Scientific Input Costs and Budgetary Constraints in University Life Sciences Research

Connie Xu (Job Market Paper), Ruby Zhang*

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Abstract

This paper examines how input market consolidation affects the output of publicly funded university life sciences research. Despite over $30 billion in annual federal funding from NIH and NSF, researchers face intensifying grant competition and stagnant award amounts while confronting rising costs for essential laboratory supplies. Since research budgets are grant-driven and largely fixed—with most funds committed to personnel salaries—consumable price increases force difficult tradeoffs that can ultimately constrain research capacity. Using transaction-level procurement data covering 4.8 million purchases across 165 universities from 2010–2019, we exploit the 2014 Thermo Fisher–Life Technologies merger as an exogenous price shock. Our difference-in-differences design reveals approximately 20% price increases in affected product markets, with no quantity substitution, indicating highly inelastic demand. We then construct an author-year panel of approximately 210,000 U.S. life science PIs and trace how merger-induced cost shocks affect research output. The average PI faces a 3.5% increase in consumables costs (roughly $620 per year), leading to 0.03 fewer publications per year, a 2.3% decline from baseline. The implied elasticity of publication output with respect to consumables costs is -0.67. These estimates are a lower bound, as we capture approximately 60% of consumables spending and study only one merger in a broader consolidation trend.

*Xu: Harvard University. Email: conniexu@g.harvard.edu. Zhang: Harvard University. Email: rzhang15@g.harvard.edu. We gratefully acknowledge funding from The Lab for Economic Applications and Policy Award, National Institute on Aging (T32-AG000186; Xu), and the National Science Foundation (DGE #2140743; Xu).

1 Introduction

Federal funding for university-based life sciences research in the United States exceeds $30 billion annually, with the National Institutes of Health and the National Science Foundation serving as primary sources. This substantial public investment supports research that generates the scientific innovations underlying new drugs and therapeutics. In recent decades, however, scientists have faced intensifying budgetary pressures from both the funding and cost sides. Grant competition has intensified and award amounts have failed to keep pace with inflation. At the same time, scientists face rising prices for essential laboratory inputs, driven largely by consolidation among scientific equipment suppliers. These dual pressures force scientists to make difficult resource allocation decisions that ultimately shape the rate and direction of biomedical discovery.

Understanding how resource constraints shape scientific output has been a central concern in the economics of science. A large literature examines factors that influence research productivity, including funding incentive structures [Azoulay et al., 2011, Manso, 2011, Jacob and Lefgren, 2011, Azoulay et al., 2021], grant evaluation processes [Jones, 2009, Li and Agha, 2015, Li et al., 2017], star scientists [Zucker et al., 1998, Azoulay et al., 2019, Waldinger, 2016, Akbulut-Yuksel and Yuksel, 2015], scientific teams [Lawani, 1986, Wuchty et al., 2007, Wu et al., 2019], and open access [Abramitzky and Sin, 2014, Boudreau and Lakhani, 2015, Hill and Stein, 2023, 2024]. However, less attention has been paid to the supply side, the markets which researchers procure inputs and how the structure of those markets affect the real purchasing power of grant dollars. This paper addresses this gap by studying how researchers adapt to input price increases in a budget-constrained setting.

For university-based life sciences researchers, budgets are largely fixed within grant cycles, leaving limited flexibility to absorb price increases. The majority of grant funds are committed to personnel salaries and benefits, with the remainder allocated primarily to laboratory consumables such as reagents and antibodies. Thus, consumables represent the only margin on which PIs can realistically adjust within an active grant. Consequently, even modest price increases can meaningfully constrain research capacity. This budget rigidity is compounded by growing pricing power among suppliers. The scientific equipment market is highly concentrated, dominated by a small number of firms including Thermo Fisher Scientific and MilliporeSigma. Suppliers privately negotiate contracts with individual universities, preventing institutions from benchmarking prices against peers. At the researcher level, switching costs are substantial—experimental protocols often require consistent use of specific inputs, making mid-experiment substitution costly.

Our empirical analysis proceeds in two steps. In the first step, we exploit the 2014 merger between Thermo Fisher Scientific and Life Technologies Corporation—a $13.6 billion transaction

combining two leading life science suppliers that attracted antitrust scrutiny and ultimately required divestiture of three product lines. We find that the merger led to approximately 20 percent price increases in affected markets, with spending rising by a similar magnitude and no quantity response. This pattern indicates that demand for laboratory consumables is highly inelastic.

In the second step, we trace how these price shocks affect downstream research productivity. We construct an author-year panel of approximately 210,000 U.S. life science PIs from 2009 to 2019 and measure each researcher's exposure to the merger using a spending-weighted index of market-level price effects. Because our procurement data do not link purchases to individual researchers at most universities, we develop a textual matching procedure that imputes PI-level exposure based on the similarity between a researcher's publication profile and those of PIs at universities where we observe researcher-linked spending through FOIA requests. Event study estimates reveal that more-exposed PIs experience a sustained decline in publication output following the merger, with an implied elasticity of publication output with respect to consumables costs of approximately -0.67. For the average PI, the merger translates to roughly \$620 per year in additional consumables costs and 0.03 fewer publications per year, a 2.3 percent decline from baseline. Scaling this up, this implies that a \$22,000 loss in consumables resources results in one less paper publication per PI per year.

This paper provides causal evidence that input market consolidation reduces the output of publicly funded research. Most of the science policy conversation has centered on the incentives in funding science. In this project, we show that research capacity depends on both funding and costs. Using novel procurement data on public university purchases, we develop a machine learning model that maps unstructured procurement text into product markets and a textual matching approach for linking researchers to their likely input bundles. Our estimates are also likely a lower bound, as we capture approximately 60 percent of consumables spending and study only one merger in an industry that has undergone extensive consolidation. The cumulative cost of this trend to scientific output is likely substantially larger, with implications for antitrust enforcement, the design of federal research funding, and university procurement practices.

2 Institutional Setting

The procurement of life science equipment for university researchers involves a complex bargaining process among manufacturers, distributors, and universities. Manufacturers such as Integrated DNA Technologies and New England Biolabs produce specialized scientific consumables. To maximize market reach, these manufacturers sell their products to distributors such as Thomas Scientific

and Quartzy. In recent decades, the supplier side has experienced significant consolidation, resulting in vertically integrated entities that control both manufacturing and distribution channels. For instance, the most dominant firm in this space, Thermo Fisher Scientific, encompasses both a manufacturing arm (Thermo Scientific) and a distribution arm (Fisher Scientific). Overall, the current distribution of scientific equipment is dominated by three main companies: Thermo Fisher Scientific, VWR, and MilliporeSigma. While universities do negotiate contracts with smaller non-integrated manufacturers, most researchers purchase inputs based on the negotiated contracts their universities have with these large vertically integrated platforms for convenience.

We study the impact of this concentrated market structure in the first part of our project. Specifically, we estimate input price shocks generated by a large acquisition of Life Technologies Corporation by Thermo Fisher Scientific in 2014. This $13.6 billion merger combined the largest and third-largest life sciences suppliers of molecular biology, cell culture and genomics products, attracting significant antitrust scrutiny. Regulators ultimately required Thermo Fisher Scientific to divest manufacturing units related to cell culture supplies, gene modulation, and magnetic beads to GE Healthcare. We leverage the fact that the merger differentially impacted product markets based on the competitive overlap between the merging entities to estimate input price shocks.

3 Data and Measurement

Our empirical analysis combines procurement records from public universities with publication metadata to observe the prices of scientific inputs and scientists' research activity.

3.1 Procurement Data

GovSpend. Our primary source for observing prices comes from GovSpend, a commercial data vendor that aggregates procurement records from public institutions. These transaction-level data contain item descriptions, prices, quantities, spending, purchase dates, supplier identifiers, and purchasing institutions. Our data extract consists of 4.8 million purchases from 165 public universities between 2010 and 2019. The breadth of coverage makes GovSpend well-suited for analyzing input prices across universities, but crucially these data do not identify which scientist made each purchase.

FOIA Requests. To attribute purchases to individual scientists, we filed Freedom of Information Act (FOIA) requests to life sciences departments at public universities. We obtained data from five universities that identify both the principal investigator (PI) and spending associated with each purchase: University of Texas at Dallas, University of Texas at Austin, University of Kansas, Texas

Tech University, and East Carolina University. The UT Dallas data are particularly useful because they include supplier stock keeping units (SKUs), a feature we exploit to build training data for our product market machine learning model.

3.2 Product Market Classification Machine Learning Model

A fundamental challenge with procurement data is that purchase records contain unstructured text descriptions (e.g., "200uL Tip Rack Reload 960/PK") rather than standardized product codes. To systematically identify equivalent inputs across suppliers, we develop a hierarchical supervised machine learning model that maps functionally substitutable items into discrete product markets. For example, our model groups "Phusion HS DNA Polymerase" and "KOD Hot Start DNA Polymerase" into the same product market of *hot start DNA polymerase*. This classification model serves as the foundation for measuring price variation across product markets and estimating scientist allocation patterns.

Labeled Training Data. Our primary training data come from UT Dallas procurement records from the Departments of Biological Sciences and Chemistry & Biochemistry spanning 2011-2024. Unlike our other procurement data, these records include SKUs, which allow us to precisely match items to supplier catalogs. We classify each item into product markets using the narrowest category listed—for instance, *Taq DNA Polymerase* rather than *Standard PCR Reagents*. This process yields over 60,000 labeled item descriptions across 1,322 distinct product markets. We also code each product market as being consumables-related or non-consumables.

Two-Step Classification Model. Our classification model operates in two steps. The first step distinguishes consumables-related items from non-consumables expenditures, which allows us to filter out non-consumables purchases such as publication fees, office supplies, and shipping fees. This improves the precision of the second step, which assigns research items to specific product markets.

Step One: Consumables vs. Non-Consumables Binary Classification. We train this step using the consumables and non-consumables item descriptions from the UT Dallas labeled data, supplemented with two additional sources: (1) California state procurement records (2012-2015) containing exclusively non-consumables purchases, and (2) Thermo Fisher Scientific's negotiated price lists with New York State that we manually coded as consumables or non-consumables. We split the combined data into a training set (80%) and a hold-out validation set (20%).

The binary classifier combines deterministic keyword rules with a logistic regression inference model. Descriptions containing keywords like polymerase or antibody are immediately classified as consumables items. Those containing keywords like shipping or furniture are classified as non-consumables. Remaining item descriptions are classified using a logistic regression trained on Term Frequency-Inverse Document Frequency (TF-IDF) text representations, with items scoring above 0.7 classified as consumables relevant.[1]

Step Two: Product Market Assignment. The second step assigns consumables items classified by step one into one of 1,322 product markets using only the UT Dallas training data. For each product market, we compute the centroid of all training examples in TF-IDF embedding space and assign new items to the product market with the highest cosine similarity.[2] We also create a set of keyword-based override rules to reduce classification errors. For example, item descriptions containing "taq" and "polymerase" are assigned to *Taq DNA Polymerase* regardless of similarity scores.

3.3 Merger Price Effects Estimation Sample

We apply our classification model to the GovSpend data, yielding 1.4 million research-related life sciences purchases across 1,202 product markets between 2010 and 2019. We restrict to 82 universities with balanced reporting across all sample years, defined as having at least 8 months of purchase activity per year. This sample captures $285 million in spending from 6,808 suppliers.

To ensure precise estimation of merger price effects, we further restrict to product markets where our model achieves high confidence. These high confidence markets have at least 20 training examples, a precision score of at least 0.8, and recall score of at least 0.8. This yields 99 product markets capturing 817,744 purchases totaling $146 million (60%) in spending from 3,275 suppliers.

3.4 Scientist Research Activity

To examine whether merger-induced price increases affect research output, we construct an author-year panel of U.S. life science principal investigators (PIs). Using PubMed queries supplemented with OpenAlex metadata, we identify researchers who published in basic, translational, or clinical life sciences journals between 2009 and 2019. We define PIs as last authors on publications, fol-

[1] We also evaluated this model using contextualized embeddings from a pre-trained BERT model, but the TF-IDF representation marginally outperformed BERT in terms of precision and accuracy while utilizing substantially lower computation requirements.

[2] We also estimated this step using embeddings from a pre-trained sentence transformer model (BERT). However, the TF-IDF approach yielded comparable accuracy with significantly lower computational cost for the centroid calculations.

lowing the convention in the biomedical sciences where last authorship typically denotes the senior researcher directing the project. We restrict our sample to authors with at least one publication in the pre-merger period (before 2014), ensuring that we observe baseline research activity for all individuals in the panel. The resulting panel comprises 209,993 PIs observed annually from 2009 to 2019. The average author in our sample publishes 1.75 papers per year, which serves as the baseline against which we measure merger-induced changes.

3.5 PI Exposure to Merger-Induced Price Shocks

Depending on their experimental needs, PIs will use different bundles of laboratory consumables. Thus, the merger's impact varies across researchers depending on the composition of their input spending. For each PI i, we construct a spending-weighted exposure index:

$$\text{Exposure}_i = \sum_m s_{im} \hat{\beta}_m \tag{1}$$

where s_{im} denotes PI i's pre-merger spending share in product market m and $\hat{\beta}_m$ is the estimated merger-induced price effect in market m from equation (1). Scientists who devote larger budget shares to product markets experiencing larger price increases receive higher exposure values. The measure has a natural interpretation where an exposure value of 0.2 corresponds to a 20 percent average increase in that PI's input costs.

Observed Exposure from FOIA Data. For PIs at universities where we obtained FOIA data with researcher-linked purchases, we directly calculate exposure using observed pre-merger spending shares. Our FOIA data from the University of Texas at Austin, East Carolina University, University of Texas at Dallas, and Texas Tech University yield 94 PIs with pre-2013 purchasing records sufficient to construct observed exposure measures. These PIs span five broad research subfields: genomics (32%), microbiology (19%), botany (18%), oncology (16%), and developmental biology (14%).

Imputed Exposure via Textual Matching. To extend the exposure measure to the full panel of 209,993 PIs, we implement a textual matching procedure that exploits the relationship between a scientist's research focus and their likely input bundle. The key assumption is that researchers working on similar topics will use the same experimental protocols, and thus have a similar spending pattern across consumables.

For each PI, we aggregate their pre-merger publication text into a single text profile: titles, abstracts, and MeSH keywords. We compute pairwise cosine similarities between the text profiles

of each target PI and the 94 FOIA PIs using TF-IDF representations. For each target PI, we select the five most textually similar FOIA PIs and construct a similarity-weighted average of their observed exposure measures:

$$\widehat{\text{Exposure}}_i = \sum_{k \in \mathcal{N}_5(i)} w_{ik} \cdot \text{Exposure}_k \tag{2}$$

where $\mathcal{N}_5(i)$ denotes the set of five nearest FOIA PIs to target PI i, and w_{ik} are cosine similarity weights normalized to sum to one. Figure 5 shows the distribution of our imputed exposure measure against the observed exposure measures.

4 Merger-Induced Price Effects

4.1 Empirical Strategy

To estimate price effects, we define treatment status based on the Federal Trade Commission's and European Commission's assessments of the merger. Treated product markets are those identified as having competitive overlap between the merging entities. In our sample of high confidence product markets, there are a total of 46 treated markets and 53 control markets. For each treated product market, we use nearest neighbor matching on pre-merger linear price trends and spending levels to identify appropriate control product markets.

Using a difference-in-differences specification at the product market level, we compare price changes in treated markets to matched controls before and after the merger.

$$y_{jmt} = \beta_0 + \beta_1 \text{PostTreat}_{mt} + \gamma_j + \delta_m + \lambda_t + \epsilon_{jmt} \tag{3}$$

where y_{jmt} denotes the average log outcome (price, quantity or spending) in market m at university j in year t. The terms γ_j, δ_m, λ_t represent university, market, and year fixed effects, respectively. The indicator variable PostTreat_{mt} equals 1 for treated markets in the post-merger period ($\geq$ 2014). The coefficient of interest, β_1, captures the merger-induced price shock. We estimate this specification separately for each product market to reflect heterogeneity in competitive conditions and demand elasticities.

4.2 Results

Our first stage results show that the Thermo Fisher and Life Technologies merger led to significant and persistent price increases in affected product markets. Event study estimates in Figure

1 show that post-merger, prices in treated markets increased by approximately 20 percent relative to control markets. Figure 2 shows that spending in the treated markets rose by a similar magnitude, while Figure 3 shows that quantities had no significant change. This pattern indicates that researchers exhibited highly inelastic demand for laboratory consumables, absorbing price shocks through higher expenditures rather than reducing consumption. Our market-level merger-induced price changes are shown in Figure 4.

5 Downstream Research Effects

5.1 Empirical Strategy

We estimate the effect of merger-induced cost increases on research output using an event study specification that interacts each PI's continuous exposure measure with relative year indicators:

$$y_{it} = \mu_i + \lambda_t + \sum_{n=-G}^{N} \beta_n [D_{i,t-n} \times \text{Exposure}_i] + \epsilon_{it} \tag{4}$$

where y_{it} denotes research output (e.g., publication count) for PI i in year t. The terms μ_i and λ_t represent PI and year fixed effects, respectively. The indicators $D_{i,t-n}$ denote relative year dummies centered on the merger year (2014), and Exposure_i is the PI's imputed exposure to merger-induced price shocks as constructed in Section 3.5. We normalize the coefficient at $t = -1$ to zero.

The coefficients β_n trace out how the publication trajectories of more-exposed PIs diverge from those of less-exposed PIs relative to the merger. PI fixed effects absorb time-invariant differences in baseline productivity, while year fixed effects capture aggregate trends in publication activity common to all researchers.

This specification estimates how publication trajectories vary with the *degree* of exposure, not a binary treatment-control comparison. A coefficient of $\beta_n = -0.8$ in a given post-merger year means that a hypothetical PI with an exposure of 1.0, that is, an 100 percent increase in their consumables costs would produce 0.8 fewer papers in that year. Since no PI has exposure this extreme, the realized effect for any individual researcher is obtained by multiplying β_n by their actual exposure value.

5.2 Results

Figure 6 presents the event study estimates for the number of papers published. In the pre-merger period, the coefficients fluctuate around zero with no discernible trend. After the merger, we

observe a sustained decline in publication counts for more-exposed PIs. The average post-period coefficient is approximately -0.8.

To interpret the magnitude, we use the observed exposure distribution from our FOIA ground truth data. The average PI's exposure to the merger is 0.035, corresponding to a 3.5 percent increase in input costs. Multiplying this by the average post-period coefficient yields $0.035 \times 0.8 \approx 0.03$ fewer papers per year. Relative to the baseline publication rate of 1.75 papers per year, this represents a 2.3 percent decline.

Translating the publication effect into dollar terms, the average PI in our FOIA sample spends approximately \$17,000 per year on consumables. A 3.5 percent cost increase implies an additional \$620 per year in consumables expenditure. The implied elasticity of publication output with respect to consumables costs is approximately -0.67: a one percent increase in consumables costs is associated with a 0.67 percent decline in publication output.[3] Another way to interpert this value is, an \$22,000 increase in consumables costs will lead to one fewer paper publication per PI per year.

These magnitudes, while modest at the individual PI level, are economically meaningful in aggregate. The average cost increase of \$620 per year will not shut down any individual laboratory. However, scaled across the roughly 210,000 life science PIs in our sample, even small per-PI effects imply a substantial cumulative reduction in scientific output attributable to a single merger event.

6 Discussion

This paper provides evidence that supplier consolidation in the life sciences equipment industry has measurable consequences for the production of publicly funded research. The 2014 Thermo Fisher and Life Technologies merger led to sustained price increases of approximately 20 percent in affected consumables markets. Demand for these products is highly inelastic as laboratories absorb the full cost increase rather than reducing consumption. At the PI level, even modest cost shocks translate into declines in publication output, with an implied elasticity of -0.67.

These estimates are likely a lower bound on the total effect of supplier consolidation on research output. Our analysis is restricted to high-confidence product markets capturing approximately 60 percent of consumables spending. Since price effects in markets we cannot classify with sufficient precision are omitted from PI exposure measures, the merger likely had an even larger increase on consumables costs. Moreover, we study a single merger in an industry that has undergone extensive consolidation over the past two decades, including Merck's acquisition of MilliporeSigma

[3] The elasticity is computed as $\frac{\%\Delta \text{Publications}}{\%\Delta \text{Costs}} = \frac{-2.3\%}{3.5\%} \approx -0.67$.

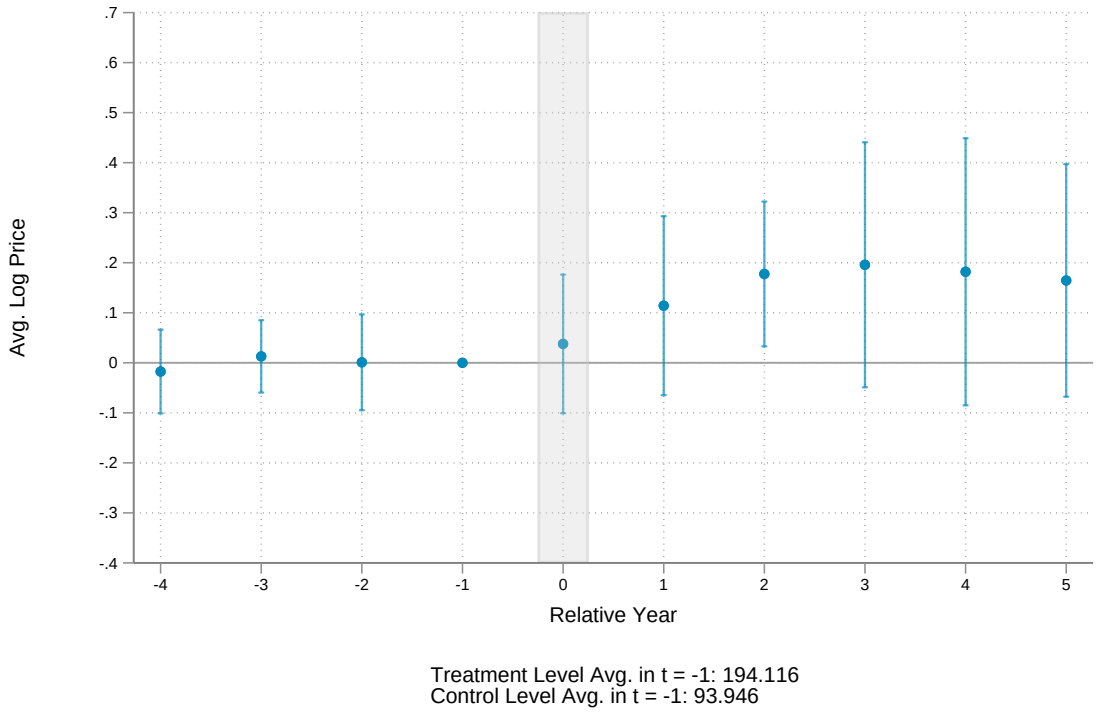
on the chemical side. The cumulative effect of this consolidation trend is likely substantially larger than what we estimate from a singular merger.

Our findings speak to a gap in the science policy literature, which has focused almost entirely on the funding side of research production—whether grant budgets are adequate, how awards should be structured, and which proposals to fund. We show that the supply side also matters. Even holding funding constant, changes in input market structure alter the effective purchasing power of research grants and thereby affect the quantity of science produced. Antitrust enforcement in scientific supplier markets is not merely a question of competitive pricing, but also has downstream consequences for the rate of publicly funded discovery.

The inelasticity of demand documented in our first stage implies that the adjustment to higher input costs does not operate through reduced consumption of affected products. Instead, laboratories must adjust through other channels. Several possible mechanisms include reallocating grand spending away from research personnel or spending more time on grant applications rather than experiments.

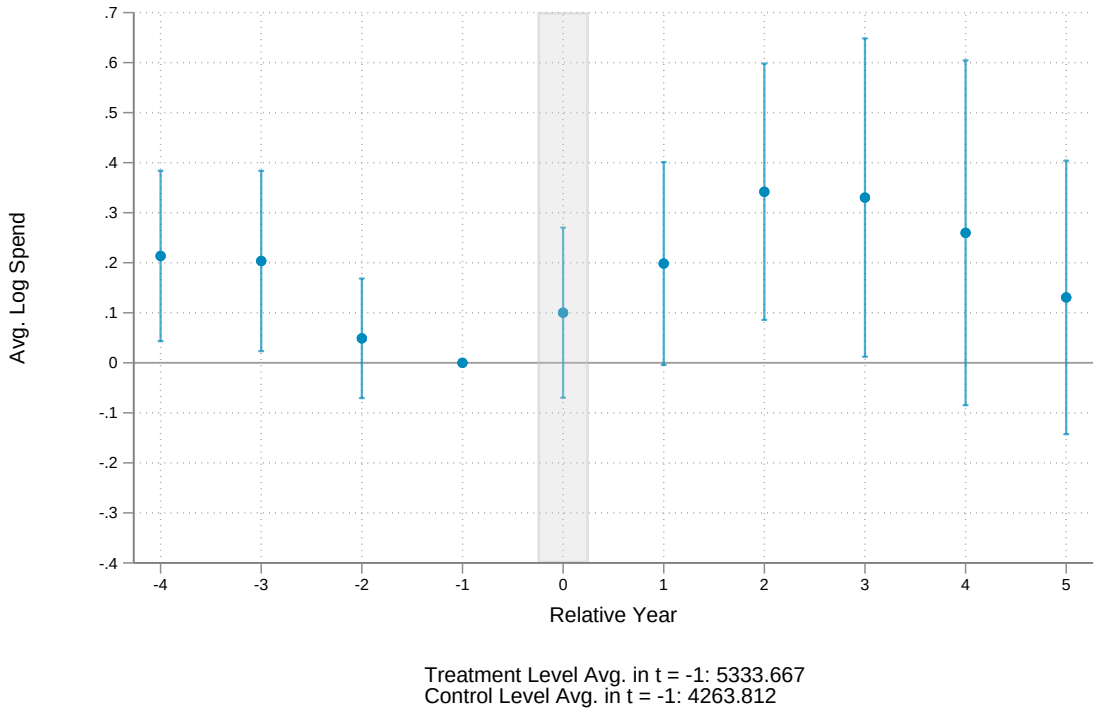
Finally, our results carry implications for several areas of policy. For antitrust review, we provide evidence that merger-induced price increases in input markets have consequences beyond the immediate buyers and propagate downstream to affect the output of publicly funded research. The FTC required divestiture of three product lines in this merger, yet significant price increases persisted across many other product markets. For funding agencies, our findings highlight an underappreciated source of erosion in the real value of grant awards. Input price inflation effectively constitutes a hidden funding cut, and agencies could partially address this by incorporating input price indices into grant adjustment mechanisms. For universities, the current system of opaque, individually negotiated supplier contracts limits price transparency and bargaining power. Collective purchasing arrangements or centralized price benchmarking across institutions could help mitigate the pricing power that concentrated suppliers currently exercise.

Figure 1. Pooled Merger-Induced Price Effects



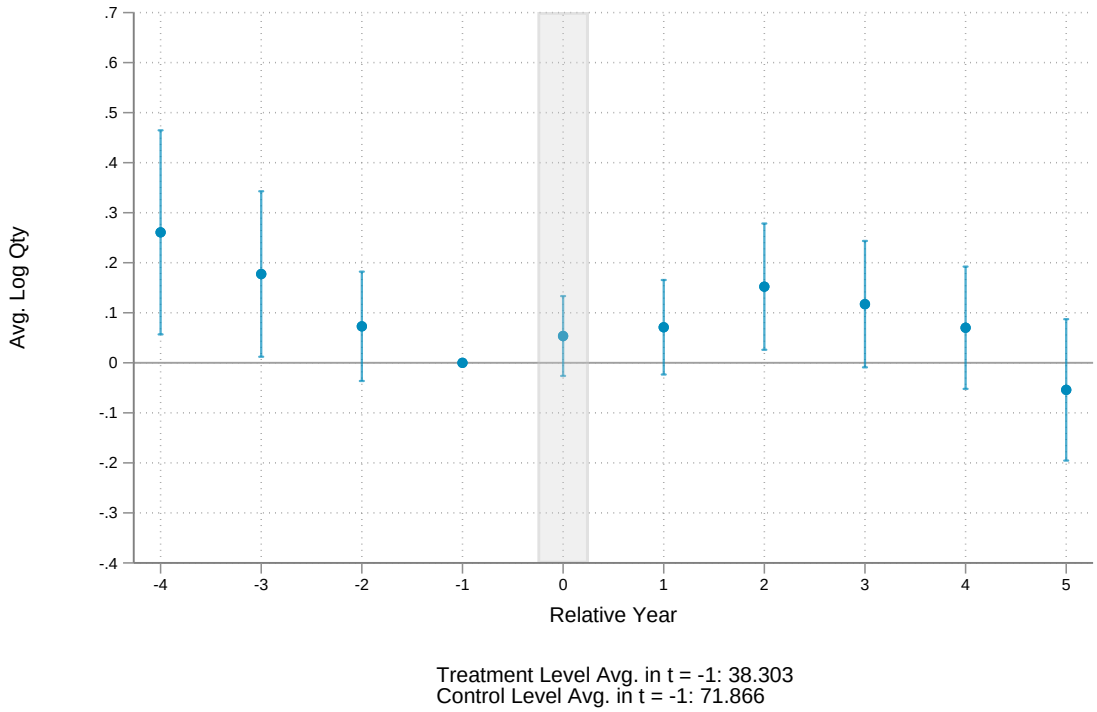
Notes: Event study estimates of the effect of the Thermo Fisher-Life Technologies merger on average log prices in treated product markets relative to matched controls. The vertical gray band indicates the merger year (2014). Coefficients are normalized to zero at $t = -1$.

Figure 2. Pooled Merger-Induced Spending Effects



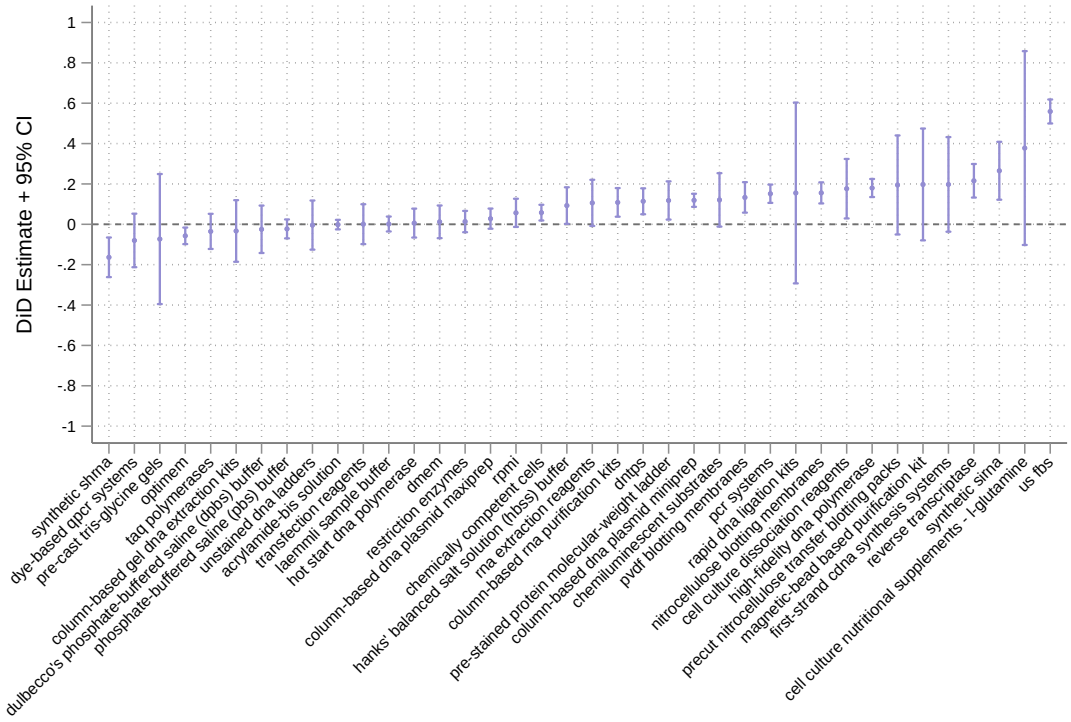
Notes: Event study estimates of the effect of the merger on average log spending in treated product markets relative to matched controls. The vertical gray band indicates the merger year (2014). Coefficients are normalized to zero at $t = -1$.

Figure 3. Pooled Merger-Induced Quantity Effects



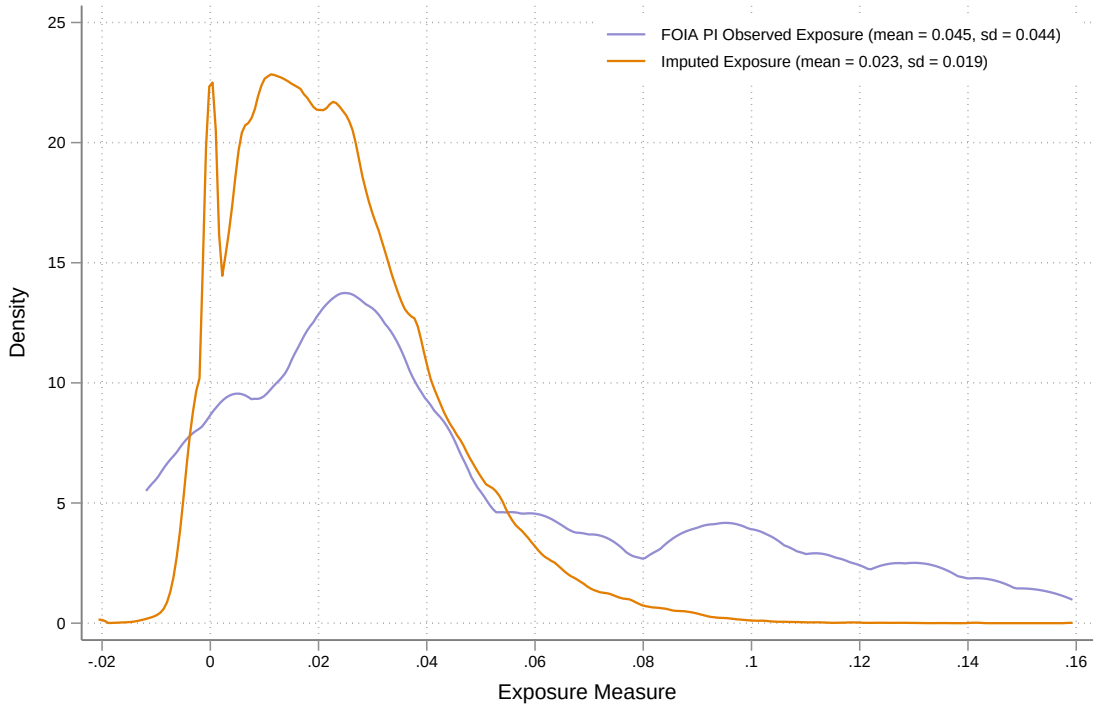
Notes: Event study estimates of the effect of the merger on average log quantity in treated product markets relative to matched controls. The vertical gray band indicates the merger year (2014). Coefficients are normalized to zero at $t = -1$.

Figure 4. Market-Level Merger-Induced Price Effects



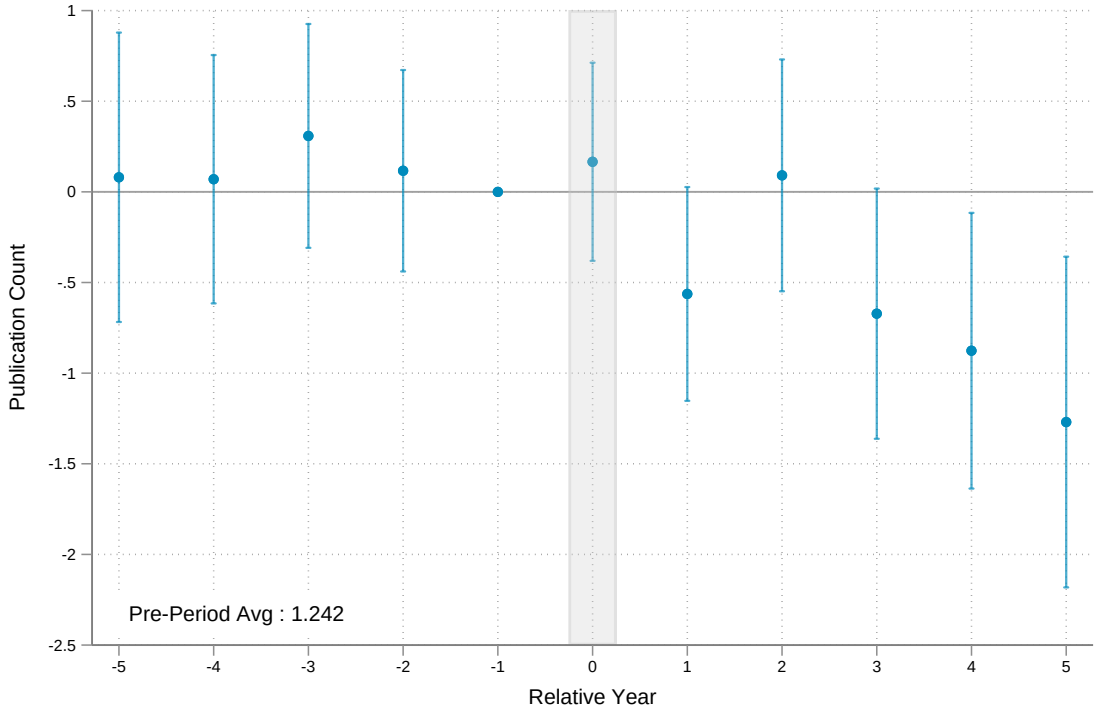
Notes: Each point represents a separate difference-in-differences estimate for one product market, with 95% confidence intervals. Markets are ranked by the size of the estimated price effect.

Figure 5. Observed and Imputed PI Exposure Distributions



Notes: The purple line shows the distribution of directly observed exposure among 94 FOIA PIs. The orange line shows the distribution of imputed exposure for the full research panel of 209,993 PIs. The imputed distribution has lower variance due to the averaging across five nearest neighbors.

Figure 6. Effect of Merger Exposure on Publication Counts



Notes: Event study estimates from equation (4), plotting coefficients on the interaction of PI exposure with relative year indicators. The vertical gray band indicates the merger year (2014). Coefficients are normalized to zero at $t = -1$.

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