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

Connie Xu (Job Market Paper), Ruby Zhang*

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Abstract

Scientists cannot easily substitute away from research inputs their experiments depend on or pass on higher costs because their discoveries are published rather than sold, leaving them exposed to rising prices in increasingly concentrated markets for life sciences inputs. How much science is lost when these inputs become more expensive, and which scientists are better able to adjust? We use the 2014 merger of two large life sciences suppliers as a shock to the prices principal investigators (PIs) pay for these inputs, drawing on novel purchase-level procurement records from U.S. public universities linked to PIs' publications. Prices in affected markets rose by almost 20 percent, while quantities declined only slightly and temporarily, consistent with highly inelastic demand. PIs facing larger increases in their input costs published less. For the average PI, input costs rose by about 2.8 percent and research output fell by about 1.2 percent, implying an elasticity of roughly −0.42. Higher input prices therefore reduce scientific production, not just raise research costs. The output losses fell disproportionately on early-career PIs. Financial resources do not fully explain this difference. Instead, our findings suggest that experience helps PIs adjust to higher prices through tacit knowledge accumulated during training and years of running a lab.

* **Xu:** Harvard University. Email: conniexu@g.harvard.edu. **Zhang:** Harvard University. Email: rzhang15@g.harvard.edu. We are deeply grateful to Amitabh Chandra, Luca Maini, and Kyle Myers for their guidance throughout this project. We thank Leila Agha, Riley League, Chloe Tanaka, and participants at the Harvard Health Economics Seminar, the Health Policy Seminar, the Labor and Public Workshop, the American Society of Health Economists conference, and the European Association for Research in Industrial Economics conference for their many helpful comments. Erika Flynn, Bradley Scott, Jonathan Silverstone, and Octavio Diaz at GovSpend and Sean Seaver at Lab Spend generously assisted and shared their expertise with the procurement data, and Bill Jia generously shared his scientific expertise. We gratefully acknowledge support from the Alfred P. Sloan Foundation's Early Career Fellowship on the Fiscal and Economic Effects of Innovation and Productivity Policies, awarded through the National Bureau of Economic Research (G-2024-22690; Xu); the Lab for Economic Applications and Policy Award; the John and Kiendl Gordon Economics Support Fund; the Institute for Humane Studies (IHS020076; Zhang); the National Institute on Aging (T32-AG000186; Xu); and the National Science Foundation (DGE-2140743; Xu). The computations in this paper were run on the FASRC Cannon cluster supported by the FAS Division of Science Research Computing Group at Harvard University. The survey involved in this paper was exempted in August 2026 under Protocol #IRB26-0945.

1 Introduction

Scientists who grow cells for research from basic cell biology to cancer rely on fetal bovine serum, a nutrient-rich supplement whose price rose by more than 50 percent after two major life sciences suppliers merged in 2014. Substituting toward cheaper alternatives is difficult because experiments are calibrated to specific products, so even small adjustments to serum composition can be scientifically risky. Fetal bovine serum is just one of many research inputs whose prices rose over the same period. These inputs are used throughout the life sciences, which receive nearly half of U.S. federal research funding and whose discoveries underpin most new drugs developed this century (NCSES, 2024; Azoulay et al., 2025). At a time when each scientific discovery requires more research effort than in the past (Bloom et al., 2020), rising input prices may further constrain scientific production and the medical innovation it supports.

Scientists buy these inputs in increasingly concentrated markets, and, unlike firms, they cannot pass higher prices on to customers because their discoveries are published rather than sold. They also have limited budget flexibility because grant funding is largely committed to personnel and additional funding takes time to secure (Stephan, 2012). These higher costs therefore fall on science—already thought to be underprovided relative to its social value (Nelson, 1959; Arrow, 1962). Even so, scientists with resources and experience may be able to offset higher costs by adjusting aspects of their research process, such as which experiments to run (Thompson and Zyontz, 2017; Tham, 2023). But when essential inputs cannot easily be replaced, these adjustments may offer little relief, and scientific production may be limited by those inputs even as funding and technology improve (Aghion et al., 2019). How much science is lost to higher input prices, and which scientists can adjust?

To answer these two questions, we use the 2014 merger of Thermo Fisher Scientific and Life Technologies Corporation, two of the largest suppliers of life sciences research inputs, as a shock to the prices principal investigators (PIs) pay for their inputs. PIs are the lead scientists

who set the research agenda and oversee the daily operations of their research labs, including purchasing decisions. The two firms competed in supplying many of the same molecular and cellular biology *consumables*—reagents, enzymes, cell culture media, and other routinely purchased inputs that are used up in the course of an experiment—so their merger provides plausibly exogenous variation in these prices. We observe these consumables prices in novel procurement records that cover 2.9 million purchases at 86 U.S. public universities from 2010 to 2019. We group these purchases into product markets, defined as consumables serving the same experimental purpose, using a text classifier trained on 368,765 purchases that we hand-label, and compare markets where the two firms competed against similar markets where they did not.

The merger raised prices in the product markets where the two firms overlapped, and these increases translated almost entirely into higher spending. Prices in affected markets rose by almost 20 percent relative to similar markets unaffected by the merger, while quantities declined only slightly and temporarily. These patterns are consistent with highly inelastic demand, so these market-level price increases raised consumables costs rather than reducing purchases. This cost increase differed across PIs because they depend on different consumables bundles. We capture this variation with an exposure measure that weights each product market's price increase by each PI's pre-merger spending share in that market and use differences in this measure to estimate the effect of higher consumables costs on scientific research output.

Our analysis of 13,515 U.S. life sciences PIs shows that higher consumables costs reduce research output. More- and less-exposed PIs followed similar publication trends before the merger, but more-exposed PIs had a larger decline in publications afterward. The merger increased the average PI's overall consumables costs by approximately 2.8 percent, and our estimates imply that research output fell by about 1.2 percent. Together, these estimates yield an elasticity of research output with respect to consumables costs of approximately −0.42.

Across our sample, PIs faced approximately $5.1 million in additional annual consumables costs and published roughly 349 fewer publications each year, equivalent to the annual research output of about 160 PIs. Most of these dollars come from the National Institutes of Health (NIH) and the National Science Foundation (NSF), so higher consumables prices transfer public research dollars to private suppliers while reducing the science those dollars produce. The value of the lost research exceeds the amount transferred whenever the marginal publication is worth more than about $14,500, roughly a year of the average PI's consumables spending in our records.

We next examine which PIs are most affected by higher costs and find larger declines in research output among early-career PIs. Among PIs less than 14 years into their careers, output fell more than three times as much as among late-career PIs, whose response is 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 is 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 spent in training. This pattern raises the question of why early-career PIs are more affected by higher costs.

One explanation is that late-career PIs have greater financial resources to absorb the cost shock. Output declines do not differ significantly by PIs' NIH funding or their universities' R&D environments. Early-career PIs also experience larger declines than late-career PIs with similar levels of NIH funding. Differences in financial resources therefore do not fully explain the larger output declines among early-career PIs.

Another possible explanation is that experience helps PIs adjust their research process and purchasing practices when consumables become more expensive. In our survey of active life sciences PIs, most of the 23 respondents report learning how to make purchasing decisions

through trial and error rather than through formal training. Several early-career PIs describe cutting back on research activity, while some late-career PIs describe modifying their research process to lower costs. Although these suggestive patterns cannot rule out other explanations such as selection into staying in research, they are consistent with experience helping PIs adjust to higher consumables prices.

Our estimates have two limitations, measurement error in the exposure measure and a small number of underlying price shocks. First, we observe spending shares for only a subset of PIs and impute the exposure measure for the rest using PIs with similar publication text. A leave-one-out imputation has a correlation of 0.20 with the observed exposure measure, so measurement error may bias our estimates toward zero. Second, the exposure measure depends on price shocks in only a few product markets, with fetal bovine serum accounting for 55 percent of its weight. Because PIs purchasing in the same markets face the same price shocks, their exposure measures may be correlated, potentially overstating the precision of PI-level inference (Borusyak et al., 2022). With shock-level standard errors, the decline remains significant at the 10 percent level. However, randomly reassigning price increases across similar markets produces declines at least as large as ours nearly half the time. This test has limited power because, with so few effective shocks, most reassignments yield similar exposure measures. Our estimates are therefore more informative about the size of the output response than about its statistical significance.

This paper makes three primary contributions. First, we show that the markets where scientists purchase their inputs shape scientific production, in part because demand for these inputs is highly inelastic. Quantities purchased did not decline relative to unaffected markets when prices rose, consistent with the difficulty and scientific risks of substituting away from products to which experimental protocols are calibrated. As a result, higher input prices translate into higher research costs and ultimately less scientific output. We add to a large literature studying the determinants of scientific productivity, including 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). More closely 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 second contribution is to show that PIs differ in their responses to higher input prices and that experience may be one explanation for these differences. PIs are both scientists and managers, but their training focuses on conducting research—leaving much of managing a lab to be learned through experience. In other settings, experience and learning by doing raise productivity (Reagans et al., 2005; Hendel and Spiegel, 2014; Papay and Kraft, 2015; Dong et al., 2024; Caplin et al., 2026), and management practices account for large differences in firm performance (Bloom and Van Reenen, 2007; Bloom et al., 2013).

Finally, we show that concentration in scientific input markets further distorts the production of publicly funded science. When input prices rise, PIs generally cannot pass them on because their discoveries are published rather than sold. We find that PIs who faced higher consumables costs after the merger published less, so higher prices reduce the amount of science produced in addition to 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). 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).

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. 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			
Labeled by product market and consumable status			
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
Labeled as non-consumables only			
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

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

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 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

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

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.

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

[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.

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 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]

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]

[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.

[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.

3.2.1 Empirical Specification

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

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

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 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). Fol-

lowing 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.

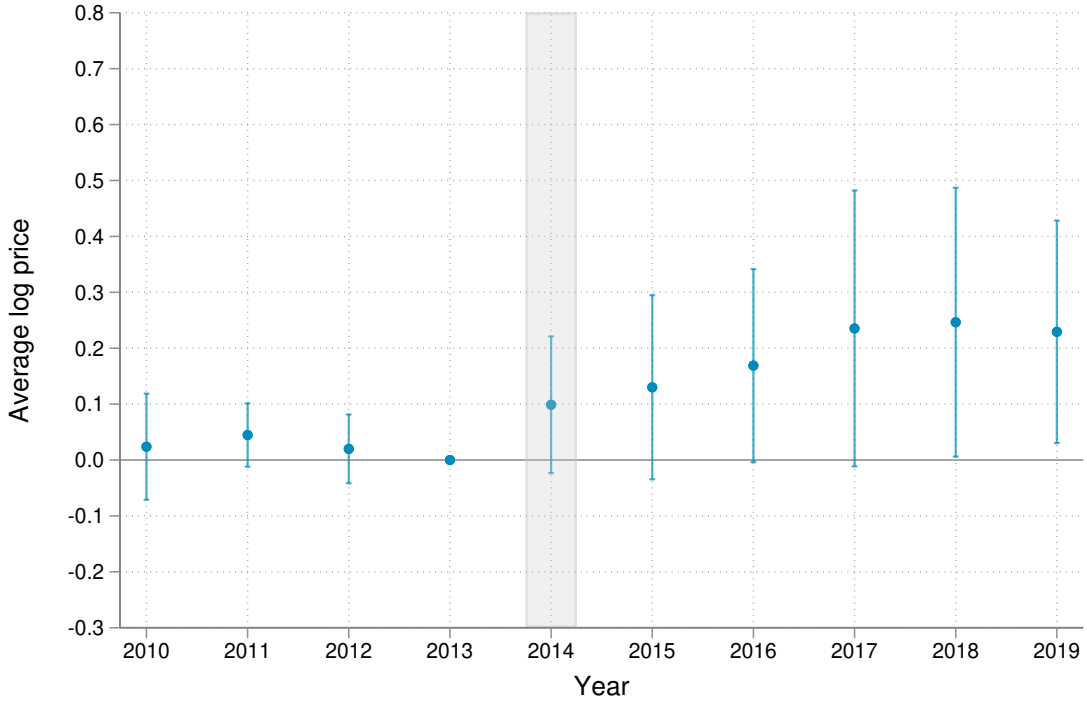
The absence of a differential quantity response may also provide suggestive evidence against a shift in item size as the source of the price increase. Since the price paid refers to an item of unobserved size, a shift toward items containing a larger amount in treated markets would raise measured price 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.

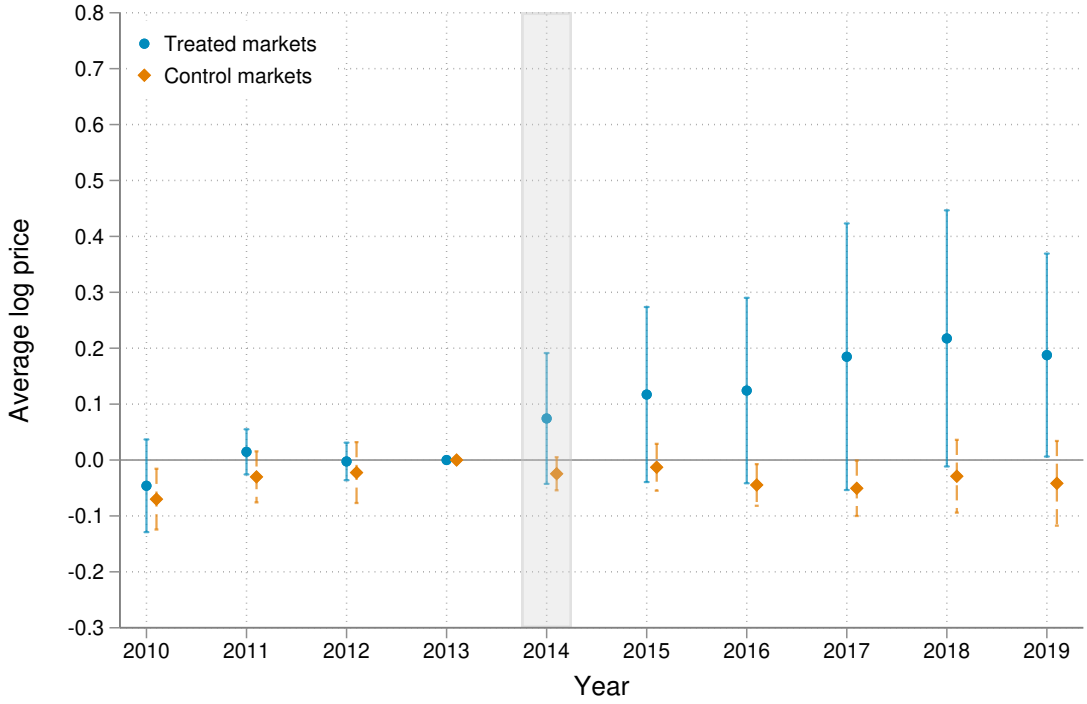
Appendix Table A3 reports pooled difference-in-differences estimates of these effects, with coefficients of 0.164 on the average log price, 0.023 on log quantity, and 0.199 on log spending. The price and spending increases are statistically significant at the 10 percent level, while the quantity response 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



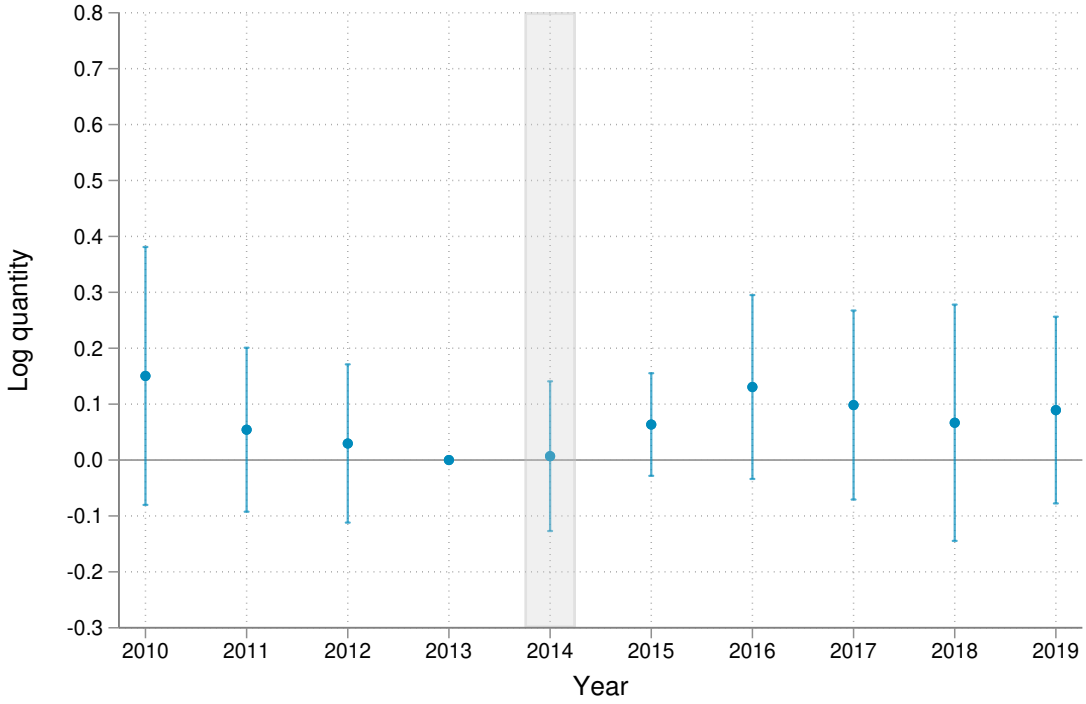
(b) Treated and control market effects



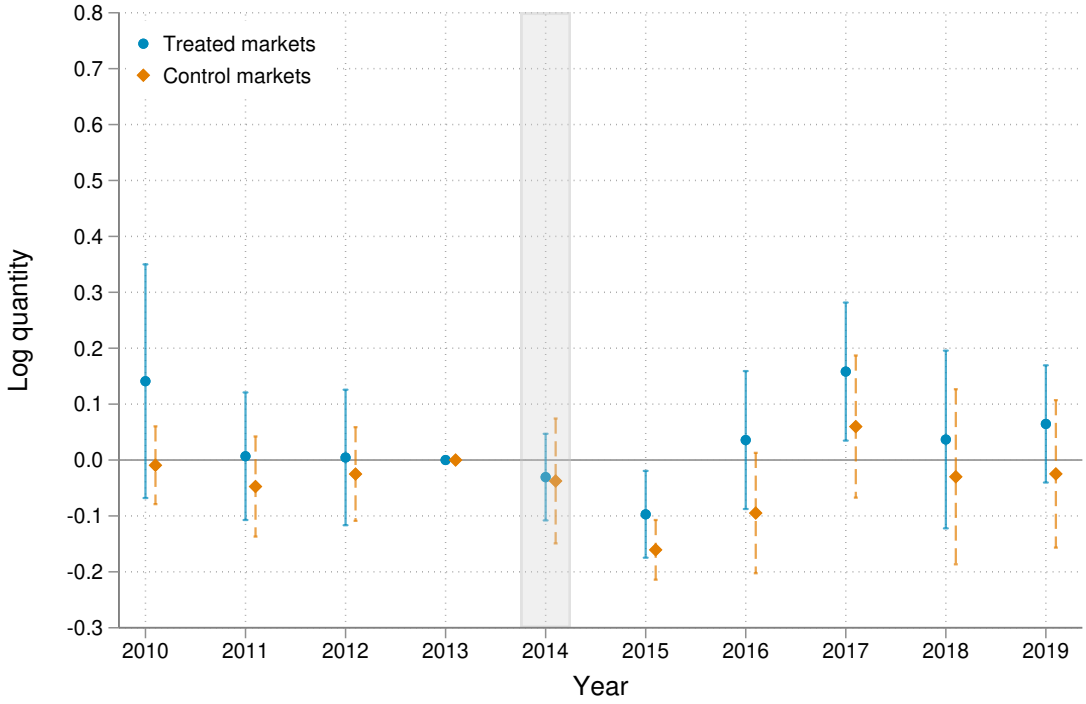
Notes: This figure shows event-study estimates of average log prices around the merger. Panel (a) shows the difference between treated and control markets. Panel (b) plots $\hat{\lambda}_t$ (control, orange) and $\hat{\lambda}_t + \hat{\beta}_n$ (treated, blue), subtracting the linear trend fitted to 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



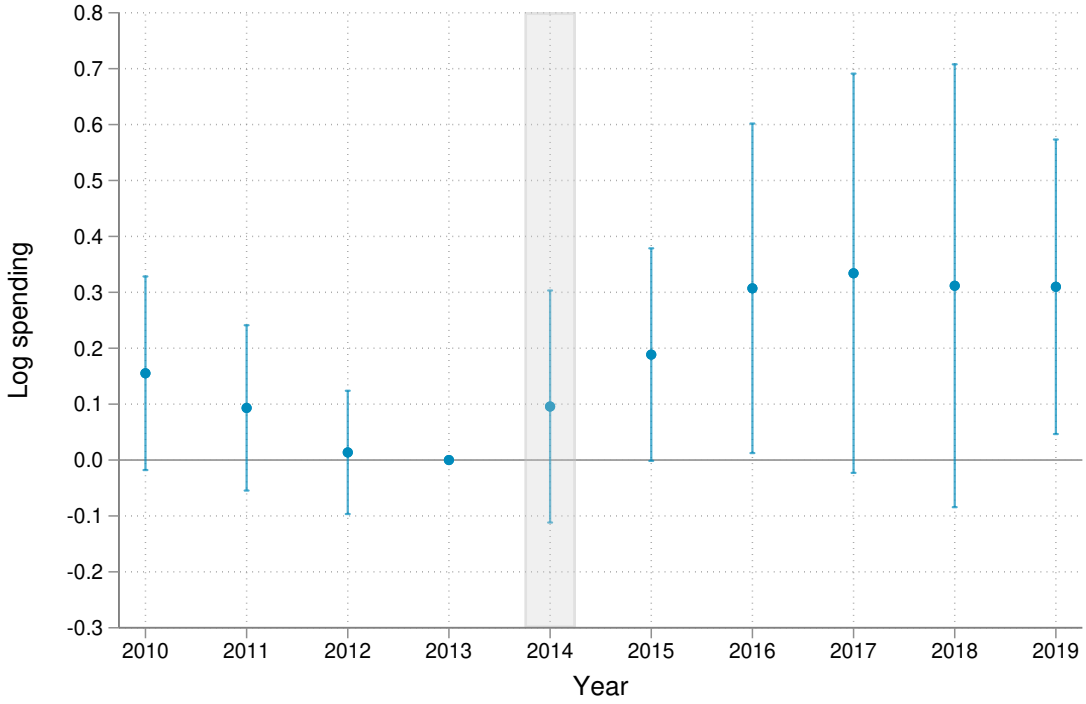
(b) Treated and control market effects



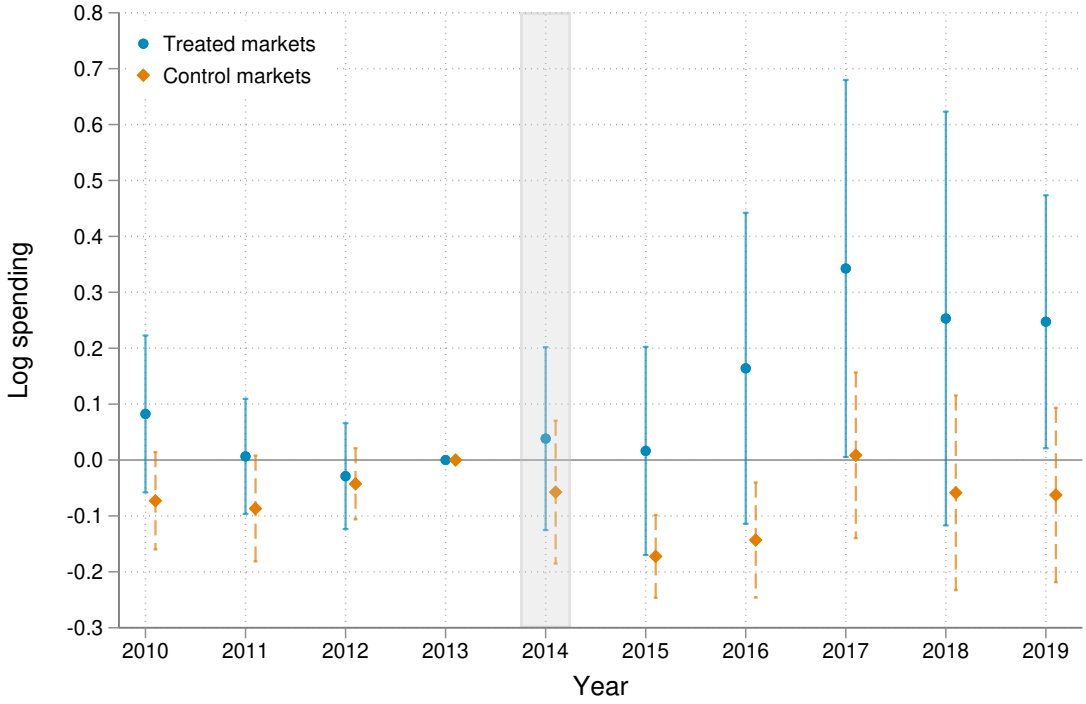
Notes: This figure shows event-study estimates of log quantity around the merger. Panel (a) shows the difference between treated and control markets. Panel (b) plots $\hat{\lambda}_t$ (control, orange) and $\hat{\lambda}_t + \hat{\beta}_n$ (treated, blue), subtracting the linear trend fitted to the control 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:

$$y_{jmt} = \beta^P_{m^*} \cdot D^T_m \cdot \text{Post}_t + \gamma_j + \delta_m + \lambda_t + \epsilon_{jmt}, \tag{2}$$

where y_{jmt} is the average log price in market m for products purchased by university j in year t, and $\beta^P_{m^*}$ 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, $\{\hat{\beta}^P_m\}_{m=1}^{46}$. 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.

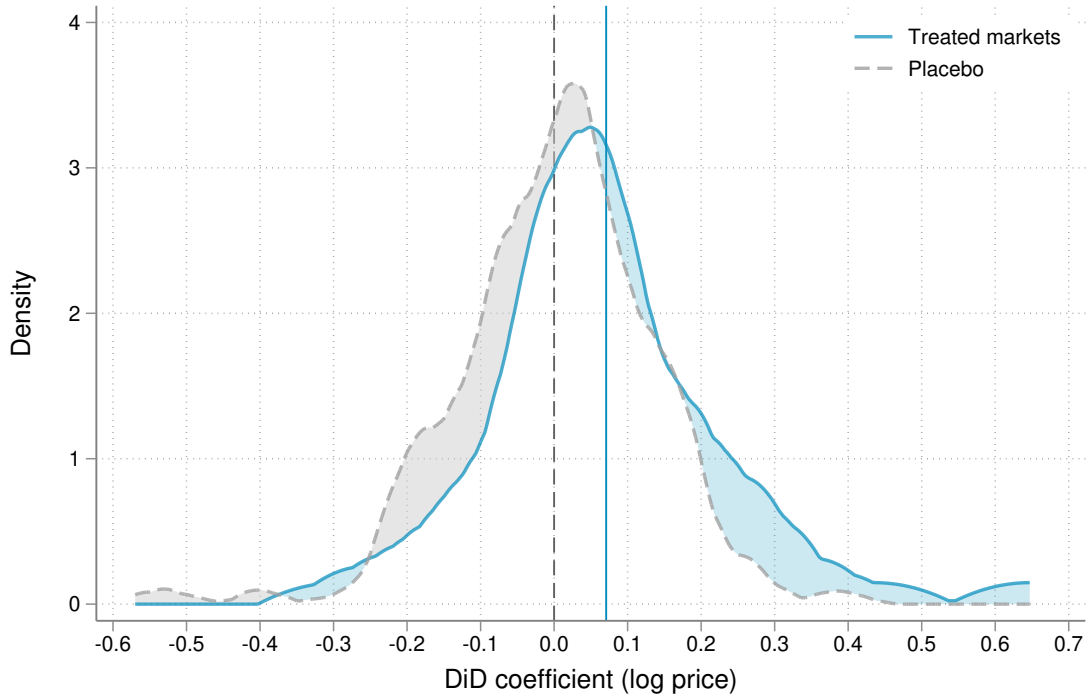
3.3.2 Results

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 university where each PI's research is actually conducted, we determine a single home university 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:

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

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:

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

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

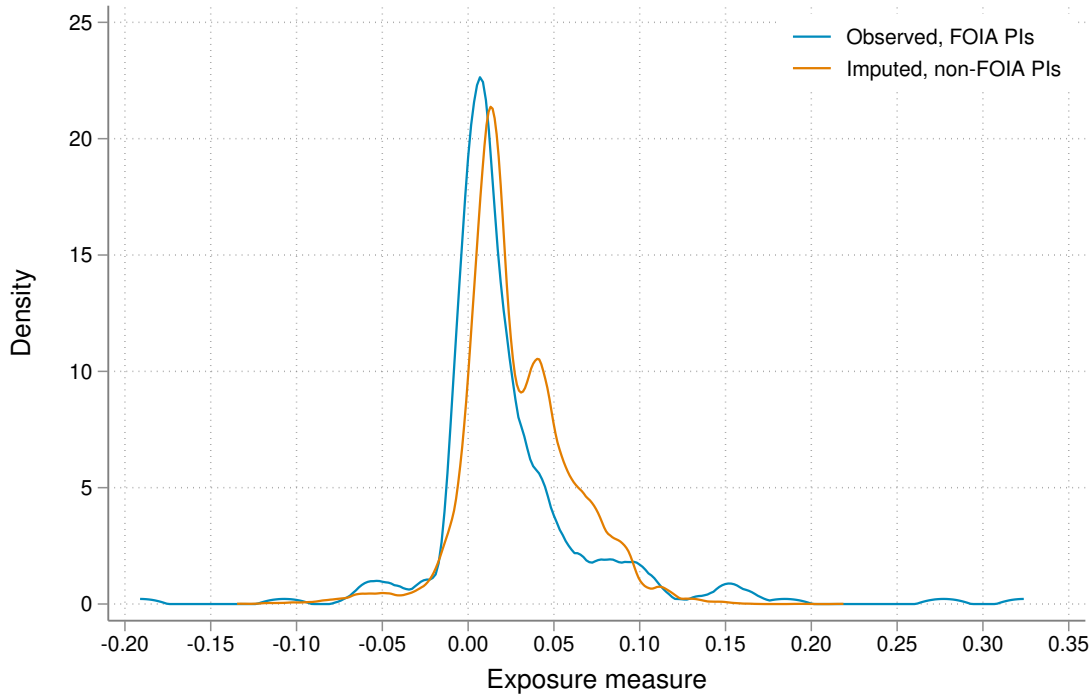
Panel A: Observed exposure of a FOIA PI *(molecular immunologist: antigen presentation)*			
Product market	Share s_{im}	Price effect $\hat{\beta}^P_m$	Contribution
Fetal bovine serum	0.050	0.435	0.022
Chemiluminescent substrates	0.062	0.154	0.010
PVDF blotting membranes	0.057	0.015	0.001
Five other treated 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 *(structural immunologist: immune protein structure)*			
Three most similar FOIA PIs	Similarity	Weight w_{ik}	Exposure
Molecular immunologist: *antigen presentation*	0.274	0.424	0.034
Cell biologist: *protein misfolding*	0.235	0.313	0.096
Crystallographer: *enzymes, immune proteins*	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.

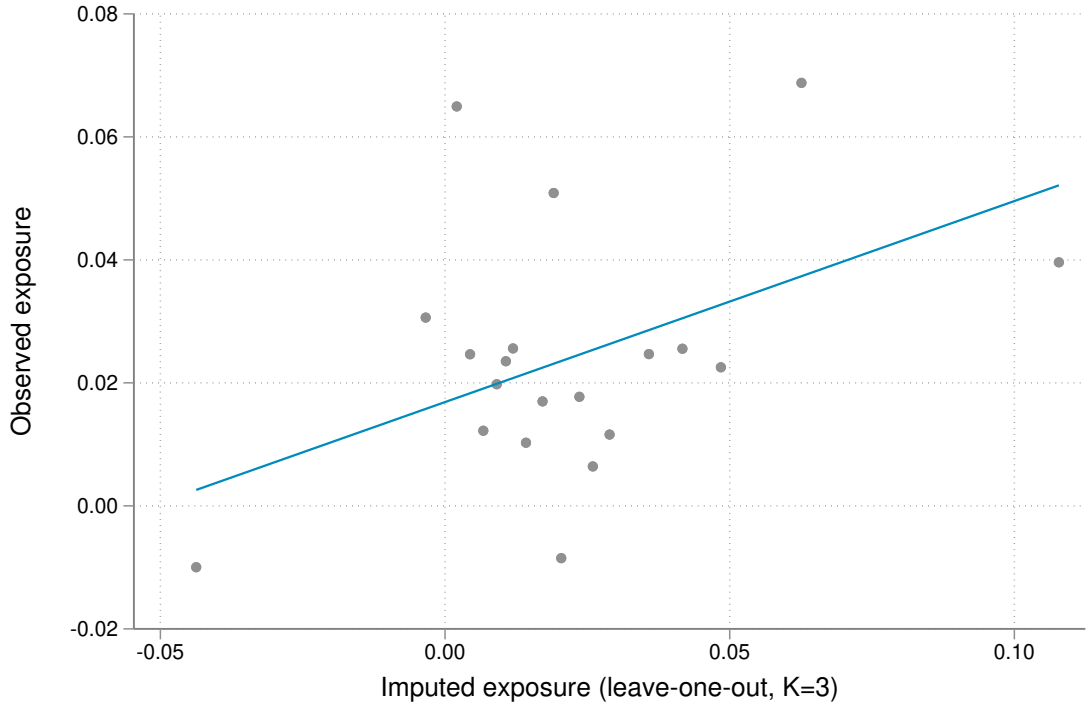
Finally, we assess whether text similarity recovers a PI's exposure measure using a leave-one-out procedure. For each FOIA PI, we impute an exposure measure from the three most similar remaining FOIA PIs and compare it with the PI's observed exposure measure. As Figure 6 shows, the two measures have 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:

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

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:

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

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.

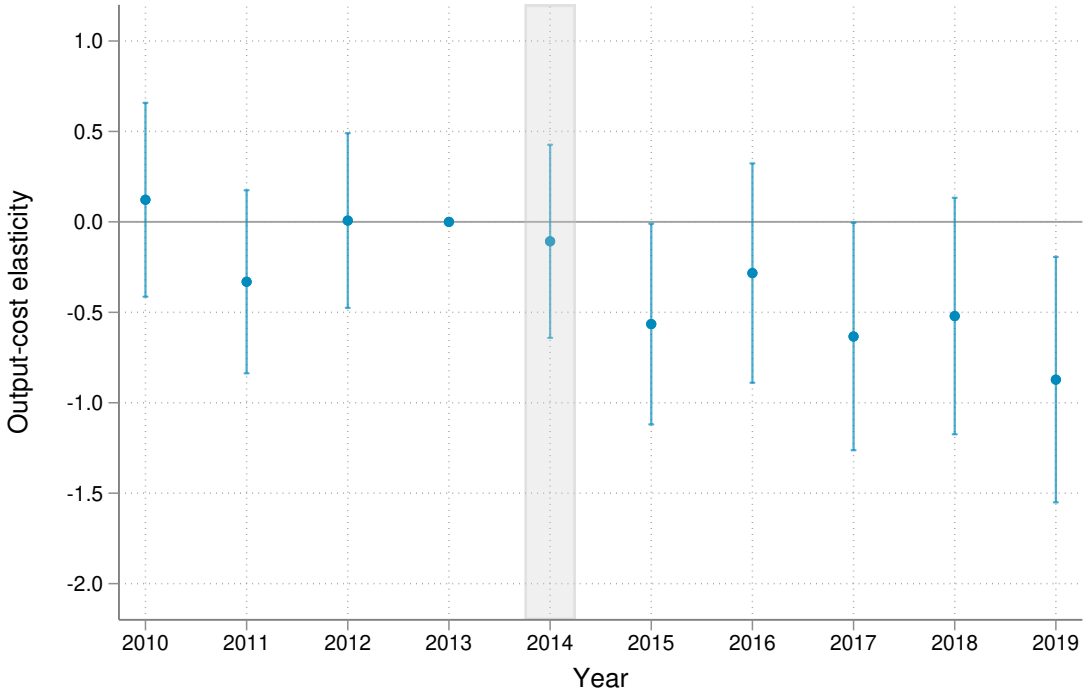
For the average PI, whose consumables costs rose by 2.8 percent, the pooled estimate implies a 1.2 percent decline in research output, or roughly 0.026 fewer publications per year.[16] This elasticity is measured with respect to consumables costs, not the PI's full grant. Consumables account for roughly 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

[15] Although exposure combines price effects from 46 markets, most of its variation comes from a few markets, equivalent to only 17 equally weighted shocks. We therefore cluster standard errors at the shock level (Borusyak et al., 2022), providing a more conservative alternative to PI-level inference ($t = 1.92$, $p = 0.06$). We also conduct randomization inference (Borusyak and Hull, 2023), reassigning price effects among markets with similar pre-merger spending and recentering exposure on its expected value under reassignment. Recentering barely changes the estimated elasticity, suggesting that the results are not driven by which markets were more likely to experience larger price increases. However, with so few effective shocks, the permutation test has limited power and does not reject the null ($p = 0.45$).

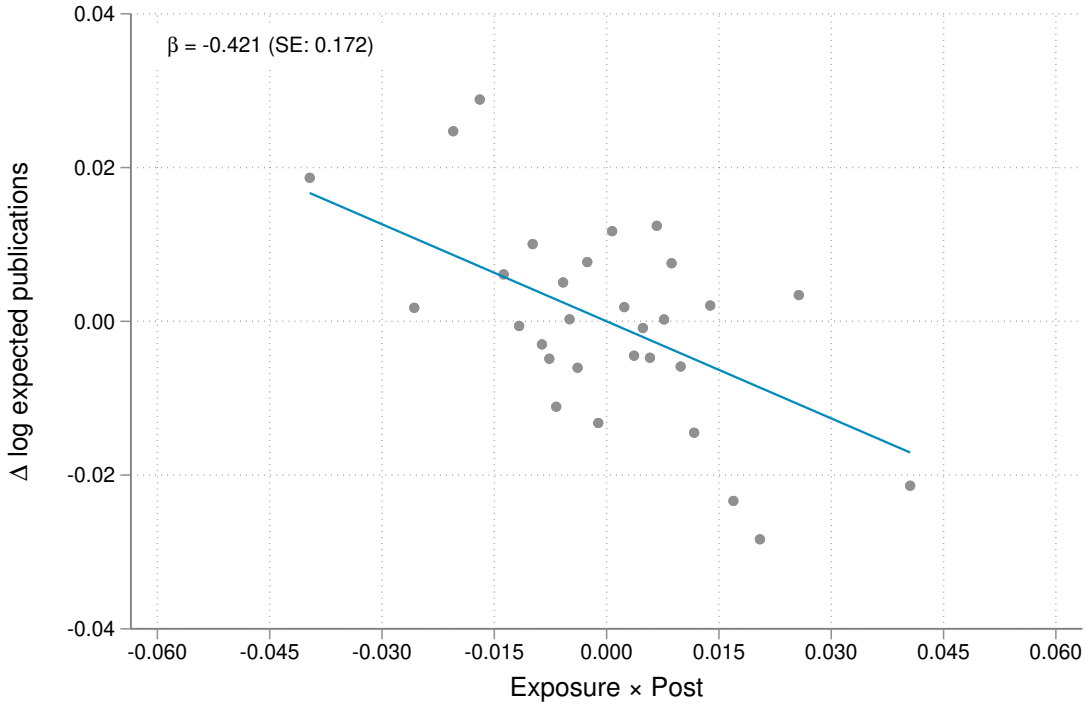
[16] We interpret this coefficient as a reduced-form elasticity rather than an elasticity with respect to realized consumables spending. Recovering the latter would require estimating the relationship between the exposure measure and actual changes in consumables spending. We observe these changes only 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.

Figure 7. Effect of Higher Consumables Prices on Publication Counts

(a) Event study



(b) Difference-in-differences



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**	−0.417**
	(0.172)	(0.171)
Treated-market share S_i	0.007	
	(0.052)	
Pre-period mean	2.16	2.16
Observations	135,150	135,150

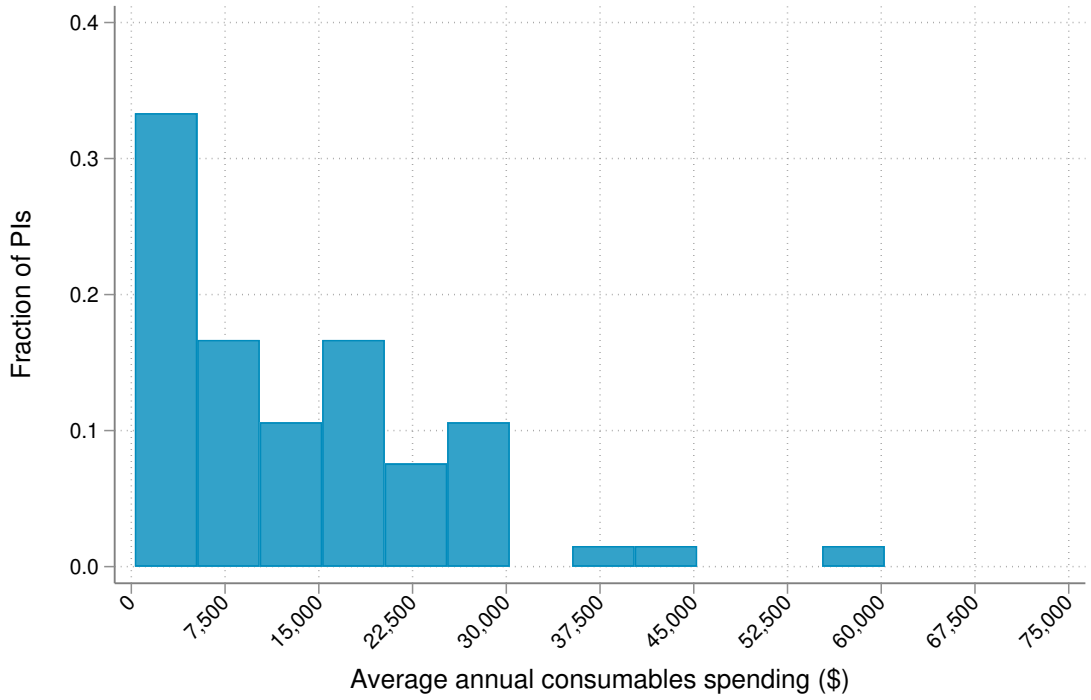
Notes: This table reports Poisson pseudo-maximum likelihood (PPML) difference-in-differences estimates of the effect of the exposure measure on annual publication counts for 13,515 PIs from 2010 to 2019. The coefficient on $\text{Exposure}_i \times \text{Post}_t$ is the elasticity of research output 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

[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 8. Distribution of Average Annual PI Consumables Spending

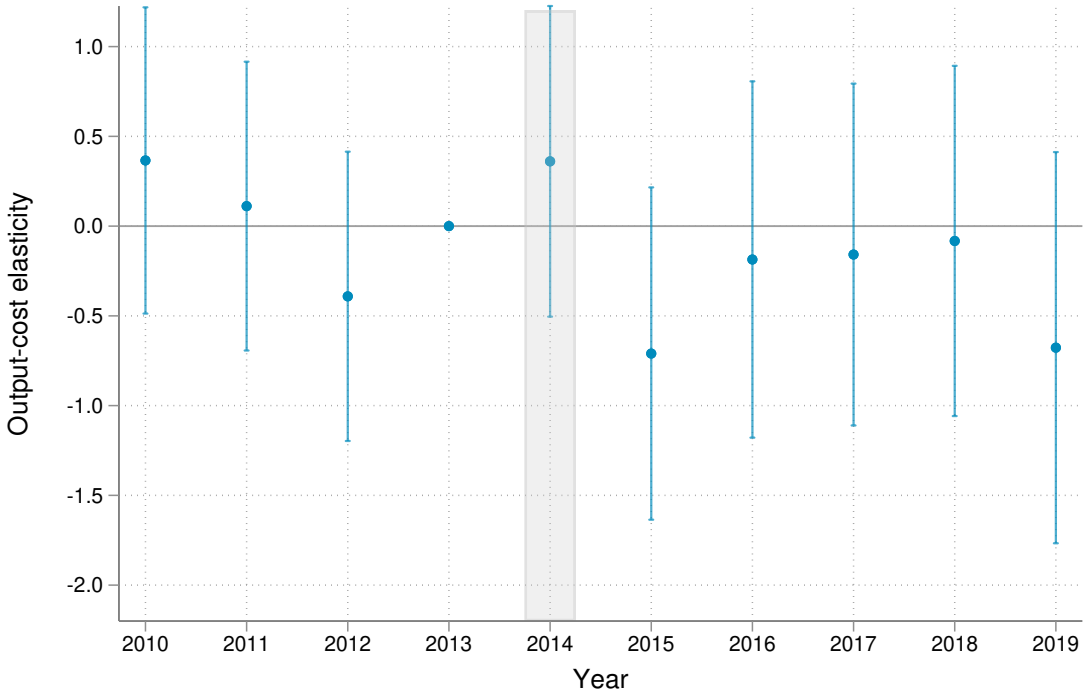


Notes: This figure shows the distribution of average annual consumables spending for the 66 FOIA PIs at UT Dallas and UMich, whose purchases are linked to them in the manually classified FOIA records, restricted to the high-confidence markets over which the exposure measure is defined. Spending is averaged 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.

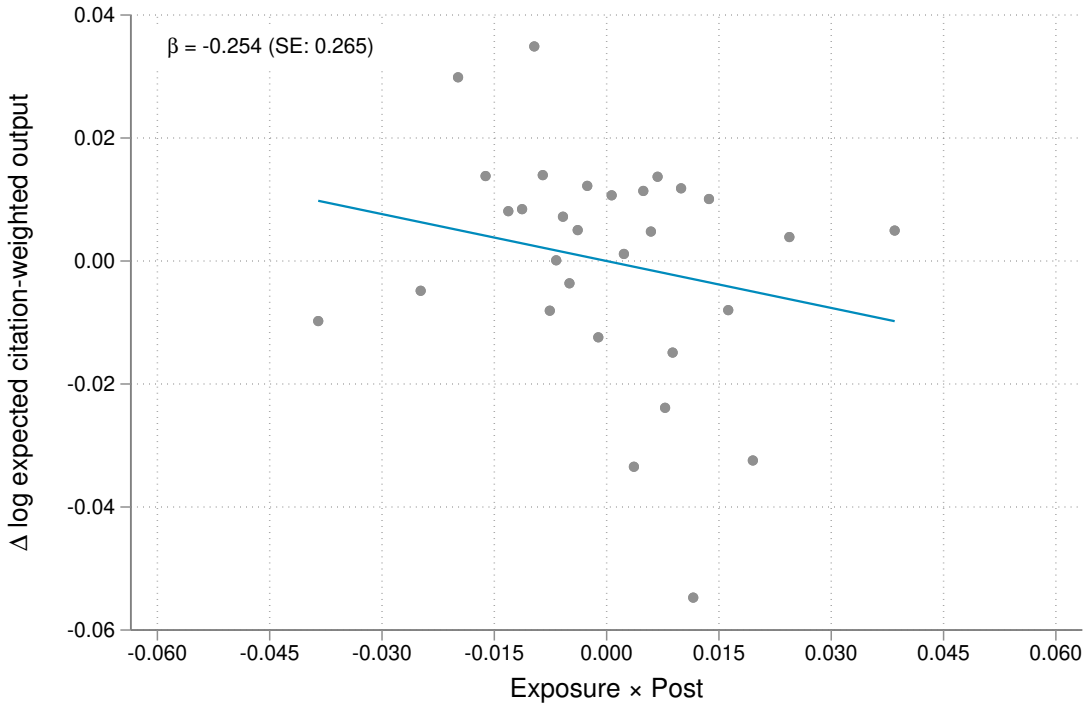
As a second measure of research output, we re-estimate equation (5) using citation-weighted output, with the results shown in Figure 9. We weight each publication by its average annual citations and rescale the weighted counts to sum to the total number of publications. This way, the measure remains 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.

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.

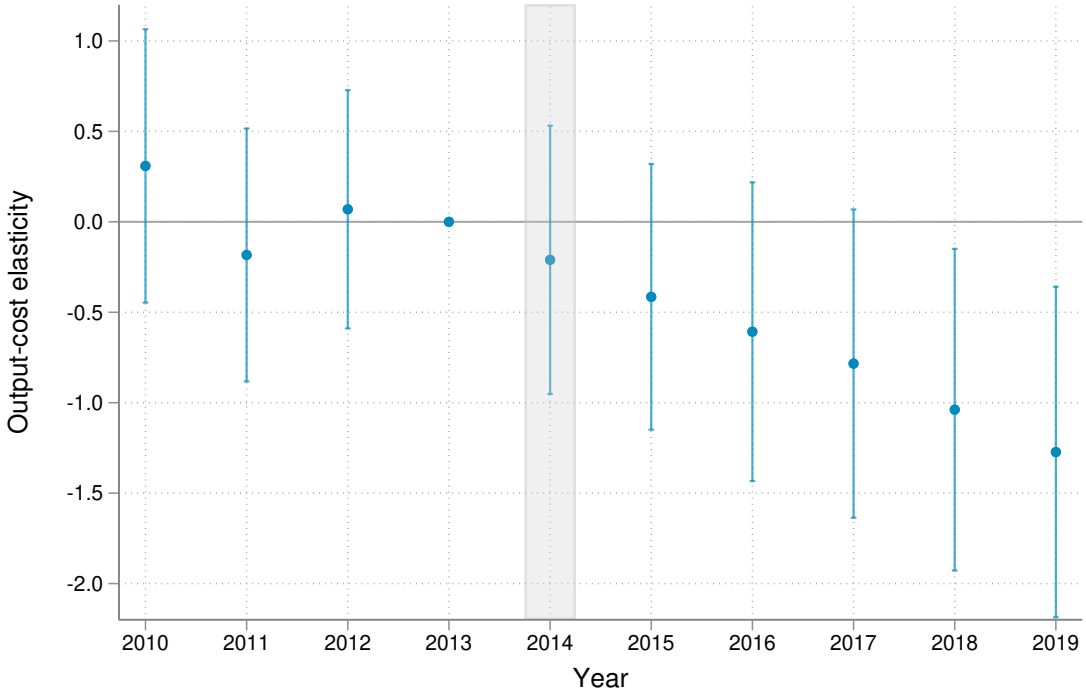
As an alternative measure, we define career stage by the number of years from a PI's first publication in any authorship position to 2014. This definition yields a larger difference, with estimates of −0.896 for early-career PIs and −0.025 for late-career PIs, a difference of −0.871 that is statistically 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.

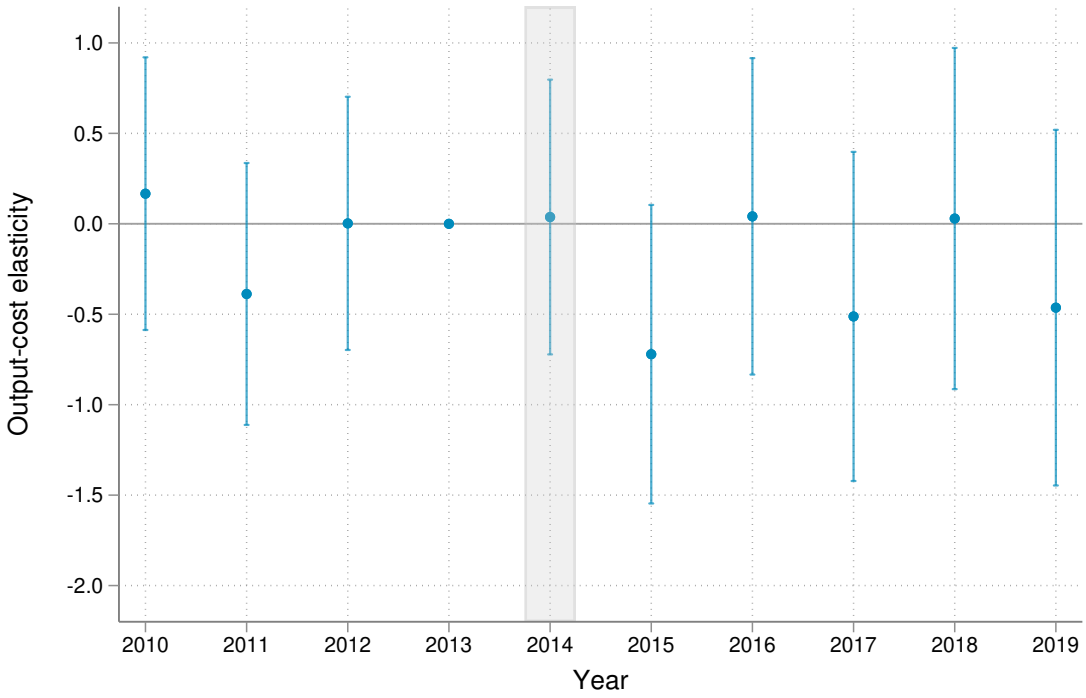
Instead, the estimated effect is negative in every subgroup, with little evidence of smaller declines among PIs with greater financial resources available to them. If anything, the estimated decline is larger among PIs with above-median baseline NIH funding (−0.420) than among those with below-median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

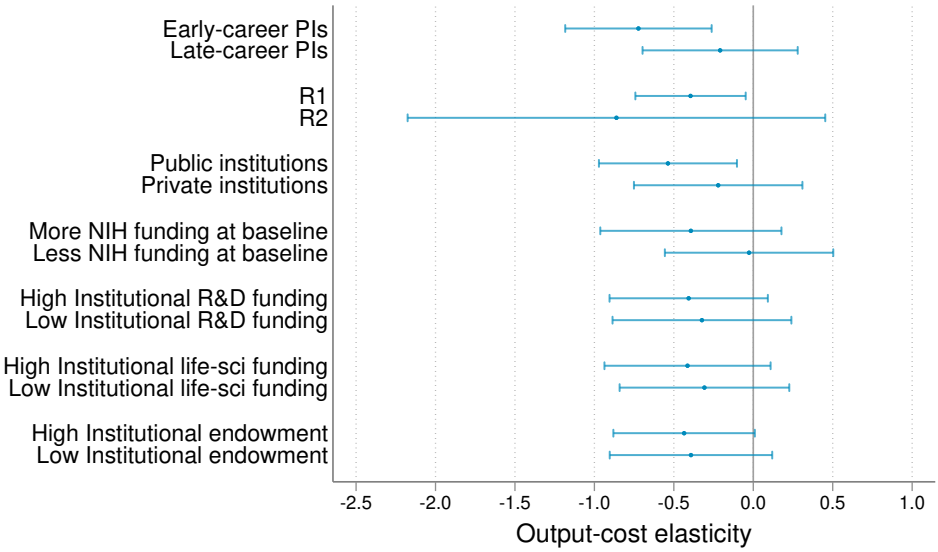
Finally, we examine whether the larger decline among early-career PIs reflects differential exit from academic research. We define exit as having a five-year gap without a last-authored publication, with the first year of the gap falling between 2014 and 2019 to avoid identifying exits that began during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

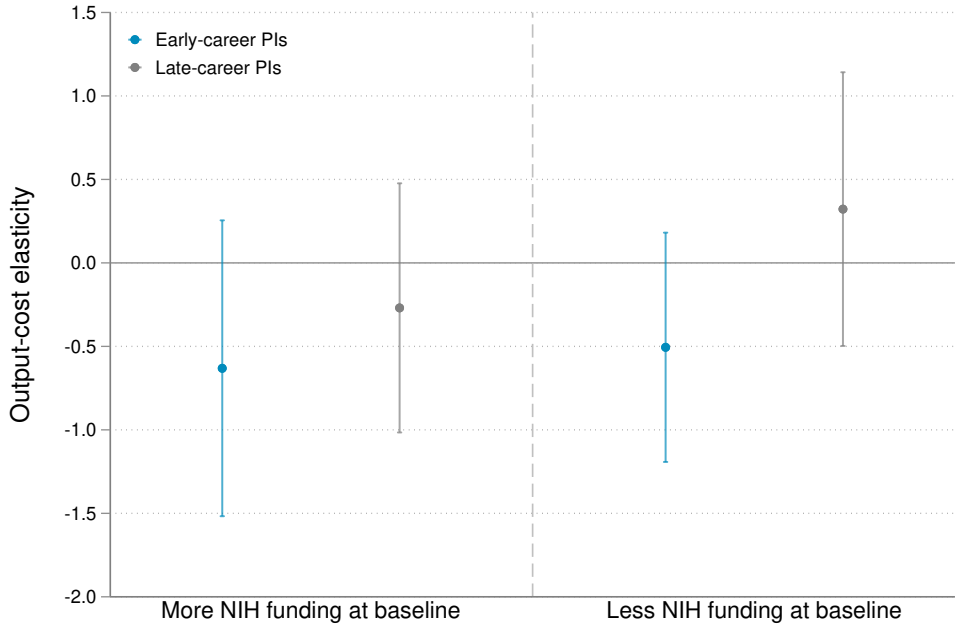
Figure 11. Effect of Higher Consumables Prices on Publication Counts by PI and Institutional Characteristics



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.

[19] We 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. The value of the lost research therefore exceeds the amount transferred to suppliers whenever the marginal publication is worth more than about $14,500, roughly a year of the average PI's consumables spending in our records.

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 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.

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

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. The value of the lost research exceeds these additional payments whenever the marginal publication is worth more than about $14,500, and valuing each lost publication at pre-merger NIH funding per publication puts the loss at roughly $67 million annually, suggesting that the consequences for science extend well 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
Panel A: Universities		
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%
Panel B: Suppliers		
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%
Panel C: Product Markets		
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 ($\geq$ 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	N
Panel A: Fixed effects				
Baseline: university, market, year	0.164*	0.023	0.199*	19,388
	(0.099)	(0.063)	(0.111)	
University × market, year	0.162*	0.050	0.225*	19,388
	(0.096)	(0.064)	(0.121)	
University × year, market	0.153	0.001	0.167	19,330
	(0.096)	(0.063)	(0.112)	
University × market, university × year	0.151*	0.033	0.199	19,318
	(0.092)	(0.068)	(0.124)	
Panel B: Comparison group and sample				
Unmatched controls	0.177*	−0.035	0.154	33,909
	(0.099)	(0.047)	(0.101)	
Excluding 15 complementary markets	0.200*	0.050	0.264**	14,773
	(0.112)	(0.075)	(0.123)	
Synthetic difference-in-differences	0.131***	0.059	0.194**	1,520
	(0.033)	(0.088)	(0.083)	

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)
Exposure × *Post*									
With S_i control	−0.421**	−0.403*	−0.415*	−0.963***	−1.119***	−1.119***	−0.209**	−0.195*	−0.195*
	(0.172)	(0.209)	(0.213)	(0.312)	(0.356)	(0.352)	(0.098)	(0.114)	(0.107)
No S_i control	−0.417**	−0.311	−0.324	−1.146***	−1.081***	−1.081***	−0.244**	−0.187*	−0.187*
	(0.171)	(0.199)	(0.211)	(0.306)	(0.339)	(0.347)	(0.096)	(0.109)	(0.104)
Implied output decline (%)	1.2	1.1	1.2	1.3	1.5	1.5	0.9	0.8	0.8
Fixed effects									
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
Exposure × *Post*					
With S_i control	−0.421**	−0.139***	−0.252	−0.273	−0.419**
	(0.172)	(0.053)	(0.248)	(0.177)	(0.211)
No S_i control	−0.417**	—	−0.289	−0.290	−0.424**
	(0.171)		(0.224)	(0.177)	(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)	$K = 4$	$K = 5$
Exposure × *Post*					
With S_i control	−0.186*	−0.404***	−0.421**	−0.376*	−0.401*
	(0.107)	(0.145)	(0.172)	(0.203)	(0.229)
No S_i control	−0.191*	−0.426***	−0.417**	−0.389*	−0.429*
	(0.107)	(0.144)	(0.171)	(0.202)	(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	−0.723***	−0.209	−0.514	135,150
(early- vs. late-career PIs)	(0.235)	(0.249)	(0.343)	
Years in research	−0.896***	−0.025	−0.871**	135,150
(early- vs. late-career PIs)	(0.237)	(0.246)	(0.342)	
Carnegie classification	−0.395**	−0.861	0.466	135,150
(R1 vs. R2)	(0.177)	(0.671)	(0.694)	
University control	−0.537**	−0.221	−0.316	135,150
(public vs. private universities)	(0.222)	(0.271)	(0.350)	
NIH funding at baseline	−0.420	−0.027	−0.393	79,990
(more vs. less NIH funding at baseline)	(0.291)	(0.271)	(0.398)	
Institutional R&D funding	−0.407	−0.323	−0.083	109,620
(high vs. low)	(0.254)	(0.287)	(0.384)	
Institutional life sciences funding	−0.414	−0.307	−0.107	109,550
(high vs. low)	(0.267)	(0.272)	(0.381)	
Institutional endowment	−0.435*	−0.392	−0.043	133,230
(high vs. low)	(0.227)	(0.261)	(0.346)	

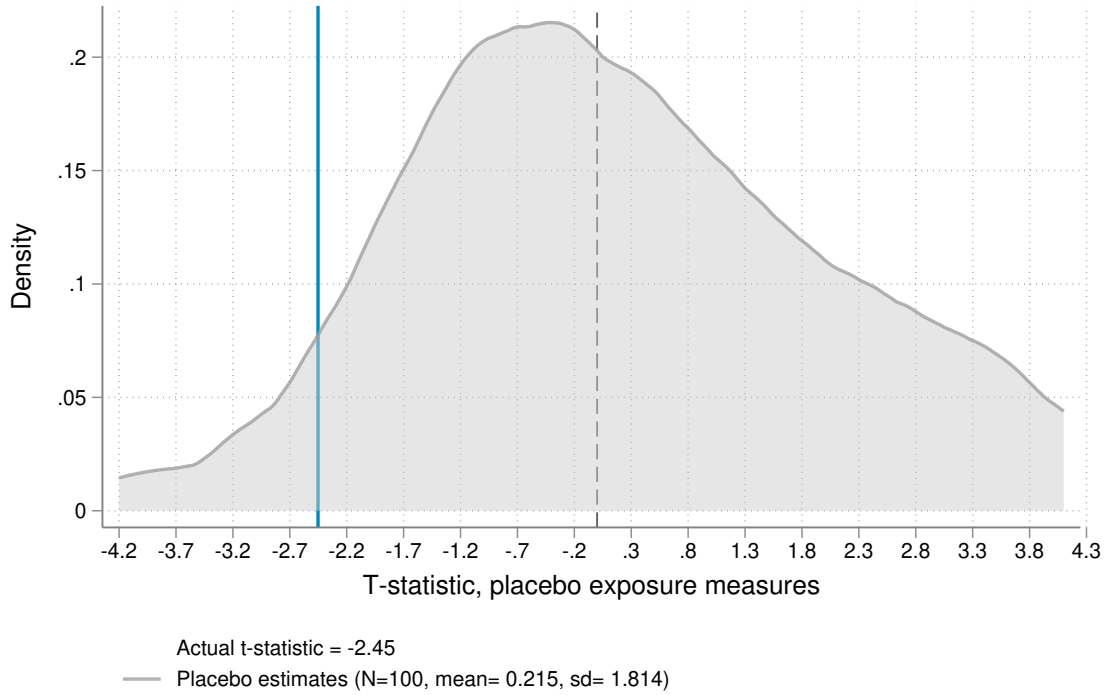
Notes: This table reports PPML difference-in-differences estimates of the effect of the exposure measure on annual publication counts for the two groups in each row, estimated jointly with the treated-market share control and PI and year fixed effects, along with their difference. Career stage splits 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	0.013
	(0.043)	(0.024)
95% confidence interval	[−0.066, 0.105]	[−0.034, 0.061]
Markets	46	46

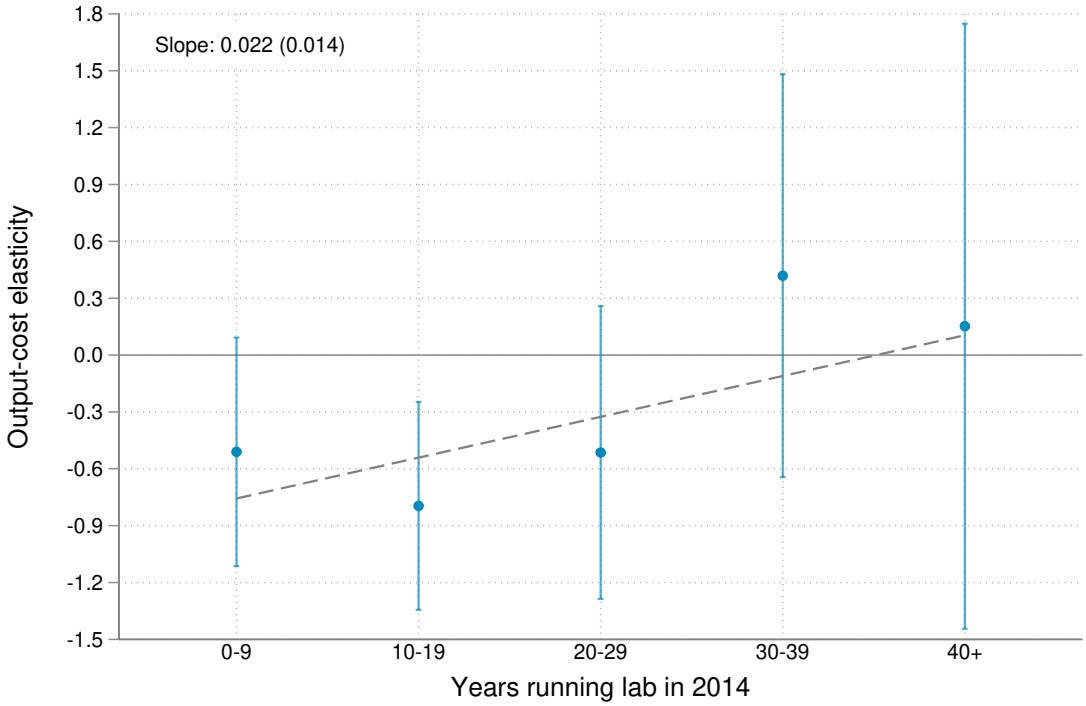
Notes: This table reports regressions of the 46 market-level price effects on buyers' pre-merger output growth, following Borusyak et al. (2022). A market's output growth is the spending-share-weighted average change in its buyers' mean annual publications from 2010–2011 to 2012–2013, residualized on 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.

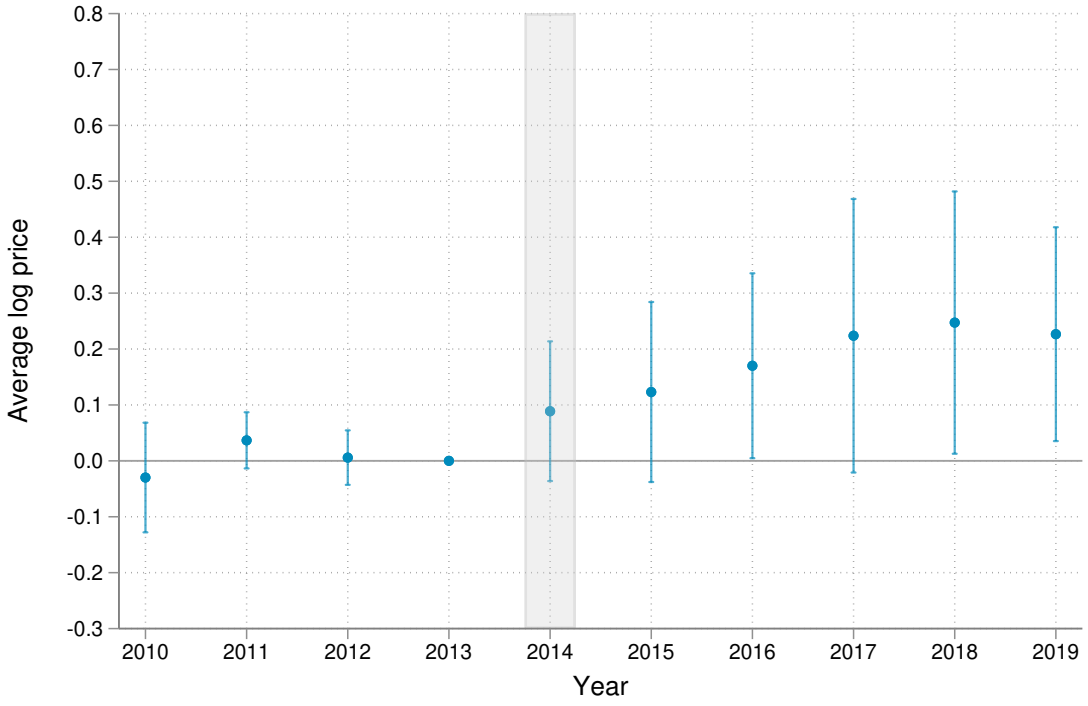
Figure A2. Effect of Higher Consumables Prices on Publication Counts by Years Running a Lab



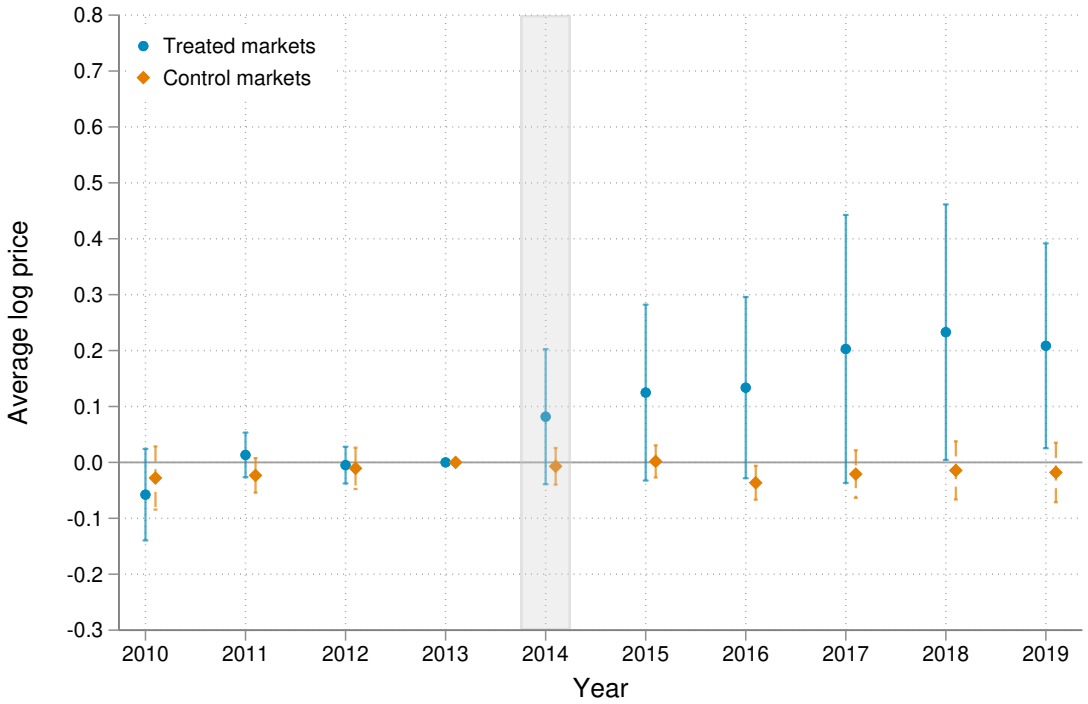
Notes: This figure shows how the effect of the exposure measure on PIs' annual publication counts varies with years running a lab. Each point reports the coefficient on $\text{Exposure}_i \times \text{Post}_t$ from equation (6) for one bin of years from a PI's first last-authored publication to 2014, 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

(a) Pooled difference



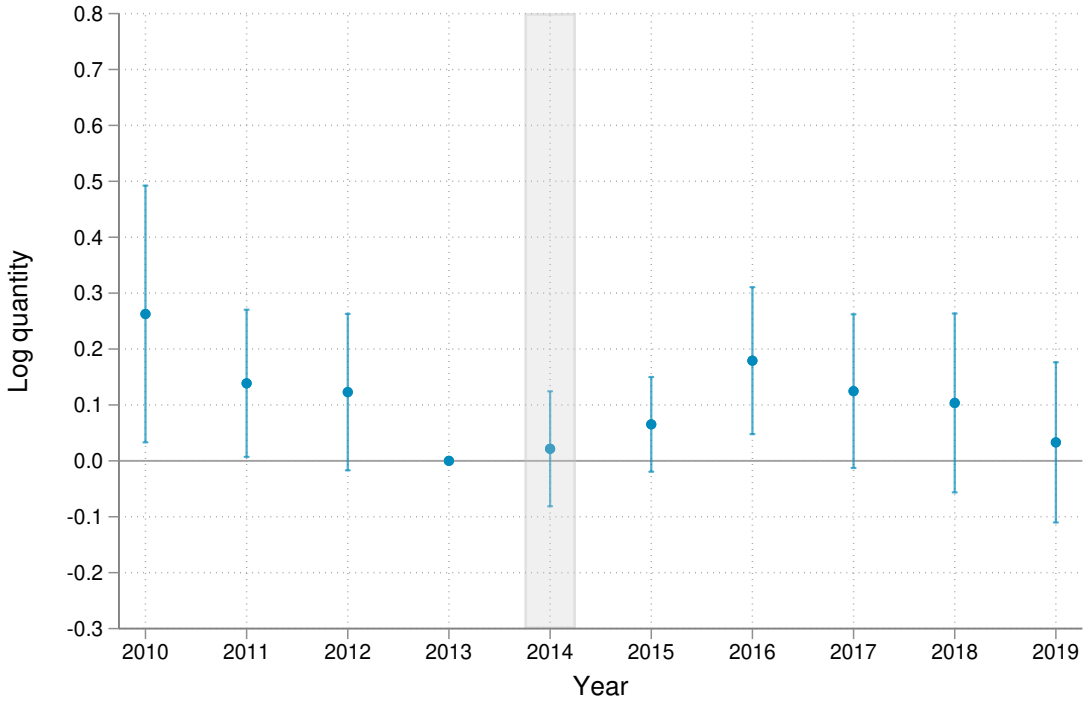
(b) Treated and control market effects



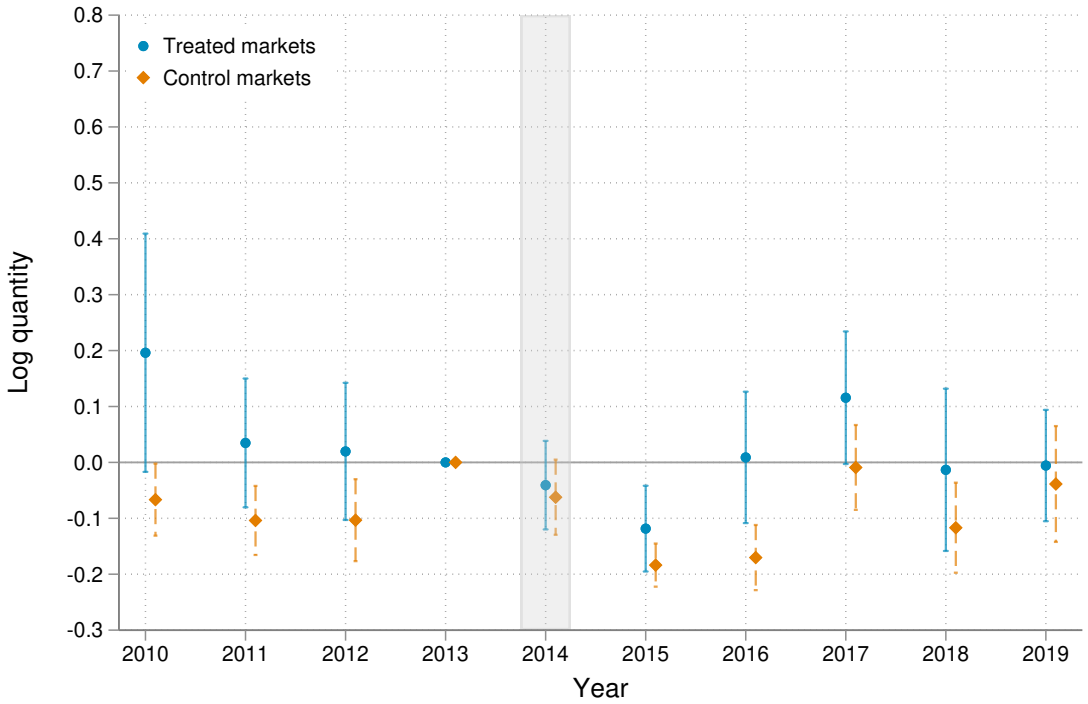
Notes: This figure shows naive event-study estimates of average log prices around the merger, using all unmatched control markets. Panel (a) shows the difference between treated and control markets. Panel (b) plots $\hat{\lambda}_t$ (control, orange) and $\hat{\lambda}_t + \hat{\beta}_n$ (treated, blue), 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



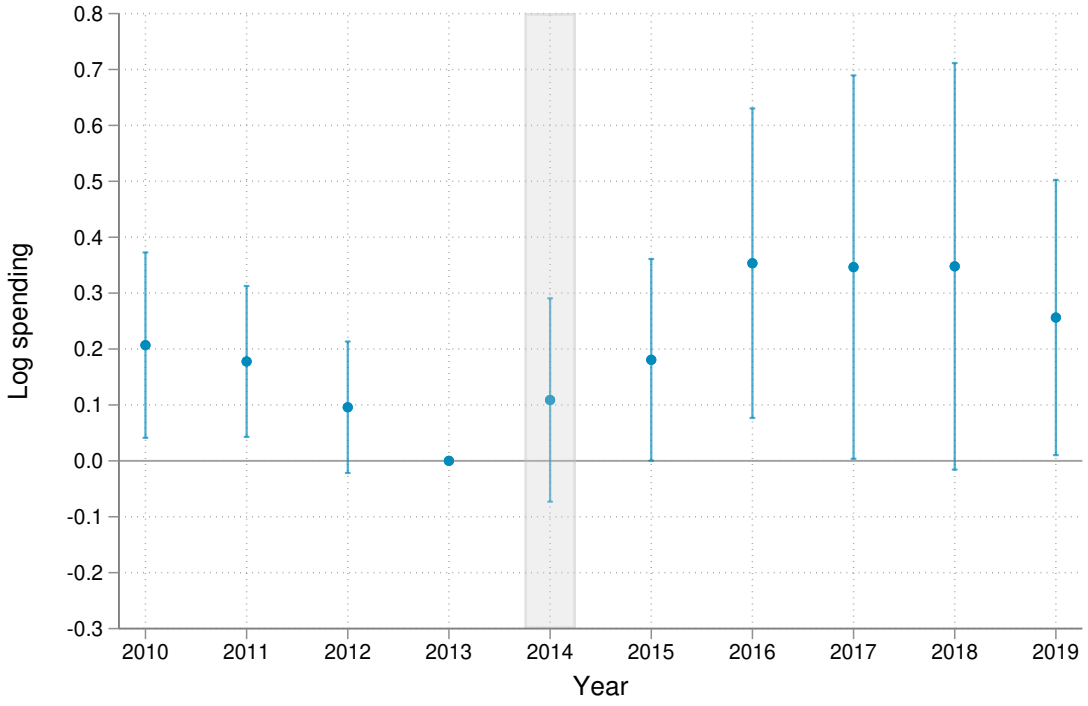
(b) Treated and control market effects



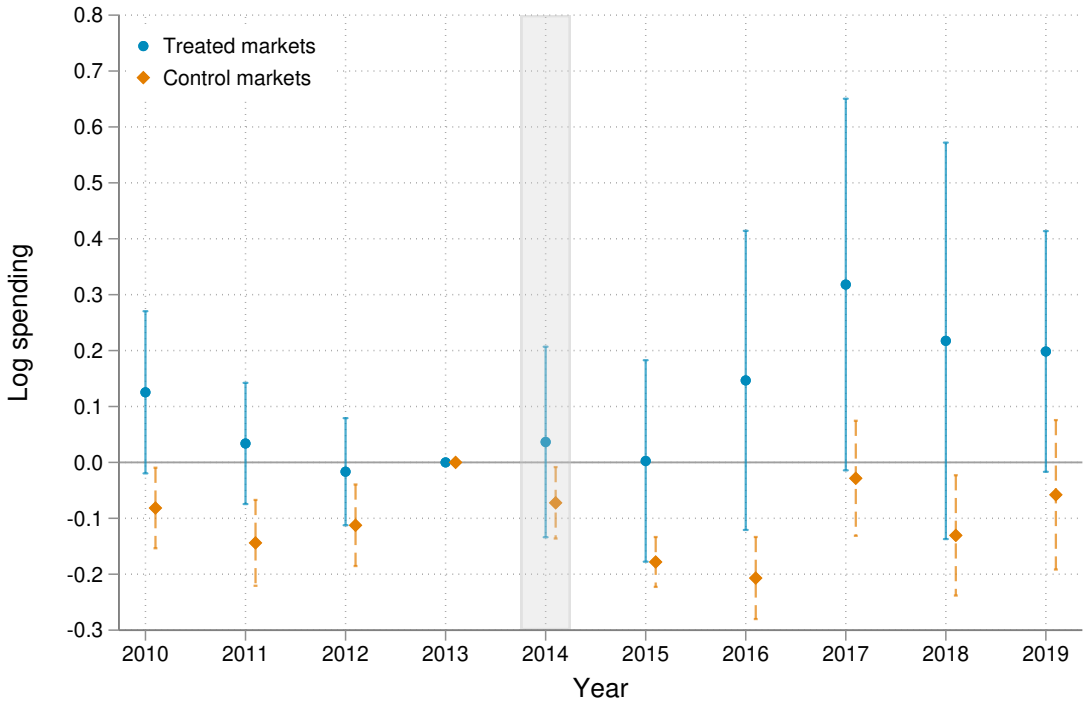
Notes: This figure shows naive event-study estimates of log quantity around the merger, using all unmatched control markets. Panel (a) shows the difference between treated and control markets. Panel (b) plots $\hat{\lambda}_t$ (control, orange) and $\hat{\lambda}_t + \hat{\beta}_n$ (treated, blue), subtracting 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

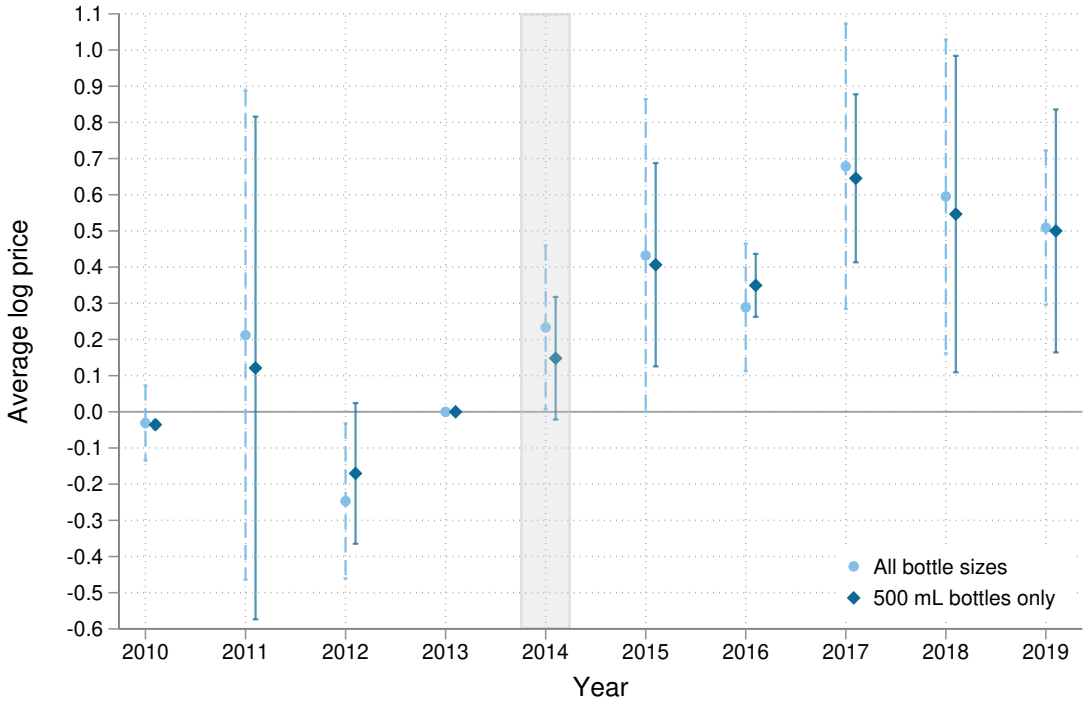


(b) Treated and control market effects



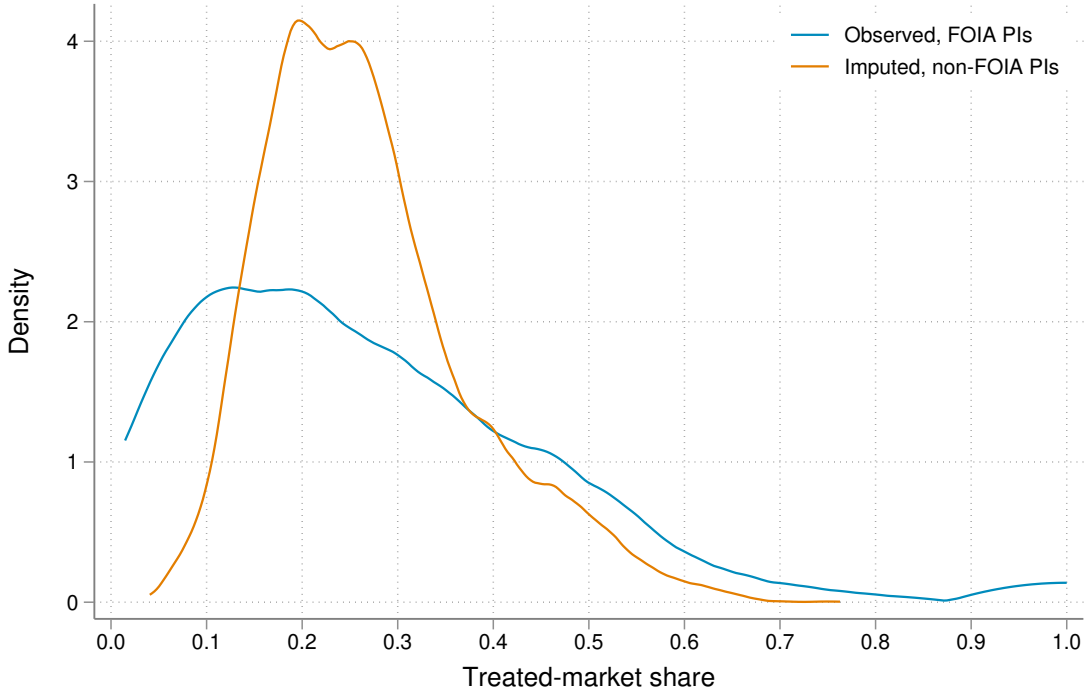
Notes: This figure shows naive event-study estimates of log spending around the merger, using all unmatched control markets. Panel (a) shows the difference between treated and control markets. Panel (b) plots $\hat{\lambda}_t$ (control, orange) and $\hat{\lambda}_t + \hat{\beta}_n$ (treated, blue), subtracting 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



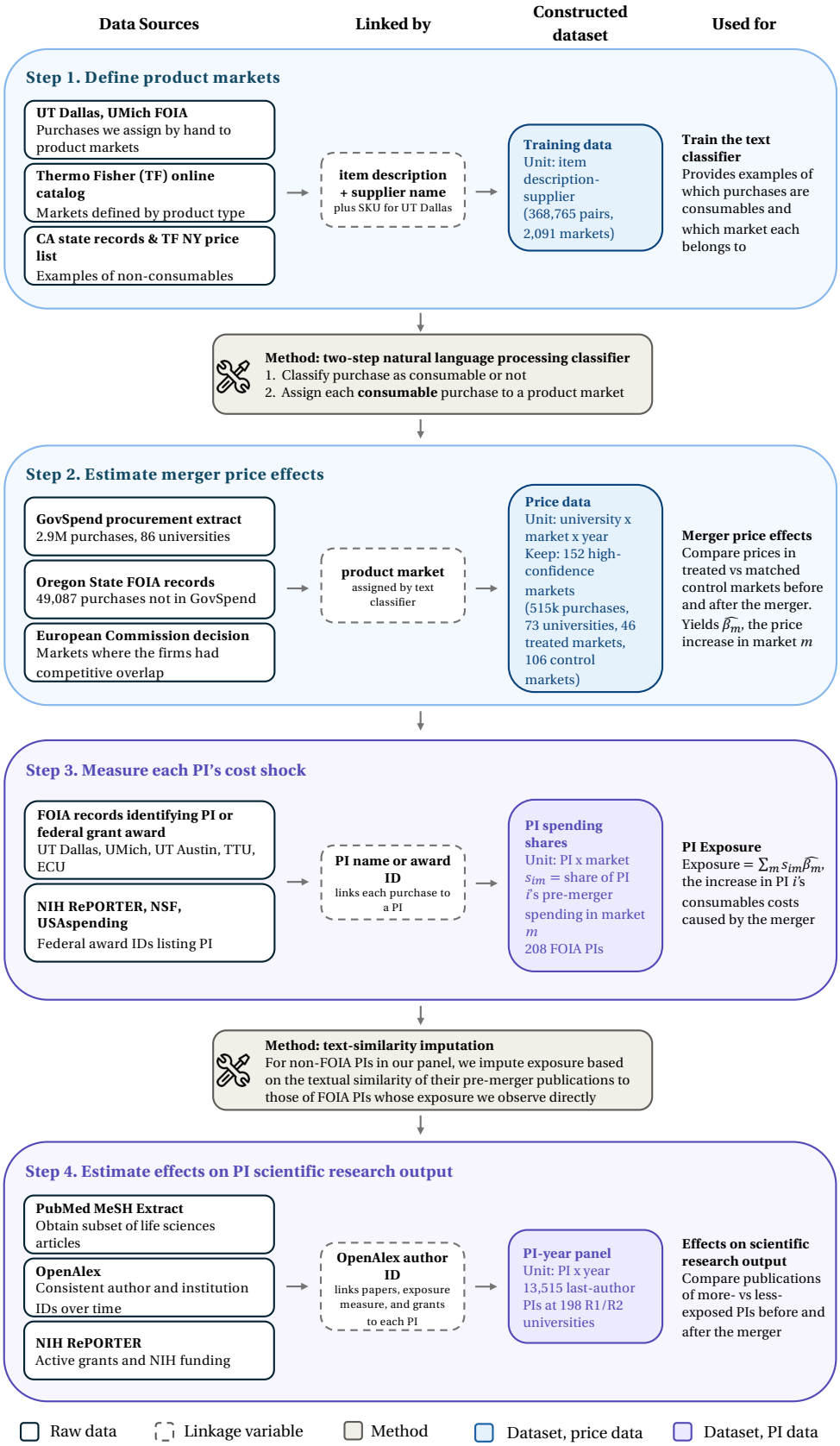
Notes: This figure shows event-study estimates of average log prices around the merger for U.S.-origin fetal bovine serum, for purchases of all bottle sizes (circles) and for purchases whose item descriptions identify 500 mL bottles, excluding recognizable multipacks (diamonds). Both sets of coefficients 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



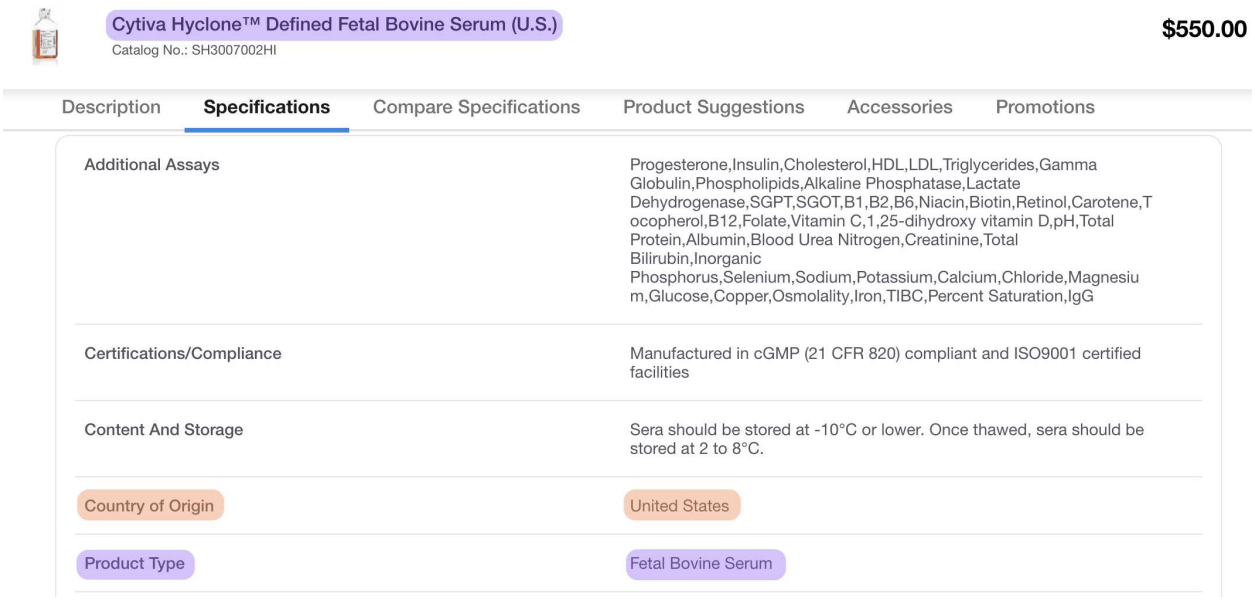
Notes: This figure shows the distributions of the observed and imputed treated-market share $S_i = \sum_{m \in \mathcal{T}} s_{im}$, which sums a PI's pre-merger spending shares across the high-confidence treated markets and enters equations (5) and (6) as a control. The blue line shows the observed 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



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 *inocculating loop*. The keywords are meant to capture all life sciences purchases rather than consumables alone.

Enzymes

Restriction endonucleases and nicking enzymes

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

HinfI
HinP1I
HpaI
HpaII
HphI
Hpy166II
Hpy188I
Hpy188III
Hpy8I
Hpy99I
HpyAV
HpyCH4III
HpyCH4IV
HpyCH4V
HpyF10VI
HpyF3I
HpySE526I
HspAI
I-CeuI
I-SceI
KasI
Kpn2I
KpnI
KpnI-HF
KroNI
Ksp22I
KspAI
KspI
Kzo9I
LguI
LmnI
Lsp1109I
LweI
MabI
MaeIII
MalI
MamI
MauBI
MbiI
MboI
MboII
MfeI
MfeI-HF
MhlI
MlsI
MluCI
MluI
MluI-HF
Mly113I
MlyI
MmeI
MnlI
Mox20I
Mph1103I
MreI
MroI
MroNI
MroXI
MscI
MseI
MslI
Msp20I
MspA1I
MspCI
MspI
MspJI
MspR9I
MssI
MteI
MunI
Mva1269I
MvaI
MwoI
NaeI
NarI
Nb.BbvCI
Nb.Bpu10I
Nb.BsmI
Nb.BsrDI
Nb.BssSI
Nb.BtsI
Nb.Mva1269I
NciI
NcoI
NcoI-HF
NdeI
NdeII
NgoMIV
NheI
NheI-HF
NlaIII
NlaIV
NmeAIII
NmuCI
NotI
NotI-HF
NruI
NruI-HF
NsbI
NsiI
NsiI-HF
NspI
NspV
Nt.AlwI
Nt.BbvCI
Nt.Bpu10I
Nt.BsmAI
Nt.BspQI
Nt.Bst9I
Nt.BstNBI
Nt.CviPII
OliI
PacI
PaeI
PaeR7I
PagI
PalAI
PaqCI
PasI
PauI
PceI
PciI
PciSI
PcsI
PctI
PdiI
PdmI
PecI
PfeI
Pfl23II
PflFI
PflMI
PfoI
PI-PspI
PI-SceI
PinAI
PkrI
Ple19I
PleI
PluTI
PmeI
PmlI
PpsI
Ppu21I
PpuMI
PscI
Pse31I
PshAI
PsiI
PsiI-v2
Psp124BI
Psp1406I
Psp5II
Psp6I
PspCI
PspEI
PspGI
PspLI
PspN4I
PspOMI
PspPI
PspPPI
PspXI
PsrI
PstI
PstI-HF
PstNI
PsuI
PsyI
PvuI
PvuI-HF
PvuII
PvuII-HF
RgaI
RigI
RsaI
RsaNI
RseI
Rsr2I
RsrII
SacI
SacI-HF
SacII
SalI
SalI-HF
SapI
SatI
Sau3AI
Sau96I
SbfI
SbfI-HF
ScaI
ScaI-HF
SchI
ScrFI
SdaI
SduI
SetI
SexAI
SfaAI
SfaNI
SfcI
SfiI
SfoI
Sfr274I
Sfr303I
SfuI
SgeI
SgfI
SgrAI
SgrBI
SgrDI
SgsI
SlaI
SmaI
SmiI
SmiMI
SmlI
SmoI
SnaBI
SpeI
SpeI-HF
SphI
SphI-HF
SrfI
Sse9I
SseBI
SsiI
SspDI
SspI
SspI-HF
SspMI
SstI
StuI
StyD4I
StyI
StyI-HF
SwaI
TaaI
TaiI
TaqI
TaqI-v2
TaqII
TasI
TatI
TauI
TfiI
Tru1I
Tru9I
TscAI
TseFI
TseI
Tsp45I
TspDTI
TspGWI
TspMI
TspRI
Tth111I
Van91I
Vha464I
VneI
VspI
WarmStart
Nt.BstNBI
XagI
XapI
XbaI
XceI
XcmI
XhoI
XhoII
XmaCI
XmaI
XmaJI
XmiI
XmnI
ZraI
ZrmI
Zsp2I

Polymerases, ligases, nucleases, proteases, and other enzymes

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

Reverse transcription

improm-ii
rev transcription
rev transcrptase
reverse transcriptase
reverse transcription
superscript

Antibodies, Proteins, and Standards

Antibodies, conjugates, and antibody targets

affinipure
anbti-bcl2
anti-elf3
Anti-Goat
Anti-Guinea Pig
Anti-Human
anti-il1a
Anti-Mouse
anti-mu
anti-rab
anti-rabb
Anti-Rabbit
Anti-Rat
Anti-Sheep
anti-sox9
antibody
b-amyloid
bamyloid
hif-1
hrp
iga
igg
igm
igy
il-1
lc3b
mAb
mcl-1
monoclonal
nfkb
pAb
polyclonal
sglt2
tmem173

Proteins, peptides, and recombinant products

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

Ladders and standards

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

Nucleic Acids and Cloning Reagents

Nucleic acids, oligonucleotides, and nucleotides

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

Vectors, competent cells, and cloning reagents

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

Nucleic acid purification kits and RNA reagents

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

Stains, Dyes, Probes, and Indicators

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

Buffers, Chemicals, and Antibiotics

Buffers, salt solutions, and water

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

Solvents and organic reagents

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

Acids and bases

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

Salts, sugars, and amino acids

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

Antibiotics, antimycotics, and disinfectants

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

Other reagents and small molecules

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

Cell Culture Media and Reagents

Basal media and balanced salt solutions

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

Sera and supplements

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

Microbiological media

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

Cell culture, dissociation, and transfection

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

Assays, Kits, and Techniques

Techniques and workflows

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

Assays and detection kits

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

Electrophoresis and blotting

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

Purification, chromatography, and concentration

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

PCR master mixes and other branded reagents

iscript
itaq
mannheim master-mix
omnimix
powerupsybrgreen
super-mix

Labware and Consumables

Glassware, vessels, and general labware

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

Pipettes and pipette tips

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

Tubes, racks, and cryogenic storage

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

Plates, dishes, flasks, and slides

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

Filters, syringes, and needles

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

Histology, protective wear, and other consumables

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

General Terms and Units

configurationid
femto
gene
hydrochloride
nmol
pmol
ppt
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	*Media:* dmem; dmem/f-12; rpmi. *Process liquids:* 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	*Enzymes:* taq polymerases; high-fidelity dna polymerase; hot start pcr systems; reverse transcriptase. *Kits:* first-strand cdna synthesis systems
Nucleic acid purification	*Molecular weight standards:* pre-stained protein ladders; unstained dna ladders
Cloning	*Enzymes:* 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	*Running and sample buffers:* laemmli sample buffer; lds sample buffer; mes-sds buffer. *Gel casting:* 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:

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

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

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

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:

$$\hat{\beta}_m^{EB} = w_m \hat{\beta}_m + (1 - w_m)\hat{\mu}, \qquad w_m = \frac{\hat{\tau}^2}{\hat{\tau}^2 + \widehat{se}_m^{\,2}}.$$

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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