

Medical Research and Health Care Finance: Evidence from Academic Medical Centers

Pierre Azoulay
MIT and NBER

Sloan School of Management
100 Main Street—E62-487
Cambridge, MA 02142

Misty Heggeness

U.S. Census Bureau and Federal
and Federal Reserve Bank of Minneapolis
4600 Silver Hill Road—Room 5K154E
Suitland, MD 20746

Jennifer Kao
UCLA

Anderson School of Management
110 Westwood Plaza—D510
Los Angeles, CA 90095

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Abstract

Academic Medical Centers (AMCs)—comprising medical schools, teaching hospitals, and research laboratories—play an important role in US biomedical innovation. The Balanced Budget Act of 1997 (BBA) changed the formula used to reimburse Medicare inpatient claims and subsidies for medical residents. We study the effect of changes in the generosity of clinical care reimbursements on the rate and direction of research performed within these institutions. We compare AMCs’ relative exposure to the reform and how these differences affect their researchers’ ability to attract NIH grant funding, as well as the quantity, impact, and content of their publications. We find that in response to the BBA, research activity increased by 10% among the average teaching hospital and 20% among major teaching hospitals, with larger effects observed for “translational” and clinical research. We find little evidence of concurrent changes in clinical outcomes.

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1 Introduction

Research dating back at least to Solow (1956) has highlighted the role that innovation plays in driving economic growth. But the production of novel ideas is ultimately filtered through institutions that provide the incentive structure for knowledge accumulation (Dasgupta and David 1994; Mokyr 2002; Rosenberg 1963). The belief that basic research ultimately generates practical insights is perhaps the central assumption in post-war science policy, and that belief appears particularly well-founded in the health care industry (Azoulay, Greenblatt, and Heggeness 2020; Cutler and McClellan 2001; Gelijns and Rosenberg 1995). Yet in that setting and beyond, we have scant systematic understanding of the ways in which institutions—both in their formal (i.e., funding models, peer review) and informal (i.e., authorship and collaboration norms, tenure systems) aspects—support the transformation of scientific ideas into technological advances.¹

In this paper, we crack open the institutional black box of Academic Medical Centers (AMCs), which, together with the National Institutes of Health (NIH) and the pharmaceutical industry, play a central role in biomedical innovation. In the United States, thirty percent of health-related research is performed inside these institutions (Commonwealth Fund 1999), which bring together in one place a medical school, an owned or closely affiliated hospital, and basic research laboratories with an explicit triple mission of patient care, teaching, and research. Within the innovation system, AMCs are uniquely able to bring together the “ideas sector” of the health care economy (i.e., biomedical research) with its “production sector” (i.e., clinical care). This, in turn, facilitates the bidirectional flow of knowledge between the laboratory bench and the patient bedside (Rosenberg 2009).

We examine how research within AMCs is shaped by the impact of an external financing shock. Traditionally, financial support for their research mission comes from three different sources: grants from the NIH and private foundations, contracts with the pharmaceutical industry, and importantly, cross-subsidies from patient care activities (Jones and Sanderson 1996).² Building on recent empirical work that examines resource allocation within organizations (e.g., Giroud and Mueller 2019), we examine how a sudden decrease in institutional funding influences the rate, impact, and direction of research within AMCs.

¹An important exception is Furman and Stern (2011), which examines the impact of biological resource centers on cumulative scientific discovery.

²Other funders include other federal agencies (e.g., the Centers for Disease Control and Prevention and the Agency for Healthcare Research and Quality) and state and local governments.

Health care financing cuts have ambiguous effects on the level of subsequent research within AMCs. Cuts in reimbursement levels may encourage hospitals and physicians to substitute effort towards patient care activities and away from research. Low levels of cross-subsidies may also make it harder for the hospital to attract productive investigators, resulting in a net decrease in subsequent research levels. On the other hand, hospitals and physicians may reduce the level of patient care activities in response to a price reduction. Instead of providing patient care, hospitals and physicians may increase time spent on research, leading to a net increase in subsequent research intensity. The implications for the subsequent quality and direction of research are similarly ambiguous. For example, financing cuts may cause researchers to decrease both high- and low-risk projects, or alternatively to focus their attention towards research activities with greater impact.

We exploit quasi-experimental variation in cuts to clinical care revenues induced by the Balanced Budget Act of 1997 (BBA). The BBA was a major reform that led to considerable reductions in the level of Medicare reimbursements to hospitals (Seshamani, Schwartz, and Volpp 2006). Following a period of growth after the introduction of Medicare and Medicaid, the growth of clinical revenues slowed in the 1990s (Chen and Goldman 2016; Smith et al. 2005). This slowdown was partially due to increased federal efforts aimed at containing rising US health care expenditures, but also to other forces, such as the diffusion of managed care delivery models (Hellerstein 1998). Our analysis exploits the fact that the BBA decreased add-on payments made to support graduate medical education, suggesting that teaching hospitals were disproportionately affected by the reform. Among teaching hospitals, some institutions were harder hit by the reform than others because of differences in their reliance on Medicare patients as well as specific subsidies that increased the price they received from Medicare for the typical discharge (MedPAC 2003).

Our empirical analysis focuses on two samples of hospitals—one that includes all teaching hospitals and one that focuses on a research-intensive set of hospitals. We assemble a rich dataset that includes, for each hospital over the period 1992-2007, grant applications, funded grants, publications, and patient outcomes.

Using a difference-in-differences model that takes advantage of cross-hospital variation in the exposure to the reform, we find that cuts to hospital financing meaningfully increased subsequent research output. We show that hospitals most affected by the BBA experienced a 10 percent increase in subsequent grant applications, funded grants, and publications. These findings stand in contrast with previous empirical work suggesting that restrictions to the funding environment can dampen subsequent research efforts (Furman, Murray, and

Stern 2012; Tabakovic and Wollmann 2019), as well as with the pronouncements of academic medical leaders at the time of the reform (Iglehart 1999).

To further characterize the impact of these cuts, we examine the consequences of the BBA on the importance and composition of subsequent research activities. Measuring the quality or impact of research is always fraught, and we analyze disparate effects of the reform along the “quality spectrum” using three separate measures: quantiles of the vintage-adjusted, article-level citation distribution, whether publications are cited in patent documents, and whether the publication appears to “disrupt” (or conversely consolidate) the prevailing scientific understanding and assumptions within a research subfield. In each case, we do not find evidence of heterogeneity along these dimensions, with the reform increasing low- and high-impact publication rates in a symmetric fashion.

However, we do find that these increases are not evenly distributed across the vertical chain of biomedical research. Laboratory-based research articles appear largely unaffected, whereas “translational” research—which is geared towards bridging the gap between basic science discoveries and clinical applications, and difficult to perform outside the AMC setting—and clinical research—including clinical trials, which tend to be supported by industry funding—increase markedly in more exposed institutions, relative to less exposed ones. These results do not accord with practitioners’ accounts (Meador 2015) and survey evidence (Weissman et al. 1999) pointing to the greater reliance of clinical investigators on institutional funds to support their research activities. On the contrary, our results are consistent with the view that researchers (or at least their employers) can “induce demand” in a manner similar to physicians shifting their practices’ emphasis away from Medicare beneficiaries onto patients covered by private insurance (He and Mellor 2012).

Finally, to better understand the overall consequences of the financing shock, we explore whether the BBA led physicians to substitute towards from research, away from improving patient care activities. Looking at 30-day risk-adjusted survival rates across four conditions at the hospital level, we do not find any systematic association between BBA-exposure and subsequent clinical outcomes, suggesting that the positive impact of the BBA on subsequent research was not offset by improvements in patient outcomes.

Our empirical analysis falls short of evaluating the overall welfare consequences of the BBA. Nonetheless, the positive impact on research investments in the medium term suggests that policy efforts aiming to decrease rents captured by health care providers do not unwittingly contribute to tear the delicate fabric of the biomedical research funding ecosystem.

Of course, our results might also reflect the specific time period we study, during which the budget of the NIH approximately doubled.

The remainder of the paper proceeds as follows. Section 2 provides background information about AMCs and health care financing shocks. Section 3 describes the data. Section 4 analyzes the effect of health care financing cuts on the rate, impact, and composition of subsequent research. Finally, Section 5 provides a discussion and concludes.

2 Background and Conceptual Framework

2.1 Academic Medical Centers and Biomedical Research

In the prototypical view of biomedical research, potential treatment discoveries undergo a sequential development process. First, researchers trained in the “basic” life sciences discover a new molecule and show that it inhibits a particular disease pathway *in vitro*. Then, they develop animal models and gather initial data on the molecule’s safety and efficacy. The new molecule is subsequently turned over to physicians, who clinically test the purported treatment in randomized controlled trials. This stylized view underlies a broad-based congressional support for the continuous public funding of biomedical research and drives most of the policy discussion.

However, this linear model of innovation, “*however flattering to the scientist and the academic, is economically naïve and simplistic in the extreme*” (Rosenberg 1994: 139). Indeed, a closer examination of major treatment discoveries reveals a significantly more complex picture. In numerous cases, the first biological insight is acquired in a clinical setting, and only subsequently do bench scientists make sense of the mechanisms by which treatment is effective (Gershon 1998). For example, scientists discovered the first antidepressant drug, iproniazid, because a related compound used to treat tuberculosis made patients so euphoric that they stopped taking it. Subsequent research on iproniazid led to the chemical theories of depression that have generated all later antidepressant agents (Wurtman and Bettiker 1995).

In general, academic physicians have played an essential role in the development of various new medical technologies that rely on alternative development pathways. In some cases, such as the development of AIDS triple therapies, successful treatments resulted from the ongoing dialog between bench and bedside scientists (Wurtman 1997). Other times, new clinical uses are discovered for therapies already introduced into clinical practice (DeMonaco,

Ali, and von Hippel 2012; Gelijns and Rosenberg 1995). Similarly, medical device users have also been instrumental in the invention of new products, from the identification of unmet clinical needs to builders of prototypes or initial field testing—a classic case of user-innovation (Gelijns and Rosenberg 1995). An extensive set of case studies lend credence to the belief that researchers within AMCs play an essential function in enabling these alternative pathways for treatment discovery, a belief strongly echoed by the academic medical establishment (Crowley and Gusella 2009).

For the past thirty years, research activities that focus on the bench-to-bedside interface have been labeled “translational.”³ Typically, translational research requires expertise in molecular biology, genetics, and a clinical subspecialty. As a result, it is often performed by physician-scientists who split their time between clinical care and research activities. Within that category of researchers, the relationship between patient care and research varies, ranging from individuals that are “interested in a disease mechanism and even occasionally interested in seeing patients,” but “almost never interact in their research with an intact patient” to individuals that “actively search for patients who may enable them to uncover the secrets of complex diseases, care for those patients, and...undertake to explore new diagnoses and therapeutic approaches to treating their disease” (Nathan 2005).

Rather than sitting midpoint on a continuum stretching from fundamental research in biology all the way to the testing of novel therapeutics in large scale clinical trials, it is more appropriate to view translational research as belonging to “Pasteur’s Quadrant,” that is, in a class of investigations bringing forth ideas that are simultaneously valuable scientifically and a useful input into the treatment discovery process (Murray 2002; Stokes 1997). A well-known example is the work of Joseph Goldstein and Michael Brown, recipients of the 1985 Nobel Prize for Medicine and Physiology. Their initial investigations were inspired by observations of their own patients suffering from familial hypercholesterolemia (Goldstein and Brown 1997). Through patient-inspired basic investigations performed at the laboratory bench, they identified the underlying root cause of this disease as a lack of low-density lipoprotein receptors. These discoveries in turn informed drug development efforts, ultimately leading to the market introduction of statins.

Distinguishing translational research from other types of biomedical research activities is not only more descriptively accurate, but also necessary to understand how wider

³The Institute of Medicine’s Clinical Research Roundtable defines translational research as the “transfer of new understandings of disease mechanisms gained in the laboratory into the development of new methods for diagnosis, therapy, and prevention and their first testing in humans” (Sung et al. 2003) though this definition does not appear to be widely agreed upon (Butler 2008; Woolf 2008).

changes in the health care system might affect the rate and direction of research efforts. First, translational research—which often focuses on uncovering the pathophysiologic mechanisms of disease (Ahrens 1992)—is very hard to appropriate, e.g., through patenting. As a result, its conduct is likely to be underfunded by private biopharmaceutical firms. Second, uniquely among the various types of biomedical research, translational activities are exceedingly difficult to perform outside of the AMC setting. In this respect they differ sharply from bench laboratory research, which often takes place in universities not affiliated with a medical school (e.g., MIT or UC Berkeley), independent research organizations (such as the Salk Institute) or pharmaceutical firms (Henderson 1994; Flier 2019). It also differs from clinical trial activities, which over the past three decades, have steadily migrated away from AMCs into a burgeoning ecosystem of for-profit experimental centers (Azoulay and Fishman 2020).

Consisting of a hospital, research laboratories, and a closely-affiliated medical school, AMCs bring together the wide range of resources, expertise, and personnel necessary to enable treatment discovery.⁴ They employ laboratory scientists, clinicians, physician-scientists, physicians-in-training, and graduate students. In addition, they attract a large number of patients with diverse phenotypes. This rare confluence entails that these institutions occupy a unique position in the biomedical research ecosystem, with a unique potential to facilitate the flow of knowledge from the laboratory bench to the patient’s bedside (Ali and Gittelman 2016; Rosenberg 2009).

2.2 Research Funding within Academic Medical Centers

To support their research activities, AMCs primarily rely on three alternative sources of funding: grants (mostly from the National Institutes of Health, but also from other federal agencies, philanthropic foundations), contracts from biotechnology and pharmaceutical firms (including but not limited to the conduct of clinical trials), and “unsponsored” expenditures (i.e., lacking sponsorship from external sources, often a euphemism for cross-subsidies from clinical care).

NIH grants account for the largest share of research funding within AMCs—close to 70%, or \$7.4 billion in 1997 (Commonwealth Fund 1999)—and AMCs capture more than two

⁴One strategy for identifying whether a hospital is “affiliated with a medical school” is if it reports a medical school affiliation to the American Medical Association. The American Hospital Association (AHA) Annual Survey indicates that more than 600 US hospitals were affiliated with a medical school in 2007, the last year of our analysis. For a subset of the analyses that follow, we employ this definition to analyze the impact of the BBA on hospitals with high research and teaching intensity.

thirds of NIH extramural grant expenditures in a typical year.⁵ However, beginning in the 1980s, the mix of research supported by NIH steadily shifted towards laboratory investigations mostly conducted by scientists holding a PhD.⁶ The perceived lack of balance has led to perennial calls by the academic medical establishment to protect funding for physician-scientists because they constitute an “endangered species” (Jain et al. 2019; Rosenberg 1999; Wyngaarden 1979). Over the past 25 years, task forces and blue ribbon commissions have suggested various avenues to reform peer review practices at NIH so as to avert a “crisis in clinical research” (Ahrens 1992; Nathan and Wilson 2003).

A second source of funding are contracts from industrial sponsors, typically (but not exclusively) for the conduct of clinical trials.⁷ Historically, AMCs’ infrastructure, proximity to patients, and clinical expertise meant that they were the natural locus for the great bulk of clinical trials sponsored by industry. This began to change in the 1990s as a new crop of for-profit experimental centers started to compete with AMCs to provide biopharmaceutical sponsors with a more streamlined and lower-cost alternative (Azoulay and Fishman 2020). Private non-academic clinical trial sites came to partly replace their academic counterparts because the academic incentive system sometimes struggles to reward the conduct of research sponsored by firms. First, fellow academics sometimes view investigators with ties to industry as “tainted” (Prasad 2020); these perceptions have become heightened following a number of scandals involving human subjects protection and conflicts of interest (Baird, Downie, and Thompson 2002; Nathan and Weatherall 2002; Stelfox et al. 1998). Second, whereas investigator-initiated research makes unique demands on the creative and scientific potential of an academic, clinical trials involve a substantial relinquishing of intellectual autonomy since the investigator must adhere to an agreed-upon plan of research designed by others. As a result, participation in this activity does not produce career benefits commensurate with those generated by NIH-sponsored research—except, perhaps, for the “key opinion leader” recruited by industry to write the trial’s clinical protocol.

The last substantial source of funding for research within AMCs falls under the nebulous umbrella of “unsponsored research.” This funding includes expenditures by institutions or group practices, using rents from clinical care activities, endowment income, or insti-

⁵Authors’ tabulations using NIH’s Compound Grant Applicant File.

⁶In 1995, PhD grantees outnumbered their MD counterparts by a ratio of 3:1, though application success rates for the two groups were similar (Nathan 1998). Furthermore, it is often suspected that successful MD applicants share the scientific interests and basic research training of PhD-holding grantees, and do not necessarily interact directly with patients for research purposes (Ahrens 1992).

⁷Industry support accounted for 14% of research expenditures within AMCs in 1997 (Commonwealth Fund 1999).

tutional reserves, and by individual faculty members who devote their own resources to conduct research, drawing from discretionary funds or working additional uncompensated hours. These cross-subsidies are not systematically quantifiable, but survey evidence suggest that they play a non-negligible role in supporting AMCs' research mission.⁸ While much less important quantitatively than sponsored research expenditures, unsponsored expenditures might support the careers of young investigators struggling to establish their own independent program of research, or those of established scientists whose traditional sources of funding have temporarily ran out. Because faculty clinical practice plans are typically a major source of these expenditures, one might expect clinical researchers (which can include PhD-holding scientists working in clinical departments such as Internal Medicine or Pediatrics) to disproportionately benefit from this source of support.

In contrast with sponsored research, where proposals undergo stringent peer review (in the case of NIH grants) or must pass a market test (in the case of clinical trials), the welfare impact of unsponsored research activities is ambiguous. First, the existence of cross-subsidies means that AMCs earn rents from their clinical care activities, so that the same quality of care might have been delivered to patients at a lower cost (Nicholson and Song 2001). Second, the lack of transparency in the disbursement of institutional funds makes it susceptible to capture by entrenched interests, potentially resulting in low-quality or wasteful research by "hobby doctors." Our evidence will indirectly speak to this question, by examining the quantity, impact, and composition of research by institutions differentially exposed to financial stress.

2.3 Medicare Payments and Financing Cuts

To provide plausibly exogenous variation in the extent of financial slack faced by AMCs and teaching hospitals, we rely on a measure of exposure to the Medicare reimbursement cuts triggered by the Balanced Budget Act of 1997.⁹

Under a system known as the Prospective Payment System, Medicare reimburses most hospitals on a per-admission basis (See Appendix A for a detailed discussion). In turn, each admission payment is a function of three types of adjustments: indirect medical education

⁸A survey conducted by the Association of American Medical Colleges found that 10 percent of the faculty-practice plan revenues were used to support research (Jones and Sanderson 1996); 43% of AMC faculty members have reported receiving institutional funding for research (Weissman et al. 1999); and, in 1997, 9% of AMC research funding corresponded to support from faculty group practices.

⁹In the typical hospital, Medicare typically accounts for 30 percent of patient care revenues (Reinhardt 2006).

(IME) subsidies, disproportionate share hospital (DSH) payments, and outliers payments (Nicholson 2002). IME payments are meant to compensate teaching hospitals for indirect expenses stemming for example from use of diagnostic services by clinically inexperienced residents or decreased productivity of nurses and support staff involved in the teaching of residents. DSH payments correspond to payments received by hospitals for the additional cost of treating poor patients. Finally, outlier adjustments are reimbursements to compensate providers for patients with exceptionally costly stays (Keeler, Carter, and Trude 1988).

The BBA reduced the scale of all three adjustments and slowed the growth of payments for all diagnosis-related groups (See Appendix A for details). As a result, Medicare inpatient payments decreased by approximately five percent between 1998 and 2000 and many hospitals saw their financial status deteriorate significantly (Dickler and Shaw 2000; Iglehart 1999; Shen and Wu 2013; Seshmani, Schwartz, and Volpp 2006). Importantly, the reform was not anticipated, as its passage depended on the delicate balance of power between a reduced Republican majority in Congress and the Clinton administration following the November 1996 Federal election (Kahn and Kuttner 1999).¹⁰

As 30 percent of inpatient visits are funded by Medicare, cuts to Medicare reimbursements can represent a significant financial strain on hospitals. The effect of financial cuts on hospital activities has been widely studied in the realm of clinical care, with inconclusive results. In theory, hospitals may respond to reduced Medicare payments by cost-shifting—i.e., increasing prices for privately-insured patients—or cost-cutting—i.e., lowering hospital costs, decreasing support for unprofitable services (Cutler 1998, David et al. 2014). The empirical evidence to date has shown that, in response to adverse financial shocks, hospitals cut costs by limiting growth in hospital staff (Bazzoli et al. 2004) and lowering the quality of care (Lindrooth, Bazzoli, and Clement 2007). In contrast, Wu (2010) finds that in response to the BBA, hospitals are limited in their ability to shift costs to private payers (mostly due to the rise in influence of managed care delivery models during this period).

The consequences of financial stress for AMCs in particular are less well-understood, with no evidence to date regarding the impact on the research mission of these institutions. Financing cuts may shift research levels by influencing AMCs' hiring practices or exit rates among incumbent researchers. For example, hospitals may decrease the rate at which they hire faculty members or replace those that have left the institution; alternatively, hospitals

¹⁰ *After* the passage of the reform, however, lobbying efforts by Medicare providers—with teaching hospitals in the frontline—proved successful in watering down some of its provisions: the Balanced Budget Refinement Act (BBRA) of 1998 slowed down the transition set by the BBA, a process continued by the Benefits Improvement and Protection Act (BIPA) of 2000 and the Medicare Modernization Act of 2003.

may redirect their hiring efforts towards individuals that can more easily obtain funding from the government (i.e., laboratory bench researchers) or the private sector (i.e., trialists).

In addition to shaping research activity along the extensive margin, the BBA may shift research activity within individuals. For existing researchers, the net effect of financing cuts on research levels theoretically hinges on the relative strength of the substitution and income effects (Jacobson et al. 2010; McGuire and Pauly 1991; Yip 1998). If the former effect dominates, physician-investigators may substitute other career-advancing or other revenue-generating activities—such industry-funded clinical trials—for clinical care. In this scenario, financing cuts would cause more easily-funded research activities to increase. If the income effect dominates, however, researchers may instead direct more effort towards patient care activities. In this setting, financing cuts may lower subsequent research levels, or alter the composition of the research portfolio, for individual researchers or the institution as a whole.

Qualitative accounts from physicians contemplating integrating a research component into their clinical practice often highlight the lumpy adjustment costs that need to be incurred in this process, with most expressing skepticism that their institutions could adequately support these efforts using the dwindling rents from clinical care activities. Because of the lack of fungibility between research and clinical care effort outside of the narrow context of clinical trials, our prior is that the extensive margin is likely to dominate and that any intensive margin (i.e., within-physician) substitution effects are likely to involve substitution of patient care or research activity towards “bedside” research—i.e., clinical trials.

Along both the extensive and intensive margins, however, our presumption is that the cuts induced by the BBA will disproportionately affect translational research—these investigations whose fundamental goal is to bridge the gap between the laboratory bench and the patient bedside.

3 Data

3.1 Data Construction and Sources

Our analysis combines data from several primary sources (i) hospital characteristics from the Healthcare Cost Report Information System (HCRIS) and the Inpatient Prospective Payment System (IPPS) Payment Impact Files; (ii) administrative data on NIH grants from the NIH IMPAC II database; (iii) publication and citation data from *PubMed* and the *Web*

of *Science*, respectively; (iv) patent-to-publication citation linkages (from the USPTO and PubMed combined); and (v) hospital-level clinical outcomes data. Figure 1 describes how these data sources fit together and how we construct the variables used in this analysis.

We leverage information from HCRIS, which contains administrative data covering the universe of Medicare-certified hospitals. We identify hospitals with information from 1992 to 2007. For each hospital record, we observe hospital characteristics data, such as the total number of patient discharges, inpatient days, IME payments, and DSH payments (cf. Section 2.3). Medicare pricing information from the 1995 IPPS Payment Impact Files are used to calculate hospitals’ average PPS price per discharge.

We supplement this hospital-level dataset with several measures of research activity. First, we link the hospital dataset to grants data from the NIH IMPAC II database.¹¹ For each grant, we obtain information on investigators, their institutions, and a number of project characteristics. Next, we collect data on publications from *PubMed*, the public-access database which indexes the scientific literature, and we obtain publication citation data from the *Web of Science* (up to 2015).

A key challenge for estimating the causal impact of the BBA is that the level of the shock (changes to Medicare funding due to the BBA) and the measures of research outcomes (NIH grants and publications) do not coincide. An analysis that examines how Medicare payments at the individual hospital-level affects NIH grants allocated at the medical-school level is likely to produce estimates that suffer from measurement error. We overcome these challenges by employing an outcome assignment mechanism that uses principal investigator (or author) addresses to allocate each grant (or publication) to the “correct” hospital.

As an example, the University of California, San Francisco medical center includes the Parnassus Heights Campus, Mt. Zion Hospital and Medical Center, and San Francisco General Hospital (see Appendix Figure B1). Each of these locations has a unique Medicare provider number and therefore receives their own specific Medicare payments. However, the three campuses share a single, common NIH institutional code. Our strategy for matching hospitals to grants consists of looking at each of the PI addresses affiliated with the UCSF NIH institutional code and allocating each PI (and grant) to one of the three hospitals.

¹¹To construct the set of relevant grants, we limit our analysis to research project awards (NIH activity code R), research career awards (NIH activity code K), program projects and centers (NIH activity codes M and P), cooperative agreements between NIH and a group of investigators (typically, NIH activity code U01), and R&D contracts to evaluate a product or device (NIH activity code N01).

We execute a similar strategy to match hospitals to publications: for each publication, we use the *Web of Science* to determine its authors’ institutional affiliation and address. This allows us to match a publication to a hospital by matching on both hospital name and address.¹²

The final sample consists of all hospitals that show evidence of teaching and research activity. To identify the set of research intensive hospitals, we make several restrictions. First, we start with a list of 1,195 unique hospitals (as captured by unique Medicare provider numbers in the HCRIS data between 1992 and 2007).¹³ We drop 210 specialty hospitals as they are not paid under Medicare’s Prospective Payment System.¹⁴ Next, we exclude any hospitals that close during the 4 year period between 1992 and 1995 (the focal pre-BBA year in our analysis) by restricting our hospital sample to those with all observations between 1992 and 1995.¹⁵ Finally, to focus on a subset of hospitals for which the BBA is most likely to induce a meaningful shift in hospital outcomes, we restrict our sample to hospitals that receive (1) at least one indirect medical education payment and (2) produce at least one publication or submit at least one NIH grant application between 1992 and 2007. This results in a final sample consisting of 780 teaching hospitals (hereafter the “teaching hospital sample”).

In addition to our primary hospital sample, we also consider a second, more research-focused subset of the teaching hospital sample (the “AMC sample”). To create this second hospital sample, we follow the definition of a “major teaching hospital” used by Burke et al. (2017). Major teaching hospitals are members of the Council of Teaching Hospitals (COTH) and have a medical school affiliation reported to the American Medical Association.¹⁶ This results in a sample of 274 hospitals.

¹²Notably, the *Web of Science* was launched in 1997. While the database contains records of articles published before 1997, the occurrence of missing author addresses is higher prior to 1998 (Liu, Hu, and Tang 2018). This does not threaten the validity of our estimates, since our regression specifications will include a full suite of calendar year effects.

¹³We address mergers and acquisitions over this time period by creating “super-hospitals” which inherit the Medicare patients, publication, and grants from their constituent units over the entire time period. Dropping these observations does not change our results.

¹⁴Specifically, “specialty hospitals” include: long term care, rehabilitation, psychiatric, pediatric, and cancer hospitals.

¹⁵Note that in the event that this subset of hospitals contains institutions whose closures were induced by the BBA, excluding this subset of hospitals may lead to an underestimate of the BBA’s impact on hospital outcomes.

¹⁶Hospital COTH status and AMA medical school affiliations are obtained from the American Hospital Association Annual Surveys from 1992 to 2007.

The primary outcomes of interest are the total number of grant applications, grant awards, and publications that accrued to the researchers affiliated with a particular hospital in a given year. However, we go beyond these raw counts by investigating how health care financing cuts shape the impact and composition of subsequent research. We rely on three measures of research impact. For our first measure of research impact, we assign each article to one of six mutually exclusive bins: those that fall in the bottom quartile of the article-level distribution of long-run citations, those that fall in the second quartile, in the third quartile, in the top quartile but not in the top ventile, in the top ventile but not the top percentile, and finally publications in the top percentile of the citation distribution. The percentile rankings are vintage-adjusted, which allows us to compare the citation impact of publications published in different years.¹⁷ Our second measure of research impact comes from identifying the number of publications that were subsequently cited by a patent (Marx and Fuegi 2020).

Finally, our third measure of research impact comes from identifying each publications’ “disruptive” impact using an index recently proposed by Funk and Owen-Smith (2017). Their citation-based measure captures the degree to which the ideas embodied in a paper consolidate or destabilize the scientific status quo. An article is considered “consolidating” if it tends to reference the same publications as the articles that will cite it in the future. Conversely, “disruptive” research draws on articles that will not be acknowledged by its own citing papers. For each hospital in the sample, we compute in every year the number of articles published that fall above the 95th percentile of the Funk & Owen-Smith d index.

To investigate how the BBA shifts the allocation of research along the bench-to-bedside continuum, we construct measures of basic laboratory research (hereafter characterized as “laboratory” research), translational research, and clinical research. To partition the research space in this way, we take advantage of Medical Subject Headings (MeSH) terms, a hierarchical controlled vocabulary maintained by the National Library of Medicine. Most publications listed in *PubMed* are tagged with a set of MeSH terms, which characterize their scientific content. Using the MeSH-based definitions outlined in Azoulay, Greenblatt, and Heggeness (2020), we designate articles as bench research if they fulfill three criteria: (i) they are *not* disease-oriented (i.e., contain no disease MeSH terms); (ii) they do not re-

¹⁷A vintage is comprised of all the articles published in a given year. To compute the quantiles of the vintage-specific, article-level distribution of citations, the relevant universe is not limited to the articles produced by researchers with addresses corresponding to the hospitals in our sample. Rather, the relevant universe includes the entire set of 17,312,059 articles that can be cross-linked between *PubMed* and the *Web of Science*.

port the results of a clinical trial (which we ascertain by examining the publication type field in *PubMed*); and (iii) they are tagged by MeSH terms denoting either the use of a molecular biology technique, the use a model organism, the study of cellular structures and macromolecules, or the study of biochemical and cellular processes.

We next identify the set of publications that can plausibly be deemed to be translational in nature. Following Azoulay, Greenblatt, and Heggeness (2020), we generate three MeSH-based measures related to translational research. First, we label a publication translational if it is (i) disease-oriented; (ii) not a clinical trial; and (iii) also tagged by a basic science keyword used to describe bench research. Next, we denote a publication as “inspiring translational research” if it is translational and is cited by at least one clinical trial publication. Finally, we identify work that “builds on translational research,” i.e., those that report the results of a clinical trial and list a translational publication in the reference list.

Our final measure of research outcomes is meant to capture research investments directly relevant for the bedside—i.e., clinical research. We focus on two measures: (i) clinical trial articles (identified using MeSH terms corresponding to clinical trials or the publication type field in *PubMed*) and (ii) “other” clinical articles, which are disease-oriented, not clinical trials, and not tagged by any bench MeSH keywords.

3.2 Financial Pressure from the BBA

To evaluate the impact of the BBA on subsequent research activity, we exploit the fact that some hospitals were more exposed to the reform than others. Following Shen (2003), we construct a “BBA Bite” variable that is the BBA-induced change in PPS price weighted by the share of Medicare patients in a base, pre-BBA year. As discussed in Section 2.3, the BBA changed the formula for Medicare subsidy payments, which are a function of teaching load and the disproportionate share of poor patients. This suggests that cross-hospital variation in the BBA’s impact comes from differences in (i) hospital characteristics (e.g. the number of residents) and (ii) the hospital’s reliance on Medicare.

To identify the effect of the BBA on PPS prices, we rely on a simulated price approach. In particular, we use pre-BBA data to simulate the revenue that hospitals would have lost under the BBA, had the reform been in effect earlier. Using pre-BBA data isolates the mechanical effect of the policy from hospitals’ endogenous responses. We simulate the average PPS price per discharge that hospitals would have received from Medicare had the BBA

occurred in 1995, two years prior to its actual implementation.¹⁸ The mechanical effect of the BBA is estimated as the difference between the simulated price per discharge and actual PPS price per discharge in 1995:

$$sim\Delta price_{h,1995} = price_{h,1995} - sim\ price_{h,1995}$$

where $price_{h,1995}$ is the log of true PPS price per discharge in 1995 and $sim\ price_{h,1995}$ is the log of simulated PPS price per discharge in 1995. Both prices are averages across all Medicare discharges. Figure A1 shows that hospitals with a larger $sim\Delta price_h$ are more research-intensive in the pre-BBA era—a finding consistent with the expectation that research-intensive, teaching hospitals are more likely to be disproportionately impacted by the BBA.

Finally, we weigh this measure by the share of a hospital’s discharges that are reimbursed by Medicare in 1995. This follows previous literature which measures the financial impact of Medicare payment changes by using the hospital’s base year Medicare discharge share (Acemoglu and Finkelstein 2008; Kaestner and Guardado 2008; Wu and Shen 2014). The overall BBA Bite is calculated as:

$$BBA_Bite_h = \left[\frac{MedicareDischarges}{TotalDischarges} \right]_{h,1995} \times sim\Delta price_{h,1995} \quad (1)$$

The distribution of BBA Bite among hospitals in the teaching hospital sample is depicted in Figure 2. The figure shows that there is substantial variation in BBA Bite: the average BBA Bite is 0.0045 with a standard deviation of 0.0035. Looking to the extremes of the distribution provide some illustrative examples: on the far left is South Bay Medical Center. In addition to having a low BBA Bite (0.00003), the California-based hospital has relatively low teaching and research intensity: the institution had three residents and produced one publication in 1997. In contrast, the St. Louis University Hospital—a similarly sized institution with a BBA Bite of 0.0184—had more than 200 residents and produced 122 publications in the same year.

3.3 Summary Statistics

Table 1 provides hospital-level summary statistics for the teaching hospital sample. As can be seen in Panel A, the mean hospital has around 16,000 patient discharges, contains 400 beds, has 100 residents and interns, and reported roughly \$10 million in combined IME

¹⁸Specifically, we compute total IME and DSH payments keeping hospital inputs fixed at the 1995 level and using the 2001 IME and DSH payment formula.

and DSH payments. Approximately a third of patient discharges correspond to Medicare patients. The average Medicare price per discharge is \$8,000.

Looking next to Panel B, the distributions of both the number of grant applications and the number of awarded grants are highly skewed (see Appendix Figure D1). For example, the mean number of grants awarded is roughly three, while one hospital (Massachusetts General Hospital) has nearly 150 grants funded during the period considered in our study. The majority of grant applications and awards correspond to new research proposals, as opposed to competitive renewals of already-funded grants. Splitting the grants by the degree of the principal investigator (MD, PhD, or MD/PhD) reveals that most grant applicants hold PhDs.

Panel C shows that the average hospital had 46 publications in a year, but that this average also masks substantial variation—ranging from a minimum of 0 publications to a maximum of roughly 1,700 (see Appendix Figure D1). Among the publications produced, 4 percent were considered disruptive (as opposed to consolidating), there were similar rates (25 percent) of bench and translational research, and nearly 38 percent were considered clinical.

Across all hospitals, there is a marked increase in the level of grant applications (Figure 3) and grants funded (Figure 4) over our study period. The BBA occurred shortly before a sustained increase in the NIH budget, which concluded in 2003 (Freeman and Van Reenen 2009; Korn et al. 2002). Consequently, most of the teaching hospitals in our sample experienced an absolute increase in the grant funding awarded to their investigators, at least in the immediate aftermath of the shock. Our regression specifications will flexibly control for this secular increase through the inclusion of calendar year effects, making it possible to examine whether more exposed hospitals experience a relative decrease in research activity following the reform, relative to less exposed hospitals.

Figure 5 shows a similar upward trends for total publications. There is a discrete shift in 1998, which is likely explained by the use of the *Web of Science* in constructing the publication dataset, as discussed above. A more pronounced upward trend is observed for translational research and “other” clinical research articles, whereas the trajectories for laboratory research and clinical trials are relatively flat.¹⁹

¹⁹For clinical trials, this likely reflects a general exodus of industry-sponsored activity away from academia during the period considered (Azoulay and Fishman 2020).

Appendix Table E1 provides summary statistics for hospitals in the AMC sample. A comparison of the analysis hospital sample and the AMC sample can be found in Appendix Table E2. Relative to hospitals in the analysis hospital file, AMC sample hospitals produce significantly more grant applications and publications, and are more likely to facilitate industry-sponsored clinical trials.

For a subset of the empirical exercises that follow, we examine the impact of hospital financing cuts on clinical outcomes in hospitals. Our main measures of clinical outcomes stem from Chandra et al.'s (2016) analysis of the relationship between hospital quality and market size. In particular, these authors construct hospital-level measures of 30-day risk-adjusted survival for four frequent conditions: acute myocardial infarction (AMI), congestive heart failure, pneumonia, and hip/knee replacements (a common pair of surgical procedures). Specifically, they construct condition-specific measures using claims and survival outcomes in three-year rolling windows.²⁰ Since the time period in the Chandra et al. (2016) study spans the pre- and post-BBA, periods, for each hospital we use the observation in 1996 (corresponding to an average over the pre-BBA years 1994, 1995, and 1996) and the observations (corresponding to an average over the post-BBA years 2000 through 2005). Of the 780 hospitals in the teaching hospital sample, we successfully match 700 hospitals to the clinical outcomes dataset. Table 1, Panel D provides summary statistics for these survival outcomes, while Appendix Figure D2 presents histograms for the distribution of the survival rates for each of the conditions.

4 Empirical Strategy and Results

Our empirical strategy thus consists of comparing research outputs, before and after the implementation of the BBA, between hospitals that faced a potentially large decrease in the level of Medicare reimbursements (and have a relatively higher BBA Bite) to those that were minimally impacted by the reform (with a smaller BBA Bite).

With h indexing hospitals and t indexing years, we estimate

$$y_{ht} = \beta BBA_Bite_h \times AfterBBA_t + \delta_h + \zeta_t + \varepsilon_{ht} \quad (2)$$

²⁰For example, the, 30-day risk-adjusted survival for 1996 is calculated using patient claims during the years 1994, 1995, and 1996.

where y_{ht} is a measure of research outcome,²¹ $AfterBBA_t$ is an indicator equal to 1 after 1997, δ_h are hospital fixed effects, and ζ_t are year fixed effects. To ease interpretation of the results, we also estimate regressions where BBA_Bite_h is an indicator for whether hospital h 's BBA Bite is above the median (0.0035).

As is traditionally the case for difference-in-differences research designs, a threat to identification could arise if the treatment variable (BBA_Bite_h) is correlated with unobserved trends in the outcome. The context of the NIH doubling provides the backdrop for one specific variant of this threat. If the research funding allocated towards research that primarily affect the elderly (e.g., Alzheimer's disease) increased relatively more post-BBA, it might benefit disproportionately hospitals with a relatively higher share of elderly patients—those with a high Medicare discharge share. We address this concern directly in Appendix C, by examining whether NIH funding changes appear “age-biased” or “age-neutral.”

4.1 Effects on Research Levels

Table 2 presents the estimates of the impact of the BBA on the number of grant applications. Panel A reports estimates of equation (2) where BBA_Bite_h is the BBA Bite in hospital h . In addition, Panel B reports estimates of equation (2) where BBA_Bite_h is an indicator for whether hospital h is a High BBA Bite hospital (i.e., a hospital with a $BBA_Bite > 0.0035$). To ease interpretation of the results, we present elasticities in the third and seventh rows.

The first column of Table 2 shows that the BBA has a positive effect on the subsequent number of grant applications. Column 1 shows that an increase in a hospital's BBA Bite translates into an increase in the total number of subsequent grant applications. Regressions that measure the direct impact of a hospital's BBA Bite yields an approximate elasticity of 0.053 and regressions that incorporate a High BBA Bite hospital indicator yields an elasticity of 0.110.

In subsequent columns, we examine the impact of cuts in Medicare reimbursement on different types of grants (by grant cycle and principal investigator type). The estimates presented in Column 2 suggest that the positive response in total grant applications is driven by an increase in applications for new proposals. In contrast, there is no statistically significant

²¹In most cases we transform the outcome using the inverse hyperbolic sine transformation— $asinh(x) = \log(x + \sqrt{x^2 + 1})$ —to accommodate the large number of zero observations, while maintaining the ability to interpret the magnitude of coefficient estimates as elasticities (Burbidge, Magee and Robb 1988; Bellemare and Wichman 2020).

effect on the number of “competing continuations,” which correspond to applications seeking to extend previously awarded grants for an additional funding cycle. This differential pattern is consistent with the view that in response to cuts to Medicare payments, AMCs may respond by hiring researchers and existing researchers may be encouraged to turn to external grants as a funding source.

Estimates in Columns 4 through 6 explore the effects of the financing cuts on research conducted by MDs, PhDs, and MD/PhDs. In all cases, we estimate a strong, positive, and statistically significant effect of the BBA Bite on the level of subsequent grant applications. The PhD and MD/PhD results are slightly larger in magnitude than the MD results: a one percent increase in BBA Bite yields a roughly eight percent increase in research conducted by PhD-holding principal investigators. In contrast, research conducted by MDs increases by five percent (though the difference between PhD and MD coefficients are not statistically significant). This accords with our priors: PhD-holding investigators are more likely to engage in research at the laboratory bench and MDs are traditionally associated with clinical and translational research. The finding that research conducted by MDs significantly increases can be explained by the fact that NIH grantees holding MD or MD/PhD degrees increasingly share similar scientific interests and methodological approaches with investigators who received traditional PhDs in the various disciplines within the life sciences domain (Ali and Gittelman 2016).

To explore the timing of these estimated effects, we estimate:

$$Y_{ht} = \alpha + \sum_z \beta_z \times 1(z) \times BBA_Bite_h + \delta_h + \tau_t + \epsilon_{ht} \quad (3)$$

where δ_h and τ_t represent hospital and year fixed effects, respectively, for hospital t and year t . z represents the “lag,” or the years relative 1997, which is the year in which the BBA is implemented. Figure 6 plots the estimates of β_z from equation (3) for total grant applications and corresponds to a dynamic version of Table 2, Panel A, Column 1. The figure also displays 95-percent confidence intervals and a dashed gray line that represents the year in which the BBA was enacted. The estimated coefficients illustrate that hospitals with high BBA Bites exhibit trends in grant applications similar to hospitals with low BBA Bites in years prior to the BBA. However, the level of grant applications increases differentially in the wake of the BBA and continues to increase afterward. The increase in grant applications is gradual, suggesting that any immediate impact of the BBA may have been mitigated by AMCs’ reliance on alternative sources of funding (e.g., clinical trial contracts with pharmaceutical firms), which we explore below.

Next, we examine the impact on the number of grants funded and total publications. We find similar results. Table 3 and Figure 7 show that following the BBA, a percent increase in a hospital’s BBA Bite is associated with an approximate 4.7 percent increase in the number of grants funded. The similar patterns for grant applications and grants funded persist when looking across grant cycle (new applications versus competing continuations) and principal investigator degree type. Turning to the effect on total publications, Column 1 of Table 4 shows that the total number of subsequent publications increases by 1.7 percent for each percent increase in BBA Bite (Panel A) and a 7.8 percent increase among High BBA Bite (Panel B) hospitals, though the coefficient in Panel A is not statistically significant. The onset of the BBA effect (Figure 8) appears immediate, suggesting that one consequence of allocating time towards more research is that existing AMC researchers may turn to publications that were previously “waiting” in the file drawer.

4.2 Effects on Research Impact

A challenge of only examining research aggregates is that AMCs and researchers may alter the nature of their research projects in response to financial strain, in which case examining hospital-level grant and publications total counts may mask how institutions and individuals reallocate their efforts among research projects with differing levels of impact. Table 4 report the effects of the shock on publication rates adjusted for three measures of impact: publication-to-publication citation impact (Columns 2-7), patent-to-publication citation impact (Columns 8-9), and “disruptiveness” (Columns 10-11).

Turning first to the effect on publication-to-publication citation impact and patent-to-publication citation impact, much of the scholarship in the economics of innovation implicitly treats citation impact as a proxy for impact or “importance” (Azoulay, Graff Zivin, and Manso 2011; Hall, Jaffe, and Trajtenberg 2005), although this assumption has come under scrutiny (Funk and Owen-Smith 2017). If the decrease in publication volume documented above was driven by articles which do not make much of a ripple, leaving the impact on highly-cited articles unchanged, we might be tempted to conclude that the effect of the reform on research activities are at most second-order, relative to the effects on the cost and quality of health care delivery in these same institutions.

As described in Section 3, publications are assigned to six mutually exclusive citation-based bins. We run the regression specified in equation (2) using each bin as a separate outcome. Looking across Columns 2 through 7, we cannot reject that the implied elasticities are essentially identical. We next examine the effect of the BBA on the number of publica-

tions that are subsequently cited by a patent, which we view as a proxy for the extent to which the work of AMC scientists shape biopharmaceutical firms’ R&D efforts. Columns 8 and 9 reveal similar effects across the number of publications that are and are not, respectively, cited by a patent. Overall, the evidence in Table 4 indicates that the effect of the reform are relatively homogeneous along the “citation as quality” dimension.

The remaining columns of Table 4 assess the extent to which the BBA disproportionately affects “disruptive” research. Using the d index proposed by Funk and Owen-Smith (2017) to partition the set of articles for each hospital into “disruptive” publications (d in the top ventile) and “consolidating” publications ($d \leq 95^{th}$ percentile). We find a slightly larger positive effect on disruptive research (Column 11) relative to consolidating research (Column 10), though the difference between the coefficients are not statistically significant. Taken together, the results suggest that the BBA ushers in an uniform increase in the level of both low and high impact scientific projects.

4.3 Effects on the Composition of the Research Portfolio

We now turn to a more detailed investigation into how a hospital’s research mix shifts in response to the BBA. In Table 5, we explore the possibility of compositional changes by examining the effect on laboratory research, translational, and clinical research.

The results indicate that basic laboratory research is largely unaffected by the BBA: while a one percent increase in BBA Bite is associated with a 1.2 percent decrease in publications of this type. However, the estimates are statistically indistinguishable from 0, likely due to the fact that our analysis is focused on hospitals that are primarily focused on translational and clinical research. Consistent with this view, we observe a strong positive response for the level of translational research: the BBA causes translational research publications to increase by 9.6 percent for each percent increase in BBA Bite. Event study estimates echo these findings (Figure 10). This amplifying effect also extends to publications that “build on translational research” (Column 3) or “inspire translational research” (Column 4).

Looking next to clinical research publications, we find that the level of clinical research—as measured using the clinical trial definition (Column 5) and “other” clinical MeSH-based (Column 6) definition—increases substantially: a one percent increase in BBA Bite is associated with a 9.8 percent increase in clinical trial publications and 4.8 percent increase

in “other” clinical research. Event study figures (Figure 11, Panel A and B) corroborate these findings.²²

In sum, the results presented in Table 5 paint a nuanced picture of compositional change in response to the health care financing cuts. The financing reform leaves bench research relatively unchanged, while triggering a sizeable increase in investigations that can plausibly be labeled “translational” or “clinical.” This runs counter to the qualitative accounts we gathered in interviews with academic leaders as well as “rank and file” clinical faculty members, which surmised that investigators who split their time between patient care and research activities would experience the effects of a reduction in cross-subsidies from their hospital’s clinical care revenues more keenly.

4.4 Countervailing Impact on Clinical Care

Our results so far are consistent with the view that financial pressures might lead these scientists to allocate their time and effort away from patient care activities, towards research. As a result, the increase in subsequent research activity may be countered by declines in the quality of clinical care. A handful of previous studies have found that AMCs are associated with better outcomes (Ayanian and Weissman, 2002; Burke et al. 2017; Keeler et al. 1992; Taylor, Whellan, and Sloan 1999). In this section, we explore whether the BBA dampened these clinical care advantages through impacting patient outcomes within the hospitals in our sample.

We estimate the impact of the BBA on risk-adjusted survival rates in the “long difference” dimension of the data:

$$\Delta Y_h^c = \beta BBA_Bite_h + Discharges_h + \varepsilon_h \quad (4)$$

where ΔY_h^c corresponds to the change in the risk-adjusted 30-day mortality rate in hospital h for condition c . Acting as a proxy for hospital size, $Discharges_h$ is the log total number of patient discharges in 1995.

Table 6 reports the results. We find that, within this sample, the passage of the BBA does not adversely impact mortality outcomes following AMIs or heart failure episodes. Survival at 30-days is of course only a crude measure of care quality and the models have rela-

²²Panel A of Figure 11 exhibits a pronounced upward trend before the BBA shock. This is not altogether surprising: some of the more exposed institutions created offices dedicated to the running of clinical trials in the early 1990s as part of an effort to stem the exodus of industry-sponsored trial activity away from academic institutions towards “for profit” independent clinical testing sites (Azoulay and Fishman 2020).

tively low explanatory power, but it seems notable that we were unable to detect consistent declines in patient outcomes concurrently with the increase in research activity experienced by hospitals more exposed to the reform.²³

4.5 Robustness checks

4.5.1 AMC Sample Analyses

In Appendix E, we perform our analysis on the AMC sample, a subset of hospitals with high research and teaching intensity. This analysis reveals results that are fully consistent with our main results. In many cases, the estimated magnitudes are even greater than those found in the main teaching hospital sample. Among research-intensive hospitals, a one percent increase in a hospital’s BBA Bite translates into a 7.9 percent increase in the total number of subsequent grant applications (Appendix Table E3) and a 8.2 percent increase in the total number of grants funded (Appendix Table E4). We find a similar increase in the number of translational and clinical research publications, though the results for translational publications and “other” clinical research is significant, likely due to the smaller sample size (Appendix Table E6). One notable difference is that AMC hospitals experience significant increase in the number of highly cited publications (i.e., publications in the top ventile of the citation distribution, Appendix Table E5), suggesting that following the BBA, researchers may have been able to dedicate ample effort towards research projects with long-term impact in environments that already contained the necessary research infrastructure and resources. As a robustness check, we confirmed that our results in the primary teaching hospital sample are not being driven by hospitals *not* found in the AMC sample.

4.5.2 Subsidy BBA Bite Analysis

In Appendix F, we examine the robustness of the core results presented in Sections 4.1 through 4.3 to an alternative measure of BBA Bite. Recall that hospital-level variation is driven by differences in the hospitals’ reliance on Medicare payments and in particular, Medicare *subsidy* payments. In this robustness check, we measure of the BBA Bite as the share of 1995 hospital patient revenues that come from IME and DSH payments (Appendix Figure F1 graphs the distribution of this version of the BBA Bite). The regression results in Appendix Figures F1 through F4 are quite similar to those in Tables 2 through 5, both

²³Most previous studies using samples not limited to teaching- and research-intensive hospitals find null to minimal impacts of the BBA on patient outcomes (Seshamani, Schwartz, and Volpp 2006; Seshamani, Zhu, and Volpp, 2006; Volpp et al. 2005). An exception is Wu and Shen (2014) who find that hospitals facing greater payment cuts experienced worse patient outcomes in the long-run.

in terms of magnitude and statistical significance. The corresponding event-study graphs, displayed in Appendix Figures F2 through F7 are fully consistent with those observed in our core set of results. As described in Section 3.2, we prefer measuring BBA Bite as the difference in simulated price per discharge and actual PPS price per discharge, weighed by the Medicare share of total discharges, as it allows us to more directly estimate the average hospital income loss as result of the BBA.

4.5.3 Alternative Functional Forms

In Appendix G, we examine the sensitivity of our benchmark results to the choice of functional form. Recall that the outcome variables are highly skewed (Figure D1). As a result, we transform outcome variables with the inverse hyperbolic sine function. In this robustness check, we use the “raw” number of grant applications, grants funded, and publications as the outcome. The grant results in Tables G1 and G2 are quite similar to those reported in Tables 2 and 3, though larger in magnitude. The effect on publications in Tables G3 and G4 are also similar to the main publication results, except there is a disproportionate increase in publications that are not subsequently cited by a patent (relative to publications that are subsequently cited by a patent) and in disruptive publications (relative to consolidating publications).

4.5.4 Instrumental Variables Estimation

Appendix H considers an alternative strategy for capturing the exogenous variation in the PPS reimbursement formula. Following Shen (2003), we construct a simulated post-BBA price change that we use to instrument the actual post-BBA price change in a series of “long-difference” regressions. The difference in simulated and actual post-BBA price changes is documented in Figure H1. Table reports the two-stage least square regression results for our primary research outcomes. The results are consistent with our core results: hospitals that experience a larger financial loss as a result of the BBA experience an increase in research outcomes. The effects are both seen in the short-run (Panel A) and long-run (Panel B), though the effects are only statistically significant for publications in the long-run.

4.5.5 NIH Budget Doubling

As discussed previously, our empirical strategy relies on the maintained assumption that any concurrent changes in hospitals’ research outcomes are not correlated with their exposure to the reform. The doubling on the NIH budget from 1998 to 2003 may violate this assumption.

Congress increased the NIH budget from \$13.7 billion to \$27.2 billion over this five-year period (Congressional Research Service 2020). If the NIH budget doubling disproportionately decreased funding for the type of research conducted by more exposed hospitals, this could lead us to overstate the true impact of the BBA on research outcomes. In Appendix C, we explore whether the doubling of the NIH budget was “age-biased.” Empirically, we examine whether NIH budget increases disproportionately benefited research on health conditions affecting elderly populations.²⁴ Funding appears to have flown slightly more towards research on diseases that targeted the elderly, but the differences are small in magnitude and not statistically significant.

5 Conclusion

We investigate how Medicare financing cuts shape institutions that play a central role in the biomedical research ecosystem: Academic Medical Centers. Using a differences-in-difference approach, we find that research activities, measured using a variety of metrics, increase in response to a reform that decreases clinical care margins. Importantly, we document evidence that these effects do not cut evenly along the vertical chain of biomedical research. Laboratory-based “bench” research appears relatively unaffected. On the opposite end of the spectrum, clinical research activity (including industry-sponsored clinical trials) increases markedly in more exposed institutions, relative to less exposed ones. This is also the case for translational research, a type of “basic patient-oriented research” (Ahrens 1992) that is both hard to appropriate and difficult to perform outside of the AMC setting. Notably, we fail to find much evidence of countervailing impacts on the quality of care within these institutions.

For the past 30 years, McGuire and Pauly’s (1991) model of physician behavior has provided health economists with a conceptual framework to analyze the effect of price changes for medical care in the presence of multiple payers. Our results can be interpreted through that lens: they are consistent with the substitution effect dominating the income effect, leading researchers to increase their research activities even though the rewards for research—in the form of federal grants—have stayed relatively constant. However, this interpretation does not do justice to the subtleties of the academic medical setting. For example, in a competitive grant system (even one with rising paylines as in the immediate aftermath of the BBA passage), it is difficult for researchers to “induce demand” in a manner similar to a

²⁴Medicare-eligible individuals are almost exclusively above 65 years old. Age-bias in the NIH research portfolio could advantage high-BBA hospitals since their investigators have privileged access to patient populations relevant for the study of these conditions.

doctor treating Medicare patients or those covered by private insurance. Research activities are subject to lumpy adjustment costs and make the allocation of time less fractional than in the clinical care setting: a physician who stepped off the research funding treadmill might find herself unable to “prime the pump” of preliminary research results necessary to make her NIH grant proposals viable.

An additional friction in the substitution process, and one regularly emphasized by academic medical leaders, is that lower Medicare reimbursements hampered AMC’s ability to cross-subsidize research activities. And yet, the combination of soft money appointments and relatively generous indirect cost recovery rates creates a channel for teaching hospitals and AMCs to quickly adjust to the financing shock through the creation of new academic positions.

Our research design and data suffers from two principal limitations. First, we analyze the effect of the BBA at the level of the teaching and research hospital. This is sensible given the hospital-level nature of the financing shock, but leaves us unable to distinguish between impacts at the intensive-margin—e.g., within-individual substitution towards certain types of research activities—and impacts at the extensive margin—e.g., changes in AMC hiring practices or patterns of exit which favor clinical and translational researchers at the expense of scientists with a “basic orientation. This is especially problematic in our context because the period of the shock coincided with a vast increase in the budget of the National Institutes of Health. The magnitude, and even direction of the effects we estimate could well have been different had it occurred in a context of funding famine (as was admittedly the case after 2003, the tail end of our observation period).

Second, we can only speculate on how the BBA shock might differ from other types of financing shocks, such as a large philanthropic donation or endowment losses driven by the 2008 stock market collapse (Dranove, Garthwaite, and Ody 2017). Our sense is that “generic” shocks might well induce hospitals to increase or decrease research activities as a whole, but would not necessarily lead to the uneven effects we uncover. Because the BBA decreased slack financial resources on which a specific constituency—academic clinical departments—typically laid claim, the reform ended up shaping not simply the rate, but also the direction of research effort.

Our results inform the debate regarding the continued existence of Medicare price surcharges that favor teaching hospitals relative to other medical institutions (Nicholson 2002). Economists have typically been skeptical of the rationales offered in defense of these sub-

sidies (Newhouse and Wilensky 2001), but a second-best argument in their favor is that the financial slack they create for AMCs could enable them to better support their social mission, including (but not limited to) research. The fact that the bottom did not fall out of translational research in the wake of the BBA, contrary to the dire pronouncements of academic medical leaders (Kassirer 1994) should lead us to regard with more skepticism self-interested claims that these subsidies must continue lest the delicate fabric of the biomedical research funding ecosystem gets torn apart.

Our empirical evidence on the effects of Medicare financing cuts demonstrate the importance of providing a more comprehensive and systematic analysis of the trade-offs in an institutional environment where seemingly disparate activities are tightly linked. As governments endeavor to reduce inefficiencies within the health care system, cost-containment initiatives may have positive or negative implications for institutions that occupy a central role in the biomedical research ecosystem. Attending to the innovation impacts of well-intentioned reform efforts is essential to ensure that new policies will in fact improve patient and societal welfare.

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Figure 1: Data Sources and Variable Construction

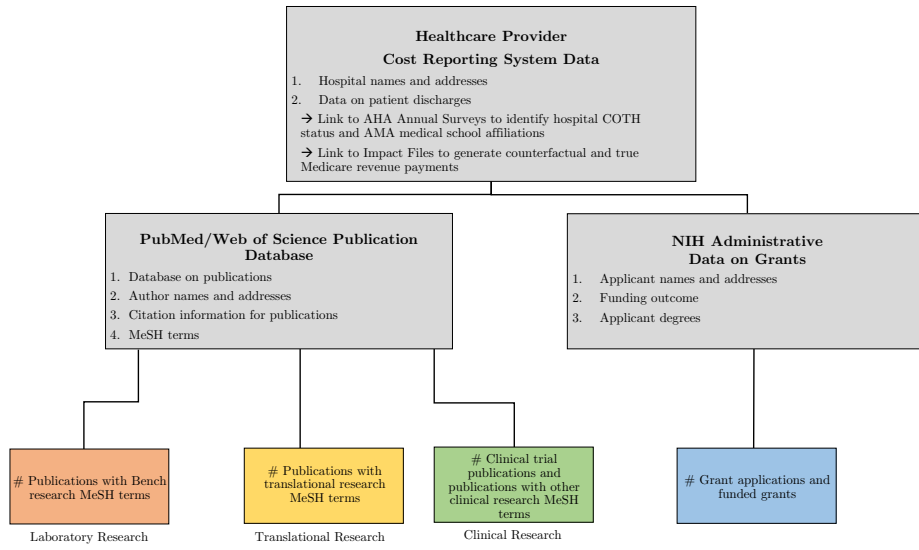
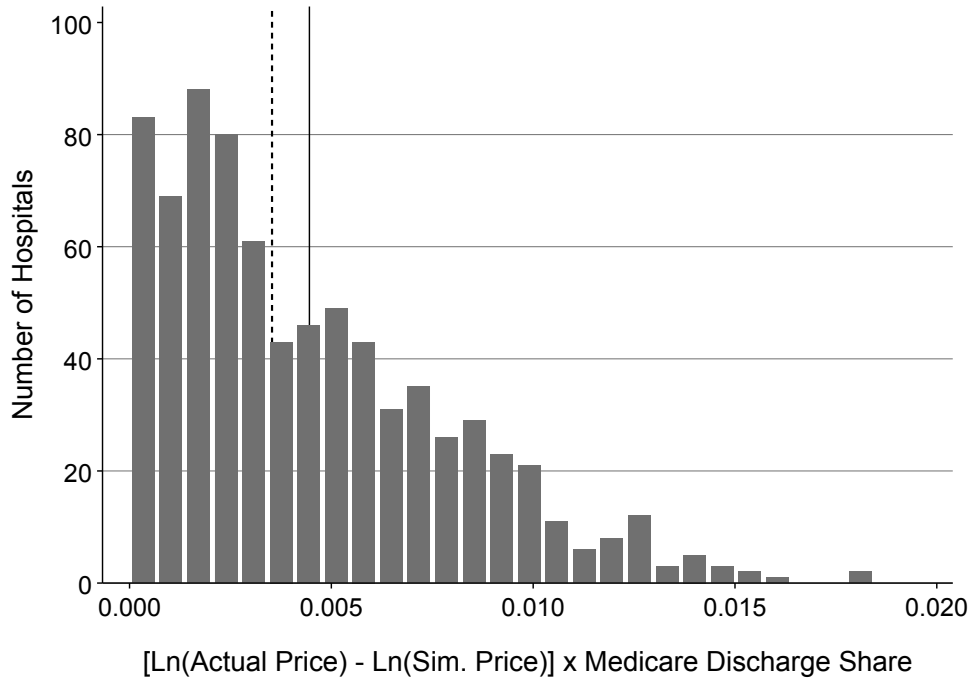
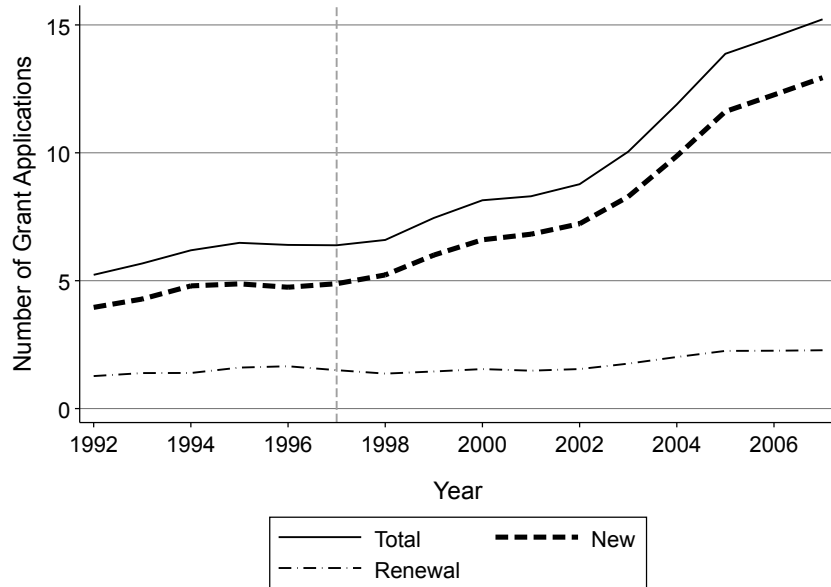


Figure 2: Distribution of BBA Bite



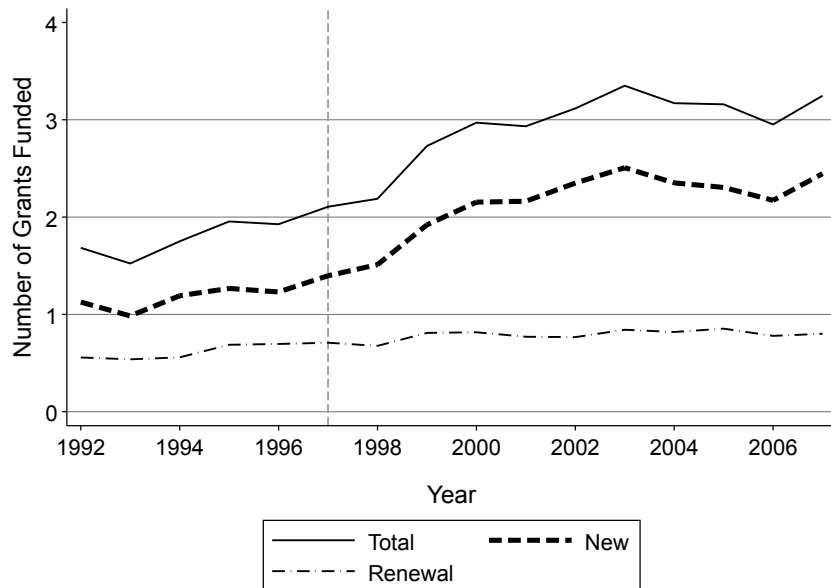
Notes: This figure shows a histogram of the BBA Bite for the teaching hospital sample, where BBA Bite is the product of (i) the difference between the (log) simulated price per discharge and actual (log) PPS price per discharge in 1995; and (ii) the Medicare share of discharges averaged over 1992-1995. The solid line indicates the mean (0.0045) of this variable and the dotted lines indicates the median (0.0035). Sources: Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files.

Figure 3: Change in NIH Grant Applications, 1992-2007



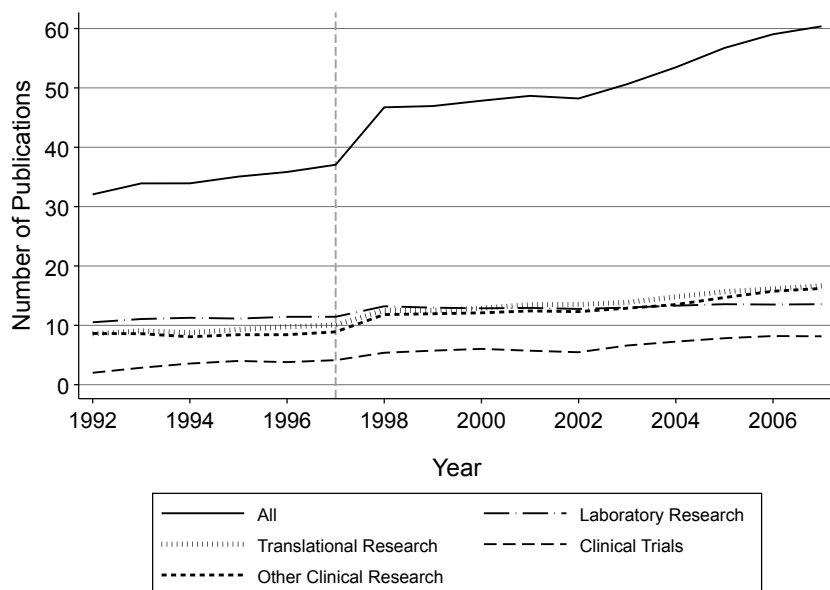
Notes: This figure plots the annual number of grant applications, averaged across all hospitals in the teaching hospital sample. The dashed line indicates the year in which the BBA came into effect. *Source:* NIH IMPAC II.

Figure 4: Change in NIH Grants Funded, 1992-2007



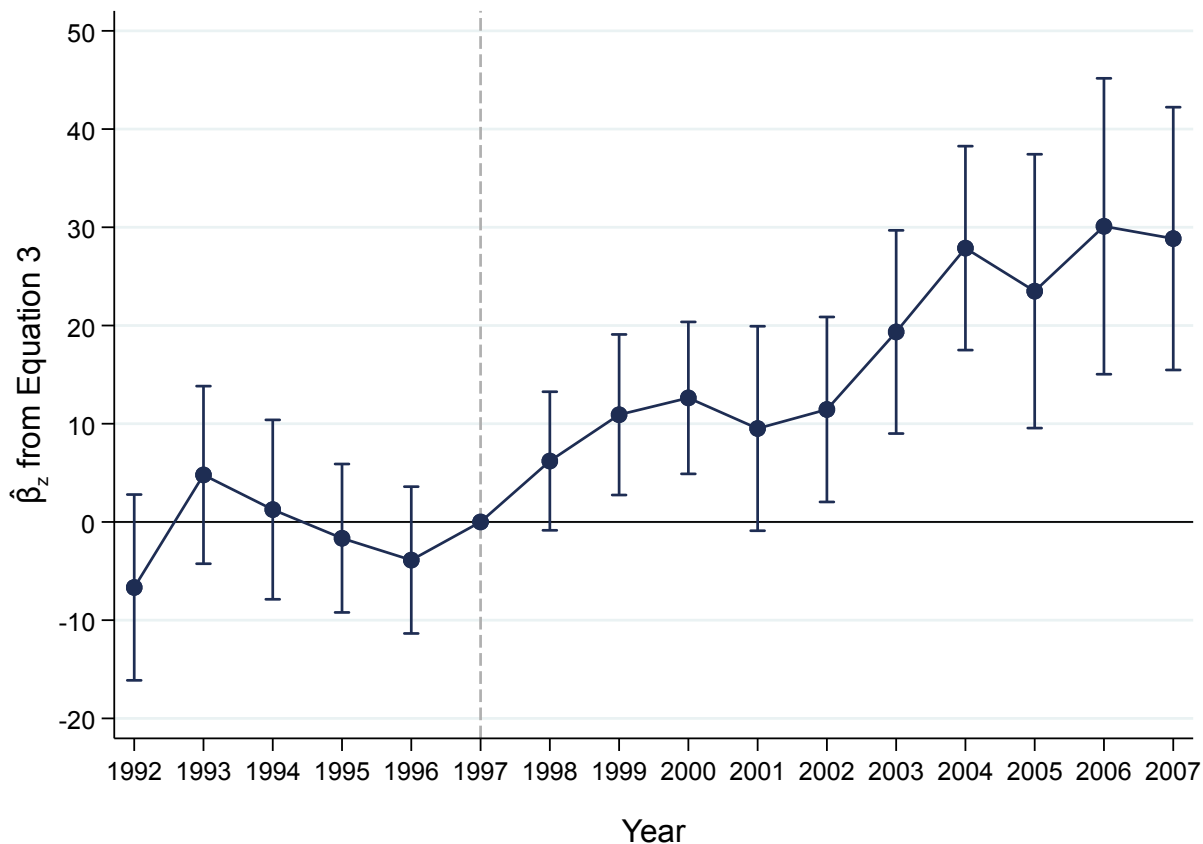
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Figure 5: Change in Publications, 1992-2007



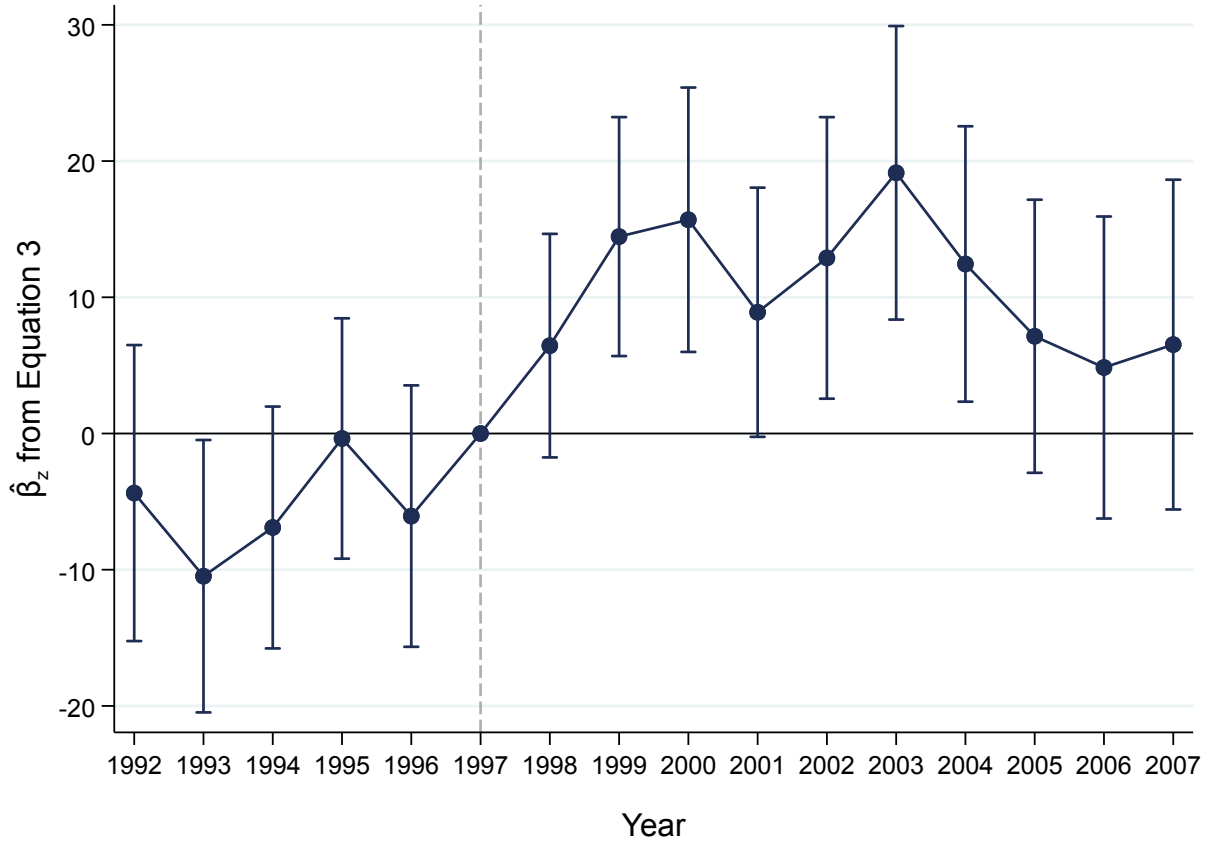
Notes: This figure plots the annual number of publications, averaged across all hospitals in the teaching hospital sample. The dashed vertical line indicates the year in which the BBA came into effect. “Laboratory Research” refers to publications that are not disease-oriented, are not clinical trial publications, and rely on either a molecular biology technique, a model organism, cellular structures and macromolecules, or biochemical and cellular processes (based on MeSH terms). “Translational Research” refers to publications that are disease-oriented, are not clinical trial publications, and rely on either a molecular biology technique, a model organism, cellular structures and macromolecules, or biochemical and cellular processes (based on MeSH terms). “Clinical Trials” refers to publications are indicated as clinical trials based on MeSH terms or the publication type field in *PubMed*. “Other Clinical Research” refers to publications that are disease-oriented, not clinical trials, and not tagged by any bench MeSH keywords. The discrete shift in total publications in 1998 is likely explained by our strategy for constructing the publication dataset, as discussed in Section 3. *Sources:* Azoulay, Greenblatt, and Heggeness (2020); PubMed; Web of Science.

Figure 6: Effect on the Number of Grant Applications



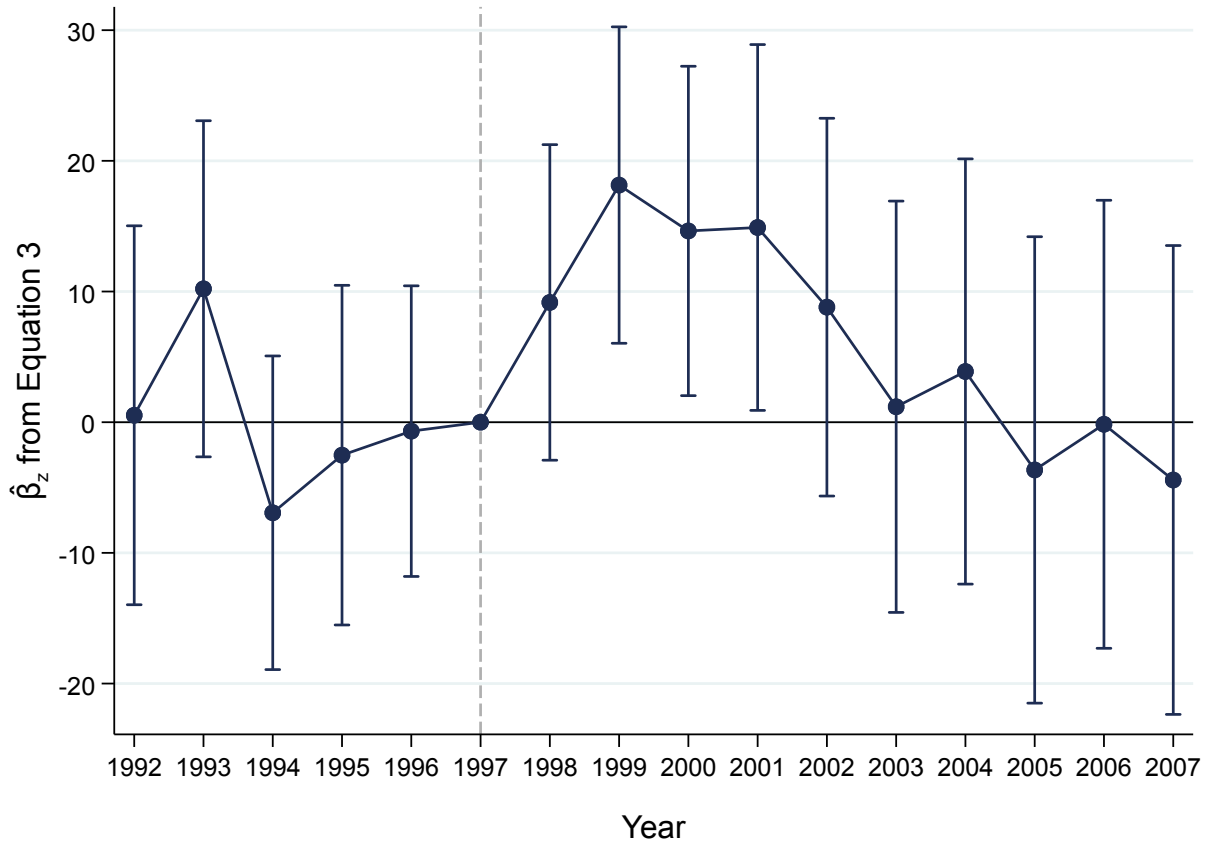
Notes: This figure plots the response in grants funded in the teaching hospital sample. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of grant applications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table 2, Panel A, Column 1 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.

Figure 7: Effect on the Number of Grants Funded



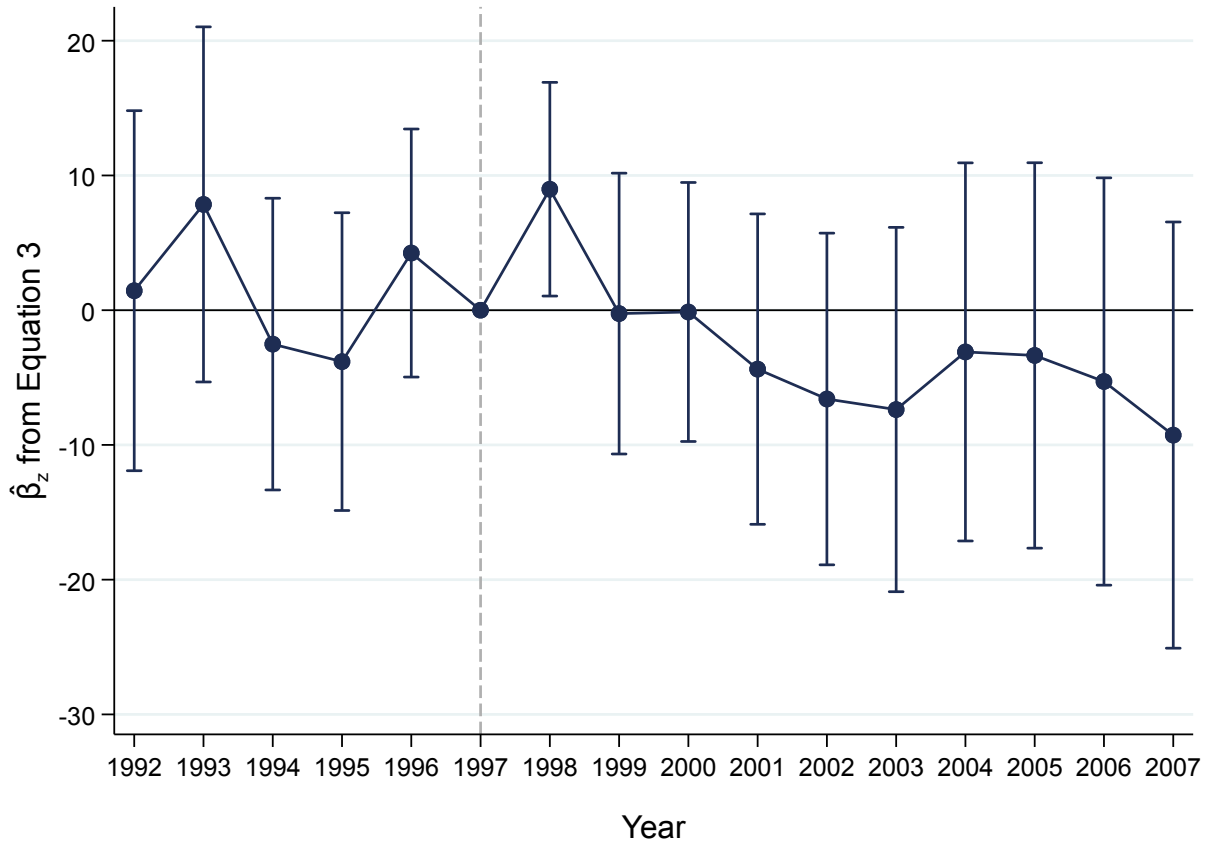
Notes: This figure plots the response in grants funded in the teaching hospital sample. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of grants funded})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table 3, Panel A, Column 1 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.

Figure 8: Effect on the Number of Publications



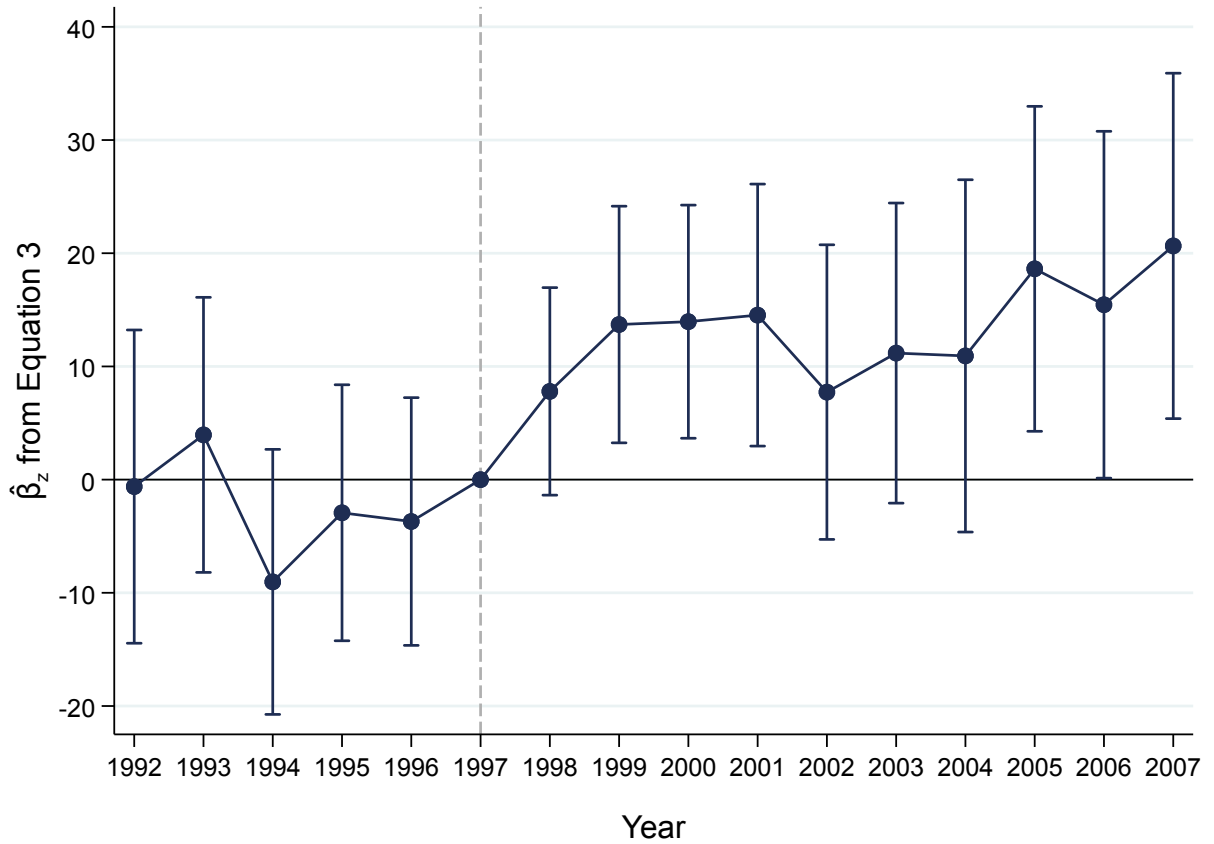
Notes: This figure plots the response in publications in the teaching hospital sample. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of publications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table 4, Panel A, Column 1 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; PubMed, Web of Science.

Figure 9: Effect on Bench Research Publications



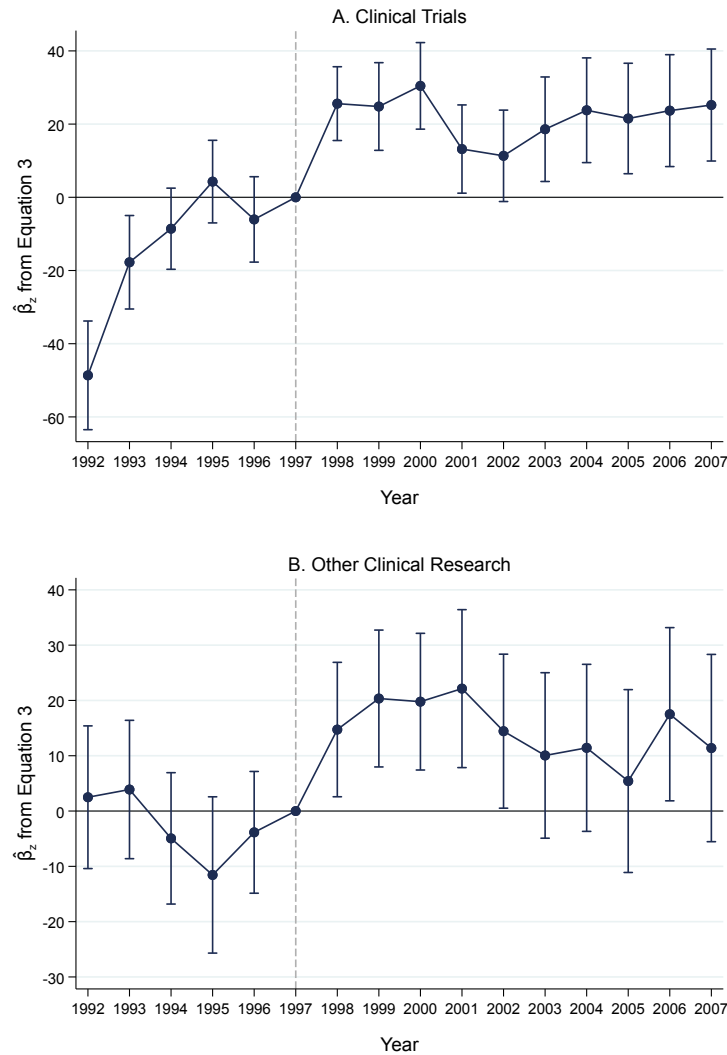
Notes: This figure plots the response in bench research publications in the teaching hospital sample. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of publications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table 5, Panel A, Column 1 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Azoulay, Greenblatt, and Heggeness (2020); PubMed; Web of Science.

Figure 10: Effect on Translational Research Publications



Notes: This figure plots the response in translational research publications in the teaching hospital sample. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of publications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table 5, Panel A, Column 2 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Azoulay, Greenblatt, and Heggeness (2020); PubMed; Web of Science.

Figure 11: Effect on Clinical Research Publications



Notes: This figure plots the response in clinical research publications in the teaching hospital sample. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of publications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table 5, Panel A, Columns 5 and 6 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Azoulay, Greenblatt, and Heggeness (2020); PubMed; Web of Science.

Table 1: Summary Statistics

	Count	Mean	Median	SD	Min	Max
Panel A. Hospital Characteristics						
Discharges (1,000s)	780	16.82	14.91	10.39	0.34	62.79
Inpatient Days (1,000s)	780	89.84	76.03	60.25	0.96	439.06
Medicare Teaching Payment (\$1,000,000s)	780	5.45	2.26	7.91	0.00	59.81
Medicare Disproportionate Share Payment (\$1,000,000s)	780	3.97	2.38	4.54	0.00	36.21
Total Revenue (\$1,000,000s)	765	486.94	374.24	410.95	14.43	3,182.46
Beds	780	360.54	319.41	202.23	29.12	1,397.62
Residents and Interns	767	101.92	41.82	139.35	0.06	1,097.72
BBA Bite (x100)	780	0.45	0.35	0.35	0.00	1.84
Medicare Share of Discharges in 1995	780	0.34	0.34	0.13	0.02	0.71
Medicare Share of Inpatient Days in 1995	780	0.43	0.46	0.15	0.03	0.79
Medicare Price Per Discharge in 1995 (\$1,000s)	780	8.30	7.48	2.85	3.67	27.48
Panel B. Grants						
<i>Number of Grant Applications</i>						
Total	780	8.82	0.00	32.97	0.00	444.00
New	780	7.15	0.00	26.43	0.00	355.75
Competitive Renewal	780	1.67	0.00	6.60	0.00	88.25
MD Principal Investigators	780	3.08	0.00	11.87	0.00	158.62
PhD Principal Investigators	780	4.26	0.00	16.22	0.00	193.38
MD-PhD Principal Investigators	780	1.36	0.00	5.81	0.00	87.75
<i>Number of Grants Funded</i>						
Total	780	2.55	0.00	10.42	0.00	147.75
New	780	1.82	0.00	7.40	0.00	106.38
Competitive Renewal	780	0.73	0.00	3.05	0.00	41.38
MD Principal Investigators	780	0.96	0.00	4.05	0.00	55.00
PhD Principal Investigators	780	1.16	0.00	4.77	0.00	61.00
MD-PhD Principal Investigators	780	0.40	0.00	1.92	0.00	30.88
Panel C. Publications						
Total	780	45.40	2.06	148.55	0.00	1,683.62
Citation Ranking: ≤ 25	780	11.19	0.81	31.02	0.00	306.12
Citation Ranking: 26-50	780	10.41	0.44	32.00	0.00	333.38
Citation Ranking: 51-75	780	11.03	0.38	37.19	0.00	413.19
Citation Ranking: 76-95	780	9.84	0.25	37.25	0.00	456.62
Citation Ranking: 96-99	780	2.27	0.06	9.98	0.00	130.56
Citation Ranking: > 99	780	0.67	0.00	3.18	0.00	45.12
Cited In a Patent	780	11.34	0.25	43.40	0.00	547.31
Not Cited In a Patent	780	34.07	1.75	106.05	0.00	1,136.31
Disruptive	780	1.69	0.12	4.86	0.00	51.00
Consolidating	780	40.72	1.75	135.60	0.00	1,551.44
Laboratory Research: Pub. with Bench MeSH	780	12.41	0.06	47.18	0.00	487.50
Translational Research: Pub. with Translational MeSH	780	12.34	0.25	42.86	0.00	516.00
Builds on Translational MeSH	780	3.83	0.25	11.94	0.00	122.25
Inspires Translational MeSH	780	6.40	0.12	23.48	0.00	297.81
Clinical Research: Clinical Trial Pub.	780	5.43	0.38	16.94	0.00	179.69
Clinical Research: Pub. with Other Clinical MeSH	780	11.54	0.94	34.80	0.00	402.31
Panel D. Clinical Outcomes (Risk-Adjusted Survival Rates [30 Days])						
Heart Attack	700	0.90	0.91	0.03	0.73	1.00
Heart failure	700	0.96	0.96	0.02	0.89	1.01
Pneumonia	700	0.98	0.98	0.02	0.89	1.04
Hip/knee	700	0.95	0.95	0.02	0.86	1.04

Notes: This table shows hospital characteristics for the hospitals in the teaching hospital sample between 1992-2007. All variables are measured yearly. For example, “Discharges (1000s)” is the average number of patients a hospital receives in a year. “Medicare Teaching Payment,” “Medicare Disproportionate Share Payment,” and “Total Revenue” are adjusted for inflation using the CPI and are measured in 1997 dollars. All hospital characteristics, grant, and publication variables have 780 observations, except for “Total Revenue” and “Residents and Interns,” because of missing data from the Healthcare Provider Cost Reporting Information System. Similarly, clinical outcomes data is only available for the subset of hospitals in the teaching hospital sample that matched to the clinical outcomes data. Clinical outcomes are measured in three-year bins—e.g., hospital-level survival rates in 2005 are estimated over patient claims in 2003, 2004, and 2005. For each hospital, we use three-year bins for four years (1996, 2002, 2005, and 2008). Each publication’s disruptiveness is measured by using the Funk and Owen-Smith (2017) disruptiveness index, denoted by d . “Disruptive” publications refer to publications with $d \leq 95^{th}$ percentile and “Consolidating” publications refers to publications with $d > 95^{th}$ percentile. See Section 3 for detailed data descriptions. *Sources:* Azoulay, Greenblatt, and Heggeness (2020); Chandra et al. (2016); Funk and Owen-Smith (2017); Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPACT II; Marx and Fuegi (forthcoming); PubMed; Web of Science.

Table 2: Effect on the Number of Grant Applications

	Grant Cycle			Principal Investigator		
	Total (1)	New (2)	Renewal (3)	MD (4)	PhD (5)	MD-PhD (6)
A. BBA Bite \times Post	19.07*** (4.284)	24.53*** (4.421)	3.314 (2.754)	16.40*** (4.298)	22.75*** (4.032)	28.53*** (4.070)
Elasticity	0.053	0.069	0.011	0.048	0.065	0.099
Adjusted R^2	0.023	0.034	0.005	0.021	0.039	0.056
Diff. Wald test p-value		0.000			0.151	0.010
B. High BBA Bite \times Post	0.105*** (0.0247)	0.136*** (0.0249)	0.00913 (0.0152)	0.0944*** (0.0216)	0.122*** (0.0213)	0.145*** (0.0219)
Elasticity	0.110	0.146	0.009	0.099	0.129	0.155
Adjusted R^2	0.019	0.028	0.005	0.018	0.032	0.043
Diff. Wald test p-value		0.000			0.211	0.038
Mean of Outcome	0.751	0.705	0.372	0.519	0.533	0.328
Nb. Observations	12,480	12,480	12,480	12,480	12,480	12,480
Nb. Hospitals	780	780	780	780	780	780

Notes: This table reports difference-in-differences estimates of the effect of the BBA on the number of grant applications, in the teaching hospital sample. Observations are at the hospital-year level. Outcomes are transformed with the inverse hyperbolic sine function. Column 1 presents results from OLS regressions. Columns 2-6 present estimates from seemingly unrelated regressions. Each coefficient is from a separate regression. The elasticity of 0.053 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 5.3 percent yearly increase in grant applications following the BBA's enactment. Similarly, a Panel B elasticity of 0.110 implies that High BBA Share hospitals experience on average a 11 percent yearly increase in grant applications in the post-BBA time period. The fourth row and eighth row show p -values from Wald tests that compare coefficients on BBA Bite \times After (Panel A) or High BBA Bite \times After (Panel B) across different columns (Column 2 vs. Column 3; Column 4 vs. Column 5; Column 4 vs. Column 6). Robust standard errors (clustered at the hospital level) are in parentheses. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.

* $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

Table 3: Effect on the Number of Grants Funded

	Grant Cycle			Principal Investigator		
	Total (1)	New (2)	Renewal (3)	MD (4)	PhD (5)	MD-PhD (6)
A. BBA Bite \times Post	15.54*** (3.325)	20.93*** (3.447)	7.571** (2.571)	13.34*** (3.239)	18.15*** (3.216)	21.95*** (3.022)
Elasticity	0.047	0.067	0.036	0.054	0.067	0.166
Adjusted R^2	0.018	0.030	0.005	0.015	0.027	0.041
Diff. Wald test p-value		0.000			0.138	0.013
B. High BBA Bite \times Post	0.0759*** (0.0181)	0.105*** (0.0190)	0.0341** (0.0120)	0.0685*** (0.0152)	0.0919*** (0.0169)	0.103*** (0.0155)
Elasticity	0.079	0.111	0.035	0.071	0.096	0.108
Adjusted R^2	0.013	0.022	0.003	0.011	0.020	0.026
Diff. Wald test p-value		0.000			0.138	0.025
Mean of Outcome	0.439	0.382	0.246	0.285	0.300	0.159
Nb. Observations	12,480	12,480	12,480	12,480	12,480	12,480
Nb. Hospitals	780	780	780	780	780	780

Notes: This table reports difference-in-differences estimates of the effect of the BBA on the number of grants funded, in the teaching hospital sample. Observations are at the hospital-year level. Outcomes are transformed with the inverse hyperbolic sine function. Column 1 presents results from OLS regressions. Columns 2-6 present estimates from seemingly unrelated regressions. Each coefficient is from a separate regression. The elasticity of 0.047 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 4.7 percent yearly increase in grant applications following the BBA's enactment. Similarly, a Panel B elasticity of 0.079 implies that High BBA Share hospitals experience on average a 7.9 percent yearly increase in grant applications in the post-BBA time period. The fourth row and eighth row show p -values from Wald tests that compare coefficients on BBA Bite \times After (Panel A) or High BBA Bite \times After (Panel B) across different columns (Column 2 vs. Column 3; Column 4 vs. Column 5; Column 4 vs. Column 6). Standard errors are in parentheses, and are clustered at the hospital level. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.

* $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

Table 4: Effect on Publication Impact

	By Citation Percentile							Cited in a Patent			By Disruption	
	Total	≤25	26-50	51-75	76-95	96-99	>99	Yes	No	Consolidating Research	Disruptive Research	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	
A. BBA Bite × Post	6.148 (5.376)	12.884** (4.488)	12.721** (4.334)	14.155*** (4.261)	16.925*** (4.590)	20.612*** (4.012)	19.501*** (3.197)	8.646* (4.433)	9.295* (5.239)	9.478* (5.315)	14.332*** (3.768)	
Elasticity	0.017	0.036	0.036	0.040	0.047	0.063	0.098	0.024	0.026	0.026	0.046	
Adjusted R^2	0.029	0.029	0.022	0.019	0.028	0.034	0.032	0.013	0.034	0.027	0.012	
Diff. Wald test p-value	-	0.019	0.021	0.018	0.002	0.002	0.009	0.874			0.270	
B. High BBA Bite × Post	0.075* (0.039)	0.110*** (0.031)	0.093** (0.029)	0.103*** (0.028)	0.109*** (0.029)	0.123*** (0.020)	0.108*** (0.016)	0.074** (0.029)	0.091** (0.038)	0.084** (0.040)	0.099*** (0.026)	
Elasticity	0.078	0.117	0.097	0.108	0.115	0.130	0.114	0.077	0.095	0.087	0.104	
Adjusted R^2	0.030	0.030	0.022	0.019	0.027	0.031	0.027	0.013	0.035	0.028	0.012	
Diff. Wald test p-value	-	0.112	0.457	0.281	0.240	0.189	0.389	0.596			0.647	
Mean of Outcome	1.991	1.347	1.153	1.089	0.962	0.469	0.232	0.976	1.876	1.822	0.800	
Nb. Observations	12,480	12,480	12,480	12,480	12,480	12,480	12,480	12,480	12,480	12,480	12,480	
Nb. Hospitals	780	780	780	780	780	780	780	780	780	780	780	

Notes: This table reports difference-in-differences estimates of the effect of the BBA on the number of publications, by impact, in the teaching hospital sample. Observations are at the hospital-year level. Outcomes are transformed with the inverse hyperbolic sine function. Estimates are from seemingly unrelated regressions and each coefficient is from a separate regression. Each publication's disruptiveness is measured by using the Funk and Owen-Smith (2017) disruptiveness index, denoted by d . Column 8 refers to publications with $d \leq 95^{\text{th}}$ percentile and Column 9 refers to publications with $d > 95^{\text{th}}$ percentile. The elasticity of 0.017 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 1.7 percent yearly increase in publications following the BBA's enactment. Similarly, the elasticity of 0.078 in Panel B implies that High BBA Bite hospitals experience on average a 7.8 percent yearly increase in publications in the post-BBA time period. The fourth row and eighth row show p -values from Wald tests that compare coefficients on BBA Bite × After (Panel A) or High BBA Bite × After (Panel B) across different columns. For Columns 2 to 7, the fourth and eight row compare estimates in Column 1 vs. estimates in the focal column. For Columns 8 and 9, the fourth and eight row show p -values from Wald tests that compare Column 8 and 9 estimates. For Columns 10 and 11, the fourth and eight row show p -values from Wald tests that compare Column 10 and Column 11. Standard errors are in parentheses, and are clustered at the hospital level. Sources: Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Funk and Owen-Smith (2017); PubMed, Web of Science.

* $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

Table 5: Effect on Publication Composition

	Laboratory Research	Translational Research			Clinical Research	
	Bench MeSH	Translational MeSH	Builds on Translational MeSH	Inspiring Translational MeSH	Clinical Trials	Other
	(1)	(2)	(3)	(4)	(5)	(6)
A. BBA Bite \times Post	-4.277 (4.840)	15.509*** (4.430)	33.239*** (4.285)	20.858*** (4.203)	34.604*** (4.481)	17.051*** (4.690)
Elasticity	-0.012	0.043	0.096	0.059	0.098	0.048
Adjusted R^2	0.001	0.015	0.069	0.025	0.089	0.023
B. High BBA Bite \times Post	-0.038 (0.029)	0.093** (0.030)	0.201*** (0.028)	0.124*** (0.027)	0.236*** (0.030)	0.137*** (0.032)
Elasticity	-0.038	0.097	0.222	0.131	0.266	0.146
Adjusted R^2	0.001	0.014	0.065	0.023	0.089	0.024
Mean of Outcome	0.826	1.062	0.798	0.804	0.950	1.398
Nb. Observations	12,480	12,480	12,480	12,480	12,480	12,480
Nb. Hospitals	780	780	780	780	780	780

Notes: This table reports difference-in-differences estimates of the effect of the BBA on bench, translational, and clinical trial research in hospitals, in the teaching hospital sample. Observations are at the hospital-year level. Outcomes are transformed with the inverse hyperbolic sine function. Estimates are from OLS regressions, and each coefficient is from a separate regression. Column 1 refers to publications that are not disease-oriented, are not clinical trial publications, and rely on either a molecular biology technique, a model organism, cellular structures and macromolecules, or biochemical and cellular processes (based on MeSH terms). Column 2 refers to publications that are disease-oriented, are not clinical trial publications, and rely on either a molecular biology technique, a model organism, cellular structures and macromolecules, or biochemical and cellular processes (based on MeSH terms). Column 3 refers to publications that report the results of a clinical trials, or are tagged by a human MeSH term and also cite a translational publication. Column 4 refers to publications that are translational and is cited by a clinical trial publication (or one that contains a human MeSH term). Column 5 refers to publications that are indicated as clinical trials based on MeSH terms or the publication type field in *PubMed*. Finally, Column 6 refers to publications that are disease-oriented, not clinical trials, and not tagged by any bench MeSH keywords. The elasticity of -0.012 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 1.2 percent yearly decrease in publications following the BBA's enactment. Similarly, the elasticity of -0.038 in Panel B implies that High BBA Bite hospitals experience on average a 3.8 percent yearly decrease in publications in the post-BBA time period. Standard errors are in parentheses, and are clustered at the hospital level. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Azoulay, Greenblatt, and Heggeness (2020); Marx and Fuegi (forthcoming); PubMed; Web of Science. * $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

Table 6: Effect on Clinical Outcomes (Changes in Risk-adjusted Survival Rates)

	Heart Attack	Heart Failure	Hip/Knee	Pneumonia
	(1)	(2)	(3)	(4)
A. BBA Bite	-0.4286 (0.4227)	-0.4028 (0.2537)	0.4099 (0.2783)	-0.0743 (0.3146)
Ln(Discharges in 1995)	0.0016 (0.0025)	0.0018 (0.0015)	-0.0003 (0.0014)	0.0046** (0.0019)
Adjusted R^2	-0.0012	0.0016	0.0004	0.0076
B. High BBA Bite	-0.0044 (0.0033)	-0.0018 (0.0020)	0.0029 (0.0020)	0.0004 (0.0023)
Ln(Discharges in 1995)	0.0018 (0.0025)	0.0016 (0.0015)	-0.0004 (0.0014)	0.0045** (0.0019)
Adjusted R^2	0.0003	-0.0004	0.0004	0.0076
Mean of Outcome	0.0270	0.0106	-0.0005	0.0147
Nb. Observations	700	700	700	700

Notes: This table displays the effect on changes in risk-adjusted survival rates among hospitals in the teaching hospital sample. The hospital sample used is the subset of the teaching hospital sample that is matched to the clinical outcomes dataset from Chandra et al. (2016). Observations are at the hospital-level. Outcomes are the difference in average survival rates between the post-BBA time period and the pre-BBA time period. Estimates are from OLS regressions and each coefficient is from a separate regression. Standard errors are in parentheses and robust. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Chandra et al. (2016).

* $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

Appendix A:

Medicare Inpatient Reimbursement

Overview of Medicare Payments. This section provides an overview of how Medicare reimburses hospitals for care provided to beneficiaries, which will be useful to understand the impact of the reform analyzed in this paper.

Since 1984, payments have been under the Prospective Payment System (PPS). Under the PPS, hospitals receive a fixed payment for a given medical diagnosis (called a “Diagnosis Related Group (DRG)”), regardless of hospital expenditures. Each DRG payment consists of three components: (i) a DRG weight, (ii) a base payment, and (iii) adjustments. Put differently, the PPS payment received by hospital h for an admission in DRG d in year t is given by:

$$PPS_{h,d,t} = f(DRG_{d,t}, p_{h,t}, adjustments_{h,t}) \quad (1)$$

where $DRG_{d,t}$ is a weight and reflects hospitals’ aggregate historical costs of treating patients in DRG d . The average DRG weight in a hospital, or the Medicare case-mix, reflects the severity of treatment for the average patient. The base payment ($p_{h,t}$) is a factor that converts the DRG weight to dollars. The base payment is updated annually and is set nationally, but is adjusted based on local market conditions, such as prices for labor. Finally, three types of adjustments are provided: indirect medical education (IME) subsidies are payments received by hospitals for training physicians, disproportionate share hospital (DSH) payments are additional payments for treating poor patients, and outlier payments are made to compensate providers for patients with exceptionally costly stays (Keeler, Carter, and Trude 1988).

The BBA changed the formula for these three adjustments. In this paper, our payment calculations are centered around changes to the IME and DSH payments, as data limitations do not allow us to calculate simulated outlier payments. We now describe IME and DSH payments in further detail.

Indirect Medical Education Subsidies. Teaching hospitals receive two supplemental payments from Medicare: direct medical education (DME) and indirect medical education (IME) payments. DME payments reimburse a teaching hospital for Medicare’s share of the direct costs of training residents, such as salaries paid to interns, residents, and teaching physicians. The IME adjustment is a percentage add-on payment to the hospital’s basic DRG payment (Fishman 1993). IME payments are meant to compensate teaching hospitals for indirect expenses stemming for example from use of diagnostic services by clinically inexperienced residents or decreased productivity of nurses and support staff involved in teaching of residents. Since 1989, the DRG payment a hospital receives for admitting a Medicare patient increases non-linearly with the hospital’s resident-to-bed ratio and a multiplier.

$$ime_{h,t} = \alpha_t \times \left[\left(1 + \frac{residents_{h,t}}{beds_{h,t}} \right)^{.405} - 1 \right] \quad (2)$$

where α is a multiplier set at 1.89 in the pre-reform period. This correspond to a price increase of approximately 7.65% for every 10% increase in a hospital's resident-to-bed ratio.

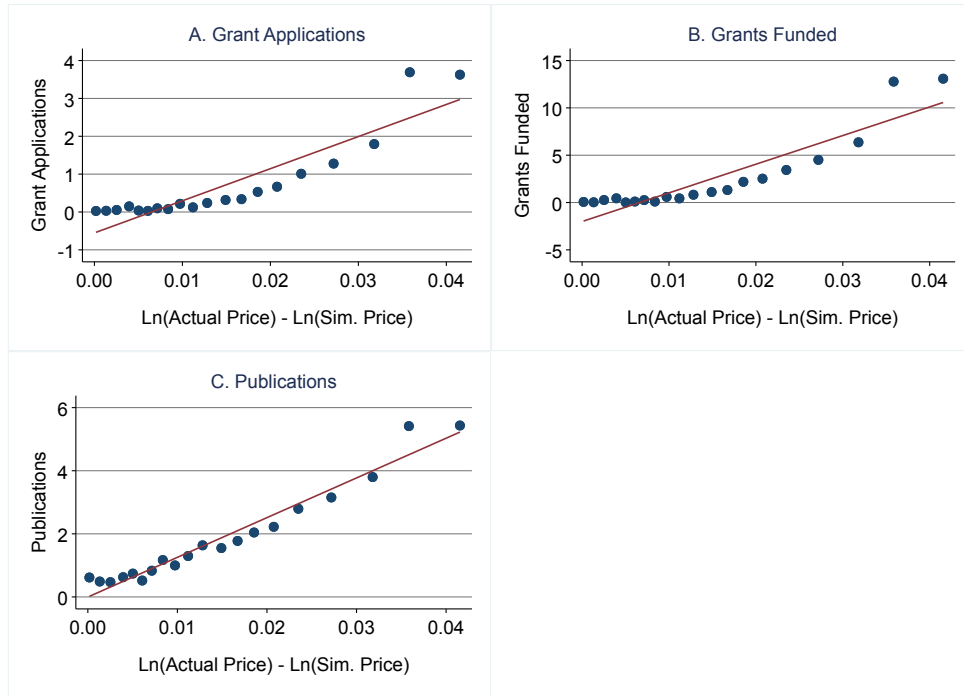
Disproportionate Share Hospital Subsidies The Medicare DSH adjustment was enacted by the Consolidated Omnibus Budget Reconciliation Act of 1985 and became effective in 1986. Like the IME adjustment, the DSH adjustment is a percentage add-on to the hospital's basic DRG payment. The key determinant of whether a hospital is eligible for this subsidy is the fraction of total patient-days allocated to poor patients. Above a certain threshold, hospitals become eligible for a DSH payment adjustment, which varies according to whether the hospital is urban or rural, is a sole community hospital, and the number of beds.ⁱ

The Balanced Budget Act. The BBA reduced both IME payments: beginning in FY1998, there were planned reductions in the IME multiplier (α in Appendix equation (2)). Similarly, the BBA reduced DSH payments through imposing an overall percentage reduction in DSH payments from FY1998 to FY2002 (e.g., the BBA reduced DSH payments by 1% in FY1998, 2% in FY1999, etc.). Subsequent reforms (BBRA and BIPA) somewhat dampened the negative effect of the BBA on IME and DSH payments. For a detailed explanation of how the BBA changed DRG payment adjustments, see Wu (2010).

Relationship Between Pre-BBA Research and the Simulated Price Change The bin scatter plot in Appendix Figure A1 describes how a hospital's average pre-BBA research levels relate to the simulated price change described in Section 3.2. Each hospital's annual grant applications (Panel A), grants funded (Panel B), and publications (Panel C) are averaged over 1992-1995 and plotted against the simulated price change.

ⁱFor more details, see <https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/dsh.html>.

Figure A1: Pre-BBA Research and Simulated Price Change

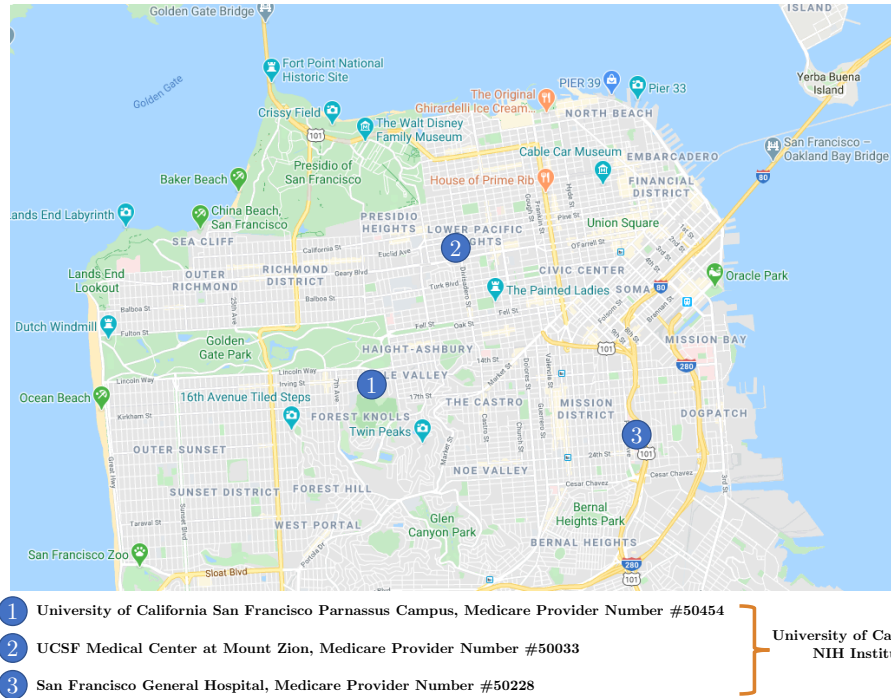


Notes: This figure plots the relationship between pre-BBA research levels (averaged over 1992-1995) and the simulated PPS price change. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II; PubMed; Web of Science.

Appendix B: Mapping Outcomes to Hospitals

Figure B1 provides an example of how NIH grant IDs and Medicare provider IDs are allocated to hospitals and medical centers. The University of California, San Francisco medical center includes the Parnassus Heights Campus, Mt. Zion Hospital and Medical Center, and San Francisco General Hospital. Each of these locations has a unique Medicare provider number and therefore receive an independent Medicare payment. However, the three campuses share a single, common NIH institutional code. Our strategy consists of looking at each of the PI addresses affiliated with the UCSF NIH institutional code and allocating each PI (and grant) to one of the three hospitals.

Figure B1: Mapping Research Activity to Hospitals



Notes: This figure shows how NIH grant IDs and Medicare provider IDs are allocated within University of California, San Francisco. *Sources:* Google Maps; Healthcare Provider Cost Reporting Information System; NIH IMPAC II.

Appendix C: Assessing the Age-Bias of NIH Budget Doubling

This Appendix explores whether the NIH budget doubling may have led to a downward bias in our estimates on research outcomes. In this empirical exercise, we use the number and composition of NIH grants funded as a proxy for NIH funding supply. Appendix Figure C1 shows trends in total NIH grants awarded to hospitals and non-hospitals by year for each year from 1980 to 2007. In Panel A, we plot the total number of grants funded by year. In Panel B, we plot the total amount of grant dollars awarded from hospitals by year. Looking at the data series in Panel A provides clear evidence of an increase in the number of grants funded from 1998 to 2003. These patterns – though less distinct – also appear in Panel B. Further, if we calculate the average amount of grant dollars awarded, approximately \$3.8 billion is awarded each year before 1998 and \$4.9 billion is allocated each year on/after 1998.

Our next goal is to characterize NIH-related funding for research primarily conducted in conditions disproportionately affecting children (i.e., “Medicare-Averse” research), research in diseases primarily common among the elderly (i.e., “Medicare-Friendly” research), and research that primarily that typically afflicts individuals of all ages (i.e., “Medicare-Neutral” research). To categorize each NIH grant, we first identify a set of Medicare-Averse, Medicare-Friendly, and Medicare-Neutral diseases as measured by ICD9 codes. For each ICD9 code, we calculate the share of individuals diagnosed with the focal condition and covered by Medicare using the 1996 and 1997 Medical Expenditure Panel Survey (MEPS), a nationally representative survey of the U.S. civilian non-institutionalized population. We assign each ICD9 code to one of four mutually exclusive bins, based on their “ICD9 Medicare Share”: ICD9 codes that fall in the bottom tenth percentile of the ICD9 Medicare Share distribution; ICD9 codes that fall between the fifty-fifth and sixty-fifth percentile; ICD9 codes that fall above the ninetieth percentile; and ICD9 codes that fall in none of the previous bins. Focusing on the first three ICD9 code bins, we keep the top 15 ICD9 codes (based on the total number of individuals diagnosed with the focal ICD9 code in 1996 and 1997) in each ICD9 code bin. This results in a total of 45 unique ICD9 codes (15 in each ICD9 code bin).

For each ICD9 code, we collect related MeSH terms using the National Library of Medicine’s Medical Text Indexer (MTI), a natural language processing tool which enables researchers to map text onto the MeSH controlled thesaurus.ⁱ This results in 93 unique MeSH terms. Next, these unique MeSH terms are categorized into three mutually-exclusive MeSH categories measuring different forms of age-bias: MeSH terms that are “Medicare-Averse”; MeSH terms that are “Medicare-Neutral”; and MeSH terms that are “Medicare-Friendly.” As expected, MeSH terms in the Medicare-Averse category correspond to diseases that primarily afflict children, such as: *Chickenpox* and *Measles*. In contrast, MeSH terms in the Medicare-Friendly category include *Glaucoma* and *Parkinson’s Disease*. Medicare-Neutral MeSH terms include diseases that are less biased towards children or the elderly, such as *Psoriasis* and *Cystitis*.

Using the Medicare-Averse, Medicare-Neutral, and Medicare-Friendly MeSH categories, we categorize each grant.ⁱⁱ To do so, we use information from the title and full-text abstract for each grant. Specifically, we

ⁱSee: <https://ii.nlm.nih.gov/MTI/>.

ⁱⁱDownloaded from the NIH Reporter web site at https://exporter.nih.gov/crisp_catalog.aspx.

map words in the title and abstract to terms from the MeSH thesaurus by using the MTI. Next, we categorize a grant as being Medicare-Averse if it is tagged with at least one Medicare-Averse MeSH term. A grant is considered Medicare-Neutral if it is not Medicare-Averse and is tagged with at least one Medicare-Neutral MeSH term. Finally, we tag each grant that is not Medicare-Averse, not Medicare-Neutral, and contains at least one Medicare-Friendly MeSH term. Any duplicates (i.e., grants that are allocated to a MeSH category more than once) are dropped. This results in 2,954 distinct grants that are Medicare-Averse, 6,012 distinct grants that are Medicare-Neutral, and 14,677 grants that are Medicare-Friendly.

Appendix Figure C2 documents the total amount of grant dollars awarded to hospitals by year in each year from 1992 to 2007 for the three MeSH categories. Looking to trends in the total number of grants funded (Panel A), we see clear evidence that the NIH awards a relatively large number of grants for Medicare-Friendly research as compared to Medicare-Averse or Medicare-Neutral research. The three groups follow each other quite closely in trends from 1992 to 1997. Between 1998 to 2004, the trends diverge with there being an disproportionate increase in Medicare-Friendly grants. Similar patterns occur among the total amount of grant dollars funds awarded (Panel B).

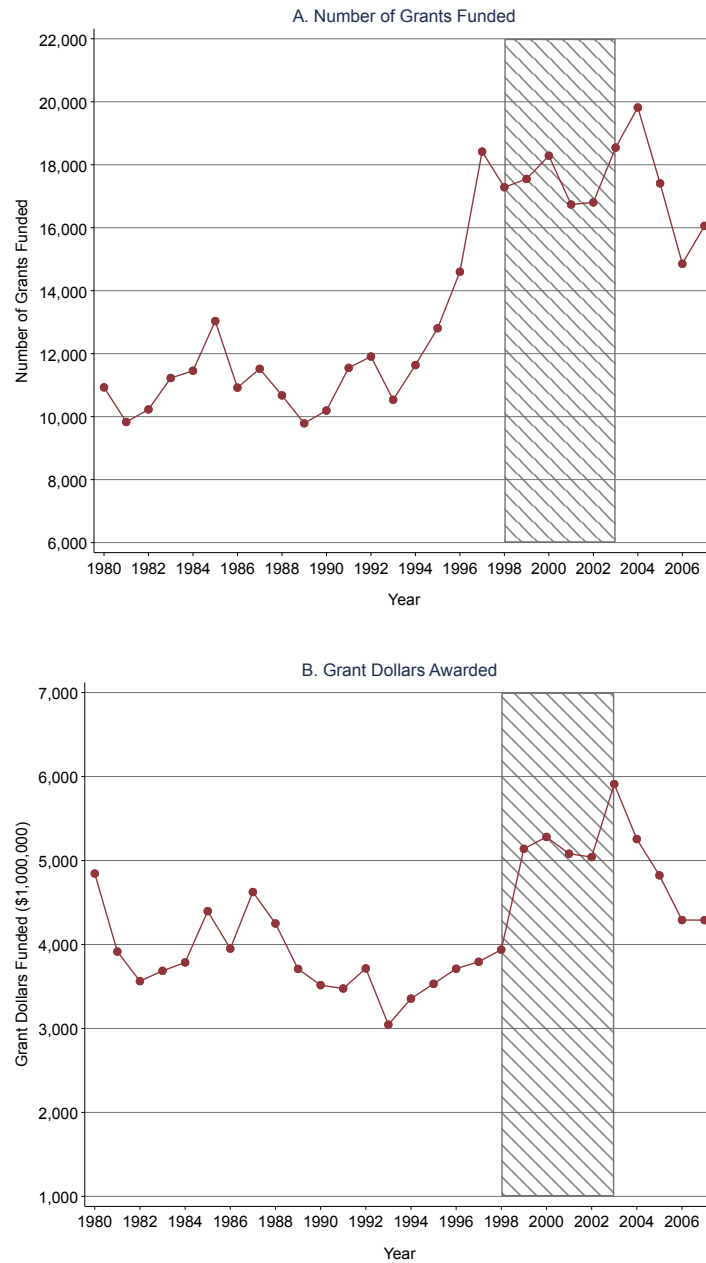
Notably, both graphs exhibit a significant decrease in 1996. This is likely related to the underlying data construction: grants in 1996 were linked to fewer MeSH terms on average (4.12 vs. 9.38 across the whole sample). As a result, grants in 1996 had a lower likelihood of being categorized as Medicare-Averse, Medicare-Neutral, or Medicare-Friendly. Despite this data limitation, the divergence in Medicare-Friendly grants – particularly in the total number of grants funded – is striking.

Finally, to empirically assess whether the trends across the three types of research are similar, we estimate year-level regressions $y_t = \beta_{1998to2003} + \varepsilon_t$ where y_t is the total number of NIH grants funded or the total amount of grant dollars awarded in year t , transformed with inverse hyperbolic sine function. $1998to2003_t$ is an indicator equal to 1 for years between 1998 and 2003, inclusive. Following our main analysis on the effect of the BBA on subsequent hospital research outcomes, we perform our estimation over the 1992-2007 period. Appendix Table C1 presents the estimates, with results from seemingly unrelated regressions.

Each column denotes a different grant type (e.g., Column 1 examines the relationship between the number of Medicare-Averse grants funded and $1998to2003_t$.) Looking to Panel A, Column 1, we see that 1998 to 2003 increase in the number of Medicare-Friendly grants funded is greater than the increase in the number of Medicare-Averse or Medicare-Neutral grants funded, though the differences are not statistically significantly different. Looking to the Panel B, we see similar trends in the amount of grant dollars funded.

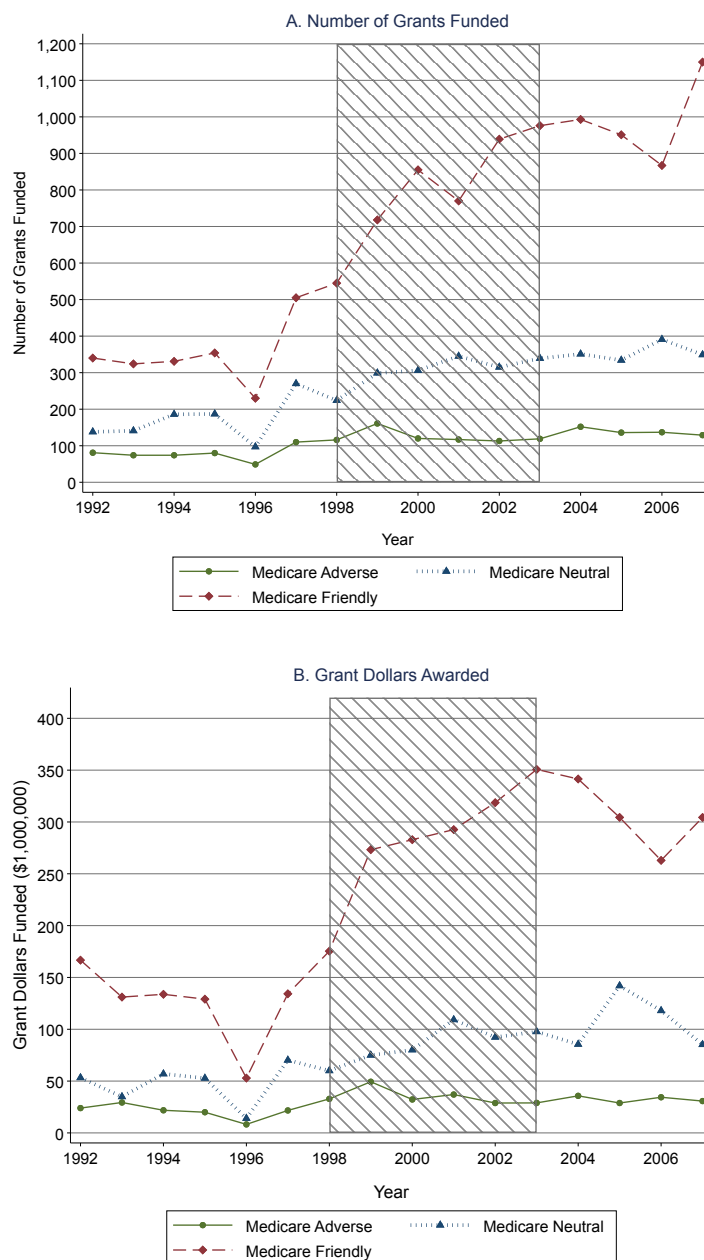
Taken together, the results in this Appendix document how research is shaped by the NIH budget doubling. The results suggest that, during the budget doubling, the NIH did not disproportionately allocated research funds away from the type of research most likely to be conducted by High Medicare Share hospitals. This analysis support the view that the NIH doubling was not age-biased and that the NIH doubling is unlikely to drive our main findings.

Figure C1: Total NIH Grants Funded



Notes: This figure plots trends in NIH grants by year. This figure is constructed from NIH grants awarded to hospitals and non-hospitals. Panel A plots the total number of grants funded by year. Panel B documents the total amount of NIH grant funds awarded in millions of 1997 dollars. The hatched region from 1998 to 2003 denotes the period in which the NIH budget increased. *Source:* NIH IMPAC II.

Figure C2: Total NIH Grants Funded



Notes: This figure plots trends in NIH grants by year for three groups of grants: grants that are Medicare-Averse, Medicare-Neutral, and Medicare-Friendly. Panel A plots the total number of NIH grants funded by year. Panel B documents the total amount of NIH grant funds awarded in millions of 1997 dollars. The hatched region from 1998 to 2003 denotes the period in which the NIH budget increased. This figure is constructed from only the subset of grants that are linked to the set of MeSH terms that are denoted as Medicare-Averse, Medicare-Neutral, or Medicare-Friendly. The sudden decrease in 1996 is related to our data construction: grants in 1996 were linked to fewer MeSH terms on average (4.12 vs. 9.38 across the whole sample). As a result, grants in 1996 had a lower likelihood of being categorized as Medicare-Averse, Medicare-Neutral, or Medicare-Friendly. For details on the sample and data construction, see the text. *Sources:* MEPS; NIH IMPAC II.

Table C1: NIH Budget Increase and Age Bias

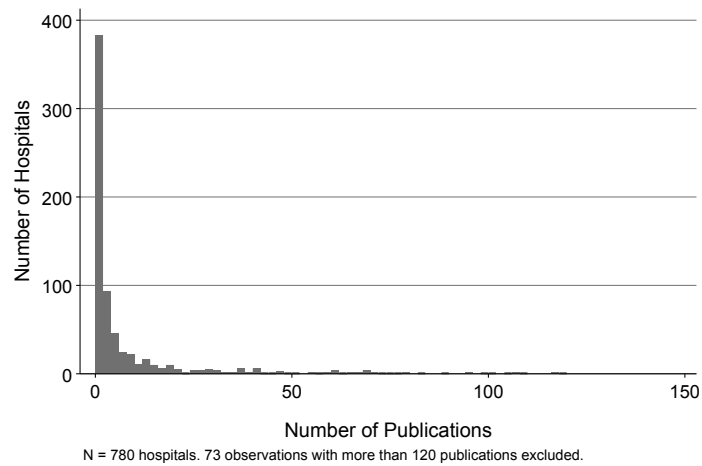
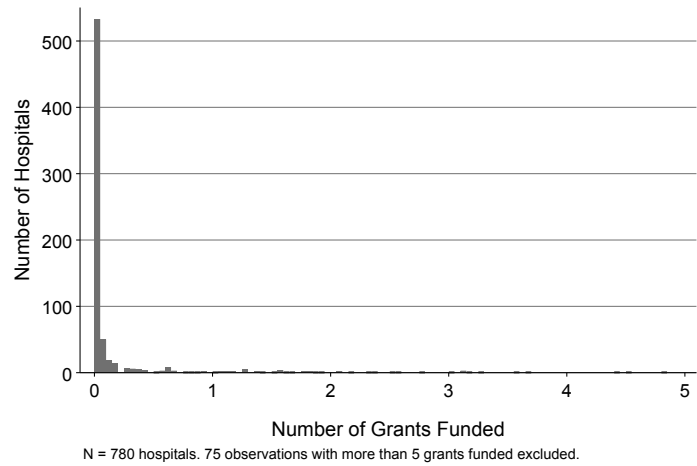
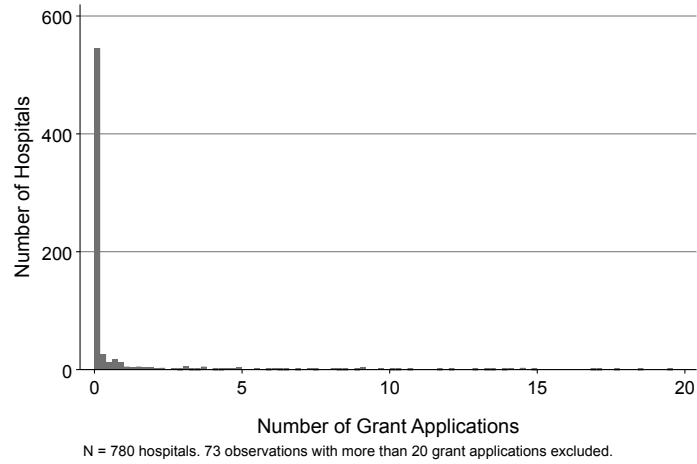
	Number of Grants Funded			Grant Dollars Awarded (\$)		
	Medicare Adverse (1)	Medicare Neutral (2)	Medicare Friendly (3)	Medicare Adverse (4)	Medicare Neutral (5)	Medicare Friendly (6)
1(1998 to 2003)	0.246** (0.122)	0.309* (0.158)	0.416** (0.195)	0.362** (0.149)	0.328 (0.215)	0.475** (0.196)
Mean of Outcome	5.355	6.209	7.100	5.355	6.209	7.100
Nb. Observations	48	48	48	48	48	48

Notes: This table reports estimates of the relationship between the NIH budget increase on age bias among NIH grants. Three types of NIH grants are examined: grants that are Medicare-Averse, Medicare-Neutral, and Medicare-Friendly. Observations are at the year level and estimations are performed over the 1992-2007 period. The sample of grants used in this analysis is constructed from the subset of grants that are linked to the set of MeSH terms that are denoted as Medicare-Averse, Medicare-Neutral, or Medicare-Friendly. Outcomes are transformed with the inverse hyperbolic sine function. Estimates are from seemingly unrelated regressions and each coefficient is from a separate regression. *Sources:* MEPS; NIH IMPAC II.
*p<0.01, **p<0.05, ***p<0.001.

Appendix D: Extra Figures and Tables

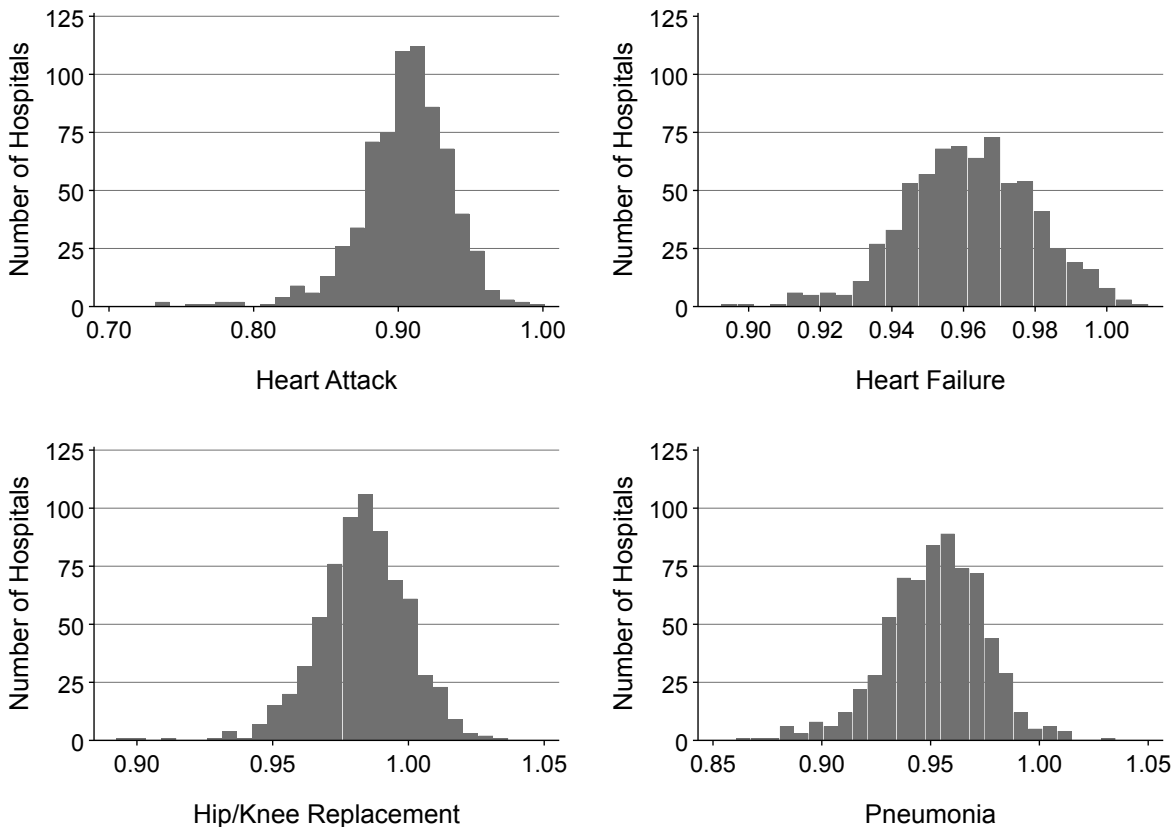
This Appendix contains additional figures and tables.

Figure D1: Distribution of Research Outcomes



Notes: These figure shows histograms of the research outcomes across hospitals in the teaching hospital sample. Sources: NIH IMPAC II; PubMed; Web of Science.

Figure D2: Risk-Adjusted 30-Day Survival Rates

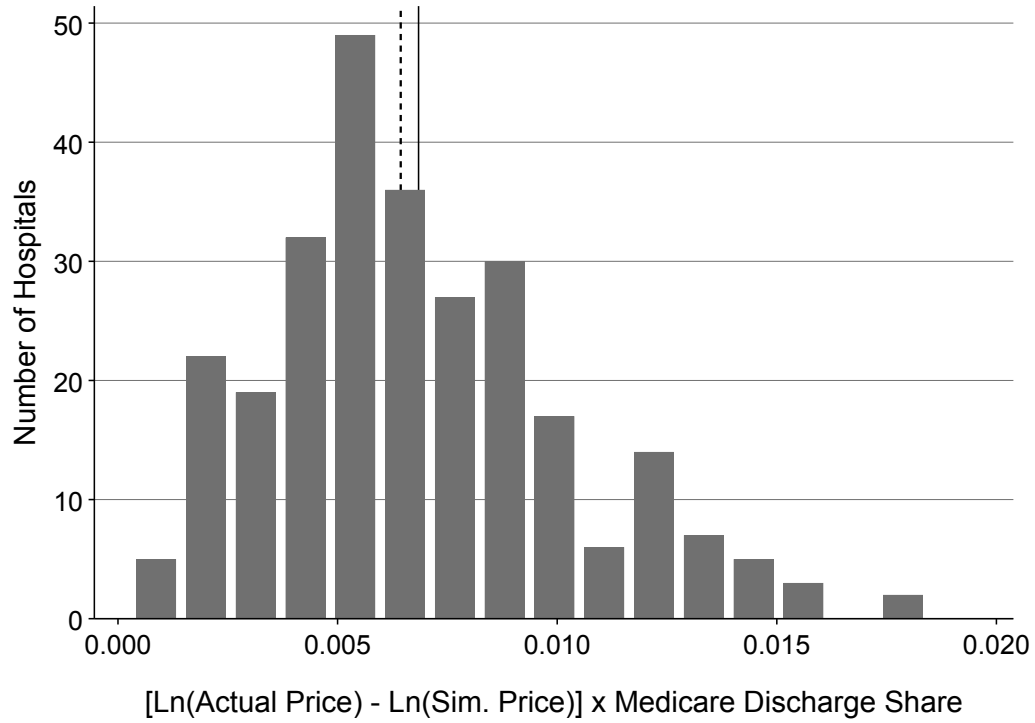


Notes: These figure shows histograms of the average risk-adjusted 30 day survival rates across hospitals in the teaching hospital sample. The clinical outcomes data characterize patient outcomes following a heart attack, heart failure, hip/knee replacement, and pneumonia. *Source:* Chandra et al. (2016).

Appendix E: Academic Medical Center Sample Results

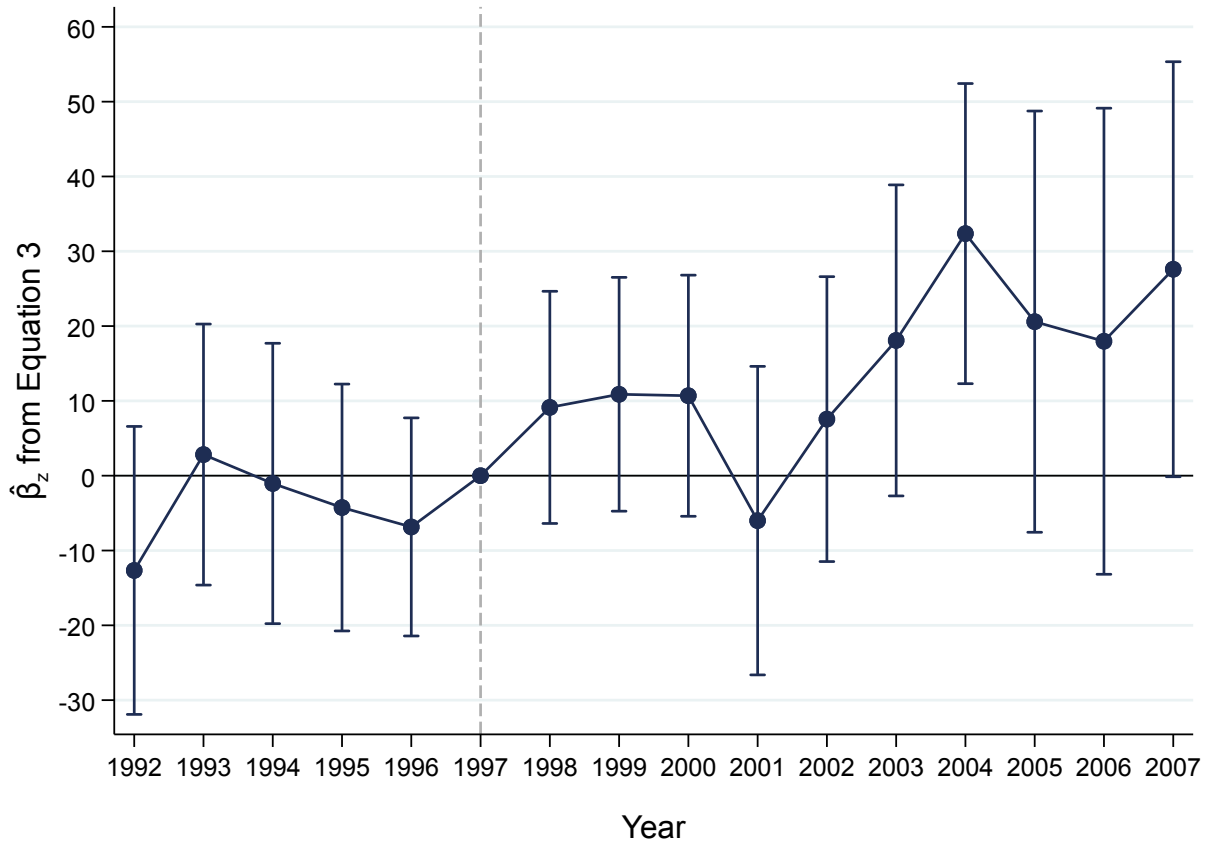
This section provides summary statistics and regression results for the Academic Medical Center sample of hospitals. See Section 3 for a description of how hospitals in this sample were identified.

Figure E1: Distribution of BBA Bite



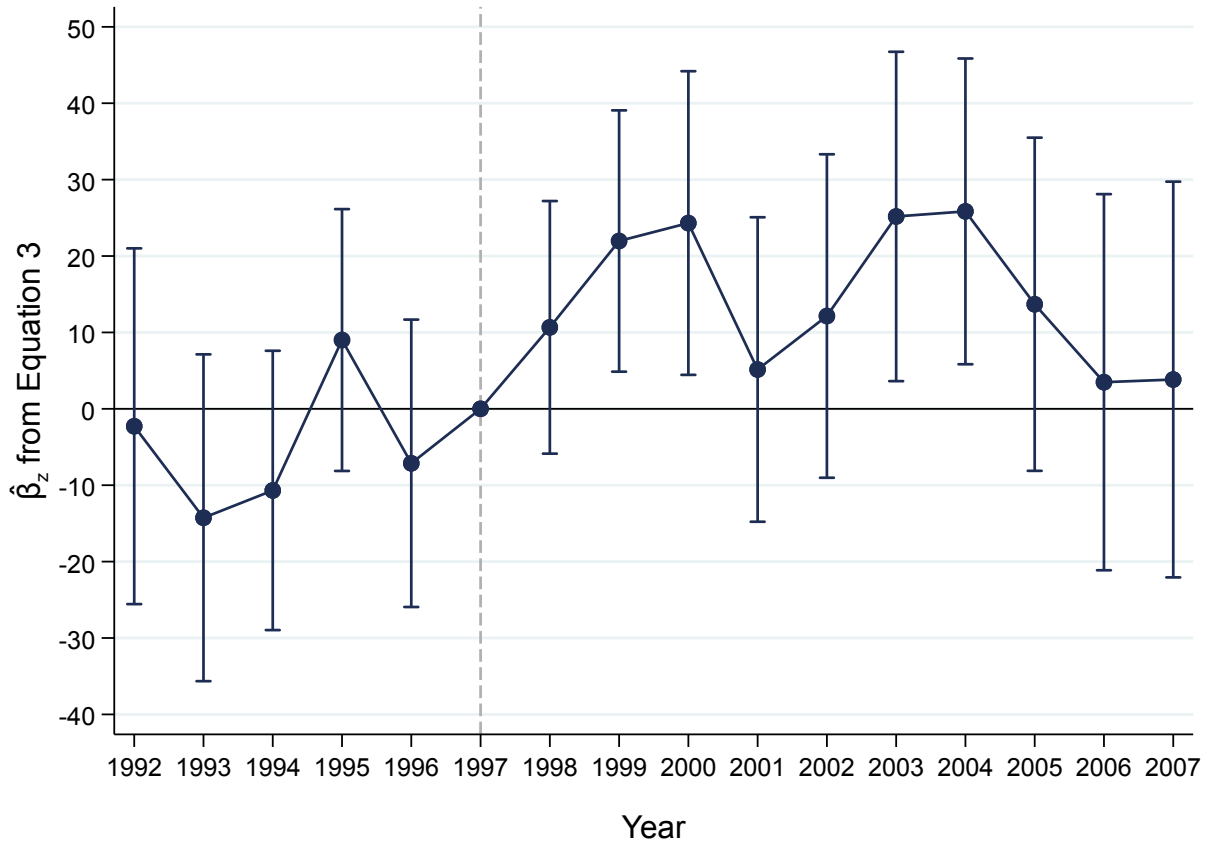
Notes: This figure shows a histogram of the BBA Bite, where BBA Bite is the difference between the simulated price per discharge and actual PPS price per discharge in 1995 in weighted by the Medicare share of discharges averaged over 1992-1995. The hospital sample used is the AMC sample. The solid line indicates the mean (0.0068) and the dotted lines indicates the median (0.0064). *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files.

Figure E2: Effect on the Number of Grant Applications



Notes: This figure plots the response in grants funded in the AMC sample. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of grant applications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table E3 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.

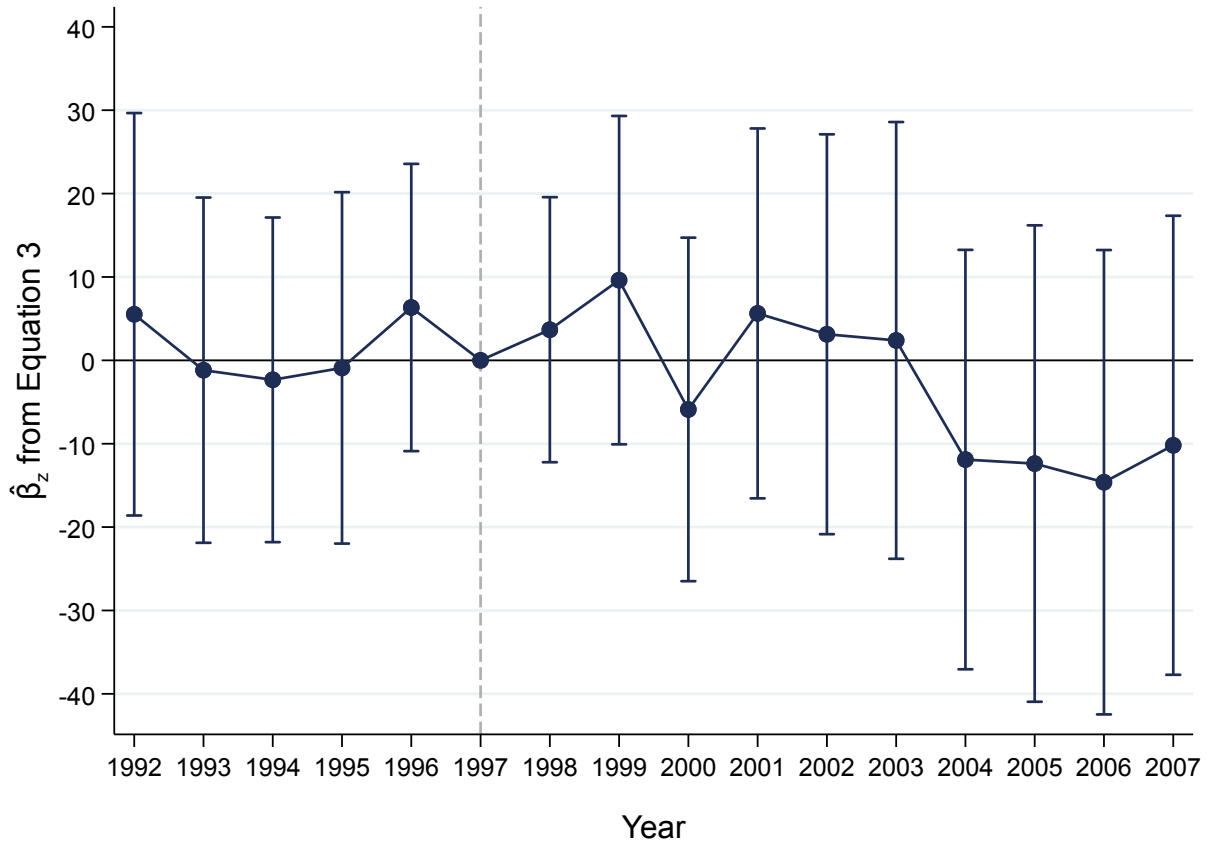
Figure E3: Effect on the Number of Grants Funded



Notes: This figure plots the response in grants funded in the AMC sample. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of grants funded})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table E4 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown.

Sources: Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.

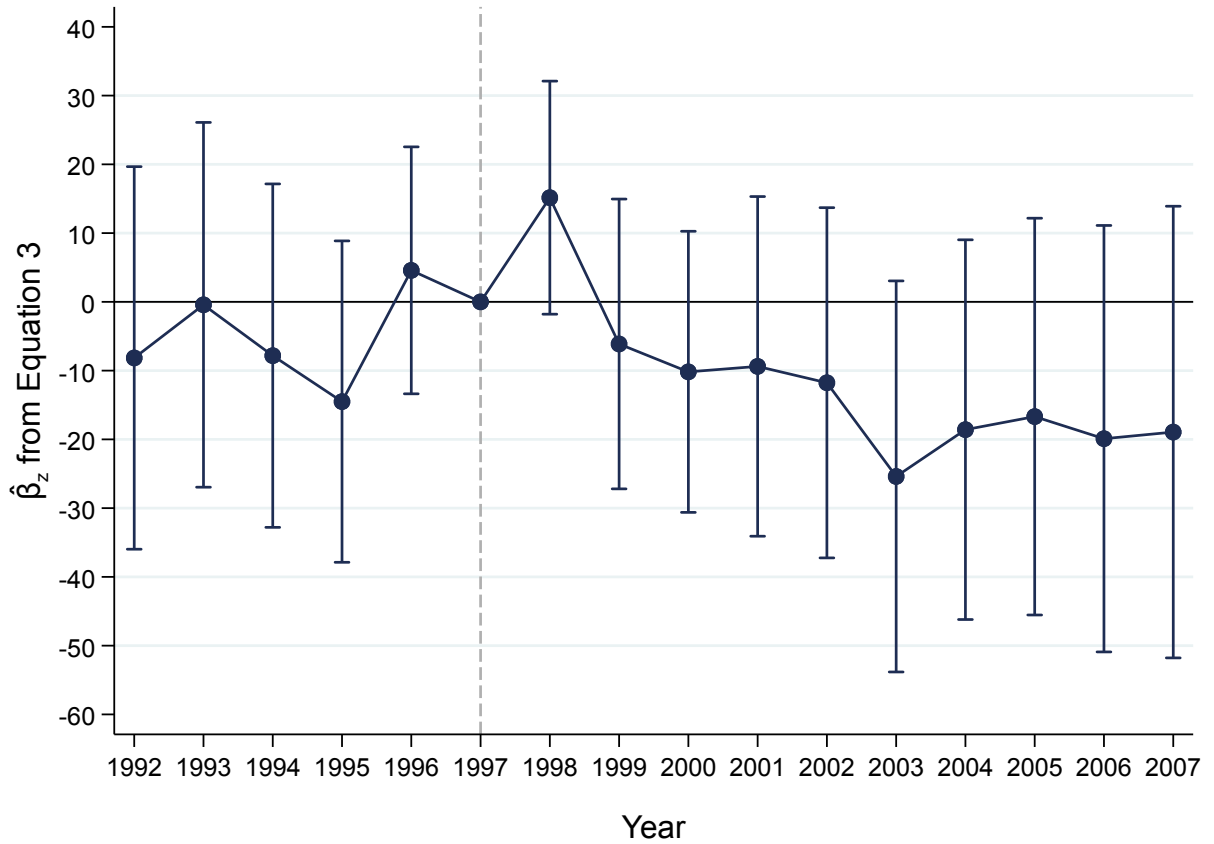
Figure E4: Effect on the Number of Publications



Notes: This figure plots the response in publications in the AMC sample. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of publications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table E5 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown.

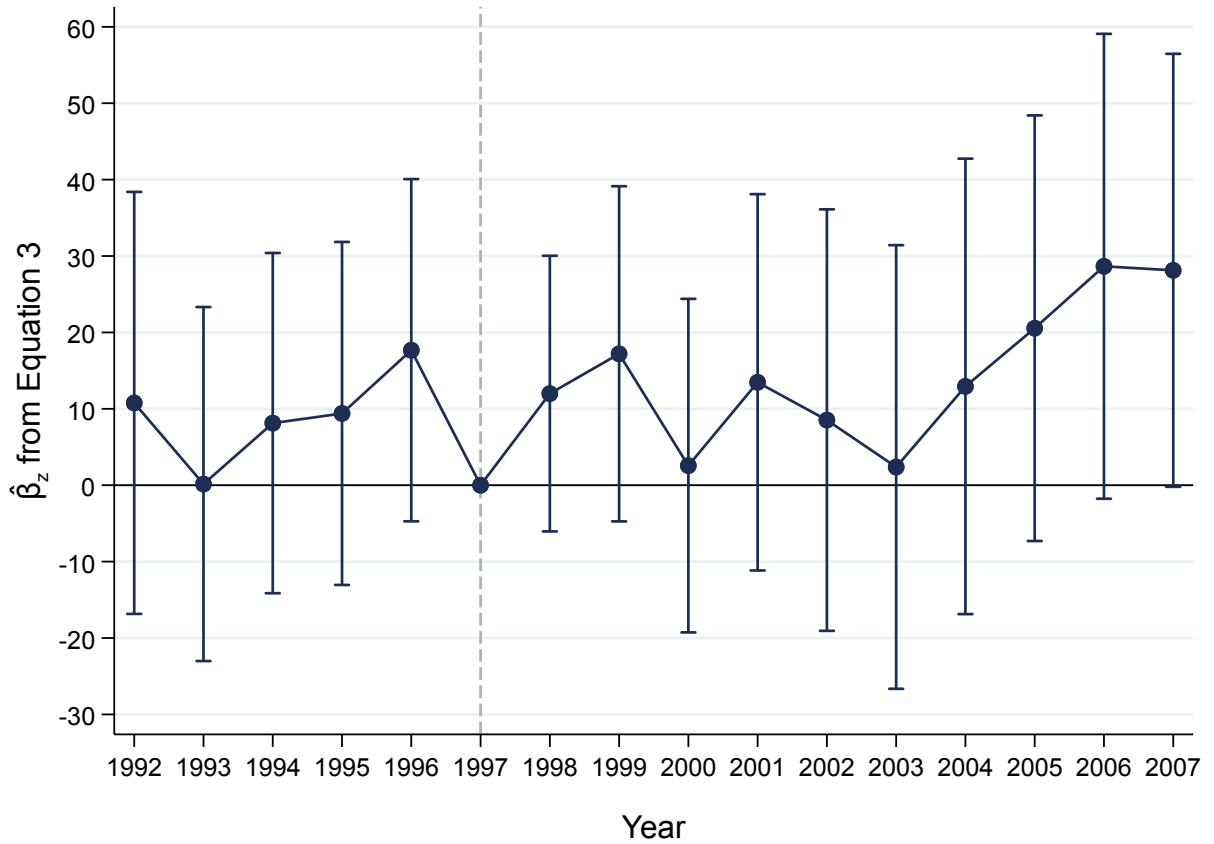
Sources: Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; PubMed, Web of Science.

Figure E5: Effect on Bench Research Research



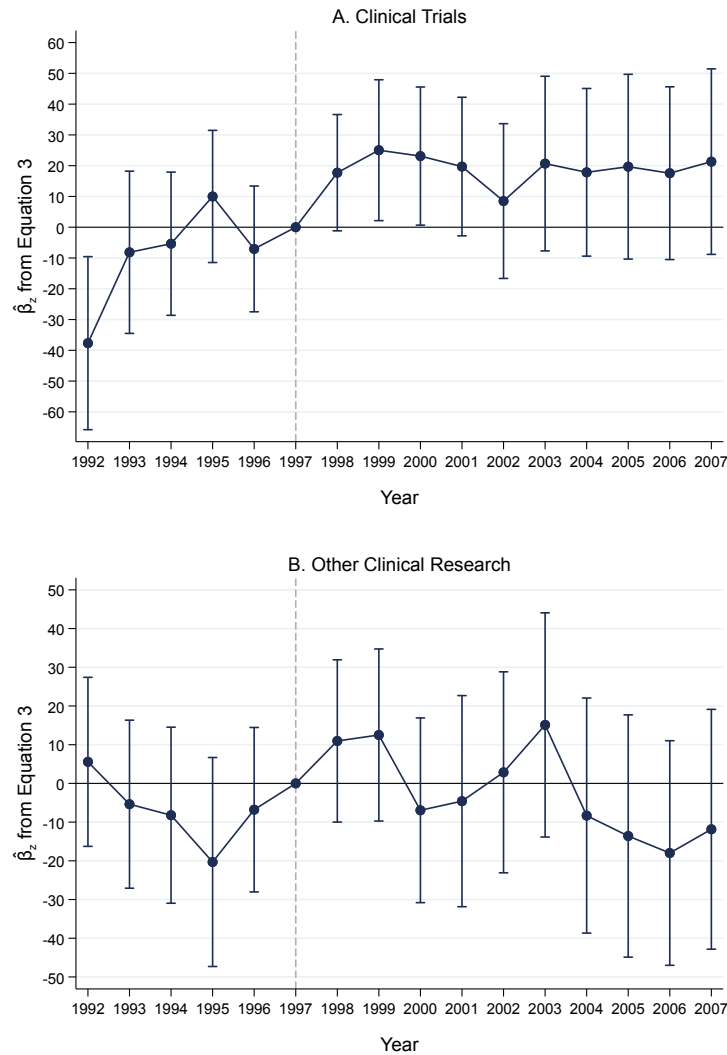
Notes: This figure plots the response in bench research publications in the AMC sample. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of publications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table E6, Panel A, Column 1 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Azoulay, Greenblatt, and Heggeness (2020); PubMed; Web of Science.

Figure E6: Effect on Translational Research Publications



Notes: This figure plots the response in translational research publications in the AMC sample. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of publications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table E6, Panel A, Column 2 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Azoulay, Greenblatt, and Heggeness (2020); PubMed; Web of Science.

Figure E7: Effect on Clinical Research Publications



Notes: This figure plots the response in clinical research publications in the AMC sample. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of publications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table ??, Panel A, Columns 5 and 6 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Azoulay, Greenblatt, and Heggeness (2020); PubMed; Web of Science.

Table E1: Summary Statistics

	Count	Mean	Median	SD	Min	Max
Panel A. Hospital Characteristics						
Discharges (1,000s)	274	24.08	22.48	10.94	4.82	62.79
Inpatient Days (1,000s)	274	134.10	124.25	64.64	30.31	439.06
Medicare Teaching Payment (\$1,000,000s)	274	11.71	8.74	10.14	0.13	59.81
Medicare Disproportionate Share Payment (\$1,000,000s)	274	6.62	5.88	5.49	0.00	36.21
Total Revenue (\$1,000,000s)	274	759.20	646.60	498.32	83.34	3,182.46
Beds	274	497.32	470.16	216.19	129.94	1,397.62
Residents and Interns	274	213.45	168.05	168.61	6.77	1,097.72
BBA Bite (x100)	274	0.68	0.64	0.34	0.03	1.84
Medicare Share of Discharges in 1995	274	0.30	0.30	0.11	0.02	0.59
Medicare Share of Inpatient Days in 1995	274	0.39	0.39	0.14	0.03	0.68
Medicare Price Per Discharge in 1995 (\$1,000s)	274	10.09	9.56	3.11	5.66	27.48
Panel B. Grants						
<i>Number of Grant Applications</i>						
Total	274	23.00	1.06	50.83	0.00	444.00
New	274	18.63	0.88	40.72	0.00	355.75
Competitive Renewal	274	4.37	0.12	10.23	0.00	88.25
MD Principal Investigators	274	7.91	0.59	18.21	0.00	158.62
PhD Principal Investigators	274	11.25	0.31	25.30	0.00	193.38
MD-PhD Principal Investigators	274	3.55	0.12	9.07	0.00	87.75
<i>Number of Grants Funded</i>						
Total	274	6.65	0.19	16.26	0.00	147.75
New	274	4.74	0.19	11.55	0.00	106.38
Competitive Renewal	274	1.90	0.00	4.75	0.00	41.38
MD Principal Investigators	274	2.49	0.09	6.30	0.00	55.00
PhD Principal Investigators	274	3.06	0.06	7.50	0.00	61.00
MD-PhD Principal Investigators	274	1.03	0.00	3.05	0.00	30.88
Panel C. Publications						
Total	274	116.32	20.56	227.74	0.31	1,683.62
Citation Ranking: ≤ 25	274	28.29	7.56	46.17	0.19	306.12
Citation Ranking: 26-50	274	26.65	5.03	48.56	0.00	333.38
Citation Ranking: 51-75	274	28.39	4.16	57.28	0.00	413.19
Citation Ranking: 76-95	274	25.39	3.50	58.20	0.00	456.62
Citation Ranking: 96-99	274	5.88	0.69	15.84	0.00	130.56
Citation Ranking: >99	274	1.74	0.19	5.11	0.00	45.12
Cited in a Patent	274	29.46	2.97	68.03	0.00	547.31
Not Cited In a Patent	274	86.87	17.03	161.22	0.31	1,136.31
Disruptive	274	4.26	1.22	7.34	0.00	51.00
Consolidating	274	104.36	17.62	208.26	0.25	1,551.44
Laboratory Research: Pub. with Bench MeSH	274	32.43	1.81	73.46	0.00	487.50
Translational Research: Pub. with Translational MeSH	274	32.08	4.38	66.29	0.00	516.00
Builds on Translational MeSH	274	9.67	2.66	18.28	0.00	122.25
Inspires Translational MeSH	274	16.64	2.03	36.68	0.00	297.81
Clinical Research: Clinical Trial Pub.	274	13.66	4.06	25.93	0.00	179.69
Clinical Research: Pub. with Other Clinical MeSH	274	28.89	8.72	52.96	0.19	402.31
Panel D. Clinical Outcomes (Risk-Adjusted Survival Rates [30 Days])						
Heart Attack	264	0.91	0.91	0.04	0.74	1.00
Heart failure	264	0.97	0.97	0.02	0.90	1.00
Pneumonia	264	0.98	0.99	0.02	0.90	1.03
Hip/knee	264	0.95	0.95	0.02	0.86	1.04

Notes: This table shows hospital characteristics for the hospitals in the AMC sample between 1992-2007. All variables are measured yearly. For example, “Discharges (1000s)” is the average number of patients a hospital receives in a year. “Medicare Teaching Payment,” “Medicare Disproportionate Share Payment,” and “Total Revenue” are adjusted for inflation using the CPI and are measured in 1997 dollars. All hospital characteristics, grant, and publication variables have 274 observations. Clinical outcomes data is only available for the subset of hospitals in the teaching hospital sample that matched to the clinical outcomes data. Clinical outcomes are measured in three-year bins—e.g., hospital-level survival rates in 2005 are estimated over patient claims in 2003, 2004, and 2005. For each hospital, we use three-year bins for four years (1996, 2002, 2005, and 2008). Each publication’s disruptiveness is measured by using the Funk and Owen-Smith (2017) disruptiveness index, denoted by d . “Disruptive” publications refer to publications with $d \leq 95^{th}$ percentile and “Consolidating” publications refers to publications with $d > 95^{th}$ percentile. See Section 3 for detailed data descriptions. *Sources:* Azoulay, Greenblatt, and Heggeness (2020); Chandra et al. (2016); Funk and Owen-Smith (2017); Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPACT II; Marx and Fuegi (forthcoming); PubMed; Web of Science.

Table E2: Comparing the Teaching Hospital and AMC Sample

	Teaching Hospital Sample			AMC Sample			P-value from T-test
	Count	Mean	SD	Count	Mean	SD	Diff. of Meant
Panel A. Hospital Characteristics							
Discharges (1,000s)	780	16.82	10.39	274	24.08	10.94	0.000***
Inpatient Days (1,000s)	780	89.84	60.25	274	134.1	64.64	0.000***
Medicare Teaching Payment (\$1,000,000s)	780	5.83	8.46	274	12.53	10.85	0.000***
Medicare Disproportionate Share Payment (\$1,000,000s)	780	4.24	4.86	274	7.08	5.88	0.000***
Total Revenue (\$1,000,000s)	765	520.91	439.62	274	812.17	533.09	0.000***
Beds	780	360.54	202.23	274	497.32	216.19	0.000***
Residents and Interns	767	101.92	139.35	274	213.45	168.61	0.000***
BBA Bite (x100)	780	0.00	0.00	274	0.01	0.00	0.000***
Medicare Share of Discharges in 1995 (\$1,000s)	780	0.34	0.13	274	0.30	0.11	0.000***
Medicare Share of Inpatient Days in 1995	780	0.43	0.15	274	0.39	0.14	0.000***
Medicare Price Per Discharge in 1995 (\$1,000s)	780	8.3	2.85	274	10.09	3.11	0.000***
Panel B. Grants							
<i>Number of Grant Applications</i>							
Total	780	8.82	32.97	274	23	50.83	0.000***
New	780	7.15	26.43	274	18.63	40.72	0.000***
Competitive Renewal	780	1.67	6.60	274	4.37	10.23	0.000***
MD Principal Investigators	780	3.08	11.87	274	7.91	18.21	0.000***
PhD Principal Investigators	780	4.26	16.22	274	11.25	25.3	0.000***
MD-PhD Principal Investigators	780	1.36	5.81	274	3.55	9.07	0.000***
<i>Number of Grants Funded</i>							
Total	780	2.55	10.42	274	6.65	16.26	0.000***
New	780	1.82	7.40	274	4.74	11.55	0.000***
Competitive Renewal	780	0.73	3.05	274	1.90	4.75	0.000***
MD Principal Investigators	780	0.96	4.05	274	2.49	6.30	0.000***
PhD Principal Investigators	780	1.16	4.77	274	3.06	7.50	0.000***
MD-PhD Principal Investigators	780	0.40	1.92	274	1.03	3.05	0.000***
Panel C. Publications							
Total	780	45.4	148.55	274	116.32	227.74	0.000***
Citation Percentile: <25	780	11.19	31.02	274	28.29	46.17	0.000***
Citation Percentile: 26-50	780	10.41	32	274	26.65	48.56	0.000***
Citation Percentile: 51-75	780	11.03	37.19	274	28.39	57.28	0.000***
Citation Percentile: 76-95	780	9.84	37.25	274	25.39	58.2	0.000***
Citation Percentile: 96-99	780	2.27	9.98	274	5.88	15.84	0.000***
Citation Percentile: >99	780	0.67	3.18	274	1.74	5.11	0.000***
Cited in a Patent	780	11.34	43.4	274	29.46	68.03	0.000***
Not Cited in a Patent	780	34.07	106.05	274	86.87	161.22	0.000***
Consolidating: Disruption Index Percentile ≥ 95	780	1.69	4.86	274	4.26	7.34	0.000***
Disruptive: Disruption Index Percentile ≥ 95	780	40.72	135.6	274	104.36	208.26	0.000***
Laboratory Research: Pub. with Bench MeSH	780	12.41	47.18	274	32.43	73.46	0.000***
Translational	780	12.34	42.86	274	32.08	66.29	0.000***
Inspiring Translational	780	3.83	11.94	274	9.67	18.28	0.000***
Builds on Translational	780	6.40	23.48	274	16.64	36.68	0.000***
Clinical Research: Clinical Trial Pub	780	5.43	16.94	274	13.66	25.93	0.000***
Clinical Research: Pub. with Other Clinical MeSH	780	11.54	34.8	274	28.89	52.96	0.000***
Panel D. Clinical Outcomes (Risk-Adjusted Survival Rates [30 Days])							
Heart Attack	700	0.90	0.03	264	0.91	0.04	0.147
Heart Failure	700	0.96	0.02	264	0.97	0.02	0.001***
Pneumonia	700	0.98	0.02	264	0.98	0.02	0.106
Hip/knee	700	0.95	0.02	264	0.95	0.02	0.428

Notes: This table compares the teaching hospital sample and the AMC sample between 1992-2007. All variables are measured yearly. For example, “Discharges (1000s)” is the average number of patients a hospital receives in a year. See Section 3 for detailed variable descriptions. *Sources:* Azoulay, Greenblatt, and Heggeness (2020); Chandra et al. (2016); Funk and Owen-Smith (2017); Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPACT II; Marx and Fuegi (forthcoming); PubMed; Web of Science.

Table E3: Effect on the Number of Grant Applications

	Grant Cycle			Principal Investigator		
	Total (1)	New (2)	Renewal (3)	MD (4)	PhD (5)	MD-PhD (6)
A. BBA Bite \times Post	18.55** (8.569)	23.16** (8.788)	9.349 (5.955)	20.22** (9.192)	22.11** (8.065)	35.10*** (7.786)
Elasticity	0.079	0.099	0.041	0.087	0.095	0.156
Adjusted R^2	0.042	0.063	0.014	0.038	0.071	0.100
Diff. Wald test p-value		0.088			0.841	0.148
B. High BBA Bite \times Post	0.139** (0.0597)	0.167** (0.0598)	0.0521 (0.0398)	0.112** (0.0545)	0.193*** (0.0511)	0.260*** (0.0557)
Elasticity	0.148	0.182	0.053	0.118	0.213	0.297
Adjusted R^2	0.043	0.064	0.014	0.036	0.076	0.103
Diff. Wald test p-value		0.031			0.119	0.013
Mean of Outcome	1.831	1.725	0.957	1.290	1.348	0.842
Nb. Observations	4384	4384	4384	4384	4384	4384
Nb. Hospitals	274	274	274	274	274	274

Notes: This table reports difference-in-differences estimates of the effect of the BBA on the number of grant applications, in the AMC sample. Observations are at the hospital-year level. Outcomes are transformed with the inverse hyperbolic sine function. Column 1 presents results from OLS regressions. Columns 2-6 present estimates from seemingly unrelated regressions. Each coefficient is from a separate regression. A Panel A elasticity of 0.079 implies that a one percentage increase in BBA Bite is associated on average with a 7.9 percent yearly increase in grant applications following the BBA's enactment. Similarly, a Panel B elasticity of 0.148 implies that High BBA Share hospitals experience on average a 14.8 percent yearly increase in grant applications in the post-BBA time period. The fourth row and eighth row show p-values from Wald tests that compare coefficients on BBA Bite \times After (Panel A) or High BBA Bite \times After (Panel B) across different columns (Column 2 vs. Column 3; Column 4 vs. Column 5; Column 4 vs. Column 6). Standard errors are in parentheses, and are clustered at the hospital level. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.

*p<0.01, **p<0.05, ***p<0.001.

Table E4: Effect on the Number of Grants Funded

	Grant Cycle			Principal Investigator		
	Total (1)	New (2)	Renewal (3)	MD (4)	PhD (5)	MD-PhD (6)
A. BBA Bite \times Post	18.85** (7.012)	25.01*** (7.017)	13.42** (5.475)	18.22** (6.981)	23.21*** (6.487)	32.49*** (5.685)
Elasticity	0.082	0.109	0.065	0.084	0.104	0.193
Adjusted R^2	0.028	0.044	0.008	0.021	0.040	0.062
Diff. Wald test p-value		0.046			0.439	0.060
B. High BBA Bite \times Post	0.131** (0.0467)	0.177*** (0.0486)	0.0752** (0.0323)	0.110** (0.0406)	0.189*** (0.0426)	0.197*** (0.0401)
Elasticity	0.138	0.194	0.078	0.116	0.208	0.218
Adjusted R^2	0.028	0.045	0.007	0.020	0.045	0.058
Diff. Wald test p-value		0.009			0.046	0.032
Mean of Outcome	1.117	0.973	0.637	0.731	0.770	0.411
Nb. Observations	4,384	4,384	4,384	4,384	4,384	4,384
Nb. Hospitals	274	274	274	274	274	274

Notes: This table reports difference-in-differences estimates of the effect of the BBA on the number of grants funded, in the AMC sample. Observations are at the hospital-year level. Outcomes are transformed with the inverse hyperbolic sine function. Column 1 presents results from OLS regressions. Columns 2-6 present estimates from seemingly unrelated regressions. Each coefficient is from a separate regression. A Panel A elasticity of 0.082 implies that a one percentage increase in BBA Bite is associated on average with a 8.2 percent yearly increase in grant applications following the BBA's enactment. Similarly, a Panel B elasticity of 0.138 implies that High BBA Share hospitals experience on average a 13.8 percent yearly increase in grant applications in the post-BBA time period. The fourth row and eighth row show p-values from Wald tests that compare coefficients on BBA Bite \times After (Panel A) or High BBA Bite \times After (Panel B) across different columns (Column 2 vs. Column 3; Column 4 vs. Column 5; Column 4 vs. Column 6). Standard errors are in parentheses, and are clustered at the hospital level. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.

*p<0.01, **p<0.05, ***p<0.001.

Table E5: Effect on Publication Impact

	By Citation Percentile											Cited in a Patent		By Disruption	
	Total	≤25	26-50	51-75	76-95	96-99	>99	Yes	No	Consolidating Research	Disruptive Research	(10)	(11)		
A. BBA Bite × Post	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)				
Elasticity	-4.293 (9.166)	-3.997 (8.251)	2.650 (8.191)	4.109 (8.208)	8.793 (8.875)	15.572* (8.139)	18.672** (6.615)	-3.090 (9.239)	-0.786 (8.838)	2.436 (10.822)	6.166 (8.305)				
Adjusted R^2	-0.018	-0.017	0.011	0.018	0.038	0.068	0.092	-0.013	-0.003	0.010	0.027				
Diff. Wald test p-value	0.081	0.070	0.056	0.051	0.064	0.062	0.051	0.033	0.093	0.067	0.026				
B. High BBA Bite × Post	-	0.944	0.127	0.132	0.029	0.015	0.009	0.742	0.632						
Elasticity	-0.030 (0.070)	-0.025 (0.064)	0.059 (0.063)	0.058 (0.061)	0.088 (0.064)	0.144** (0.049)	0.127** (0.040)	-0.013 (0.068)	-0.003 (0.068)	0.005 (0.081)	0.089 (0.059)				
Adjusted R^2	-0.030	-0.026	0.060	0.059	0.091	0.155	0.135	-0.013	-0.004	0.005	0.092				
Diff. Wald test p-value	0.081	0.070	0.057	0.051	0.065	0.064	0.051	0.032	0.093	0.067	0.028				
Mean of Outcome	-	0.887	0.014	0.024	0.011	0.005	0.023	0.856	0.146						
Nb. Observations	3,826	2,787	2,505	2,396	2,162	1,130	0,579	2,217	3,640	3,603	1,786				
Nb. Hospitals	4,384	4,384	4,384	4,384	4,384	4,384	4,384	4,384	4,384	4,384	4,384				
	274	274	274	274	274	274	274	274	274	274	274				

Notes: This table reports difference-in-differences estimates of the effect of the BBA on the number of publications, by impact, in the AMC sample. Observations are at the hospital-year level. Outcomes are transformed with the inverse hyperbolic sine function. Estimates are from seemingly unrelated regressions and each coefficient is from a separate regression. Each publication's disruptiveness is measured by using the Funk and Owen-Smith (2017) disruptiveness index, denoted by d. Column 8 refers to publications with $d \leq 95$ th percentile and Column 9 refers to publications with $d > 95$ th percentile. The elasticity of -0.018 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 1.8 percent yearly decrease in publications following the BBA's enactment. Similarly, the elasticity of -0.030 in Panel B implies that High BBA Bite hospitals experience on average a 3 percent yearly decrease in publications in the post-BBA time period. The fourth row and eighth row show p-values from Wald tests that compare coefficients on BBA Bite × After (Panel A) or High BBA Bite × After (Panel B) across different columns. For Columns 2 to 7, the fourth and eighth row compare estimates in Column 1 vs. estimates in the focal column. For Columns 8 and 9, the fourth and eighth row show p-values from Wald tests that compare Column 8 and 9 estimates. For Columns 10 and 11, the fourth and eighth row show p-values from Wald tests that compare Column 10 and Column 11. Standard errors are in parentheses, and are clustered at the hospital level. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Funk and Owen-Smith (2017); PubMed, Web of Science.

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.001$.

Table E6: Effect on Publication Composition

	Laboratory Research	Translational Research			Clinical Research	
	Bench MeSH	Translational MeSH	Builds on Translational MeSH	Inspiring Translational MeSH	Clinical Trials	Other
	(1)	(2)	(3)	(4)	(5)	(6)
A. BBA Bite \times Post	-7.791 (9.733)	6.955 (8.800)	29.981*** (8.349)	17.025** (8.122)	27.155** (8.437)	3.670 (8.846)
Elasticity	-0.033	0.030	0.129	0.073	0.116	0.016
Adjusted R^2	0.001	0.041	0.148	0.057	0.193	0.071
B. High BBA Bite \times Post	-0.052 (0.074)	0.069 (0.070)	0.184** (0.059)	0.140** (0.062)	0.182** (0.062)	0.050 (0.064)
Elasticity	-0.053	0.069	0.200	0.148	0.197	0.049
Adjusted R^2	0.001	0.042	0.147	0.058	0.192	0.071
Mean of Outcome	2.005	2.400	1.781	1.874	2.061	2.829
Nb. Observations	4,384	4,384	4,384	4,384	4,384	4,384
Nb. Hospitals	274	274	274	274	274	274

Notes: This table reports difference-in-differences estimates of the effect of the BBA on bench, translational, and clinical trial research in hospitals, in the AMC sample. Observations are at the hospital-year level. Outcomes are transformed with the inverse hyperbolic sine function. Estimates are from OLS regressions, and each coefficient is from a separate regression. Column 1 refers to publications that are not disease-oriented, are not clinical trial publications, and rely on either a molecular biology technique, a model organism, cellular structures and macromolecules, or biochemical and cellular processes (based on MeSH terms). Column 2 refers to publications that are disease-oriented, are not clinical trial publications, and rely on either a molecular biology technique, a model organism, cellular structures and macromolecules, or biochemical and cellular processes (based on MeSH terms). Column 3 refers to publications that report the results of a clinical trials, or are tagged by a human MeSH term and also cite a translational publication. Column 4 refers to publications that are translational and is cited by a clinical trial publication (or one that contains a human MeSH term). Column 5 refers to publications that are indicated as clinical trials based on MeSH terms or the publication type field in *PubMed*. Finally, Column 6 refers to publications that are disease-oriented, not clinical trials, and not tagged by any bench MeSH keywords. The elasticity of -0.033 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 3.3 percent yearly decrease in publications following the BBA's enactment. Similarly, the elasticity of -0.053 in Panel B implies that High BBA Bite hospitals experience on average a 5.3 percent yearly decrease in publications in the post-BBA time period. Standard errors are in parentheses, and are clustered at the hospital level. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Azoulay, Greenblatt, and Heggeness (2020); Marx and Fuegi (forthcoming); PubMed; Web of Science. * $p < 0.01$, ** $p < 0.05$, *** $p < 0.001$.

Table E7: Effect on Clinical Outcomes (Changes in Risk-adjusted Survival Rates)

	Heart Attack	Heart Failure	Hip/Knee	Pneumonia
	(1)	(2)	(3)	(4)
A. BBA Bite	-0.0903 (0.8047)	-0.1854 (0.4799)	0.3631 (0.4726)	-0.3402 (0.5631)
Ln(Discharges in 1995)	0.0064 (0.0053)	0.0086** (0.0033)	0.0016 (0.0036)	0.0108** (0.0038)
Adjusted R^2	-0.0025	0.0214	-0.0049	0.0232
B. High BBA Bite	0.0029 (0.0055)	-0.0047 (0.0031)	0.0022 (0.0032)	-0.0016 (0.0038)
Ln(Discharges in 1995)	0.0067 (0.0053)	0.0084** (0.0033)	0.0015 (0.0036)	0.0109** (0.0038)
Adjusted R^2	-0.0015	0.0296	-0.0053	0.0225
Mean of Outcome	0.0268	0.0103	0.0010	0.0175
Nb. Observations	264	264	264	264

Notes: This table displays the effect on changes in risk-adjusted survival rates among hospitals in the AMC sample. The hospital sample used is the subset of the teaching hospital sample that is matched to the clinical outcomes dataset from Chandra et al. (2016). Observations are at the hospital-level. Outcomes are the difference in average survival rates between the post-BBA time period and the pre-BBA time period. Estimates are from OLS regressions and each coefficient is from a separate regression. Standard errors are in parentheses and robust. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Chandra et al. (2016).
* $p < 0.01$, ** $p < 0.05$, *** $p < 0.001$.

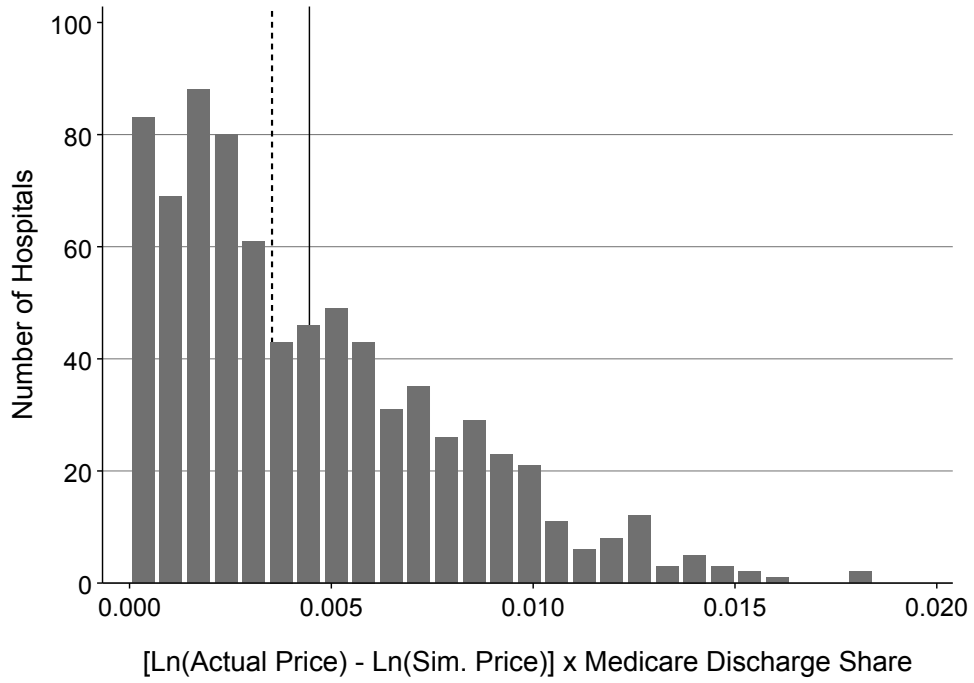
Appendix F: Subsidy BBA Bite Results

This section provides summary statistics and regression results for the subsidy BBA Bite analysis. In this analysis, BBA Bite is calculated as:

$$BBA_Bite_h = \frac{IME_{h,1995} + DSH_{h,1995}}{TotalRevenue_{h,1995}}$$

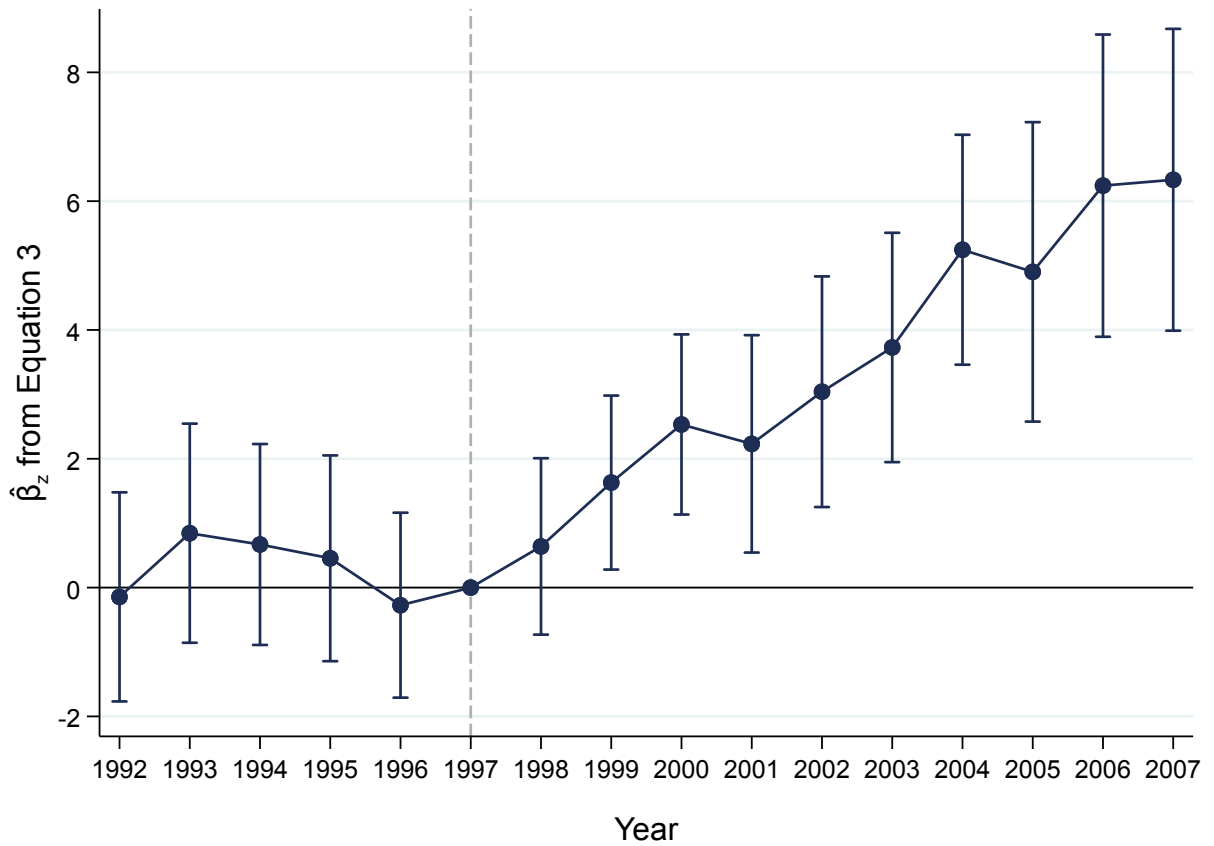
where $IME_{h,1995}$ is total indirect medical education payments for hospital h , $DSH_{h,1995}$ is disproportionate share payments for hospital h , and $TotalRevenue_{h,1995}$ is the total patient revenues for hospital h . All values correspond to payments in 1995.

Figure F1: Distribution of BBA Bite



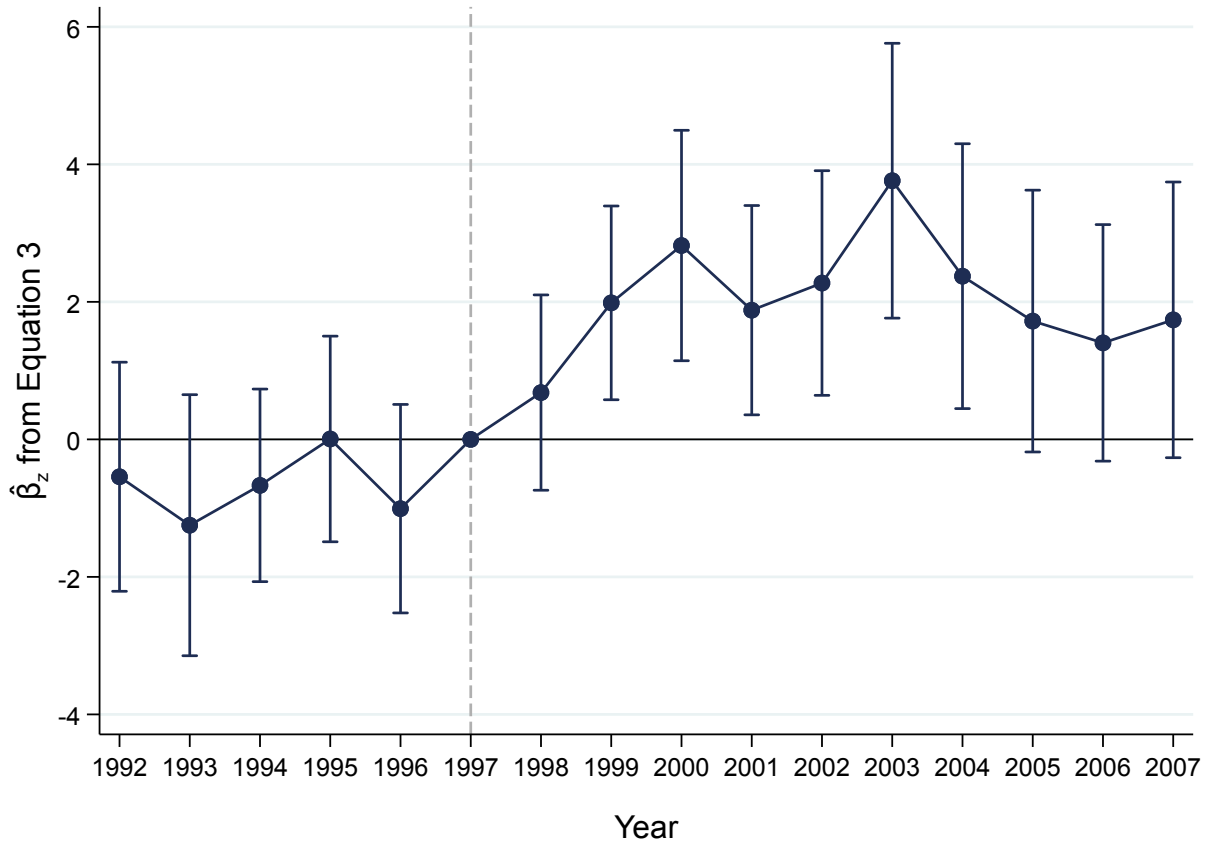
Notes: This figure shows a histogram of the BBA Bite for the teaching hospital sample, where BBA Bite is the share of 1995 patient revenues that come from IME and DSH payments. The solid line indicates the mean (0.0267) of this variable and the dotted lines indicates the median (0.0229). *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files.

Figure F2: Effect on the Number of Grant Applications



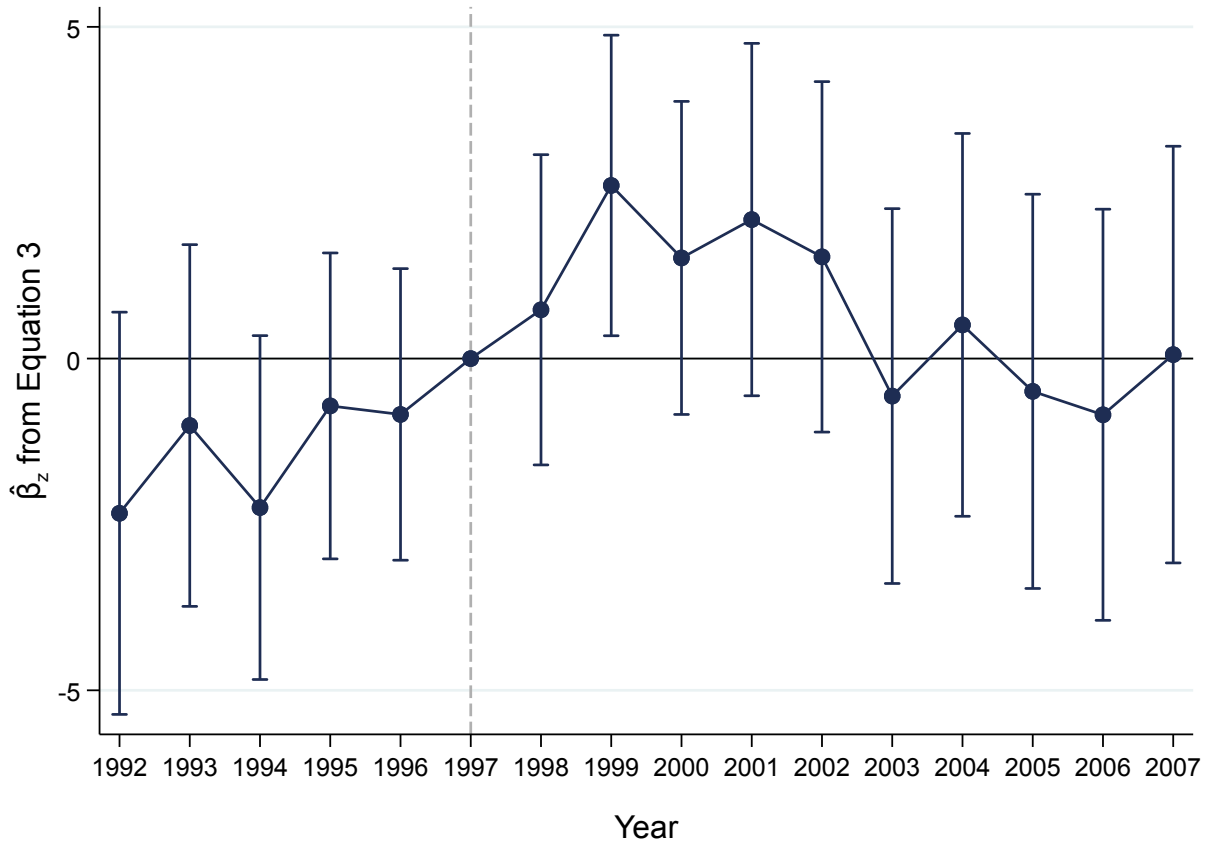
Notes: This figure plots the response in grants funded in the teaching hospital sample, where BBA Bite is the share of 1995 patient revenues that come from IME and DSH payments. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of grant applications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table F1, Panel A, Column 1 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.

Figure F3: Effect on the Number of Grants Funded



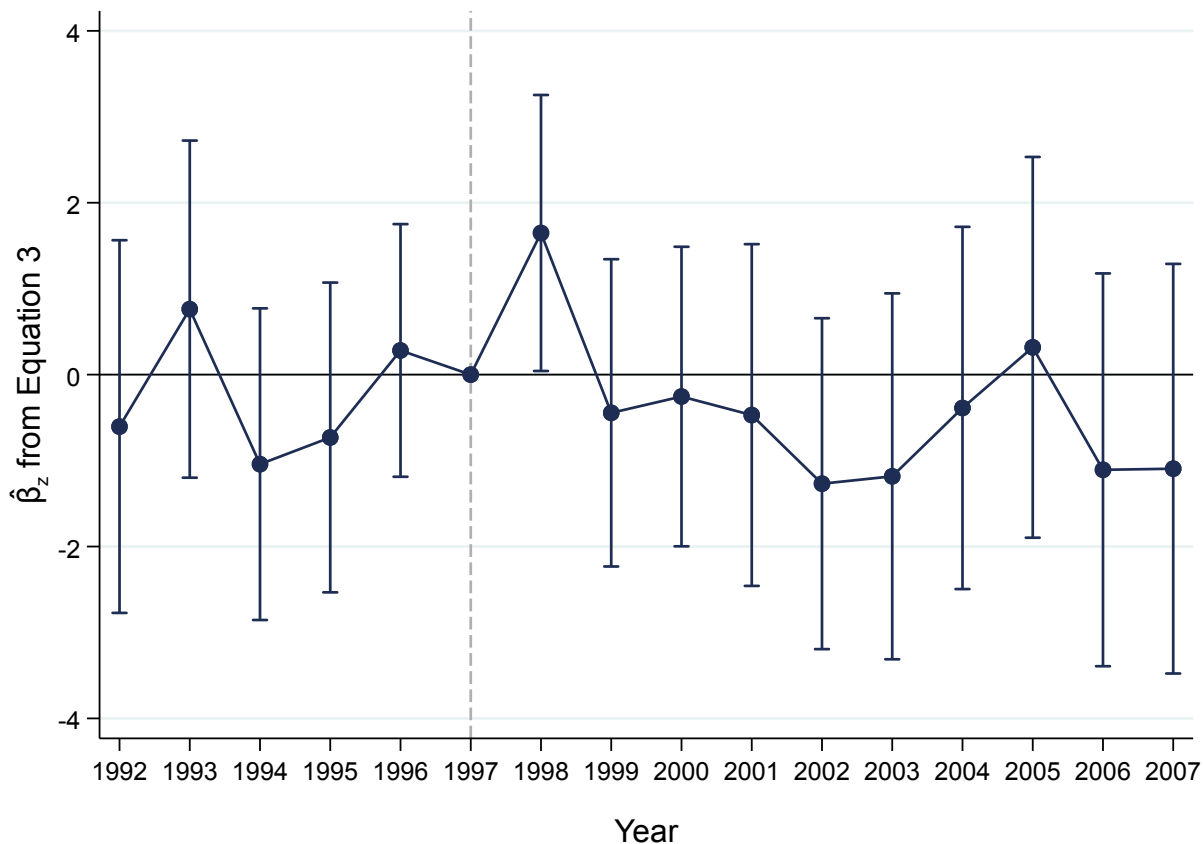
Notes: This figure plots the response in grants funded in the teaching hospital sample, where BBA Bite is the share of 1995 patient revenues that come from IME and DSH payments. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of grants funded})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table F2, Panel A, Column 1 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.

Figure F4: Effect on the Number of Publications



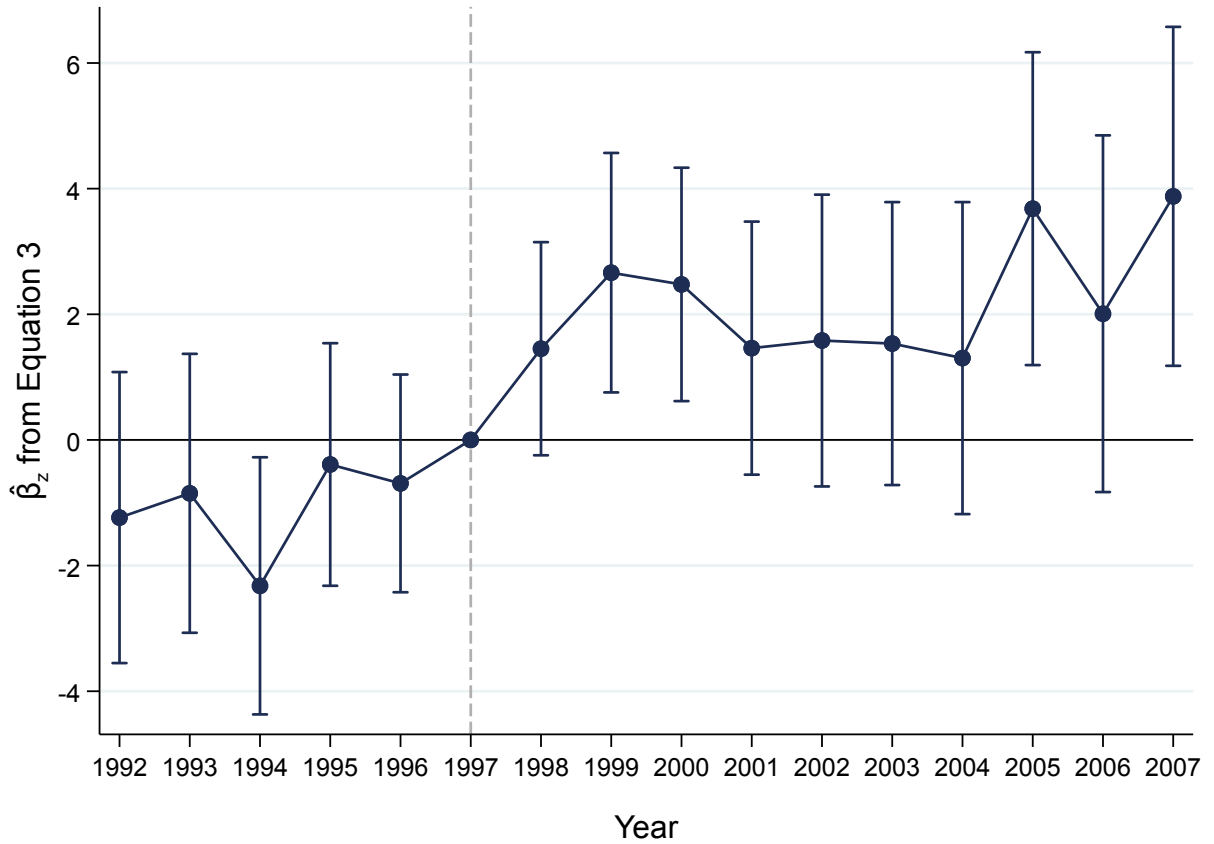
Notes: This figure plots the response in publications in the teaching hospital sample, where BBA Bite is the share of 1995 patient revenues that come from IME and DSH payments. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of publications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table F3, Panel A, Column 1 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; PubMed, Web of Science.

Figure F5: Effect on Bench Research Publications



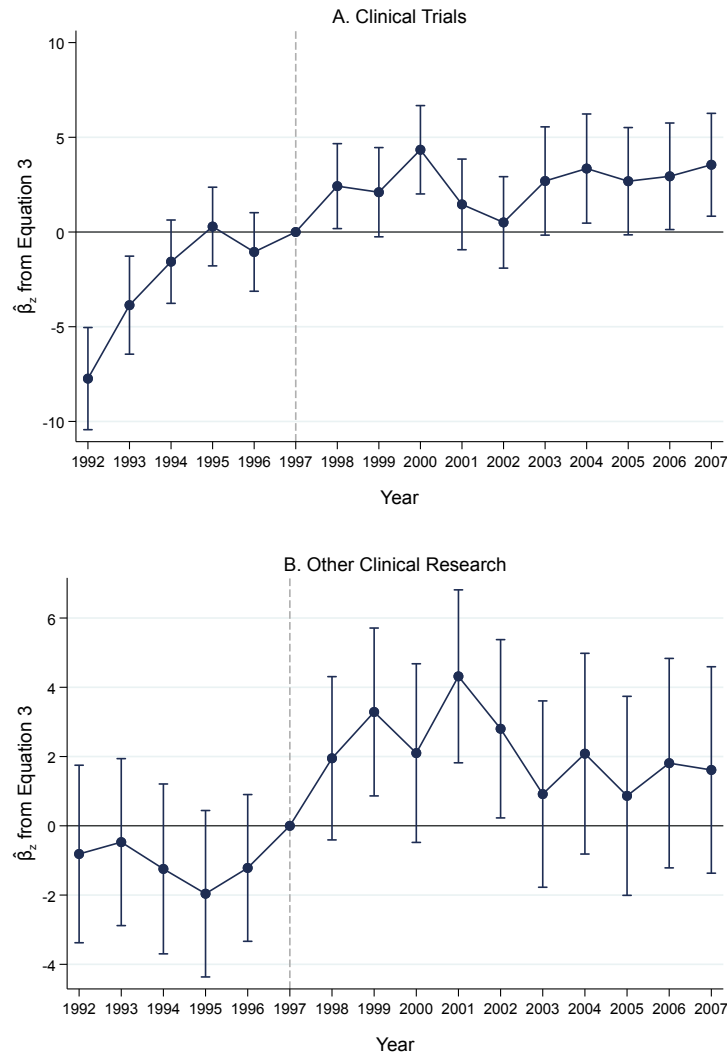
Notes: This figure plots the response in bench research publications in the teaching hospital sample, where BBA Bite is the share of 1995 patient revenues that come from IME and DSH payments. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of publications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table F4, Panel A, Column 1 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Azoulay, Greenblatt, and Heggeness (2020); PubMed; Web of Science.

Figure F6: Effect on Translational Research Publications



Notes: This figure plots the response in translational research publications in the teaching hospital sample, where BBA Bite is the share of 1995 patient revenues that come from IME and DSH payments. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of publications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table F4, Panel A, Column 2 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Azoulay, Greenblatt, and Heggeness (2020); PubMed; Web of Science.

Figure F7: Effect on Clinical Research Publications



Notes: This figure plots the response in clinical research publications in the teaching hospital sample, where BBA Bite is the share of 1995 patient revenues that come from IME and DSH payments. Each dot corresponds to coefficient estimates stemming from the event study specification described in Section 4.1, in which $\text{asinh}(\text{number of publications})$ is regressed onto year effects, hospital effects, as well as interaction terms between a hospital's BBA Bite interacted with the number of years before/after the BBA. Coefficient estimates correspond to a dynamic version of coefficient estimates found in Table F4, Panel A, Columns 5 and 6 and are from OLS models. The 95% confidence interval (corresponding to robust standard errors, clustered around hospital) around these estimates is shown. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Azoulay, Greenblatt, and Heggeness (2020); PubMed; Web of Science.

Table F1: Effect on the Number of Grant Applications

	Grant Cycle			Principal Investigator		
	Total (1)	New (2)	Renewal (3)	MD (4)	PhD (5)	MD-PhD (6)
A. BBA Bite \times Post	3.394*** (0.651)	4.075*** (0.670)	0.820* (0.449)	2.732*** (0.653)	3.577*** (0.571)	4.624*** (0.731)
Elasticity	0.057	0.069	0.016	0.048	0.061	0.096
Adjusted R^2	0.023	0.032	0.006	0.020	0.036	0.052
Diff. Wald test p-value		0.000			0.230	0.013
B. High BBA Bite \times Post	0.118*** (0.0252)	0.141*** (0.0255)	0.0328** (0.0155)	0.0860*** (0.0221)	0.137*** (0.0217)	0.159*** (0.0223)
Elasticity	0.125	0.151	0.033	0.090	0.147	0.172
Adjusted R^2	0.021	0.029	0.006	0.018	0.035	0.046
Diff. Wald test p-value		0.000			0.021	0.003
Mean of Outcome	0.751	0.705	0.372	0.519	0.533	0.328
Nb. Observations	12,192	12,192	12,192	12,192	12,192	12,192
Nb. Hospitals	762	762	762	762	762	762

Notes: This table reports difference-in-differences estimates of the effect of the BBA on the number of grant applications, in the teaching hospital sample. BBA Bite is the share of 1995 patient revenues that come from IME and DSH payments. Observations are at the hospital-year level. Outcomes are transformed with the inverse hyperbolic sine function. Column 1 presents results from OLS regressions. Columns 2-6 present estimates from seemingly unrelated regressions. Each coefficient is from a separate regression. The elasticity of 0.057 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 5.7 percent yearly increase in grant applications following the BBA’s enactment. Similarly, a Panel B elasticity of 0.125 implies that High BBA Share hospitals experience on average a 12.5 percent yearly increase in grant applications in the post-BBA time period. The fourth row and eighth row show p -values from Wald tests that compare coefficients on BBA Bite \times After (Panel A) or High BBA Bite \times After (Panel B) across different columns (Column 2 vs. Column 3; Column 4 vs. Column 5; Column 4 vs. Column 6). Robust standard errors (clustered at the hospital level) are in parentheses. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.
* $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

Table F2: Effect on the Number of Grants Funded

	Grant Cycle			Principal Investigator		
	Total (1)	New (2)	Renewal (3)	MD (4)	PhD (5)	MD-PhD (6)
A. BBA Bite \times Post	2.641*** (0.531)	3.552*** (0.592)	0.952** (0.377)	1.972*** (0.499)	2.818*** (0.547)	3.219*** (0.513)
Elasticity	0.047	0.068	0.027	0.047	0.062	0.146
Adjusted R^2	0.017	0.029	0.003	0.012	0.024	0.033
Diff. Wald test p-value		0.000			0.155	0.013
B. High BBA Bite \times Post	0.0926*** (0.0184)	0.115*** (0.0193)	0.0435*** (0.0123)	0.0629*** (0.0156)	0.108*** (0.0172)	0.105*** (0.0158)
Elasticity	0.097	0.122	0.044	0.065	0.114	0.111
Adjusted R^2	0.015	0.023	0.004	0.010	0.023	0.027
Diff. Wald test p-value		0.000			0.005	0.006
Mean of Outcome	0.439	0.382	0.246	0.285	0.300	0.159
Nb. Observations	12,192	12,192	12,192	12,192	12,192	12,192
Nb. Hospitals	762	762	762	762	762	762

Notes: This table reports difference-in-differences estimates of the effect of the BBA on the number of grants funded, in the teaching hospital sample. BBA Bite is the share of 1995 patient revenues that come from IME and DSH payments. Observations are at the hospital-year level. Outcomes are transformed with the inverse hyperbolic sine function. Column 1 presents results from OLS regressions. Columns 2-6 present estimates from seemingly unrelated regressions. Each coefficient is from a separate regression. The elasticity of 0.047 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 4.7 percent yearly increase in grant applications following the BBA’s enactment. Similarly, a Panel B elasticity of 0.097 implies that High BBA Share hospitals experience on average a 9.7 percent yearly increase in grant applications in the post-BBA time period. The fourth row and eighth row show p -values from Wald tests that compare coefficients on BBA Bite \times After (Panel A) or High BBA Bite \times After (Panel B) across different columns (Column 2 vs. Column 3; Column 4 vs. Column 5; Column 4 vs. Column 6). Standard errors are in parentheses, and are clustered at the hospital level. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.
* $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

Table F3: Effect on Publication Impact

	Total										
	By Citation Percentile					Cited in a Patent			By Disruption		
	≤25	26-50	51-75	76-95	96-99	>99	Yes	No	Consolidating Research	Disruptive Research	
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	
A. BBA Bite × Post	1.905* (1.021)	1.920** (0.732)	3.141*** (0.747)	2.980*** (0.760)	2.934*** (0.618)	2.523*** (0.517)	1.578** (0.730)	2.146** (0.999)	2.030** (0.963)	2.645*** (0.642)	
Elasticity	0.032	0.041	0.053	0.050	0.053	0.076	0.026	0.036	0.034	0.051	
Adjusted R ²	0.031	0.023	0.022	0.028	0.031	0.026	0.014	0.036	0.029	0.013	
Diff. Wald test p-value	-	0.250	0.090	0.170	0.284	0.554	0.488		0.436		
B. High BBA Bite × Post	0.023 (0.040)	0.070** (0.032)	0.068** (0.029)	0.083** (0.029)	0.107*** (0.021)	0.096*** (0.016)	0.057** (0.029)	0.034 (0.038)	0.024 (0.041)	0.065** (0.026)	
Elasticity	0.023	0.072	0.070	0.086	0.113	0.100	0.059	0.035	0.024	0.067	
Adjusted R ²	0.030	0.029	0.020	0.026	0.030	0.026	0.013	0.035	0.027	0.010	
Diff. Wald test p-value	-	0.034	0.017	0.036	0.020	0.059	0.468		0.218		
Mean of Outcome	1.991	1.153	1.089	0.962	0.469	0.232	0.976	1.876	1.822	0.800	
Nb. Observations	12,480	12,480	12,480	12,480	12,480	12,480	12,480	12,480	12,480	12,480	
Nb. Hospitals	762	762	762	762	762	762	762	762	762	762	

Notes: This table reports difference-in-differences estimates of the effect of the BBA on the number of publications, by impact, in the teaching hospital sample. BBA Bite is the share of 1995 patient revenues that come from IME and DSH payments. Observations are at the hospital-year level. Outcomes are transformed with the inverse hyperbolic sine function. Estimates are from seemingly unrelated regressions and each coefficient is from a separate regression. Each publication's disruptiveness is measured by using the Funk and Owen-Smith (2017) disruptiveness index, denoted by d . Column 8 refers to publications with $d \leq 95^{th}$ percentile and Column 9 refers to publications with $d > 95^{th}$ percentile. The elasticity of 0.032 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 3.2 percent yearly increase in publications following the BBA's enactment. Similarly, the elasticity of 0.023 in Panel B implies that High BBA Bite hospitals experience on average a 2.3 percent yearly increase in publications in the post-BBA time period. The fourth row and eighth row show p -values from Wald tests that compare coefficients on BBA Bite × After (Panel A) or High BBA Bite × After (Panel B) across different columns. For Columns 2 to 7, the fourth and eighth row compare estimates in Column 1 vs. estimates in the focal column. For Columns 8 and 9, the fourth and eighth row show p -values from Wald tests that compare Column 8 and 9 estimates. For Columns 10 and 11, the fourth and eighth row show p -values from Wald tests that compare Column 10 and Column 11. Standard errors are in parentheses, and are clustered at the hospital level. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Funk and Owen-Smith (2017); PubMed, Web of Science.

* $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

Table F4: Effect on Publication Composition

	Laboratory Research	Translational Research			Clinical Research	
	Bench MeSH	Translational MeSH	Builds on Translational MeSH	Inspiring Translational MeSH	Clinical Trials	Other
	(1)	(2)	(3)	(4)	(5)	(6)
A. BBA Bite \times Post	-0.202 (0.796)	3.119*** (0.781)	4.767*** (0.802)	3.815*** (0.753)	4.927*** (0.822)	3.125*** (0.846)
Elasticity	-0.003	0.052	0.082	0.064	0.084	0.052
Adjusted R^2	0.000	0.018	0.065	0.028	0.086	0.024
B. High BBA Bite \times Post	-0.022 (0.029)	0.094** (0.031)	0.170*** (0.029)	0.124*** (0.027)	0.188*** (0.031)	0.081** (0.033)
Elasticity	-0.022	0.098	0.185	0.132	0.207	0.083
Adjusted R^2	0.000	0.016	0.063	0.025	0.085	0.022
Mean of Outcome	0.826	1.062	0.798	0.804	0.950	1.398
Nb. Observations	12,480	12,480	12,480	12,480	12,480	12,480
Nb. Hospitals	762	762	762	762	762	762

Notes: This table reports difference-in-differences estimates of the effect of the BBA on bench, translational, and clinical trial research in hospitals, in the teaching hospital sample. BBA Bite is the share of 1995 patient revenues that come from IME and DSH payments. Observations are at the hospital-year level. Outcomes are transformed with the inverse hyperbolic sine function. Estimates are from OLS regressions, and each coefficient is from a separate regression. Column 1 refers to publications that are not disease-oriented, are not clinical trial publications, and rely on either a molecular biology technique, a model organism, cellular structures and macromolecules, or biochemical and cellular processes (based on MeSH terms). Column 2 refers to publications that are disease-oriented, are not clinical trial publications, and rely on either a molecular biology technique, a model organism, cellular structures and macromolecules, or biochemical and cellular processes (based on MeSH terms). Column 3 refers to publications that report the results of a clinical trials, or are tagged by a human MeSH term and also cite a translational publication. Column 4 refers to publications that are translational and is cited by a clinical trial publication (or one that contains a human MeSH term). Column 5 refers to publications that are indicated as clinical trials based on MeSH terms or the publication type field in *PubMed*. Finally, Column 6 refers to publications that are disease-oriented, not clinical trials, and not tagged by any bench MeSH keywords. The elasticity of -0.003 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 0.3 percent yearly decrease in publications following the BBA's enactment. Similarly, the elasticity of -0.022 in Panel B implies that High BBA Bite hospitals experience on average a 2.2 percent yearly decrease in publications in the post-BBA time period. Standard errors are in parentheses, and are clustered at the hospital level. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Azoulay, Greenblatt, and Heggeness (2020); Marx and Fuegi (forthcoming); PubMed; Web of Science.

* $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

Appendix G: Alternative Functional Form Results

This section provides summary statistics and regression results for an alternative functional form where outcomes are the “raw” number of grant applications, grants funded, and publications.

Table G1: Effect on the Number of Grant Applications

	Grant Cycle			Principal Investigator		
	Total (1)	New (2)	Renewal (3)	MD (4)	PhD (5)	MD-PhD (6)
A. BBA Bite \times Post	1763.9*** (325.0)	1637.4*** (295.7)	126.4*** (34.82)	523.9*** (100.6)	863.6*** (152.1)	370.9*** (85.97)
Elasticity	0.557	0.638	0.210	0.473	0.564	0.757
Adjusted R^2	0.086	0.092	0.029	0.068	0.081	0.067
Diff. t-test p-value		0.000			0.000	0.004
B. High BBA Bite \times Post	8.681*** (1.324)	8.012*** (1.187)	0.669*** (0.161)	2.557*** (0.419)	4.333*** (0.664)	1.760*** (0.312)
Elasticity	0.984	1.121	0.400	0.829	1.016	1.290
Adjusted R^2	0.066	0.069	0.025	0.051	0.063	0.049
Diff. t-test p-value		0.000			0.000	0.000
Mean of Outcome	8.824	7.150	1.674	3.082	4.265	1.364
Nb. Observations	12,480	12,480	12,480	12,480	12,480	12,480
Nb. Hospitals	780	780	780	780	780	780

Notes: This table reports difference-in-differences estimates of the effect of the BBA on the “raw” number of grant applications, in the teaching hospital sample. Observations are at the hospital-year level. Column 1 presents results from OLS regressions. Columns 2-6 present estimates from seemingly unrelated regressions. Each coefficient is from a separate regression. The elasticity of 0.557 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 55.7 percent yearly increase in grant applications following the BBA’s enactment. Similarly, a Panel B elasticity of 0.984 implies that High BBA Share hospitals experience on average a 98.4 percent yearly increase in grant applications in the post-BBA time period. The fourth row and eighth row show p -values from Wald tests that compare coefficients on BBA Bite \times After (Panel A) or High BBA Bite \times After (Panel B) across different columns (Column 2 vs. Column 3; Column 4 vs. Column 5; Column 4 vs. Column 6). Robust standard errors (clustered at the hospital level) are in parentheses. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.

* $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

Table G2: Effect on the Number of Grants Funded

	Grant Cycle			Principal Investigator		
	Total (1)	New (2)	Renewal (3)	MD (4)	PhD (5)	MD-PhD (6)
A. BBA Bite \times Post	473.3*** (95.54)	408.4*** (81.42)	64.92*** (16.69)	154.3*** (29.89)	210.1*** (42.30)	105.1*** (26.90)
Elasticity	0.517	0.626	0.248	0.446	0.504	0.738
Adjusted R^2	0.079	0.087	0.018	0.051	0.062	0.053
Diff. t-test p-value		0.000			0.012	0.005
B. High BBA Bite \times Post	2.294*** (0.382)	1.951*** (0.314)	0.344*** (0.0795)	0.766*** (0.134)	1.031*** (0.175)	0.477*** (0.0917)
Elasticity	0.901	1.073	0.471	0.796	0.888	1.203
Adjusted R^2	0.053	0.057	0.013	0.035	0.043	0.033
Diff. t-test p-value		0.000			0.010	0.000
Mean of Outcome	2.548	1.817	0.730	0.963	1.162	0.396
Nb. Observations	12480	12480	12480	12480	12480	12480
Nb. Hospitals	780	780	780	780	780	780

Notes: This table reports difference-in-differences estimates of the effect of the BBA on the “raw” number of grants funded, in the teaching hospital sample. Observations are at the hospital-year level. Column 1 presents results from OLS regressions. Columns 2-6 present estimates from seemingly unrelated regressions. Each coefficient is from a separate regression. The elasticity of 0.517 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 51.7 percent yearly increase in grant applications following the BBA’s enactment. Similarly, a Panel B elasticity of 0.901 implies that High BBA Share hospitals experience on average a 90.1 percent yearly increase in grant applications in the post-BBA time period. The fourth row and eighth row show p -values from Wald tests that compare coefficients on BBA Bite \times After (Panel A) or High BBA Bite \times After (Panel B) across different columns (Column 2 vs. Column 3; Column 4 vs. Column 5; Column 4 vs. Column 6). Standard errors are in parentheses, and are clustered at the hospital level. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II.

* $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

Table G3: Effect on Publication Impact

	Total										
	By Citation Percentile					Cited in a Patent			By Disruption		
	≤25	26-50	51-75	76-95	96-99	>99	Yes	No	Consolidating Research	Disruptive Research	
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	
A. BBA Bite × Post	6096.601*** (1255.635)	1342.864*** (254.425)	1557.072*** (320.290)	1476.787*** (327.773)	353.511*** (92.528)	116.201*** (28.784)	1035.713*** (271.988)	5060.888*** (994.506)	5419.923*** (1115.450)	216.404*** (46.837)	
Elasticity	0.374	0.359	0.393	0.418	0.434	0.485	0.254	0.414	0.371	0.356	
Adjusted R^2	0.110	0.110	0.100	0.093	0.062	0.046	0.062	0.115	0.100	0.062	
Diff. Wald test p-value	-	-	-	-	-	-	0.000	0.000	0.000	0.000	
B. High BBA Bite × Post	30.434*** (4.827)	6.676*** (0.996)	7.812*** (1.269)	7.167*** (1.245)	1.687*** (0.341)	0.566*** (0.113)	5.097*** (1.042)	25.337*** (3.850)	25.426*** (4.378)	1.035*** (0.175)	
Elasticity	0.670	0.641	0.708	0.728	0.743	0.849	0.450	0.744	0.624	0.611	
Adjusted R^2	0.080	0.079	0.072	0.065	0.043	0.032	0.043	0.085	0.069	0.042	
Diff. Wald test p-value	-	-	-	-	-	-	0.000	0.000	0.000	0.000	
Mean of Outcome	45.404	10.407	11.030	9.844	2.271	0.667	11.337	34.067	40.717	1.692	
Nb. Observations	12,480	12,480	12,480	12,480	12,480	12,480	12,480	12,480	12,480	12,480	
Nb. Hospitals	780	780	780	780	780	780	780	780	780	780	

Notes: This table reports difference-in-differences estimates of the effect of the BBA on the “raw” number of publications, by impact, in the teaching hospital sample. Observations are at the hospital-year level. Estimates are from seemingly unrelated regressions and each coefficient is from a separate regression. Each publication’s disruptiveness is measured by using the Funk and Owen-Smith (2017) disruptiveness index, denoted by d . Column 8 refers to publications with $d \leq 95$ th percentile and Column 9 refers to publications with $d > 95$ th percentile. The elasticity of 0.374 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 37.4 percent yearly increase in publications following the BBA’s enactment. Similarly, the elasticity of 0.670 in Panel B implies that High BBA Bite hospitals experience on average a 67 percent yearly increase in publications in the post-BBA time period. The fourth row and eighth row show p -values from Wald tests that compare coefficients on BBA Bite × After (Panel A) or High BBA Bite × After (Panel B) across different columns. For Columns 8 and 9, the fourth and eighth row show p -values from Wald tests that compare Column 8 and 9 estimates. For Columns 10 and 11, the fourth and eighth row show p -values from Wald tests that compare Column 10 and Column 11. Standard errors are in parentheses, and are clustered at the hospital level. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Funk and Owen-Smith (2017); PubMed, Web of Science.

* $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

Table G4: Effect on Publication Composition

	Laboratory Research	Translational Research			Clinical Research	
	Bench MeSH (1)	Translational MeSH (2)	Builds on Translational MeSH (3)	Inspiring Translational MeSH (4)	Clinical Trials (5)	Other (6)
A. BBA Bite \times Post	603.412** (202.160)	1743.066*** (348.490)	790.506*** (164.228)	993.187*** (202.837)	1181.045*** (239.737)	1754.212*** (374.711)
Elasticity	0.135	0.393	0.575	0.432	0.606	0.423
Adjusted R^2	0.022	0.094	0.103	0.089	0.111	0.100
B. High BBA Bite \times Post	3.610*** (1.017)	8.708*** (1.469)	3.805*** (0.613)	4.774*** (0.837)	5.736*** (0.899)	8.490*** (1.384)
Elasticity	0.291	0.705	0.993	0.746	1.057	0.735
Adjusted R^2	0.019	0.068	0.073	0.061	0.080	0.071
Mean of Outcome	12.413	12.345	3.831	6.398	5.426	11.544
Nb. Observations	12,480	12,480	12,480	12,480	12,480	12,480
Nb. Hospitals	780	780	780	780	780	780

Notes: This table reports difference-in-differences estimates of the effect of the BBA on the “raw” number of bench, translational, and clinical trial research publications in hospitals, in the teaching hospital sample. Observations are at the hospital-year level. Estimates are from OLS regressions, and each coefficient is from a separate regression. Column 1 refers to publications that are not disease-oriented, are not clinical trial publications, and rely on either a molecular biology technique, a model organism, cellular structures and macromolecules, or biochemical and cellular processes (based on MeSH terms). Column 2 refers to publications that are disease-oriented, are not clinical trial publications, and rely on either a molecular biology technique, a model organism, cellular structures and macromolecules, or biochemical and cellular processes (based on MeSH terms). Column 3 refers to publications that report the results of a clinical trials, or are tagged by a human MeSH term and also cite a translational publication. Column 4 refers to publications that are translational and is cited by a clinical trial publication (or one that contains a human MeSH term). Column 5 refers to publications that are indicated as clinical trials based on MeSH terms or the publication type field in *PubMed*. Finally, Column 6 refers to publications that are disease-oriented, not clinical trials, and not tagged by any bench MeSH keywords. The elasticity of 0.135 in Panel A implies that a one percentage increase in BBA Bite is associated on average with a 13.5 percent yearly increase in publications following the BBA’s enactment. Similarly, the elasticity of 0.291 in Panel B implies that High BBA Bite hospitals experience on average a 29.1 percent yearly increase in publications in the post-BBA time period. Standard errors are in parentheses, and are clustered at the hospital level. *Sources:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; Azoulay, Greenblatt, and Heggeness (2020); Marx and Fuegi (forthcoming); PubMed; Web of Science.

* $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

Appendix H: Instrumental Variables Estimation

This section provides regression results for the instrumental variables estimation. As with the BBA Bite specification described in Section 3.2, this empirical strategy only captures exogenous variation in the PPS reimbursement formula.

Following Shen (2003), we estimate hospital-level “long-difference” regressions separately for the two periods, 1995-1999 and 1995-2007. For each period, we estimate the following equation:

$$Research_{h,t_2} - Research_{h,1995} = \beta [ActualPrice_{h,t_2} - NoBBAPrice_{h,t_2}] \times \left[\frac{MedicareDischarges}{TotalDischarges} \right]_{h,1995} + \delta Discharges_{h,1995}$$

where $Research_{h,t_2}$ denotes research in hospital h in the final year of the period t_2 , and $Discharges_{h,1995}$ is the number of discharges in 1995. $ActualPrice_{h,t_2}$ is the true PPS price per discharge for hospital h in year t_2 . To capture the impact of the BBA, we compute $NoBBAPrice_{h,t_2}$, a “no BBA” PPS price per discharge which is the price that hospital h would have received in t_2 had there been no changes to the PPS formula. We do this by multiplying the PPS price per discharge in 1995 by the inflation rate (i.e., the market basket index) for each year until t_2 (Cutler 1998). As in Section 3.2, we weigh the change in PPS price per discharge by the hospital’s reliance on Medicare, as measured by the share of discharges that are covered by Medicare. To aid the interpretation of the coefficients, we multiply the weighed difference in the true and “no BBA” PPS price per discharge by 1000. Figure H2, Panel A displays the distribution of the resulting variable when $t_2 = 1999$. If the BBA leads to an increase in subsequent research levels, we would expect $\beta < 0$.

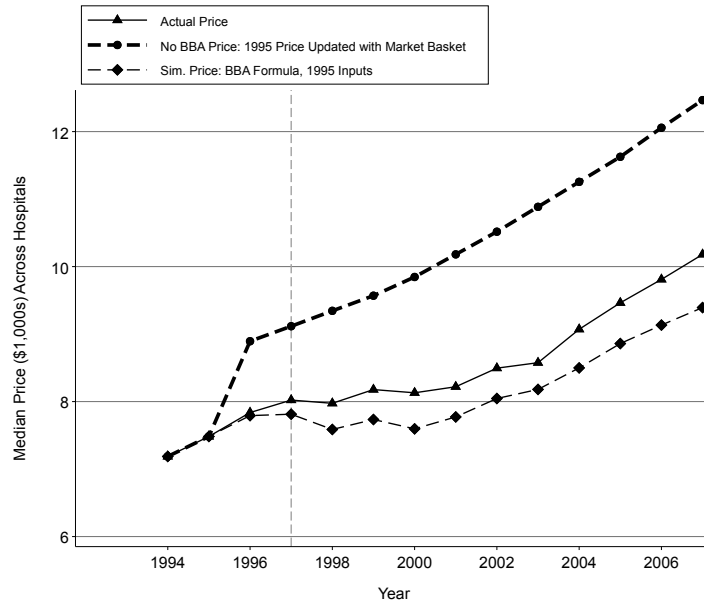
One concern is that $ActualPrice_{h,t_2} - NoBBAPrice_{h,t_2}$ may not accurately capture the true financial effect of the BBA if hospitals respond to the reform by manipulating parts of the reimbursement formula – i.e., by changing the average patient case-mix. To identify the true financial effect of the BBA, we calculate a simulated price based on the updated PPS reimbursement formula, but with inputs held fixed at the pre-BBA (i.e., 1995) level. Figure H1 shows the relationship between the actual, simulated, and no BBA PPS price per discharge and Figure H2, Panel B shows the distribution of the simulated price change, weighed by the hospital’s Medicare share of discharges.

With these price variables, we estimate the following equation in the first stage:

$$[ActualPrice_{h,t_2} - NoBBAPrice_{h,t_2}] \times \left[\frac{MedicareDischarges}{TotalDischarges} \right]_{h,1995} = \gamma [SimPrice_{h,t_2} - NoBBAPrice_{h,t_2}] \times \left[\frac{MedicareDischarges}{TotalDischarges} \right]_{h,1995} + \delta Discharges_{h,1995}$$

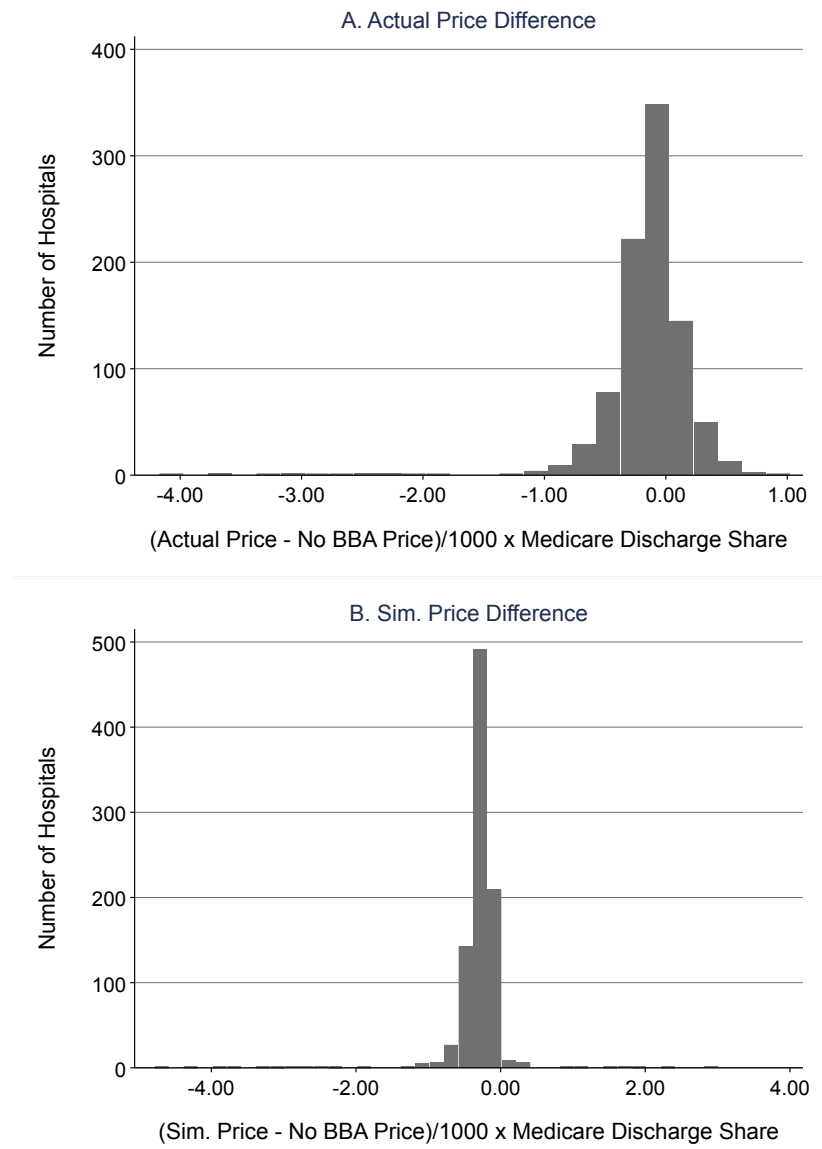
The 2SLS estimates in Table H1 reports the two-stage least square regression results for our primary research outcomes. The results are consistent with our core results: hospitals that experience a larger financial loss as a result of the BBA experience an increase in research outcomes. The effects are both seen in the short-run (Panel A) and long-run (Panel B), though the effects are only statistically significant for publications in the long-run.

Figure H1: Trends in Actual, Simulated, and No BBA Medicare Prices



Notes: This figure plots the median level of actual, simulated, and no BBA PPS price per discharge, averaged across hospitals in the teaching hospital sample. The dashed line indicates the year in which the BBA came into effect. The dashed line indicates the year in which the BBA came into effect. *Sources:* Healthcare Provider Cost Reporting Information System, Inpatient Prospective Payment System Payment Impact Files.

Figure H2: Distribution in Price Changes



Notes: This figure shows a histogram of the true change (Panel A) and the simulated change (Panel B) in average PPS price per discharge, weighed by the Medicare share of discharges. The sample is the teaching hospital sample. *Sources:* Healthcare Provider Cost Reporting Information System, Inpatient Prospective Payment System Payment Impact Files.

Table H1: Effect on Research Levels

	First Stage	Grant Applications		Grants Funded		Total Pubs	
	Δ Actual Price (1)	OLS (2)	IV (3)	OLS (4)	IV (5)	OLS (6)	IV (7)
A. 1995 – 1999							
Δ Sim. Price	0.713*** (0.0808)						
Δ True Price		0.237 (0.371)	0.202 (0.449)	0.0933 (0.207)	-0.193 (0.326)	-0.449 (2.506)	-5.784 (4.122)
Discharges in 1995	-0.000512 (0.00125)	0.118*** (0.0349)	0.118*** (0.0348)	0.0877*** (0.0226)	0.0876*** (0.0225)	1.398*** (0.283)	1.395*** (0.282)
Cragg-Donald Wald F-Stat	44						
Mean of Outcome	-0.17	0.98	0.98	0.78	0.78	11.95	11.95
Observations	776	776	776	776	776	776	776
B. 1995 – 2007							
Δ Sim. Price	0.857*** (0.0468)						
Δ True Price		0.321 (1.035)	-1.113 (1.404)	0.108 (0.185)	-0.128 (0.240)	-3.619 (3.651)	-8.800* (4.747)
Discharges in 1995	-0.00382* (0.00213)	0.915*** (0.250)	0.897*** (0.248)	0.129** (0.0463)	0.126** (0.0459)	2.601*** (0.669)	2.534*** (0.663)
Cragg-Donald Wald F-Stat	214						
Mean of Outcome	-0.48	8.78	8.78	1.30	1.30	25.69	25.69
Observations	739	739	739	739	739	739	739

Notes: This table reports “long-difference” 2SLS estimates of the effect of the BBA on the number of grant applications, grants funded, and publications, in the teaching hospital sample. Observations are at the hospital-level. Panel A examines the short-run effect of the BBA, by estimating the change in research outcomes between 1995 and 1999. Panel B investigates the long-run effect of the BBA, by estimating the change in research outcomes between 1995 and 2007. For ease of interpretation, “Discharges in 1995” are the number of discharges in 1995 divided by 1000. Robust standard errors are in parentheses. *Source:* Healthcare Provider Cost Reporting Information System; Inpatient Prospective Payment System Payment Impact Files; NIH IMPAC II; PubMed.

* $p < 0.01$, ** $p < .05$, *** $p < 0.001$.

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