

Managing the Rising Cost of Science: Supplier Consolidation in the Academic Life Sciences

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Abstract

Many scientific inputs are sold in increasingly concentrated markets that expose scientists to rising prices, while experimental protocols calibrated to specific products make it difficult to substitute away from them. How much science is lost when these inputs become more expensive, and which scientists are better able to adjust? Using purchase-level procurement records, we follow a merger of two large life sciences suppliers from the prices principal investigators (PIs) pay to the research they produce. Post-merger prices in affected markets rose by almost 20 percent. Quantities declined only slightly and temporarily in all markets, indicating limited demand response. PIs facing larger increases in their input costs published less. For the average PI, input costs rose by about 2.8 percent, and our estimates imply a 1.2 percent decline in research output. Higher input prices can therefore reduce scientific production, not just raise research costs. The output losses appear larger among early-career PIs. Financial resources do not appear to fully explain this difference. Instead, our findings suggest that experience may help PIs adjust to higher prices, potentially through tacit knowledge accumulated through training and years of running a lab.

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1 Introduction

Scientific discovery is a resource-intensive process that depends not only on ideas and research talent, but also on experimental inputs sold in increasingly concentrated supplier markets—leaving scientists exposed to price increases for some of their most essential inputs ([European Commission, 2008](#); [Federal Trade Commission, 2014](#)). Substituting away from inputs whose prices have risen is difficult because experimental protocols are calibrated to specific products, making adjustments costly to implement and scientifically risky ([Bradbury and Plückthun, 2015](#); [Freedman et al., 2015](#)). Higher input prices can therefore translate into higher research costs that scientists cannot easily avoid.

Even so, bearing these higher research costs does not necessarily mean producing less science. Scientists can adjust along many dimensions of their research process, including which experiments to run, whom to hire, and what to purchase from which suppliers ([Zhuo, 2023](#)). How effectively scientists can adjust, however, may depend on the resources and capabilities available to them. Financial resources may provide one advantage by allowing scientists to continue their planned research when it becomes more expensive ([Ganguli, 2017](#); [Tham, 2023](#)). Experience may provide another, as scientists accumulate tacit knowledge over their careers about how to reorganize their research to be more cost-effective ([Thompson and Zyontz, 2017](#); [Coppola et al., 2025](#)). How scientists respond to higher input prices can therefore reveal both whether these prices constrain scientific production and what enables some scientists to adapt to them more effectively than others.

To answer these two questions, we use the 2014 merger of Thermo Fisher Scientific and Life Technologies Corporation, two of the largest life sciences input suppliers, as a shock to the prices principal investigators (PIs) pay for their inputs. The two firms overlapped in supplying a range of molecular and cellular biology *consumables*—routinely purchased experimental inputs such as reagents, enzymes, and cell culture media—so the merger generates plausibly exogenous

variation in the prices PIs pay for these consumables. We assemble novel procurement records covering 2.9 million purchases at 86 U.S. public universities from 2010 to 2019, which allow us to observe the specific consumables purchased and the prices paid for them.

We first establish that the merger raised prices in the product markets where the merging firms competed and that these higher prices translated almost entirely into higher spending. To identify these product markets, we hand-label 368,765 purchases into groups of consumables that can be used interchangeably for the same experimental purpose and use these labels to train a natural language processing classifier. Using a matched difference-in-differences design, we compare product markets with pre-merger competitive overlap to similar product markets unaffected by the merger. Prices in affected markets rose by almost 20 percent relative to comparison markets. Quantities declined temporarily in both groups, but showed no differential decline in affected markets. Together, these results suggest that demand for these consumables is highly inelastic. Spending therefore rose by roughly the same amount as prices, increasing the cost of PIs' consumables purchases.

The merger raised PIs' consumables costs by different amounts because their experimental methods rely on different bundles of consumables. The price increase itself also differed across affected product markets, and we estimate it separately for each market using the same matched difference-in-differences design. We capture both sources of variation with a PI-level exposure measure that weights each product market's estimated price increase by the PI's pre-merger spending share in that market. We then leverage differences in exposure to estimate the effect of higher consumables costs on scientific research output among 13,515 U.S. life sciences PIs.

Our analysis suggests that higher consumables costs reduce scientific research output. Event-study estimates show a sustained decline in publications among more-exposed relative to less-exposed PIs following the merger. The merger raised the average PI's overall consumables costs by approximately 2.8 percent, and our estimates imply that scientific research output fell

by about 1.2 percent. These magnitudes imply an elasticity of scientific research output with respect to consumables costs of approximately -0.42 . In dollar terms, one fewer publication per year corresponds to approximately \$14,500 in higher annual consumables costs, roughly what the average PI in our procurement records spent on these consumables in a year.

We next ask whether the effect of higher costs differs across PIs and find that the output loss appears larger among early-career PIs. Among PIs less than 14 years into their careers, scientific research output declined more sharply as consumables costs rose, while the response among late-career PIs is smaller and not statistically distinguishable from zero. We measure career stage as years since a PI's first last-authored publication, which proxies for how long the PI has been independently running a lab. The gap between the two groups is large but imprecisely estimated using this measure, and becomes larger and statistically significant when career stage is instead measured by years since a PI's first publication of any kind, which includes time as a trainee. This career-stage difference raises the question of why early-career PIs appear more affected by higher costs.

One possible explanation is that late-career PIs have greater financial resources with which to absorb the cost shock. Early-career PIs receive less funding from the National Institutes of Health (NIH) on average, so differences in funding could explain why their output fell more. Yet we find little evidence that greater financial resources reduce the effect of higher costs. Output declines do not appear to differ significantly by PIs' NIH funding or their universities' R&D environments. Moreover, when we compare early- and late-career PIs with similar levels of NIH funding, early-career PIs still show larger declines, although these differences are imprecisely estimated. Differences in financial resources therefore do not appear to fully explain the larger decline among early-career PIs.

Another possible explanation is that late-career PIs have learned through experience how to reorganize their research and purchasing when consumables prices rise. Our survey of

currently active life sciences PIs provides suggestive evidence consistent with this explanation. Most of the 23 respondents report learning how to make purchasing decisions through trial and error rather than through formal training. In the written responses, several early-career PIs describe cutting back on research activity, while some late-career PIs describe changes to their research process that may lower costs. Although these patterns are suggestive and cannot rule out other explanations for the larger decline among early-career PIs, they are consistent with experience helping PIs adjust to higher consumables prices.

Across our sample, the merger implies approximately \$5.1 million per year in higher consumables costs and roughly 349 fewer publications per year, the annual total output of about 160 PIs in our sample. This research is funded primarily by federal grants from agencies such as the NIH and the National Science Foundation (NSF), so higher consumables prices can transfer public research dollars to private suppliers while reducing the science produced with those dollars. Using average pre-merger NIH funding per publication as a benchmark, the lost research could be worth roughly \$67 million per year, considerably more than the \$5.1 million transferred to suppliers.

This paper makes three primary contributions. First, we show that scientific production can be shaped by the markets supplying experimental inputs. Prior work studies how funding shapes the amount and direction of research ([Jacob and Lefgren, 2011](#); [Howell, 2017](#); [Li et al., 2017](#); [Tabakovic and Wollmann, 2019](#); [Myers, 2020](#); [Azoulay et al., 2021](#); [Babina et al., 2023](#); [Tham, 2023](#); [Tham et al., 2024](#); [Myers and Tham, 2026](#)). Other work shows how access to research materials, infrastructure, equipment, and technologies affects scientific production ([Furman and Stern, 2011](#); [Williams, 2013](#); [Murray et al., 2016](#); [Waldinger, 2016](#); [Furman and Teodoridis, 2020](#); [Baruffaldi and Gaessler, 2021](#); [McKeon and Boudou, 2024](#)). In this paper, we argue that the markets supplying these inputs may matter as well, since they determine the prices scientists pay. Related work on scientific input markets shows that lower prices for scientific books increased subsequent research building on them ([Biasi and Moser, 2021](#))

and that consolidation among academic publishers raised journal prices ([McCabe, 2002](#)). Our results provide evidence that when supplier consolidation raised consumables prices, quantities purchased did not fall relative to other markets, and PIs whose consumables costs rose more produced fewer publications.

Our second contribution is to show that PIs appear to differ in their responses to higher input prices and to provide suggestive evidence that experience may help explain these differences. A large literature documents productivity gains from experience and learning by doing ([Reagans et al., 2005](#); [Hendel and Spiegel, 2014](#); [Papay and Kraft, 2015](#); [Dong et al., 2024](#); [Caplin et al., 2026](#)), while related work shows that management practices can generate large differences in productivity across firms ([Bloom and Van Reenen, 2007](#); [Bloom et al., 2013](#)). PIs are both scientists and managers of their labs, but their training focuses largely on conducting research—leaving many aspects of managing a lab to be learned through experience. Our survey findings suggest that PIs learn through trial and error and that this accumulated experience may also help PIs sustain research output when input prices rise.

Finally, we show how concentration in scientific input markets can further distort the production of publicly funded science. Merger retrospectives often estimate how consolidation affects prices paid by buyers ([Dafny et al., 2012](#); [Ashenfelter et al., 2014](#)), while studies of market power in publicly funded markets examine how much public spending is captured by private firms rather than passed through to intended beneficiaries ([Duggan et al., 2016](#); [Cabral et al., 2018](#)). When supplier concentration raises input prices, PIs generally cannot pass these higher prices on to output prices because scientific knowledge is typically shared through publications rather than sold. Higher prices can therefore reduce the amount of science produced rather than just transferring public research dollars to private suppliers. This loss is particularly costly because PIs capture only a fraction of the social value of their discoveries, so science is already thought to be produced below socially optimal levels ([Nelson, 1959](#); [Arrow, 1962](#)).

Thus, concentration in scientific input markets can compound an existing distortion in the production of scientific knowledge.

2 Institutional Setting

Life sciences PIs manage large research labs where they oversee not only the research agenda but also teams of students, postdoctoral fellows, and lab managers. PIs are also responsible for covering the costs of running their labs, including paying the salaries of their research team and purchasing the consumables required for their experiments. These expenses are primarily funded by the PI's own research grants, which typically provide a set amount of funding over several years. Thus, PIs must decide not only which research projects to pursue but also how to allocate limited grant funding across their research expenses.

In this section, we first explain why PIs have limited ability to substitute away from consumables and expand their research budgets when prices rise. We then describe the scientific input supplier industry, where inelastic demand for consumables interacts with increasing supplier consolidation, and introduce the details of the merger we leverage.

2.1 Managing a Research Lab

PIs face several constraints in managing their research labs that limit their ability to respond when consumables prices rise. PIs cannot easily avoid higher consumables prices because looking for cheaper alternatives and switching products are both costly. Finding a lower price for the same product requires comparing prices across suppliers or negotiating discounts from individual sales representatives—a fragmented process that takes time away from research.

Even when cheaper alternatives do exist, switching costs are high enough that PIs are unlikely to reduce their purchases when prices rise. Experimental protocols are calibrated to specific consumables (Walsh et al., 2005, 2007), so adopting a new supplier's product can require weeks or months of revalidation and carries the risk that experimental results will not

reproduce ([Lorsch et al., 2014](#); [Torrington, 2021](#); [Rehman, 2022](#)). Variability in consumables is itself a well-documented source of irreproducibility ([Bradbury and Plückthun, 2015](#); [Weber et al., 2022](#)), and surveys attribute a substantial share of failed replications to the sensitivity of consumables ([Freedman et al., 2015](#); [Baker, 2016](#)). PIs are therefore unlikely to stop buying consumables when they become more expensive, making demand for these products likely to be highly inelastic.

PIs also cannot easily increase the total amount of funding available to them to help absorb these higher costs in the short run. Federal grants from agencies such as the NIH and NSF fund the vast majority of academic life sciences research and are the main source PIs rely on for funding personnel, equipment, and supplies ([Azoulay et al., 2019](#)). These grants provide PIs with a set budget to produce research over a period that typically lasts three to five years ([Azoulay et al., 2011](#); [Stephan, 2012](#); [Tham, 2023](#); [Carnehl et al., 2025](#)). Awarded amounts are not typically renegotiated within a grant cycle, so PIs facing higher prices in the middle of their cycle must cover the increase with the funding they already have. PIs are able to seek additional grant funding, but new grants take time to secure and generally arrive in later cycles ([Jacob and Lefgren, 2011](#)).

Within a grant cycle, most direct costs are also committed to areas a PI cannot easily adjust. Personnel costs represent roughly 80 percent of a typical NIH research budget and cannot be cut on short notice without breaking multi-year commitments ([Stephan, 2012](#); [National Institute of Allergy and Infectious Diseases, 2026](#)). Supplies and equipment together account for the remaining 20 percent. A majority of this is spent on consumables because large equipment such as freezers and microscopes is often funded through institutional support and shared across research groups ([Ehrenberg et al., 2003](#); [Goldstein and Avasthi, 2021](#)). This makes consumables one of the few margins of spending a PI can adjust within an active grant cycle, yet that flexibility is also constrained, as previously discussed.

A PI facing higher consumables prices is then likely to make adjustments elsewhere in the research process if they must continue purchasing the same consumables and cannot increase their budget in the short run. They may defer hiring to later grant cycles, divert time from research toward raising additional funds, or run fewer experiments overall. Higher consumables prices can therefore affect research even when the quantity of consumables purchased changes little.

2.2 Market Structure of the Scientific Input Supplier Industry

Consumables are produced and sold by a small number of firms that cater to PIs at universities as well as at biopharmaceutical companies. The inelastic demand described in the previous subsection becomes particularly consequential as prices in this industry rise when suppliers consolidate. Since PIs have difficulty substituting away from the consumables they already use, suppliers have more power to raise prices without losing buyers.

Years of consolidation have left the scientific input supplier industry dominated by a few full-line firms, most notably Thermo Fisher Scientific, Avantor, and MilliporeSigma ([European Commission, 2013](#); [Berkrot, 2014](#)). These full-line firms both manufacture their own products and operate broad distribution networks that sell products made by other manufacturers. Smaller independent manufacturers, such as New England Biolabs, typically specialize in making particular types of consumables and reach university PIs through the distribution networks of these larger full-line firms. PIs typically purchase consumables through their university's purchasing platform, which directly incorporates the prices the university has negotiated with these full-line firms. In our conversations with procurement offices at several universities, most reported relying heavily on Thermo Fisher Scientific and Avantor as their primary suppliers of life sciences products.

Universities negotiate with suppliers over prices, but these negotiations provide limited protection against price increases. The negotiated contracts typically establish volume dis-

counts from the list prices that suppliers themselves set and can raise. As a result, even a university with a fixed negotiated discount can face higher prices after industry consolidation if a supplier raises its list price. Negotiations are also often decentralized across universities and sometimes across schools or departments within the same university. Because these contracts are private, universities have little information about the prices negotiated elsewhere, so two peer universities can unknowingly pay different prices for the same product ([Kridelbaugh, 2018](#); [Innovative Bioscience, n.d.](#)).

Universities also have limited leverage to discipline higher supplier prices by shifting their purchases elsewhere. They account for less than 15 percent of Thermo Fisher Scientific's revenues, making them a relatively small customer segment ([Thermo Fisher Scientific Inc., 2026](#)). Hospitals and pharmacies, by contrast, can secure lower prices for devices and drugs by steering volume across competing suppliers ([Ellison and Snyder, 2010](#); [Grennan, 2013](#)). Universities have less scope to redirect demand because PIs' experimental protocols often tie their purchases to specific products and suppliers.

2.2.1 The Thermo Fisher Scientific–Life Technologies Merger

One major consolidation in this supplier industry occurred when Thermo Fisher Scientific acquired Life Technologies for \$13.6 billion, combining two of the industry's largest suppliers. At the time of the merger, Thermo Fisher Scientific was the industry's largest full-line supplier of laboratory instruments and consumables, with \$13.1 billion in annual revenue, while Life Technologies was the second-largest supplier of life sciences consumables, with \$3.9 billion in annual revenue ([S&P Global, 2010](#); [Life Technologies Corporation, 2012](#); [Thermo Fisher Scientific Inc., 2014](#)). The deal was announced in April 2013 and completed on February 3, 2014 ([Thermo Fisher Scientific Inc., 2014](#)).

The two firms competed across a broad range of consumables used in molecular and cellular biology research. In a subset of these markets, the two firms were among only a few

major suppliers. Antitrust authorities expressed particular concern about these markets, which included cell culture media and sera and several gene-modulation products. In some of these markets, the combined firm would hold at least half of worldwide sales ([European Commission, 2013](#); [Federal Trade Commission, 2014](#)).

Antitrust authorities therefore required Thermo Fisher Scientific to divest its cell culture media and sera, gene-modulation, and magnetic-bead businesses to the manufacturer GE Healthcare.¹ The sale gave GE Healthcare the assets and intellectual property needed to manufacture these product lines independently.

Importantly, however, the divestitures only changed who manufactured these products, but not necessarily how PIs purchased them or at what price. This is because Thermo Fisher Scientific sells its own products and those made by other manufacturers through its distribution network, Fisher Scientific. The divested products could continue to be purchased through Fisher Scientific after GE Healthcare took over their manufacturing process, so the change in manufacturer did not necessarily require PIs to change their purchasing behavior. PIs therefore continued to pay the prices their universities negotiated with Fisher Scientific, even for the divested products.

3 Effect of the Thermo Fisher Scientific–Life Technologies Merger on Prices and Spending

In this section, we show how the merger affected the prices PIs paid for consumables and how these price increases translated into higher spending. We first construct a dataset of university consumables purchases and explain how we assign purchases to product markets. We then estimate the merger's average effects on prices, quantities, and spending. Finally, we estimate

¹ See the European Commission's clearance decision in [Case COMP/M.6944](#) and the Federal Trade Commission's analysis of the consent order ([File No. 131-0134](#)).

a separate price effect for each impacted consumables market, which allows us to capture differences in how the merger affected PIs.

3.1 Data on Consumables Prices

Estimating the merger’s effect on consumables prices requires data on what PIs paid for specific products before and after the merger. We assemble these data from university procurement records, where each entry represents a purchase. Because each university uses a different procurement system, these records are not standardized and contain no common identifier for purchases of the same product. Our main data challenge is therefore to identify the product represented by each purchase and determine which products belong to the same *product market*—defined as a set of products that can be used interchangeably for the same experimental purpose.

We address this challenge by building a natural language processing (NLP) classifier that uses item descriptions and supplier names. The classifier works in two steps. It first separates consumables from non-consumables, and then assigns each consumables purchase to a product market. We train the classifier on a set of purchases that we label by hand and then apply it to the procurement records used to estimate the merger’s effects.

3.1.1 Data Sources

We construct two datasets. The *price data* contain the purchases used to estimate the merger’s effects on prices, quantities, and spending. The *training data* contain labeled examples used to train the NLP classifier. Table 1 summarizes the sources used to construct each dataset, which we describe in turn below. The top panel of Appendix Figure A8 shows how these sources combine to form the two datasets and where each enters our analysis.

Table 1. Data Sources

Source	Obtained from	Purchases	Coverage
Panel A: Price data			
GovSpend extract	Contract with commercial procurement-data vendor	2.9 million (2010–2019)	86 public universities
Oregon State University records	FOIA request	49,087 (2010–2019)	All departments
Panel B: Training data			
<i>Labeled by product market and consumable status</i>			
UT Dallas procurement records	FOIA request	61,882 (2011–2024)	Departments of Biological Sciences and Chemistry & Biochemistry
UMich procurement records	FOIA request	306,883 (2010–2019)	Departments of Molecular, Cellular and Developmental Biology, Biological Chemistry, and Pharmacology
<i>Labeled as non-consumables only</i>			
California state procurement records	California Open Data Portal	162,717 (2012–2015)	Non-life sciences state purchase orders
Thermo Fisher Scientific negotiated price list	2025 New York State contract	5,997	Furniture, equipment, and apparel categories

Notes: This table lists the sources of the price data used to estimate the merger's effects in Panel A and of the training data used to train the classifier in Panel B. A purchase is a single entry in a procurement record. FOIA denotes the Freedom of Information Act.

Price Data. GovSpend is a commercial procurement-data vendor that aggregates publicly available procurement records from U.S. public entities through open records requests and partnerships with institutional purchasing portals. We obtain an extract of 2.9 million life sciences purchases across 86 public universities from 2010 to 2019. Each purchase reports the item description, price paid, quantity ordered, total spending, purchase date, supplier name, and purchasing university. Appendix B describes how we construct this extract.

We also obtain additional procurement records through Freedom of Information Act (FOIA) requests filed with public universities. Nine universities provided records with purchase-level

prices from before the merger: East Carolina University (ECU), Texas Tech University (TTU), University of Kansas (UKansas), University of Florida (UF), University of South Florida (USF), University of Texas at Austin (UT Austin), University of Texas at Dallas (UT Dallas), University of Michigan (UMich), and Oregon State University (OSU). Eight of these universities are already included in the GovSpend extract, so we only add the procurement records from OSU to the price data.²

Training Data. We construct the training data from four sources. We hand-label purchases from UT Dallas and UMich procurement records by grouping them into product markets and classifying each market as consumable or non-consumable. We supplement these data with examples of non-consumables from California state procurement records and Thermo Fisher Scientific’s negotiated price list with the State of New York.

The UT Dallas and UMich records offer different advantages for constructing the training data. For UT Dallas, we have supplier catalog numbers (SKUs) in addition to item descriptions and supplier names, allowing us to identify products that cannot be reliably determined from the description and supplier alone. While the UMich records do not include SKUs, UMich is the largest university in our FOIA data, and its records span a broader set of life sciences departments, which expands the range of products represented in the training data.

Since the first classification step must distinguish consumables from a broad range of non-consumables, we add two sources of training examples of non-consumables. First, we use publicly available California state procurement records from 2012 to 2015 and keep 162,717 purchases whose United Nations Standard Products and Services Code (UNSPSC) falls in segments unrelated to life sciences consumables. Second, we use Thermo Fisher Scientific’s 2025 negotiated price list with the State of New York and keep 5,997 products listed under the furniture, equipment, and apparel categories. From both sources, we use only the item

² For UT Dallas and UMich, we replace the GovSpend records for these two universities with our hand-labeled FOIA records.

descriptions as training data. The notes to Appendix Table [A2](#) list the UNSPSC segments kept from the California records.

3.1.2 Classification of Purchases into Product Markets

The classifier operates in two steps: (1) determining whether the product purchased is a consumable and (2) assigning consumables purchases to product markets. We first explain how we define product markets and construct the training labels. We then describe the two-step classification algorithm.

Product-Market Definitions and Labeled Training Data. To identify which products can be used interchangeably for the same experimental purpose, we define product markets using Thermo Fisher Scientific’s online product catalog ([Fisher Scientific, 2026](#)). As the largest full-line supplier and distributor of life sciences products ([Federal Trade Commission, 2014](#)), Thermo Fisher Scientific offers a catalog that covers products from a wide range of manufacturers, making it a useful reference for identifying products purchased from many different suppliers.

We use the catalog to assign each item description–supplier pair in the UT Dallas and UMich records to a product market. We search for the purchased product in the catalog using its description and supplier name and, for UT Dallas purchases, SKUs when available. We then use the “product type” listed on the corresponding catalog page as the initial product-market assignment.

For products covered by the European Commission’s (EC) analysis of the merger, we refine these initial assignments using the EC’s findings on substitutability ([European Commission, 2013](#)). In some cases, the EC distinguishes products within a catalog product type that are not interchangeable in practice. For example, Thermo Fisher Scientific lists fetal bovine serum as a single product type, whereas the EC finds that fetal bovine serum from different geographic origins is not substitutable. We therefore separate fetal bovine serum into product markets based on country of origin. Appendix Figure [A9](#) provides a visual example.

We then hand-label each product market as consumable or non-consumable. Consumables markets include products such as *pipette tips*, *latex gloves*, and *Taq DNA polymerase*, whereas non-consumables markets include products such as *desktops*, *lab cabinets*, and *hotplates*. To train the classifier’s first step, which distinguishes consumables from non-consumables, we combine these UT Dallas and UMich labels with the additional examples of non-consumables from the California procurement records and Thermo Fisher Scientific price list described previously. The resulting training data contain 368,765 item description–supplier pairs from UT Dallas and UMich, 162,717 item descriptions from the California records, and 5,997 item descriptions from the price list. The UT Dallas and UMich pairs are assigned to 2,091 product markets, of which 1,105 are consumables markets.

Classification Algorithm. The first step of the classifier separates consumables from non-consumables. We combine keyword rules with a logistic regression on term frequency–inverse document frequency (TF-IDF) representations of the item descriptions and supplier names.³ The keyword rules classify clear cases directly. For instance, item descriptions containing keywords such as *polymerase* or *antibody* are classified as consumables, and descriptions containing keywords such as *shipping* or *furniture* are classified as non-consumables. The logistic regression uses the training data and classifies the remaining purchases.

The second step assigns each consumables purchase to one of the 1,105 product markets using nearest-neighbor matching in TF-IDF space. To distinguish closely related markets with similar descriptions, we use keyword rules for terms that clearly identify a particular market. For example, descriptions containing “taq” and “polymerase” but not “hot start” are assigned to *Taq DNA Polymerase* rather than *Hot Start DNA Polymerase*. When a keyword rule and the nearest-neighbor match disagree, the keyword rule takes precedence.

³ We ran a BERT-based alternative and found that the TF-IDF text representations outperformed it at substantially lower computational cost.

Some product markets that we can distinguish by hand have item descriptions that are too similar for the classifier to distinguish reliably. In these cases, we combine them into a broader market for classification and estimation. For example, primary antibodies targeting different antigens are not substitutes and are therefore labeled as separate markets by hand. However, their item descriptions are too similar for the classifier to reliably assign purchases to the correct product market, so we combine them into a single *Primary Antibodies* market.⁴

3.1.3 Final Estimation Sample

We impose three restrictions on the classified purchases to construct the final estimation sample. First, to keep the composition of universities stable over time, we retain universities that consistently report procurement records from 2010 to 2019.⁵

Second, we keep only product markets that the classifier assigns reliably. We evaluate our classifier on the hand-labeled UT Dallas and UMich purchases. For each product market, precision is the share of purchases assigned to that market that belong to it, and recall is the share of purchases that belong to that market that are correctly assigned to it. Both scores fall when there are few labeled training examples for that product market. Thus, we only keep product markets with at least 25 labeled examples and precision and recall of at least 0.8. Product markets that meet these thresholds account for 55 percent of consumables spending in our price data (\$115 million). Appendix Table A2 reports average precision and recall scores for both steps of the classifier.

Finally, we exclude 34 markets that experienced other major shocks during the sample period, so that price movements unrelated to the merger do not enter our estimates. Examples of excluded markets include laboratory filtration following Danaher's 2015 acquisition of Pall

⁴ We aggregate markets that relate to labware, such as beakers, cuvettes, and vials, and markets such as antibodies and cell lines. These markets lie outside the two firms' competitive overlap, so this aggregation does not change the definition of any market in that overlap.

⁵ A university is defined as reporting consistently if its procurement records cover at least eight months of each year.

and synthetic DNA oligonucleotides following the entry of Twist Bioscience and the expansion of Integrated DNA Technologies. None of these excluded markets is among the markets in which Thermo Fisher Scientific and Life Technologies competed before the merger.

The final estimation sample contains roughly 515,000 purchases from 73 universities across 152 product markets, accounting for 36 percent of total consumables spending in our price data (\$76 million). We refer to these 152 product markets as *high-confidence markets*. We aggregate these purchases to the university–product market–year level for estimation. Appendix Table A1 provides descriptive statistics on the top universities, suppliers, and product markets in the final estimation sample.

3.1.4 Price, Quantity, and Spending Variables

Each purchase reports the number of items ordered and the price paid for each item. The records do not report the amount contained in each item, so we do not observe the unit price—the price per mL, gram, or other standardized unit. For example, a purchase of three bottles of fetal bovine serum reports the price per bottle but not whether each bottle contains 50 mL or 500 mL.

We use these records to construct measures of quantity, price, and spending at the university–product market–year level. For each purchase, price is the amount paid per item, quantity is the number of items ordered, and spending is the product of price and quantity. We aggregate quantity and spending by summing across purchases within each university–product market–year and taking the log of each total. For price, we instead take the log of the per-item price for each purchase and average these values within each university–product market–year. Table 2 summarizes these definitions.

Because we do not observe the amount contained in each item, a shift in item size could affect both our price and quantity measures. For example, if fetal bovine serum were sold in larger bottles after the merger, the price per bottle could increase even if the price per mL

remained unchanged. At the same time, fewer bottles would be needed to purchase the same amount of serum. We therefore examine price and quantity together to distinguish changes in prices from a shift in item size.

Table 2. Key Variables

Variable	Symbol	Measure
Price	P_{jmt}	Average price per item across purchases by university j in product market m and year t
Quantity	Q_{jmt}	Total number of items ordered by university j in product market m and year t
Spending	S_{jmt}	Total spending by university j in product market m and year t

Notes: This table defines the price, quantity, and spending variables used in the estimation. A purchase is a single entry in a procurement record, which reports the number of items ordered and the price per item, but not the amount contained in each item (e.g., bottle volume). Spending is price multiplied by quantity. Quantity and spending are summed across purchases within each university–product market–year before taking logs, while price per item is logged before averaging across purchases.

3.2 Average Merger Effects on Prices, Quantities, and Spending

We first establish that the merger raised prices on average across treated product markets, with little relative change in quantities and a corresponding increase in spending. To estimate the overall effect, we pool treated markets and their matched controls and estimate an event-study specification.

Defining Treated and Control Markets. The EC identified twelve consumables areas in which Thermo Fisher Scientific and Life Technologies had pre-merger competitive overlap ([Case COMP/M.6944](#)). Because our product markets are narrower than these areas, we map our high-confidence product markets into the EC’s analysis. We define a product market as treated ($D_m^T = 1$) if it falls within one of these twelve areas or is complementary to a product market that does.⁶

⁶ A natural alternative would be to compute the Herfindahl–Hirschman Index (HHI) directly from procurement records, since HHI captures pre-merger market concentration. Doing this in our data is hard because GovSpend records supplier names as free-text fields rather than standardized identifiers, so the same firm often appears under multiple variants (e.g., “Thermo Fisher Scientific,” “Thermo Fisher Sci.,” and “ThermoFisher”). While manual cleaning of these fields helps, residual noise still propagates into any firm-level market share calculation and makes HHI a noisy proxy for market concentration.

Of our 152 high-confidence product markets, 46 are treated under this definition, including 15 complementary markets. Although not directly mentioned by the EC, these complementary products are purchased and used alongside products that are—for example, running buffers are required for pre-cast gels—so their prices may also respond to the merger. Our estimates are robust to excluding these markets. Appendix C maps our treated product markets to the EC’s analysis.

All remaining high-confidence markets serve as candidate controls ($D_m^T = 0$). For each treated market m^* , we construct a set of up to two matched controls from these candidate control markets using nearest-neighbor matching on the pre-period average and slope of log prices. Matching is performed with replacement, so the same control market may be matched to multiple treated markets. This procedure yields 51 distinct control markets across the 46 treated-market comparisons.⁷

3.2.1 Empirical Specification

We pool the 46 treated markets and their matched controls in a single event-study regression for each outcome,

$$y_{jmt} = \sum_{\substack{n=-4 \\ n \neq -1}}^5 \beta_n \mathbf{1}\{t - 2014 = n\} \times D_m^T + \gamma_j + \delta_m + \lambda_t + \epsilon_{jmt}, \quad (1)$$

where y_{jmt} is the log outcome (price, quantity, or spending) in market m for products purchased by university j in year t , $\mathbf{1}\{t - 2014 = n\}$ indicates that year t is n years from the merger year 2014, D_m^T equals one for treated markets, and γ_j , δ_m , and λ_t are university, market, and year fixed effects. The specification omits $n = -1$, so each β_n gives the difference between treated and matched control markets relative to the year immediately before the

⁷ Appendix Figures A3, A4, and A5 reproduce the three event studies without matching, comparing treated markets to the full set of candidate control markets.

merger. Observations are weighted by each market's total 2013 spending, and standard errors are clustered at the market level.

Identification rests on the common-trends assumption that, absent the merger, treated and matched control markets would have followed the same counterfactual trajectory in each outcome. We examine pre-merger trends to assess the validity of this assumption.

3.2.2 Results

We find that treated product markets experienced persistent and growing price increases following the merger. Quantities temporarily fell after the merger, but by similar amounts in treated and control markets. As a result, higher prices in treated markets translated into higher spending.

Figure 1 presents the price effect in two panels: Panel (a) plots the pooled difference between treated and control markets, and Panel (b) plots the treated and control price trajectories separately, each normalized to the year before the merger. The flat pre-trend in the pooled difference supports the plausibility of the identifying assumption behind equation (1). Following the merger, the pooled difference jumps in 2014 and climbs steadily, from roughly 10 percent in the first post-merger year to 23 percent by 2019, averaging almost 20 percent over the post-merger period. The separate trajectories by treatment status show that this divergence is driven by rising prices in treated markets, while prices in control markets remained relatively flat aside from a slight decline from the second post-merger year onward.

Treated quantities did not fall relative to controls after the merger, consistent with the idea that substituting away from these products is difficult. Figure 2 plots the pooled difference between treated and control quantities in Panel (a) and their separate trajectories in Panel (b). Despite the substantial relative price increase in treated markets, the pooled quantity difference in Panel (a) remains statistically indistinguishable from zero in every year, which suggests highly inelastic demand. Panel (b) shows a temporary decline of about 10 percent

in both treated and control markets in the year immediately after the merger. This common decline may reflect a temporary tightening of research budgets that reduced consumables purchases across all markets.

Because quantities did not differentially change between treated and control markets, the relative increase in treated prices translated into higher treated spending. Panel (a) of Figure 3 shows a pooled spending increase of roughly 25 percent. Panel (b) shows that treated spending rose steadily after the merger, while control spending remained relatively flat aside from a small decline in the two years after the merger.

Together, the price, quantity, and spending effects characterize demand for the treated consumables as highly inelastic. Treated quantities barely moved relative to controls despite the almost 20 percent price increase, so the higher price passed almost entirely into higher spending on the same consumables rather than into substitution toward cheaper alternatives or smaller quantities ordered.

The absence of a differential quantity response may also provide suggestive evidence against a shift in item size as the source of the price increase. Since the price paid refers to an item of unobserved size, a shift toward items containing a larger amount in treated markets would raise measured price while lowering the quantity ordered in treated markets relative to controls. Treated and control quantities instead moved together after the merger. If anything, the quantity ordered in treated markets rose slightly after 2015, though not significantly. This would be consistent with a shift toward items containing a smaller amount, which would bias our measured price increase downward rather than upward. The price increase therefore likely reflects a change in the unit price of the same set of products rather than a change in item size.

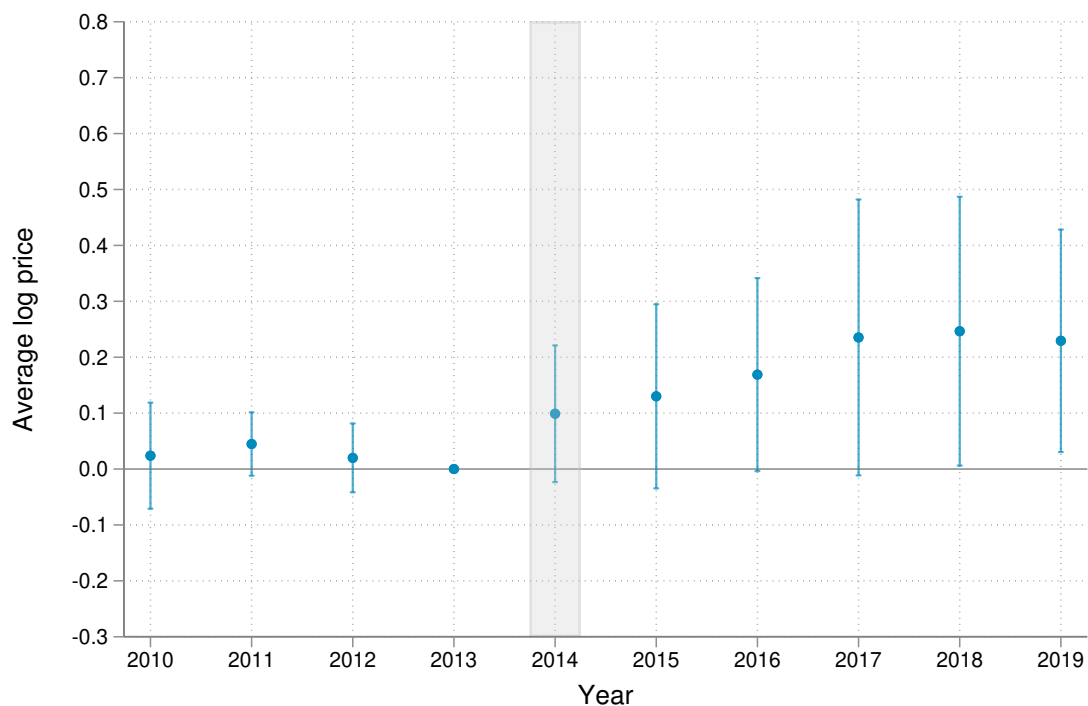
We provide a more direct check using fetal bovine serum, one of the largest treated markets by spending. We identify purchases of 500 mL bottles from item descriptions, allowing us to hold item size fixed. Using the same control markets and specification, we estimate a price increase

of 58 percent for 500 mL bottles, compared with 62 percent for bottles of all sizes. Appendix Figure A6 shows the corresponding event study. This comparison provides further suggestive evidence that the estimated price increases reflect changes in unit prices rather than item size.

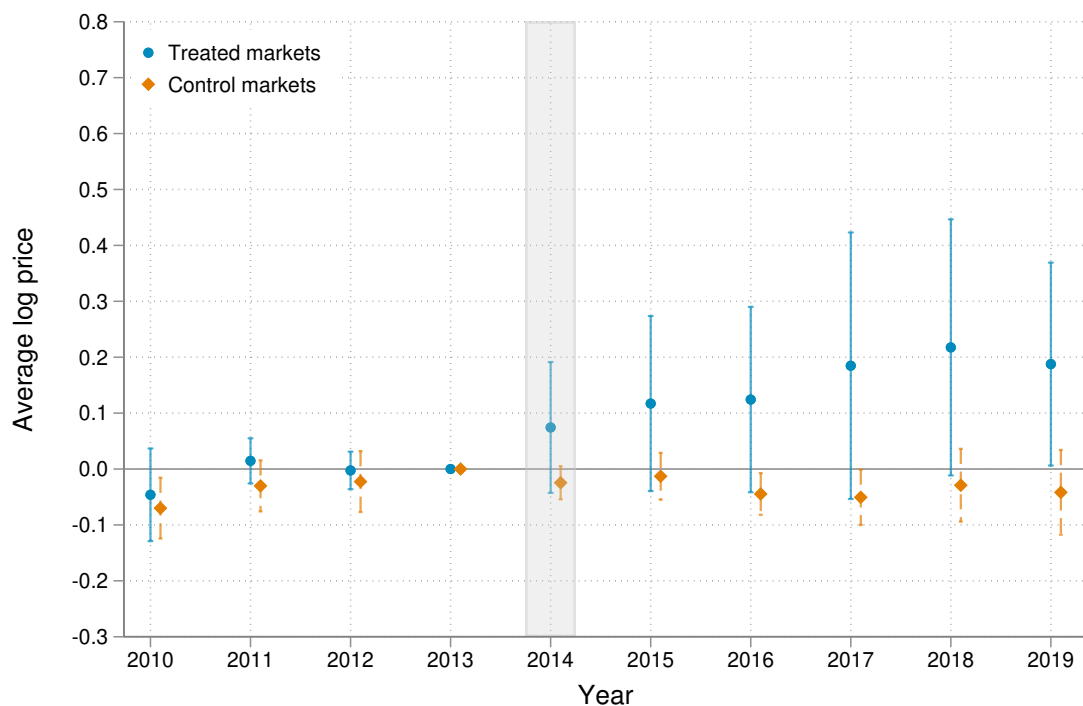
Appendix Table A3 reports pooled difference-in-differences estimates of these effects, with coefficients of 0.164 on the average log price, 0.023 on log quantity, and 0.199 on log spending. The price and spending increases are statistically significant at the 10 percent level, while the quantity response is small and statistically indistinguishable from zero. The price increase is similar in magnitude under alternative fixed effects, when treated markets are compared with all candidate control markets, and when the complementary markets are excluded. A synthetic difference-in-differences estimator yields a somewhat smaller but more precisely estimated price increase, with a coefficient of 0.131, no significant quantity response, and a similar increase in spending.

Figure 1. Pooled Merger Effects on Prices

(a) Pooled difference



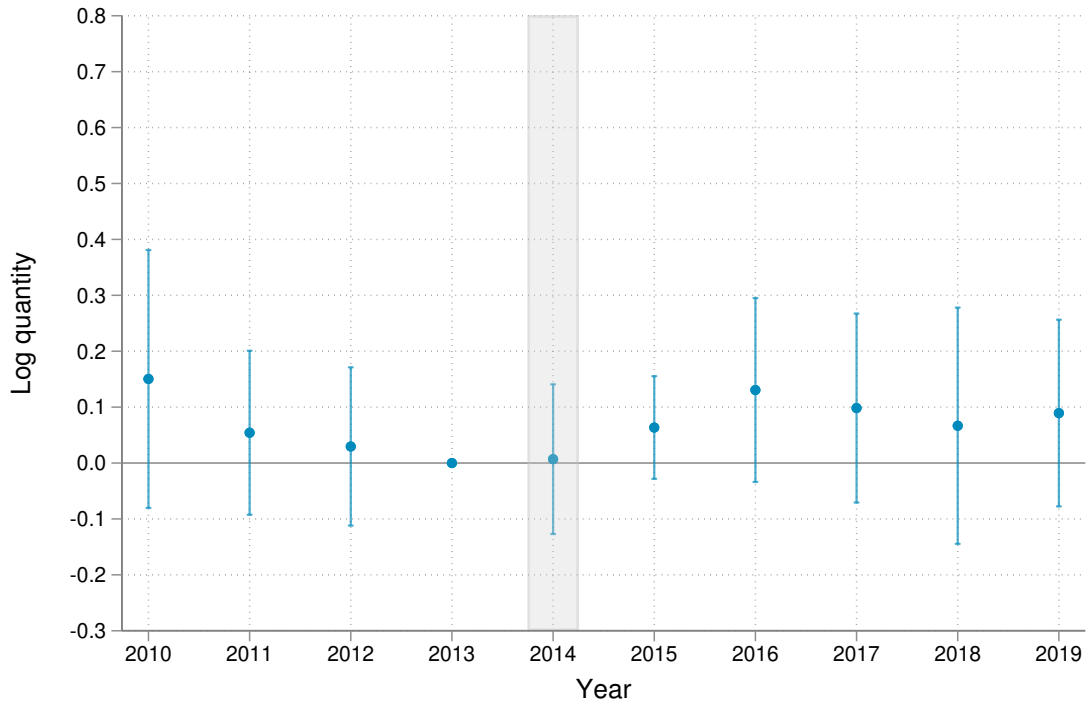
(b) Treated and control market effects



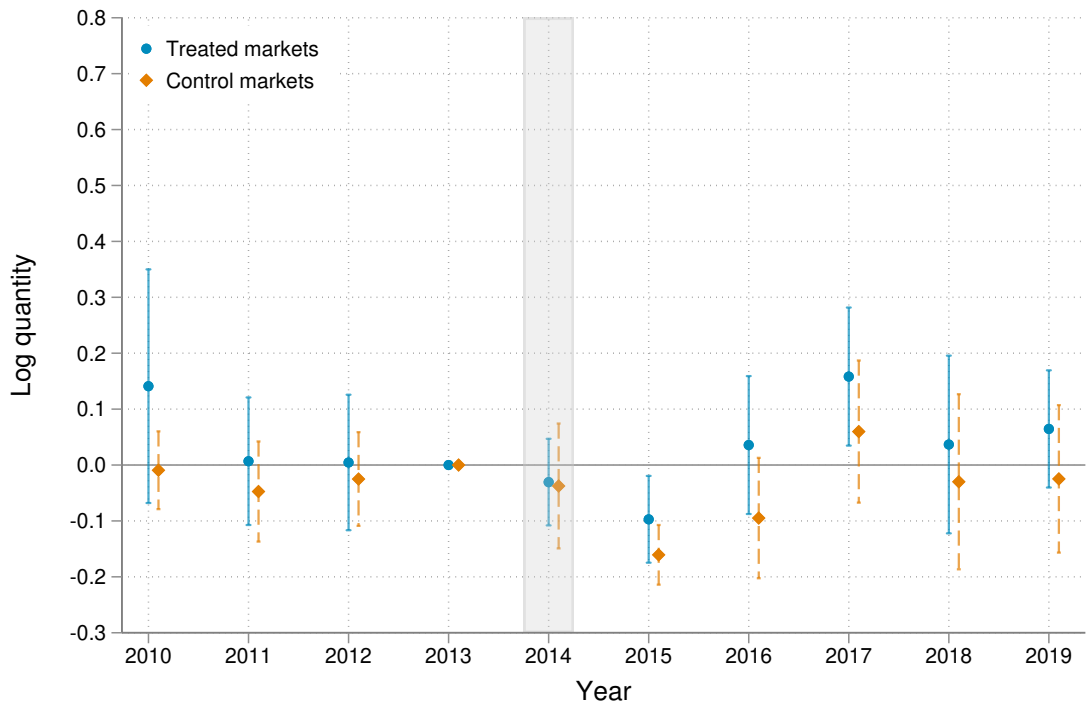
Notes: This figure shows event-study estimates of average log prices around the merger. Panel (a) shows the difference between treated and control markets. Panel (b) plots $\hat{\lambda}_t$ (control, orange) and $\hat{\lambda}_t + \hat{\beta}_n$ (treated, blue), subtracting the linear trend fitted to the control path from both. Standard errors are clustered by market. For Panel (b), they account for covariance among coefficients in each plotted path. The gray band marks the merger in 2014. The average price in $n = -1$ is \$147.47 in treated markets and \$110.44 in matched control markets.

Figure 2. Pooled Merger Effects on Quantities

(a) Pooled difference

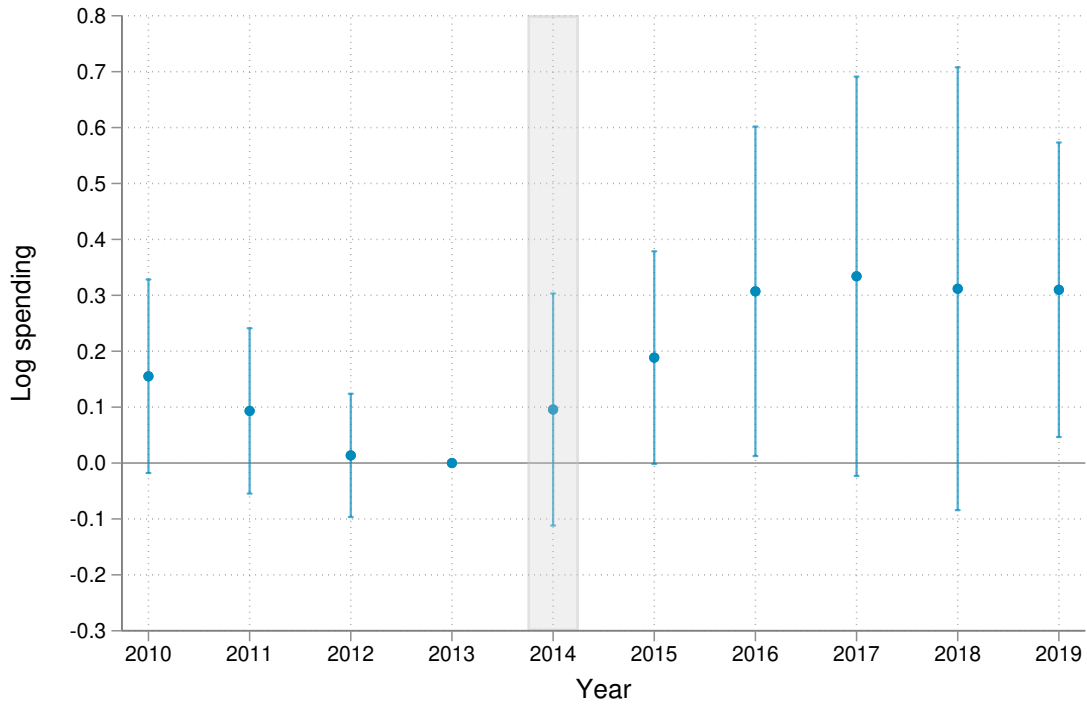


(b) Treated and control market effects

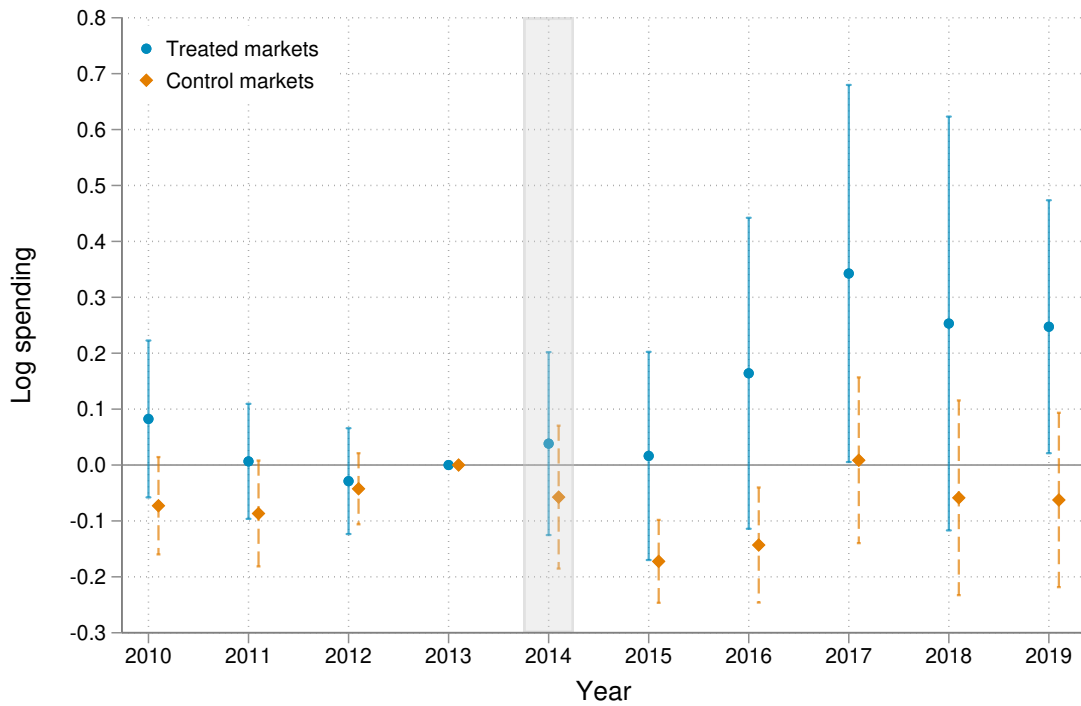


Notes: This figure shows event-study estimates of log quantity around the merger. Panel (a) shows the difference between treated and control markets. Panel (b) plots $\hat{\lambda}_t$ (control, orange) and $\hat{\lambda}_t + \hat{\beta}_n$ (treated, blue), subtracting the linear trend fitted to the control path from both. Standard errors are clustered by market. For Panel (b), they account for covariance among coefficients in each plotted path. The gray band marks the merger in 2014. The average quantity ordered in $n = -1$ is 17.2 in treated markets and 25.1 in matched control markets.

Figure 3. Pooled Merger Effects on Spending
(a) Pooled difference



(b) Treated and control market effects



Notes: This figure shows event-study estimates of log spending around the merger. Panel (a) shows the difference between treated and control markets. Panel (b) plots $\hat{\lambda}_t$ (control, orange) and $\hat{\lambda}_t + \hat{\beta}_n$ (treated, blue), subtracting the linear trend fitted to the control path from both. Standard errors are clustered by market. For Panel (b), they account for covariance among coefficients in each plotted path. The gray band marks the merger in 2014. Average spending in $n = -1$ is \$2,068 in treated markets and \$1,974 in matched control markets.

3.3 Market-Level Price Effects

We next estimate a separate price effect for each treated market using a difference-in-differences design with the same matched control markets as before. These market-level estimates allow two PIs with the same share of spending in treated markets to differ in their exposure to the merger, depending on which treated consumables make up their pre-merger consumables bundles.

3.3.1 Empirical Specification

For each treated market m^* , our difference-in-differences specification replaces the relative-year indicators of equation (1) with a post-merger indicator $\text{Post}_t = \mathbf{1}\{t \geq 2014\}$ and is estimated using that treated market and its matched controls:

$$y_{jmt} = \beta_{m^*}^P \cdot D_m^T \cdot \text{Post}_t + \gamma_j + \delta_m + \lambda_t + \epsilon_{jmt}, \quad (2)$$

where y_{jmt} is the average log price in market m for products purchased by university j in year t , and $\beta_{m^*}^P$ is the estimated price effect for treated market m^* . The terms γ_j , δ_m , and λ_t are university, market, and year fixed effects. Observations are weighted by 2013 market spending, and standard errors are clustered at the market level.

Estimating equation (2) separately for each treated market produces the 46 market-level price effects, $\{\hat{\beta}_m^P\}_{m=1}^{46}$. Because each estimate is based on a relatively small sample of university–product market–year observations, these estimates are more likely to be noisy. We therefore apply empirical Bayes shrinkage to reduce this noise and use the shrunk estimates throughout the remainder of the paper. Appendix D details the procedure.

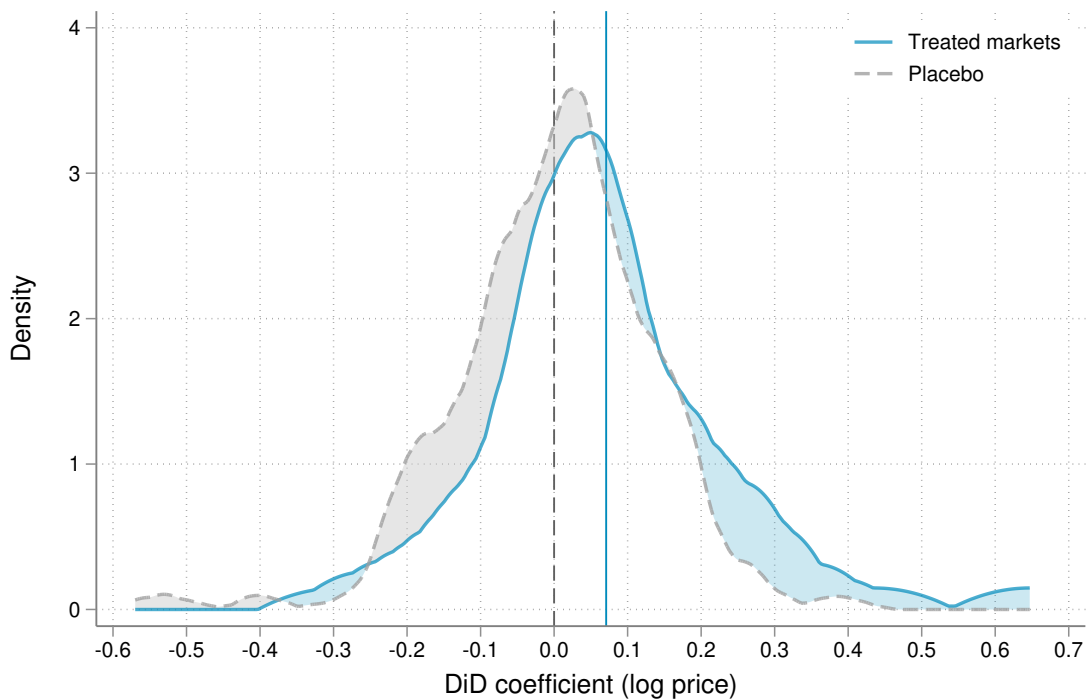
3.3.2 Results

Figure 4 shows the distribution of estimated price effects across treated markets and compares it with a placebo distribution constructed by randomly assigning treatment status across control

markets. The placebo distribution captures the dispersion in market-level estimates that can arise from sampling variation alone.

The treated distribution is centered well above zero, at 0.071, whereas the placebo distribution is centered at zero. This unweighted mean of the market-level effects is smaller than the pooled estimate of 0.164 from Section 3.2.2 because the pooled specification gives greater weight to higher-spending treated markets. Randomization inference rejects the null that the mean treated effect could be generated by placebo treatment assignments, and a Kolmogorov–Smirnov test rejects equality of the treated and placebo distributions.

Figure 4. Market-Level Price Effects



Notes: This figure shows the unweighted distribution of the market-level difference-in-differences price effects $\hat{\beta}_m^P$ across the 46 treated markets (solid) against a placebo distribution (dashed). The placebo distribution pools 100 random reassignments of treated status among the control markets, each the size of the treated set, for 4,600 placebo estimates. The same empirical Bayes shrinkage is applied to both distributions. The treated effects have a mean of 0.071 and a standard deviation of 0.164, and the placebo effects have a mean of 0.002 and a standard deviation of 0.134. Randomization inference compares the mean treated effect to the 100 placebo means ($p < 0.01$), and a Kolmogorov–Smirnov test compares the two distributions ($p = 0.035$).

4 The Effect of Higher Input Prices on Scientific Research Output

This section examines how the higher consumables prices generated by the merger affected scientific research output. We measure research output with an annual panel of PI publications. Since the merger had only a minimal effect on quantities purchased in treated markets relative to controls, we measure each PI's exposure to the price increases as the change in the cost of their pre-merger consumables bundle. We first describe the data and the construction of these measures, then test whether more-exposed PIs publish less after the merger and examine which types of PIs are better able to adjust.

4.1 Data Linking PI Spending to Publications

Estimating the effect of the price increases on research output requires linking each PI's publications to their pre-merger consumables spending. Publications are readily observable from bibliographic databases, but spending is harder to measure, since most of the procurement records from Section 3 do not identify the PI associated with each purchase.

To address this challenge, we use a subset of our FOIA procurement records that identify the PI or the federal award associated with each purchase. These records let us measure each PI's pre-merger spending across product markets, which we combine with the market-level price effects estimated in Section 3 to construct each PI's exposure measure. They cover only some of the PIs in the publication data, so we impute the exposure measure for the remaining PIs based on the similarity of their research to that of the PIs whose purchases we observe. Appendix Figure A8 summarizes the data sources and sample construction.

4.1.1 Publication Records

We construct the publication measures from two large bibliographic databases, PubMed and OpenAlex. We use PubMed to define the universe of life sciences publications and OpenAlex

to link these publications to individual PIs across years. The publication records also provide titles, abstracts, and Medical Subject Headings (MeSH), which we use to measure similarity in the type of research conducted by PIs.

PubMed MeSH Extract. PubMed is the National Library of Medicine’s database of biomedical and life sciences publications, and it indexes each publication with MeSH descriptors—a curated taxonomy of biomedical topics. Our PubMed query covers the descriptors *Anatomy*, *Chemicals and Drugs*, *Organisms*, *Phenomena and Processes*, *Diseases*, *Anesthesia and Analgesia*, *Therapeutics*, and *Clinical Study*, which together capture basic, translational, and clinical life sciences research.⁸ We restrict our sample to journal articles and exclude comments, case reports, technical notes, letters, and reviews.

Within this publication sample, we measure a PI’s scientific research output as the number of journal articles on which they are listed as the *last author*. This choice follows the authorship norms in the life sciences, where the first author is typically the scientist who did most of the experimental work—usually a graduate student or postdoctoral researcher—and the last author is typically the PI, who runs the research lab and funds its research.

OpenAlex. OpenAlex is a comprehensive open catalog of the global research system, developed by the nonprofit OurResearch (Priem et al., 2022). Its key advantage over PubMed is that it provides consistent author and institutional identifiers that allow us to easily track PI publication records over time. OpenAlex aggregates and standardizes information from sources including PubMed, Microsoft Academic Graph, Crossref, and ORCID.⁹ It disambiguates authors by combining name variants with publication records, citation patterns, and ORCID identifiers, and it standardizes institutional affiliations using a machine learning model.

⁸ Our results are similar when we drop the clinical life sciences publications from our sample (not reported).

⁹ Microsoft Academic Graph was a bibliographic database maintained by Microsoft Research until 2021. Crossref is a nonprofit registry of publication metadata and digital object identifiers (DOIs), and Open Researcher and Contributor ID (ORCID) is a nonprofit registry of persistent author identifiers.

Authors often list multiple affiliations, so to identify the institution where each PI's research is actually conducted, we determine a single home institution per year based on their full publication history. We assign each PI the affiliation they list most often in a given year.¹⁰

4.1.2 PI Spending

Among the FOIA records introduced in Section 3.1.1, purchases from five universities can also be linked to individual PIs: UT Dallas, UMich, UT Austin, TTU, and ECU. In addition to prices, these records report either the name of the PI responsible for the purchase or the federal award number used to fund it. When only the federal award number is available, we identify the PI associated with the award using NIH RePORTER, NSF Award Search, USAspending.gov, and publication acknowledgments. In total, we are able to attribute 402,515 of the 479,423 purchases (87% of spending) to a PI.

As described in Section 3.1.2, the UT Dallas and UMich purchases have hand-assigned product-market labels, while purchases from the other three universities are assigned to product markets using our NLP classifier. Each purchase contains information on a PI and a product market, which allows us to measure each PI's pre-merger spending by product market.

4.1.3 PI Exposure to Higher Input Prices

We construct each PI's exposure to the merger as a shift-share measure built from the market-level price effects. We observe this measure directly for PIs whose purchases we observe and impute it for the remaining PIs using publication text similarity.

¹⁰ If two affiliations are tied, we choose the one the PI also lists in the previous year. If the tie remains, we use the following year, and we break any remaining ties at random. We merge medical schools and health systems that are part of a university into that university, so that NYU Langone Health, for example, is merged into New York University. In contrast, we keep separately branded hospitals distinct from their affiliated universities, so that Mass General Brigham is not merged into Harvard University.

Construction. A PI's exposure measure is the percentage increase in the cost of their pre-merger consumables bundle, which we construct by weighting each market's estimated price effect by the PI's pre-merger spending share in that market:

$$\text{Exposure}_i = \sum_m s_{im} \hat{\beta}_m^P, \quad (3)$$

where s_{im} denotes PI i 's pre-merger spending share in product market m and $\hat{\beta}_m^P$ is the empirical Bayes shrunk price effect in market m from equation (2). Intuitively, a PI who spent half of their pre-merger consumables budget in unaffected markets and half in a market where the merger increased prices by 20 percent has an exposure measure of 0.1, corresponding to a 10 percent increase in the cost of their pre-merger consumables bundle.

We calculate s_{im} relative to the PI's total pre-merger spending across the high-confidence markets defined in Section 3.1.3. $\hat{\beta}_m^P$ is estimated only for the treated markets, so only spending shares in treated markets enter the exposure measure. These shares therefore sum to the fraction of the PI's high-confidence pre-merger spending in treated markets, rather than to one. We denote this fraction by $S_i = \sum_{m \in \mathcal{T}} s_{im}$, where $\mathcal{T}$ is the set of treated markets, and refer to it as the PI's treated-market share.

The exposure measure varies across PIs for two reasons: (1) differences in the composition of their pre-merger consumables spending (the s_{im} shares), which reflect different research areas and experimental protocols, and (2) differences across markets in the price effects (the $\hat{\beta}_m^P$ shifts). Some PIs have a negative exposure measure, reflecting a decrease in the cost of their pre-merger bundle. We keep these PIs in our sample because dropping them would condition on the treatment variable and discard identifying variation.¹¹

¹¹ Appendix Table A5 reports the estimate for the positive-exposure subsample. The estimate has the same sign but is smaller and less precise.

Imputation. We can only calculate the exposure measure directly for PIs whose pre-merger purchases we observe. To use these PIs for the imputation, we also require that they have pre-merger publications. Among the PIs identified in the FOIA records, 208 meet both requirements, and we refer to these as our FOIA PIs.

For each non-FOIA PI with pre-merger publications, we impute an exposure measure using the observed exposure measures of FOIA PIs conducting similar research. The intuition is that PIs working on similar topics are likely to use similar experimental protocols and consumables bundles. We measure text similarity using the cosine similarity between TF-IDF representations of each PI's pre-merger publications, based on titles, abstracts, and MeSH terms. We then identify the three most similar FOIA PIs and impute an exposure measure as a weighted average of the FOIA PIs' observed exposure measures:

$$\widehat{\text{Exposure}}_i = \sum_{k \in \mathcal{N}_3(i)} w_{ik} \cdot \text{Exposure}_k, \quad (4)$$

where $\mathcal{N}_3(i)$ denotes the three most similar FOIA PIs. The weights w_{ik} are proportional to squared cosine similarity and sum to one, placing greater weight on the more similar FOIA PIs.

We impute the exposure measure only for PIs whose research is represented among our FOIA PIs. To do so, we group PIs into thirty research clusters using k-means textual clustering of pre-merger publications and retain only PIs whose cluster contains at least one FOIA PI.

To illustrate the procedure, Table 3 provides examples of both steps. In Panel A, we construct the exposure measure for a FOIA PI who works in molecular immunology. Before the merger, this PI spent 18.8 percent of their spending in high-confidence markets on treated markets, mostly on fetal bovine serum, chemiluminescent substrates, and PVDF blotting membranes. Although these three markets had similar shares of spending, the estimated price effect for fetal bovine serum is substantially larger, 0.435. As a result, fetal bovine serum accounts for approximately two-thirds of the PI's exposure measure of 0.034. This example illustrates that

the exposure measure depends not only on how much a PI spends in treated markets, but also on which treated markets they purchase from.

Panel B shows how we impute the exposure measure for a non-FOIA PI who works in structural immunology. We do not observe this PI's purchases, so we compare their pre-merger publications with those of each FOIA PI and identify the three most similar. These end up being the molecular immunologist from Panel A, a cell biologist studying protein misfolding, and a crystallographer studying enzymes and immune proteins. We square their cosine similarity scores, which gives relatively more weight to the most similar PI, and normalize them so that the three weights sum to one. Averaging across the three FOIA PIs' observed exposure measures with these weights yields an imputed exposure measure of 0.047.

Table 3. Example of Constructing Observed and Imputed Exposure Measures

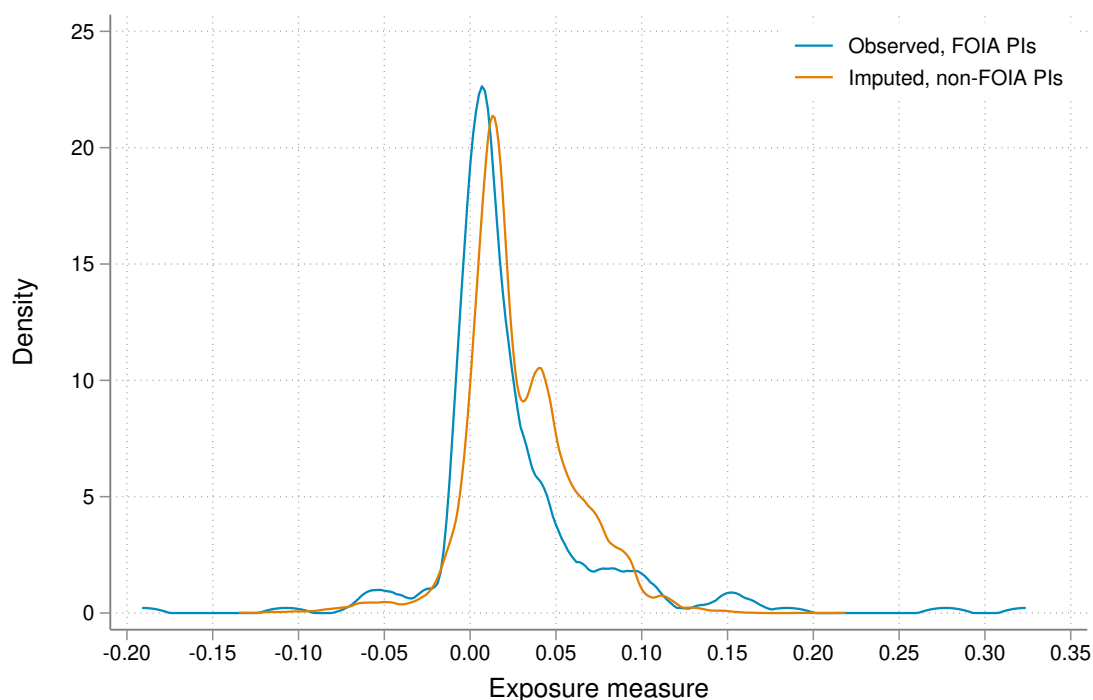
Panel A: Observed exposure of a FOIA PI (<i>molecular immunologist: antigen presentation</i>)			
Product market	Share s_{im}	Price effect $\hat{\beta}_m^p$	Contribution
Fetal bovine serum	0.050	0.435	0.022
Chemiluminescent substrates	0.062	0.154	0.010
PVDF blotting membranes	0.057	0.015	0.001
Five other treated markets	0.019	0.074	0.001
Untreated markets	0.812	0.000	0.000
Total (S_i and exposure measure)	0.188		0.034
Panel B: Imputed exposure of a non-FOIA PI (<i>structural immunologist: immune protein structure</i>)			
Three most similar FOIA PIs	Similarity	Weight w_{ik}	Exposure
Molecular immunologist: <i>antigen presentation</i>	0.274	0.424	0.034
Cell biologist: <i>protein misfolding</i>	0.235	0.313	0.096
Crystallographer: <i>enzymes, immune proteins</i>	0.215	0.262	0.012
Imputed exposure measure		1.000	0.047

Notes: This table shows how we construct the exposure measure for two example PIs. Panel A applies equation (3) to a FOIA PI, and Panel B applies equation (4) to a non-FOIA PI. Spending shares are relative to pre-merger spending in high-confidence markets, and imputation weights are proportional to squared text similarity and sum to one. PIs are identified by research subfield rather than name.

Figure 5 compares the distributions of observed and imputed exposure measures. Imputed exposure measures are centered near the observed exposure measures but are slightly less spread out, since averaging across three nearest neighbors compresses the distribution. Across the panel, the average PI faced a 2.8 percent increase in the cost of their pre-merger consumables bundle.

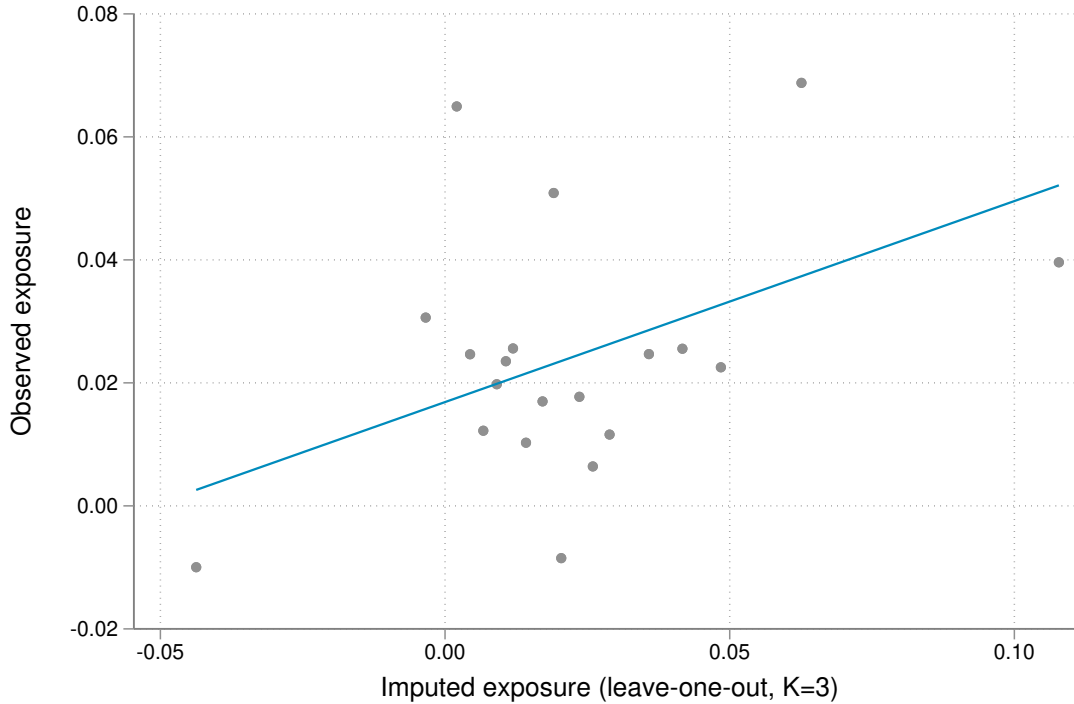
Finally, we assess whether text similarity recovers a PI's exposure measure using a leave-one-out procedure. For each FOIA PI, we impute an exposure measure from the three most similar remaining FOIA PIs and compare it with the PI's observed exposure measure. As Figure 6 shows, the two measures have a correlation of 0.20, and a regression of the observed measure on the imputed measure yields a slope of 0.33 that is statistically different from both zero and one. The imputed measure captures part of the variation in the observed measure, but with noise. This measurement error likely attenuates estimates based on the imputed measure toward zero, so our estimates may understate the magnitude of the effect.

Figure 5. Observed and Imputed PI Exposure Distributions



Notes: This figure shows the distributions of the observed and imputed exposure measures. The blue line shows the observed exposure measure for the 208 FOIA PIs, and the orange line shows the imputed exposure measure for the 13,433 non-FOIA PIs in the panel. The observed measure has a mean of 0.024 and a standard deviation of 0.049, and the imputed measure has a mean of 0.028 and a standard deviation of 0.032.

Figure 6. Leave-One-Out Validation of Imputed PI Exposure



Notes: This figure shows a binned scatter of the observed exposure measure against the leave-one-out imputed exposure measure for the 208 FOIA PIs. Each FOIA PI's imputed exposure measure is constructed from the three most similar remaining FOIA PIs, using the same procedure as for non-FOIA PIs. The correlation between the two measures is 0.20, and the slope of the fitted line is 0.33 (SE 0.11), with an intercept of 0.017.

4.1.4 Estimation Sample

We construct the estimation sample from U.S. life sciences authors who appear as the last author on at least one journal article between 2010 and 2019. We restrict the sample to PIs at R1 or R2 universities under the *Carnegie Classification* and to PIs who did not move universities between 2010 and 2019.¹²

The resulting PI-year panel is balanced from 2010 to 2019, with publication counts recorded as zero in years that a PI did not publish. The final panel comprises 13,515 PIs at 198 universities, with an average of 2.16 publications per PI-year before the merger. Of the 208 FOIA PIs used for the imputation, 82 also meet the sample criteria and enter the panel, and we impute the exposure measure for the remaining 13,433 non-FOIA PIs. We also link PIs in the panel to NIH

¹² This restriction ties each PI's fixed effect to one university so that changes in institutional environments do not drive our results.

RePORTER records using fuzzy name matching to measure their NIH funding. We match by name 7,999 of the 13,515 PIs (59%).

Table 4 compares PIs above and below the median exposure measure on pre-merger outcomes and characteristics. More-exposed PIs had a higher treated-market share, somewhat higher pre-merger research output, and slightly fewer years running a lab. The two groups were similar in NIH funding and the share at public universities.

Table 4. Balance Across More- and Less-Exposed PIs

	Less exposed		More exposed		Difference			
	Mean	SD	Mean	SD	Coef.	(SE)	p-value	N
Panel A: Pre-period (2010–2013) PI averages								
Publications (last author)	2.095	1.279	2.228	1.466	0.134	(0.024)	0.000	13,515
Publications (any position)	4.060	2.691	4.259	2.952	0.199	(0.049)	0.000	13,515
Citation-weighted output	4.017	4.419	4.502	5.189	0.486	(0.083)	0.000	13,515
Active NIH grants	1.039	0.868	1.081	0.911	0.042	(0.020)	0.037	7,999
NIH funding (\$ thousands)	416.715	528.285	414.551	469.564	−2.164	(11.181)	0.847	7,999
Panel B: PI characteristics								
Exposure measure	0.005	0.018	0.052	0.024	0.047	(0.000)	0.000	13,515
Treated-market share S_i	0.246	0.113	0.291	0.101	0.045	(0.002)	0.000	13,515
Years running a lab in 2014	17.335	11.436	16.566	11.310	−0.769	(0.196)	0.000	13,515
Public university	0.614	0.487	0.607	0.489	−0.008	(0.008)	0.355	13,515
Matched to NIH records	0.588	0.492	0.596	0.491	0.008	(0.008)	0.367	13,515

Notes: This table compares PIs above and below the median exposure measure (0.021) among 13,515 PIs, with one observation per PI. Panel A reports pre-merger averages (2010–2013). NIH outcomes are available for 7,999 PIs matched to NIH records (3,974 less-exposed and 4,025 more-exposed). Panel B reports PI characteristics. Years running a lab is measured in 2014 as years since a PI's first last-authored publication. Public university and matched to NIH records are shares. Differences are more-exposed minus less-exposed means, with heteroskedasticity-robust standard errors in parentheses. N denotes the number of PIs in each row.

4.2 Average Effect on Research Output

In this subsection, we compare changes in publications across PIs with different exposure measures. We find evidence that PIs who faced larger increases in the cost of their pre-merger consumables bundle published less after the merger.

4.2.1 Empirical Specification

Our empirical design is an event study that treats each PI's exposure measure as a continuous treatment and compares the publication trajectories of more- and less-exposed PIs around the 2014 merger. Specifically, we interact each PI's exposure measure with relative-year indicators and estimate the following specification for publication counts:

$$E[y_{it} \mid \mu_i, \lambda_t] = \exp \left(\mu_i + \lambda_t + \sum_{\substack{n=-4 \\ n \neq -1}}^5 \beta_n \mathbf{1}\{t - 2014 = n\} \times \text{Exposure}_i + \sum_{\substack{n=-4 \\ n \neq -1}}^5 \psi_n \mathbf{1}\{t - 2014 = n\} \times S_i \right), \quad (5)$$

where y_{it} is the raw publication count for PI i in year t . The terms μ_i and λ_t are PI and year fixed effects, and $\mathbf{1}\{t - 2014 = n\}$ indicates that year t is n years from 2014. We omit $n = -1$, so each β_n measures the relationship between the exposure measure and research output relative to the year immediately before the merger.

To estimate the average effect, we also use a pooled version of equation (5) that replaces the relative-year indicators with a single post-merger indicator:

$$E[y_{it} \mid \mu_i, \lambda_t] = \exp \left(\mu_i + \lambda_t + \beta \text{Post}_t \times \text{Exposure}_i + \psi \text{Post}_t \times S_i \right), \quad (6)$$

where $\text{Post}_t = \mathbf{1}\{t \geq 2014\}$.

We estimate equations (5) and (6) using Poisson pseudo-maximum likelihood (PPML), which accommodates the many zero publication counts in our data and estimates proportional changes in expected research output (Chen and Roth, 2024). The exposure measure captures the percentage increase in the cost of a PI's pre-merger consumables bundle, so the coefficients β_n and β can be interpreted as the elasticity of research output with respect to consumables costs. We cluster standard errors at the PI level.

A PI can have a higher exposure measure because a larger share of their spending went to treated markets or because, within treated markets, more of it went to markets with larger price increases. We aim to isolate the second source of variation, which reflects differences in the price effects across markets. We therefore control for the PI's treated-market share, S_i , interacted with the relative-year indicators, with coefficients ψ_n in equation (5) and ψ in equation (6).¹³ Following [Borusyak et al. \(2022\)](#), this control also accounts for the fact that the spending shares in the exposure measure do not sum to one. The coefficients β_n and β thus compare PIs with similar treated-market shares whose pre-merger purchases exposed them to different price increases.

Our identification relies on the exogeneity of the market-level price effects generated by the merger, and not of PIs' pre-merger spending shares ([Goldsmith-Pinkham et al., 2020](#); [Borusyak et al., 2022](#)). These shares can reflect research field, experimental protocols, lab size, and other PI characteristics that also affect research output. Consistent with this possibility, more-exposed PIs had somewhat higher pre-merger research output and were slightly earlier in their careers, as shown in Table 4. Identification instead requires that price effects across product markets are unrelated to the counterfactual research trajectories of PIs who purchase from those markets, conditional on the treated-market share. In other words, PIs whose output would have declined even without the merger must not systematically purchase from markets with larger price increases.

This assumption seems plausible because differences in price effects across markets largely reflect the merging firms' pre-merger product portfolios and competitive landscape, rather than the research trajectories of the PIs who purchase those products.¹⁴ Appendix Table A7 reports a shock-level balance test that is consistent with this identifying assumption.

¹³ For non-FOIA PIs, the treated-market share S_i is imputed with the same neighbors as the exposure measure, and Appendix Figure A7 compares its imputed distribution with the observed distribution among FOIA PIs.

¹⁴ Consistent with this explanation, estimated price effects are larger in markets with higher pre-merger HHI ($r = 0.156$). Because supplier-name inconsistencies make HHI noisy, we interpret this correlation as suggestive evidence.

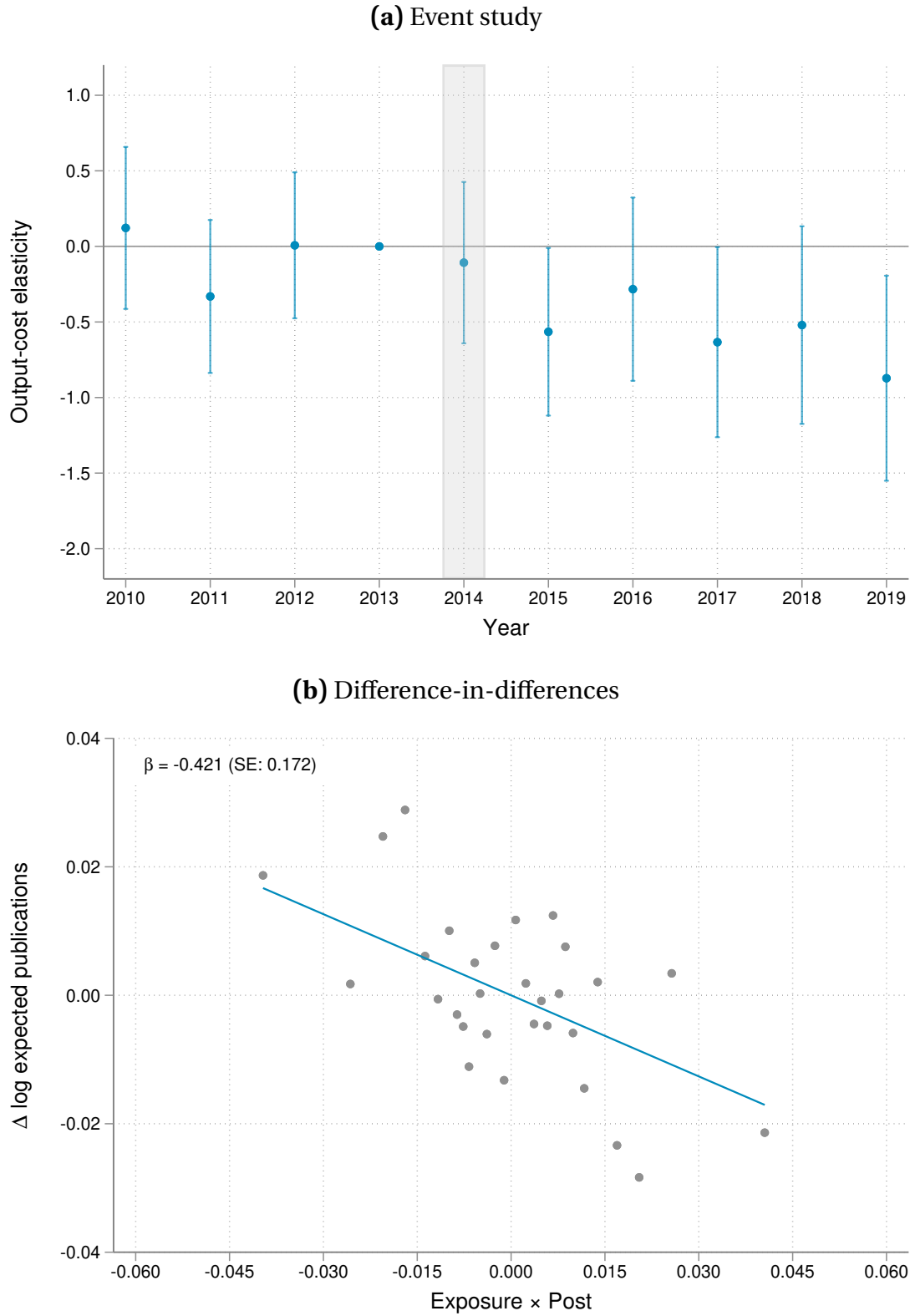
4.2.2 Results

Our estimates suggest that higher consumables prices reduced research output. The estimates imply an elasticity of research output with respect to consumables costs of approximately -0.42 . Panel (a) of Figure 7 plots our event-study estimates and shows that the pre-merger coefficients are individually insignificant and exhibit no systematic trend, while the post-merger coefficients are negative and grow in magnitude over time. Thus, more- and less-exposed PIs do not appear to have been on systematically different publication trajectories before the merger, but more-exposed PIs faced a larger decline in research output after the merger.

Table 5 reports estimates of equation (6), which pools the post-merger years, and Panel (b) of Figure 7 shows the corresponding binned scatterplot. In our preferred specification, which controls for the treated-market share, the estimated elasticity is -0.421 , close to the estimate of -0.417 without the control.¹⁵ This similarity suggests that the estimated decline is not driven by differences across PIs in their overall spending share in treated markets.

¹⁵ The exposure measure aggregates 46 market-level price effects, but its variation is equivalent to that of only about 17 equally weighted markets. As an alternative to PI-level inference, we conduct randomization inference (Borusyak and Hull, 2023), reassigning price effects among markets with similar pre-merger spending and recentering the exposure measure on market spending. This test asks whether the estimated decline depends on which markets received the larger price effects. Given the small number of effective shocks, this procedure has limited power and does not reject the null ($p = 0.45$).

Figure 7. Effect of Higher Consumables Prices on Publication Counts



Notes: This figure shows the effect of the exposure measure on PIs' annual publication counts. Panel (a) plots the event-study coefficients β_n from equation (5), normalized to zero at $n = -1$. Panel (b) is a binned scatter of publication counts against $\text{Exposure}_i \times \text{Post}_t$ after partialing out PI and year fixed effects and the treated-market share control, with slope $\beta = -0.421$ (SE 0.172) from equation (6). Standard errors are clustered by PI. The gray band marks the merger in 2014. The sample is the 13,515 PIs at 198 universities, with a pre-merger mean of 2.16 publications per PI-year.

Table 5. Effect of Higher Consumables Prices on Research Output

	(1) With share control	(2) Without share control
Exposure measure	−0.421** (0.172)	−0.417** (0.171)
Treated-market share S_i	0.007 (0.052)	
Pre-period mean	2.16	2.16
Observations	135,150	135,150

Notes: This table reports Poisson pseudo-maximum likelihood (PPML) difference-in-differences estimates of the effect of the exposure measure on annual publication counts for 13,515 PIs from 2010 to 2019. The coefficient on $\text{Exposure}_i \times \text{Post}_t$ is the elasticity of research output with respect to consumables costs. All specifications include PI and year fixed effects. Column (1), our preferred specification, controls for the treated-market share following [Borusyak et al. \(2022\)](#), and column (2) omits this control. Standard errors clustered by PI are in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

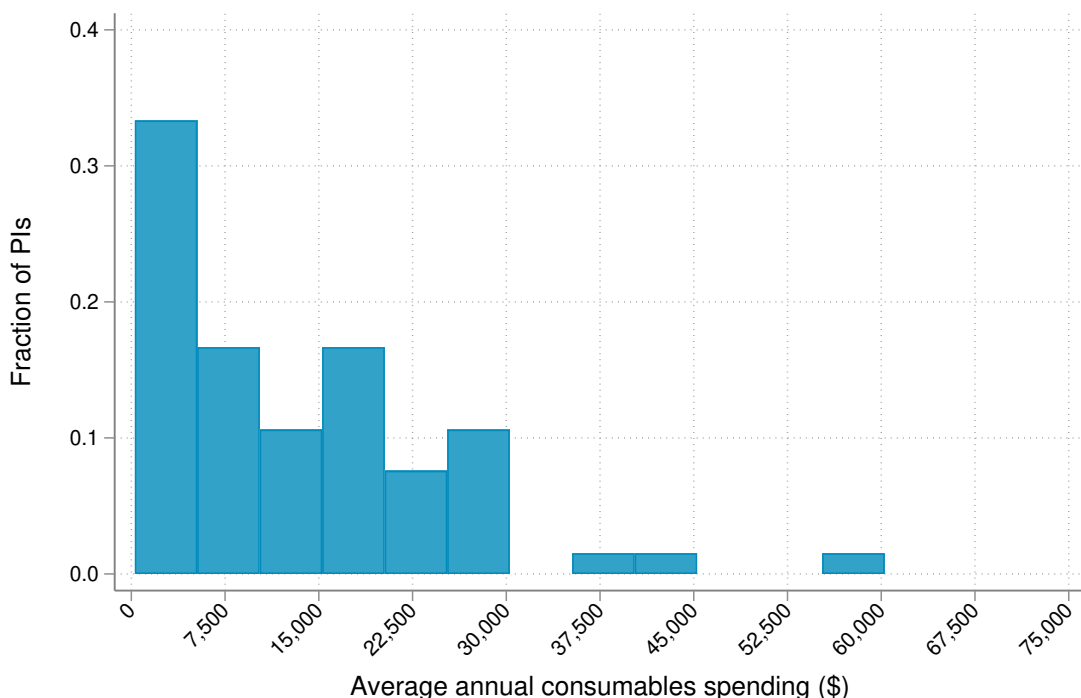
For the average PI, whose consumables costs rose by 2.8 percent, the pooled estimate implies a 1.2 percent decline in research output, or roughly 0.026 fewer publications per year.¹⁶ This elasticity is measured with respect to consumables costs, not the PI’s full grant. Consumables account for roughly 10 to 20 percent of a grant’s direct costs. In order to interpret this estimate as an elasticity with respect to lost grant funding, we would have to assume that a dollar lost to higher consumables costs affects research output in the same way as a dollar lost in grant funding—an assumption our design cannot support.

To put this magnitude in dollar terms, we use the consumables spending of FOIA PIs at UT Dallas and UMich, whose purchases we classify by hand. As [Figure 8](#) shows, these PIs spent about \$13,300 per year in high-confidence markets before the merger. Applying the average PI’s 2.8 percent cost increase to this spending and comparing it with the estimated

¹⁶We interpret this coefficient as a reduced-form elasticity rather than an elasticity with respect to realized consumables spending. Recovering the latter would require estimating the relationship between the exposure measure and actual changes in consumables spending. We observe these changes only for the FOIA PIs, a sample too small to estimate this relationship precisely. This limitation does not apply to our exposure imputation because research topics predict what PIs purchased before the merger, but not how their spending changed afterward.

decline in output implies one fewer publication per year for every \$14,500 increase in annual consumables costs.¹⁷

Figure 8. Distribution of Average Annual PI Consumables Spending

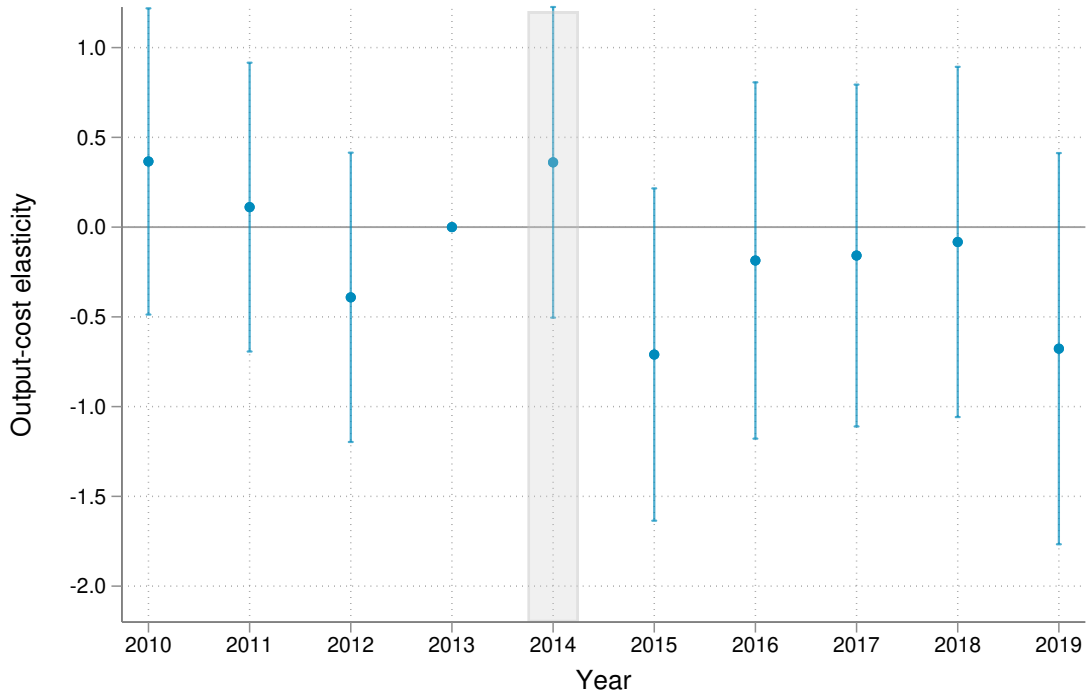


Notes: This figure shows the distribution of average annual consumables spending for the 66 FOIA PIs at UT Dallas and UMich, whose purchases are linked to them in the manually classified FOIA records, restricted to the high-confidence markets over which the exposure measure is defined. Spending is averaged over the pre-merger years, 2010 to 2013, in which each PI appears in the records. Mean spending is around \$13,300 per PI per year, with a standard deviation of \$11,300 and a median of \$11,100. The interquartile range runs from \$4,400 to \$19,700, and average spending ranges from \$274 to \$59,000.

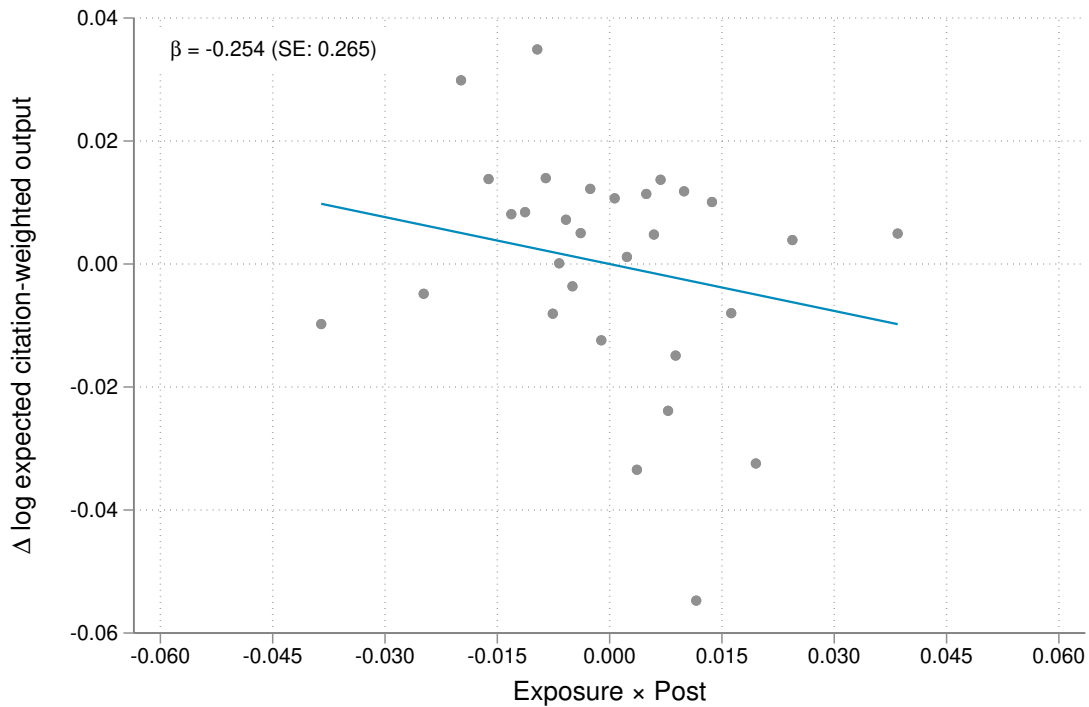
As a second measure of research output, we re-estimate equation (5) using citation-weighted output, with the results shown in Figure 9. We weight each publication by its average annual citations and rescale the weighted counts to sum to the total number of publications. This way, the measure remains in units of publications and is comparable to the raw count. The estimated decline is too imprecise to distinguish from either zero or our main publication-count estimate, so we draw no conclusions about the composition of the forgone publications.

¹⁷ A 2.8 percent increase on annual spending of \$13,300 amounts to about \$377 per PI per year. Dividing by the estimated decline of 0.026 publications per PI per year gives approximately \$14,500 per publication. Both calculations use unrounded values.

Figure 9. Effect of Higher Consumables Prices on Citation-Weighted Output
(a) Event study



(b) Difference-in-differences



Notes: This figure shows the effect of the exposure measure on PIs' annual citation-weighted output, which weights each publication by its average annual citations and rescales the counts to sum to the number of publications. Panel (a) plots the event-study coefficients β_n from equation (5), normalized to zero at $n = -1$. Panel (b) is a binned scatter of citation-weighted output against $\text{Exposure}_i \times \text{Post}_t$ after partialing out PI and year fixed effects and the treated-market share control, with slope $\beta = -0.254$ (SE 0.265) from equation (6). Standard errors are clustered by PI. The gray band marks the merger in 2014. The sample is the 13,515 PIs at 198 universities, with a pre-merger mean of 4.26 citation-weighted publications per PI-year.

Robustness. The estimated decline in research output is similar across alternative functional forms and fixed effects, as shown in Appendix Table A4. OLS estimates using publication counts or the log of one plus publications imply declines similar to the baseline PPML estimate. The estimate is also largely unchanged when we allow the year fixed effects to vary by research cluster, combined with either PI or university fixed effects.

The estimate remains negative across alternative approaches to constructing the exposure measure, as shown in Appendix Table A5. Renormalizing each PI's spending shares across treated markets, rather than controlling for the treated-market share, yields a larger implied decline. We also examine sensitivity to the quality of the imputation. Restricting the sample to the top half of imputed PIs with the strongest text matches yields a decline similar to the baseline, while weighting PIs by match quality produces a smaller and less precise estimate. Imputing from two to five nearest FOIA PIs yields similar declines, whereas using only one neighbor produces a smaller decline, consistent with greater imputation noise.

Finally, we conduct a placebo test to assess whether a decline of the size we estimate could arise by chance. We construct 100 placebo exposure measures by replacing the merger's estimated price effects with those from the same placebo draws of control markets used in Figure 4. For each draw, we re-estimate equation (6). If the decline arose by chance, placebo estimates as negative as the one we estimate would be common. As shown in Appendix Figure A1, however, only 4 of the 100 placebo estimates have a t -statistic as negative as that of our estimated effect.

4.3 Mechanisms

Having found evidence that higher consumables prices reduced research output, we next ask how this decline varies across PIs. The estimates provide suggestive evidence that early-career PIs faced a larger decline.

We define career stage as the time a PI has been running an independent lab, measured as the number of years from a PI's first last-authored publication to 2014, and split PIs at the median of 14 years. Figure 10 suggests that the decline among early-career PIs emerges after the merger and grows through the end of the sample, while the decline among late-career PIs is smaller and imprecisely estimated. The pooled difference-in-differences estimates show the same pattern, with estimates of -0.723 for early-career PIs and -0.209 for late-career PIs, although the difference of -0.514 ($p = 0.13$) is not statistically significant at conventional levels.

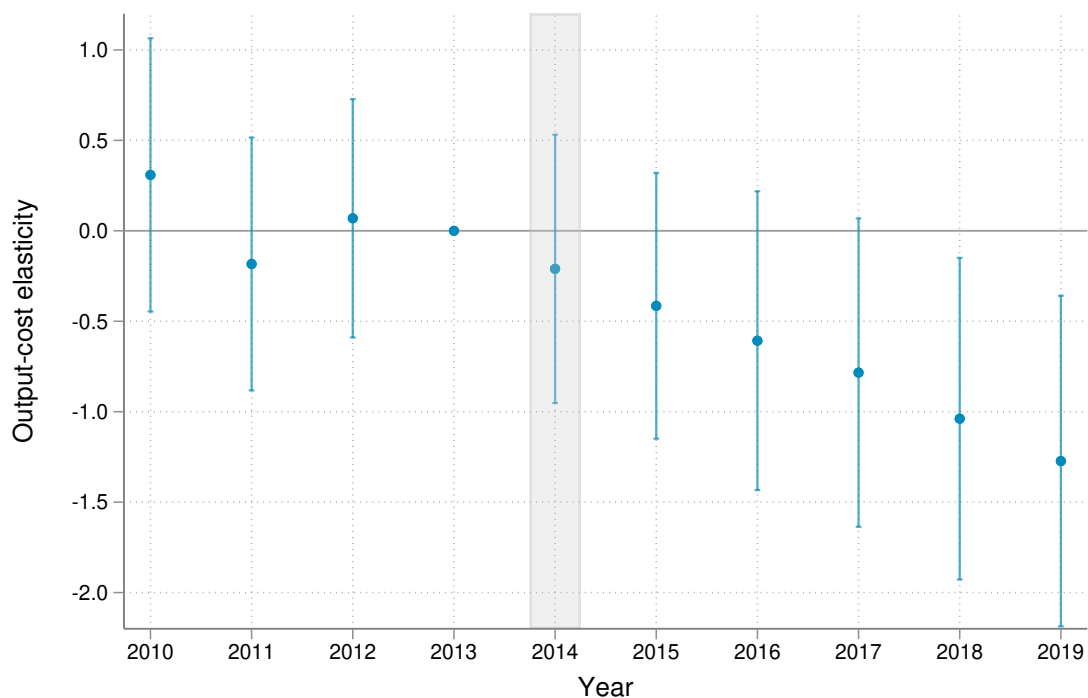
As an alternative measure, we define career stage by the number of years from a PI's first publication in any authorship position to 2014. This definition yields a larger difference, with estimates of -0.896 for early-career PIs and -0.025 for late-career PIs, a difference of -0.871 that is statistically significant at the 5 percent level. This measure captures research experience accumulated during PhD and postdoctoral training in addition to experience running an independent lab. The two measures are highly correlated, and both suggest larger declines among early-career PIs. Appendix Table A6 reports the estimates for both measures, and Appendix Figure A2 shows the estimates across five groups of PIs defined by years running a lab.

One natural explanation for the larger decline among early-career PIs is differences in financial resources, since late-career PIs may hold larger grants or work at better-resourced universities that help them absorb higher consumables costs. Figure 11 compares estimates by baseline NIH funding and university research funding and endowment. If financial resources provided a buffer, we would expect smaller declines among better-funded PIs and those at better-resourced universities.

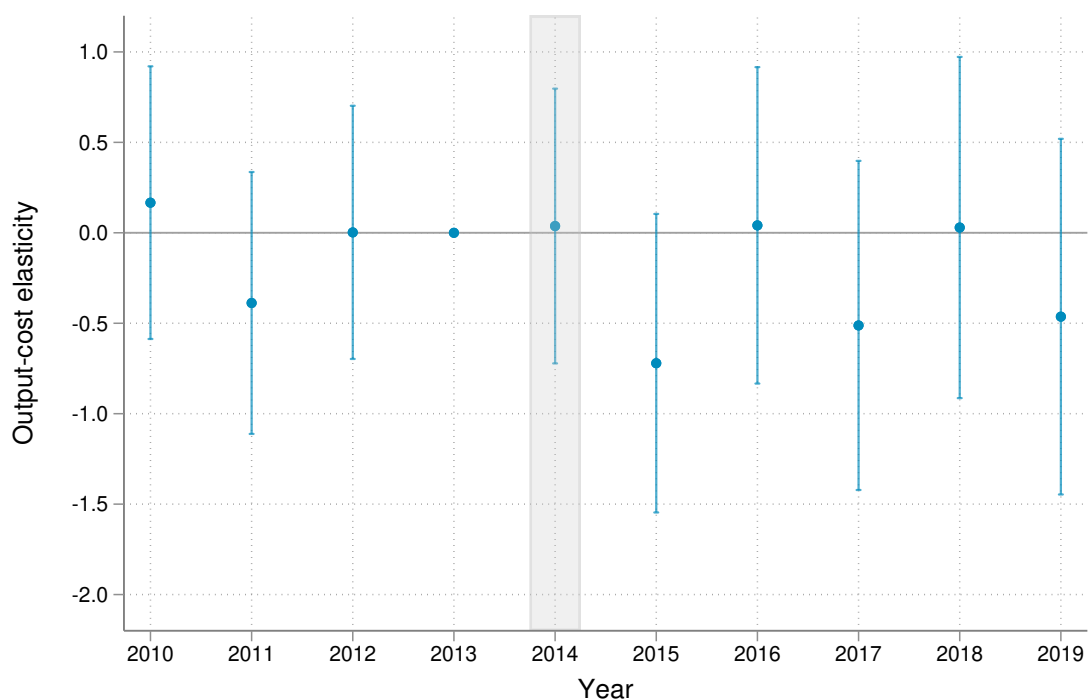
Instead, the estimated effect is negative in every subgroup, with little evidence of smaller declines among PIs with greater financial resources available to them. If anything, the estimated decline is larger among PIs with above-median baseline NIH funding (-0.420) than among those with below-median funding (-0.027), as Appendix Table A6 shows, although this difference

Figure 10. Effect of Higher Consumables Prices on Publication Counts by Career Stage

(a) Early-career PIs



(b) Late-career PIs



Notes: This figure shows the effect of the exposure measure on PIs' annual publication counts separately for early- and late-career PIs, estimated in a single regression that extends equation (5) with separate exposure-by-relative-year interactions for each career stage. Coefficients are normalized to zero at $n = -1$. Standard errors are clustered by PI. The gray band marks the merger in 2014. Career stage is split at the median of 14 years from a PI's first last-authored publication to 2014, yielding 6,613 early-career and 6,902 late-career PIs.

is imprecisely estimated. This comparison looks at the 7,999 PIs matched to NIH records, so it can only speak to differences among NIH-funded PIs.

Baseline funding and career stage are also positively correlated with each other, so we examine whether the career-stage pattern persists among PIs with similar funding. Figure 12 divides the NIH-matched sample into four groups by career stage and above- or below-median pre-merger NIH funding. Within both funding groups, the point estimates are more negative for early-career PIs than for late-career PIs, although these estimates are imprecise. Differences in baseline funding therefore do not appear to fully account for the career-stage pattern.¹⁸

Even if differences in financial resources do not fully explain the career-stage pattern, early-career PIs might be more affected because they spend a larger share of their funding on consumables. Our exposure measure only captures the percentage increase in the cost of a PI's pre-merger consumables bundle, not the increase in cost relative to a PI's total budget. That is, the same exposure measure could represent a larger financial burden for PIs who spend more of their budget on consumables. We examine this possibility using the 54 FOIA PIs matched to NIH awards, for whom we observe both consumables spending and NIH funding. Among these PIs, consumables spending accounted for 7.1 percent of NIH funding for early-career PIs and 5.7 percent for late-career PIs. The difference is not statistically significant in this small sample and is modest relative to the more than threefold difference in the point estimates of output decline across the full panel.

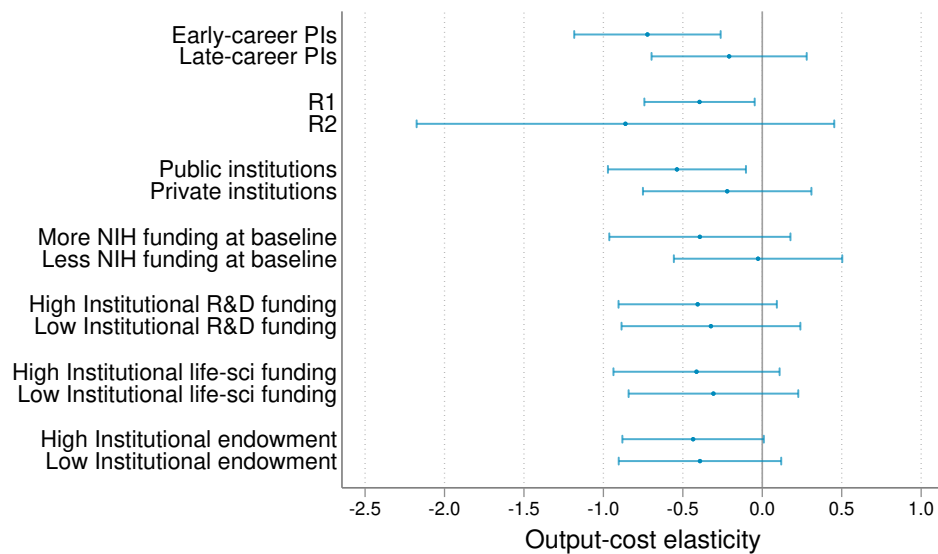
Finally, we examine whether the larger decline among early-career PIs reflects differential exit from academic research. We define exit as having a five-year gap without a last-authored publication, with the first year of the gap falling between 2014 and 2019 to avoid identifying exits that began during the COVID-19 pandemic. We find little evidence that the exposure

¹⁸ As a robustness check, we reweight late-career PIs to match the distribution of early-career PIs across pre-merger research topics, publication output, and NIH funding categories. The estimated career-stage gap remains negative and is larger in magnitude, although imprecisely estimated (-0.90 , $p = 0.06$).

measure predicts exit for either early- or late-career PIs, though these estimates are imprecise.¹⁹ These results suggest that differential exit is unlikely to explain the career-stage pattern.

Together, these results provide little evidence that differences in observed financial resources, consumables spending relative to funding, or differential exit explain the larger decline among early-career PIs. We cannot rule out a role for unobserved funding from other sources, such as foundations or industry. Aside from financial resources, the pattern may also reflect tacit knowledge gained through experience. This includes knowledge such as which experiments to prioritize, which products can substitute for one another, and how to reorganize laboratory work when consumables prices rise.

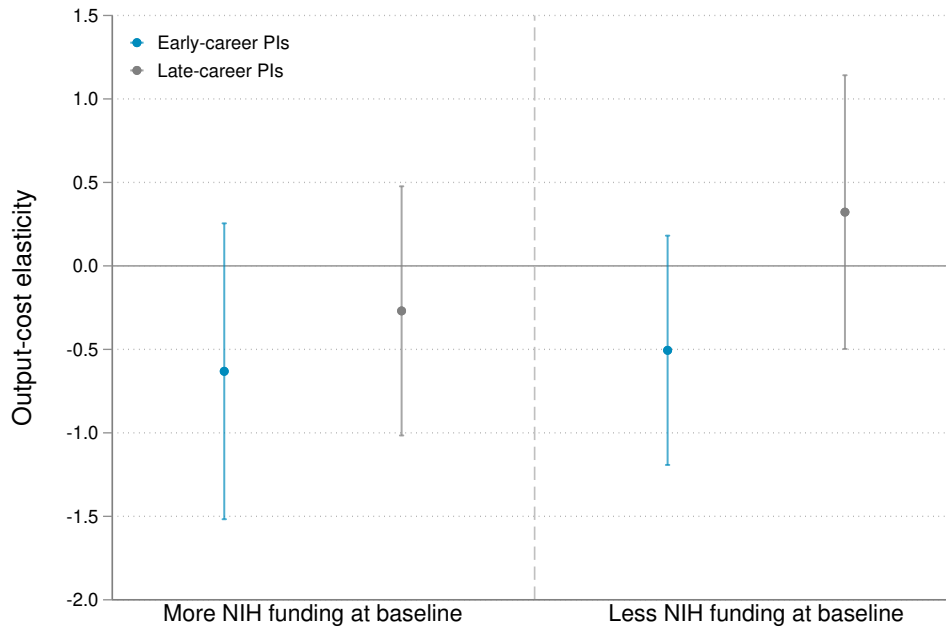
Figure 11. Effect of Higher Consumables Prices on Publication Counts by PI and Institutional Characteristics



Notes: This figure shows how the effect of the exposure measure on PIs' annual publication counts varies across PI and institutional characteristics. Each row reports the coefficient on $\text{Exposure}_i \times \text{Post}_t$ from equation (6) for one group, with both groups of each split estimated in one regression. R1 or R2 status follows the *Carnegie Classification*, institutional research and development funding and life sciences funding come from the National Science Foundation Higher Education Research and Development (HERD) Survey, and endowment comes from the Integrated Postsecondary Education Data System (IPEDS). Continuous characteristics are split at their pre-merger median. Horizontal lines are 95% confidence intervals from standard errors clustered by PI.

¹⁹We estimate a linear probability model separately for early- and late-career PIs, with one observation per PI, controlling for the treated-market share and research-cluster fixed effects. The coefficient on the exposure measure is -0.013 (SE 0.172) for early-career PIs and -0.069 (SE 0.213) for late-career PIs, with standard errors clustered by university.

Figure 12. Effect of Higher Consumables Prices on Publication Counts by Career Stage and Baseline NIH Funding



Notes: This figure shows how the effect of the exposure measure on PIs' annual publication counts varies by career stage and baseline NIH funding. Each point reports the coefficient on $\text{Exposure}_i \times \text{Post}_t$ from equation (6) for one of four groups defined by career stage and below- or above-median pre-merger NIH funding, with all four groups estimated in one regression on the 7,999 NIH-matched PIs. Vertical lines are 95% confidence intervals from standard errors clustered by PI.

5 Discussion

The preceding results provide evidence that higher consumables prices reduce research output and suggest that the decline is larger among early-career PIs. In this section, we first consider the broader implications of these declines for scientific research. We then draw on a survey of active life sciences PIs to examine how they learn to make purchasing decisions and whether experience may help them adjust to higher prices.

5.1 The Incidence of Higher Input Prices

We first consider what these losses in research output imply for science more broadly. Our results show that spending increased in the treated markets without a corresponding decline in quantities, while more-exposed PIs experienced declines in research output. Science therefore bears the burden of higher prices in two ways, through a transfer of research funds to private suppliers and through a decline in research output. Although the decline in output is modest

for any individual PI, the same price increases affected PIs across many universities, so the aggregate consequences are potentially much larger.

These losses are particularly costly because scientific research is generally thought to generate social returns that likely exceed private returns—leading to underprovision in private markets and providing a rationale for government funding (Nelson, 1959; Arrow, 1962; Bryan and Williams, 2021). Unlike firms selling products, PIs generally cannot pass higher costs on to buyers by raising output prices. This is because scientific knowledge is typically shared through publications rather than sold and PIs are rewarded primarily through recognition rather than revenue. Thus, higher consumables prices can further reduce scientific production in a setting where research is already underprovided relative to its social value.

To assess the aggregate scale of these losses, we apply our estimates to all 13,515 PIs in our panel. Before the merger, these PIs produced approximately 29,200 publications per year, averaging 2.16 per PI. Extrapolating pre-merger average annual consumables spending of \$13,300 per PI in the procurement data to the full panel yields approximately \$179 million in annual consumables spending. Applying our estimated effects to these pre-merger levels implies approximately 349 fewer publications per year and \$5.1 million annually in additional consumables costs. This decline in publications is equivalent to the annual output of about 160 PIs at the pre-merger mean, with each lost publication corresponding to approximately \$14,500 in additional consumables costs.

To get a sense of the potential social value of the lost research, we use pre-merger NIH funding per publication as a benchmark. Among the NIH-funded PIs in our panel, the average funding cost of a publication before the merger—measured as total funding divided by total last-author publications—was approximately \$192,000 per publication.²⁰ If each lost publication would have been worth at least what it cost to fund, the 349 fewer publications each year may

²⁰ Funding includes indirect costs because separate direct and indirect cost fields are available only for awards funded from fiscal year 2012 onward.

represent roughly \$67 million in lost social value. This assumption may be reasonable given evidence that the social benefits of innovation are several times larger than its investment costs ([Jones and Summers, 2020](#)), although these average returns may not apply to the particular research lost in our setting. If the assumption holds, the value of the lost research would be considerably larger than the \$5.1 million in additional annual payments to suppliers, suggesting that the transfer alone may understate the burden of higher prices on science.

These calculations may understate the aggregate losses for several reasons. Our panel includes only PIs at R1 and R2 universities who did not move, excluding scientists at other universities and biopharmaceutical companies that also purchase consumables in the treated markets. Our spending calculation also excludes markets where the merging firms competed but where we cannot reliably classify products. In addition, measurement error in the imputed exposure measure may attenuate the estimated response toward zero, so the decline in research output could be larger than we estimate.

The consequences of these losses in research output may also extend to downstream innovation. [Li et al. \(2017\)](#) find that publications from about 30 percent of NIH grants are cited by private-sector patents, including publications from 5 percent of grants that are cited by patents associated with FDA-approved drugs. [Azoulay et al. \(2019\)](#) further provide causal evidence that an additional \$10 million in NIH funding generates 2.7 private-sector patents. While these studies cannot tell us how our estimated losses in research output translate into fewer patents or drugs, they suggest that higher consumables prices may reduce the knowledge available for future medical innovations, including new drugs and therapies.

5.2 What Allows a PI to Adjust to Higher Input Prices?

We now consider why some PIs appear to have experienced larger declines in research output than others. Our results suggest that the decline is larger among early-career PIs. This could potentially be because late-career PIs had larger grants, worked at better-resourced universities,

or had more financial slack to absorb higher costs. We find little evidence that PIs with greater financial resources experienced smaller declines, suggesting that financial resources alone may not fully explain the career-stage pattern.

An alternative explanation is that experience may help PIs adjust to higher consumables prices. Tacit knowledge of which materials can be substituted, which experimental protocols can be modified, and how to scale experiments without compromising the research may help PIs limit the effects of higher prices on their output. PIs likely accumulate this knowledge through training and years of running a lab where they learn from experiments and failures along the way. Early-career PIs have had less time to acquire this knowledge and may have fewer ways to adjust when prices rise. Under this interpretation, career stage may proxy for accumulated tacit knowledge about how to adjust research practices to higher costs.

To explore whether experience helps PIs adjust to higher consumables prices, we survey active U.S. life sciences PIs about how they learned to make purchasing decisions and how they respond when prices rise. [Appendix E](#) provides the full survey instrument and implementation details. As of September 28, 2026, we have received 23 responses from 292 invitations. Of these, 13 are from early-career PIs and 10 from late-career PIs, using the same cutoff of 14 years running a lab as in our main analysis. Since we have a small and self-selected sample, we interpret the responses only as suggestive evidence on the role of experience in shaping how PIs adjust to higher prices.

The survey responses suggest that PIs may learn to make purchasing decisions largely through experience rather than formal training. Most respondents report learning through trial and error after starting their own labs. Those who learned from others most often cite a PhD or postdoctoral advisor or a lab manager, while only two respondents report receiving institutional training. These responses suggest that PIs may acquire some purchasing knowledge while working in other labs and continue learning as they run their own. This pattern is consistent

with the possibility that early-career PIs have had less time to accumulate knowledge that could help them adjust when prices rise.

One thing PIs may learn through experience is how to adjust the research process itself when prices rise. Some late-career PIs describe changes to experimental methods and choices that could reduce costs. One reports having “*changed [the] method of propagating virus to save costs,*” while another reports that “*we decided to use a different technique.*” Others describe “*plan[ning] more carefully the experiments*” or choosing “*experiments that cost less.*” When pipette tips became scarce and expensive, another PI considered “*getting a tip washer,*” potentially substituting equipment for a costly consumable.

In contrast, some early-career PIs describe responding to higher prices by scaling back their experiments. One reports that key reagents have doubled in price since the lab opened in 2018 and that the lab is “*constantly trying to scale down experiments to reduce cost.*” Another reports running four replicates instead of six to conserve supplies, while a third writes that “*[e]verything is more expensive and we can only do less.*”

Some early-career PIs also describe efforts to adjust, though their responses suggest that finding cheaper alternatives without compromising an experiment can be difficult. One reports that higher prices change “*what experiments we do*” and that they “*try to negotiate with vendors or find different suppliers if the supply is critical.*” Another “*tried cheaper products, but had to switch back to the original because the cheaper ones did not work as well,*” while a third cannot switch certain inputs “*for fear of ruining the experiment.*” Knowing which substitutions and changes to research methods will work without compromising an experiment may be the kind of knowledge that PIs accumulate through years of running a lab.

Taken together, these survey responses suggest that accumulated experience may help explain the larger decline in research output among early-career PIs, but cannot establish that

experience drives this pattern. The smaller decline among late-career PIs may also reflect selection rather than learning, since these PIs are those who remained in science until the merger.

In this respect, PIs may resemble managers, whose experience can shape how they respond to shocks (Reagans et al., 2005; Lee and Van den Steen, 2010; Lamorgese et al., 2024). Although PIs are trained to conduct research, running a lab also requires managing people, budgets, and purchasing decisions, skills that may be learned largely through experience. Similar decisions matter for firms, where differences in management practices help explain differences in productivity (Bloom and Van Reenen, 2007; Bloom et al., 2013). Our findings suggest that PIs' ability to respond to higher consumables prices may depend not only on financial resources but also on the managerial knowledge they accumulate over time.

6 Conclusion

Input prices can shape not only how much PIs spend, but also how much science they produce. This paper leverages the 2014 merger of Thermo Fisher Scientific and Life Technologies to examine how higher consumables prices affect scientific production. Using purchase-level procurement records, we find that prices rose in consumables markets where the merging firms competed, while quantities declined slightly and only temporarily across all markets. These patterns are suggestive of highly inelastic demand, with higher prices translating into greater spending on consumables. We find that PIs more exposed to these price increases ended up producing fewer publications, and these declines appear larger among early-career PIs.

Higher input prices therefore affect science in two ways, through a transfer of research funds to private suppliers and through a decline in research output. For the average PI in our sample, the merger raised consumables costs by 2.8 percent and reduced research output by about 1.2 percent. Across all PIs, these changes translate to approximately \$5.1 million annually in higher consumables costs and roughly 349 fewer publications per year. Using pre-merger NIH funding per publication as a benchmark for valuation, we value the lost research

at roughly \$67 million annually, suggesting that the consequences for science extend beyond the additional payments to suppliers.

These findings highlight scientific input markets as an important consideration in the design and administration of public research funding. The NIH already tracks changes in the cost of biomedical research through the Biomedical Research and Development Price Index (BRDPI), which informs congressional budget negotiations by estimating the funding needed to maintain the purchasing power of research expenditures ([National Institutes of Health, 2025](#)). However, this aggregate index may miss large price increases in individual input markets, which can impose significant costs on PIs who depend on those inputs while having little effect on the overall index. Examining these input markets alongside the BRDPI can help identify where price increases occur and which PIs are most exposed to them.

University purchasing environments can also affect how much of these price increases PIs ultimately pay. Improving price transparency, such as by making supplier prices easier to compare and providing information on substitute products, may help PIs find cheaper alternatives. Moreover, greater coordination of purchasing across departments or universities could strengthen universities' ability to negotiate lower prices with suppliers.

Even with the same university purchasing environment, PIs may differ in how well they can adjust to higher consumables prices. Differences in financial resources alone do not appear to fully explain the larger decline in research output among early-career PIs, and our estimates and survey evidence suggest that experience may play a role. Running a lab requires PIs to make decisions beyond doing the science itself, from managing research teams and allocating funding across expenses to choosing which products to purchase and from which suppliers. Tacit knowledge accumulated through experience may help PIs navigate these decisions when consumables prices rise. However, PIs are primarily trained as scientists, and most of our survey respondents report learning how to make purchasing decisions through trial and error after

starting their own labs. Thus, knowing how to reorganize projects, identify substitutes, and modify experimental protocols when prices rise may be learned largely on the job—knowledge that early-career PIs have not had the time to accumulate.

There are several questions open for future work. Publications capture only one way scientists may respond to higher input prices. Higher prices may also change which projects scientists pursue and shift research toward less resource-intensive questions. The larger decline among early-career PIs raises a separate question about longer-run effects. If early-career PIs are less able to adjust, price increases early in a PI's career could affect future funding, career progression, or retention in science. Finally, if experience helps PIs adjust to higher prices, an important question is whether this tacit knowledge can be passed on to other scientists rather than learned only through years of running a lab.

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A Appendix Tables and Figures

Table A1. Top Universities, Suppliers, and Product Markets by Consumables Spending

	Total Spending (\$)	% of Total
<i>Panel A: Universities</i>		
University of Florida	19,430,311	25.7%
University of Michigan at Ann Arbor	8,810,009	11.7%
Georgia Institute of Technology	7,286,855	9.6%
University of Kentucky	4,043,671	5.4%
Wayne State University	3,856,417	5.1%
Texas Tech University	3,509,126	4.6%
Texas A&M University	3,108,487	4.1%
Florida State University	2,978,085	3.9%
East Carolina University	2,862,949	3.8%
Washington State University	2,754,592	3.6%
<i>Panel B: Suppliers</i>		
Thermo Fisher Scientific	34,901,935	46.2%
VWR	12,656,994	16.8%
Life Technologies	5,290,377	7.0%
MilliporeSigma	4,248,725	5.6%
Bio-Rad Laboratories	1,946,443	2.6%
Qiagen	1,903,158	2.5%
USA Scientific	1,405,545	1.9%
Atlanta Biologicals	1,061,611	1.4%
New England Biolabs	841,844	1.1%
Genesee Scientific	679,065	0.9%
<i>Panel C: Product Markets</i>		
Pipette Tips	6,319,587	8.4%
U.S.-Origin Fetal Bovine Serum	5,810,406	7.7%
Serological Pipettes	4,763,075	6.3%
Vials	3,452,481	4.6%
Cell Culture Plates	2,596,718	3.4%
Petri Dishes	2,348,829	3.1%
Microcentrifuge Tubes	1,982,841	2.6%
Cell Culture Flasks	1,753,628	2.3%
Cell Culture Dishes	1,340,948	1.8%
Cuvettes	1,326,283	1.8%

Notes: This table lists total consumables spending from 2010 to 2019 in the final estimation sample of high-confidence product markets, with shares of the sample total. Thermo Fisher Scientific and Life Technologies are the merging firms.

Table A2. Classifier Performance on Labeled Purchases

	Precision	Recall	Observations
Panel A: Consumables versus non-consumables classifier			
Consumables	0.962	0.984	31,551
Non-consumables	0.933	0.853	8,324
Panel B: Product market classifier			
All consumables categories	0.535	0.704	295,622
Large markets (≥ 25 training examples)	0.738	0.733	291,394

Notes: This table reports the precision and recall of the classifier on hand-labeled UT Dallas and UMich purchases. Panel A uses item descriptions held out from training, and Panel B uses all labeled consumables purchases, on which the product-market assignments are fit. Panel B conditions on true consumables and averages precision and recall equally across product markets, and its large-markets row keeps markets with at least 25 training examples, which cover 98.6 percent of true consumables. The non-consumable training examples from the California procurement records are purchases in UNSPSC segments unrelated to life sciences consumables, namely segments 14, 21–27, 30–32, 39–40, 43–50, 52–60, 70–84, and 86–95. Segments 10–13, 15, 20, 41, 42, 51, and 85, which cover laboratory and medical products, chemicals and raw materials, pharmaceuticals, and live organisms, are excluded.

Table A3. Robustness of the Pooled Merger Effects

	Average log price	Log quantity	Log spending	<i>N</i>
Panel A: Fixed effects				
Baseline: university, market, year	0.164* (0.099)	0.023 (0.063)	0.199* (0.111)	19,388
University $\times$ market, year	0.162* (0.096)	0.050 (0.064)	0.225* (0.121)	19,388
University $\times$ year, market	0.153 (0.096)	0.001 (0.063)	0.167 (0.112)	19,330
University $\times$ market, university $\times$ year	0.151* (0.092)	0.033 (0.068)	0.199 (0.124)	19,318
Panel B: Comparison group and sample				
Unmatched controls	0.177* (0.099)	−0.035 (0.047)	0.154 (0.101)	33,909
Excluding 15 complementary markets	0.200* (0.112)	0.050 (0.075)	0.264** (0.123)	14,773
Synthetic difference-in-differences	0.131*** (0.033)	0.059 (0.088)	0.194** (0.083)	1,520

Notes: This table reports the pooled difference-in-differences coefficient on $D_m^T \times \text{Post}_t$ from separate log-outcome regressions on the university–product market–year panel, 2010–2019, weighted by 2013 spending. Panel A varies the fixed effects in the matched sample. Panel B keeps university, market, and year fixed effects and varies the comparison group. The unmatched-controls row uses all candidate control markets, the complementary-markets row drops the 15 treated markets included as complements together with their matched controls, and the synthetic difference-in-differences row applies the estimator of Arkhangelsky et al. (2021), with the treated unit the 2013-spending-weighted average of treated markets and standard errors from 200 placebo draws of control markets. These estimates are unshrunk and differ from the empirical Bayes price effects $\hat{\beta}_m^P$ used elsewhere. Standard errors clustered by market, unless noted, are in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4. Robustness of the Output Effect to Functional Form and Fixed Effects

	Poisson			OLS Levels			OLS Log		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Exposure × Post</i>									
With S_i control	−0.421** (0.172)	−0.403* (0.209)	−0.415* (0.213)	−0.963*** (0.312)	−1.119*** (0.356)	−1.119*** (0.352)	−0.209** (0.098)	−0.195* (0.114)	−0.195* (0.107)
No S_i control	−0.417** (0.171)	−0.311 (0.199)	−0.324 (0.211)	−1.146*** (0.306)	−1.081*** (0.339)	−1.081*** (0.347)	−0.244** (0.096)	−0.187* (0.109)	−0.187* (0.104)
Implied output decline (%)	1.2	1.1	1.2	1.3	1.5	1.5	0.9	0.8	0.8
<i>Fixed effects</i>									
PI + year	✓			✓			✓		
PI + cluster × year		✓			✓			✓	
University + cluster × year			✓			✓			✓
Pre-period mean	2.16	2.16	2.16	2.16	2.16	2.16	2.16	2.16	2.16
Observations	135,150	135,150	135,150	135,150	135,150	135,150	135,150	135,150	135,150

Notes: This table reports difference-in-differences estimates of the effect of the exposure measure on annual publication counts under alternative estimators and fixed effects, with and without the treated-market share S_i as a control. Within each estimator, the first column uses PI and year fixed effects, the second adds research-cluster-by-year fixed effects, and the third replaces PI with university fixed effects and controls for the levels of exposure and S_i . The OLS Log outcome is the log of one plus the count. The implied output decline applies the with- S_i coefficient to the average exposure of 0.028, as a percent of the pre-period mean. In the OLS Log columns, we also multiply by one plus the pre-period mean to convert the change in the log of one plus the count into a change in the count. Column (1) with the share control is the specification in Table 5. Standard errors clustered by PI are in parentheses, except in columns (3), (6), and (9), where they are clustered by university. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5. Robustness of the Output Effect to the Exposure Measure

Panel A: Exposure construction					
	(1) Baseline	(2) Renormalized shares	(3) Positive exposure	(4) Similarity- weighted	(5) High- similarity
<i>Exposure × Post</i>					
With S_i control	−0.421** (0.172)	−0.139*** (0.053)	−0.252 (0.248)	−0.273 (0.177)	−0.419** (0.211)
No S_i control	−0.417** (0.171)	—	−0.289 (0.224)	−0.290 (0.177)	−0.424** (0.212)
Implied output decline (%)	1.2	1.5	0.9	0.7	1.1
Pre-period mean	2.16	2.16	2.16	2.16	2.43
Observations	135,150	135,150	120,700	135,150	67,980
Panel B: Number of nearest FOIA PIs in the imputation					
	$K = 1$	$K = 2$	$K = 3$ (baseline)	$K = 4$	$K = 5$
<i>Exposure × Post</i>					
With S_i control	−0.186* (0.107)	−0.404*** (0.145)	−0.421** (0.172)	−0.376* (0.203)	−0.401* (0.229)
No S_i control	−0.191* (0.107)	−0.426*** (0.144)	−0.417** (0.171)	−0.389* (0.202)	−0.429* (0.229)
Implied output decline (%)	0.5	1.1	1.2	1.1	1.1
Pre-period mean	2.16	2.16	2.16	2.16	2.16
Observations	135,150	135,150	135,150	135,150	135,150

Notes: This table reports how the estimated effect of the exposure measure on annual publication counts changes with the construction of the exposure measure. Each column is a PPML difference-in-differences regression as in column (1) of Table 5. In Panel A, column (2) renormalizes each PI's market shares to sum to one, so the no-control row does not apply, column (3) keeps PIs with strictly positive exposure, column (4) weights each PI by the maximum text similarity of their publications to a FOIA PI, and column (5) keeps the top half of imputed PIs by that similarity along with all FOIA PIs. Panel B varies the number of nearest FOIA PIs averaged to impute each non-FOIA PI's exposure measure and S_i , with FOIA PIs keeping their observed values. The implied output decline applies each column's with- S_i coefficient to its average exposure, as a percent of the pre-period mean. Standard errors clustered by PI are in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6. Heterogeneity in the Output Effect

	(1) Group 1	(2) Group 2	(3) Difference	(4) Observations
Years running a lab (<i>early- vs. late-career PIs</i>)	-0.723*** (0.235)	-0.209 (0.249)	-0.514 (0.343)	135,150
Years in research (<i>early- vs. late-career PIs</i>)	-0.896*** (0.237)	-0.025 (0.246)	-0.871** (0.342)	135,150
Carnegie classification (<i>R1 vs. R2</i>)	-0.395** (0.177)	-0.861 (0.671)	0.466 (0.694)	135,150
Institution control (<i>public vs. private institutions</i>)	-0.537** (0.222)	-0.221 (0.271)	-0.316 (0.350)	135,150
NIH funding at baseline (<i>more vs. less NIH funding at baseline</i>)	-0.420 (0.291)	-0.027 (0.271)	-0.393 (0.398)	79,990
Institutional R&D funding (<i>high vs. low</i>)	-0.407 (0.254)	-0.323 (0.287)	-0.083 (0.384)	109,620
Institutional life sciences funding (<i>high vs. low</i>)	-0.414 (0.267)	-0.307 (0.272)	-0.107 (0.381)	109,550
Institutional endowment (<i>high vs. low</i>)	-0.435* (0.227)	-0.392 (0.261)	-0.043 (0.346)	133,230

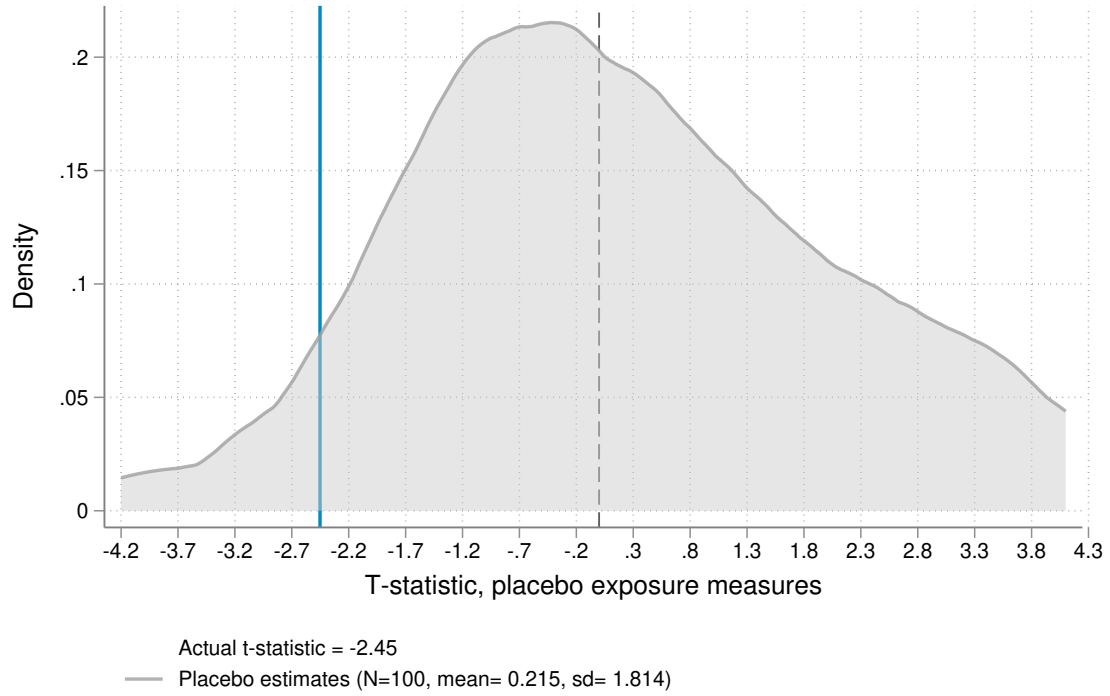
Notes: This table reports PPML difference-in-differences estimates of the effect of the exposure measure on annual publication counts for the two groups in each row, estimated jointly with the treated-market share control and PI and year fixed effects, along with their difference. Career stage splits PIs at the median years from their first last-authored publication to 2014 (14) or from their first publication in any authorship position. The NIH funding split uses the 7,999 NIH-matched PIs, and the institutional splits use PIs at universities with available institutional data, so the number of observations varies across rows. Standard errors clustered by PI are in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7. Shock-Level Balance of the Market-Level Price Effects

	Weighted (1)	Unweighted (2)
Buyers' pre-merger output growth (per SD)	0.020 (0.043)	0.013 (0.024)
95% confidence interval	[-0.066, 0.105]	[-0.034, 0.061]
Markets	46	46

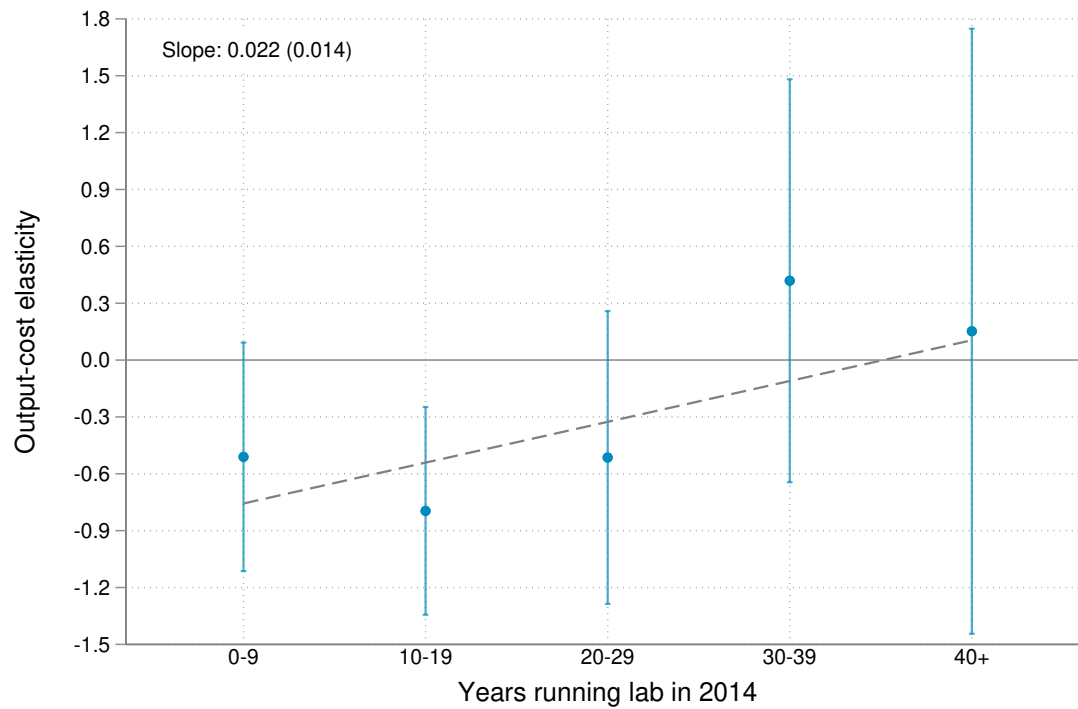
Notes: This table reports regressions of the 46 market-level price effects on buyers' pre-merger output growth, following [Borusyak et al. \(2022\)](#). A market's output growth is the spending-share-weighted average change in its buyers' mean annual publications from 2010–2011 to 2012–2013, residualized on S_i and standardized across markets (one standard deviation is 0.057 publications per year). Column (1) weights markets by their mean spending share, as in the exposure measure, and column (2) weights them equally. The effective number of shocks is 17.3. Heteroskedasticity-robust standard errors are in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1. Placebo Test for the Output Effect



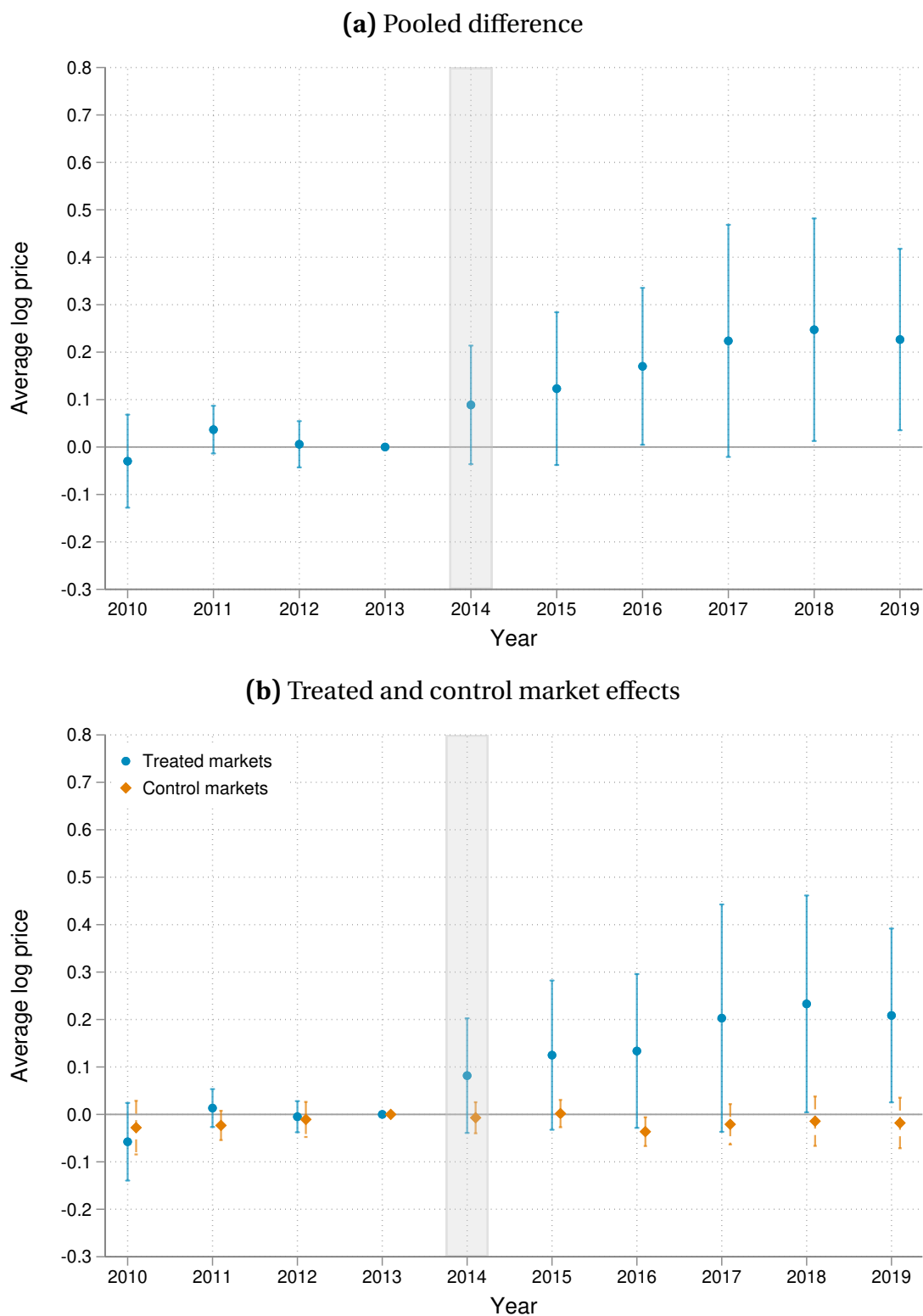
Notes: This figure shows the distribution of t -statistics on $\text{Exposure}_i \times \text{Post}_t$ from 100 placebo regressions. Each placebo rebuilds the exposure measure from price effects estimated in a random draw of control markets, passing them through the same shrinkage and imputation steps, and re-estimates column (1) of Table 5. The solid vertical line marks the actual t -statistic of -2.45, the dashed line marks zero, and 4 of the 100 placebo t -statistics are as negative as the actual one. The placebo t -statistics have a mean of 0.22 and a standard deviation of 1.81.

Figure A2. Effect of Higher Consumables Prices on Publication Counts by Years Running a Lab



Notes: This figure shows how the effect of the exposure measure on PIs' annual publication counts varies with years running a lab. Each point reports the coefficient on $\text{Exposure}_i \times \text{Post}_t$ from equation (6) for one bin of years from a PI's first last-authored publication to 2014, with all bins estimated in one regression. Vertical lines are 95% confidence intervals from standard errors clustered by PI, and the dashed line is a linear fit across bins with slope 0.022 (SE 0.014). The sample is the 13,515 PIs at 198 universities.

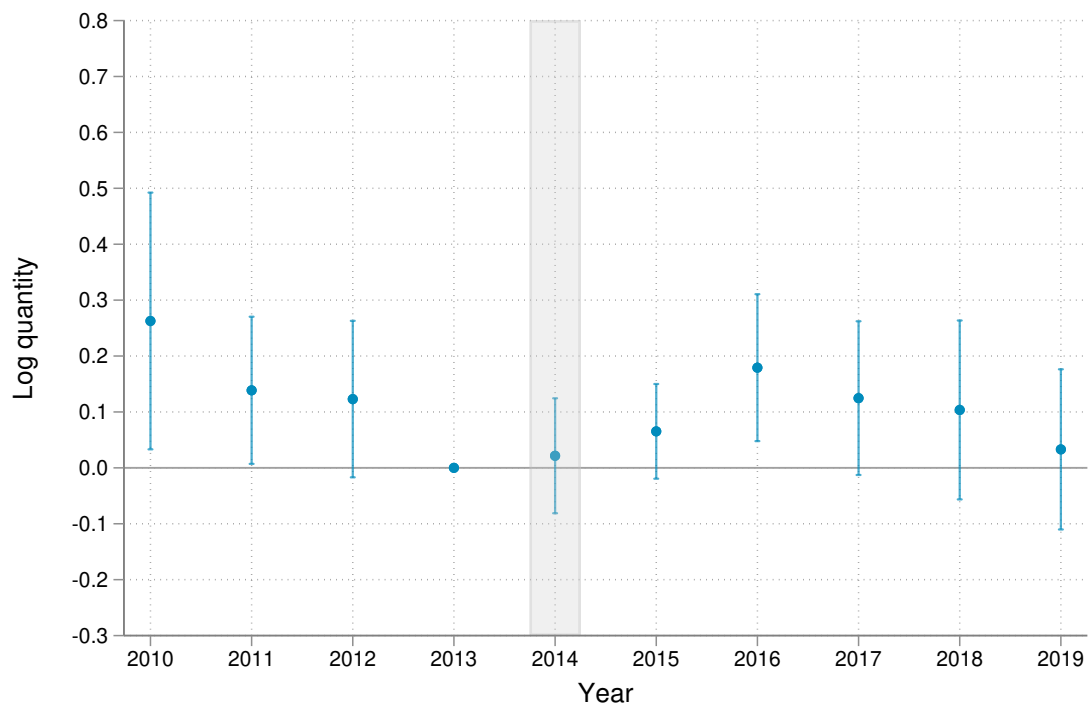
Figure A3. Pooled Merger Effects on Prices, Naive Specification



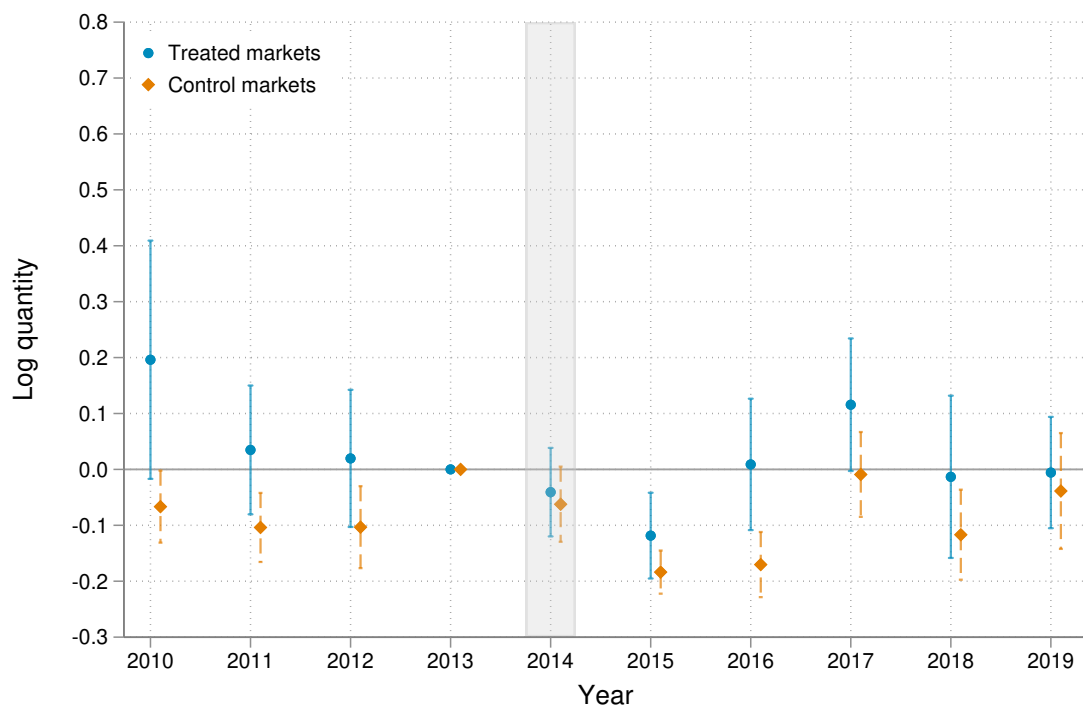
Notes: This figure shows naive event-study estimates of average log prices around the merger, using all unmatched control markets. Panel (a) shows the difference between treated and control markets. Panel (b) plots $\hat{\lambda}_t$ (control, orange) and $\hat{\lambda}_t + \hat{\beta}_n$ (treated, blue), subtracting the linear trend fitted to the control path from both. Standard errors are clustered by market. For Panel (b), they account for covariance among coefficients in each plotted path. The gray band marks the merger in 2014. The average price in $n = -1$ is \$147.47 in treated markets and \$86.38 in control markets.

Figure A4. Pooled Merger Effects on Quantities, Naive Specification

(a) Pooled difference



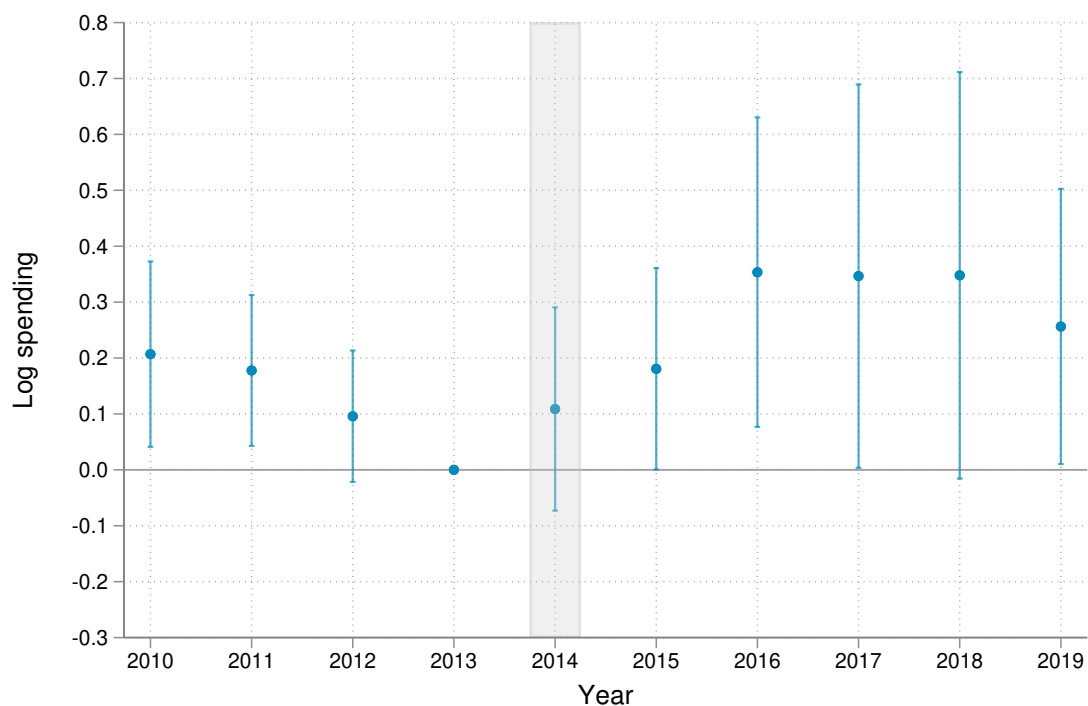
(b) Treated and control market effects



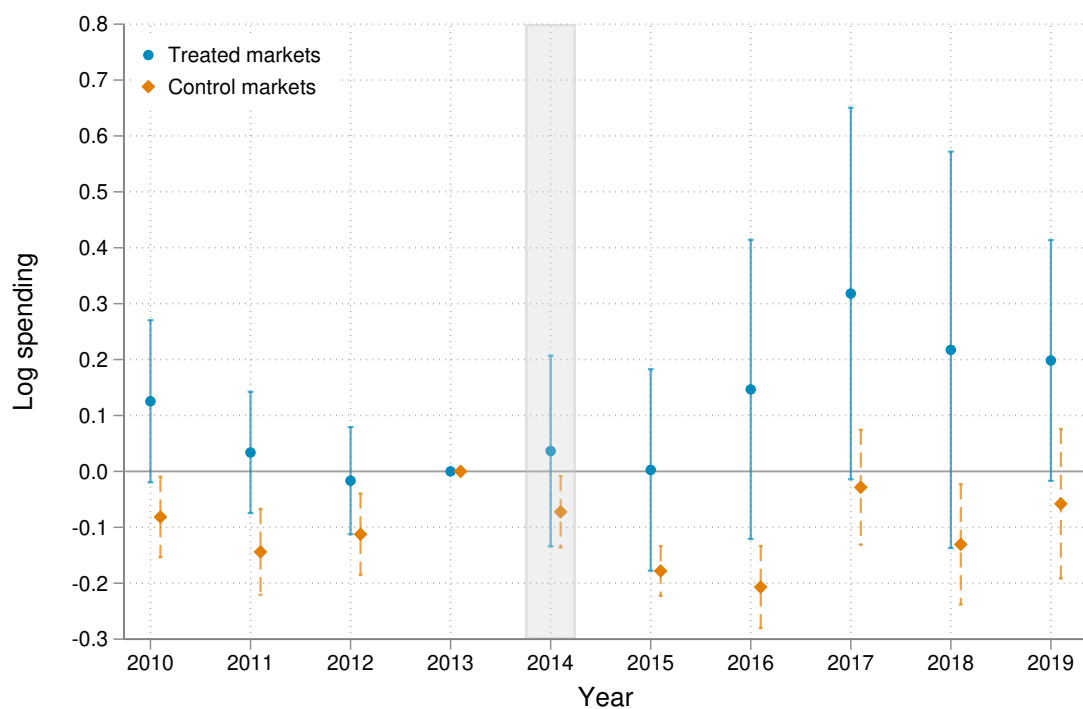
Notes: This figure shows naive event-study estimates of log quantity around the merger, using all unmatched control markets. Panel (a) shows the difference between treated and control markets. Panel (b) plots $\hat{\lambda}_t$ (control, orange) and $\hat{\lambda}_t + \hat{\beta}_n$ (treated, blue), subtracting the linear trend fitted to the control path from both. Standard errors are clustered by market. For Panel (b), they account for covariance among coefficients in each plotted path. The gray band marks the merger in 2014. The average quantity ordered in $n = -1$ is 17.2 in treated markets and 30.0 in control markets.

Figure A5. Pooled Merger Effects on Spending, Naive Specification

(a) Pooled difference

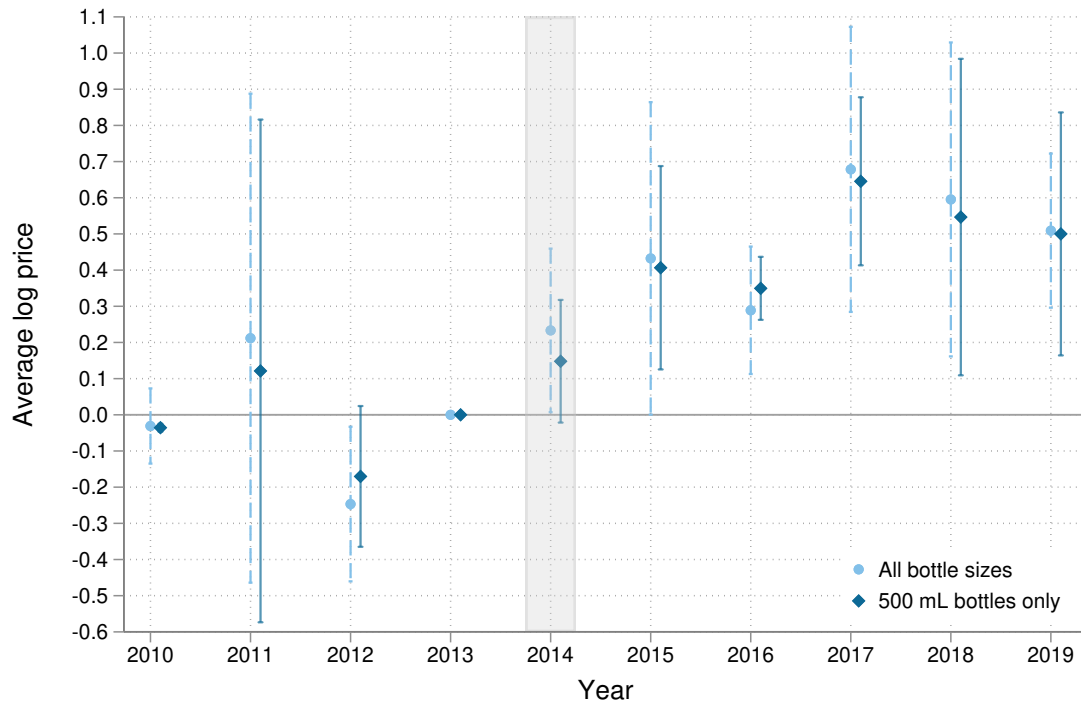


(b) Treated and control market effects



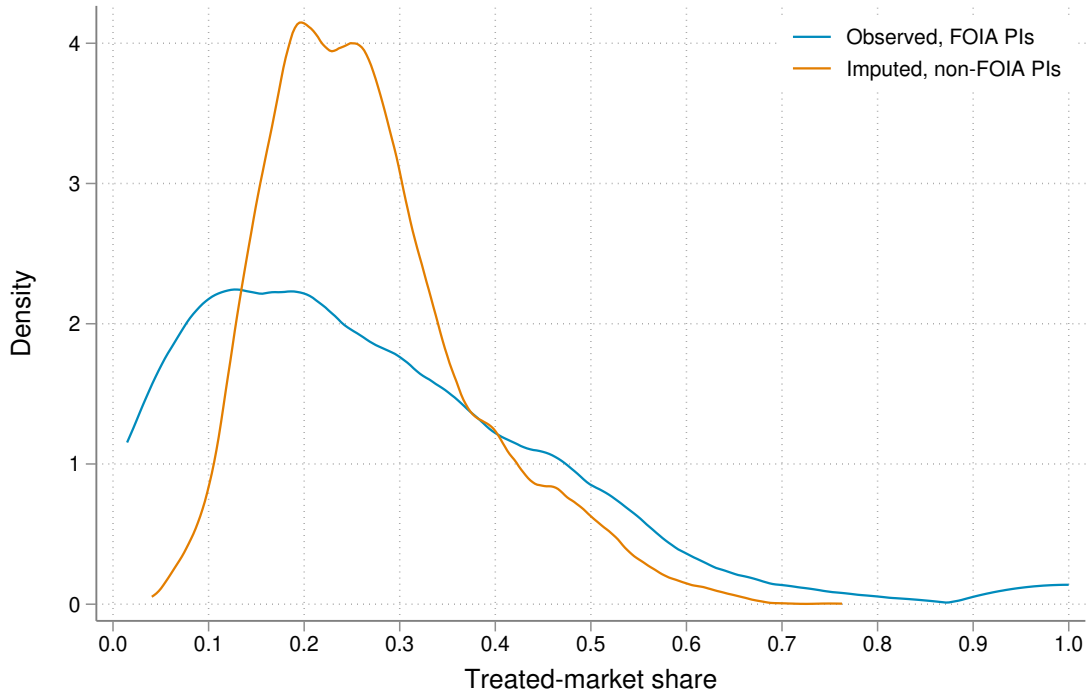
Notes: This figure shows naive event-study estimates of log spending around the merger, using all unmatched control markets. Panel (a) shows the difference between treated and control markets. Panel (b) plots $\hat{\lambda}_t$ (control, orange) and $\hat{\lambda}_t + \hat{\beta}_n$ (treated, blue), subtracting the linear trend fitted to the control path from both. Standard errors are clustered by market. For Panel (b), they account for covariance among coefficients in each plotted path. The gray band marks the merger in 2014. Average spending in $n = -1$ is \$2,068 in treated markets and \$1,753 in control markets.

Figure A6. Merger Effects on Fetal Bovine Serum Prices by Bottle Size



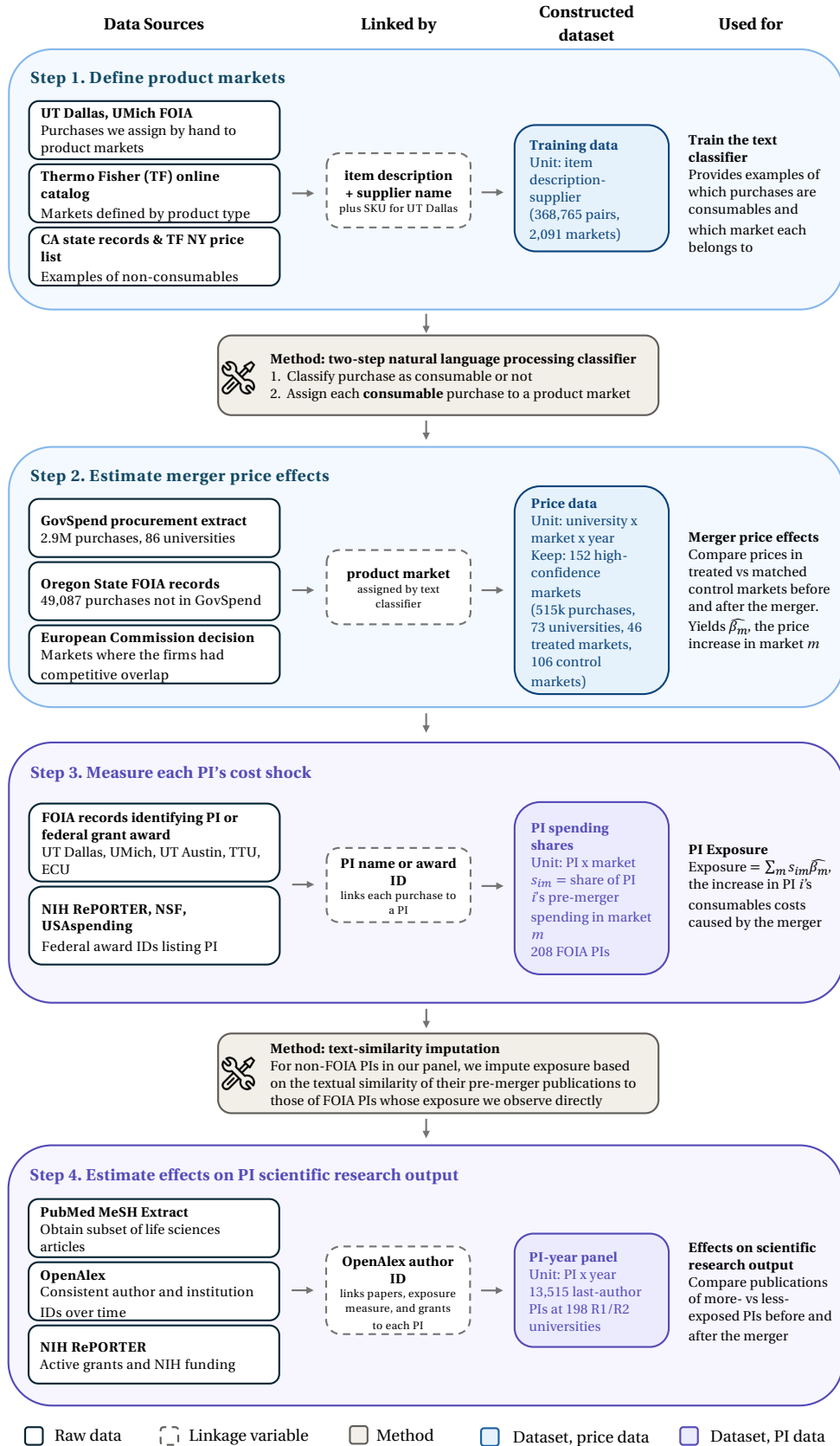
Notes: This figure shows event-study estimates of average log prices around the merger for U.S.-origin fetal bovine serum, for purchases of all bottle sizes (circles) and for purchases whose item descriptions identify 500 mL bottles, excluding recognizable multipacks (diamonds). Both sets of coefficients are differences between fetal bovine serum and its matched control markets, estimated with the same specification as Figure 1 and normalized to zero at $n = -1$. The gray band marks the merger in 2014. The 500 mL restriction holds bottle size fixed but does not hold product identity fixed. The pooled difference-in-differences estimates are 0.481 log points for all bottle sizes and 0.457 for 500 mL bottles, both before empirical Bayes shrinkage. The 500 mL sample keeps 2,229 of the 5,781 fetal bovine serum purchases, from 28 of the 43 universities that buy it, with the control markets unchanged.

Figure A7. Observed and Imputed Treated-Market Share Distributions



Notes: This figure shows the distributions of the observed and imputed treated-market share $S_i = \sum_{m \in \mathcal{T}} s_{im}$, which sums a PI's pre-merger spending shares across the high-confidence treated markets and enters equations (5) and (6) as a control. The blue line shows the observed share for the 208 FOIA PIs, and the orange line shows the imputed share for the 13,433 non-FOIA PIs in the panel. The observed share has a mean of 0.270 and a standard deviation of 0.199, and the imputed share has a mean of 0.262 and a standard deviation of 0.109.

Figure A8. Data Sources and Constructed Datasets



Notes: This figure maps the data sources and construction steps for the price dataset (blue) and the PI spending and publication dataset (purple). White boxes mark raw sources, dashed boxes mark linking variables, and gray boxes mark methods. See Sections 3.1 and 4.1.

Figure A9. Product Type Field in a Supplier Catalog Entry



Cytiva Hyclone™ Defined Fetal Bovine Serum (U.S.)
Catalog No.: SH3007002HI

\$550.00

Description	Specifications	Compare Specifications	Product Suggestions	Accessories	Promotions
Additional Assays	Progesterone,Insulin,Cholesterol,HDL,LDL,Triglycerides,Gamma Globulin,Phospholipids,Alkaline Phosphatase,Lactate Dehydrogenase,SGPT,SGOT,B1,B2,B6,Niacin,Biotin,Retinol,Carotene,Tocopherol,B12,Folate,Vitamin C,1,25-dihydroxy vitamin D,pH,Total Protein,Albumin,Blood Urea Nitrogen,Creatinine,Total Bilirubin,Inorganic Phosphorus,Selenium,Sodium,Potassium,Calcium,Chloride,Magnesium,Glucose,Copper,Osmolality,Iron,TIBC,Percent Saturation,IgG				
Certifications/Compliance	Manufactured in cGMP (21 CFR 820) compliant and ISO9001 certified facilities				
Content And Storage	Sera should be stored at -10°C or lower. Once thawed, sera should be stored at 2 to 8°C.				
Country of Origin	United States				
Product Type	Fetal Bovine Serum				

Notes: This figure shows the specifications page for a Cytiva HyClone fetal bovine serum in Thermo Fisher Scientific's online catalog. The highlighted Product Type field, Fetal Bovine Serum, gives the initial product-market assignment. For this type of product, the European Commission's decision treats markets from different countries as separate, so we also use the Country of Origin field to assign this product to the market for U.S.-origin fetal bovine serum.

B Keyword Filters for the GovSpend Extract

This appendix lists the 1,505 keywords that define our GovSpend extract. The extract keeps every purchase at a public university whose item description contains one of these keywords as a substring, so *centrifuge tube* also returns *centrifuge tubes* and *microcentrifuge tubes*. Item descriptions are free text entered by purchasing staff and vendors, so the list includes abbreviations, truncated stems, and common misspellings, such as *fltr*, *sod bicarb*, and *inoculating loop*. The keywords are meant to capture all life sciences purchases rather than consumables alone.

Enzymes

Restriction endonucleases and nicking enzymes

AanI	AscI	Bme1390I	BsgI	BssHII	BtgZI	Eco47I
AarI	AseI	Bme18I	Bsh1236I	BssMI	BtrI	Eco47III
AatII	AsiGI	BmeRI	Bsh1285I	BssNAI	BtsCI	Eco52I
AbsI	AsiSI	BmgBI	BshFI	BssNI	BtsI-v2	Eco53kI
Acc16I	Asp718I	BmiI	BshNI	BssSI-v2	BtsIMutI	Eco57I
Acc36I	AspA2I	BmrFI	BshTI	BssT1I	BtuMI	Eco72I
Acc65I	AspEI	BmrI	BshVI	Bst1107I	BveI	Eco81I
AccB1I	AspLEI	BmtI	BsiEI	Bst2BI	Cac8I	Eco88I
AccB7I	AspS9I	BmtI-HF	BsiHKAI	Bst2UI	CaiI	Eco91I
AccBSI	AsuC2I	BmuI	BsiHKCI	Bst4CI	CciI	EcoICRI
AccI	AsuHPI	BmyI	BsiSI	Bst6I	CciNI	EcoNI
AccII	AsuII	BoxI	BsiWI	Bst98I	CellI	EcoO109I
AccIII	AsuNHI	Bpil	BsiWI-HF	BstACI	CfoI	EcoP15I
Acil	AvaI	BpII	BslFI	BstAFI	Cfr10I	EcoRI
AcII	AvaII	BpmI	BslI	BstAPI	Cfr13I	EcoRI-HF
AcIWI	AviII	Bpu10I	BsmAI	BstAUI	Cfr42I	EcoRII
AcoI	AvrII	Bpu1102I	BsmBI-v2	BstBAI	Cfr9I	EcoRV
AcsI	AxyI	Bpu14I	BsmFI	BstBI	Clal	EcoRV-HF
AcuI	BaeGI	BpuEI	BsmI	BstC8I	CpoI	EcoT38I
AcvI	BaeI	BpuMI	BsnI	BstDEI	CseI	EgeI
AcyI	BalI	Bsa29I	Bso31I	BstDSI	Csp6I	EheI
AdeI	BamHI	BsaAI	BsoBI	BstEII	CspAI	ErhI
AfeI	BamHI-HF	BsaBI	Bsp119I	BstEII-HF	CspCI	Esp3I
AfiI	BanI	BsaHI	Bsp120I	BstENI	CviJI	FaeI
AfII	BanII	Bsal	Bsp1286I	BstF5I	CviKI-1	FaiI
AfIII	BarI	BsaI-HFv2	Bsp13I	BstFNI	CviQI	FalI
AgeI	BauI	BsaJI	Bsp1407I	BstH2I	DdeI	FaqI
AgeI-HF	BbrPI	BsaMI	Bsp143I	BstHHI	DinI	FatI
AgsI	BbsI	BsaWI	Bsp1720I	BstKTI	DpnI	FauI
AhdI	BbsI-HF	BsaXI	Bsp19I	BstMAI	DpnII	FauNDI
AhII	Bbv12I	Bsc4I	Bsp68I	BstMBI	DraI	FbII
AjiI	BbvCI	Bse118I	BspACI	BstMCI	DraIII	Fnu4HI
AjnI	BbvI	Bse1I	BspCNI	BstMWI	DraIII-HF	FokI
AjuI	BccI	Bse21I	BspDI	BstNI	DrdI	FriOI
AleI	BceAI	Bse3DI	BspEI	BstNSI	Dril	FseI
AleI-v2	BcgI	Bse8I	BspFNI	BstPAI	DsaI	Fsp4HI
AloI	BciVI	BseAI	BspHI	BstSCI	DseDI	FspAI
AluBI	BclI	BseBI	BspLI	BstSFI	EaeI	FspBI
AluI	BclI-HF	BseCI	BspMI	BstSLI	EagI	FspI
Alw21I	BcnI	BseDI	BspOI	BstSNI	EagI-HF	GsaI
Alw26I	BcoDI	BseGI	BspPI	BstUI	Eam1104I	GsuI
Alw44I	BcuI	BseJI	BspQI	BstV1I	Eam1105I	HaeII
AlwI	BfaI	BseLI	BspQI-HF	BstV2I	EarI	HaeIII
AlwNI	BfmI	BseMI	BspTI	BstX2I	EciI	HgaI
Ama87I	BfrI	BseMII	BsrBI	BstXI	Ecl136II	HhaI
Aor13HI	BfuAI	BseNI	BsrDI	BstYI	EclXI	Hin1I
Apal	BfuI	BsePI	BsrFI-v2	BstZ17I-HF	Eco105I	Hin1II
ApalI	BglI	BseRI	BsrGI	Bsu15I	Eco130I	Hin6I
ApeKI	BglII	BseSI	BsrGI-HF	Bsu36I	Eco147I	HincII
ApoI	BlnI	BseX3I	BsrI	BsuI	Eco24I	HindII
ApoI-HF	BlpI	BseXI	BssAI	BsuRI	Eco31I	HindIII
ArsI	BmcAI	BseYI	BssECI	BtgI	Eco32I	HindIII-HF

Hinfl	MboII	Nb.BtsI	PceI	PspPI	SfaNI	TaqI
HinP1I	MfeI	Nb.Mva1269I	PciI	PspPPI	SfcI	TaqI-v2
HpaI	MfeI-HF	NciI	PciSI	PspXI	SfiI	TaqII
HpaII	MhlI	NcoI	PcsI	PsrI	SfoI	TasI
HphI	MlsI	NcoI-HF	PctI	PstI	Sfr274I	TatI
Hpy166II	MluCI	NdeI	PdiI	PstI-HF	Sfr303I	TauI
Hpy188I	MluI	NdeII	Pdml	PstNI	SfuI	TfiI
Hpy188III	MluI-HF	NgoMIV	PecI	PsuI	SgeI	Tru1I
Hpy8I	Mly113I	NheI	PfeI	PsyI	Sgfl	Tru9I
Hpy99I	MlyI	NheI-HF	Pfl23II	PvuI	SgrAI	TscAI
HpyAV	MmeI	NlaII	PfIF	PvuI-HF	SgrBI	TseFI
HpyCH4III	MnlI	NlaIV	PfIMI	PvuII	SgrDI	TseI
HpyCH4IV	Mox20I	NmeAIII	PfoI	PvuII-HF	SgsI	Tsp45I
HpyCH4V	Mph1103I	NmuCI	PI-PspI	RgaI	SlaI	TspDTI
HpyF10VI	MreI	NotI	PI-Scel	RigI	SmaI	TspGWI
HpyF3I	MroI	NotI-HF	PinAI	RsaI	SmiI	TspMI
HpySE526I	MroNI	NruI	PkrI	RsaNI	SmiMI	TspRI
HspAI	MroXI	NruI-HF	Ple19I	RseI	SmlI	Tth111I
I-CeuI	MscI	NsbI	PleI	Rsr2I	SmoI	Van91I
I-SceI	MseI	Nsil	PluTI	RsrII	SnaBI	Vha464I
KasI	MslI	Nsil-HF	PmeI	SacI	SpeI	VneI
Kpn2I	Msp20I	NspI	PmlI	SacI-HF	SpeI-HF	VspI
KpnI	MspA1I	NspV	PpsI	SacII	SphI	WarmStart
KpnI-HF	MspCI	Nt.AlwI	Ppu21I	Sall	SphI-HF	Nt.BstNBI
KroNI	MspI	Nt.BbvCI	PpuMI	Sall-HF	SrfI	XagI
Ksp22I	MspJI	Nt.Bpu10I	PscI	SapI	SsegI	XapI
KspAI	MspR9I	Nt.BsmAI	Pse31I	SatI	SseBI	XbaI
KspI	MssI	Nt.BspQI	PshAI	Sau3AI	Ssil	XceI
Kzo9I	MteI	Nt.Bst9I	Psil	Sau96I	SspDI	XcmI
LguI	MunI	Nt.BstNBI	Psil-v2	Sbfl	SspI	XhoI
LmnI	Mva1269I	Nt.CviPII	Psp124BI	Sbfl-HF	SspI-HF	XhoII
Lsp1109I	MvaI	OliI	Psp1406I	ScaI	SspMI	XmaCI
LweI	MwoI	PacI	Psp5II	ScaI-HF	SstI	XmaI
MabI	NaeI	PaeI	Psp6I	SchI	StuI	XmaJI
MaeIII	NarI	PaeR7I	PspCI	ScrFI	StyD4I	Xmil
Mall	Nb.BbvCI	PagI	PspEI	SdaI	Styl	XmnI
MamI	Nb.Bpu10I	PalAI	PspGI	SduI	Styl-HF	ZraI
MauBI	Nb.BsmI	PaqCI	PspLI	SetI	SwaI	ZrmI
MbiI	Nb.BsrDI	PasI	PspN4I	SexAI	TaaI	Zsp2I
MboI	Nb.BssSI	Paul	PspOMI	SfaAI	Tail	

Polymerases, ligases, nucleases, proteases, and other enzymes

collagenase	elastase	kinase	Mutanolysin	rnase	transferase
dehydrogenase	enzyme	liberase	peroxidase	t4	trypsin
deoxyribonuclease	exonuclease	ligase	phosphatase	t4 dna	WarmStart
dipase	hi-fi	luciferase	polymerase	t5	
dispace	high-fidelity	luciferin	protease	t7	
dnase	hot-start	lysozyme	proteinase	taq	

Reverse transcription

improm-ii	rev transcription	rev transcrptase	reverse transcriptase	reverse transcription	superscript
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Antibodies, Proteins, and Standards

Antibodies, conjugates, and antibody targets

affinipure	anti-il1a	Anti-Rat	hif-1	il-1	pAb
anbti-bcl2	Anti-Mouse	Anti-Sheep	hrp	lc3b	polyclonal
anti-elf3	anti-mu	anti-sox9	iga	mAb	sglt2
Anti-Goat	anti-rab	antibody	igg	mcl-1	tnem173
Anti-Guinea Pig	anti-rabb	b-amyloid	igm	monoclonal	
Anti-Human	Anti-Rabbit	bamyloid	igy	nfkB	

Proteins, peptides, and recombinant products

albumin	casein	growth factor	recombinant human	streptavidin
avidin	collagen	hemin	recombinant mouse	wheat germ
beta-actin	cytochrome	peptide	reombinant	agglutinin
bsa	gelatin	protein	rhil	

Ladders and standards

bp ladder	icp standard	ladder gel	pre-stain	protein ladder	unstained protein
dna ladder	kb plus	nativemark	precision plus	protein standard	
generuler	ladder dna	Pageruler	prot std	spectra	

Nucleic Acids and Cloning Reagents

Nucleic acids, oligonucleotides, and nucleotides

adenosine 5 triphosphate	deoxynuc deoxynucleotide	dntp	nucleic acids	rna
atp	deoxyribonucleic acid	dsdna	oligo	rna ladder
cdna		glycogen	primer	RNAi
cytosine	dna	hexamer	ribonuclease	shrna
		mirna	ribonucleic acid	srna

Vectors, competent cells, and cloning reagents

chem comp	comp e.coli	iptg	plasmid	x-gal
comp cell	competent cell	one shot	t-vector	
comp e coli	competent e coli	pgem	top10	

Nucleic acid purification kits and RNA reagents

ampure	genejet	mini-prep	rna-protect	rrasin	zymo
dneasy	maxi-prep	mprep	rnaclean	superase	
ez-10 column	megascript	nucleospin	rnaseout	trizol	
gel extraction	midi-prep	ribolock	rnasezap	trizol reagent	
gel-pcr	minelute	ribominus	rneasy	zeoprep	

Stains, Dyes, Probes, and Indicators

acridine orange	dab	fam-mgb	hematoxylin	pH	sudan black
alcian blue	dapi	fast green	hoechst	ph strip	sybr
alexa fluor	Diamidino-2- phenylindole	FITC	lysotracker	ponceau	sybr-green
aniline blue		fluor	mitosox	protein stain	sypro
biebrich scarlet	dye	fluorescein	neurotrace	ram stain	texas red
brilliant violet	em stain	fluoro gel	nile red	rhodamine	toluidine blue
coomassie	eosin	fluoromount	orange ii	rose bengal	trypan blue
cresyl violet	eosin y	gel stain	perox test	silversnap	
crystal violet	ethidium bromide	golgistain	peroxide test	stain	

Buffers, Chemicals, and Antibiotics

Buffers, salt solutions, and water

bis-tris	edta	extraction solution	sds	tris acetate edta	trishydrox-
buffer	egs	hepes	tae	tris base	metaminometh
chaps	eliza buffer	mes	tbe	tris borate edta	water molecular
deionized water	ethlenediamintetac	nuclease-free water	tbe pp	tris glycine	water molecular bio
diluent	ethlenediamin-	pbs	tbs	tris glycine sds	
dpbs	tetacetic	RIPA	tris	tris-hcl	

Solvents and organic reagents

2-propanol	chloroform	ethano	glycerol	paraformaldehyde	tetrahydrofuran
acetone	dimetformamide	ethanol	hexanes	peg	xylene
acetonitrile	dimethyl-sulfoxide	ethyl acetate	isopropanol	phenol	
alcohol proof	dimethylformamide	ethyl alcohol	methanol	poly ethylene glycol	
alcohol reagent	dmf	formaldehyde	methyl-sulfoxide	methyl ether	
butyllithium	dmsa	formldhyd	methylene chlor	polyethylene glycol	

Acids and bases

acetic ac	boric acid	hydrochlor ac	phosphoric acid	sodium hydroxide	triflroacetic ac
ammonium	citric acid	hydrochloric acid	potassium hydroxide	sulfuric ac	trifluoroacetic
hydroxide	formic acid	nitric acid	sodium hydroxd	sulfurif ac	

Salts, sugars, and amino acids

adenine	d-glucose	mag sulf	potassium	sodium azide	sodium nitrite
aluminum chloride	d-mannitol	magensium chloride	phosphate	sodium bicarbonate	sodium phosphate
ammonium acetate	glucose	magnesium chloride	sod bicarb	sodium carbonate	sodium pyruvate
ammonium chloride	glycine	pot carbonate	sod chloride	sodium chloride	sucrose
calcium acetate	l-cysteine	pot phosphate	sod hydride	sodium citrate	zinc chloride
calcium carbonate	l-glutamine	potassium carbonate	sod phos	sodium dodecyl	
calcium chloride	lithium chloride	potassium chloride	sod phosphate	sulfate	
d-fructose	lysine		sodium acetate	sodium hydride	

Antibiotics, antimycotics, and disinfectants

amphotericin	carbenicillin	g418	metronidazole	penicillin-	tobramycin
ampicillin	cefoxitin	geneticin	neomycin	streptomycin	trimethoprim
antimycin	ceftriaxone	gentamicin	nigericin	plasmocin	vancomycin
antimycotic	chloramphenicol	gentamycin	normocin	puromycin	zeocin
bacitracin	ciprofloxacin	germicidal	nystatin	spectinomycin	
blastcidin	clindamycin	hygromycin	pen-strep	streptomycin	
bleach	daptomycin	kanamycin	penicillin	streptozotocin	
bleomycin	doxycycline	levofloxacin		tetracycline	

Other reagents and small molecules

actinomycin	dmog	hydrogen perox	mlclr sieves	protease inhib	triton
amide	doxorubicin	igepal	mole sieves	silica	tween
anisomycin	drierite	imidazole	molecular sieve	silica gel	urea
biotin	dtc	inositol	nhs ester	tcep	
carbon dioxide	edc	lectin	oligomycin	tpen	
deuterium oxide	folic acid	lipopolysaccharide	percoll	tris 2 carboxyethyl	
dextran	glutathione	maldi matrix	phosphatase inhib	phosphine	
digitonin	hbtu	mitomycin	pma	hydrochloro	

Cell Culture Media and Reagents

Basal media and balanced salt solutions

brff-hpc1	eagle s	hank balanced	megm	modified eagle	sf-900
dmehigh	earles	hbss	mem neaa	medium	stemprom
dmem	emem	hibernate a	mem non-essential	neurobasal	
dmemw	f-12 nutrient	insect medium	minimum essential	opti-mem	
dmm	gibco	keratinocyte sfm	medium	rpmi	
dulbecco	ham s	leibovitz s		serum-free	

Sera and supplements

amino acid	calf serum	fbs	fetal bovine serum	horse serum	matrigel
b-27	donkey serum	fbs hi	glutamax	hyclone	usda tested serum
bovine growth serum	fb essence	fbs usda	goat serum	hyq	vitamin supplement

Microbiological media

agar	casamino	horse blood	mueller hinton	soc medium	yeast
brain heart infusion	chromagar	lb broth	peptone	tryptone	
broth	enterococcus	lb media	sheep blood	tryptose	

Cell culture, dissociation, and transfection

accutase	cell culture	cell dissociation	tc	transfection	
cell	cell detachment	lipofectamine	tis cult	transfection reagent	
cell cult	cell dissoc	nucleofector	tissue culture	turbfect	

Assays, Kits, and Techniques

Techniques and workflows

apoptosis	dna assembly	mutagenesis	qpcr	synthesis	
cell lysis	ligation	pcr	rt qpcr	terminal labling	
cloning	lysis	purification	sequencing	terminl labling	

Assays and detection kits

alphascreen	background	cell viability	duolink	pierce	thiazolyl blue
assay	suppressor	celltiter	duoset	pierce protein	tetrazolium
assay ki	bca	colorimetric kit	elisa	premo	bromide
assay kit	bradford	colorimetric kt	eliza kit	protein assay	tsa plus
assay kt	bright clo	deadend system	live cell	sigmafast	xenolight
assy	bright-glo	det kit	live/dead	smartflare	
	cell proliferation	detection kit	MTT		

Electrophoresis and blotting

acrylamide	electrophoresis	mini-gel	north2south	restore plus	western blot
agarose	gel loading	mini-trans	nupage	supersignal	western blotting
ammonium	gel system	n tetramethylethyle	polyacrylamide	temed	
persulfate	immobilon	nativepage	protean	tetramethylethy	
blotting membrane	instapage	nitrcl	protogel	trans-blot	
clarity western	laemmli	nitrocellulose	pvdif membrane	transfer-buf	

Purification, chromatography, and concentration

amicon ultra cncntrfugl	concentrator	float-a-lyzer	magnetic bead	sephadex	uplc column
amicon	db myone	guard column	myone	sepharose	vivaspin
bio-gel	dynabead	hiload	nap 25	slide-a-lyzer	vivaspinturbo
chromatography	dynamag	hispur	ni-nta	slide-a-lyzr	zorax
column	filter column	histrap	polysep	spin column	zorbox
concentrator	filter columnhiprep	hitrap	rediseq	superdex	

PCR master mixes and other branded reagents

iscript	mannheim	omnimix	super-mix
itaq	master-mix	powerupsybrgreen	

Labware and Consumables

Glassware, vessels, and general labware

beaker	crystallizing	funnl	reagnt reservoir	stir-bar	wgh boat
bottle	cuvette	graduated cylinder	reservoir rgnt	stirbar	
btl	cyl grad	lab scoop	scoopula	stirring bar	
btle	cylinder ml	micro spatula	spin-bar	stop-cock	
combitip	finntip	ppfunl	spoon spatula	weigh boat	
cork-ring	funnel	reagent reservoir	spoonula	weigh dish	

Pipettes and pipette tips

96 rack	eptips	lr tip	pipette tip	stripet	tip str fltr
barrier tip	filter tip	macro tip	pipettor	strpet	tip-rack
beveltdip	fisherbrand elite	maxi tips	pipt tp	strpette	trans ppt
beveled-tip	fltr tip	microtip	ppettor	tip bulk	xl tip
bevtip	gel tip	pipet	refill tip	tip filter	
channel-pipette	graduated tip	pipet tip	serological	tip fltr	
channelpipette	low reten	pipetman	sftftil	tip rack	
cliptip	low retention	pipette	softfil	tip ster fltr	

Tubes, racks, and cryogenic storage

capillary tube	cryo fiberbox	culture tube	microcentrifuge	safe-lock	tube strip
cardboard freezer	cryobox	emr tube	microfuge	scintillation vial	tube strp
box	cryodot	epp	microtube	tb	vial
cent tbe	cryoelite	eppendorf	micrtb	tb cnt	vial cryogenic
cent tube	cryolabel	epr tube	mltbe	test tube	vial scint
centrifuge tube	cryotube	lobnd	nmr tube	tube conic	
conicl tbe	cryovial	mcrtb rck	nunc conicl	tube grad	
cryo	cult tube	mct	safe-lck	tube rack	

Plates, dishes, flasks, and slides

96wl	cover glass	flask	microslide	plate tc	tissue dish
cap strip	coverslip	flsk	multidish	plt	top seal
cell dish	cul dish	gls cv	nunc	plt 96	well plate
cellstar	culture dish	micro-slide	pcr plate	slide chamber	well plt
chamber sld	culture insert	microscope slide	pcr well	slide superfr	well-plate
chamber slide	culture plate	microscop sld	petri	tc dish	well-plt
clearseal	culture well	microscpe slide	plate 96	tc plate	
cov glass	cvr glas	microseal	plate flat	tc-flsk	

Filters, syringes, and needles

aspirator pes	extract thimble	fltr ppr	puradisc	syringe	thimble sgl
bottle top filter	filter paper	fltrbt	stericup	syringe fil	whatman
centrifugal	filter ppr	fltrbtpa	syr	syringe filter	
centrifugal filter	flt	millipak	syr flt	syrg	
centrifugal filter unit	fltr	milx	syr fltr	synre	
cncntrfgl	fltr paper	needle	syr-filt	tb syr	

Histology, protective wear, and other consumables

aluminum foil	embedding cassette	histosette	latex bulb	pap pen	tissue tek
antifade	embedding medium	inoc loop	lysing matrix	paraffin	weighing paper
cell scraper	face-mask	inoculating loop	mask	parafilm	weighing ppr
cell strainer	face-msk	inoculating loop	mountant	rubber bulb	wrapping film
embed medium	glove	kimwipe	mounting media	thermal paper	
embed resin	glv	lab-coat	mounting medium	tissue grinder	

General Terms and Units

configurationid	gene	nmol	ppt
femto	hydrochloride	pmol	umol

C Treated and Control Product Markets

This appendix lists the 152 high-confidence product markets that enter the estimation of the price effects, 46 treated and 106 control. A market is high-confidence if it has at least 25 training examples and precision and recall of at least 0.8, and is not among the 34 markets with contemporaneous shocks described in Section 3.1.3.

A market is treated on one of two conditions. It is *directly documented* when the European Commission's clearance decision ([Case COMP/M.6944](#)) names it, or the product family containing it, as an area of pre-merger competitive overlap between Thermo Fisher Scientific and Life Technologies. It is a *complement* when the decision does not name it but it is purchased alongside a documented market in the same experimental workflow, so that the merged firm could plausibly reprice it as part of the bundle.

Table A8 maps each treated market to the decision's broader product market, with the documented markets in Panel A and the complements in Panel B, covering the seven of the decision's twelve consumables areas that contain at least one high-confidence market. Robustness estimates restrict treatment to Panel A. Control markets fall outside the merging firms' overlap and are listed by category after the table.

Table A8. High-Confidence Treated Markets Mapped to Case COMP/M.6944

Product market in the decision	Our product markets
Panel A: Directly documented markets	
Media for cell culture and process liquids	<i>Media:</i> dmem; dmem/f-12; rpmi. <i>Process liquids:</i> phosphate-buffered saline (pbs) buffer; dulbecco's phosphate-buffered saline (dpbs) buffer; hanks' balanced salt solution (hbss) buffer; tris-edta (te) buffer
Sera for cell culture	us fbs; donkey serum; goat serum; horse serum
Nucleic acid amplification reagents	<i>Enzymes:</i> taq polymerases; high-fidelity dna polymerase; hot start pcr systems; reverse transcriptase. <i>Kits:</i> first-strand cdna synthesis systems
Nucleic acid purification	<i>Molecular weight standards:</i> pre-stained protein ladders; unstained dna ladders
Cloning	<i>Enzymes:</i> dnase i; rnase inhibitors; klenow fragment; t4 polynucleotide kinase
SDS-PAGE	pre-cast bis-tris gels; pre-cast tbe gels; pre-cast tris-glycine gels; pre-cast tris-tricine gels; nucleic acid gel stains; protein gel stains
Western blotting	nitrocellulose blotting membranes; pvdf blotting membranes; chemiluminescent substrates
Panel B: Complements of documented markets	
Media for cell culture	cell culture dissociation reagents; tryptone; yeast extract
Sera for cell culture; Western blotting	bovine serum albumin

Product market in the decision	Our product markets
Nucleic acid purification	column-based dna plasmid miniprep, midiprep, and maxiprep kits; gel dna extraction kits; microbial dna purification kits; rna stabilization reagent
Cloning	site-directed mutagenesis systems
SDS-PAGE	<i>Running and sample buffers:</i> laemmli sample buffer; lds sample buffer; mes-sds buffer. <i>Gel casting:</i> acrylamide/bis solution

Notes: This table maps the product markets named in the European Commission's clearance decision, Case COMP/M.6944, to our finer product markets within them. Panel A markets are named in the decision, directly or through their product family. Panel B markets are purchased alongside a Panel A market within the same experimental workflow, and the purification-kit complements also draw on the kit-level overlap in the predecessor decision, Case COMP/M.5264. Robustness estimates restrict treatment to Panel A.

Control Markets

- **Bulk chemicals, acids, and solvents.** Acetone, chloroform, ethyl acetate, isopropanol, methanol, tetrahydrofuran (THF), trifluoroacetic acid (TFA), xylenes, phenols, glycerol, glycine, nitric acid, sulfuric acid, boric acid, hydrogen peroxide, bleach, ammonium chloride, ammonium persulfate, lithium chloride, magnesium chloride, potassium carbonate, potassium phosphate, sodium acetate, sodium azide, sodium bicarbonate, sodium chloride, sodium citrate, sodium hydroxide, sodium sulfate, and zinc chloride.
- **Buffering agents.** HEPES buffer, MES buffer, and MOPS buffer.
- **Antibiotics and selection reagents.** Ampicillin, carbenicillin, chloramphenicol, hygromycin, penicillin-streptomycin, puromycin, zeocin, and IPTG.
- **Detergents, lysis, and reducing reagents.** Digitonin, SDS (sodium dodecyl sulfate), Triton X-100, Tween detergents, DTT, TCEP, and protease inhibitor cocktails.
- **Stains, substrates, and detection kits.** Apoptosis detection kits, bioluminescence assay kits, colorimetric substrates (DAB, MTT, and TMB), histology and cell stains, phalloidin conjugates, viability stains, western blot stripping buffers, and PAP pens.
- **Separation media and other molecular biology reagents.** Agarose, dNTPs, GST-tag affinity resins, size-exclusion resins, spin desalting columns, and dialysis cassettes.
- **Cell culture and microbiology reagents.** Carbon dioxide, laminin, polylysines, thrombin, dehydrated bacterial broth, and inoculating loops and needles.

- **Labware, plasticware, and glassware.** Cell culture dishes, flasks, plates, and tubes, coverslips, microscope slides, cell scrapers, cell strainers, cryovials, cuvettes, beakers, boiling flasks, dewar flasks, disposable pipettes, serological pipettes, pipette tips, extraction thimbles, film and foil wrapping, filter papers, funnels, graduated cylinders, lab coats, laboratory spatulas, latex gloves, media bottles, microcentrifuge tubes, PCR tube strips, petri dishes, spray bottles, square glass bottles, stir bars, storage jars, vials, wash bottles, weigh boats, and weighing papers.

D Empirical Bayes Shrinkage of Market-Level Price Effects

We estimate the price effect separately for each of the 46 treated markets. Some estimates may be noisy because certain markets contain relatively few observations. Because these estimates enter the PI-level exposure measure, random estimation error could make the measure reflect noise rather than true differences in price effects across markets. Following the empirical Bayes approach of [Efron and Morris \(1973\)](#); [Morris \(1983\)](#), we shrink the estimated price effects toward a common cross-market mean.

We use a model in which each market-level estimate is a noisy measure of its true price effect and true effects vary around a common mean across markets:

$$\hat{\beta}_m \mid \beta_m \sim N(\beta_m, \widehat{se}_m^2), \quad \beta_m \sim N(\mu, \tau^2).$$

Here, $\widehat{se}_m^2$ is the reported sampling variance, and τ^2 is the variance of the true effects β_m around their mean μ . We estimate μ and τ^2 from the market-level data. The estimate $\hat{\mu}$ determines the center of the distribution, while $\hat{\tau}^2$ determines the strength of the shrinkage. We first estimate

$$\hat{\tau}^2 = \max \left\{ 0, \text{Var}(\hat{\beta}_m) - \overline{\widehat{se}_m^2} \right\} = 0.031,$$

where the observed cross-market variance is approximately 0.033 and the average reported sampling variance is 0.002. Thus, $\hat{\tau}^2 = 0.033 - 0.002 = 0.031$.

We estimate μ using an inverse-variance-weighted average, which gives more weight to markets with more precise estimates:

$$\hat{\mu} = \frac{\sum_m \hat{\beta}_m / \widehat{se}_m^2}{\sum_m 1 / \widehat{se}_m^2} = 0.18.$$

Using these estimates, we calculate a shrunken price effect for each market:

$$\hat{\beta}_m^{EB} = w_m \hat{\beta}_m + (1 - w_m) \hat{\mu}, \quad w_m = \frac{\hat{\tau}^2}{\hat{\tau}^2 + \hat{s}e_m^2}.$$

This weighted average is the posterior mean of the true market effect. More precise estimates stay closer to their original values, while less precise estimates move more toward the common mean. The median weight is 0.99, and the cross-market standard deviation falls from 0.182 to 0.164. We use the shrunken price effects, $\hat{\beta}_m^P$, throughout the paper.

The reported standard errors may understate sampling noise because each estimate uses only one treated market and up to two matched controls. As a check, we use placebo estimates in Figure 4. Because placebo assignments do not include an actual merger, their cross-market dispersion provides a benchmark for sampling noise. Their variance is 0.020, compared with an average reported sampling variance of 0.002. We add the difference, 0.018, to each reported variance. This lowers the signal share from 0.94 to 0.39 and produces weights between 0.25 and 0.42.

The placebo-adjusted effects are very similar to the baseline shrunken effects (correlation 0.998). Using them in the PI-level exposure measure in Section 4 changes the pooled output coefficient from -0.421 to -1.01 (SE 0.413), but leaves the t -statistic essentially unchanged. The sign and significance of the output effect therefore do not depend on the shrinkage choice, but the scale of the elasticity does.

E Survey of Life Sciences PIs

We survey active U.S. life sciences PIs about how they make purchasing decisions, recruiting respondents by email in two stages. A pilot of 54 PIs at ten universities, drawn in equal numbers from assistant, associate, and full professors, gauged response rates. The main wave, launched on August 13, 2026, targets large R1 and R2 universities. At each we select up to three life sciences departments, collect the faculty listed on each department's website with the assistance of a large language model (Claude Opus 5), and invite a random half of them. As of September 28, 2026, we have emailed 292 PIs at public and private universities and received 23 responses, a response rate of about 8 percent. The questionnaire is administered through Google Forms and was deemed exempt by the Harvard University IRB (IRB26-0945). Data collection is ongoing, so we treat the results as preliminary. The full instrument follows.

Research Practices and Supply Costs in Life Science Laboratories

What is the purpose of this research?

Every lab buys reagents, consumables, and equipment, but surprisingly little is known about how those purchasing decisions actually get made, who makes them, or how they change over a research career. This survey asks how your lab handles supplies.

This survey is for investigators who currently run their own research laboratory (principal investigator, lab head, or equivalent) at an academic, medical, or nonprofit research institution in the United States.

The researchers are Connie Xu and Ruby Zhang, PhD candidates in Health Policy (Economics) and Economics at Harvard University.

What can I expect if I take part in this research?

You will complete a short online survey. It takes about four minutes and there is nothing to prepare. We are interested in how things actually work in practice, not in best practice, so there are no right answers.

The survey asks how long you have been running your own lab, what field you work in, how large your lab is, roughly what your lab spends per year on consumable supplies, how your lab handles purchasing, and what your lab does when the price of something goes up.

You will complete the survey once. You may skip any question, and you may close the browser at any point without finishing.

Your responses are confidential and will be reported only in aggregate. We do not ask for your name or the name of your institution.

At the end of the survey you may choose to leave an email address if you would be willing to have a longer conversation with us about the same topic. That address is used only to contact you about an interview, and it is deleted once we have finished arranging interviews. The interview would be a single conversation of about 30 minutes over Zoom, at a time you choose, and it is not recorded. Leaving your address does not commit you to anything: if we contact you, you can decline, and we would go through a separate consent process before any interview began. If you do not leave an email address, we will not contact you again.

Short quotations from written comments may appear in academic publications. Quotations will not be accompanied by your name, your institution, or any other detail that would identify you or your laboratory.

If identifiers are removed from the information collected during this research, that information may be used by the research team for future research studies without your additional informed consent. It will not be shared with or distributed to investigators outside the research team.

There is no compensation for taking part, and no direct benefit to you. Risks are minimal: the questions concern professional purchasing practices and laboratory budgets, not your personal finances or health.

What should I know about a research study?

- Whether or not you take part is up to you.
- Your participation is completely voluntary.
- You can choose not to take part.
- You can agree to take part and later change your mind.
- Your decision will not be held against you.
- Your refusal to participate will not result in any consequences or any loss of benefits that you are otherwise entitled to receive.
- You can ask all the questions you want before you decide.

Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt you, contact Connie Xu at conniexu@g.harvard.edu.

By continuing to the next page, you agree to take part in this study.

* Indicates required question

About your lab

1. What year did you start running your own lab? *

2. What best describes your field? *

Check all that apply.

- ☐ Life sciences, mainly experimental (bench work)
☐ Life sciences, mainly computational
☐ Chemistry
☐ Engineering, physics, or materials science
☐ Prefer not to say
☐ Other:

3. Which best describes your the institution your lab is based in? *

Mark only one oval.

- ☐ Public University
☐ Private University
☐ Academic medical center or hospital
☐ Nonprofit or independent research institute
☐ Prefer not to say
☐ Other:

4. How many people work in your lab, including you? Type NA if you'd rather not answer. *

How your lab buys supplies

5. Who places most supply orders for your lab? *

Mark only one oval.

- ☐ I do
- ☐ A lab manager or technician
- ☐ Students and postdocs order what they need
- ☐ A purchasing office
- ☐ Prefer not to say
- ☐ Other: _____

6. Which of the following does your lab currently do? Select all that apply. *

Check all that apply.

- ☐ Compare prices across suppliers before ordering
- ☐ Request quotes or negotiate prices with vendors
- ☐ Order through your institution's purchasing system to get negotiated prices
- ☐ Maintain a standing list of preferred products or vendors
- ☐ Track supply spending against the budget regularly
- ☐ Set rules about what lab members can order without approval
- ☐ None of these
- ☐ Prefer not to say
- ☐ Other: _____

7. Now think back to your first two years running your own lab. Which of these did you ^{*} do then? Select all that apply.

Check all that apply.

- ☐ Compare prices across suppliers before ordering
- ☐ Request quotes or negotiate prices with vendors
- ☐ Order through your institution's purchasing system to get negotiated prices
- ☐ Maintain a standing list of preferred products or vendors
- ☐ Track supply spending against the budget regularly
- ☐ Set rules about what lab members can order without approval
- ☐ None of these
- ☐ I do not remember
- ☐ Prefer not to say
- ☐ Other: _____

8. How did you learn to manage supply purchasing for a lab? Select all that apply. ^{*}

Check all that apply.

- ☐ Trial and error once I had my own lab
- ☐ From my PhD or postdoc advisor
- ☐ From a lab manager or technician
- ☐ From colleagues or other PIs
- ☐ Institutional training or onboarding
- ☐ Someone else handles it
- ☐ I have not really learned it
- ☐ Prefer not to say
- ☐ Other: _____

When costs go up

9. Think of the most recent time the price of something your lab buys went up noticeably. What did your lab do? Select all that apply. *

Check all that apply.

- ☐ Switched to a cheaper supplier or brand
- ☐ Bought in larger quantities, or coordinated orders with other labs
- ☐ Made reagents or solutions in-house instead of buying pre-made kits
- ☐ Used less material per experiment (smaller volumes, fewer replicates)
- ☐ Ran fewer experiments, or dropped conditions
- ☐ Delayed or reduced hiring (postdoc, technician, student support)
- ☐ Delayed or reduced equipment purchases
- ☐ Shifted costs onto a different grant or fund
- ☐ Applied for additional funding
- ☐ Nothing, we absorbed it
- ☐ This has not happened, or I have not noticed it happening
- ☐ Prefer not to say
- ☐ Other: _____

10. By roughly how much would the price of something you buy regularly have to rise before you changed something about how the lab works? *

Mark only one oval.

- ☐ Less than 5%
- ☐ 5 to 10%
- ☐ 10 to 25%
- ☐ 25 to 50%
- ☐ More than 50%
- ☐ I would not change anything
- ☐ Prefer not to say

11. Since you started running your lab, has a change in supply costs ever affected how you work? If so, describe what happened and what you did. Anything else you would like to add about supply costs or purchasing is welcome here. *

12. Roughly what does your lab spend per year on consumable supplies and reagents? Please exclude salaries, instruments and equipment, and core facility fees (sequencing, mass spec, imaging). *

Mark only one oval.

- ☐ Under \$10,000
- ☐ \$10,000 to \$49,999
- ☐ \$50,000 to \$149,999
- ☐ \$150,000 to \$499,999
- ☐ \$500,000 or more
- ☐ Not sure
- ☐ Prefer not to stay
- ☐ Other:

13. Roughly what percentage of your lab's total annual budget does that represent? Include salaries and all other direct costs, but exclude indirect or overhead costs. Type NA if you'd rather not answer. *

14. Thermo Fisher acquired Life Technologies (Invitrogen, Applied Biosystems, Gibco) * in early 2014. Did you notice any price change in those brands at the time?

Mark only one oval.

- ☐ Yes, noticeable increase
- ☐ Yes, slight increase
- ☐ No change I noticed
- ☐ I was not running a lab in 2014
- ☐ I did not buy those brands
- ☐ Do not remember
- ☐ Prefer not to say
- ☐ Other:

15. We are also speaking with PIs for about 30 minutes about how labs manage supply costs. If you would be willing to have that conversation, please leave your email address. This is optional, and your address will be stored separately from your responses and used only to contact you about an interview.

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