rogers 2023), procurement (Slavtchev and Wiederhold 2016, Che, Iossa and Rey 2021, Clemens and Rogers 2023), and public funding (Azoulay et al. 2019) affect innovation within targeted diseases, technologies, or industries. These estimates are central to evaluating policy, but they do not by themselves reveal what happens to the inventive human capital previously active in affected areas. A decline in treated-category innovation, for example, may reflect a reduction in aggregate innovation, or the redirection of inventors toward other technologies. More directly, Ji and Rogers (2026) studies the same Medicare DME price reform and documents large effects on product introductions, patenting, market structure, and quality. We extend this work by shifting the unit of analysis from product categories and firms to inventors whose expertise was tied to affected technologies. Our results show that inventors do redirect effort beyond affected technologies, so declines in treated categories do not map one-for-one into inventor exit. But the adjustment is costly: subsequent patents receive fewer citations and initially involve larger teams, indicating that reallocation does not fully preserve the productivity of specialized inventive labor.

Third, this paper contributes to the literature on labor market responses to health care regulation, where prior work has focused on how public insurance and payment rules shape physicians' earnings, labor supply, and specialty allocation (Gottlieb et al., 2025), provider participation and staffing (Garthwaite, 2012; Buchmueller, Miller and Vujicic, 2016; Dillender, 2022), and sectoral employment following insurance expansions (Finkelstein, 2007; Kondo and Shigeoka, 2013; Hackmann et al., 2025). We extend this supply-side perspective to the innovation workforce, where we find that even though exposed inventors do not experience large employment or earnings changes, their inventive activity is redirected and becomes less impactful.

The rest of the paper is organized as follows: Section I describes the background setting; Section II describes the data and sample and variable definitions; Section III describes our empirical strategy; Section IV reports our results; Section V concludes.

## I. Background

### Medical Device and Durable Medical Equipment

Medical devices are instruments or apparatuses intended for the diagnosis, treatment, or prevention of disease. Durable medical equipment (DME) is a class of medical devices used in the home to manage chronic illness or support recov-

ery outside institutional care. Examples include oxygen equipment, wheelchairs, nebulizers, CPAP machines, hospital beds, infusion pumps, and walkers. DME is an area of significant R&D activity, with innovation in the sector contributing to profound improvements in quality of life.

#### Medicare Payment Reform for DME

Medicare covers DME under Part B according to administered prices. Medicare is a major payer of DME, accounting for 39% of the total market revenue in 2003 (Ji and Rogers, 2026). The reform we study originated in the Medicare Modernization Act of 2003, which authorized CMS to reduce DME payments through competitive bidding. The policy was motivated by concerns that existing fee-schedule payments, which were derived largely from late-1980s list prices and updated over time, exceeded competitive market prices. In 2004, CMS advisory meetings identified oxygen equipment, wheelchairs, and nebulizers as high-spending categories likely to be included in the reform. CMS later announced additional categories, and by 2019 thirteen DME categories were subject to price reductions.[1] Implementation occurred in waves: a nationwide 9.5 percent cut in 2009, auctions in nine metropolitan areas beginning in 2011, expansion to 100 metropolitan areas in 2013, and broader nationwide application of auction-generated prices beginning in 2016. The timeline is illustrated in Figure A1. As shown in Figure A2, across affected categories, Medicare prices fell by 61 percent on average over the subsequent seven to ten years relative to unaffected categories. Annual Medicare spending in affected categories decreased from approximately $4.5 billion to $2 billion, while spending in unaffected categories increased from $4.5 billion to $6 billion.

## II. Data, Sample, and Outcomes

### *A. Data Sources*

Our analysis leverages unique linked data from the Census Bureau and the U.S. Patent and Trademark Office (USPTO) on the universe of U.S. inventors, their patents, and their labor market outcomes.

#### Longitudinal Employer-Household Dynamics (LEHD) Data from Census

We draw labor market outcomes from the LEHD Job History File (JHF) for 2000–2019. The JHF is constructed from earnings records collected through state unemployment insurance (UI) programs, commonly referred to as UI wage records. These records consist of quarterly earnings reports submitted by employers for all UI-covered employees to state agencies, which are then shared with the

[1]The treated categories are oxygen equipment, wheelchairs, nebulizers, CPAP, enteral nutrition, hospital beds, walkers, negative pressure wound therapy, support surfaces, commodes/bedpans/urinals, patient lifts, infusion pumps, and transcutaneous electrical nerve stimulation.

Census Bureau through a cooperative partnership. A key strength of the JHF is its longitudinal structure, which allows job spells to be tracked continuously over time.[2] A limitation of the data is that they do not capture employment or earnings outside the UI system, including self-employment, independent contracting, and other forms of non-wage income.

Moreover, we obtain inventor demographic characteristics—race, gender, date of birth, and educational attainment—from the LEHD Individual Characteristics File (ICF).

#### Patent data from USPTO

We use the USPTO PatentView database, covering all utility patents granted between 1996 and 2019, to construct patent-level outcomes including patent counts, patent classifications, and measures of inventor "pivots" (changing from one technology area to another). To link inventors to their Census records, we use the Census Bureau's Intellectual Property Public Patent Data Census Protected Identification Keys (PIKs) Crosswalk, which provides linkages between USPTO inventor identifiers and Census Bureau's individual identifiers (PIKs) (Akcigit and Goldschlag 2022). Because the crosswalk begins in 2000, our analysis sample is restricted to inventors with at least one patent granted from 2000 onward.

### *B. Sample Construction*

We begin by identifying patents affected by the Medicare price reform, using the algorithm from Ji and Rogers (2026) which maps patents into treated and non-treated DME categories, and classify them as device patents and non-device patents.

#### Treatment Group

An inventor is classified as *treated* if at least 50 percent of her patent portfolio over the pre-period 1996–2004 consists of DME patents affected by the Medicare reimbursement change. We define treatment timing relative to the 2004 policy announcement, which we set as event year zero for all treated inventors. Although the actual reimbursement reductions were implemented on a staggered schedule, we use the initial announcement year of 2004 as the reference period because forward-looking inventors (and the firms that employ them) would respond to the policy change once it became public information.

#### Matched Control Group

We match each treated inventor to four control inventors using the following procedure. We first construct our sample of potential control inventors who have

[2]This continuity is maintained even when an employer's State Employer Identification Number (SEIN) changes, for example because of firm restructuring.

at least one medical device patent during the pre-period but do not meet the treated threshold, which ensures that treated and control inventors are drawn from the same broad technological field. We then match each treated inventor, with replacement, to four control inventors. The matching finds the nearest-neighbor on date of birth among inventors with the same pre-period patent count, which proxies for inventor experience and productivity.

#### LEHD Sample Restriction

For labor market outcomes, we first restrict the sample to inventors observed in the JHF as of 2000 Q1, the first quarter in which 41 states participated in the LEHD. This restriction is necessary because non-participation by an inventor's state in earlier quarters would mechanically generate apparent non-employment spells; conditioning on being observed in 2000 Q1 ensures that subsequent absences from the JHF reflect genuine employment transitions rather than data coverage gaps. We then conduct the same process to match 4 control inventors to each treated inventor.

#### Panel structure

Our final analysis sample is a balanced inventor-year panel covering 1996–2019. For each inventor-year, we assign zero patents if the inventor does not appear in the patent data that year, and zero earnings together with a non-employment indicator if the inventor does not appear in the JHF that year (conditional on the LEHD sample restriction described above).

### *C. Variable Definitions*

#### Patent outcomes

For each inventor $i$ in year $t$, we construct five patent-count outcomes. $Patents_{it}$ is the total number of utility patents granted to inventor $i$ with application year $t$. *Medical Device* $Patents_{it}$ is the subset of these patents classified as medical devices. *DME* $Patents_{it}$ further restricts to medical device patents classified as durable medical equipment. We decompose DME patents into *Treated DME* $Patents_{it}$, those affected by the 2004 Medicare reimbursement change, and *Non-Treated DME* $Patents_{it}$, those not affected. For inventor-years in which we observe no patenting activity, each of these counts is set to zero. For each patent filed in year $t$ associated with an inventor $i$ in our sample, we normalize citation counts. The normalization factor is the average, across the patent's assigned IPC codes, of the mean number of citations received by all PatentsView patents filed in year $t$ within each IPC code. Following Hall, Jaffe and Trajtenberg (2001), *Normalized Patent Citations* $Ratio_{it}$ is an average across patents filed in year $t$ by inventor $i$ of the number of citations for each patent as of 2019 divided by the the patent's citation count normalization factor. *Normalized Patent Citations Log* $Difference_{it}$

is an average across patents filed in year $t$ by inventor $i$ of the log difference between the number of citations for each patent as of 2019 and the the patent's citation count normalization factor.

### Labor market outcomes

We construct three annual labor market outcomes from the JHF. $Log\ Earnings_{it}$ is the natural logarithm of total earnings, summed across all jobs and quarters within calendar year $t$. $Employed_{it}$ is an indicator equal to one if inventor $i$'s total annual earnings exceed \$2,000, a threshold that screens out trivial or temporary employment. $Changed\ Jobs_{it}$ is an indicator equal to one if inventor $i$'s highest-earning employer in year $t$ differs from her highest-earning employer in year $t-1$.

For inventor-years in which the inventor does not appear in the JHF (conditional on the LEHD sample restriction), earnings are set to zero, $Employed_{it}$ is set to zero, and $Changed\ Jobs_{it}$ is set to zero.

### Summary statistics

Table 1 reports summary statistics for the full inventor sample, the matched sample, and the treated and control groups within the matched sample. The full sample consists of inventors with at least one medical device patent between 1996 and 2003, while the matched sample is constructed using nearest-neighbor matching on birth date and pre-period patent counts. The matching procedure substantially improves balance between treated and control inventors: both groups have identical average age (45.9 years) and cumulative pre-period patent counts (2.75 patents), consistent with the matching design.

Inventors in the sample are predominantly male, white, and highly educated. Relative to the full sample, inventors in the matched sample exhibit lower overall patenting activity, reflecting the restriction to inventors comparable to the treated group. By construction, treated inventors are substantially more concentrated in Medicare-affected DME technologies prior to the reform. Treated inventors average 2.12 cumulative DME patents before 2004, compared with 0.15 among matched controls, while matched controls have essentially no treated DME patents. At the same time, treated and control inventors remain similar in total cumulative patenting and pre-period earnings, suggesting that the primary difference between the groups lies in the composition rather than the overall scale of inventive activity.

## III. Empirical Approach

Our identification strategy compares the trajectories of treated inventors—those whose pre-period patent portfolios were concentrated in affected DME technologies—to those of otherwise similar medical device inventors who were not directly exposed to the reimbursement change. We implement this strategy using both an event study and a difference-in-differences framework.

### A. *Event Study Specification*

Our main specification is an event study that traces out the dynamic response of each outcome to the policy announcement. For inventor $i$ in calendar year $t$, we estimate

$$Y_{it} = \alpha_i + \gamma_t + \sum_{\substack{k=-8 \\ k\neq -1}}^{15} \delta_k \cdot \mathbf{1}\{t - 2004 = k\} \cdot \text{Treated}_i + \varepsilon_{it}, \tag{1}$$

where $Y_{it}$ is the outcome of interest, $\alpha_i$ is an inventor fixed effect, and $\gamma_t$ is a calendar year fixed effect. The event-time indicators $\mathbf{1}\{t - 2004 = k\}$ are interacted with the treatment indicator $\text{Treated}_i$, with $k = -1$ (calendar year 2003) omitted as the reference period. Because our panel spans 1996–2019 and event zero corresponds to 2004, event time ranges from $k = -8$ to $k = 15$. The inventor fixed effects $\alpha_i$ absorb all time-invariant differences across inventors, while the year fixed effects $\gamma_t$ absorb common shocks affecting all medical device inventors in a given year, such as aggregate trends in patenting or labor market conditions. Standard errors are clustered at the inventor level to allow for arbitrary serial correlation in $\varepsilon_{it}$. The coefficients of interest are $\{\delta_k\}$.

### B. *Difference-in-Differences Specifications*

To summarize the average effects of the policy change, we complement the event study with three difference-in-differences specifications:

$$Y_{it} = \alpha_i + \gamma_t + \beta \cdot \text{Treated}_i \cdot \text{Post}_t + \varepsilon_{it}, \tag{2}$$

where $\text{Post}_t = \mathbf{1}\{t \geq 2004\}$. The coefficient $\beta$ captures the average treatment effect on the treated. We estimate three versions of equation (2) that differ in the post-period observations included:

1) *Pooled.* We include all post-period years ($k = 0, 1, \ldots, 15$), yielding an average effect over the full horizon.

2) *Short-run.* We drop all observations with event time $k \geq 9$ and estimate the effect over the immediate post-announcement period ($k = 0, \ldots, 8$).

3) *Long-run.* We drop all observations with event time $0 \leq k \leq 8$ and estimate the effect over the post-implementation horizon ($k = 9, \ldots, 15$).

In all specifications, we estimate equations (1) and (2) on the matched samples described in Section II: the patent-outcome matched sample for patent outcomes and the LEHD-outcome matched sample for labor market outcomes.

## IV. Results

### A. Patenting Responses

Table 2 Panel A reports difference-in-differences estimates for patenting outcomes, while Figure 1 presents the corresponding event-study estimates. Following the 2004 Medicare reimbursement reform, treated inventors sharply reduced patenting activity in affected DME technologies. The probability of producing any treated patent declines by 13.3 percentage points on average over the post-period, with similarly large effects in both the short and long run.

At the same time, we find evidence of inventive reallocation toward other technological areas. Treated inventors become significantly more likely to patent outside affected DME technologies, particularly in non-device technologies. The probability of producing any non-device patent increases by 2.9 percentage points overall, with larger effects in the long run. By contrast, overall patenting activity remains broadly stable: we find no statistically significant effect on the probability of producing any patent. This pattern suggests that the reimbursement shock altered the direction of inventive effort more than the overall level of inventive activity.

### B. Labor Market Outcomes

Panel B of Table 2 reports estimates for labor market outcomes, with corresponding event studies shown in Figure 2. Despite substantial changes in the direction of inventive activity, we find limited evidence that the reform generated large disruptions in inventors' labor market outcomes. Treated inventors experience small and statistically insignificant declines in employment and earnings relative to matched controls. The estimated effects on full-year employment and log earnings are negative throughout the post-period but imprecisely estimated.

We also find no evidence that treated inventors were more likely to change employers following the reimbursement shock. The estimated effect on job mobility is close to zero in both the short and long run. Together, these results suggest that inventors were generally able to remain employed despite the decline in profitability of their specialized technologies.

### C. Patent Quality and Teamwork

Panel C of Table 2 examines how the reimbursement reform affected the quality and organization of inventive activity, with corresponding event studies presented in Figure 3. We find that patents produced by treated inventors receive substantially fewer citations following the reform. Both citation measures decline significantly in the post-period, with larger effects emerging in the long run. These patterns suggest that the technologies and projects pursued after the reform were less influential or economically valuable on average than inventors' pre-reform work.

At the same time, treated inventors become more likely to work in larger inventor teams. The number of inventors per patent increases by 0.22 on average in the full post-period, with the strongest effects concentrated in the short run. One interpretation is that inventors responded to the decline in returns to their specialized expertise by working more with collaborators who provided complementary knowledge, helping them move into less familiar technological areas.

## V. Discussion

This paper follows inventors specialized in DME technologies whose expected returns fell after Medicare price cuts. Exposed inventors reduce patenting in affected DME categories but do not significantly reduce their overall probability of patenting or labor-market attachment. Instead, they redirect inventive activity toward other fields, especially outside medical devices, while increasingly working in larger teams and producing patents with fewer normalized citations.

A natural question is how these inventor-level results relate to prior evidence from Ji and Rogers (2026) that the same Medicare price reform reduced aggregate innovation in affected DME categories. While Ji and Rogers (2026) shows that the price reform reduced the flow of new ideas and products into affected DME markets, our inventor-level estimates measure whether the workers who previously generated those ideas continued to innovate or if they redirected their inventive efforts. Viewed through this lens, the results are mutually reinforcing. The decline in exposed inventors' affected-DME patenting mirrors the aggregate contraction in treated-category innovation documented in Ji and Rogers (2026). But the absence of a significant decline in their overall probability of patenting indicates that the lost DME innovation was not driven solely by permanent exit of incumbent inventors from invention.

Moreover, because aggregate patent counts measure unique inventions while inventor-level outcomes follow people, increased team size can weaken the link between individual patenting and the number of patents produced: a given amount of inventor-level activity corresponds to fewer unique patents when more inventors are listed on each patent.

Our findings therefore refine the interpretation of the aggregate innovation loss. The reform reduced the production of new affected-DME technologies, but the specialized human capital embodied in incumbent inventors was partly redeployed rather than fully destroyed. Specialized inventive human capital appears portable enough to sustain continued inventive activity and labor-market participation, but redeployment is incomplete: it changes the direction of invention, relies more heavily on collaboration, and is associated with lower measured impact. More broadly, policy shocks to product-market returns can reduce innovation in targeted sectors even when the skilled workers behind that innovation remain employed and continue inventing elsewhere.

More broadly, the results suggest that regulation can reshape not only the amount of innovation, but also the allocation of innovative labor across scientific

problems. Prices and reimbursement rules affect which technological opportunities are worth pursuing, and therefore where specialized researchers deploy their expertise. When public policy lowers returns in a socially important sector, some human capital may be preserved through reallocation, but the original sector may still lose ideas, products, and cumulative knowledge. The portability of specialized expertise therefore mitigates the labor-market costs of regulatory shocks, but it does not eliminate the dynamic innovation costs of weakening incentives in targeted markets.

Table 1—: Summary Statistics

| | Full Sample | Matched Sample | Treated | Control |
|---|---|---|---|---|
| Age, 2003 | 45.4 (10.55) | 45.93 (11.36) | 45.93 (11.36) | 45.93 (11.35) |
| Male | 0.88 (0.32) | 0.87 (0.33) | 0.87 (0.33) | 0.87 (0.33) |
| White | 0.83 (0.38) | 0.86 (0.35) | 0.91 (0.28) | 0.84 (0.36) |
| BA or higher | 0.71 (0.45) | 0.68 (0.47) | 0.63 (0.48) | 0.69 (0.46) |
| Number of patents, 2003 | 0.88 (1.93) | 0.44 (0.92) | 0.48 (0.96) | 0.43 (0.90) |
| Number of patents, cumulative | 6.21 (11.21) | 2.75 (3.46) | 2.75 (3.46) | 2.75 (3.46) |
| Number of device patents, 2003 | 0.38 (0.87) | 0.31 (0.66) | 0.43 (0.90) | 0.27 (0.57) |
| Number of device patents, cumulative | 2.40 (4.28) | 1.73 (2.07) | 2.42 (3.06) | 1.56 (1.68) |
| Number of DME patents, 2003 | 0.049 (0.32) | 0.095 (0.42) | 0.38 (0.82) | 0.38 (0.17) |
| Number of DME patents, cumulative | 0.29 (1.40) | 0.55 (1.45) | 2.12 (2.33) | 0.15 (0.70) |
| Number of treated DME patents, 2003 | 0.0055 (0.11) | 0.076 (0.39) | 0.38 (0.82) | 0 (0) |
| Number of treated DME patents, cumulative | 0.030 (0.37) | 0.42 (1.31) | 2.08 (2.26) | 0 (0) |
| Earnings, 2003[†] | 121,200 (290,800) | 111,500 (222,700) | 122,000 (385,500) | 108,800 (157,600) |
| Earnings, cumulative[†§] | 498,800 (1,418,000) | 444,300 (594,200) | 446,600 (666,300) | 443,700 (574,800) |
| Number of inventors[§§] | 106,000 | 7,700 | 1,500 | 6,200 |

*Notes:* The table reports summary statistics for the full sample and matched inventor samples. Unless otherwise indicated, entries are means with standard deviations in parentheses. The full sample consists of inventors with at least one device patent between 1996 and 2003. The matched sample is constructed using nearest-neighbor matching on birth date and the number of patents filed between 1996 and 2003. The LEHD subsamples additionally restrict attention to inventors observed in the LEHD data and present in the data in 2000 Q1. Cumulative outcomes are the sum of all years from 1996 to 2003. Earnings are measured in nominal dollars. All samples exclude individuals with missing or implausible birth dates.

[†]uses the LEHD sample: number of inventors = 79,500; 5,400; 1,100; 4,300.[§§]

[§]rounded per Census requirement that means and standard deviations can only report four significance digits.

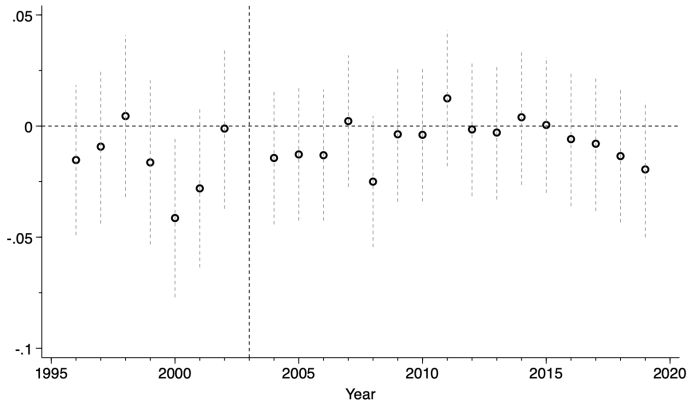
[§§]rounded per the Census requirement that counts between 1,000 and 9,999 are rounded to the nearest 100; counts between 10,000 and 99,999 are round to the nearest 500; counts between 100,000 and 999,000 are rounded to the nearest 1,000.

Table 2—: Difference-in-Differences Estimates

| | Overall | Short run | Long run |
|---|---|---|---|
| *Panel A. Patent outcomes* | | | |
| Any patent | 0.007 | 0.007 | 0.007 |
| | (0.006) | (0.007) | (0.008) |
| Any treated patent | -0.133*** | -0.116*** | -0.156*** |
| | (0.004) | (0.004) | (0.004) |
| Any device patent | -0.013** | -0.005 | -0.022*** |
| | (0.005) | (0.006) | (0.006) |
| Any non-device patent | 0.029*** | 0.020*** | 0.042*** |
| | (0.004) | (0.004) | (0.005) |
| *Panel B. Labor-market outcomes* | | | |
| Whether full-year employed | -0.018 | -0.017 | -0.019 |
| | (0.011) | (0.011) | (0.015) |
| Whether changed jobs | -0.005 | -0.005 | -0.005 |
| | (0.003) | (0.003) | (0.004) |
| Log earnings | -0.035 | -0.019 | -0.056 |
| | (0.026) | (0.024) | (0.037) |
| *Panel C. Citations and teamwork* | | | |
| Normalized citations, difference | -0.545*** | -0.415*** | -0.814*** |
| | (0.045) | (0.049) | (0.065) |
| Normalized citations, ratio | -0.918*** | -0.750*** | -1.418*** |
| | (0.135) | (0.137) | (0.201) |
| Inventors per patent | 0.217** | 0.324*** | 0.082 |
| | (0.093) | (0.097) | (0.154) |

*Notes:* The table reports difference-in-differences estimates of the effect of treatment on inventor outcomes. Each row corresponds to a separate dependent variable. Columns report estimates from specifications using the full post-treatment period, the short-run post-treatment period, and the long-run post-treatment period, respectively. Standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively.

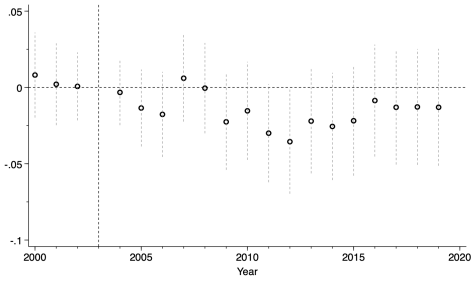
Figure 1. : Patenting.



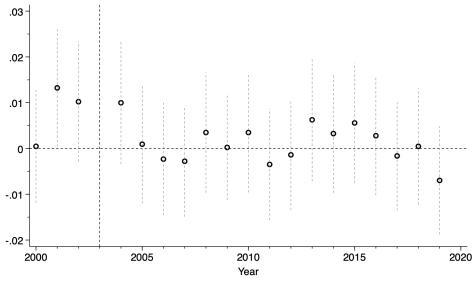

*Note:* The figure reports coefficients from estimating equation (1). The outcome is whether an inventor files any patent in a given year. 95% confidence intervals are shown in dashed lines.

Figure 2. : Labor Market Outcomes.

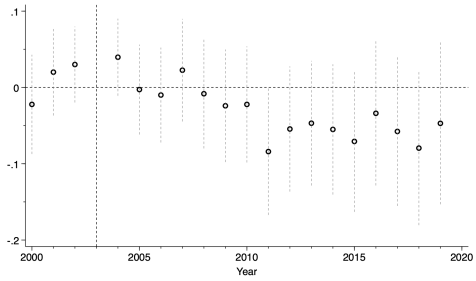
(a) Whether full-year employed




(b) Whether changed jobs



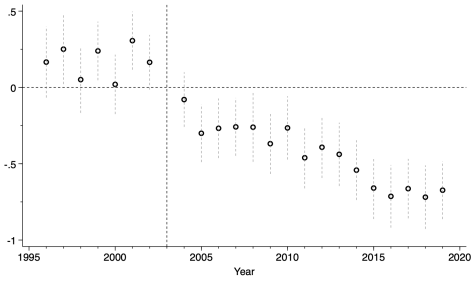

(c) Log earnings



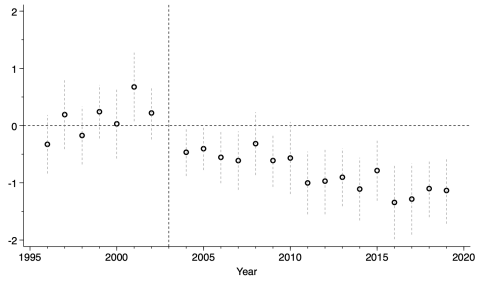

*Note:* The figure reports coefficients from estimating equation (1). 95% confidence intervals are shown in dashed lines.

Figure 3. : Patent Quality and Teamwork.

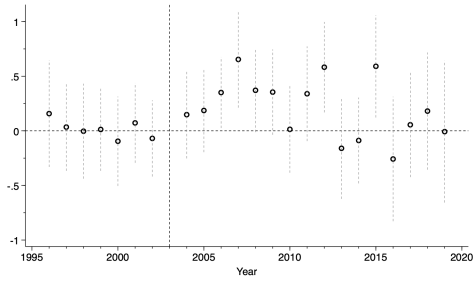
(a) Normalized citations, difference




(b) Normalized citations, ratio




(c) Inventors per patent




*Note:* The figure reports coefficients from estimating equation (1). 95% confidence intervals are shown in dashed lines.

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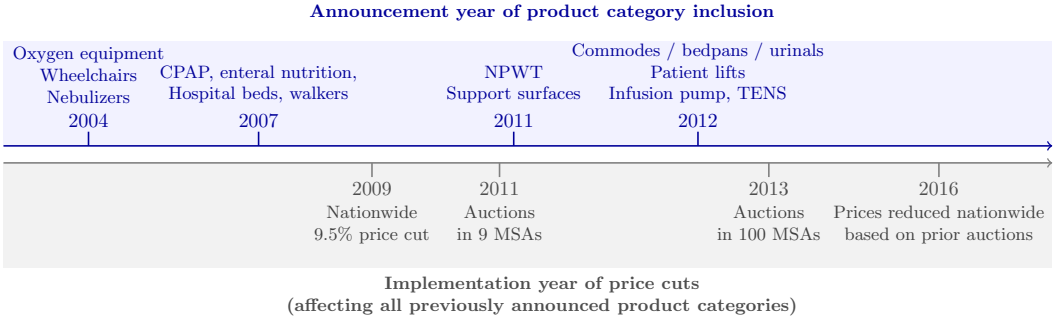
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# Appendix

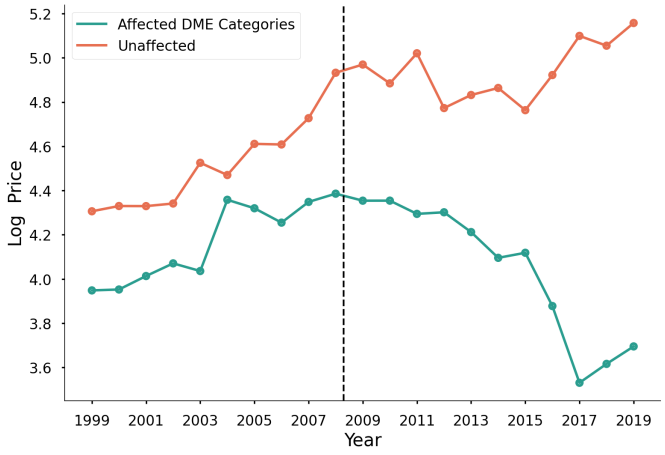
## Figure A1. : Timeline of Product Category Announcements and Price Cuts



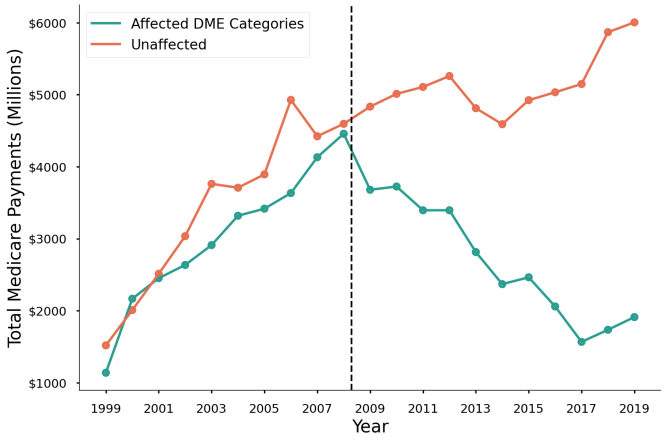

Note: The figure presents the timeline of product-category announcements (top) and the corresponding implementation dates of the price cuts (bottom). At each implementation date, the price reductions apply to all product categories announced previously. Thus, the 2011 auction included the product categories announced in 2004 and 2007, while the categories announced in 2011 were first incorporated into the 2013 auction. The figure is replicated from Ji and Rogers (2026).

Figure A2. : Raw Trends in Medicare Price and Payments

(a) Log Medicare Price




(b) Medicare Payments




Note: The figure plots the trends in average log Medicare price in panel (a) and total Medicare reimbursements in panel (b), separately for DME categories subject to the price cuts and those that are not. The figure is replicated from Ji and Rogers (2026).