How Do Health Systems Capitalize on Public Programs? Side Effects of the 340B Drug Pricing Program*

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Abstract

Many government programs are designed to transfer resources to disadvantaged people and organizations that provide public services, but these programs often inadvertently create incentives for agents to exploit their provisions. Assessing how agents differentially game programs is essential to understand their incidence and correct market distortions. In this paper, I study how hospitals heterogeneously gamed the 340B Drug Pricing Program — a federal program intended to aid providers that treat low-income patients by requiring drug makers to sell drugs to participants at steep discounts. I focus on the role of health systems, which coordinate the business functions of numerous providers and may thereby facilitate passing 340B discounts on to drugs administered outside hospital walls. Using a staggered adoption design, I find that 340B increased hospitals' Medicare spending on cancer drugs by an average of $200,000 per year. Remarkably, this increase was entirely driven by health system-affiliated hospitals, which increased infusions by 72 percent. System hospitals increased medical oncologist employment only modestly, indicating that 340B did not lead hospitals to forge many new relationships with physicians through practice acquisitions. System hospitals also did not increase cancer screening or adopt new non-medical cancer treatments, indicating little effort to attract new patients. Instead, my analysis suggests that health systems necessarily have advantages in gaming programs like 340B, but resulting distortions may be substantially mitigated by regulation of billing practices.

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Many government programs are designed to transfer resources to individuals in need and organizations that provide valuable public services. However, these programs often create incentives for agents to "game" them to benefit in ways that were not intended by policy makers. Economic distortions ensue from gaming of programs across many domains: taxpayers manipulate earnings to maximize tax credits (Chetty et al. 2013), health care providers bill public health insurance plans for inappropriate or fraudulent claims (Shi 2023), private health plans inflate patient health risk to increase reimbursement (Geruso & Layton 2020), firms relabel general expenses as research and development to avail themselves of generous tax credits (Chen et al. 2021), firms strategically develop products to meet the minimum criteria for government environmental certification (Houde 2022), and drug makers use FDA safety requirements to delay the entry of generic competition (Vokinger et al. 2017). Examples of gaming like these have been studied extensively, yet scholars have placed less emphasis on identifying characteristics that enable individuals and firms to game policies.

An underemphasis on agents' comparative advantage in gaming is concerning for two reasons. First, it obscures the incidence of policies, potentially casting blame where it is unwarranted and misguiding policy makers who are eager to craft reforms to eliminate gaming. Second, a focus only on aggregate responses minimizes the importance of economic mediators in the production of gaming. While policies may create the incentive to game, differences in gaming behavior are partially a product of different economic circumstances, not just a reflection of psychological differences in willingness-to-game. Furthermore, research on how economic factors lead to heterogeneity in gaming may be particularly valuable to policy makers, who have access to a wealth of economic data and policy tools to affect economic incentives but little ability to impact attitudes towards gaming.

In this paper, I study the role of health systems in the heterogeneous gaming of the 340B Drug Pricing Program, a U.S. federal program intended to help hospitals that provide care to low-income and uninsured patients. The 340B program requires drug makers to offer participating hospitals steep discounts on drugs, which hospitals can then administer on-site or at off-site outpatient de-

partments.[1] The program was intended to allow a handful of safety net hospitals to stretch their resources; however, the program has since expanded significantly: throughout the 1990s, only 90 hospitals participated (about 2 percent), but as of 2019, over 2,400 hospitals (53 percent) participated. Moreover, hospitals that registered for 340B in recent years serve communities that tend to be wealthier and better insured than those served by earlier participants (Conti & Bach 2014). At the same time, increased ownership of oncology practices by hospitals has driven concern that the program is being misused to obtain discounts on expensive drugs primarily administered to patients with generous health coverage.

Discounts on drugs through the 340B Program make administering drugs especially profitable for participating hospitals. This incentivizes these hospitals to administer more discounted drugs, but to do so they must identify more patients to treat. Hospitals might reasonably attract more cancer patients by increasing cancer screening or improving the quality of oncology care by offering more complementary services or investing in new cancer care technologies, passing on some of the benefits of the program to patients. However, because discounted drugs may be administered at off-campus outpatient departments, 340B hospitals might alternatively seek to integrate with outpatient facilities to pass their discounts on to drugs administered at those sites, increasing profit. To date, the latter mechanism has been explored in several papers with results that — at face value — are somewhat contradictory.[2] I advance a related but distinct hypothesis: existing integration of hospitals and outpatient clinics within health systems — organizations that own and manage multiple sites of care — facilitates gaming by allowing outpatient clinics to be relabeled as hospital outpatient departments (HOPDs) of 340B hospitals and thereby pass discounts on to more sites of care.

To administer discounted drugs at off-campus HOPDs, 340B hospitals must register those fa-

[1] They may also dispense retail pharmaceuticals at a hospital-owned or contract pharmacy. Infused drugs, by their nature, are not retail pharmaceuticals and are instead administered in an outpatient setting, either on the hospital's campus or at an off-site outpatient facility.

[2] Alpert et al. (2017) found no effect of 340B on hospital or health system ownership of oncology practices. In contrast, both Desai & McWilliams (2018) and Jung et al. (2018) found that 340B increased HOPD Medicare spending on cancer drugs and Desai and McWilliams found that 340B hospitals employed more oncologists. While these results may seem contradictory at face value, health system integration may lead to substantial increases in HOPD-based care among a fixed set of providers.

cilities with the Health Resources and Services Administration (HRSA) and demonstrate that those facilities are "integral part[s] of the 'hospital.'" Specifically, hospitals must report those facilities as reimbursable on the hospital's Medicare Cost Report, a process that involves substantial financial integration between the hospital and facility (*Notice Regarding Section 602 of the Veterans Health Care Act of 1992 Outpatient Hospital Facilities* 1994). However, because health systems often coordinate business functions across multiple facilities, they may be able to swiftly respond to a single affiliated hospital joining 340B by changing how off-site outpatient facilities bill Medicare to qualify them as financially integrated with that hospital. Doing so would effectively allow systems to game the 340B program by relabeling sites of care as departments of 340B hospitals without further acquisitions. Thus, the integration of business functions within health systems may facilitate gaming of the 340B program.

To provide evidence on heterogeneous gaming of 340B, I evaluate how participation in the program differentially impacted how hospitals bill Medicare for infused cancer therapies. Medicare Part B, the health insurance benefit that covers professionally administered drugs and outpatient services for elderly Americans, bases reimbursement of these drugs on non-340B acquisition prices plus a small markup. Coupled with generous Part B reimbursement, administering 340B-discounted cancer drugs is reliably profitable: one study estimated that profits on 340B-discounted cancer drugs reimbursed by Medicare Part B in 2016 totaled nearly $1 billion, over half of the profits on all drugs reimbursed by Part B in that year (Conti et al. 2019).[3,4]

I assess how 340B affected hospitals' billing of cancer drugs using a staggered adoption design that compares the trend in oncology care billed by newly-340B hospitals to the trend among later participants. I find that 340B participation increased the average number of Part B chemotherapy in-

[3]However, in 2018, Medicare implemented payment cuts for 340B hospitals, decreasing reimbursement for 340B-discounted drugs to 77.5% of average sales price and thereby eliminating much of the savings hospitals could earn from the discounts. This was deemed unlawful by the Supreme Court in 2022, and CMS has since proposed a remedy of a single $9 billion lump sum payment to 340B hospitals (*Remedy for the 340B-Acquired Drug Payment Policy for Calendar Years 2018-2022* 2023).

[4]Moreover, a focus on drugs covered by Medicare is convenient for mapping empirics to theory: because off-campus HOPDs must be listed as reimbursable on a hospital's Medicare Cost Report to qualify for 340B, care performed at off-campus HOPDs will generally be billed to Medicare using that hospital's provider number and thus their claims will appear in the Outpatient file the same as any claim performed on the hospital's campus.

fusions in HOPDs by 62 (35 percent) and spending by $213,000 (42 percent). These increases were entirely driven by hospitals that are members of health systems, which increased chemotherapy spending by $355,000 on average (69 percent). In contrast, independent hospitals only increased spending by 4 percent, a statistically insignificant change. I show that the differential effects of 340B by health system membership are not explained by correlation between health system membership and other (observed) explanatory variables, suggesting that aspects of system-ness are responsible for the difference of effects. Participation led system hospitals to only modestly increase the number of medical oncologists attending any care billed by the hospital and yet substantially increased the number of HOPD infusions attended by medical oncologists. Moreover, infusions attended by historically high-volume medical oncologists increased disproportionately: the share of HOPD infusions attended by the top 25 percent of medical oncologists (by historical patient volume) more than doubled from 8 to 18 percent. These results indicate that system hospitals by-and-large did not create new relationships with physicians and instead maximized profitable care provided by existing affiliates.

I also find little evidence that system hospitals attempted to expand their market size by screening for more patients or increasing quality to compete for patient referrals. Participation in 340B did not increase HOPD screenings for breast and colon cancer nor did hospitals increase adoption of full-field digital mammography in place of screen-film mammography. Participation in 340B also did not increase system hospitals' employment of radiation oncologists or surgical oncologists, who provide highly complementary services. Likewise, the program did not lead hospitals to increase the number of breast or colorectal cancer surgeries nor adopt novel laparoscopic or robotic methods for colon cancer surgery. I do find that 340B hospitals increased use of intensity-modulated radiation therapy more than control hospitals, but otherwise they did not increase use of novel radiation therapy techniques. On net, I find little evidence that system hospitals engaged in efforts to expand their market size through increased screening or improving quality of cancer care.

Finally, I show that acquisitions of 340B and non-340B hospitals respectively increase and decrease those hospitals' billing for cancer drugs when they are acquired by a system with other

340B and non-340B hospitals in the same geographic market, suggesting that acquisitions lead to profitable restructuring. In total, my results demonstrate that system hospitals were the primary driver of the expansion of hospital-based chemotherapy and further suggest that characteristics of health systems facilitated gaming of the program by relabeling care as hospital-based. This paper is most related to a growing literature on the incidence and effects of the 340B program. In particular, my results help reconcile the findings of Alpert et al. (2017) and Desai & McWilliams (2018), who respectively find that 340B had no effect on hospital and health system acquisition of oncology practices and significant effects on HOPD-based cancer drug use. My results suggest that, instead of 340B increasing hospital or health system ownership of oncology practices, existing integration (in the form of health systems) allows systems to bill for care in such a way to increase profits without expanding system membership or changing medical practice. Thus, while participation in health systems may be inelastic, intra-system coordination can enable strategic responses that allow for a profitable expansion of HOPD-based care among a fixed set of providers.

This paper is also related to the literature on the effects of consolidation in health care markets. Despite numerous proposed pathways for cost savings, evidence that consolidation in hospital markets reduces costs has been scarce (Burns & Pauly 2002, Dranove & Lindrooth 2003, Gaynor & Town 2011, Dafny & Lee 2015). However, a recent paper by Andreyeva et al. (2023) finds that acquisitions of independent hospitals by systems results in substantial reductions in total costs, driven by decreased costs of support function employment, capital, and financing. In this paper, I also find that integration can lead to cost reductions, albeit reductions rooted in systems' ability to game policies that preferentially treat a subset of sites of care. Large initial investments in the coordination of business functions across many sites of care may pay off for health systems if it makes them more capable of responding strategically to policy changes moving forward.

Lastly, this paper is most generally related to the broad literature on gaming of public programs. I highlight how initial characteristics of certain firms — specifically, health system membership — may lead to drastically different gaming responses. These responses are not due to some hospital managers being especially cunning or because some hospitals happen to operate in information-

rich environments, but because characteristics of certain hospitals facilitate gaming of a particular policy. Because health systems coordinate numerous facets of their operation across many facilities, policy that privileges particular units may generally have effects that extend beyond that unit. Among the many pitfalls that policy makers must avoid, extra care must be taken in designing policy targeted towards individual units of multi-unit enterprises due to high potential for gaming.

Section 1 describes the history and key features of the 340B program, focusing on its relevance to HOPD cancer drug spending, and presents a case study of cancer drug spending in Pittsburgh. Section 2 describes the data employed for estimating the effects of 340B on care, and Section 3 details the methodology and assumptions behind causal identification. Section 4 presents these estimates, and Section 5 concludes with a discussion of their implications.

1 Background

1.1 The 340B Drug Pricing Program

The 340B Drug Pricing Program was created in 1992 as a provision of the Veteran's Health Care Act and was intended to ensure access to outpatient drugs at safety net hospitals. The program, which is administered by the Health Resources and Services Administration (HRSA), requires drug manufacturers that participate in the Medicaid or Medicare Part B programs to sell drugs to participating health providers (known as covered entities) at significant discounts.[5] Covered entities can then dispense discounted drugs to any of their patients (regardless of their health plan), receive full reimbursement from payers, and pocket the difference.[6] Today, after a series of expansions, over half

[5] Given these programs enroll tens of millions of elderly Americans, drug manufacturers do not commonly opt out of these programs, especially cancer drug makers.

[6] A notable exception is fee-for-service Medicaid. Medicaid has a statutory right to prescription drug discounts and drugs may not receive multiple discounts. Covered entities elect to either "carve-in" by dispensing 340B drugs to Medicaid patients or "carve-out" by maintaining separate inventories of non-340B drugs for Medicaid patients. Carving-in precludes the necessity of maintaining separate inventories, but covered entities must ensure that drugs do not receive duplicate discounts. Moreover, under the 2016 Medicaid Covered Outpatient Drug Rule, states must reimburse covered entities at the discounted 340B price (plus a small mark-up) for fee-for-service beneficiaries. States are not required to reimburse at this rate for Medicaid managed care, but nevertheless, states are increasingly either forcing providers to carve-out Medicaid MCO patients or reimbursing at the 340B price.

of hospitals in the United States are 340B covered entities. Yet the origins of 340B are humble: it was conceived as a narrow policy response to issues created by the Medicaid Drug Rebate Program, which unintentionally disincentivized pharmaceutical firms from offering discounts to safety net hospitals by requiring them to give the same discounts to Medicaid (Thomas & Schulman 2020). By creating a separate discount program for safety net hospitals, drug makers could pass on savings to safety net hospitals without being required to offer lower prices to state Medicaid programs.

Hospitals generally qualify for 340B via their disproportionate share hospital (DSH) adjustment, which is intended to measure the share of patients with low income.[7,8] Any non-profit or government hospital with DSH adjustment above 11.75 percent qualifies for 340B, although hospitals must opt into the program by registering themselves and any offsite clinics with HRSA.[9,10]

Drug prices are regulated by 340B through a price cap known as the 340B ceiling price. The ceiling price is equal to the average price offered to wholesalers and retail pharmacies (AMP) less a discount. For most brand name drugs, that discount is the greater of 23.1 percent of AMP and the best price offered by the manufacturer. For example, if AMP were $100 and the manufacturer's best price were $80, then the discount would total $23.10 and the 340B ceiling price $76.90; if the manufacturer dropped their best price to $70, then the discount would increase to $30 and the ceiling price would drop to $70. 340B discounts are confidential but are reported to typically range between 20 to 50 percent, representing significant discounts from AMP.[11] Nevertheless, discounts are only valuable to covered entities to the extent that reimbursement stays high: if payers reduce reimbursement of 340B participants because they face lower acquisition costs, the profit margin on

[7]For-profit hospitals are not eligible to participate in 340B.

[8]The DSH adjustment is a piecewise function of the Disproportionate Patient Percentage (DPP), which in turn is the sum of the hospital's Medicare SSI percentage (the share of total Medicare inpatient days attributable to patients also entitled to Supplemental Security Income) and the Medicaid percentage (the share of total inpatient days attributable to patients eligible for Medicaid but not Medicare Part A).

[9]The Affordable Care Act expanded eligibility in 2010 to include all critical access hospitals, sole community hospitals and rural referral centers with DSH adjustment above 8 percent, and children's hospitals and freestanding cancer hospitals that qualify via a metric that differs from DSH. Note that as of 2019 there were only two cancer hospitals that qualified for 340B via this alternate criterion.

[10]The registration process is fairly simple. Hospitals are required to provide their most recent Medicare cost report and documentation of outpatient facilities and contract pharmacies (if any) during a quarterly enrollment period. If they meet the requirements, hospitals can begin participating at the beginning of the following quarter.

[11]This suggests that the 23.1 percent lower bound on discounts tends to not be binding. Rather, the best prices that manufacturers offer distributors dictate the 340B ceiling price.

cancer drugs will fall, muting the financial benefit of 340B. However, rather than negotiating prices like many commercial insurers, Medicare Part B reimburses providers administratively, typically paying 106 percent of average sales price.[12] This price gives 340B covered entities a significant profit margin on drugs themselves (but covered entities also incur some costs from the act of drug administration).[13] The American Hospital Association (AHA) claims that 340B savings on drug acquisition costs allow hospitals to expand health services to their communities. The 340B Drug Pricing Program is indeed intended to support uncompensated care at safety net hospitals, yet it includes no provisions to dictate how savings be appropriated. The lack of restrictions on 340B profits coupled with soaring purchases of 340B-discounted drugs have raised concerns that the program is not expanding health care to vulnerable populations. Research has largely supported these concerns: studies have found that 340B expanded fastest in high-income areas and participating hospitals did not increase provision of uncompensated care (Conti & Bach 2014, Desai & McWilliams 2021). In any case, 340B discounts yield significant savings for hospitals, and hospitals appreciate the value of the program to their finances.[14]

1.2 Health Systems

While there are several definitions of what constitutes a health system, the key distinguishing factor is a notion of ownership of multiple health care facilities by a single central organization (Furukawa et al. 2020). For instance, AHA defines a health system as a central organization that owns, leases,

[12] Average sales price (ASP) is equal to total sales of a drug net of all price concessions divided by the total number of units sold in a quarter. It measures a conceptually similar concept as AMP and tends to be within a few percent of AMP. Congress recognizes this similarity in its policy: CMS is authorized to substitute the lower of the two prices for reimbursement if there is more than a 5 percent difference. Because the two are so close, basing the 340B discount on a percent of AMP is very similar to basing the discount on a percent of ASP. Thus, even though the discount is based on AMP and Part B reimbursement on ASP, in practice, the profit margin on 340B drugs acquired at the highest possible ceiling price of 76.9 percent can be approximated as (1.06-0.769)×ASP=0.291 ×ASP.

[13] There are also many 340B covered entities that are not hospitals. These are predominately Federally Qualified Health Clinics and lookalikes, which provide primary care to medically underserved populations, and varieties of specialized clinics like Black Lung clinics, Ryan White HIV/AIDS clinics, and family planning clinics. None of these clinics are common sites for medical oncology care.

[14] One manifestation of hospitals' vested interest is AHA's lawsuit against CMS for differentially decreasing Part B reimbursement of 340B drugs in 2018. The AHA brought the suit before the Supreme Court in 2022, alleging that payment cuts were illegal because CMS did not first survey providers' acquisition costs. The Court found in favor of AHA and determined that drug makers owed 340B providers $9 billion.

sponsors, or contract-manages two or more hospitals or a single hospital and three or more other health care organizations. As of 2023, there were 407 health systems in the United States that owned 67 percent of all U.S. hospitals (American Hospital Association 2023*a*). Among these systems, there are several notable for-profit chains including HCA, Community Health Systems, and Tenet Healthcare. However, these for-profit chains own only 14 percent of hospitals, while non-profit systems own 46 percent of hospitals (Furukawa et al. 2020). On the other hand, large non-profit systems like Kaiser Permanente, UPMC, and Mass General Brigham earn tens of billions in annual revenues and are some of the most dominant players in their local markets.

What purpose do systems serve and what makes them so successful? Devers et al. (1994) emphasizes that systems are organizations that facilitate the coordination of business functions, clinical services, and physician incentives across many different facilities. This integration across many facilities has wide ranging implications for firm behavior. On one hand, systems may increase profits by integrating with their competition and raising prices across the board (Gaynor & Town 2011). On the other hand, integration may allow systems to reduce costs through economies of scale and scope. For example, a recent paper by Andreyeva et al. (2023) found that acquisitions of independent hospitals reduced costs of support function employment, capital, and financing. However, integration also gives systems more options in how they bill the Medicare program for care. Therefore strategic systems may be able to adjust billing practices to increase profits.

In Figure 2, I depict a model of Medicare billing for outpatient services. Patients with Medicare coverage seek care at a facility — either a hospital or an outpatient clinic — that may be owned by a health system. In turn, the facility bills Medicare either as a freestanding clinic or as a department of a hospital. Billing as a hospital department is advantageous because it entitles hospitals to bill Medicare based on a different fee schedule that regularly yields higher payments (Medicare Payment Advisory Comission 2022). Additionally, because outpatient clinics that bill Medicare as departments of 340B hospitals (so-called provider-based facilities) report their costs to CMS on their Medicare cost report, they are considered "financially integrated" by HRSA and are therefore eligible to register with the 340B program. Thus, health systems have incentive to bill Medicare as

HOPDs due to higher payments and even greater incentive to bill as HOPDs of 340B hospitals to obtain higher payments and discount eligibility.

This model makes several predictions. First, a single system hospital becoming eligible for 340B incentivizes health systems to switch billing of care at outpatient practices to the newly-340B hospital. This change should be reflected in increased billing of drugs and services by 340B hospitals. Simultaneously, affiliated outpatient practices and non-340B hospitals in the same system and market should decrease Medicare billing. Second, independent hospitals by their nature are not integrated with off-site facilities and therefore cannot modify billing practices to increase discounted drug administration. Third, the total number of drug infusions among people living near the hospital should not change if hospitals are merely modifying billing practices. Finally, the effects of hospital acquisition should depend both on whether the acquired hospital participates in 340B and the status of other hospitals in the system. Importantly, unlike previous research, this conceptual model highlights that systems can increase discounted drug administration without further acquisitions or market expansion. In the following case study, I provide an illustration of this relabeling phenomenon.

1.3 Case Study

To understand the role health systems play in billing for cancer care, it is useful to consider the evolution of the site of cancer drug spending among Medicare beneficiaries living in Pittsburgh, Pennsylvania. Pittsburgh is home to the headquarters of the University of Pittsburgh Medical Center (UPMC), a non-profit health system with over 40 hospitals and 800 doctors' offices and outpatient sites across the state of Pennsylvania (UPMC 2023). UPMC hospitals in Pittsburgh include UPMC Presbyterian — a top-ranked regional hospital and the system's flagship tertiary care hospital — and UPMC Magee-Womens Hospital — a hospital that specializes in women's health care and joined UPMC in 1999 (PHC4 1999). The hospitals are located less than a mile from one another in Pittsburgh's Oakland neighborhood; however, Magee-Womens has participated in the 340B program since 2003 based on its status as a disproportionate share hospital.

Figure 3 depicts fee-for-service Medicare spending on infused cancer drugs among beneficiaries living in the hospital referral region surrounding Pittsburgh. Spending is further decomposed by the type of entity billing Medicare for drugs: either a physician (or group of physicians) or a hospital. Among hospitals, I separately total payments to UPMC Presbyterian and Magee-Womens. Throughout the 2000s, physicians billed Medicare for the vast majority of Pittsburghers' infused cancer drug use; although, as the decade wore on, physicians decreased billing of infused drugs and hospitals increased their share. By the early 2010s, hospitals billed for over half of cancer drug spending. UPMC Presbyterian alone billed for one third of spending in 2013. Yet, two years later in 2015, UPMC Presbyterian billed for $0 of cancer drug spending, its share of local spending fully replaced by new spending at Magee-Womens, which had no history of billing Medicare for more than a trivial fraction of cancer drug spending before the prior year. In the year 2014, in which the two hospitals billed approximately the same amount, UPMC Presbyterian billed for over 97% of the hospitals' combined spending in the first 4 months of the year and less than 1% in the last 7 months.[15].

How did Medicare billing in Pittsburgh change so rapidly? The discontinuous nature of the change suggests that competition among hospitals was not an important factor because the process of competition generally takes time to reach equilibrium. The increase in billing at Magee-Womens could be consistent with collaboration between the hospitals to treat patients at a hospital that can provide cancer drugs at lower cost due to its eligibility for 340B discounts. However, this too seems unlikely because, while Magee-Womens provides some services to men, its cancer program is entirely focused on women's cancers and over half of the newly billed patients are men.[16] A plausible explanation is that facilities that formerly billed care as outpatient departments of UPMC Presbyterian started billing care as outpatient departments of Magee-Womens. This is consistent with a large

[15]Figure A3 depicts the monthly fraction of infusions billed by UPMC Magee-Womens out of all infusions billed by either Magee-Womens or UPMC Presbyterian in 2014. Magee-Womens's share of infusions discontinuously increases from 0 percent in May 2014 to 100 percent in June 2014. Note that the share has been censored to set cells that represent care for 10 or fewer patients to zero.

[16]Magee-Womens cancer program is focused on breast cancer and gynecologic cancers (*Women's Cancer Program at Magee* 2015). Although men may be diagnosed with breast cancer, it is far rarer than one-third of all men's cancer diagnoses in Pittsburgh. Magee-Womens offers infusion services on site, but these services are limited to treatments for autoimmune disorders (*Magee Infusion Center of UPMC - Treatment of Autoimmune Disorders* 2023).

fraction of drugs being administered to men and women, despite the fact that Magee-Womens did not offer those services on site. While it is not possible to observe site of care over 2013–2015, by 2019 68 percent of Magee-Womens cancer drug spending was for drugs administered in a different zip code than the hospital itself, indicating that off-campus drug infusions comprised the majority of Magee-Womens's infusions within 5 years of the shift in billing. Importantly, billing care as a department of Magee-Womens would allow off-campus facilities to be listed as reimbursable on Magee-Womens Medicare Cost Report, making them eligible to administer 340B-discounted drugs to their patients after registering with HRSA.[17] However, this raises the question of whether 340B played an important motivation for UPMC to change its cancer drug billing practices, especially considering Magee-Womens had been a 340B hospital for over a decade at the time of the shift in billing. One piece of evidence is that in January 2015, Magee-Womens registered 13 comprehensive cancer centers as child sites with the 340B program. Previously, the hospital had only registered community health centers as child sites.[18] The timing lines up with the increase in Magee-Womens's cancer drug billing in the prior year: if that increase was related to relabeling of comprehensive cancer centers as departments of Magee-Womens, their costs and charges would appear on the hospital's next Medicare Cost Report and could then register with HRSA as child sites of Magee-Womens to qualify for 340B discounts.

What can we learn from Pittsburgh? First, physicians have drastically decreased the amount they bill Medicare for cancer drugs while hospitals increased their spending in excess of that decline. This pattern is emblematic of a broad trend: while hospitals billed Medicare for only 8 percent of Part B cancer drug spending in 2000, they billed for 53 percent as of 2019. Moreover, HOPD-based cancer drug administration has increased disproportionately in markets with 340B hospitals (Jung et al. 2018). This demonstrates that hospitals, particularly 340B members, now play a substantial role in cancer drug administration across the country. Second, because the physical location

[17] Guidelines for becoming an eligible outpatient facility were established in 1994. Off-site outpatient facilities must be "listed as reimbursable on the hospital's most recently filed Medicare cost report and have associated outpatient expenses and charges in order to be eligible to register for the 340B Program as a child site" (*Notice Regarding Section 602 of the Veterans Health Care Act of 1992 Outpatient Hospital Facilities* 1994, 340B Prime Vendor Program 2023).

[18] See Table A1.

of the billing hospital is not necessarily the site of care, increases in care billed by hospitals may not reflect a change in the site of care, and rather may reflect only a change in the affiliations between clinics and hospitals. Nonetheless, the identity of the billing provider has important implications for 340B discount eligibility. Lastly, the discontinuous change in billing reflects the importance of relationships between providers for cancer drug administration. Specifically, the existing integration of hospitals and other facilities within UPMC suggests that the system may have coordinated the change in billing practice to qualify more UPMC facilities for discounts. More generally, it invites the question: how fundamental are health systems to gaming of the 340B program? In the following sections, I will attempt to shed light on this question.

2 Data

2.1 Cancer drug utilization

For each year in the period 1999-2019, I use 20 percent Medicare beneficiary summary files to identify a cohort of beneficiaries who were continuously enrolled in fee-for-service Medicare throughout that year. I then restrict the sample to years in which beneficiaries were age 66 or older, were entitled to Medicare due to Old-Age and Survivors Insurance, and were living in one of the 306 Hospital Referral Regions (HRRs) created by Dartmouth Atlas. The resulting sample follows 12,680,565 Medicare beneficiaries over 102,785,628 beneficiary-years. I then use diagnosis codes from Medicare claims to determine whether and when each beneficiary was first diagnosed with any of six cancers: breast cancer, brain cancer, colorectal cancer, lung cancer, prostate cancer, or non-Hodgkin's lymphoma (NHL). Diagnoses were determined to be valid if they were reported on an inpatient claim or if the same diagnosis was reported on another claim within a year of the initial diagnosis. Among all beneficiaries, 19.5 percent have a cancer diagnosis between 1999-2019. The final sample consists of 2,387,056 beneficiaries observed over 14,142,741 post-diagnosis beneficiary-

years.[19] Table 1 reports summary statistics for the full sample of beneficiaries and the subset of beneficiaries with cancer diagnoses. Beneficiaries with previously diagnosed cancer are observed an average of 2.2 fewer years than the average beneficiary and are 15 percentage points more likely to die over the course of the sample window. Prostate, breast, and lung cancers are the three most prevalent cancers in the sample, while colorectal, NHL, and brain cancers are the three least.

I use 20 percent Medicare claims files to identify procedures. Cancer drugs are commonly infused in HOPDs and physician practices and thus are reported primarily in the Outpatient and Carrier files, which include outpatient claims submitted by hospitals and physicians, respectively. I search these files for claims that report HCPCS codes beginning with "J9". These drugs encompass chemotherapies such as doxorubicin (J9000), immunotherapies such as Keytruda (pembrolizumab, J9271), and targeted therapies such as Avastin (bevacizumab, J9035). While distinctions between these drug classes are clinically relevant, they are all reimbursed by Medicare according to the same rules, and hospitals are eligible for 340B discounts on each; therefore, I do not distinguish between them in the following analyses and refer to them as cancer drugs or chemotherapy interchangeably. The notion of a cancer drug infusion that I use is the beneficiary-date pair: regardless of the volume of cancer drug procedure codes reported on a single day for a single beneficiary, any beneficiary-date with one or more codes constitutes a single infusion. I quantify cancer drug spending using the allowed amount: the sum of payments made by Medicare, the beneficiary, and other payers to the provider. For my primary analyses, I total annual procedures and spending for each hospital using the provider identifier reported in the Outpatient file. Procedures with non-positive allowed amount are excluded from all aggregations. I multiply hospital totals by 5 to account for the use of a 20 percent random sample.

[19] A small number of beneficiaries are not included in the cancer sample because the years in which they are continuously enrolled in fee-for-service Medicare all precede the year of their diagnosis.

2.2 Physicians

I determine hospitals' employment of oncologists using the Outpatient and Medicare Data on Provider Practice and Specialty (MD-PPAS) files. First, I use MD-PPAS to assign a single specialty to each National Provider Identifier (NPI) by determining the most frequently reported specialty code over the period 2008–2017.[20] I classify medical oncologists as those physicians with specialty codes "83 – Hematology/oncology", "90 – Medical oncology", or "98 – Gynecological/oncology", and separately identify radiation oncologists and surgical oncologists using codes 92 and 91, respectively. I then link oncologist NPIs to outpatient claims either by directly linking to the attending physician's NPI or via a UPIN crosswalk file and count the number of claims reported for each physician-hospital pair in each year.[21] I classify oncologists as employed by a hospital in a particular year if they were reported as attending on one or more claims in that year. I then link medical oncologists to HOPD chemotherapy using the attending physician reported on Outpatient claims for chemotherapy. I additionally quantify oncologists' patient volume using evaluation and management (E/M) codes reported in the Outpatient and Carrier files over the five year period of 2000–2004.[22] For each oncologist and beneficiary, I determine the first year in which a claim was reported for E/M. Then I count the number of first claims for each oncologist over the period and divide by the number of years in which the oncologist had any claims to calculate average volume. Among oncologists with any claims in this period, I calculate the 75th percentile of average volume (160 patients per year) and determine which oncologists fell in the top 25 percent and which fell in the bottom 75 percent or submitted no claims for E/M in this period.

2.3 Hospitals

I use the 340B Covered Entity Database maintained by the Health Resources and Services Administration to determine annual participation in 340B. The database includes participation and

[20] In the case of a tie, I assign the most recently reported of the tied specialties.

[21] The crosswalk file was kindly furnished by SEER-Medicare. See Parsons et al. (2017) for details.

[22] I use this period to determine oncologist volume because it predates 340B participation among the hospitals in the analytic sample and thus is unlikely to be impacted by 340B participation.

termination dates and classifications (disproportionate share hospital/critical access hospital/etc.) of 340B covered entities. I define participating years as those in which hospitals participate in 340B for one or more days. I determine hospitals' health system membership using the American Hospital Association (AHA) Annual Survey, which reports unique identifiers for each health system. The AHA survey counts hospitals as being members of systems if they are a multi-hospital system or a diversified freestanding hospital.[23] In this paper, I will limit the definition of a health system to include only multi-hospital systems, which are those that have "two or more hospitals owned, leased, sponsored, or contract managed by a central organization." (American Hospital Association 2023*b*) I integrate hospital-level data on hospital capacity, accreditations (e.g. cancer hospital or teaching hospital status), disproportionate share hospital adjustment, and more from the AHA Survey, CMS Provider of Service files, and hospital cost reports.

3 Methodology

The key challenge of estimating the impact of 340B on care is that 340B hospitals differ from non-340B hospitals in ways that meaningfully affect how they provide care. For instance, most 340B hospitals qualify for the program on the basis of a high disproportionate share (DSH) adjustment, a metric which is intended to reflect the extent to which hospitals serve low-income patients. Even conditional on DSH adjustment, hospitals that register to participate in 340B likely do so on the basis of unobservable characteristics that are correlated with outpatient cancer drug use. Moreover, controlling for observables is unlikely to be a satisfying solution because hospitals that participate in 340B must register to do so, and therefore are likely the hospitals that believe they have the most to gain from participation.

To address selection into 340B, I estimate the effect of 340B on outpatient hospital health care utilization, using a staggered adoption design. Specifically, I use a stacked difference-in-differences

[23] A single diversified hospital system includes one hospital and three or more pre- or post-acute care organizations that are owned, leased, sponsored, or contract managed by a central organization (American Hospital Association 2023*b*).

model that compares the post-340B change in outcomes among hospitals that begin participating between 2005 and 2013 to control hospitals that begin participating 7 or more years later. With this design, causal identification rests on a parallel trends assumption: hospitals that began participating in 340B would have followed the same trend in outcomes as control hospitals had they not begun participating.

There are two major threats to the parallel trends assumption: first, most 340B hospitals qualify on the basis of a high disproportionate share adjustment (DSH), which may be correlated with factors that have time varying effects on outpatient cancer drug infusions. Indeed, hospitals that begin participating between 2005 and 2013 tend to have higher DSH in the year prior to their participation than later participants. If, for instance, the increasing price of cancer drugs disproportionately decreased their use at high-DSH hospitals because those hospitals are undercompensated for drug administrations, this would tend to negatively bias the effect of 340B. Second, the fact that hospitals must opt into 340B by registering with the Office of Pharmacy Affairs raises concerns that participating hospitals join the program only once they decide to administer more outpatient drugs and moreover that those hospitals would have increased use even without 340B.

I implement the stacked difference-in-differences model according to the method outlined in Cengiz et al. (2019) and Wing (2021). I first identify all hospitals that begin participating in 340B as a DSH hospital between 2005 and 2013 (the event years). For each event year, I create a panel sub-dataset that includes the subset of hospitals that begin participating in 340B in that year and control hospitals that begin participating as a DSH hospital at least 7 years after the event year and no later than 2020. Within each sub-dataset, I include a 12-year window of hospital-year observations beginning five years prior to the event year and ending six years after the event year, using only hospitals are observed throughout the duration of the window. The control hospitals serve as ”clean controls” in the sense that none are treated within the event study window. For instance, the 2005 event comprises hospital-year observations spanning the period 2000–2011 for hospitals that begin participating in 340B in 2005 and control hospitals that begin participating between 2012 and 2020. I then combine each sub-dataset into one stacked dataset.

A key benefit of stacked difference-in-differences is transparent estimation of an average causal effect as a weighted sum of event-specific estimates. These events are depicted in Figure 4, which illustrates the composition of treated and control groups for each event, including the number of hospitals included in each group by first participation year and the window of years used to construct the event's sub-dataset.[24] Stacked difference-in-differences also allows for simple and transparent stratification of the sub-datasets according to characteristics observed in the year prior to the event year (or any other year relative to the event). For each sub-dataset, I can simply split the data using values of a variable (e.g. system membership) as they are observed in the year prior to the event. This crucially allows for sample stratification by system membership in the year prior to treatment, allowing me to test for effect heterogeneity related to health system membership.

Table 2 reports hospital characteristic means in the year preceding event years (e.g. 2004 for the 2005 event). The stacked panel includes 435 treated DSH hospitals and 310 DSH hospitals that serve as controls for at least one event year.[25] While control hospitals are similar on numerous dimensions to treated hospitals prior to 340B participation, treated hospitals, which qualify for the program based on a high DSH adjustment tend to have higher DSH (15.3 v. 9.7, $p < 0.001$). These hospitals are also more likely to be major teaching hospitals (0.14 v. 0.09, $p < 0.05$) and are less likely to have an accredited cancer program (0.52 v. 0.60, $p < 0.05$). Nevertheless, prior to treatment, control hospitals bill Medicare for a similar number of chemotherapy infusions and employ a similar number of oncologists as new 340B hospitals.

$$Y_{htd} = \alpha_{hd} + \lambda_{td} + X'_{htd}\Gamma + \beta^{DD}(Treat_{hd} \times Post_{td}) + \beta^{0}(Treat_{hd} \times TY_{td}) + u_{htd} \qquad (1)$$

To estimate the effect of 340B on HOPD cancer drug use, I estimate Equation 1 by ordinary least squares. Y_{htd} represents the utilization outcome for hospital h in year t for event d. $Treat_{hd}$ indi-

[24] In Figure A4, I depict trends in the main outcome measure separately for each of the nine event-years. Visual inspection of pre-trends conditional on event evidences violation only for the 2013 event, which uses the fewest control hospitals and therefore is prone to relatively extreme variation in trends. Omitting this event does not substantially impact the main estimates.

[25] Note that hospitals treated in 2012 and 2013 also serve as clean controls for the 2005 and 2006 events; therefore, these groups are not mutually exclusive.

cates whether hospital h is used as a treated hospital in event d and $Post_{td} = 1\{t > d\}$ indicates whether year t is after the event year. The model also includes hospital-by-event fixed effects α_{hd}, year-by-event fixed effects λ_{td}, and time-varying covariates X_{htd} including the DSH adjustment, a dummy variable indicating DSH is above the 340B cutoff, and market-level average age, cancer diagnosis rate, female share, and Black share.

The coefficient of interest β^{DD} can be interpreted as an average over events of the additional difference in cancer drug use between new 340B participants and later participants in the 6 years after the new participants join 340B relative to the difference in the 5 years before joining. Because hospitals are only partially treated in the first year of 340B participation, I separately estimate a coefficient β^0 which captures the additional difference in utilization between treatment and control in the year treated hospitals begin participating in 340B (indicated by $TY_{td} = 1\{t = d\}$) relative to the pre-period difference. Under the parallel trends assumption, these terms represents average causal effects.

To contextualize the size of these effects, I estimate the counterfactual implied by the difference-in-differences model: the expected value of the outcome after treatment conditional on being a new 340B participant had those hospitals not been treated. In other words, this is average HOPD cancer drug use of new 340B participants after they are treated less the treatment effect β^{DD}.[26] In all models, I two-way cluster standard errors by hospital referral region and hospital system.[27]

[26] In practice I estimate the counterfactual using regression estimates. The difference-in-differences model implies expected counterfactual outpatient drug use is $E[Y_{htd}(0)|Treat_{hd} \times Post_{td} = 1] = \alpha_{hd} + \lambda_{td} + X'_{htd}\Gamma$. I estimate this using the sample analogue of each term.

[27] Note that for proper statistical inference with a stacked design, utilization of the cross-sectional units (here, hospitals) must be allowed to co-vary across events and time. Thus, Wing (2021) suggests clustering at the cross-sectional level. By two-way clustering at the HRR and system levels, I nest hospital clustering as a special case and further allow errors to be informative about utilization of other hospitals in the same HRR and market.

4 Results

4.1 Effect on HOPD Cancer Drug Billing

Table 3 reports estimates of Equation 1. In the six years following the start of 340B participation, newly-participating hospitals significantly increased outpatient cancer drug claims compared to later participants, as measured by the annual number of infusions, cancer patients with HOPD infusion claims, and outpatient cancer drug spending. 340B increased annual infusions by 62 on average, a 35 percent increase over the number of infusions that treated hospitals would have billed had they instead followed the same trend as control hospitals.

Similarly, new 340B hospitals increased the number of cancer patients billed for HOPD infusions by an average of 10 more than later participants and increased annual HOPD cancer drug spending by $213,000 more than later participants, 34 and 42 percent increases, respectively (relative to the counterfactual). Figure 5 presents estimates of a dynamic event study specification that allows the average effect of 340B to vary by the number of years since treated hospitals began 340B participation. After beginning participation, the difference between 340B and control hospitals grows year over year, indicating that HOPD cancer drug use does not uniformly increase post-participation. Moreover, the coefficients are all near zero in the pre-period indicating that there was no pre-existing difference in chemotherapy trends between new 340B hospitals and later participants.

Robustness

The causal interpretation of these estimates rests on the validity of a parallel trends assumption — that treated hospitals would have followed the same path of chemotherapy use as control hospitals had they not started participating in 340B. The fact that Figure 5 shows parallel trends prior to treatment is suggestive that these parallel trends would have continued if not for 340B; however, I cannot definitively rule out that trends would have diverged after the event year because counterfactual trends are fundamentally unobservable. Therefore, I present additional specifications

that demonstrate the robustness of this finding to inclusion of time-varying controls and different choices of control groups. First, Column (3) of Table 3 reports estimates of Equation 1 that weight the control group according to a propensity-score to balance characteristics across treatment arms.[28] Column (4) estimates the model using only the subset of control hospitals that are treated 7 to 9 years after each event, removing controls that are treated at times furthest from each event, making as-good-as-random timing of participation more plausible. Nevertheless, using control hospitals that begin participating in 340B seven or more years after the treated hospitals may concern the reader that treated hospitals would have increased cancer drug utilization more than controls regardless of 340B participation. Thus, in additional analyses, I reconstruct the stacked panel to include controls that begin participating sooner after treated hospitals and use the Callaway and Sant'anna difference-in-differences estimator to estimate a model that uses hospitals as controls in any year prior to their participation.[29] None of these estimates substantively differ from the baseline specification reported in Column (2). In total, these estimates indicate a statistically and economically significant effect of 340B on hospital-based cancer care.

4.2 Heterogeneity by System Membership

To assess heterogeneity in the effect of 340B related to health system membership, I estimate Equation 1 separately for hospitals that are system members or independent in the year prior to each event and present the estimates in Table 4. System hospitals increased average infusions by 72 percent (+115 infusions, $p < 0.01$), while independent hospitals did not significantly increase infusions (-7.3 infusions, $p = 0.77$). A test of the difference of coefficients rejects equal effects ($p < 0.05$).[30] Figure 6 shows that parallel pre-trends hold conditional on health system membership, suggesting that 340B hospitals both in and not in systems plausibly would have followed the same trend in

[28] For each event, I estimate a LASSO-penalized logistic regression that predicts 340B participation in the event year using numerous hospital characteristics. Then, I use the LASSO-logit predicted probabilities to reweight control observations. See Appendix A.1 for details on implementation.

[29] See Figure A5 and Figure A6.

[30] I estimate the difference of effects by interacting all terms in Equation 1 with an indicator for system membership in the year prior to treatment. I then perform a t-test on the coefficient multiplying the term $Treat_{hd} \times Post_{td} \times System_{hd}$ to test the significance of the difference of effects.

cancer drug administration as the control hospitals.

While system hospitals significantly increase billing for cancer drugs, Figure 7 shows that 340B does not make patients with previous cancer diagnoses who live within 5 miles of the hospital any more likely to be treated with chemotherapy. Moreover, Figure 8 shows that previously undiagnosed beneficiaries living near a hospital are no more more likely to be diagnosed with cancer after that hospital becomes 340B. Thus, I find no evidence that 340B leads hospitals to engage in activities to expand their markets.

$$\begin{aligned} Y_{htd} = \exp\Big(&\alpha_{hd} + \lambda_{td} + \rho_{td} System_{hd} + X'_{ht}\Gamma \\ &+ \beta^{DD}(Treat_{hd} \times Post_{td}) + \beta^{DD0}(Treat_{hd} \times TY_{td}) + \\ &+ \beta^{DDD}(Treat_{hd} \times Post_{td} \times System_{hd}) + \beta^{DDD0}(Treat_{hd} \times TY_{td} \times System_{hd}) \\ &+ \beta^{DDDW}(Treat_{hd} \times Post_{td} \times W_{hd}) + \beta^{DDDW0}(Treat_{hd} \times TY_{td} \times W_{hd})\Big) + u_{htd}. \end{aligned} \tag{2}$$

Robustness

These results demonstrate that the overall effect of 340B on outpatient cancer drug use is driven in large part by system hospitals. However, this does not imply that health system membership causes hospitals to respond more strongly to 340B. If factors correlated with system membership drive larger effects of 340B, then those effects would overstate the contribution of systems to the effect of 340B. I test whether system-level heterogeneity in the effect of 340B can be explained by heterogeneous responses in other variables by estimating the triple difference model represented by Equation 2. This specification allows for the difference in trends to between new 340B participants and later participants to vary based on whether hospitals are system members by including an interaction term $\beta^{DDD} Treat_{hd} \times Post_{td} \times System_{hd}$. Moreover, it allows for the difference in trends to vary based on the level of other observed variables W_{hd}, a difference captured by the coefficient β^{DDDW}. If effect heterogeneity by system membership is merely a reflection of correlation with observed variables that actually cause effect heterogeneity, then including these interaction terms will tend to attenuate β^{DDD} towards zero. In all specifications, I estimate Poisson regression

models so that coefficients approximately represent percent differences in expected cancer drug use.

In Table 5, I estimate Equation 2. I find no evidence that heterogeneity in the effects of of 340B by hospital rurality, teaching status, cancer program accreditation, government affiliation, DSH adjustment, number of beds, or the number of other 340B or non-340B providers in a hospital's market explain the observed difference of effects by health system membership, suggesting that health system membership may itself cause a greater policy response to 340B participation.

4.3 System Hospitals: Oncologist Employment

Figure 9 shows that 340B also differentially impacted medical oncologist employment. New 340B system hospitals modestly increased employment of medical oncologists by 1 additional oncologist on average relative to control hospitals (an 8 percent increase). [31] In contrast, 340B did not increase hospital employment of medical oncologists at independent 340B hospitals. System hospitals increased employment of both the top 25 percent and bottom 75 percent of physicians by volume by a statistically insignificant 8 percent. Moreover, Table 6 shows that 340B did not cause system hospitals to increase employment of other types of oncologists (radiation or surgical) despite the fact that these specialists are often members of the same physician groups as medical oncologists. Nevertheless, 340B substantially increased the number of HOPD infusions attended by both historically high- and low-volume medical oncologists: HOPD infusions attended by historically low-volume oncologists increased by 81 — a 75 percent increase — and those attended by historically high-volume oncologists increased by an average of 33 — an over 250 percent increase. This implies that 340B increased the share of HOPD infusions attended by high-volume medical oncologists from 8 to 18 percent, more than doubling the share of HOPD infusions they attended.[32] This indicates that contracting with more oncologists was not nearly as important to

[31] The coefficient on $Treat \times Post$ in the model of total medical oncologist employment is only significant at $p < 0.1$. However, this masks significant long-run effects of 340B on medical oncologist employment, which are depicted in Figure 9.

[32] The difference-in-differences model implies that high-volume oncologists would have attended 13 HOPD infusions for the average system hospital had those hospitals not participated in 340B, but due to 340B, they attended 48.

driving increases in hospital-based chemotherapy as increasing the amount of hospital-based care performed by a fixed number of oncologists.

4.4 System Hospitals: Screening and Quality Competition

Lastly, I test whether increased cancer drug spending at system hospitals is related to patient acquisition efforts by assessing whether 340B led these hospitals to increase screening for cancer patients or quality competition, including expansion of complementary cancer services or adoption of new technologies. Table 7 shows that 340B did not increase system hospital-based screening of breast cancer (as measured by mammograms, ultrasound, and core biopsy) or colorectal cancer (as measured by colonoscopy). There is also no clear evidence that 340B led system hospitals to adopt full-field digital mammography as a replacement for screen-film mammography. Additionally, Table 8 shows that 340B did not cause system hospitals to increase breast or colorectal cancer surgery, nor did it cause hospitals to increase use of lumpectomy, a less invasive alternative to mastectomy, or minimally-invasive colectomy procedures (laparoscopic or robotic colectomy). I do find that 340B system hospitals increased use of intensity-modulated radiation therapy (IMRT, a novel radiation technique) more than control hospitals; however, event study coefficients exhibit a pattern of positive pre-trends in this outcome, suggesting this may not reflect an effect of the program itself. In total, this set of results indicates that 340B did not cause hospitals to change their role in cancer care delivery beyond billing for more cancer drugs, and furthermore it is consistent with gaming of 340B by strategically changing billing practices to receive 340B discounts.

Similarly, I estimate that the total number of system hospital infusions (including those with no attending medical oncologist) would have been 160, but because of 340B, it increased to 275. Therefore the composition would have been 13 / 160 = 8 percent high volume oncologists without 340B and due to 340B it increased to 48 / 275 = 18 percent high-volume.

4.5 Acquisitions

Lastly, I estimate an empirical model of hospital acquisitions. I do this by creating another stacked dataset wherein the events correspond to the first year treated hospitals are acquired.[33] I limit the sample to only include acquisition events between 2010 and 2016 to coincide with the HOPD cancer drug billing depicted in Figure 1b. I also limit the sample to only hospitals that are independent prior to acquisition to ensure that control hospitals are not in the systems acquiring treated hospitals, as this could bias the impact of acquisition. I then split the sample by the 340B status of the acquired hospital and the status of other hospitals in the same market and system: for instance, 340B hospitals acquired by a system with one or more other 340B hospitals and one or more other non-340B hospitals. I then estimate Poisson fixed effects models akin to Equation 1.

Figure 10 depicts event study estimates for hospitals acquired by a system with both other 340B and non-340B hospitals. Acquisition by this type of system increases cancer drugs billed by 340B hospitals and decreases drugs billed by non-340B hospitals. The increase in 340B billing is consistent with systems relabeling outpatient facilities as 340B HOPDs, although if those facilities were within 35 miles of another 340B hospital, the systems could already ostensibly relabel in such a manner. On the other hand, the acquisition of non-340B hospitals leads those hospitals to significantly decrease cancer drug billing, which is consistent with relabeling of the acquired hospital's off-site facilities as 340B HOPDs.[34]

5 Discussion

In this paper, I provide evidence that hospitals game the 340B Drug Pricing Program to expand discounts to more sites of care and that health systems facilitate this gaming, including by rela-

[33] Acquisitions are defined as hospital-years in which a hospital's AHA system identifier differs from both of the previous two years and is the same as the following two years.

[34] In the appendix, I present triple difference estimates that identify the additional effect of acquisition for 340B hospitals for several types of systems. In aggregate, I do not detect a significant effect of acquisition for either type of hospital, and I am not powered to detect effects for acquisitions by systems with only other 340B hospitals or only other non-340B hospitals. Acquisition of non-340B hospitals by systems with both decrease infusions billed by 40 percent (-0.51 log points), whereas acquisition of 340B hospitals by these systems increase infusions billed by 43 percent (+0.36 log points).

beling facilities as HOPDs. I estimated difference-in-differences models that characterize the heterogeneous effects of 340B, and in doing so, I provide suggestive evidence on the importance of health systems to gaming the program. However, I must acknowledge some key limitations. First, causal identification depends on a restrictive parallel trends assumption that, after beginning 340B participation, hospitals would have followed the same trends in cancer drug use as hospitals that begin participating seven or more years later. I perform an array of robustness exercises, using alternative control groups and introducing time-varying controls, and find that none exhibit significant pre-trends or overturn the results of the baseline specification. Nevertheless, the parallel trends assumption is fundamentally untestable. If hospitals' timing of participation is not as good as random— for example, if hospitals that strategically increased their DSH adjustment to qualify for 340B would have increased care regardless of whether they became eligible for 340B — then the parallel trends assumption could be violated.

Second, although the effect of 340B participation on hospital-based chemotherapy is entirely driven by health system members, the difference of effects could reflect a different mediating variable that is correlated with system membership. I test whether heterogeneous effects are better explained by other observable variables and find that none explain away the substantially larger effect of 340B on HOPD cancer drug use of system hospitals. Nonetheless, heterogeneous effects may emerge from unobserved variables correlated with system membership.

Third, while I can observe system ownership of hospitals, I cannot observe their ownership of oncology practices or the actual site of care. An increase in HOPD cancer drug infusions only among system-affiliated hospitals is consistent with comparative advantage in gaming, and I attempt to rule out alternative explanations, including increased patient acquisition efforts and improved care quality at HOPDs. Moreover, I provide case study evidence that shows relabeling of sites of care is a way in which systems may substantially increase discounted cancer drug infusions. As the case study suggests, systems may rapidly move billing of care across organizational boundaries without corresponding changes in the site of care and may be motivated to do so by 340B discounts. Nevertheless, while system hospitals seem particularly adept at increasing discounted

care, there is some uncertainty in the way in which they do so at scale that could be supplemented by more information on system ownership and site of care.

The 340B program was intended to allow hospitals to stretch scarce resources to better serve their communities by requiring drug makers to provide discounts to participants. Due to the program's incentives, a massive expansion of participation, and increased health system ownership of oncology practices, concern over the program's unintended consequences has ballooned. The 340B program may not have driven health system ownership of oncology practices, but my results demonstrate that health systems have been by far the most successful at increasing discounted cancer drug administration, a response that may reflect comparative advantage in gaming of the program due to coordination of finance, legal services, and drug procurement within systems. The incentive to relabel oncology clinics as off-campus HOPDs to administer discounted drugs at those facilities may be effectively eliminated by legislation that requires discounted drugs to be administered within a hospital's walls, perhaps with carve-outs for certain types of community health clinics. However, professional drug administration may be less constrained by specialist employment in other areas of medicine, and hospitals also dispense 340B-discounted retail pharmaceuticals through in-house pharmacies and contract pharmacy arrangements (Kakani 2023). In those settings a broader set of hospitals may be able to effectively respond to 340B incentives. Thus, the role of health systems in facilitating the gaming of 340B in different areas of medicine and, more broadly, gaming of policies that create incentives for only a subset of health care facilities may be a promising topic for future research.

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Tables

Table 1: Cohort summary statistics

	(1) All beneficiaries	(2) Beneficiaries with prior cancer diagnosis
Characteristics		
Age	76.0	77.6
Female	0.582	0.470
Male	0.418	0.530
White	0.875	0.885
Black	0.0734	0.0773
Hispanic	0.0150	0.0105
Asian	0.0156	0.0107
Native American	0.00394	0.00290
Other race	0.0122	0.00978
Years observed	8.11	5.92
Share who die in sample	0.499	0.649
Cancer diagnosis rate		
Any cancer	0.195	1.00
Brain	0.00589	0.0302
Breast	0.0487	0.254
Colorectal	0.0361	0.183
Lung	0.0464	0.232
NHL	0.0179	0.0918
Prostate	0.0631	0.328
Observations		
# of beneficiaries	12680565.	2387056.
# of beneficiary-years	102785628.	14142741.

This table reports average characteristics of beneficiaries among all beneficiaries that meet Medicare enrollment criteria within a 20 percent sample of Medicare beneficiaries (Column (1)) and the subset of beneficiaries that were diagnosed with brain cancer, breast cancer, colorectal cancer, lung cancer, non-Hodgkin's lymphoma, or prostate cancer between the years 1999-2019 (Column (2)). Beneficiaries are included in the Column (1) sample in any year that they met the enrollment criteria, and in the Column (2) sample in any year that they also met the diagnosis criteria. The enrollment criteria for a particular beneficiary and year is the following: continuously enrollment in fee-for-service Medicare throughout that year, age 66 or older, entitled to Medicare due to Old-Age and Survivors Insurance, and living in one of the 306 Hospital Referral Regions created by Dartmouth Atlas. Age, sex, and race are reported as a share of all beneficiary-years. Years observed, share of beneficiaries who die in the sample, and diagnosis rates are reported as a share of all beneficiaries.

Table 2: Hospital balance table

	(1) Treated Mean	(2) Control Mean	(3) T-statistic
Hospital Characteristics			
Disproportionate share adjustment	15.281	9.719	7.334***
Beds (CMS)	313.9	289.6	1.418
Beds (AHA)	291.5	261.3	1.774†
Rural	0.288	0.215	1.876†
Major teaching hospital	0.139	0.090	2.381*
Minor teaching hospital	0.278	0.319	-1.209
Accredited by Joint Commission	0.905	0.931	-1.206
Accredited by Commission on Cancer	0.515	0.601	-2.127*
Affiliated with med school	0.176	0.148	1.098
In health system	0.566	0.598	-0.751
In large system (10+ hospitals)	0.292	0.294	-0.047
Hospitals in system	11.6	11.7	-0.055
Other 340B hospitals in system	1.72	1.36	1.365
Cancer treatment			
Chemotherapy infusions	118.1	110.3	0.384
NK-1 receptor antagonists	2.5	1.7	0.902
Oncologists			
Medical	8.5	9.3	-1.303
Radiation	2.1	2.2	-0.410
Surgical	0.4	0.4	-1.129
Screening procedures			
Screening mammograms	973	929	0.609
Colonoscopies	227	200	1.573
PSA screens	393	444	-0.998
Annual incidence in hospital's zip			
Any cancer	0.0180	0.0189	-1.633
First 340B year	2005-2013	2012-2020	
# Hospitals	431	309	
# Hospital-events	431	1416	
# Hospital-event-years	5172	16992	

†p < 0.10, *p < 0.05, **p < 0.01, ***p < 0.001

This table reports average hospital characteristics in the year prior to each stacked panel event. For example, for hospitals that are treated or clean controls in the 2005 event, the data includes those hospitals' values in 2004. T-statistics are obtained from bivariate regressions of each variable on treatment status using all hospital-event-year observations in the year prior to the event. Because hospital-years may be repeated, standard errors are clustered at the hospital referral region level in all regressions, allowing characteristics to be correlated within hospital, and more generally within market, over events and time. Hospitals that start participating in 340B in 2012 or 2013 appear once in the treated group, and because they are clean controls for at least one year in the treated group, they also appear once or twice in the control group.

Table 3: Difference-in-differences estimates of the effect of 340B on HOPD chemotherapy use

Dependent Variables:	Chemo infusions					Patients	Spending
Model:	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Poisson	(6) OLS	(7) OLS
Variables							
Treat × Post	64.49**	62.35**	65.79**	74.89**	0.2791*	10.39**	213,091.0**
	(22.00)	(21.35)	(24.37)	(23.17)	(0.1208)	(3.174)	(74,336.4)
Treat × Treatment year	8.406	5.849	18.81	4.853	0.0394	1.712	14,231.1
	(16.60)	(15.63)	(21.85)	(18.84)	(0.0860)	(2.258)	(49,718.4)
Fixed-effects							
Hospital-Event	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Event	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates		Yes	Yes	Yes	Yes	Yes	Yes
Treated hospitals	431	431	431	431	431	431	431
Control hospitals	309	309	309	302	309	309	309
Observations	22,164	22,164	22,164	14,724	22,164	22,164	22,164
Treated hospital counterfactual mean	173.38	175.52	172.08	162.98	179.95	30.23	508,031.92
Percent change (relative to counterfactual)	37.19	35.52	38.23	45.95	32.19	34.36	41.94

Clustered (Hospital referral region & Health system) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, †: 0.1*

This table reports estimates of Equation 1. The coefficient on Treat × Post measures the increase in chemotherapy use in treated hospitals in the six years after they begin participating in 340B relative to clean control hospitals. Column 1 reports the specification using including hospital-by-event and year-by-event fixed effects but no covariates as controls. Column 2 reports the main specification with time-varying controls. Column 3 reweights control observations according to their propensity score. Column 4 restricts control hospitals to those that are treated between 7 and 9 years after the event. Column 5 reports Poisson regression coefficients. Columns 6 and 7 report the main linear specification using cancer drug patients and spending as dependent variables, respectively.

Table 4: 340B effect heterogeneity by health system affiliation

	System hospitals			Independent hospitals		
	Chemotherapy		Med. Oncologists	Chemotherapy		Med. Oncologists
Dependent Variables:	Infusions	Spending	Employment	Infusions	Spending	Employment
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Treat × Post	115.0**	354,566.3**	1.018†	-7.277	22,492.8	0.1544
	(35.75)	(123,265.8)	(0.5307)	(25.38)	(87,020.4)	(0.5661)
Treat × Treatment year	11.82	30,989.3	0.1036	-2.053	-6,955.0	-0.0675
	(23.64)	(77,065.0)	(0.3645)	(17.11)	(53,776.1)	(0.3047)
Fixed-effects						
Hospital-Event	Yes	Yes	Yes	Yes	Yes	Yes
Year-Event	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Treated hospitals	244	244	244	187	187	187
Control hospitals	193	193	193	137	137	137
Observations	13,092	13,092	12,082	9,072	9,072	8,362
Treated hospital counterfactual mean	159.92	513,556.31	13.19	196.80	506,823.11	10.04
Percent change (relative to counterfactual)	71.91	69.04	7.72	-3.70	4.44	1.54

Clustered (Hospital referral region & Health system) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, †: 0.1*

This table reports ordinary least squares estimates of Equation 1 separately for system and independent hospitals. Physician identifiers are not reliably reported in 2006, so that year is omitted in Columns (3) and (6).

Table 5: 340B effect heterogeneity by health system affiliation: alternate specifications

Dependent Variable:	Chemo infusions									
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables										
Treat × Post	-0.0935	-0.0223	-0.0121	0.0071	0.0028	-0.2353	-0.1237	-0.2647	-0.0401	0.2066
	(0.1330)	(0.1517)	(0.1589)	(0.2042)	(0.1523)	(0.2340)	(0.6508)	(0.1739)	(0.1855)	(1.013)
Treat × Post × Health system	0.6602**	0.6206**	0.6524**	0.6891**	0.5962*	0.6616**	0.6569**	0.6074**	0.6856**	0.5848*
	(0.2383)	(0.2388)	(0.2387)	(0.2426)	(0.2420)	(0.2398)	(0.2443)	(0.2187)	(0.2334)	(0.2302)
Treat × Post × Rural		-0.2401								-0.4152
		(0.2370)								(0.3095)
Treat × Post × Teaching hospital			-0.2532							-0.4824
			(0.2207)							(0.3194)
Treat × Post × Accredited cancer program				-0.1620						-0.4410
				(0.2391)						(0.2938)
Treat × Post × Government hospital					-0.5876*					-0.5968*
					(0.2660)					(0.3009)
Treat × Post × Disproportionate share adjustment						0.0047				-0.0055
						(0.0186)				(0.0193)
Treat × Post × Log(Beds)							0.0028			0.0458
							(0.1139)			(0.1966)
Treat × Post × Other 340B hospitals in HRR								0.0545†		0.0740*
								(0.0279)		(0.0295)
Treat × Post × Other non-340B hospitals in HRR									-0.0037	-0.0112*
									(0.0061)	(0.0054)
Fixed-effects										
Hospital-Event	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Event	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Treated hospitals	431	431	431	431	431	431	431	431	431	431
Control hospitals	309	309	309	309	309	309	309	309	309	309
Observations	22,164	22,164	22,164	22,164	22,164	22,164	22,164	22,164	22,164	22,164
RMSE	167.78	167.88	167.74	167.77	167.67	167.41	167.82	164.94	166.75	162.29

Clustered (Hospital referral region & Health system) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, †: 0.1*

This table reports Poisson pseudo-maximum likelihood estimates of Equation 1, modified to interact all terms with an indicator of hospital i's health system membership. With the exception of Column 1, each column additionally includes controls for heterogeneous time trends of the form Post × Z and Treat × Post × Z, where Z is a time-invariant interacting variable. Coefficients on the latter terms are reported to demonstrate that effect heterogeneity in system-affiliation does not merely reflect correlation with effect heterogeneity in the Z variables.

Table 6: System hospitals: effect of 340B on HOPD oncologist employment

	Medical oncologists						Other oncologists	
	Employment			Infusions attended			Employment	
Dependent Variables:	All	Top 25%	Bottom 75%	All	Top 25%	Bottom 75%	Radiation	Surgical
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Treat × Post	1.018†	0.1852	0.8331†	114.4**	33.35***	81.08**	0.0140	0.0038
	(0.5307)	(0.1126)	(0.4918)	(34.51)	(9.118)	(28.35)	(0.1625)	(0.0659)
Treat × Treatment year	0.1036	-0.0809	0.1845	22.16	13.94	8.218	-0.0102	-0.0636
	(0.3645)	(0.0915)	(0.3282)	(26.29)	(9.746)	(18.27)	(0.1285)	(0.0472)
Fixed-effects								
Hospital-Event	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Event	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Treated hospitals	244	244	244	244	244	244	244	244
Control hospitals	193	193	193	193	193	193	193	193
Observations	12,082	12,082	12,082	12,082	12,082	12,082	12,082	12,082
Treated hospital counterfactual mean	13.19	2.40	10.78	121.17	12.99	108.18	3.47	0.67
Percent change (relative to counterfactual)	7.72	7.70	7.73	94.44	256.72	74.95	0.40	0.57

Clustered (Hospital referral region & Health system) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, †: 0.1*

This table reports ordinary least squares estimates of Equation 1 using the subsample of system hospitals. Column 1 reports an estimate for all attending oncologists. Columns 2 and 3 report estimates for the top 25 percent and bottom 75 percent of oncologists by patient volume, respectively. Columns 4 through 6 report the number of chemotherapy infusions performed by oncologists in hospital outpatient departments in total and by patient volume. Note that the estimate in Column 4 differs from Column 1 of Table 3 because medical practitioners other than oncologists may be listed as attending physicians on an outpatient claim. Columns 7 and 8 report estimates for oncologists that do not typically infuse cancer drugs.

Table 7: System hospitals: effect of 340B on cancer screening

	Breast cancer screening					Colonoscopy
	Mammograms			Ultrasound	Core biopsy	
Dependent Variables:	All	Film	Digital			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Treat × Post	66.49	-47.27	113.8	4.505	2.668	11.60
	(51.82)	(69.34)	(83.51)	(7.327)	(1.822)	(12.19)
Treat × Treatment year	22.44	-19.86	42.29	-3.225	0.8219	4.713
	(37.74)	(45.58)	(51.11)	(5.090)	(1.387)	(8.933)
Fixed-effects						
Hospital-Event	Yes	Yes	Yes	Yes	Yes	Yes
Year-Event	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Treated hospitals	244	244	244	244	244	244
Control hospitals	193	193	193	193	193	193
Observations	13,092	13,092	13,092	13,092	13,092	13,092
Treated hospital counterfactual mean	1,217.54	255.94	961.60	96.64	23.51	227.13
Percent change (relative to counterfactual)	5.46	-18.47	11.83	4.66	11.35	5.11

Clustered (Hospital referral region & Health system) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, †: 0.1*

This table reports ordinary least squares estimates of Equation 1 for the use of different cancer screening technologies. The coefficient on Treat × Post measures the increase in the outcome of treated hospitals in the six years after they begin participating in 340B relative to clean control hospitals.

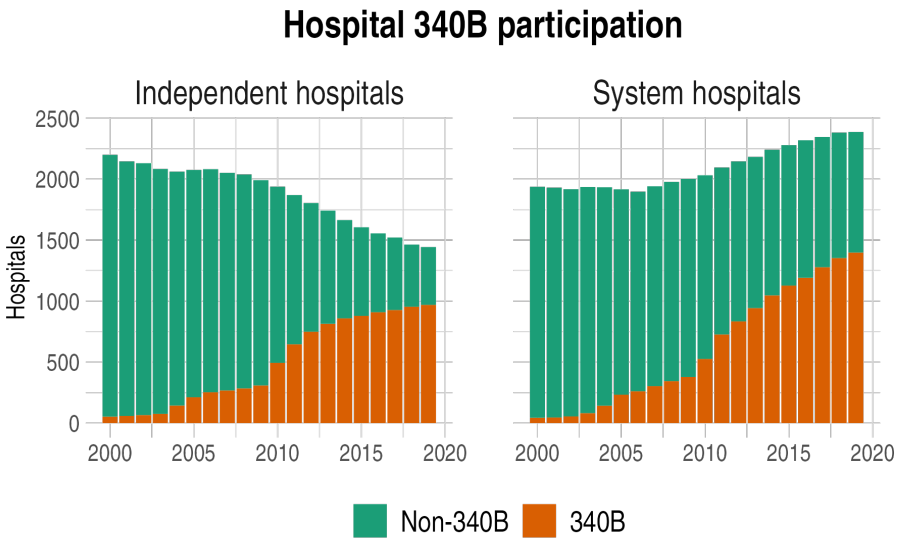
Table 8: System hospitals: effect of 340B on non-medical oncology

	Breast surgery		Colectomy			Radiation	
Dependent Variables:	Mastectomies	Lumpectomies	Open	Laparoscopic	Robotic	IMRT	SBRT
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Treat × Post	-0.1789	0.2109	1.221	-0.3184	-0.0171	119.0**	-0.9087
	(0.5660)	(1.028)	(0.9556)	(0.4183)	(0.0824)	(36.39)	(4.867)
Treat × Treatment year	-0.2232	-0.1541	0.0274	-0.2562	-0.0016	99.78**	-0.6944
	(0.6691)	(0.7559)	(0.7902)	(0.3955)	(0.0444)	(33.25)	(2.809)
Fixed-effects							
Hospital-Event	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Event	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Treated hospitals	244	244	244	244	244	244	244
Control hospitals	193	193	193	193	193	193	193
Observations	13,092	13,092	13,092	13,092	13,092	13,092	13,092
Treated hospital counterfactual mean	10.56	13.37	10.14	4.30	0.32	268.32	21.83
Percent change (relative to counterfactual)	-1.69	1.58	12.04	-7.41	-5.31	44.36	-4.16

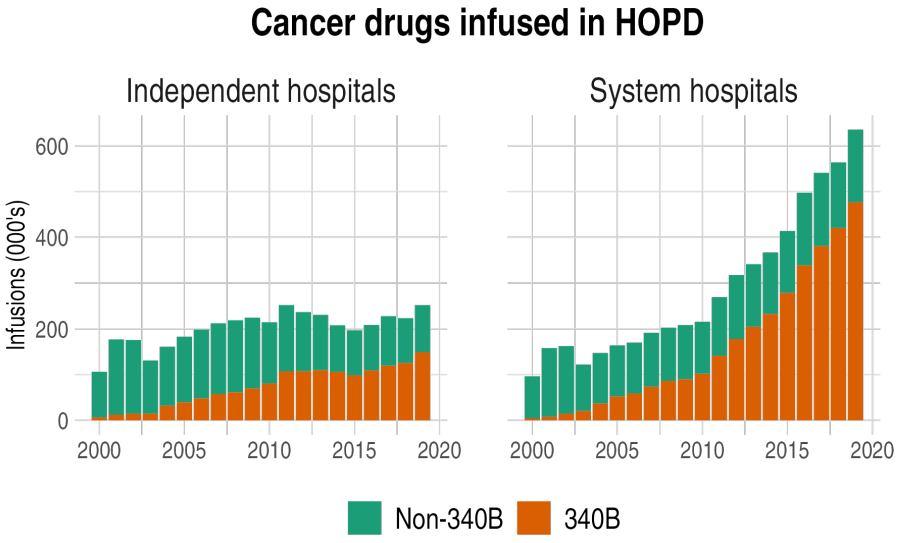
Clustered (Hospital referral region & Health system) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, †: 0.1*

This table reports ordinary least squares estimates of Equation 1 for the use of different cancer treatment technologies. The coefficient on Treat × Post measures the increase in the outcome of treated hospitals in the six years after they begin participating in 340B relative to clean control hospitals.

Figures



(a) Hospitals



(b) Cancer drug infusions

Figure 1: Trends in 340B hospitals and cancer care 2000–2019

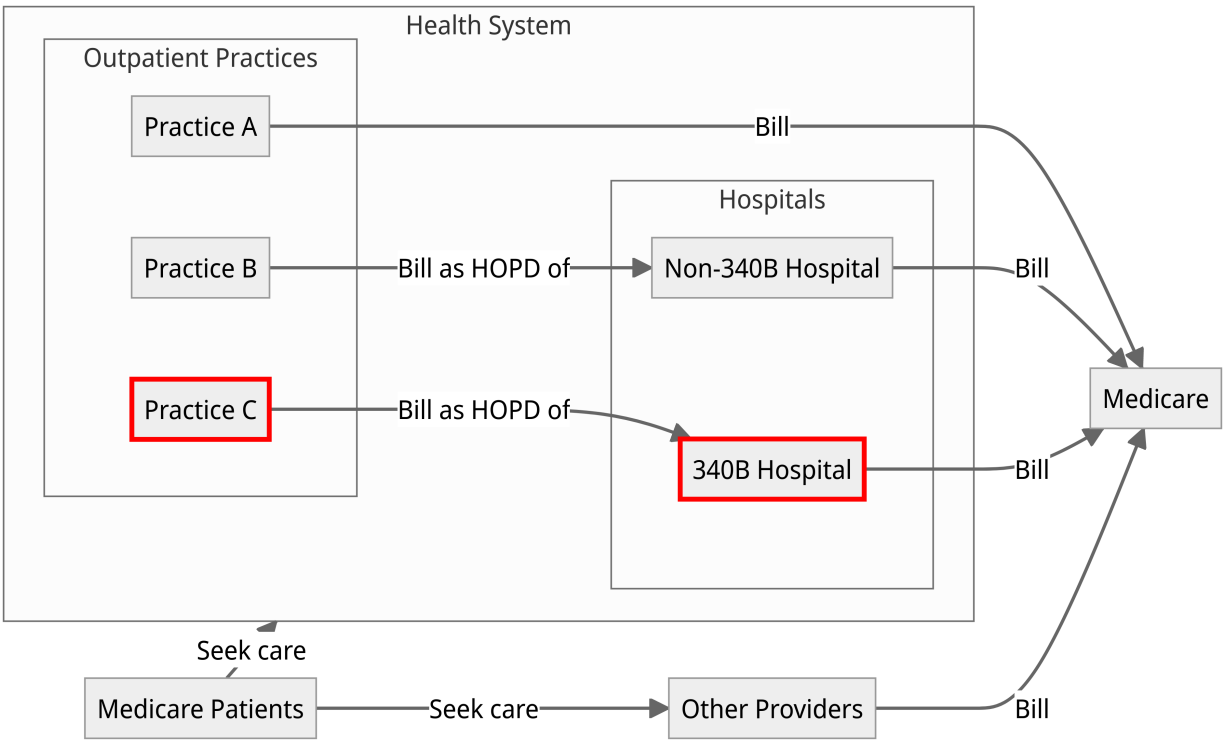


Figure 2: Health system relationships

This diagram depicts a model health system. Facilities eligible to administer 340B-discounted drugs are outlined in red. Medicare patients seek care from a provider in the health system (a hospital or an outpatient practice) or another provider. Hospitals bill Medicare for care delivered on site or at "provider-based" outpatient practices. Practice A bills Medicare as a freestanding facility, not using a hospital's provider number. Practice B bills Medicare as a HOPD of a non-340B hospital, entitling the hospital to receive facility fees for that care. Practice C bills Medicare as a HOPD of a 340B hospital; entitling the hospital to receive facility fees for that care *and* making Practice C eligible to register for 340B.

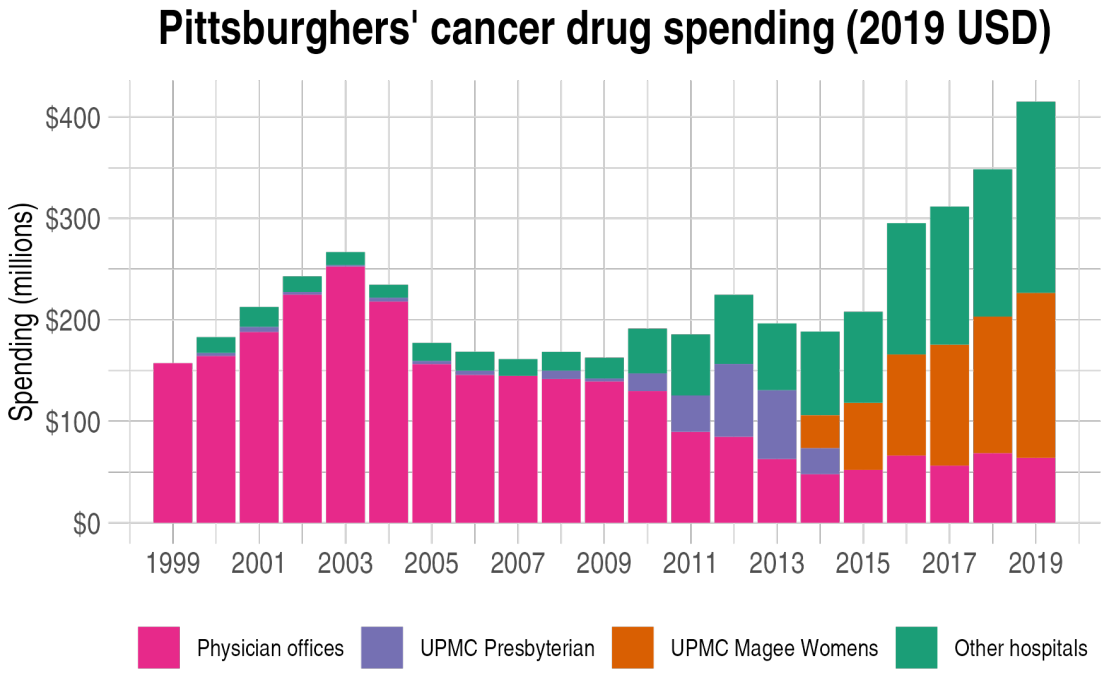


Figure 3: Case study: cancer drug spending among Pittsburghers by entity billing Medicare This figure depicts total annual cancer drug spending among fee-for-service Medicare beneficiaries living in Pittsburgh. Cancer drug infusions in physician offices decrease significantly over the course of the period and shift to the hospital outpatient setting. Starting in 2011, spending increases significantly at UPMC Presbyterian (non-340B) before completely vanishing in 2015, its share replaced by UPMC Magee-Womens (340B). Spending in cells that comprise 10 or fewer beneficiaries are censored by setting them equal to $0.

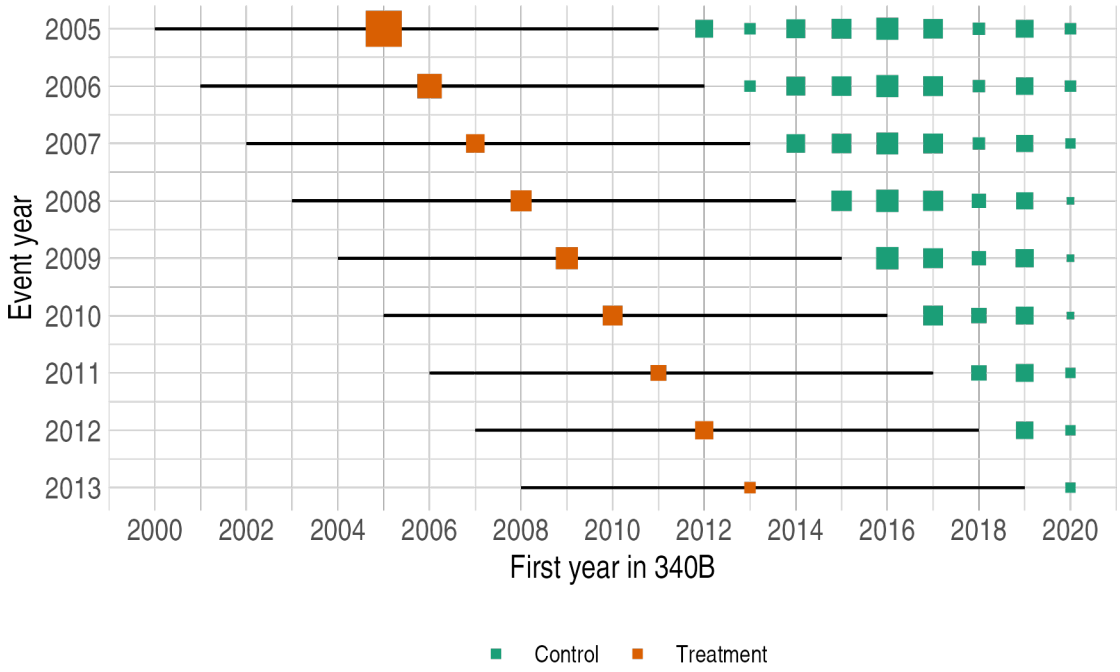


Figure 4: Event study comparisons

This figure depicts the construction of the stacked hospital panel by event year and hospitals' first 340B participation year. Orange squares depict treatment hospitals and green squares depict control hospitals. The size of each square is proportional to the number of hospitals included in the dataset. For instance, for the 2005 event, all treated hospitals begin participating in 2005, and all control hospitals begin participating in 2012 or later. The black segment indicates that the window of years used in the 2005 event dataset includes 2000–2011. The number of control hospitals with a given first 340B year varies slightly across events because I require that control hospitals be operating for the duration of the window, which varies by event.

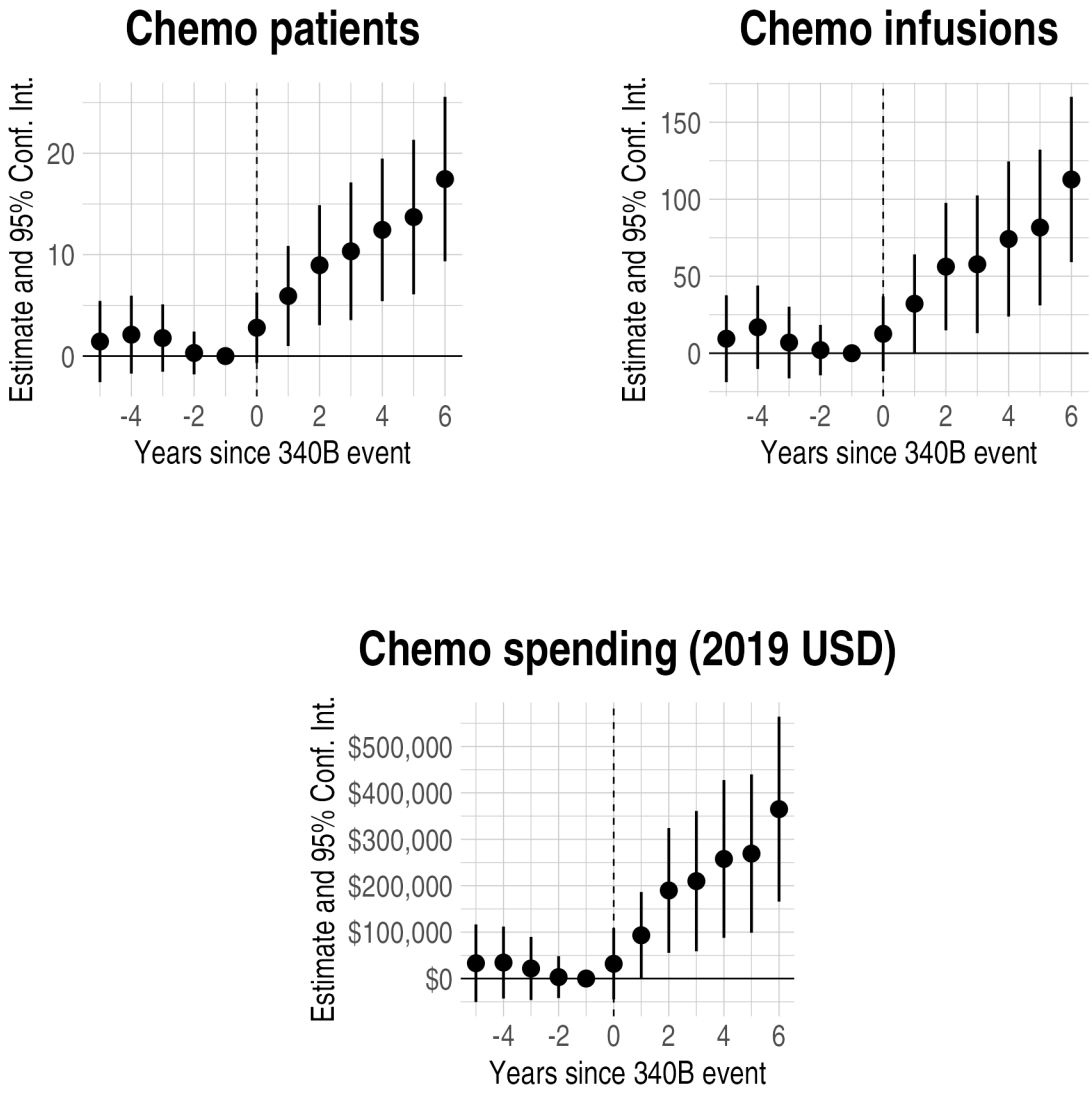


Figure 5: Event study coefficient plots

This figure reports ordinary least squares estimates of event study coefficients. For each event beginning at time d, the treated group includes all DSH hospitals that begin 340B in d and the control group includes all hospitals that begin 340B as a DSH hospital in year $d + 7$ or later. The coefficients reflect the difference in trends between new 340B DSH hospitals and later participants for each event, controlling for time-varying covariates, hospital-event fixed effects, and year-event fixed effects.

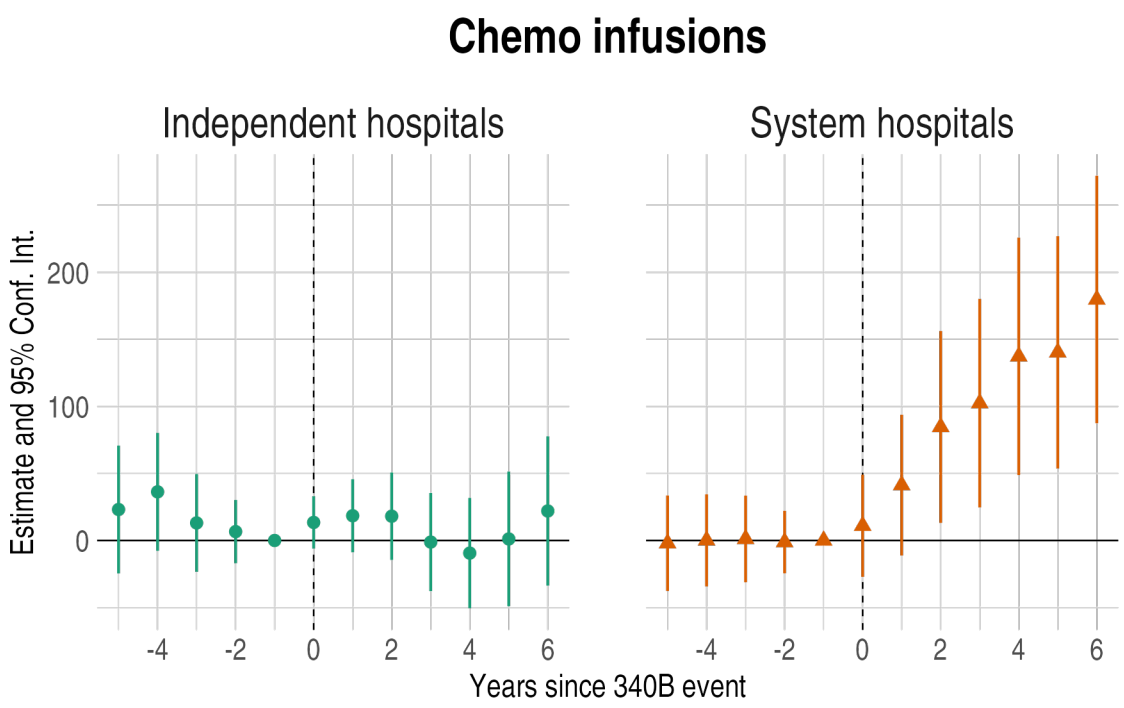


Figure 6: Event study coefficient plots by health system membership

This table reports ordinary least squares estimates of event study coefficients disaggregated into samples of independent and system hospitals. For each event beginning at time d, the treated group includes all DSH hospitals that begin 340B in d and the control group includes all hospitals that begin 340B as a DSH hospital in year $d + 7$ or later. The system hospital sample only includes hospital-events in which the hospital was a member of a multi-hospital system in year $d - 1$. The independent hospital sample includes all other hospital-events. The coefficients reflect the difference in trends between new 340B DSH hospitals and later participants for each event, controlling for hospital-event and year-event fixed effects.

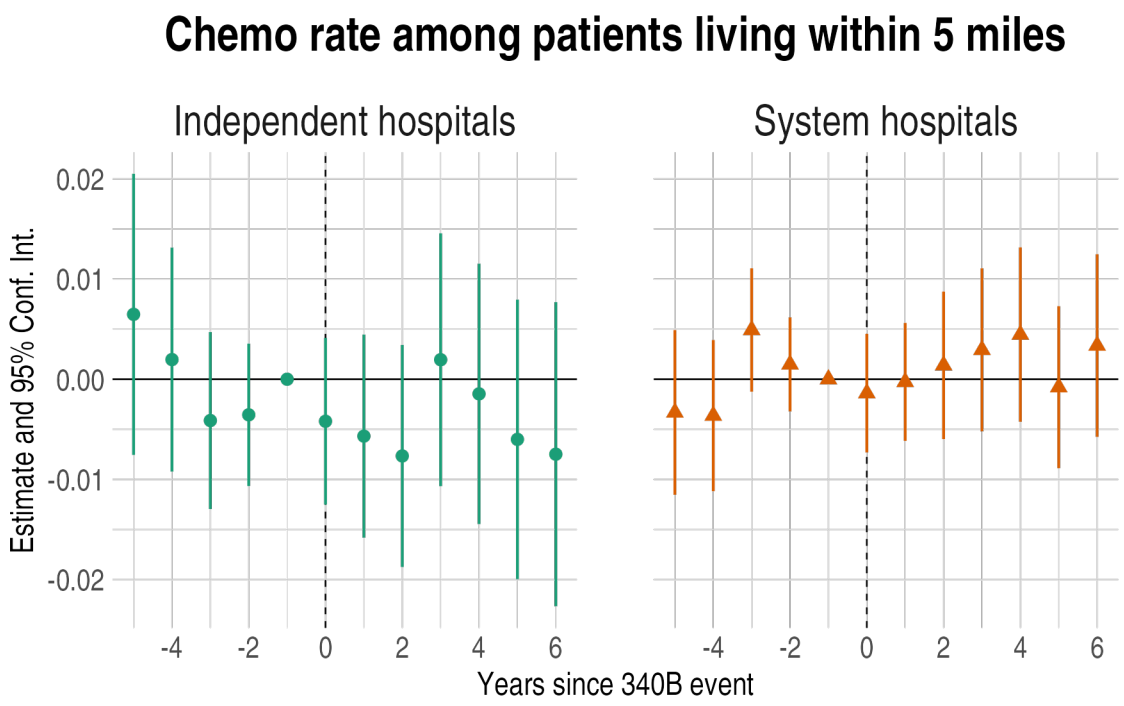


Figure 7: Event study coefficient plots by health system membership

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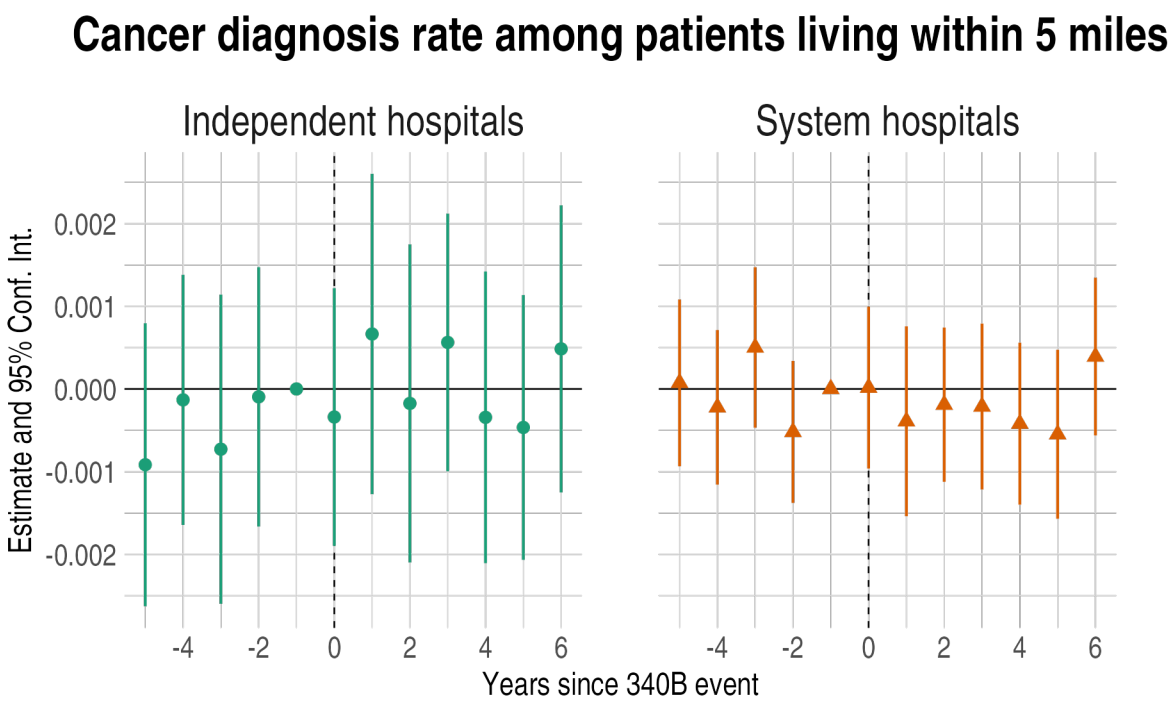

Figure 8: Event study coefficient plots by health system membership

This table reports ordinary least squares estimates of event study coefficients disaggregated into samples of independent and system hospitals. For each event beginning at time d, the treated group includes all DSH hospitals that begin 340B in d and the control group includes all hospitals that begin 340B as a DSH hospital in year $d + 7$ or later. The system hospital sample only includes hospital-events in which the hospital was a member of a multi-hospital system in year $d - 1$. The independent hospital sample includes all other hospital-events. The coefficients reflect the difference in trends between new 340B DSH hospitals and later participants for each event, controlling for hospital-event and year-event fixed effects.

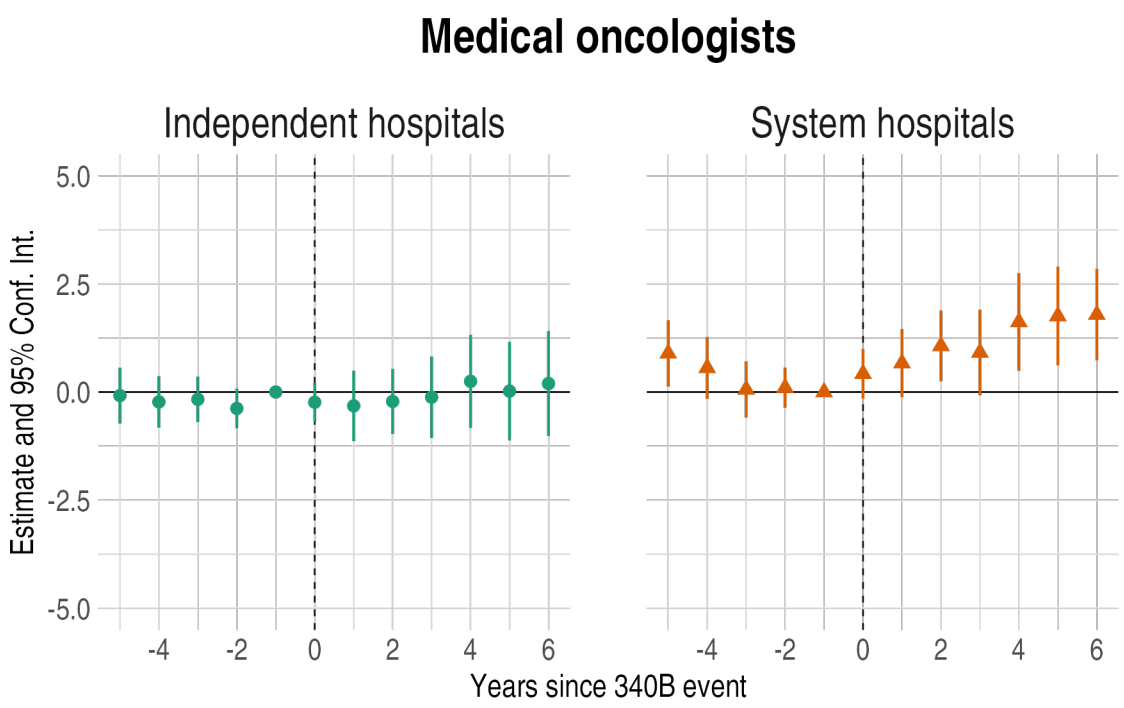

Figure 9: Event study coefficient plots by health system membership

This table reports ordinary least squares estimates of event study coefficients disaggregated into samples of independent and system hospitals. For each event beginning at time d, the treated group includes all DSH hospitals that begin 340B in d and the control group includes all hospitals that begin 340B as a DSH hospital in year $d + 7$ or later. The system hospital sample only includes hospital-events in which the hospital was a member of a multi-hospital system in year $d - 1$. The independent hospital sample includes all other hospital-events. The coefficients reflect the difference in trends between new 340B DSH hospitals and later participants for each event, controlling for hospital-event and year-event fixed effects.

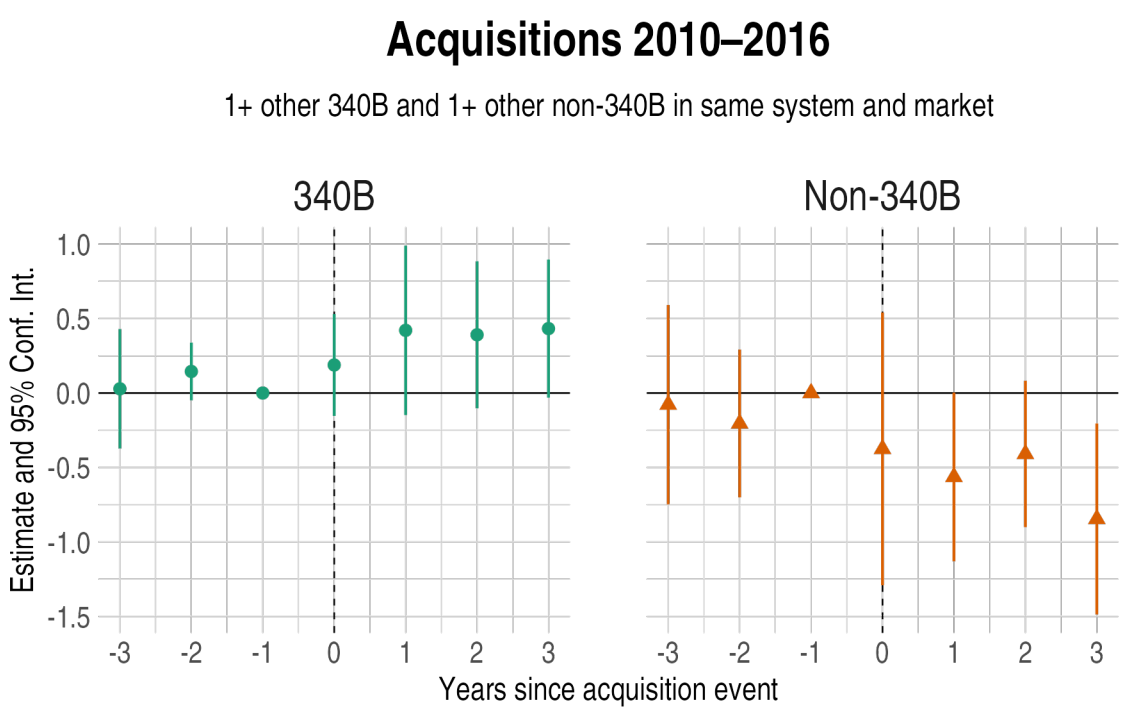

Figure 10: Acquisition event study coefficients by type of acquired hospital

This table reports Poisson pseudo-maximum likelihood estimates of event study coefficients using a sample of independent hospitals that are acquired by systems with 1 or more other 340B hospitals and 1 or more other non-340B hospitals in the same system and market between 2010 and 2016 (as well as control hospitals that are not acquired). The sample is disaggregated into sub-samples of acquired 340B and non-340B hospitals. For each acquisition event beginning at time d, the treated group includes all DSH hospitals that are first acquired in d and the control group includes all hospitals that are first acquired in year $d + 4$ or later (or are never acquired). The coefficients reflect the difference in (log-scaled) trends between newly-acquired DSH hospitals and controls.

A.1 Propensity Score Estimation

In Table 3, I report difference-in-differences estimates using reweighted control groups. I do this by estimating a family of binary treatment assignment models $m_d(.)$ that each predict treatment for a particular event-year sub-dataset. I then calculate predicted probabilities and reweight control observations appropriately.

I assume $m_d(.)$ is a logistic regression model and model the log-odds as a linear function of the following features: an intercept, a quadratic in the uncapped DSH score and its interaction with a dummy for DSH falling above the 11.75% cutoff for 340B, the number of hospital beds and the natural log of beds, dummies for the provider of services hospital region code, the number of other 340B hospitals in the hospital's HRR, the number of other non-340B hospitals in the hospital's HRR, and all two-way interactions of dummies for being a government hospital, being a rural hospital, being a member of a multi-hospital system, being a major teaching hospital, being Joint Commission accredited, and having an accredited cancer program. All variables are measured in the year of the event (e.g system status for the 2005 dataset corresponds to being a multi-hospital system in 2005).

Because I allow many variables to enter the models, which may lead to overfitting and unstable sample weights, I introduce a LASSO penalty to the log-likelihood, which selects a subset of features to predict 340B participation within each dataset. The resulting objective function for $m_d(.)$ is given in Equation 3

$$-\sum_{h\in\mathcal{H}_d} Treat_{hd}\log(p_{hd}) + (1-Treat_{hd})\log(1-p_{hd}) + \lambda_d\sum_{k=0}^{K}|\beta_k| \tag{3}$$

In this formulation, $\mathcal{H}_d$ are the hospitals used a treated or control units in event d, λ_d is the event-specific penalty parameter, which I choose by cross-validation, and $\beta_k, k = 0\ldots K$ are the linear parameters for the $K+1$ linear terms. The algorithm to implement this method is as follows:

1. Loop over each sub-dataset $\mathcal{D}_d, d = 2005,\ldots,2013$ to estimate a model of treatment assignment on each sub-dataset.

   (a) Using the function `cv.glmnet` from the R package `glmnet`, estimate a penalized logistic regression model $\widehat{Treat}_{hd} = m_d(.)$ using the dataset $\mathcal{D}_d$ with the penalty chosen by 10-fold cross-validation to be that penalty that minimizes the mean cross-validated error.

   (b) Obtain predicted probabilities $\hat{p}_{hd} = \widehat{Treat}_{hd}$ for each hospital in $\mathcal{D}_d$.

2. Calculate sample weights $w_{hdt} = \begin{cases} 1 & \text{if } Treat_{hd} = 1, \\ \hat{p}_{hd}/(1-\hat{p}_{hd}) & \text{if } Treat_{hd} = 0 \end{cases}$.

3. Estimate Equation 1 by weighted least squares using the full stacked dataset.

A.2 Appendix Figures

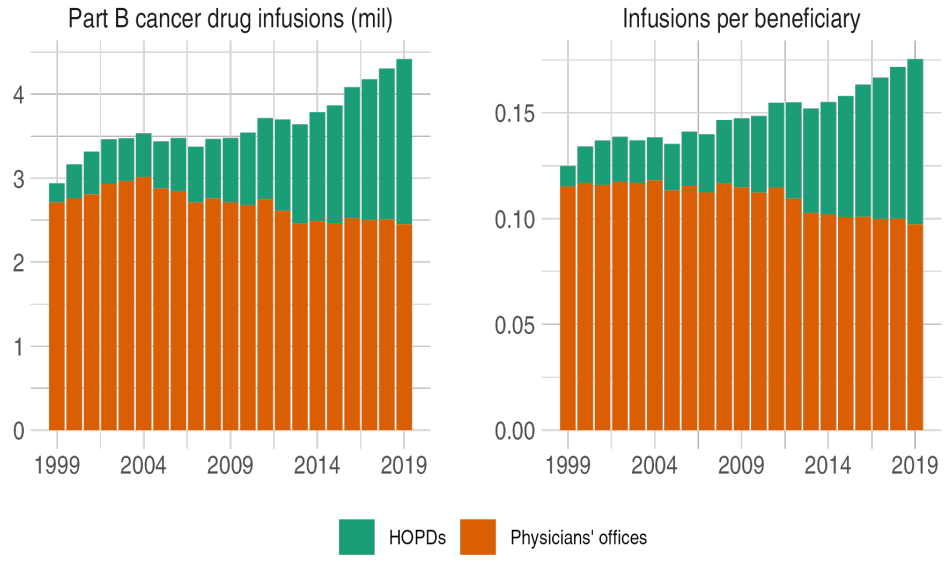

Figure A1: Part B cancer drug infusions by billing organization

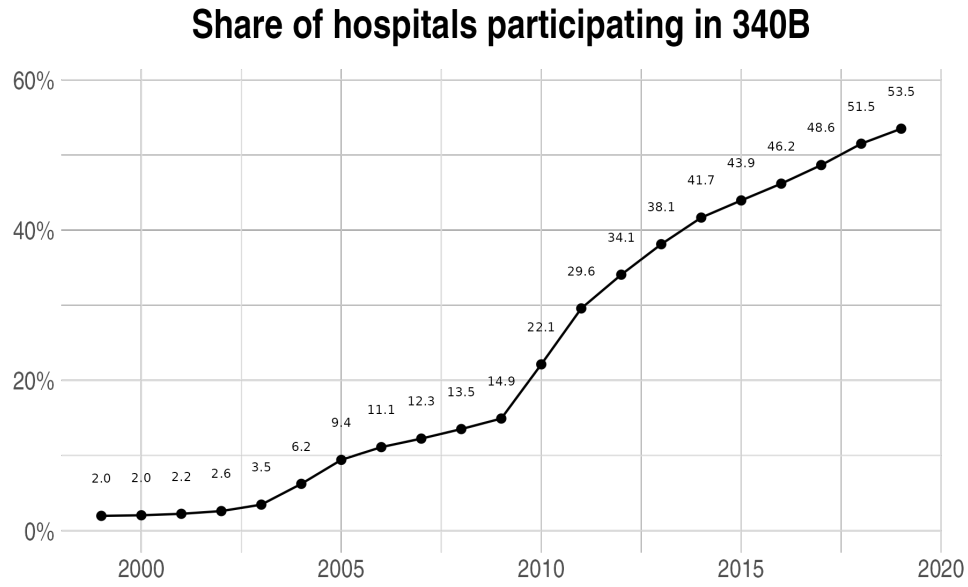

Figure A2: Annual participation in 340B: all acute care hospitals

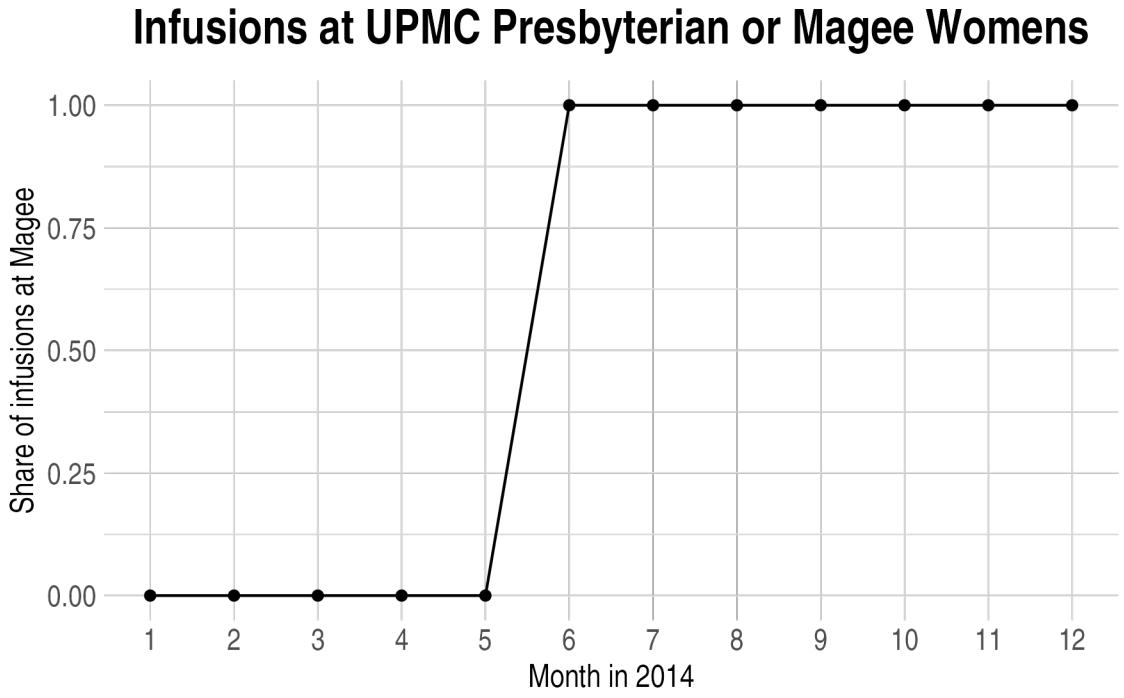

Figure A3: Infusions by billing hospital among Pittsburghers in 2014

This figure depicts cancer drug spending among fee-for-service Medicare beneficiaries living in the Pittsburgh Hospital Referral Region and billed by UPMC Presbyterian or UPMC Magee-Womens in 2014. Infusions in hospital-months that comprise 10 or fewer beneficiaries are censored by setting them equal to 0. In June, the share of procedures billed by UPMC Presbyterian (non-340B) discontinuously falls to 0 percent, while the share billed by Magee-Womens rises to 100 percent.

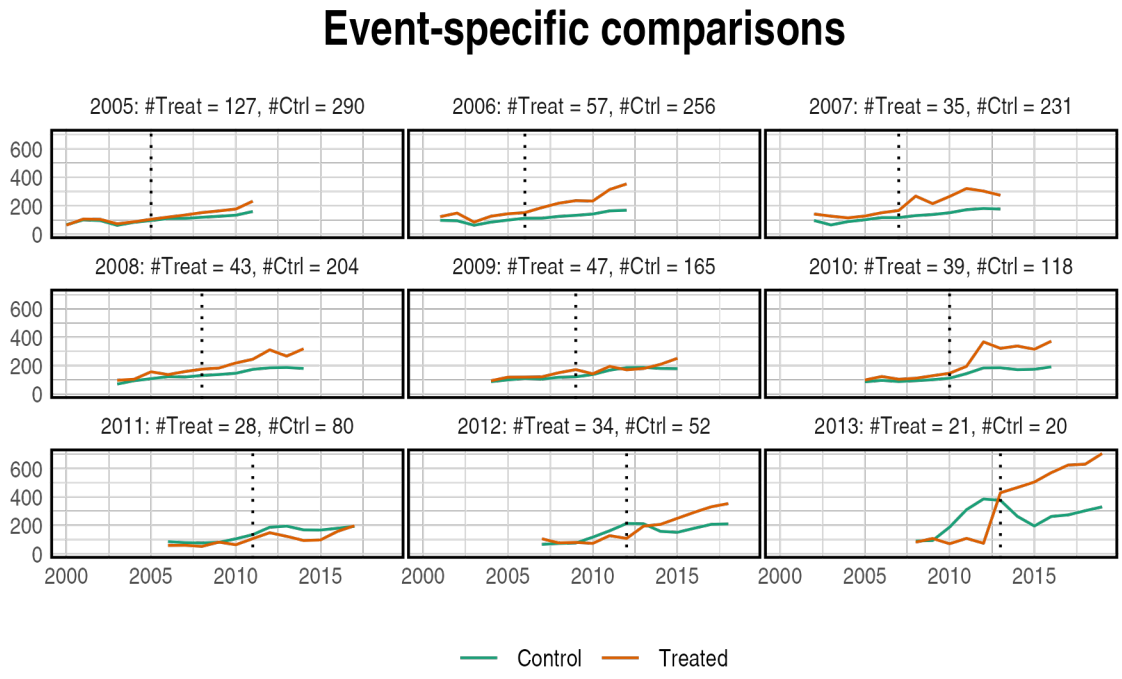

Figure A4: Unstacked event-specific trends in chemotherapy use

This figure depicts raw trends in cancer drug use for each of the 9 events that comprise the stacked panel of hospitals over the window of years used for estimation. A visual inspection of pre-trends shows that 8 of 9 have broadly parallel trends between treated and control hospitals. The single outlier is the 2013 event, which shows that control hospitals that became 340B DSH hospitals in 2020 grew relatively faster than hospitals that became 340B DSH hospitals in 2013 in the years prior to the latter group's participation in the program. The 2013 event comprises a small fraction of hospitals, and results are not sensitive to removing it from the sample.

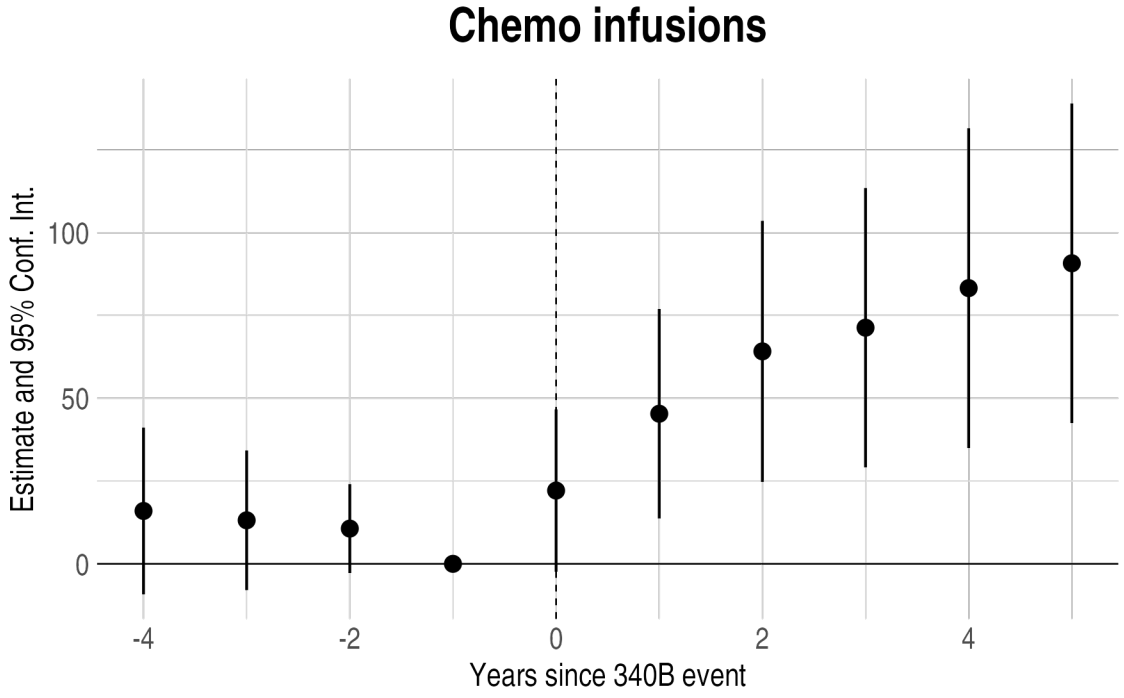

Figure A5: Stacked sample event study coefficients using shorter window: chemotherapy infusions

This figure reports ordinary least squares estimates of event study coefficients. For each event beginning at time d, the treated group includes all DSH hospitals that begin 340B in d and the control group includes all hospitals that begin 340B as a DSH hospital in year $d + 6$ or later. The coefficients reflect the difference in trends between new 340B DSH hospitals and later participants for each event, controlling for time-varying covariates, hospital-event fixed effects, and year-event fixed effects.

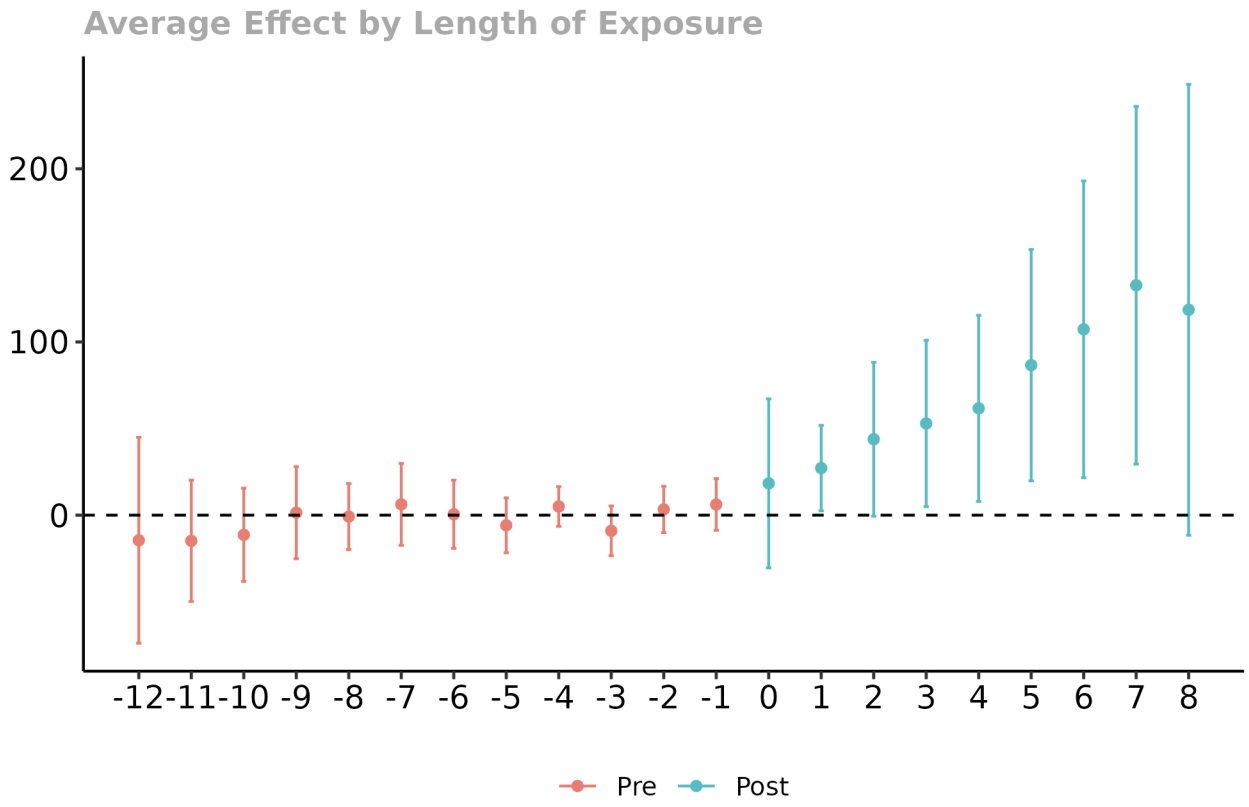

Figure A6: Callaway and Sant'anna event study coefficients: chemotherapy infusions
This figure reports Callaway & Sant'Anna (2021) estimates of event study coefficients using hospitals that begin participating in 340B between 2005 and 2014. In each year, hospitals that are not-yet-treated serve as controls for participating hospitals. Therefore, the subset of hospitals that begin participating between 2005 and 2013, which are employed in the paper's main specification, also identify these event study coefficients (hospitals that begin participating in 2014 are only used as controls).

A.3 Appendix Tables

Table A1: Magee-Womens 340B-registered off-site clinics

Date	Registered Outpatient Clinic	
10/22/2007	Magee at Clairton	Community health centers
10/22/2007	Magee at Monroeville	
10/22/2007	Magee at Wilkinsburg	
5/15/2012	Magee at Mt. Oliver	
1/12/2015	Hillman CancerCenter / Second Floor	Comprehensive cancer centers
1/12/2015	Hillman CancerCenter / The Mario Lemieux Center for Blood Cancers	
1/12/2015	Hillman CancerCenter / Third Floor	
1/12/2015	UPMC CancerCenter at St. Margaret	
1/12/2015	UPMC CancerCenter at UPMC Passavant / North Hills	
1/12/2015	UPMC CancerCenter at UPMC Passavant / North Hills HOA HBC	
1/12/2015	UPMC CancerCenter, Beaver	
1/12/2015	UPMC CancerCenter, Jefferson	
1/12/2015	UPMC CancerCenter, Monroeville	
1/12/2015	UPMC CancerCenter, Natrona Heights	
1/12/2015	UPMC CancerCenter, Sewickley	
1/12/2015	UPMC CancerCenter, Upper St. Clair (Drake)	
1/12/2015	UPMC CancerCenter, Washington	

These 340B child sites were identified from a search of the 340B Covered Entity Database on October 8, 2023. Child sites that registered in 2020 or later are omitted (340B Office of Pharmacy Affairs 2023).

This table reports Poisson pseudo-maximum likelihood estimates of a triple difference model between 2010 and 2016 (as well as control hospitals that are not acquired). For each acquisition event beginning at time d, the treated group includes all DSH hospitals that are first acquired in d and the control group includes all hospitals that are first acquired in year $d + 4$ or later (or are never acquired). The coefficient on Treat $\times$ Post represents the average log-point effect of acquisition of non-340B hospitals. The coefficient on 340B $\times$

Table A2: Cancer drug effect heterogeneity by cancer

Dependent Variable:	Chemo infusions						
Cancer	All cancers	Brain	Breast	Colorectal	Lung	NHL	Prostate
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Treat × Post	62.35**	1.898*	17.27*	10.09*	12.37*	18.81***	14.56**
	(21.35)	(0.8627)	(7.054)	(4.664)	(6.029)	(5.352)	(4.959)
Treat × Treatment year	5.849	-0.2903	4.712	1.690	-0.9999	-2.275	3.085
	(15.63)	(0.8659)	(5.394)	(3.775)	(4.538)	(4.611)	(3.717)
Fixed-effects							
Hospital-Event	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Event	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,164	22,164	22,164	22,164	22,164	22,164	22,164
Treated hospital counterfactual mean	175.52	3.05	49.27	33.44	45.36	37.53	36.41
Percent change (relative to counterfactual)	35.52	62.31	35.04	30.19	27.26	50.11	39.99

Clustered (Hospital referral region & Health system) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, †: 0.1*

Treat × Post represents the additional log-point effect of acquisition on 340B hospitals.

Table A3: Acquisition effects 2010–2016

	Chemotherapy infusions			
	All Acquisitions	Only other 340B	Only other Non-340B	Both
Model:	(1)	(2)	(3)	(4)
Variables				
Treat × Post	0.2998	0.2414	0.1860	-0.5080*
	(0.1976)	(0.6985)	(0.3545)	(0.2501)
340B × Treat × Post	-0.2461	-0.2492	-0.0964	0.8638*
	(0.2109)	(0.7109)	(0.3766)	(0.3550)
Fixed-effects				
Hospital-Event	Yes	Yes	Yes	Yes
Year-Event-340B	Yes	Yes	Yes	Yes
Treated hospitals	144	31	35	37
Control hospitals	339	339	339	339
Observations	13,440	12,649	12,677	12,691

Clustered (Health system & Hospital referral region) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, †: 0.1*