Turbocharging Profits?
Contract Gaming and Revenue Allocation in Healthcare*

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Abstract

Firms often exploit weaknesses in government contracts to boost revenues, yet little is known about how they allocate these funds. We study how hospitals allocated $3 billion obtained from gaming a Medicare loophole. The average gaming hospital increased Medicare and total revenue by around 10%, implying large spillovers on other payers. Nonprofit hospitals deployed most funds toward operating costs. For-profits–driven by a large chain–deducted funds off their balance sheets, distributing them to executives and shareholders. Accordingly, we detect reductions in mortality only at nonprofits. Our results imply that the consequences of engineered windfalls vary substantially by hospital ownership.

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1 Introduction

Governments frequently contract with private firms to deliver goods and services in sectors such as education, healthcare, infrastructure, and defense. Design flaws or ambiguities in these contracts provide opportunities for "gaming" in which firms strategically exploit these contract imperfections to increase revenue beyond the intention of policymakers. There is evidence of contract gaming and fraud across a range of government programs and countries (Jacob and Levitt, 2003; Dafny, 2005; Decarolis, 2014; Carrillo et al., 2023; Griffin et al., 2023). In the United States, this behavior contributes to the hundreds of billions of dollars the federal government spends annually on improper payments (Government Accountability Office, 2025).

Despite the significant costs that contract gaming imposes on government budgets and taxpayers, little is known about which firms engage in this behavior and how they allocate the "engineered" windfall. Although money is fungible, managers may allocate revenue from gaming differently from funds obtained from standard business practices or policy-driven windfalls. For example, managers might perceive revenue from gaming as illegitimate or transient, limiting its utility for long-term productive commitments like permanent staff (Wang et al., 2021). Moreover, governments typically contract with a mix of for-profit and nonprofit organizations with distinct missions and objectives that could influence managerial decision-making and how funds are allocated (Weisbrod, 1988). Understanding this heterogeneity is thus crucial for policymakers seeking to optimize the targeting and efficacy of their oversight efforts.

We study contract gaming and firm behavior in the context of U.S. healthcare, where the presence of private intermediaries, information frictions, and contracting complexity creates frequent opportunities for gaming (Leder-Luis and Malani, 2025). Specifically, we study how hospitals allocate the revenue obtained from exploiting a payment loophole in Medicare, the large public insurer that accounts for 12% of federal expenditures but 34% of improper payments (Government Accountability Office, 2025). The loophole occurred in Medicare's "outlier" payments program. For most patients, Medicare uses a fixed-price contract (Laffont and Tirole, 1993) that does not pay hospitals for costs of care at the margin. Outlier payments pay hospitals for some of the marginal costs of treating patients who require resource-intensive care. However, due to flawed implementation, hospitals could inflate outlier payments by "turbocharging": rapidly increasing their list prices, commonly referred to as charges. We conservatively estimate that hospitals that gamed this program received $3 billion in excess Medicare payments between 1998 and 2003 before the loophole was closed.

Several features of this episode make it an ideal setting to study contract gaming and its consequences. First, turbocharging often involves a top-down administrative decision by hospital managers to inflate charges across all patients via a simple change in hospital bookkeeping. Second, some hospitals were subject to large policy-driven payment cuts that may have incentivized gaming and were located near consulting firms that advised hospital managers on this practice (U.S. Department of Justice, 2008).[1] These features allow us to exploit conditionally random variation in gaming behavior. Third, the revenue at stake from this behavior was substantial, with turbocharging hospitals raising their effective Medicare payment rates by 22% at the peak of the episode.

Which types of hospitals gamed the Medicare loophole? We find that hospitals that engaged in turbocharging, which we refer to as "gamers", experienced larger Medicare payment cuts under the Balanced Budget Act of 1997 (BBA97), suggesting the cuts spurred hospitals to search for offsetting revenues. We also find that hospital ownership type is highly predictive of turbocharging. For-profit hospitals are heavily over-represented among gamers, consistent with their managers having stronger incentives to maximize profits since they can distribute profits to themselves (Hansmann, 1980). Non-profit hospitals were less likely to engage in turbocharging, consistent with theories of non-profit behavior emphasizing their mission-driven objectives and non-distribution constraint (Weisbrod, 1988). Lastly, almost no government-owned hospitals engaged in turbocharging, likely because these hospitals operate under soft budget constraints (Kornai et al., 2003).

We use a matched difference-in-differences approach to estimate the causal effect of gaming outlier payments on hospital revenue, the allocation of the windfall gain, and the downstream effects on quality of care. We match on BBA97 payment cut parameters to compare gamer hospitals to those that had a similar motive to exploit the loophole but did not, resulting in an analytic sample of 120 gamers and 1,396 matched comparator hospitals. We find that, on average, gamer hospitals obtain nearly $17 million in excess outlier payments, translating to a 10% increase in total Medicare inpatient revenue between 1998 and 2003. The rapid growth in hospital list prices at gamer hospitals may also impact other payers because they often benchmark their payment rates to list prices (Bai and Anderson, 2016; Cooper et al., 2019) or piggyback on Medicare's contract design, thus inheriting its flaws (Clemens et al., 2017; Clemens and Gottlieb, 2017). Indeed, we detect large spillover effects onto other insurers: total hospital revenue increases by nearly $80 million at gamer hospitals, a similar amount to Medicare revenue in percent terms.

What do hospitals do with the engineered windfall? We trace the flow of funds into three mutually exclusive and exhaustive categories. First, we find that about two-fifths

[1]While all hospitals could, in theory, engage in turbocharging, not all hospitals had the same motives or incentives to do so. For example, hospitals may have been concerned about violating the False Claims Act and the negative publicity from excessive charge growth, especially hospitals already facing regulatory scrutiny. Hospitals that treat few outlier patients would also have less to gain from manipulating payments.

of the revenue obtained from turbocharging flowed toward operating costs, although the estimate is imprecise. Second, we study changes in net worth (defined as assets less liabilities) and find minimal effects, including no detected change in fixed assets that might benefit patients, such as land, buildings, and equipment. Third, we consider the only remaining destination for revenue: to flow off the hospital's balance sheet. These funds are often transferred to a hospital's parent organization, which could use them for various purposes, such as executive compensation. We find that half of the estimated total excess revenue obtained from turbocharging flows off the balance sheet.

These findings obscure economically meaningful and statistically significant differences between the way nonprofit and for-profit hospitals allocate this revenue. Among nonprofit gamers, revenues flow predominantly to operating costs. In particular, nonprofits increase spending on non-labor operating costs that could enhance care delivery, such as spending on adult and pediatric routine care, pharmacy, drugs and medical supplies, operating room, and emergency room costs. In contrast, for-profit gamers transfer all of the excess revenue off their balance sheets. This behavior is driven by Tenet Corporation hospitals–the second-largest publicly traded healthcare chain at the time–which account for three-fourths of the for-profit gamers in our sample. We find that Tenet dramatically increased executive compensation and stock buybacks during the gaming period. Back-of-the-envelope calculations suggest that roughly $1 billion was funneled toward Tenet's executives and shareholders.

Given these differences in the use of funds, we next investigate changes in standard metrics of quality of care and focus on mortality, which has an unambiguous welfare implication. We find an improvement in mortality rates at nonprofit hospitals and no change at for-profit hospitals. Our estimates translate to nonprofit gamers reducing mortality rates by 3% following an 8% increase in Medicare spending. This implies a lower return on hospital spending than reported by prior studies but aligns remarkably well once we account for the fact that about one-third of the excess revenue at nonprofit gamers was not directed to patient care (Doyle et al., 2015; Silver, 2021). Since nonprofit gamers used the windfall to improve patient health, we can conclude that these providers were not on the "flat of the curve" and that they may even have been underpaid. This striking result highlights that gaming by firms can sometimes benefit program enrollees.

This paper contributes to four strands of literature and has several policy implications. First, we extend the research studying how firms respond to windfall gains. Much of this literature has focused on firm responses to winning lawsuits, grants, or bonuses (Blanchard et al., 1994; Howell and Brown, 2022; Cespedes et al., 2023). Within healthcare, adjacent literature has studied how healthcare providers respond to policy-driven price and wealth shocks (Duggan, 2000; Kaestner and Guardado, 2008; Clemens and Gottlieb, 2014; Cabral et al., 2018; Gross et al., 2024). Some prior studies have examined how firms game contracts, for example, by "upcoding" patient or beneficiary risk to increase revenue (Dafny, 2005; Sacarny, 2018; Silverman and Skinner, 2004; Cook and Averett, 2020; Geruso and Layton, 2020). However, these studies do not directly examine how the excess funds are deployed.

Managers may view funds obtained by gaming contracts as less legitimate and less permanent than revenue obtained from regular income or intended policy changes (Wang et al., 2021). Such compartmentalization of revenue into separate "mental accounts" may lead managers to spend engineered windfalls differently (Thaler, 1985). Consistent with this theory, several studies on policy-driven windfalls find that excess firm revenue funds capital spending or benefits employees (Saez et al., 2019; Howell and Brown, 2022), while we find minimal evidence of such behavior among gamer hospitals. For-profit hospitals, largely driven by Tenet, transfer the majority of funds off the balance sheet. Even among nonprofit hospitals, excess revenue is not spent on long-term commitments such as fixed capital or additional staff; instead, it is spent on immediate operating needs. To the extent these uses of funds from gaming are out of step with policymakers' priorities, our results would support efforts to design stricter contracts or conduct more extensive oversight.

Second, we contribute to the literature on the ownership and performance of healthcare organizations. Many studies of US hospitals have found evidence that nonprofits often behave like for-profits (Dranove and Ludwick, 1999; Duggan, 2000; Sloan et al., 2001; Capps et al., 2020). However, in theory, nonprofit and government-owned organizations should provide public goods or services that might be under-supplied by purely profit-driven organizations (Weisbrod, 1988; Shleifer, 1998). Our results are consistent with these theoretical predictions of distinct responses by government, nonprofit, and for-profit hospitals in their propensity to exploit the loophole and, conditional on doing so, in how they allocate excess revenue (Newhouse, 1970; Rose-Ackerman, 1996; Glaeser and Shleifer, 2001; Garthwaite et al., 2018). In particular, we find that nonprofit hospitals spend more on patient care and improve quality by reducing mortality rates, while for-profit gamers admit healthier patients and correspondingly reduce staff FTE, with no detected improvement in quality. These results highlight that contract imperfections can result in meaningful changes in patient care and patient allocation across hospitals – gaming can represent more than just a transfer of funds from taxpayers to firms.

Third, our results demonstrate the potential for large spillover effects of contract imperfections in government programs onto private participants (Clemens and Gottlieb, 2017; Clemens et al., 2017; Einav et al., 2020). In this setting, the cumulative loss to non-Medicare insurers was greater than that to Medicare. Among private insurers, these cost increases likely translated into rising premiums, with downstream effects for consumers and employment (Brot-Goldberg et al., 2024). Benevolent policymakers would internalize these negative externalities when considering investments in contract design or oversight programs. These findings are also relevant to other instances in which providers manipulate charges or costs to increase their revenue. For example, such behavior has been noted among nursing homes aiming to appear less profitable to raise public reimbursements (Gandhi and Olenski, 2024).

Lastly, we contribute to the literature on forensic economics (Zitzewitz, 2012), which includes research on employee gaming of incentive contracts (Oyer, 1998; Larkin, 2014) and fiscal shenanigans by state governments (Baicker and Staiger, 2005). A related literature demonstrates the value of improving payment design and investing in disciplinary mechanisms to curb fraud and abuse (Howard and McCarthy, 2021; Leder-Luis, 2023; Perez and Wing, 2019; Shi, 2024; Eliason et al., 2025). We complement these studies by showing that the social value of spending due to gaming of public programs is not uniformly high or low and varies significantly by the firm's ownership type. This finding suggests policymakers may benefit from targeting their monitoring and oversight efforts at actors that deploy funds from gaming in less socially valuable ways, like the for-profits in this episode.

2 Background

2.1 Medicare and outlier payments

The origins of this episode can be traced to 1983 when Medicare implemented a prospective payment system to reimburse hospitals for inpatient stays (Appendix A.1 reviews the history in more detail). The system paid hospitals a fixed price per inpatient episode irrespective of realized costs of treatment, aiming to provide a strong incentive to minimize production costs (Laffont and Tirole, 1993). In practice, the system used diagnosis and procedure codes to classify patients into payment categories called Diagnosis-Related Groups (DRGs). Each DRG had a standardized relative price called a weight; to pay hospitals, a weight was converted to dollars based on market and hospital characteristics. Within a DRG, hospitals incurred the full marginal cost of treatment.

This payment system created two potential problems. First, it gave hospitals an incentive to avoid admitting patients who would be costly to treat within a DRG. For example, hospitals would lose money by treating a patient who was likely to need ventilator support for months. Second, hospitals now had an incentive to shirk on care for patients who were admitted by discharging them earlier than medically appropriate.

To address these issues, the system included an insurance program called outlier payments. The program had the form of an insurance policy in which hospitals paid the full cost of treatment until costs in excess of the DRG payment exceeded a deductible, at which point Medicare paid 80% of further costs. For example, consider a procedure with a DRG payment of \$10,000. If the outlier payments deductible is \$20,000 and the hospital's reported cost to treat a very ill patient is \$100,000, then the hospital receives 80% of the cost beyond \$30,000, or \$56,000 in outlier payments.

However, as in many contracting settings, the federal government agency administering Medicare, the Centers for Medicaid and Medicare Services (CMS), could not observe the true costs of treatment, and so it relied on costs reported by hospitals. These were calculated in a convoluted fashion, where the hospitals reported the list price or "charges" for each patient stay, and CMS deflated this list price using a cost-to-charge ratio to arrive at the expected cost. Hospitals calculate a patient's charges by finely tracking the procedures, supplies, and other services used in their care and then pricing them according to a set of list prices called the chargemaster. Hospitals have wide latitude to set these list prices, untethering them from actual costs (Dobson et al., 2005).[2] While some details have changed over time, the essence of the outlier payment system has remained unchanged since the 1980s (Appendix B).

2.2 Opportunities to game payments

Medicare's approach to calculating outlier payments gave hospitals the opportunity to game the system by inflating their charges – a practice referred to as "turbocharging" (CMS, 2016). A hospital's charges rendered in year t were typically deflated by cost-to-charge ratios from year $t-3$ or $t-4$. This delay occurred because the ratios came from hospital cost reports that could take years to finalize.

If costs and charges grew at the same rate in the intervening years, the delay would not matter. However, if hospitals grew their charges rapidly, Medicare would not account for that growth for several years. Therefore, a hospital's patients would appear much costlier than they actually were and yield more outlier payments in the interim.[3]

Figure 1 illustrates this phenomenon by showing the evolution of "costs" at the most extreme gamer hospital in our data, a nonprofit facility in New Jersey. Specifically, it shows histograms of deflated charges, less DRG payments, across patients in each fiscal year. Beyond the deductible (the vertical red line), Medicare paid the hospital 80% of the remaining cost.

[2]The cost-to-charge ratio used to deflate charges is taken from a hospital's most recently settled cost report. It represents the sum of all hospital costs divided by the sum of charges across all patients treated in a given reporting year.

[3]Hospitals with particularly extreme turbocharging could also exploit a related loophole. If a hospital's log-cost-to-charge ratio were more than 3 standard deviations away from the national average, Medicare considered it a data error and instead used the average ratio of other rural or urban hospitals in the state. By rapidly increasing charges, hospitals could drive down the ratio to the point that Medicare treated it as an error. Going forward, their heavily marked-up charges would be deflated by the markup of the average hospital, making patients look exceptionally expensive.

In the lead-up to the turbocharging period (1997), only 5.3% of patients surpassed the deductible. As turbocharging grew (2000–2003), the cost distribution shifted to the right. CMS concurrently raised the deductible from under $10,000 in 1997 to over $30,000 in 2003, attempting to curtail the growth in outlier payments. Even still, 22.0% of patients cleared the deductible in 2003. After the loopholes were closed, the cost distribution perceived by CMS shifted back to the left, and in 2004, only 6.6% of patients cleared the deductible.

In the 1990s, there were three key developments that gave hospital managers more reason to consider gaming. First, the return to gaming slowly rose as Medicare directed more funds to the outlier program we study, taking funds away from another form of outlier payment that reimbursed hospitals for unusually long patient stays. To do so, Medicare lowered the deductible for high-cost outlier payments, increasing the number of patients triggering these payments. Second, the scope for gaming also grew as bureaucratic delays led to longer lag times to settle cost reports. In turn, the charges were deflated by older cost-to-charge ratios, "providing hospitals with a longer timeframe within which to continue gaming the system" (United States Senate, 2003). Third, and most acutely, the Balanced Budget Act of 1997 (BBA97) substantially reduced Medicare DRG payments to hospitals, while leaving outlier payments largely unchanged (O'Sullivan et al., 1997). The law froze or cut annual payment updates and add-on payments for teaching and safety net hospitals. The cuts began in fiscal year 1998 and were so substantial that for the first time in its history, Medicare paid hospitals less in one year than it had the previous year (Merck et al., 2001).

Hospital stakeholders suggested that pressures from BBA97 led hospitals to game outlier payments as a new source of revenue. For instance, a New Jersey Hospital Association economist suggested that hospitals in the state gamed because they were disproportionately hit by BBA97 cuts (Jaklevic, 2003). Likewise, the president of the California Nurses Association described the outlier payment gaming as "an end run around" BBA97 and efforts by HMOs to control costs (Rawlings and Aaron, 2005). Some consulting firms also counseled nearby hospital managers to exploit the payment loopholes, driving geographic clustering of gaming behavior. For example, a New Jersey consulting firm settled with the US Department of Justice (DOJ) to resolve allegations that it advised nearly a dozen hospitals to increase charges and inflate their outlier payments (U.S. Department of Justice, 2008).

As the BBA97 cuts phased in, many hospitals began rapidly growing their charges and came to reap higher outlier payments. These charge increases also applied to all billing at the hospital, including non-Medicare insurers. Gaming continued for several years with little recognition by CMS. The agency noticed that outlier payments were coming in above target (see Figure 2) but did not connect these developments to excess charge growth (United States Senate, 2003). Their strategy to curb payments was to raise the deductible, tripling it between late 1998 and late 2002, as indicated in Figure 1. Raising the deductible reduces outlier payments, all else equal, but hospitals were gaming the system so aggressively that aggregate payments remained above Medicare's target.

2.3 The legal disputes and aftermath

In October 2002, a financial analyst released a report showing that the Tenet Corporation, the second largest publicly traded for-profit chain, relied much more heavily on outlier payments than previously known (Galloro, 2002). At approximately the same time, the Justice Department began investigating Tenet hospitals in California for Medicare fraud, and a whistleblower suit was filed in federal court alleging that over a dozen Pennsylvania and New Jersey area hospitals, including both Tenet hospitals and nonprofit hospitals, had fraudulently manipulated the outlier payment system (Leder-Luis, 2023; U.S. v. Tenet et al., 2002). The news stories in the ensuing period highlighted that several hospitals and hospital systems were receiving surprisingly high outlier payments (Stark and Goldstein, 2002; Jaklevic, 2003). See Appendix A.2 for more details on the legal disputes.

Following these events, CMS closed the loopholes with a series of policy changes in August and October 2003. It instructed contractors to use more recent cost reports to calculate the cost-to-charge ratio so that charge growth would be reflected more quickly in payment calculations. It also created a framework to recompute outlier payments later and, if necessary, recover excess payments. These changes ended this era of gaming. Figure 2 shows the sudden drop in payments in 2004, and Figure 1 shows that the perceived cost distribution of the most extreme gamer in our data shifted far to the left in 2004.

In the aftermath, federal agencies sued dozens of hospitals and health systems for fraudulent billing under the False Claims Act, all of which settled without admitting wrongdoing. Tenet, for example, paid $788 million to settle allegations related to outlier payments (U.S. Department of Justice, 2006). Hospitals defended their actions as a response to "flawed public policy, not fraud or illegal activity" (United States Senate, 2003) and the then-CMS Administrator described the scheme as "program abuse" and said it was "arguable" that it was legal (United States Senate, 2003).

Given this legal ambiguity, fewer hospitals were prosecuted than engaged in outlier payment manipulation.[4] Using a statistical approach, we provide evidence that gaming was far more widespread than the set of hospitals that were sued. However, because our method cannot determine whether hospitals acted with intent to defraud Medicare, we refer to these practices as "gaming" rather than fraud throughout this paper.

[4] As with most False Claims Act cases, federal agencies mainly pursued hospitals where whistleblowers stepped forward with clear evidence of payment manipulation.

2.4 Theories of Hospital Behavior

What does economic theory say about which hospitals may be most likely to game Medicare and how they use the funds? First, we expect a hospital's ownership type (i.e., whether government, nonprofit, or for-profit) to be a key determinant of hospital behavior because it shapes the organization's scope to distribute profits and the fiduciary responsibilities of managers. For-profits can distribute profits to executives and shareholders, while nonprofits are barred from doing so. Both nonprofit and for-profit managers have a fiduciary responsibility to act in the best interests of their organization, which in nonprofits is often perceived as fulfilling a charitable mission, and in for-profits is often perceived as maximizing shareholder returns.

Drawing on these features, for-profits may be more likely to engage in gaming of payment contracts to boost profits than nonprofit hospitals. Theories of hospital and firm behavior (see e.g. Sloan, 2000; David et al., 2007) have viewed nonprofit hospitals as relatively focused on maximizing social welfare and have suggested that they tend to attract decision-makers who prioritize this mission (Rose-Ackerman, 1996; Besley and Ghatak, 2005). Other work has highlighted nonprofit status as a signal of noncontractible quality – since nonprofits cannot distribute profits to owners, patients may trust that they invest excess revenue in quality improvement (Arrow, 1963; Hansmann, 1980; Glaeser and Shleifer, 2001; Jones et al., 2017). Alternatively, nonprofits may operate as "for-profits in disguise," seeking to maximize profits while disguised as charitable organizations (Weisbrod, 1988). In practice, nonprofits are probably neither pure profit nor pure welfare maximizers (Newhouse, 1970).

These theories of hospital ownership provide insight into how hospitals may allocate excess revenue obtained from contract gaming. For example, nonprofits have implicit constraints based on their reputation as providers of charity care and explicit constraints due to non-distribution requirements that may motivate them to spend excess revenue on patient care. Altruistic managers at nonprofits may also seek to advance nonprofit goals, such as expanding access to care or improving quality. In contrast, bound by their fiduciary responsibilities, for-profit managers could instead use surplus funds as an opportunity to distribute profits to their shareholders, as well as themselves.

Second, hospitals may spend profits differently based on the legitimacy and permanence of the funds. Behavioral economists have suggested that individuals tend to compartmentalize their finances into separate "mental accounts" (Thaler, 1985). Such behavioral biases may also afflict hospital managers, who could tag funds obtained from contract gaming as less legitimate, hold them in a distinct mental account, and spend them differently from other funds. A related phenomenon is the "flypaper" effect, which suggests organizations use government funds in accordance with their intended purpose rather than integrating them into their budget for more optimal use (Hines and Thaler, 1995; Singhal, 2008). Managers may also view funds obtained from gaming as temporary and, therefore, may choose to spend the revenue on more immediate operating needs rather than long-term commitments. Indeed, the loophole hospitals exploited in this setting proved to be transitory.

3 Data

This study combines a wide array of data sources to identify the set of hospitals eligible for outlier payments, determine which hospitals potentially gamed these payments, and observe their clinical and financial behavior. We observe almost all data between 1994–2006 and use this period unless otherwise noted. We adjust all monetary outcomes for inflation and display them in real 2000 dollars (FRED, 2025). Our set of hospitals is essentially the universe of those paid by Medicare under DRGs and thus eligible for outlier payments. We draw this list from a Dartmouth Institute tracking file (Austin et al., 2019).[5] To observe hospital characteristics, we link this file with CMS Providers of Services data and American Hospital Association survey data (Sacarny, 2019; National Bureau of Economic Research, 2025; HUD, 2025; American Hospital Association, 2025).

We directly observe the parameters that CMS contractors used to calculate payments through the CMS Impact file and Provider-Specific File (National Bureau of Economic Research, 2023; CMS, 2025b). We use hospital cost report data to track financial information, including revenues and expenses (Sacarny, 2022; National Bureau of Economic Research, 2010; CMS, 2025a; HCFA, 1995).[6] To observe patient-level charges and Medicare payments, including outlier payments, we use 100% fee-for-service Medicare hospital claims.

We also use Medicare claims and enrollment data to track hospital clinical performance (ResDAC, 2025b,a). We assemble a cohort of Medicare patients hospitalized for non-deferrable conditions via the emergency department (Card et al., 2009; Doyle et al., 2015). The data includes rich patient covariates, including demographics, diagnosis histories, and the diagnosis

[5]We use this file to track hospitals even if they switch Medicare identifiers. To focus on hospitals eligible for outlier payments, we drop hospitals that ever convert to critical access facilities, which are paid using a different system.

[6]We pre-process the cost reports to address potential data issues. First, we rebase them from fiscal years to calendar years (see Sacarny, 2022). Second, we remove potentially erroneous extreme values by winsorizing all variables 1% on each side within-year. Third, in rare (0.2% of hospital-years) cases when a hospital regularly submits reports but exactly one is missing, we interpolate the missing report as the average of the previous and next one.

for which the patient was admitted.[7] As outcomes, we track 30-day risk-adjusted mortality and readmission rates, the same metrics currently used by CMS to measure hospital quality (Gupta, 2021). The non-deferrability of these conditions helps mitigate concerns about the selection of patients into hospitalization (Card et al., 2009). Studies have also validated these observational quality metrics by showing that they are strongly correlated with the quality measured from patients who were quasi-randomized to hospitals (Doyle et al., 2019; Hull, 2020).

Lastly, we use Securities and Exchange Commission (SEC) filing data available through Compustat and online to determine executive compensation and shareholder payouts for publicly traded hospital systems (S&P, 2025b,a; Securities and Exchange Comission, 2025). Specifically, we present the total salary and bonus for the top five highest-paid executives. We also present a measure of the total compensation made by executives in a given year, including the value realized from option exercises (Kaplan and Rauh, 2010). For nonprofit hospitals, we use IRS form 990 data to determine total compensation for top executives, defined as officers, directors, trustees, and other key employees (National Center for Charitable Statistics, 2023, 2024).[8]

4 Research Design

4.1 Designating hospitals as gamers

The first task is to determine which hospitals likely did and did not game the outlier payment system. We develop an algorithm that focuses on growth in charges and outlier payments, drawing on the methods CMS used while addressing their weaknesses.[9] Our algorithm uses a simulated payments strategy that holds the patient mix and the payment formulas fixed. This strategy isolates the growth in outlier payments that came from the hospital's pre-existing distribution of charges across its patients and its realized charge growth. Specifically, we

[7]The cohort consists of patients admitted through the ED for any of 29 principal diagnosis categories described in Doyle et al.. The cohort construction approach is described in Chandra et al. (2024) and Gaynor et al. (2199). The data consists of index admissions, defined as the patient's first admission for a non-deferrable emergency in a year. Patient covariates include demographics, defined as age-race-sex interactions; histories of 23 diagnoses drawn from previous hospitalizations in the prior year; and fixed effects for the principal diagnosis ICD-9 category. We omit the 0.4% of hospital-years with 1-4 patients from regression analyses.

[8]To link our individual hospital sample to the 990 data, we identify the tax EIN of hospitals using a publicly available crosswalk, when available (Community Benefit Insight, 2025). If not, we match hospitals with the 990 data based on their name and location.

[9]One logical but flawed approach would be to simply adopt CMS's approach. Like us, CMS focused on charge and outlier growth. However, they used only 3-4 years of data, raising the risk of flagging hospitals that experienced transient shocks. Moreover, they used realized outlier payments, which were affected by changes in payment formulas. In turn, CMS's efforts to cut payments, like raising the deductible, could have blunted a hospital's growth in outlier payments and made gaming less apparent. Our approach addresses these concerns.

use the hospital's fiscal year 1995-1996 patient mix and simulate the payments the hospital would have received for them in fiscal years 1993–2003. The simulation leaves patients' DRGs unchanged, fixes the formula that calculates outlier payments (e.g., the deductible), but scales patients' charges so that they grow according to their actual trajectory during this period. We describe the method in detail in Appendix B.

We then fit a hospital-specific trend break model for two outcomes, the logarithm of observed average charges and the ratio of simulated outlier to non-outlier (DRG) payments:

$$o_{ht} = \alpha_h + \alpha_t + \beta_h^{pre} t + \beta_h^{post} (t - B) \, 1 \, [t \geq B] + \delta \ln (drgweight_{ht}) + \epsilon_{ht}, \tag{1}$$

where h indexes hospitals, t indexes time in quarters, and o_{ht} is the outcome. The model controls for hospital and quarter fixed effects, hospital-specific pre- and post-break trends, and the logarithm of the average DRG weight at the facility. B is the break, defined as the end of fiscal year 1996. This approach uses long periods to estimate the pre- and post-trends to limit the influence of transitory shocks and regression to the mean. It also controls for patient mix through DRG weights to account for growth in charges that might come from admitting sicker patients rather than gaming. We estimate this model using data from fiscal years 1993–2003 and limit to hospitals that treated patients in every quarter during this time.

We define the estimated increase in the outcome, $\hat{d}_h$, as the hospital's fitted value at the end of the sample period less its fitted value at the break, ignoring the effect of DRG weights. We assume that hospitals with large increases in their charge rates and their ratio of outlier payments over this period are the likely gamers. To be conservative, we set a high bar to make this determination: hospitals in the top decile of $\hat{d}_h$ on both dimensions are flagged as gamers. Hospitals below the 85^{th} percentile on both dimensions are assumed to have likely not manipulated their charges. We consider the space between the 85^{th} and 90^{th} percentiles to be indeterminate and exclude hospitals in this range from the analytic sample. In Section 5.5 we show our results are robust to using several alternative thresholds to define gamer and non-gamer hospitals.

Appendix Figure D.1 illustrates the joint distribution of $\hat{d}_h$ and highlights the gamer, non-gamer, and indeterminate hospitals. Panels (a) and (b) plot the joint distributions in percentiles and absolute values, respectively. We flag 180 hospitals as gamers, 2,530 as non-gamers, and 533 as indeterminate. Appendix Figure D.2 shows that among gamers, nonprofit and for-profit hospitals have common support of turbocharging intensity and engage in a similar intensity of gaming on average.

As with the approach used by CMS, we cannot say with certainty that every hospital designated as a gamer using this approach manipulated charges to reap excess Medicare outlier payments. Here, we find it reassuring that the set of hospitals designated as gamers overlaps closely with those accused by the DOJ based on whistleblower witness testimony. Note that the DOJ only brought lawsuits against a select set of hospitals. This set does not represent all hospitals that engaged in gaming. Of the 33 accused hospitals we could find using court documents and press releases, 26 (79%) were also flagged under this algorithm, 1 was designated a non-gamer, and the rest were in the indeterminate range. We also designated all but 3% of Tenet hospitals as gamers or indeterminate.[10] From hereon, for brevity, we refer to the hospitals tagged by our algorithm as gamers and the remaining hospitals retained in the sample as non-gamers.

4.2 Characteristics of gamer hospitals

Which hospital characteristics are associated with turbocharging? To shed light on this, we examined the association between turbocharging behavior and various hospital attributes measured in 1997. Figure 3 presents the mean values of select hospital attributes (e.g., % owned by a system) by decile of charge growth over 1998–2003, the period of interest. Panel A shows that hospitals in the top decile of charge growth were disproportionately likely to be for-profit owned. Although for-profit hospitals comprise about 15% of all hospitals, they are nearly 40% of hospitals in the top decile. Nonprofit hospitals are represented in all deciles of charge growth in a relatively stable fashion. In contrast, government-owned hospitals are disproportionately likely to be in the bottom two deciles of charge growth. These patterns are consistent with the theoretical predictions discussed in Section 2.4 about hospital ownership and the incentive of managers to maximize revenue. Panel B shows that hospitals in the top decile of charge growth are also disproportionately system-owned. Panels C and D examine the attributes that determined the size of the BBA97 payment cuts. The plots show that hospitals facing greater Medicare cuts, such as those located in markets with a higher wage index, were also disproportionately more likely to increase their charges.

To study these patterns formally, Appendix Table D.1 presents regressions predicting whether a hospital is in the top decile of charge growth or is flagged by our algorithm as a gamer based on characteristics recorded in 1997. These two outcomes are highly correlated, but differ in the case of hospitals with high charge growth that did not experience high growth in their (simulated) outlier share of total Medicare payments. Since results are qualitatively similar regardless of the outcome, we focus on the latter outcome for brevity.

[10] The Tenet lawsuit was against the entire corporation rather than a specific facility, so Tenet hospitals are not among the 33 we identify as accused. However, of the 94 hospitals affiliated with Tenet between 1998-2001, we classify 60 (64%) as gamers, 3 (3%) as non-gamers, and the remainder as indeterminate. Court records describe Tenet leadership as ordering different and tailored charge increases across hospitals, which is consistent with our classifications (SEC v. Tenet, 2007).

As seen in the bivariate regression results in Column 2, gaming hospitals are more likely to be for-profit, part of a health system, in an urban area, and have greater bed capacity. Column 4 shows that the association between gaming and for-profit ownership remains similar in magnitude even after conditioning on all the other attributes like system membership or bed capacity. Gaming hospitals also have higher mortality and readmission risk scores, suggesting that they may serve a higher-risk patient population.[11] The payment parameters most impacted by BBA97, which include the wage index and adjustments for safety net and teaching hospitals, are also highly predictive of gaming (discussed in more detail in the following section).

4.3 Construction of sample and matching

Given these differences in the characteristics of gaming and non-gaming hospitals, our goal is to construct a control group that minimizes the risk of bias in our estimates. We begin by restricting to the set of gamer and non-gamer hospitals open from 1994–2006. We next remove non-gamer hospitals located within 5 miles of gamer facilities. This restriction helps to address a potential Stable Unit Treatment Values Assumption (SUTVA) violation from non-gamer hospitals being influenced by their gamer peers. For instance, gamer hospitals might increase patient volume by "stealing" patients from non-gamer hospitals. Similarly, we remove hospitals that were ever affiliated with Tenet from the non-gamer group since the chain's gaming revenue may have been diverted to these facilities (this restriction only drops 3 hospitals that were Tenet-affiliated during 1998-2001). Finally, because exceptionally few government-run hospitals gamed payments, we drop all of these facilities from the sample. These restrictions reduce the sample to 145 gamer and 1,655 non-gamer hospitals.

An additional concern is the potential endogeneity of gaming. Hospitals may have gamed due to geographic coincidence, like locating near a consulting firm that advocated this strategy, and geographic clustering is apparent when we map flagged facilities (Appendix Figure D.3). This behavior might also reflect an effort to counteract payment reductions from BBA97. This driver of gaming presents a threat to our differences-in-differences research design because the shocks from BBA97 disproportionately affected certain hospitals, such as safety net and teaching facilities, and had their own effects on hospital behavior (Kaestner and Guardado, 2008; Azoulay et al., 2020).

A standard approach to address this endogeneity is to match gaming hospitals to non-gaming hospitals based on hospital characteristics before the gaming occurred. We match

[11] We regress an indicator for mortality or readmission on patient demographics, illness histories, and principal diagnosis categories. This regression is run only for patients at the comparator hospitals. Then, using the regression coefficients, we predict the probability of mortality or readmission for all non-deferrable patients. Finally, we average it to the hospital-year level.

on the payment parameters BBA97 affected: the add-on payment for safety net facilities, the add-on payment for teaching facilities, and the wage index.[12] We use these parameters at their 1997 values, which were established before BBA97. In addition, we match on the hospital's Medicare share of inpatients in terciles, since the Medicare share determines the hospital's overall shock from Medicare policies. Because we combine matching with differences-in-differences, our approach assumes that the matched comparison group provides a valid counterfactual trajectory for the gamer group.

Our baseline approach uses coarsened exact matching (CEM), although we demonstrate the robustness of our key results to a number of alternative methods. CEM coarsens the matching covariates into bins and then matches "treated" units (gamers) to "untreated" units (non-gamers) exactly on those coarsened covariates (Iacus et al., 2012; King and Nielsen, 2019). We generate weights to target the effect of gaming on the hospitals that gamed, i.e., the treatment on the treated (TOT) estimand. We call the reweighted non-gamer hospitals matched comparators.

After matching, our sample includes 120 gamer hospitals (78 nonprofit and 42 for-profit) and 1,396 non-gamer hospitals (1,196 nonprofit and 200 for-profit). Table 1 provides summary statistics on the gaming hospitals and the matched comparators. Panel A includes the payment parameters we matched on and Panel B includes other key characteristics. As expected, the averages are similar between the groups on the matched variables. Appendix Table D.2 shows the characteristics of the samples step-by-step as we move from the full set of hospitals to the set analyzed in the regressions. This table shows that the matching approach makes the groups much more observably similar on the covariates on which both were and were not directly matched. Appendix Table D.3 presents descriptive statistics for hospitals in the final analysis sample by type of ownership.

Hospitals owned by Tenet make up three-fourths of the for-profit gamer hospitals in our final analytic sample.[13] Therefore, in the analyses that follow, the behavior of for-profit gamer hospitals disproportionately reflects the behavior of Tenet. As the major publicly traded system engaged in turbocharging, we use Tenet filings with the SEC to examine executive compensation and shareholder payouts.

[12]While BBA97 did not change the wage index, it did limit annual payment updates. This policy essentially reduced payments to all hospitals by a common percent amount. We match on the wage index because these reductions impacted high-wage areas more in absolute terms.

[13]There are 42 for-profit gamers and 32 are part of Tenet. Eight of the non-Tenet for-profit gamers were part of the largest hospital chain at the time, the Hospital Corporation of America (HCA). HCA was already under federal scrutiny for another gaming episode (U.S. Department of Justice, 2003), potentially limiting its ability to game outlier payments.

4.4 Empirical strategy

Having assembled the gamer and matched comparator hospitals, we implement a difference-in-differences (D-D) research design to estimate the causal effect of manipulating the outlier payment program on income, use of funds, and other operational outcomes. The trends for the gaming hospitals over 1994–2006 are compared against those for the matched comparator hospitals. The period 1994–1997 represents the years before hospitals started turbocharging. We set 1997 as the last year before gaming because of the important role of BBA97 in triggering this response by hospitals.

The period 1998–2006 has three distinct phases. The early phase, 1998–2000, is the period when hospitals began to game outlier payments, while the late phase, 2001-2003, represents the height of gaming. The after phase, 2004–2006, immediately follows CMS closing the payment loophole. We estimate separate D-D coefficients corresponding to each of these phases using the following model.

$$y_{ht} = \alpha_h + \alpha_t + \beta_1 \cdot D_h \cdot early_t + \beta_2 \cdot D_h \cdot late_t + \beta_3 \cdot D_h \cdot after_t + X_{ht}\Theta + \epsilon_{ht}, \qquad (2)$$

where y_{ht} is the outcome of interest for hospital h in year t. D_h is a flag for hospitals tagged as gamers by our algorithm, as described in the previous section. β_1 captures the average difference in outcomes between gamers and non-gamers over the period 1998–2000, relative to the average over the years 1994–1997. Similarly, β_2 captures the average difference in outcomes in the late gaming period, relative to the pre-gaming period. We primarily focus on these coefficients.[14] X_{ht} is a time-varying control for Medicare Advantage penetration in the hospital's market.[15] ϵ_{ht} represents idiosyncratic unobserved factors that may also determine the outcome. We cluster standard errors by hospital, which is the level of treatment in this setting.

To interpret the coefficients β_1 and β_2 as the causal effects of exploiting the loophole, we impose the standard D-D "parallel trends" assumption. Here, that assumption says that outcomes for gamers and comparators would have progressed on common trends through the entire analysis period had the gamer group not engaged in the gaming behavior. As always, this identifying assumption is untestable because the gamer hospitals by definition engaged in gaming behavior. However, an event study can provide suggestive evidence on the plausibility of the claim by showing whether gamers and comparators were on differential trends before the former group of hospitals began to game outlier payments. The event study also helps to

[14]Appendix Tables D.4, D.5 and D.6 report all coefficients, including β_3, the effect during the post-gaming period.

[15]We define markets as Health Service Areas (HSAs), which are collections of counties in which hospital use is relatively self-contained (Pickle et al., 1996; National Cancer Institute, 2023).

assess effect dynamics. We therefore estimate the following model:

$$y_{ht} = \alpha_h + \alpha_t + \sum_{s \neq 1997} \gamma_s \cdot D_h \cdot 1\left[t = s\right] + X_{ht}\Theta + \epsilon_{ht}, \tag{3}$$

A hospital's decision to exploit the loophole is non-random and, as shown in Table D.1, varies based on hospital characteristics. While selection into gaming is an inherent feature of this setting, we mitigate concerns that hospital selection drives our results in the following ways. First, the matching design enables us to identify comparison hospitals that were similarly impacted by BBA97's changes to Medicare payments. As discussed in Section 2, this gaming episode appears to be prompted in large part due to the payment cuts instituted by BBA97. By comparing gaming hospitals to facilities that also faced observably similar payment cuts, we plausibly isolate a valid counterfactual. Second, consistent with our identifying assumption, we reassuringly find little evidence of trend deviations before 1998. Third, we observe that Medicare revenues at gaming and comparator hospitals reconverge after CMS closes the loophole. Although the post-gaming period is complicated by legal uncertainty and settlements, this convergence further suggests that the groups would have been on similar trends absent the gaming.

5 Results

This section presents our main results on the excess revenue hospitals generated by exploiting the loophole, how they allocated this revenue, changes in operations, and in patient outcomes of interest. Table 2 presents the main D-D estimates for the pooled sample, nonprofit and for-profit hospitals for the gaming period (1998-2003).[16]

5.1 Excess revenue

Figure 4 presents event studies on the inflow and outflow of funds using 1997 as the reference year and demarcates the gaming period (1998–2003) with vertical dashed lines. Figure 5 presents event studies distinguishing effects for for-profits and nonprofits.[17] To visualize our findings, Figure 6 presents Sankey plots of the flow of funds for nonprofit and for-profit gamer hospitals.

We begin by confirming that hospital charges increase differentially at hospitals identified

[16] Appendix Tables D.4, D.5, and D.6 provide full regression output by the period of gaming (early, late, and after) for pooled, nonprofit, and for-profit samples, respectively.

[17] We do so by matching for-profit gamers to the pool of non-gamers via CEM with the same coarsening as in the main analyses. Then, we estimate equations 2 and 3 using this sample. Next, we repeat the method for nonprofit gamers.

as gamers by our algorithm: gamers increase their charges by 59% over the 6-year gaming period relative to comparators, peaking at 96% higher in the latter half of the period (Appendix Figure D.4 Panel a). We then quantify the excess outlier payment revenue gained by the gamers due to turbocharging. Gamers and non-gamers had similar trends until 1998, when revenue increased differentially for gamers, peaking in 2002. As expected, there was a sharp drop in 2004, the first full year in which the loophole was closed. Payments then returned to baseline. Summing over the 6-year gaming period, the average gamer obtains over $17.3M in excess outlier payment revenue. We, therefore, can estimate that gamers obtained $3.1 billion in excess outlier payments by multiplying 180 (the full set of gamers) by $17.3M.

Next, we consider changes in Medicare inpatient revenue, a broader measure of income that includes DRG payments. We find comparable increases in total Medicare inpatient revenue and outlier payments, which is to be expected since increasing charges should not affect DRG payments absent other mechanisms. This pattern is reassuring since it suggests that significant changes on other margins, such as increasing the volume of Medicare patients or procedure intensity did not occur. To quantify the effective increase in Medicare payment rates hospitals receive from this aggregate payment change, we also consider the effects on payments per patient. We find that gaming raises rates by 22% in the late gaming period (Appendix Figure D.4 Panel b).

Lastly, we broaden the income measure to include revenue from all payers. We do so because turbocharging may have spillover effects on payments made by other insurers. Such spillovers could manifest if an insurer's pricing is set as a proportion of the hospital's list price. Previous studies have found that up to 40% of commercial insurer contracts set prices based on list prices, a practice that was even more prevalent during our study period (Cooper et al., 2019; Weber et al., 2021). Another potential channel would be if other insurers mimic Medicare's payment systems and also make outlier payments.[18]

We find that the total revenue increases by $13.3M per year, representing a $79.7M increase over the whole period. This represents a 12% increase over baseline revenue, a strikingly similar relative increase to that observed for Medicare payments. Unlike the patterns in outlier payments and Medicare revenue, we find that some increase in all-payer revenue persists beyond 2003. This might reflect the enduring increase in charges propagating to persistently elevated commercial insurance prices. Our results, therefore, imply large and durable spillover effects of turbocharging on private insurers and, consequently, on employers

[18]For instance, California's Workers' Compensation program used essentially the same system as Medicare and was also affected by gaming (DeMoro, 2003; Wynn, 2003). Some contracts with private insurers had a similar structure, with hospitals eligible to receive insurance-like "stop-loss" payments that depended on charges. Filings from Tenet indicate that these payments became a significant source of revenue for the firm during the gaming period, then declined precipitously (Tenet Healthcare Corporation, 2003, 2004).

and employees that fund private health insurance plans.

We find comparable absolute increases in outlier payments, Medicare payments, and all-payer revenue for nonprofit and for-profit gamer hospitals. Nonprofits display elevated levels of all-payer revenue even after the loophole is closed, suggesting longer-term spillovers to other payers.

5.2 Allocation of excess revenue

How do gaming hospitals allocate the funds obtained from turbocharging? Each dollar of excess revenue must either flow toward increasing operating costs or profits (nonprofits often refer to profits as surplus). Hospitals can use greater profits for two purposes. First, they could be used to increase net worth, which represents a hospital's total assets net of liabilities. Hospitals can increase short-term or long-term assets like cash reserves or fixed capital (e.g., purchase of new equipment) or reduce liabilities by paying down short-term or long-term debt. Second, profits can be transferred from the hospital to another entity (e.g., its parent firm), thus not affecting its assets or liabilities. We observe these transfers in the hospital cost reports submitted to CMS and refer to them as net deductions (our analysis considers deductions net of additions to the hospital's balance sheet, i.e., the net transfer off balance sheets). Appendix C provides accounting identities and further details on these categories.

Operating costs. We begin by examining the overall effect of gaming on operating costs. We find minimal evidence of pre-trends before 1998. Operating costs then began to increase in 2000, representing a \$33.1M increase in operating costs during the 6-year gaming period (not statistically significant). After the loophole is closed, the costs subsequently decrease.

The statistically insignificant effect on operating costs reflects the average of increases observed among nonprofit gamers and decreases observed among for-profit gamers. Nonprofit hospitals primarily allocate excess revenue to operating costs: the average nonprofit increases operating costs by \$57.6M during the 6-year gaming period (significant at the 10% level). In contrast, for-profits reduce operating costs by \$13.5M over this period, although this estimate is statistically insignificant. The operating costs of nonprofit hospitals also remain high after the loophole is closed, commensurate with their elevated all-payer revenue.

Net worth. Next we examine the overall effect of gaming on a hospital's net worth. While the series lacks a pre-trend, it follows a sawtooth pattern during the gaming period, returning to baseline by 2004, when the loophole is closed. The increase in net worth of \$3.8M over the 6-year gaming period is not statistically significant and represents only about 5% of the total increase in revenue.

For nonprofits, we find that net worth increases by \$8.5M over the 6-year period (not statistically significant), whereas for-profits reduce net worth by \$27.1M (significant at the 10% level). The estimate for the for-profit gamers is only marginally significant, and the underlying changes in assets and liabilities are small and statistically insignificant. Overall, based on these results, it does not appear that either type of hospital devoted excess revenue to capital purchases, such as land, buildings, and equipment.

Net deductions. Finally, we examine the overall effect of gaming on the remaining destination for excess revenue: net deductions. We observe similar trends between gamer and non-gamer hospitals before 1998 and a sharp increase in deductions that closely follows the increase in all-payer revenue. Net deductions increase by \$6.6M per year, representing an aggregate increase of \$39.6M over the 6-year gaming period.

The effect is mostly driven by for-profit hospitals: net deductions significantly increase by \$78.4M over the 6-year gaming period. In contrast, nonprofits increase net deductions by \$18.3M over this period (significant at the 10% level). Therefore, for-profit hospitals are predominantly sending their excess all-payer revenue off the balance sheet. These transfers can reflect funds sent to the hospital's parent organization, which could be disbursed to executives or shareholders for publicly traded firms or to other hospital affiliates.[19] While the cost report data alone does not permit us to examine the ultimate uses of these deductions, Section 5.3 explores whether revenue is transferred to executives and shareholders at for-profit hospitals.

Summary. As seen in the Sankey plots (Figure 6), a key finding is that nonprofits spent 64% (57.6/89.9) of their excess all-payer revenue on operating costs, while for-profit hospitals spent 132% (78.4/59.6) on net deductions. Net deductions exceed 100% because, in addition to increasing revenue, for-profits reduced operating costs and net worth (albeit statistically imprecisely) and used these proceeds to increase net deductions. We can reject the null hypothesis that the effects on operating costs are the same between nonprofits and for-profits at the 10% level and that the effects on net worth and net deductions are the same at the 5% level. Hence, nonprofits and for-profits allocated excess revenue differently in an economically meaningful and statistically significant way.

5.3 Effects on hospital operations

In this section, we focus on whether gaming affects hospital operations. Since we find that nonprofit and for-profit gamer hospitals used the excess funds differently, we examine how

[19] For example, in California cost reports, the list of additions and deductions includes a line for "intercompany transfers." Unfortunately, older Medicare cost report data does not provide the lines that add to net deductions.

spending on patient care, hospital staff, and executives differed by ownership type.

Inputs to care. We begin by examining whether there were changes in inpatient volume since those could influence hospital operations. Table 2 Panel C presents the point estimates and Figure 7 presents the corresponding event studies. We find small and statistically insignificant effects for both nonprofits and for-profits. This implies that the revenue increases observed are primarily driven by an increase in reimbursement per patient and helps explain the lack of spending on assets, as hospitals did not expand care services.

Next, we examine spending on labor costs, which are typically the largest component of operating costs for a hospital. Recall that nonprofit gamer hospitals spent most of the excess revenue on operating costs, while for-profit hospitals reduced their spending on operating costs. In Table 2 Panel B, we show that total salaries increase by less than one-fourth of the increase in operating costs at nonprofits. Among for-profits, salaries decrease by roughly the same magnitude as operating costs. On full-time equivalent (FTE) employment, we find a small and marginally significant decrease at nonprofit gamers. In contrast, we detect a large and statistically significant decrease in employment at for-profit gamers.

Since nonprofit hospitals increase operating costs but do not increase spending on salaries, they must be increasing spending on non-salary inputs. Focusing on nonprofits, we categorize all non-salary operating costs listed on Medicare cost reports as administrative or clinical expenses, following Himmelstein et al. (2014) and Wang et al. (2023). The administrative category includes spending on information systems, medical records, and general facility administration. Examples of clinical categories include spending on adult and pediatric routine care, pharmacy, drugs and medical supplies, patient dietary services, the operating room, and the emergency room.[20] Because we only observe costs at this finer level starting in 1997, we conduct a D-D analysis using only one "pre" year of data. As shown in Appendix Table D.7 Panel B, clinical costs account for three-fifths of the increase in non-salary spending, and the effect is significant at the 10% level. We detect small and statistically insignificant effects in the remaining categories.

Executive compensation and shareholder payouts. While nonprofits spent the majority of the revenue windfall on operating costs, for-profits–driven by the Tenet Corporation–transferred the majority off the balance sheet. Therefore, we investigate whether hospitals used this revenue to increase compensation for key executives, like CEOs and other top-level managers. Executives are employed at both the system (i.e., the parent organization)

[20] Cost reports do not provide a more detailed breakdown than the levels described here. These studies also allocate some expenses to a mixed clinical and administrative category, which includes spending on maintenance, repairs, and plant operations.

and hospital levels. Compensation to system-level executives represents a potential use of funds deducted from hospital balance sheets since the compensation costs for these employees may not be allocated to individual hospitals.

We present this analysis separately for system-level executives at publicly traded for-profit firms, whose compensation we observe through SEC filings, and hospital-level executives at nonprofit firms, whose compensation we observe through tax filings. Unfortunately, data on executive compensation for privately held for-profit hospitals is not systematically collected or made available for research. Since few health systems were publicly traded during our sample period, we can only study compensation at a single for-profit firm that gamed – Tenet Corporation. Given that there is only one "treated" firm for this analysis, we present time series analyses of executive compensation at Tenet compared to an average of the four other publicly traded for-profit health systems consistently observed in the data.

We find that Tenet's executive compensation follows a pattern similar to that of outlier payments. Figure 8 Panel (a) shows total executive salary and bonus, and Panel (b) expands the measure to include stock options exercised. By these metrics, Tenet's compensation for its top five highest paid executives reached a peak of \$13.4M and \$92.5M in 2001, respectively, before falling in the year the Tenet scandal broke. No such patterns are observed among the non-Tenet systems.

Publicly traded firms can also disburse profits to shareholders. As seen in Figure 8 Panel (c), Tenet shareholder payouts also coincide with the gaming period, with shareholders receiving \$923M between 2000 and 2004. Although non-Tenet systems also sporadically disbursed profits to shareholders, Tenet only did so during the gaming period. Through a back-of-the-envelope calculation, we estimate that roughly 40% of Tenet's excess total revenue was disbursed to the five highest-paid executives and to shareholders.[21] Tenet could have also used the excess revenue to engage in "empire building" by acquiring other hospitals. However, we do not observe unusual acquisition activity by Tenet relative to other hospital chains during the gaming period.

Among nonprofit hospitals, we observe trends in compensation for key hospital-level executives for a large number of both gamer and comparator firms and, therefore, analyze this outcome using the baseline model. In complete contrast to the patterns observed for Tenet, we do not observe any increase in compensation during 1998–2003 (Figure 8 Panel d). These results strongly suggest a divergence with regard to the use of funds for executive pay

[21]The 60 Tenet gamer hospitals received \$7.9M in all-payer revenue per year (similar to the amount reported for all for-profits in Table 2). Therefore, Tenet distributed \$1.1B of the \$2.9B estimated windfall to executives and shareholders. However, taking into account that Tenet's incremental profits would be subject to state and federal taxes, executives and shareholders received more than 50% of the windfall after tax.

between for-profit and nonprofit hospitals. However, since the executive compensation data are from Tenet, we caution that this result may not necessarily reflect how other for-profit gamers used such windfalls.

Summary. In this section, we provide evidence that nonprofit hospitals spend a substantial portion of the excess revenue on clinical care inputs, whereas for-profit hospitals (as represented by Tenet) divert much of it toward executive compensation and shareholder payouts. Given the temporary nature of the loophole, hospital managers in both nonprofit and for-profit hospitals may have been reluctant to spend the money on long-term commitments such as labor or capital inputs, instead spending on immediate operating needs (nonprofits) or sending revenue off the balance sheet (for-profits). Additionally, the difference between how managers at nonprofit and for-profit firms used surplus funds is consistent with organizational theories of distinct responses based on ownership type.

5.4 Quality of care

In this section, we investigate whether patient health outcomes improve at gamer hospitals. As discussed in Section 3, we examine changes in standard measures of quality used by Medicare and other payers in pay-for-performance programs to improve hospital quality, such as 30-day readmission and mortality rates.

Patient selection. Before testing for changes in the quality of care, we look for signs of patient selection as measured by the average observable mortality and readmission risk scores of hospitals' non-deferrable patients, described previously. Gaming may lead hospitals to select patients differently because it changes the relative prices of patients, affecting the aggregate revenue windfall. Reimbursements for *ex ante* costly (likely high-risk score) patients will tend to rise substantially for hospitals gaming outlier payments. However, gaming will also lead lower-risk score patients to appear more costly to Medicare and they could thus become eligible for outlier payments, raising their reimbursements, too. Finally, some gamer hospitals may use the excess revenue from outlier payments to fulfill other organizational objectives (e.g., a social mission to serve higher cost patients), a kind of wealth effect. Taken together, the impact of gaming on patient selection is thus an empirical question.

The overall results in Table 2 Panel D show a statistically insignificant decline in predicted mortality risk matched by a small but significant increase in predicted readmission risk. The corresponding dynamic effects are presented in Figure 9 Panels (a) and (b).

However, we observe distinct changes in patient risk between nonprofit and for-profit hospitals, readily apparent in Panels (c) and (d) of Figure 9. Nonprofit gamers treated a modestly higher-risk patient population during the gaming period, with the predicted mortality rate increasing by 0.29 percentage points, about 2% of the baseline risk. Note that nonprofit gamers increase operating costs by 7%, while patient volume does not change and patient complexity increases by 2% or less. These results imply that nonprofit gamers increase care inputs per patient even after adjusting for changes in complexity.

In contrast, for-profit gamers treated a lower-risk patient population during the gaming period. The predicted mortality dropped by 0.86 percentage points or 6% of the baseline risk. For-profit gamers cut operating costs, mainly driven by a 7% decrease in salaries. Hence, the decrease in labor inputs at for-profit gamers appears commensurate with the decrease in patient complexity. Given the multiplicity of substitution and income effects described above, this pattern of selecting less complex patients and reducing staff inputs is consistent with profit maximization by for-profit gamers. Due to turbocharging, these hospitals could draw outlier payments even on less-complex patients. These hospitals increased revenue and reduced operating costs simultaneously, thus boosting profits during this period.

Patient outcomes. Next, we test whether patient outcomes changed. To begin, in each year's sample of non-deferrable patients, we regress patient mortality (or readmission) on patient covariates and hospital fixed effects. We extract the fixed effects, which can be interpreted as the hospital's risk-adjusted mortality or readmission rate (Chandra et al., 2016). These fixed effects become the outcome variables in the hospital-level event study or the D-D model.

Table 2 Panel E presents the coefficients on these two patient health endpoints. Overall, we find a small and statistically insignificant decline in mortality alongside an increase in readmissions of 0.3 percentage points, about 3% of the baseline mean. Event studies reaffirm these findings, with no clear pre-trends or changes during or after the gaming period (Figure 10 Panels (a) and (b)).

However, we again find that these aggregate effects obscure important differences between nonprofit and for-profit hospitals. The additional spending on patient care by nonprofit gamers may have helped improve their quality of care because patient mortality decreased by 0.4 percentage points, about 3% of the baseline mean. This coefficient is precisely estimated and we can reject the null hypothesis of no change in mortality at the 5% level of significance (CI -0.03 to -0.80 percentage points). In contrast, we estimate a small statistically insignificant increase in mortality at for-profit gamers. Figure 10 Panel (c) presents the corresponding event study plots for mortality by type of ownership. Consistent with the D-D coefficients, the dynamic effects indicate opposite patterns for nonprofit and for-profit gamers. In the case of nonprofit gamers, there appears to be a stable decline in mortality which persists beyond the gaming period.

Assuming that the decrease in mortality at nonprofit gamers is a causal effect of incremental spending, our estimates imply that mortality among Medicare patients decreases by 3% for an 8% increase in Medicare spending. To interpret the magnitude of this effect, it is instructive to compare it to equivalent estimates of mortality returns to hospital spending reported by recent studies. For example, Doyle et al. (2015) find that hospitals reduce mortality among Medicare patients by about 5% for a 10% increase in spending. Similarly, Silver (2021) reports a 5.5% reduction in mortality among high-risk patients in the emergency department for a 10% increase in resource use. Hence, the mortality improvement delivered by nonprofit hospitals using incremental funds from gaming is lower than what could be obtained by reallocating patients to higher-spending providers. This is not surprising since only 64% of gaming revenue is spent on operating costs. If we account for this diversion, the mortality improvement relative to spending aligns closely with previous estimates.

We detect a modest increase in readmission rates at nonprofit gamers of 0.6 percentage points and a small insignificant decrease in readmissions at for-profit gamers. Figure 10 Panel (d) presents the corresponding dynamic effects. We interpret these patterns with caution, particularly for nonprofits. First, since mortality and readmission are competing risks for patients, these measures may be negatively correlated (as Chandra et al. 2016 found for similar patient cohorts). Here, we expect the marginal patient at a gamer non-profit who survives due to higher spending to be in poor health and at high risk of readmission. We therefore view the increase in readmission at nonprofit gamers as a *consequence* of their mortality improvement.[22] Second, setting aside the issue of competing risks, we value a hospital's ability to keep patients alive more than its ability to prevent a repeat admission since the welfare implication of a readmission is ambiguous.

Overall, we interpret the results as implying an increase in quality at nonprofit gamers and no change at for-profit gamers. While it is unsurprising that quality would not improve when for-profits made no investments into care inputs, it is perhaps surprising that quality did not deteriorate given the reduction in labor spending. One reason why quality would remain unchanged following labor cuts is that for-profits commensurately reduced the complexity of their patient mix, as described in the previous section.

5.5 Additional Analyses

This section describes results from tests that help validate our preferred interpretation of the main results and robustness checks that test the sensitivity of our key results to changing

[22]Prior studies have made a similar argument with regard to the use of readmissions as a pay-for-performance metric and urged that, unless differential selection is accounted for, hospitals with low mortality rates will be unfairly penalized (Gorodeski et al., 2010; Laudicella et al., 2013).

important assumptions or methods.

Alternative explanations. We attribute changes in gamer hospitals' use of funds to turbocharging. However, if these hospitals concurrently engaged in other strategies to increase revenue, the observed changes could partially reflect these actions. To examine this possibility, in Table D.8 we consider three additional outcomes where we expect second order or minimal changes due to turbocharging. These outcomes are in the spirit of a falsification test, but should not be viewed as true placebos since the gamers experienced a price shock that could, in theory, affect most outcomes of interest.

We first examine non-outlier Medicare payments. If hospitals *only* turbocharged to game outlier payments, then we should not find a change in the remaining components of Medicare payments, which are prospectively set and unrelated to the hospital's contemporaneous chargemaster rates. However, other strategies like upcoding patient risk, changing the service mix toward more lucrative procedures, or admitting more patients would increase these payments. The first row of Table D.8 shows that effects on non-outlier Medicare payments are negligible and insignificant overall and for the subsets of nonprofit and for-profit gamers.

Next, we consider two outcomes that are not directly related to Medicare: patient volume and bed capacity. Revenue-raising strategies outside turbocharging, like pressuring emergency departments to admit low-acuity patients, could influence non-Medicare volume. Likewise, alternative cost-cutting strategies could lead to bed count reductions, and we would not otherwise expect large changes in bed counts from a transitory price shock. Reassuringly, Table D.8 shows no detected effects on these outcomes.

Overall, these findings suggest that our key results reflect the causal effects of gaming Medicare outlier payments. This interpretation is also consistent with the composition of the final settlement between the Department of Justice and Tenet, the major for-profit gamer in our sample. Of the $880M settlement, 90% (approximately $790M) covered Tenet's receipt of excessive outlier payments, with the remainder resolving other allegations of fraud (U.S. Department of Justice, 2006).

Robustness checks. We next show robustness to our definitions of gamer and non-gamer hospitals, our specification, and the matching approach (Appendix Figures D.5 and D.6). We compare a host of alternative estimates to our baseline approach for the key outcomes: the flow of funds for hospitals (upper plot in each figure), and the two measures of hospital inputs, patient selection, and patient outcomes (lower plot). To simplify the presentation, we focus on average effects across the gaming period.

Appendix Figure D.5 presents three types of modifications to our strategy for identifying gamers. First, we modify the algorithm to use *realized* outlier payments rather than simulated outlier payments. This approach does not change our findings. Second, we use only charge growth to identify gamers and non-gamers rather than additionally applying our gamer and non-gamer growth thresholds to the ratio of outlier payments to DRG payments. The results are similar using this method, though the scale of revenue is, as expected, smaller than in the baseline approach.

Third, we modify the charge and outlier share growth thresholds used to define a hospital as a likely gamer or non-gamer. In the baseline model, we define gamers as above the 90^{th} percentile of growth in both charges and outlier share (resulting in 120 gamers after matching) and non-gamers as below the 85^{th} percentile of growth in both (1,396 non-gamer controls after matching).

Our estimates are qualitatively similar under four alternative approaches, regardless of whether they are more or less restrictive. First, we drop the gamer threshold from the 90^{th} to the 85^{th} percentile, adding "indeterminate" hospitals to the gamer group and raising its size to 175 hospitals. Next, we make the gamer growth threshold 1 standard deviation above the mean, rather than the 90^{th} percentile, a more restrictive definition that yields 85 hospitals. Third, we use the baseline gamer definition, but lower the non-gamer group threshold from the 85^{th} to the 50^{th} percentile, restricting the controls to 636 hospitals. Finally, we make the gamer definition even more lenient, lowering it to the 75^{th} percentile and yielding 318 gamers (we concurrently lower the non-gamer threshold to 50^{th} percentile).

Appendix Figure D.6 provides three types of robustness checks to the model specification and matching approach. First, we consider an alternative approach to using Coarsened Exact Matching (CEM) to reweight the comparator set of hospitals as in our baseline model. Specifically, we use fixed effects to effectively match gaming hospitals to observably similar comparator hospitals. To do so, we leverage the strata emitted by CEM. Each stratum is a set of hospitals with identical coarsened matching covariates (i.e., payment parameters and Medicare share). We augment our main specification with strata-year fixed effects and drop the CEM weights, an approach similar to running difference-in-differences stratum-by-stratum and averaging the results. As expected, this approach yields estimates similar to those from the baseline method.

Second, to assess sensitivity to alternative matching strategies, we replicate our estimates using the Mahalanobis-distance based matching approach, which picks for each treated unit the comparison unit that is closest in Mahalanobis distance along the matching covariates. We also consider Propensity Score Matching (PSM). We estimate a propensity score as a function of the matching covariates we used in CEM, then reweight the comparators to again target the TOT estimand. Figure D.6 shows that the estimates are quite similar to the baseline even after these modifications, though under PSM, effects on all-payer revenue and operating costs are slightly attenuated.

Third, having assessed robustness to the matching strategy, we next turn to the D-D model. This model assumes that absent gaming, the gamers and matched comparators would have evolved on parallel trends. We relax this assumption and allow the two groups to evolve on differential trends in a linear fashion. We include an additional term in the model which interacts an indicator for gamer hospitals with a linear time trend. The estimates are similar with this modification, though in some cases more imprecise.

6 Discussion and Conclusion

In this paper, we study how hospitals allocated revenue obtained from exploiting a loophole in Medicare's outlier payments program – a practice referred to as "turbocharging." CMS was first warned of the potential for turbocharging in 1988, suggesting these vulnerabilities could have been anticipated by policymakers (see HCFA 1988; the warning is reproduced in Appendix A.1). Our work estimates that the agency's failure to close the loophole in a timely fashion cost Medicare at least $3 billion, with large spillover effects for other payers. When pooling all hospitals identified as gamers, we find uneven evidence that revenue obtained from gaming is used in ways that might benefit patients. About half the excess revenue flows toward operating costs, while the rest is transferred off the hospital balance sheets, likely to their parent organizations.

However, we find economically and statistically significant heterogeneity in outcomes by ownership type. Nonprofit hospitals mainly allocated excess revenue to increasing operating costs, particularly non-salary clinical costs. This spending appears to influence the quality of care: Nonprofit hospitals achieved a notable improvement in mortality rates. This result suggests nonprofits were not previously operating on the "flat of the curve," and may have been underpaid.

In contrast, for-profit hospitals drove the observed transfer of funds off the balance sheets and reduced spending on staff FTE, contributing to a decline in operating costs. This behavior can primarily be attributed to the Tenet Corporation, which allocated most of the revenue obtained from gaming to executive compensation and shareholder payouts. Consistent with the argument that greater spending on patient care decreases mortality, there were no quality improvements among for-profit hospitals since little of the excess revenue was invested in the hospital. These results are consistent with, in the case of Tenet, gaming resulting in a transfer of funds from taxpayers and consumers (through private insurers) to executives and shareholders.

Our results provide several insights into hospital behavior. Previous studies have found evidence that for-profit and nonprofit hospitals often behave similarly (Dranove and Ludwick, 1999; Duggan, 2000; Capps et al., 2020). We instead find differences between for-profits and nonprofits in their propensity to game payments and how they use the revenue, consistent with the theoretical literature on distinct responses based on firm ownership. While we find that both nonprofits and for-profits immediately spend rather than save or invest the windfall, nonprofit hospitals spend the money on patient care needs. Such spending is also consistent with the flypaper effect because it is aligned with the purpose of the outlier payments. Therefore, these findings provide insights into how the source of funds can influence hospital spending.

The loophole in the outlier payments program also serves as a warning of the broad and long-term costs of contract design flaws. Despite the time-limited nature of the gaming episode, hospitals appear to have learned that by rapidly growing charges, they could extract higher payments from other payers. Indeed, we find evidence of persistently high charges even after the loophole closed. Private insurers are likely to pass on these costs to enrollees in the form of higher premiums (Brot-Goldberg et al., 2024). These spillovers highlight the interplay between Medicare's payment design and the cost and efficiency of other insurers.

Overall, we provide new evidence on how firms in healthcare allocate windfalls engineered from gaming government contracts. However, the issue of intermediaries exploiting contract imperfections to increase their revenue at taxpayer expense is not limited to healthcare. Federal, state, and local governments are increasingly spending their budgets on social programs that span multiple sectors of the economy and are typically delivered through private firms. These include, among others, food vouchers redeemed in grocery stores, K-12 education delivered by charter schools, and COVID-19 relief funds provided to small businesses. Our results highlight the potential social value of investing in strong contract design and close oversight of privately delivered public programs. More research is needed across sectors to assess the opportunities for and consequences of contract gaming in tax-funded programs.

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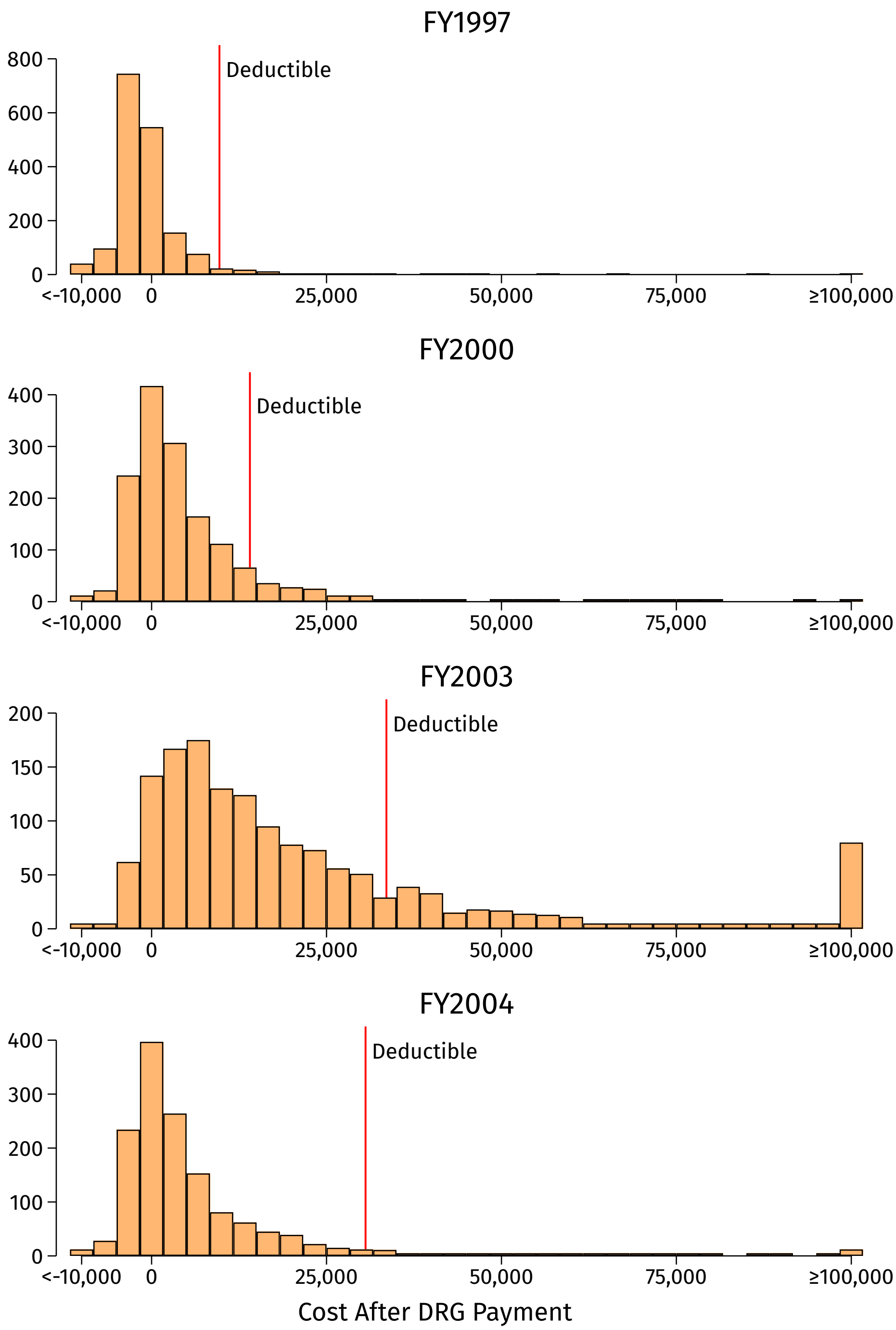


Figure 1: Evolution of excess "cost" distributions at an extreme gamer hospital

Notes: This figure shows histograms of the excess "cost" distributions of patients at the most extreme gamer hospital in our data. Each panel depicts a different fiscal year. Excess costs were defined as the hospital's submitted charges deflated by the cost-to-charge ratio used by the payment contractor, less the DRG payment (i.e. $BILLCOST_i - DRGPAY_i$ as defined in Appendix B). Bars indicating patient counts between 1 and 10 set to 5.5 to follow CMS cell suppression rules. The vertical red line indicates the national deductible for outlier payments ($\overline{THRESH}_t$ in Appendix B). Hospitals received payments equal to 80% of costs beyond this threshold.

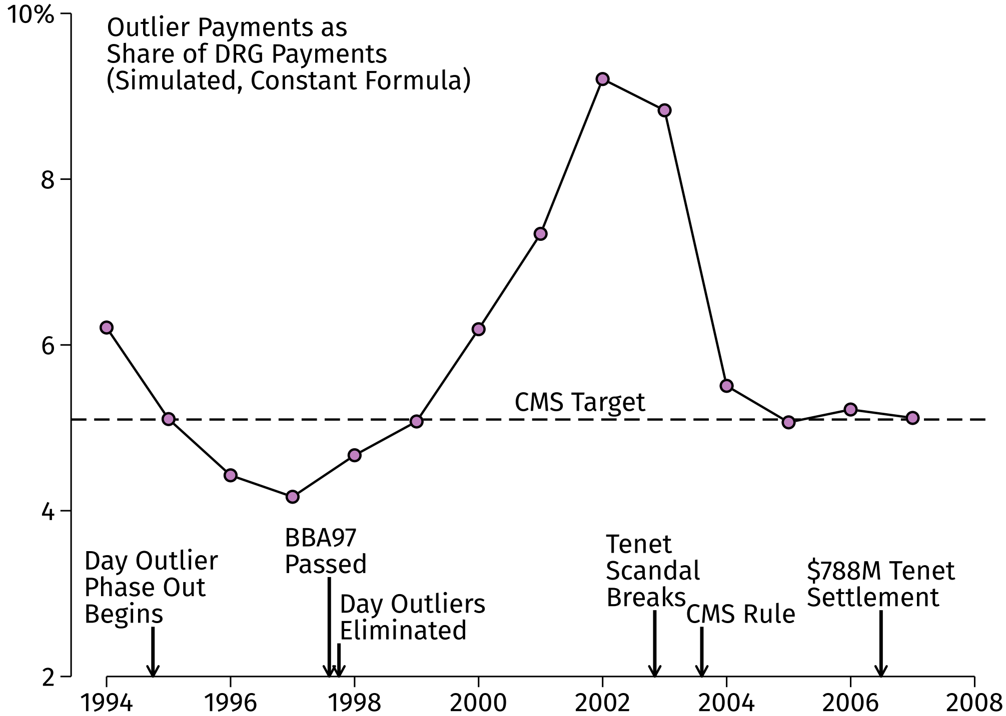


Figure 2: Trend in Medicare outlier payments

Notes: The figure presents aggregate outlier payments as a share of aggregate DRG (non-outlier) Medicare inpatient payments, using our simulation approach holding fixed payment formulas. We also note key events associated with the episode over this period. Appendix Figure D.7 shows the same time series using actual payment data.

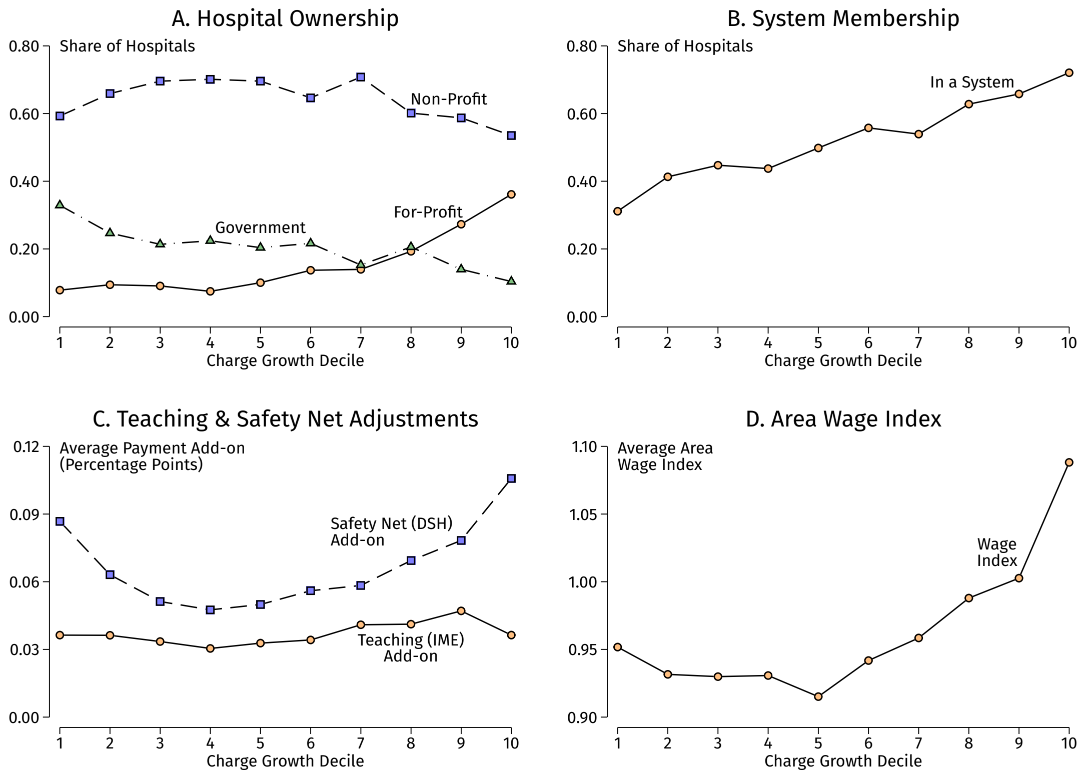


Figure 3: Characteristics of Hospitals by Charge Growth Decile

Notes: Each panel of this figure shows the association between charge growth during 1998–2003 and a hospital characteristic or set of characteristics. Hospitals are binned according to their decile of charge growth, displayed along the X-axis. Each point is the average characteristic of hospitals in the given decile. Panel A shows hospital ownership type, Panel B shows the share of hospitals in a system, Panel C shows average payment add-ons for teaching and safety-net hospitals, and Panel D shows the average area wage index. Characteristic values are taken at their 1997 values.

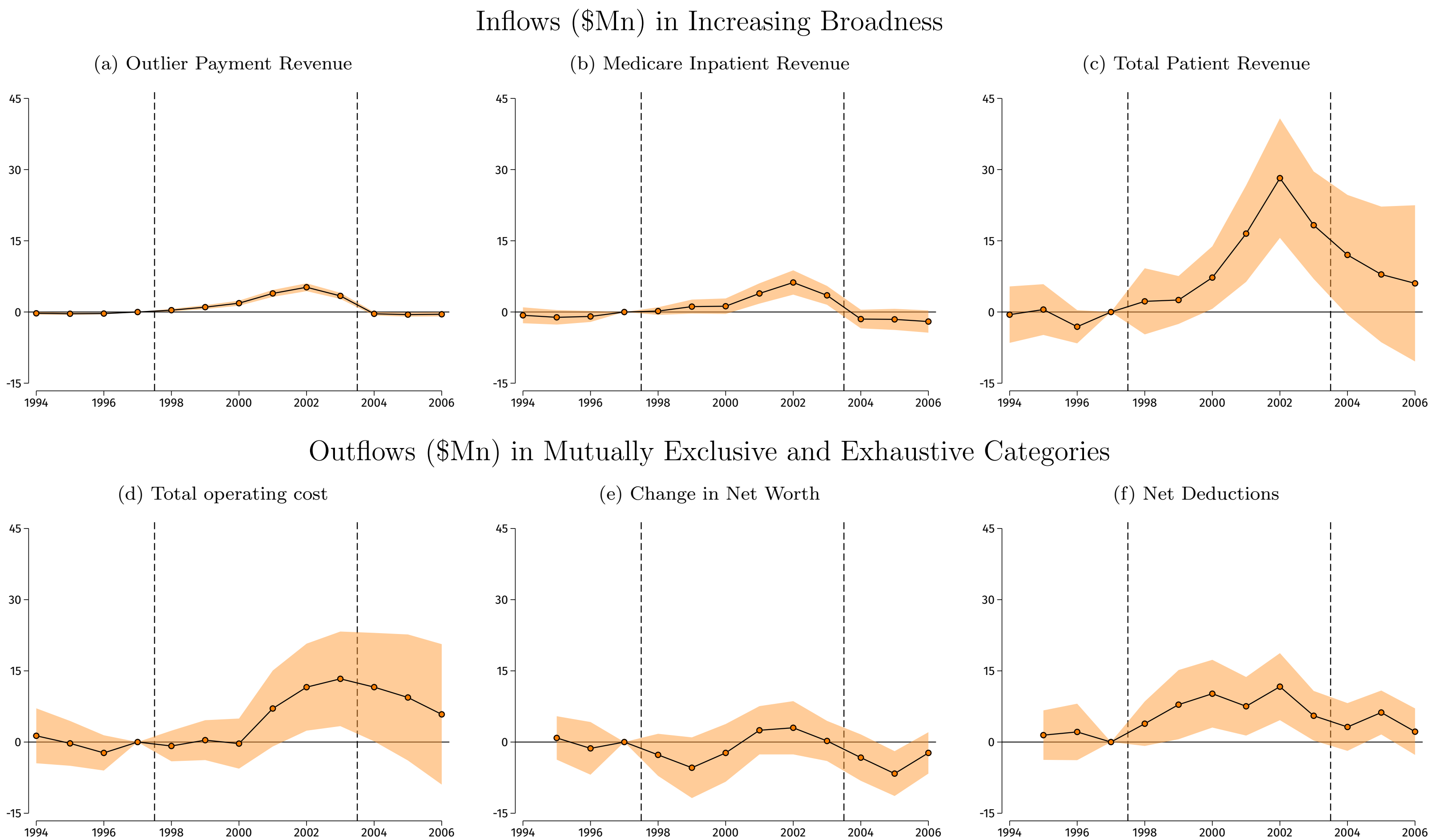


Figure 4: Flow of funds

Notes: The figure presents event study plots obtained by estimating the dynamic effects model in Equation 3 using our main analysis sample. The outcomes here are various measures of income (outlier revenue, Medicare inpatient revenue, and total patient revenue), costs (operating costs), and changes in balance sheet items (change in net worth, net deductions), as reported in the Medicare cost reports for the corresponding years. All values are expressed in millions of real year 2000 dollars. All coefficients are estimated relative to 1997 as the reference year. The shaded area represents 95% confidence intervals. Standard errors are clustered by hospital.

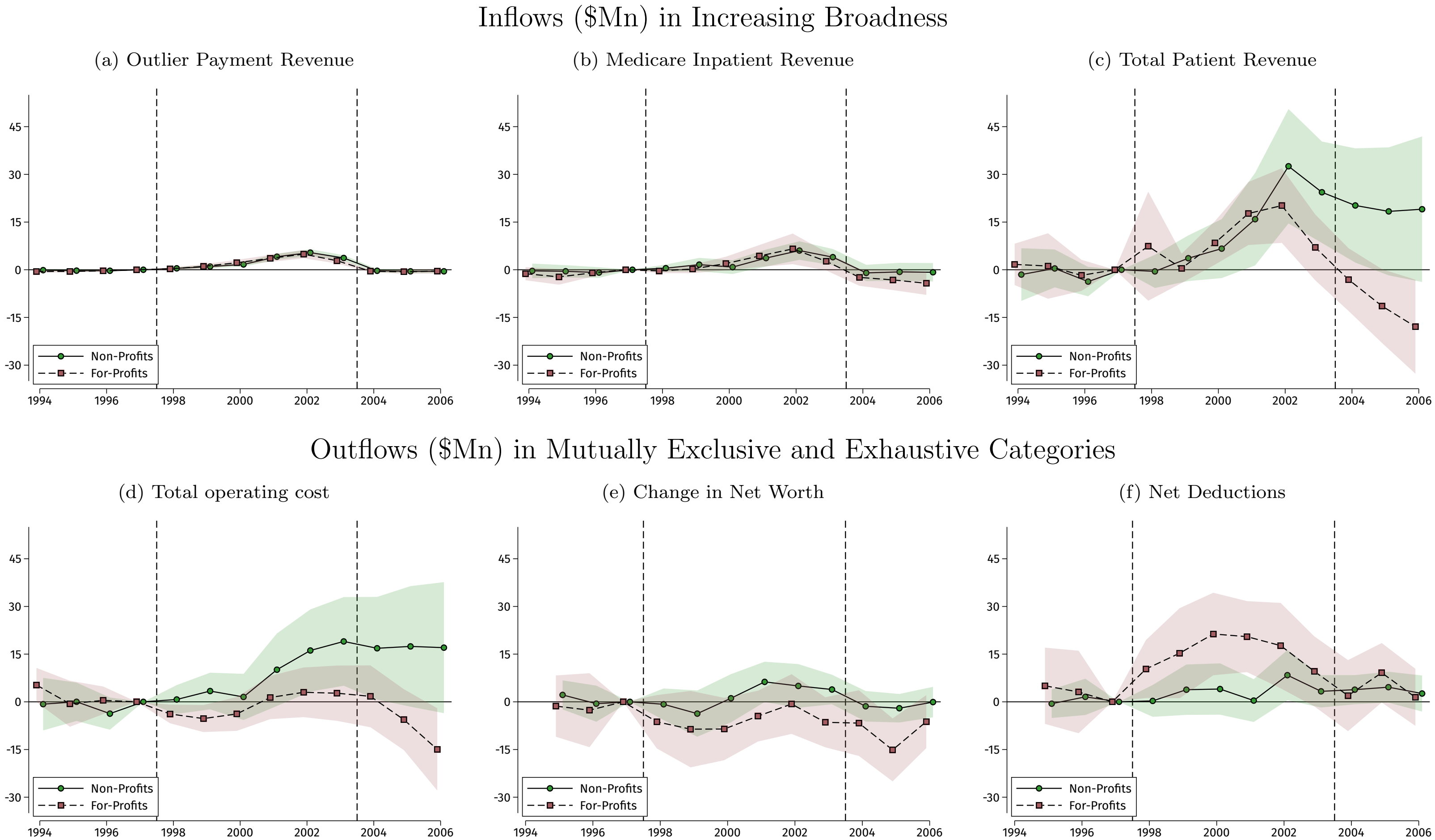
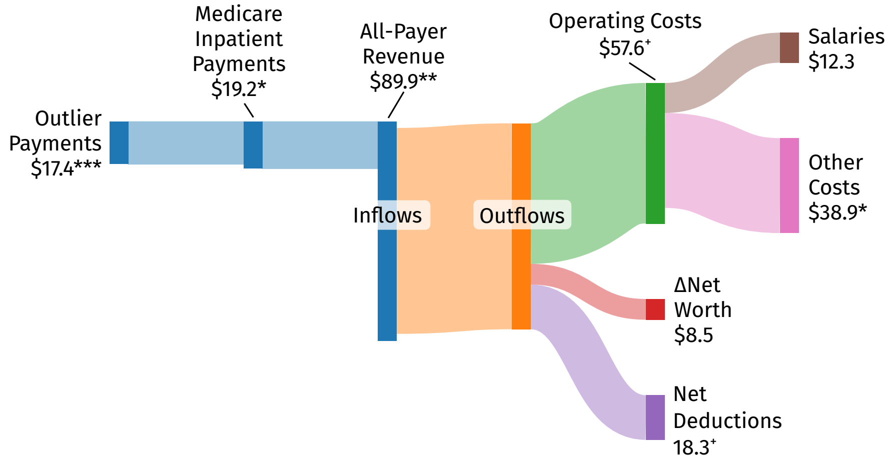


Figure 5: Flow of funds for nonprofits and for-profits

<u>Notes:</u> The figure presents event study plots obtained by estimating the dynamic effects model in Equation 3 separately for nonprofits and for-profits. The outcomes here are various measures of income (outlier revenue, Medicare inpatient revenue, and total patient revenue), costs (operating costs), and changes in balance sheet items (change in net worth, net deductions), as reported in the Medicare cost reports for the corresponding years. All values are expressed in millions of real year 2000 dollars. All coefficients are estimated relative to 1997 as the reference year. The shaded area represents 95% confidence intervals. Standard errors are clustered by hospital.

(a) Flow of Funds at Nonprofit gamers



(b) Flow of Funds at For-profit gamers

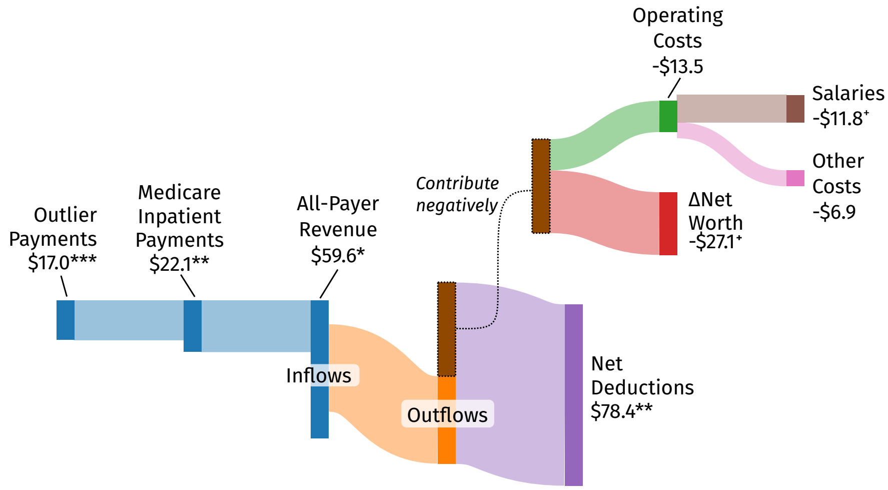


Figure 6: Sankey plots of flow of funds for nonprofits and for-profits

<u>Notes:</u> The figure presents Sankey plots of hospital income (in increasing broadness) and outflows (in mutually exclusive and exhaustive categories) obtained by estimating Equation 2 separately for nonprofits and for-profits. The estimates are drawn from columns 4 and 6 of Table 2. All values are expressed in millions of real year 2000 dollars. The estimates for sub-categories do not necessarily sum to the estimated effect for the parent category due to variable-specific data cleaning like winsorizing; the use of slightly different samples for net deductions and net worth, since we do not observe them for 1994; and our use of all-payer revenue rather than total income. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

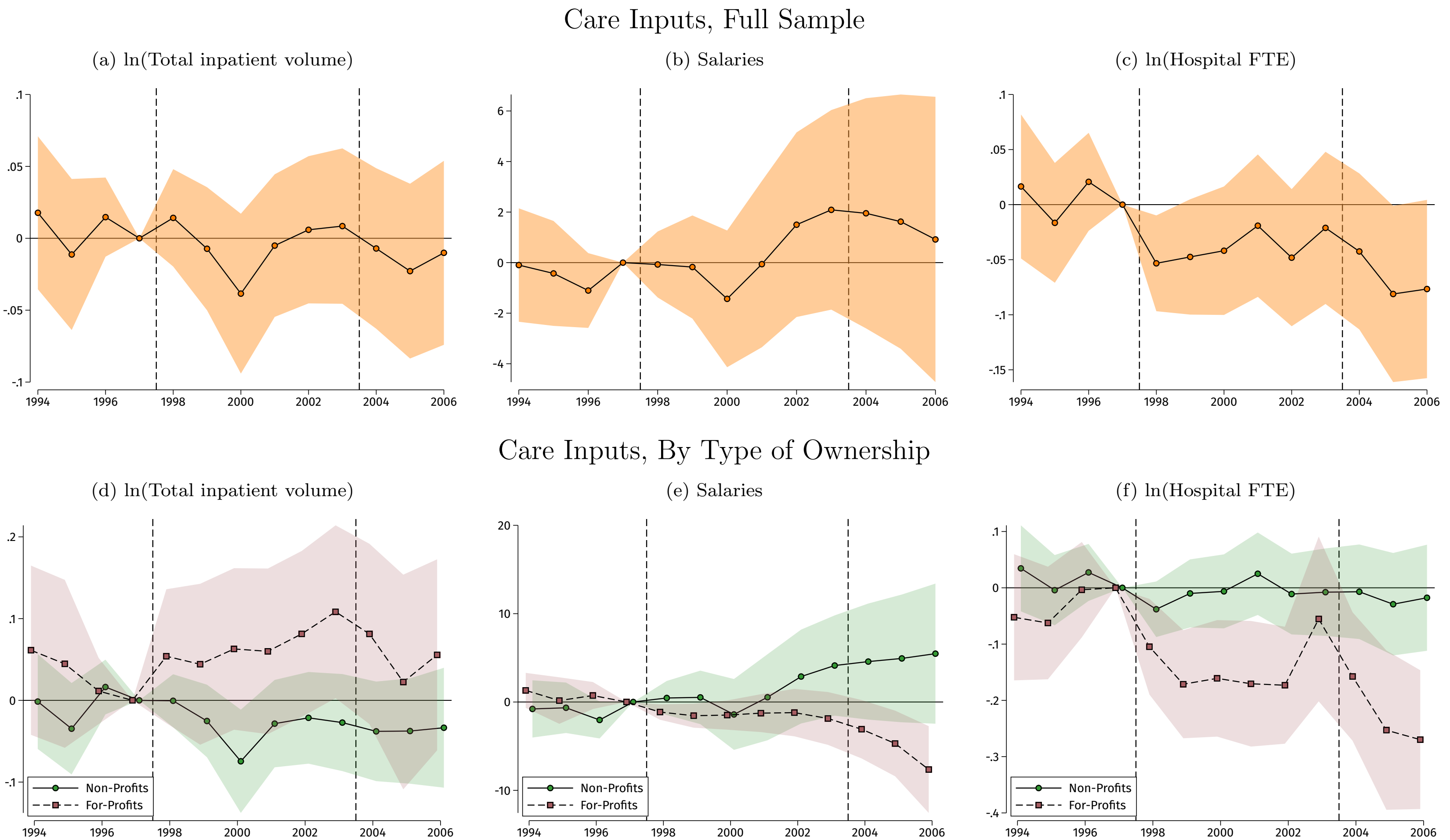


Figure 7: Care Inputs

Notes: The figure presents event study plots obtained by estimating the dynamic effects model in Equation 3 using our main analysis sample (panels a-c) and separately for nonprofits and for-profits (panels d-f). The outcomes here are measures of care inputs. Effects on total inpatient volume and hospital FTE are estimated with Poisson models. Data on inputs is sourced from the Medicare cost reports. All coefficients are estimated relative to 1997 as the reference year. The shaded area represents 95% confidence intervals. Standard errors are clustered by hospital.

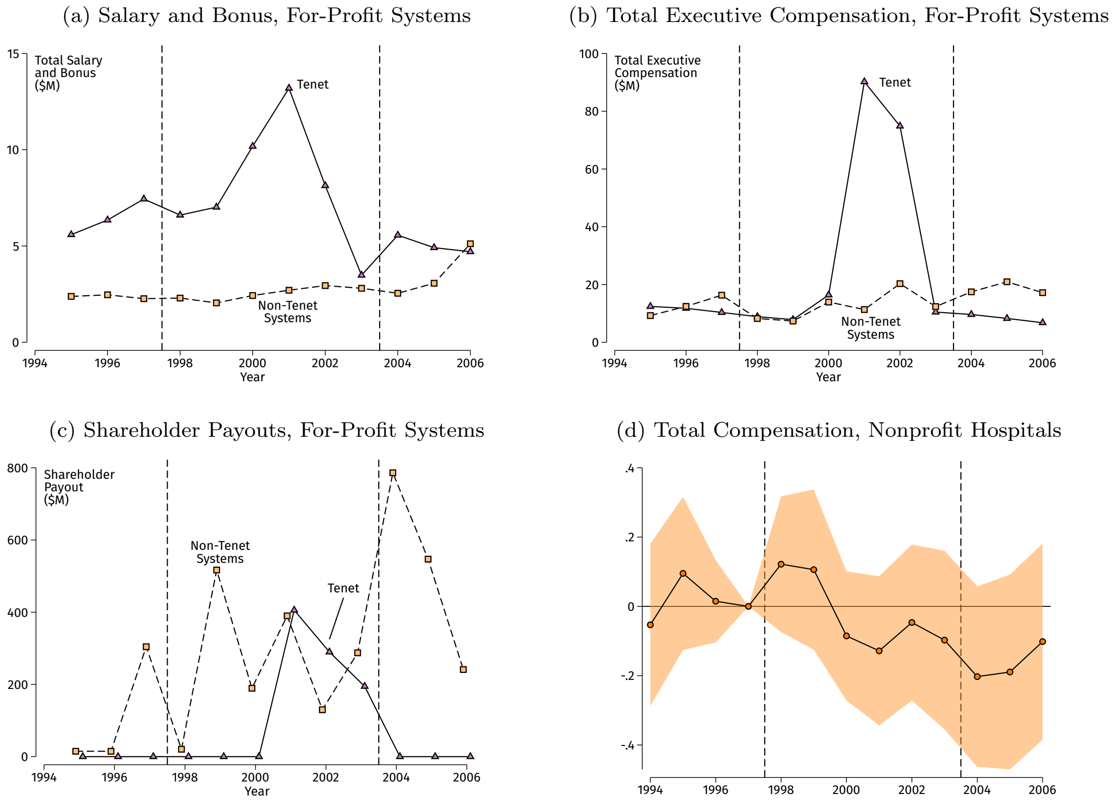


Figure 8: Compensation of Executives and Shareholders

<u>Notes:</u> Panel (a) presents the average total salary and bonus for the 5 highest-paid executives in for-profit systems for Tenet compared to the following non-Tenet systems with data available from 1995-2006: Health Management Associates, Health Corporation of America, Sunlink, and Universal Health Systems. Data is not consistently available for all of these systems before 1995. Panel (b) is an extension of Panel (a) but instead shows a broader measure of executive compensation available in Compustat that captures the total compensation realized by an executive in a given year. Panel (c) presents the total shareholder payouts representing the sum of dividends and the purchase of common and preferred stock. Panel (d) presents the event study plot obtained by estimating the dynamic effects model in Equation 3 for the compensation of key individuals at nonprofit gamers, measured using the Form 990 data. Total compensation represents all salary and bonus payments made to a nonprofit hospital's officers, directors, trustees, and other key employees.

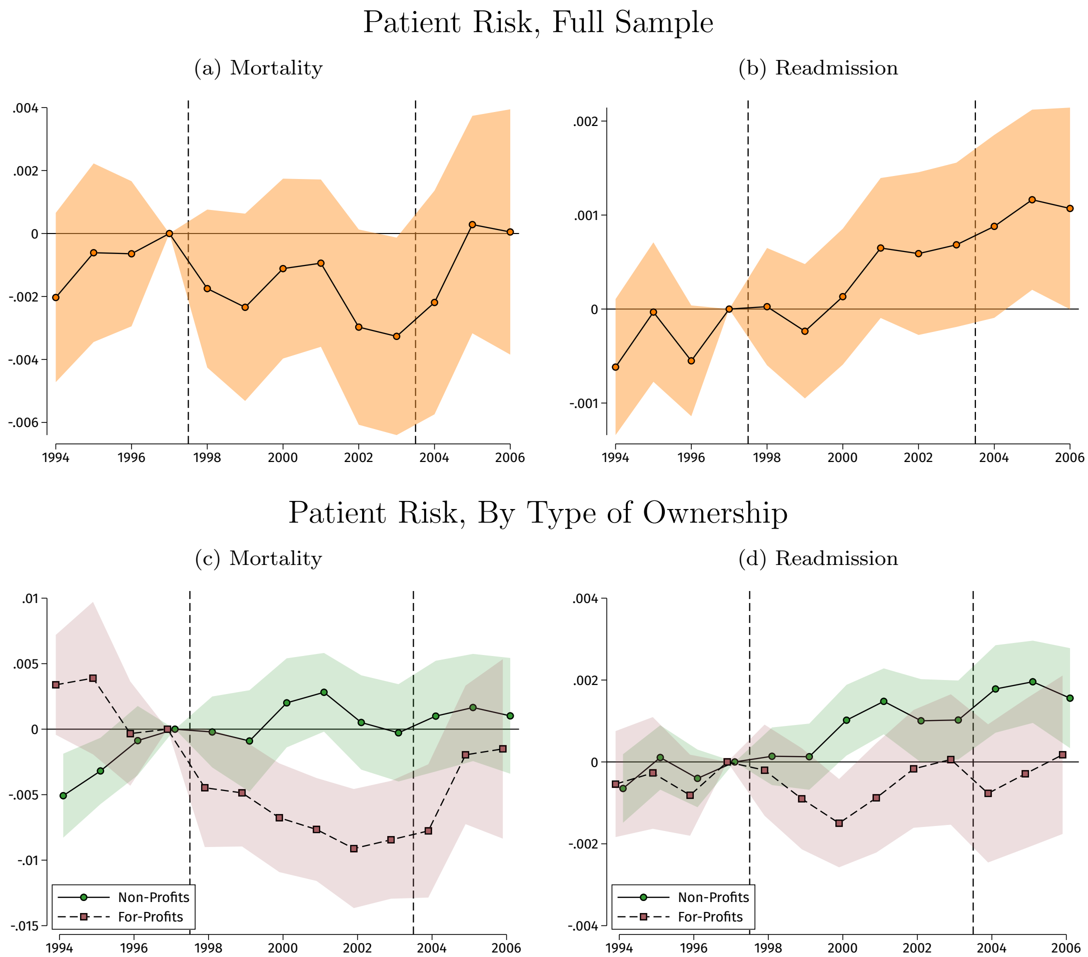


Figure 9: Patient Risk Scores

<u>Notes:</u> The figure presents event study plots obtained by estimating the dynamic effects model in Equation 3 using our main analysis sample (panels a and b) and separately for nonprofits and for-profits (panels c and d). The outcomes here are measures of observable risk of adverse outcomes for the cohort of patients admitted with non-deferrable conditions (predicted 30-day mortality and readmission rate). Predicted risk calculated using data on Medicare fee-for-service patients admitted with non-deferrable conditions. All coefficients are estimated relative to 1997 as the reference year. The shaded area represents 95% confidence intervals. Standard errors are clustered by hospital.

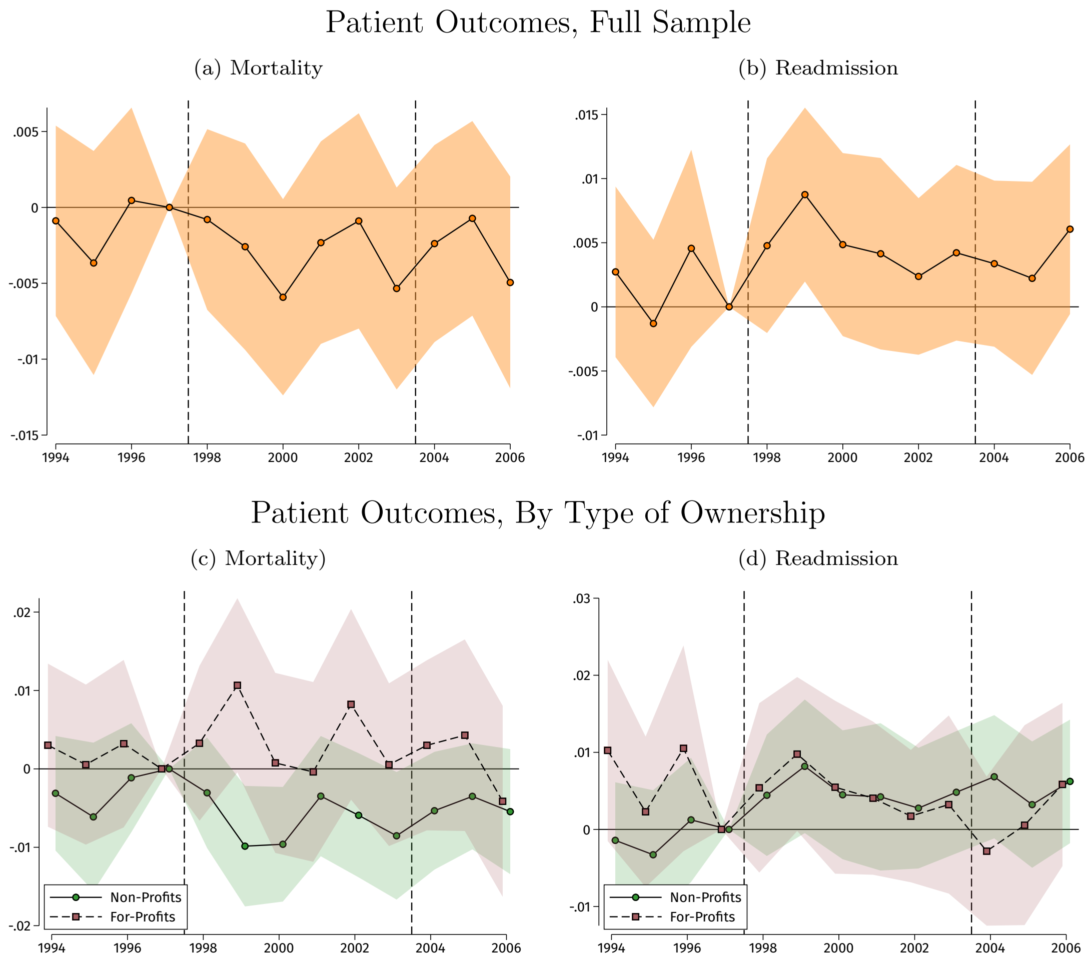


Figure 10: Patient Health Outcomes

Notes: The figure presents event study plots obtained by estimating the dynamic effects model in Equation 3 using our main analysis sample (panels a and b) and separately for nonprofits and for-profits (panels c and d). The outcomes here are measures of adverse health outcomes for the cohort of patients admitted with non-deferrable conditions (risk-adjusted 30-day mortality and readmission rates). Health outcomes observed using data on Medicare fee-for-service patients admitted with non-deferrable conditions. All coefficients are estimated relative to 1997 as the reference year. The shaded area represents 95% confidence intervals. Standard errors are clustered by hospital.

Table 1: Summary Statistics

	(1) Gamers	(2) Matched Comparators
A. Payment Inputs Used for Matching		
Wage Index	1.099	1.086
Safety Net (DSH) Adjustment	0.0898	0.0789
Teaching (IME) Adjustment	0.0301	0.0275
Medicare Inpatient Share	0.360	0.361
B. Additional Hospital Characteristics		
Beds	275.3	226.1
In System	0.730	0.523
Medicare Inpatient Payments	34.34	27.62
All-Payer Revenue	114.9	101.2
Ownership		
Nonprofit	0.650	0.866
For-Profit	0.350	0.134
Location		
Rural	0.0417	0.106
Urban	0.958	0.894
C. Risk Scores (Non-Deferrable Patients)		
Mortality	0.138	0.134
Readmission	0.135	0.136
D. Risk-Adjusted Outcomes (Non-Deferrable Patients)		
Mortality	0.140	0.139
Readmission	0.139	0.137
Hospitals	120	1,396

Notes: The table presents descriptive statistics on the hospitals in our analysis sample. Column 1 presents the mean values for the turbocharging hospitals we designate as gamers, while column 2 presents the corresponding values for the matched comparator hospitals. Panel A presents values for the variables used to match gamers to non-gamers. Panel B presents values for other relevant attributes or outcomes of interest. Panel C reports the estimated risk of mortality and readmission among non-deferrable Medicare fee-for-service patients. Panel D reports realized mortality and readmission rates among these patients after adjusting for observable risk. All values are computed using data from 1997 except for the Medicare inpatient share, which is the 1994-1997 average. Revenue values are expressed in millions of real year 2000 dollars. DSH: disproportionate share, IME: indirect medical education.

Table 2: Main Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled		Nonprofits		For-Profits	
	DV Mean	1998–2003	DV Mean	1998–2003	DV Mean	1998–2003
Panel A. Income in Increasing Broadness						
Medicare Outlier Payments	1.715	2.875***	1.908	2.903***	1.355	2.832***
		(0.257)		(0.310)		(0.453)
Medicare Inpatient Payments	32.94	3.384***	38.61	3.198*	22.42	3.684**
		(0.993)		(1.299)		(1.405)
All-Payer Revenue	111.0	13.29**	127.6	14.97**	80.51	9.933*
		(4.191)		(5.800)		(4.761)
Panel B. Outflows in Mutually Exclusive Categories						
Operating Costs	111.9	5.512	132.8	9.594$^+$	73.21	-2.253
		(3.744)		(5.286)		(3.223)
Salaries	46.92	0.715	57.50	2.054	27.29	-1.969$^+$
		(1.622)		(2.395)		(1.082)
ΔNet Worth	5.199	-0.630	4.682	1.422	6.139	-4.517$^+$
		(1.383)		(1.569)		(2.534)
ΔTotal Assets	4.156	2.654	4.444	5.100*	3.628	-1.830
		(1.736)		(2.329)		(2.253)
ΔFixed Assets	0.707	0.118	0.781	0.579	0.568	-0.803
		(0.769)		(1.018)		(1.034)
ΔLiabilities (subtracted)	-0.662	2.739*	-0.300	3.524*	-1.337	1.483
		(1.265)		(1.625)		(1.839)
Net Deductions	1.703	6.580***	0.540	3.055$^+$	3.818	13.07**
		(1.960)		(1.821)		(4.216)
Panel C. Care Inputs						
ln(Total Inpatient Volume)	10,812.4	-0.00895	12,576.0	-0.0245	7,432.2	0.0412
		(0.0218)		(0.0252)		(0.0393)
ln(Hospital FTE)	1,076.8	-0.0436$^+$	1,306.4	-0.0222	633.8	-0.111**
		(0.0262)		(0.0309)		(0.0425)
Panel D. Patient Risk (Non-Deferrable Conditions)						
Mortality	0.134	-0.00125	0.132	0.00294**	0.139	-0.00862***
		(0.00113)		(0.00112)		(0.00174)
Readmission	0.135	0.000607*	0.134	0.00103**	0.136	-0.000192
		(0.000274)		(0.000326)		(0.000456)
Panel E. Patient Outcomes (Non-Deferrable Conditions)						
Mortality	0.139	-0.00196	0.137	-0.00415*	0.141	0.00215
		(0.00182)		(0.00197)		(0.00333)
Readmission	0.134	0.00335$^+$	0.133	0.00568*	0.136	-0.000820
		(0.00183)		(0.00232)		(0.00251)

Notes: This table presents our main pooled, nonprofit, and for-profit results. Each row presents effects on a dependent variable estimated using Equation 2. The columns sequentially show results for all gamers, nonprofit gamers, and for-profit gamers. The odd columns show the means of the dependent variables for gamers during 1994-1997. The even columns present the average coefficient for gaming for the 1998–2003 period. Standard errors are in parentheses and are clustered by hospital. Results do not necessarily match accounting identities due to variable-specific data cleaning like winsorizing; the use of slightly different samples for net deductions and variables measured as changes (Δ), since we do not observe them for 1994; and our use of all-payer revenue rather than total income. $^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix To:
Turbocharging Profits? Contract Gaming and Revenue Allocation in Healthcare

Atul Gupta, Ambar La Forgia, and Adam Sacarny

October 2025

A Additional Details on Outlier Payments and the Legal Disputes

A.1 History of Outlier Payments

Outlier payments were originally implemented as a part of Medicare's shift from retrospective to prospective payment in 1983. While hospitals had previously been reimbursed for essentially all of their costs by Medicare, the new system would reimburse them for the expected cost of a typical, similar patient, defined as patients in the same Diagnosis-Related Group (DRG). Policymakers sought to use this fixed price payment approach (Laffont and Tirole, 1993) to incentivize hospitals to deliver care efficiently.

Policymakers included outlier payments in prospective payment to reduce the financial risk and cream-skimming incentives of the new payment scheme (Carter and Farley, 1992). There were originally two types of outlier payments: day outliers and cost outliers. The former system paid hospitals per diem rates when their patients had unusually long lengths of stay, while the latter paid hospitals when their patients had unusually high "costs". Originally, most payments (about 85%, according to HCFA 1988b, pp. 19515) were for day outliers, but over time, the system shifted to make the majority (and by FY1998, the entirety) of payments through the cost outlier system. In the main text, unless otherwise noted, we use outlier payments and cost outlier payments synonymously.

The key input to determine a hospital's payment for a patient under the cost outlier system is a measure of the cost of treating the patient. In practice, this measure is calculated by multiplying the charges (i.e., list prices) on a Medicare claim by a ratio of cost-to-charges. This approach can be seen in the formulas of Appendix B including equation B.7.

At first, Medicare multiplied the charges by a single national cost-to-charge ratio. The resulting number was used as the measure of hospital costs and determined the hospital's cost outlier payment. The approach failed to account for differences across hospitals in charge markups. Medicare sought to address this concern by using hospital-specific cost-to-charge ratios. They made the change in late 1989, stating that they believed it was "essential to ensure that outlier payments are made for cases that have extraordinarily high costs, and not merely high charges" (HCFA, 1988a, pp. 38503). Costs would be measured from the hospital's most recent settled cost report, while charges would be measured by summing the billed charges for patients during the same period as the cost report.

Prior to this change, hospitals could have gamed outlier payments by growing their charges, since Medicare did not even account for differences in markups across hospitals. However, cost outlier payments were small at the time, limiting the return on gaming. There had also been other barriers: If a patient qualified for both day and cost outlier payments, the hospital only received the former; and in the early years, hospitals had to follow a burdensome process of requesting cost outlier payments from Medicare contractors (Philipps and Wineberg, 1984; HCFA, 1985, pp. 12755).

After the switch to hospital-specific cost-to-charge ratios, gaming was possible due to the lag in updating the cost-to-charge ratio from the cost reports. This mechanism is described in Section 2.2 and was the primary avenue through which hospitals eventually gamed outlier payments during the episode we study.

Strikingly, Medicare was warned in 1988 about the possibility of gaming at the time of these changes. The agency's rulemaking includes a public comment expressing concern that hospitals could game this system by manipulating their charges, much as they ultimately did between 1998 and 2003. Policymakers responded with skepticism, noting that cost-to-charge ratios would update (eventually), gaming would implicate payments from other payers, it could be counteracted by raising the outlier payments "deductible", and the return to gaming was low relative to the disruption it would cause:

> *Comment*: Some commenters were concerned that the increased emphasis on cost outliers in the proposed policy would provide an incentive for hospitals to increase their charges and to manipulate their charge structures.
>
> *Response*: Cost outliers are identified by, and the amount of cost outlier payment determined by, comparing the charges for the case, adjusted by a cost- to-charge ratio, to the cost outlier threshold. Since both the cost-to-charge ratio (whether national or hospital-specific) and the threshold are constant for the payment period, the payment received by the hospital can be increased by increasing charges. In addition, hospitals can conceivably change their charge structures, just as is the case at present, to maximize their outlier payments.
>
> Although concern about this type of incentive is appropriate, we believe that there are several factors that will mitigate its effects. First, increases in a hospital's overall charges relative to costs will be reflected in the cost-to-charge ratio assigned to the hospital in the future. This is one of the strong arguments for the use of hospital-specific cost-to-charge ratios. Second, many hospitals are restricted in their ability to arbitrarily increase their charges by the fact that they must deal with other third-party payers, some of whom base their payments on charges. In addition, several states place restrictions on hospital charge increases. Third, a general acceleration in hospital charge increases can be incorporated into the setting of thresholds in future years, which would limit the potential benefit to hospitals.
>
> Fourth, outlier payments comprise a small percentage of total hospital payments under the prospective payment system, diluting the incentive for hospitals to disrupt their operations by drastically and continually manipulating charges.
>
> It must be pointed out that this incentive to manipulate charges is not new; in fact, any measure of cost (including length of stay) that is based on an indicator that is within the control of the provider provides an incentive to manipulate that indicator. As previously stated, we will continue to investigate potential improvements in the measurement of case-level costs. (HCFA, 1988a, pp. 38509)

The 1989 reform also opened a loophole that made it easier to game outlier payments. Because the switch to hospital-specific cost-to-charge ratios meant relying on potentially noisy data, policymakers included a provision to identify and remove seemingly erroneous values. Specifically, if a hospital's log-cost-to-charge ratio was outside 3 standard deviations of the national average, Medicare would instead give the hospital the average cost-to-charge ratio of other urban (if it was urban) or rural (if it was rural) hospitals in its state. This seemingly innocuous provision meant that if a hospital raised its charges enormously, it could lower its cost-to-charge ratio until Medicare thought it was a data error. The hospital would then have its inflated charges discounted by the markup of the average other hospital in its state, resulting in large outlier payments (see footnote 3).

Together, these changes created the vulnerabilities in the outlier payments program that hospitals would later exploit much as the commenter warned in 1988. As we explain in Section 2.2 of the main text, several additional developments in the ensuing years would touch off years of gaming. Lags in updating the cost-to-charge ratios grew, expanding the scope for gaming. Medicare phased out day outliers and moved their budget to cost outliers, raising the return on gaming. Finally, the Balanced Budget Act of 1997 cut hospital DRG payments, sending hospitals searching for alternative sources of revenue.

A.2 Additional Details on the Legal Disputes

We now provide additional details of the outlier payments controversies and subsequent lawsuits. The news media referred to the gaming of outlier payments as one of the biggest scandals in Medicare's history, with substantial news coverage starting in late 2002 (Abelson, 2002; Pollack, 2003; Eichenwald, 2003; Jaklevic, 2003; Bernstein, 2012). These articles, as well as legal documents, provide anecdotal evidence that a diverse set of hospitals grew their charges to obtain more outlier payments.

The lawsuits frequently cite communications with hospital leadership. For example, in a lawsuit filed against New York's Beth Israel Hospital an "executive wrote of 'feeling a bit giddy' at the thought of 'getting $10M of outlier revenue,' while another advised caution because she had become wary that Beth Israel's turbocharging would be detected" (Bernstein, 2012). When pressed by journalists to understand why these hospitals sought additional outlier payments, the "senior vice president of health economics at the New Jersey Hospital Association acknowledged that some New Jersey hospitals may have tried to find 'some mechanism to effectuate an increase' in their bottom lines" (Jaklevic, 2003). The materials also provide evidence on how hospitals may have learned of the loopholes. A whistleblower lawsuit filed in New Jersey state court alleges that the consulting firms Besler and Company and Shusko Consulting were the architects of the schemes, advising nearly a dozen hospital executives to engage in this behavior (United States District Court District of New Jersey: 3rd Circuit: Newark, 2010).

Much of the news focused on the for-profit hospital chain Tenet, the subject of Leder-Luis (2023)'s study. This was in part due to Tenet's size and the magnitude of its turbocharge: When charging Tenet with civil fraud, the SEC stated that "by fiscal 2002, Tenet's outlier revenue comprised over 40% of its earnings per share" (Securities and Exchange Comission, 2007). As in cases that targeted nonprofit hospitals, legal documents against Tenet presented evidence that leadership knowingly orchestrated this scheme. The chief operating officer, Thomas Mackey, was one of the parties sued. The case against him (Securities and Exchange Comission, 2009) detailed his role and the mechanism by which Tenet gamed outlier payments:

> The complaint alleges that Mackey, of Keswick, Virginia, was the principal architect of Tenet's scheme to inflate its earnings by exploiting Medicare's outlier reimbursement regulations, which provided for additional reimbursement to hospitals to cover the additional costs for treating extraordinarily sick patients. Mackey realized that additional outlier reimbursement could be triggered simply by increasing Tenet's gross charges, regardless of the actual cost incurred by

> Tenet to treat its Medicare patients. In 1999, and under Mackey's direction, Tenet management calculated the precise increase to Tenet's gross charges needed to boost its revenue from Medicare outlier payments to a level that would allow Tenet to reach its earnings targets. For the next three years, Mackey continued to oversee aggressive gross charge increases by Tenet.

This quote and other materials included in the lawsuits against Tenet suggest that this behavior was a top-down administrative strategy to increase revenues. Unsurprisingly, we find that most hospitals within the Tenet system engaged in gaming according to our definition, and we detect it in many of the other hospitals mentioned in the lawsuits. Ultimately, whistleblowers came forward in many of these organizations, which helped to pressure the government to close the loophole and pursue legal cases against the turbocharging hospitals (U.S. Department of Justice, 2006a,b, 2010).

Based on its own algorithm to identify gaming, CMS suggested 123 hospitals engaged in turbocharging, but did not provide a list of these hospitals (United States Senate, 2003). Using our methodology, which addresses several weaknesses in the CMS algorithm (see Section 4.1 of the main text), we tagged 180 hospitals as turbochargers. However, this is a conservative estimate based on restrictive cut-offs and more hospitals likely gamed the outlier payments program during this period.

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B Calculating and Simulating Outlier Payments

This appendix describes the formulas used by CMS to make outlier payments and explains how we calculate payments holding formulas constant. To do so, we make a number of simplifying assumptions, which we detail below.

B.1 Calculating DRG Payments

Because the hospital's "deductible" for outlier payments depends on the hospital's DRG payments, we begin by calculating the DRG payments. The payments for patient i in DRG d, at hospital h, in fiscal year t can be given by the following formula:

$$DRGPAY_i = WEIGHT_{d,t} \times BASE_{u(h),t} \times \left(\theta_t^L WAGE_{h,t} + \theta_t^{NL} COLA_{h,t}\right), \tag{B.1}$$

where $WEIGHT$ is the weight of the DRG, a measure of expected resource utilization that is updated annually; $BASE$ is the national base payment rate for the hospital's area urbanicity $u(h)$ (large urban area, other urban area, or rural) in that year; θ^L and θ^{NL} are the labor and non-labor shares, respectively; $WAGE$ is the hospital's area wage index; and $COLA$ is the area cost-of-living adjustment (which increases non-labor payments in Alaska and Hawaii).

We collected $WEIGHT$ from annual DRG weight files posted online by the NBER (National Bureau of Economic Research, 2025). $BASE$ and θ came from the PC PRICER COBOL code available from CMS (CMS, 2021). $WAGE$ and $COLA$ came from annual CMS Impact files.

In practice, this formula matches Medicare's actual formula for operating DRG payments for the years in question. It does not include capital payments; operating payments make up the bulk of total payments during the gaming period. The formula here also omits some add-on payments and adjustments. For instance, the formula does not include adjustments for teaching or safety net hospitals. It also omits a change to the θ that puts more weight on non-labor costs for low wage index hospitals starting in FY2005, after the main gaming period had ended.

B.2 Calculating Outlier Payments

Formula-Constant Payment Threshold

We next turn to calculating outlier payments. As with the DRG payment calculation, we focus again on operating payments and not capital payments, though the two use similar formulas. The first key calculation is determining the cost threshold beyond which hospitals will receive these payments. The threshold is hospital-specific and calculated as follows:

$$THRESH_{h,t} = \overline{THRESH}_t \times \left(\theta_t^L WAGE_{h,t} + \theta_t^{NL} COLA_{h,t}\right) \times OPSH_{h,t}, \tag{B.2}$$

where $\overline{THRESH}$ is a national threshold published by Medicare each fiscal year and the term in parentheses adjusts it for the hospital's area wage index and area cost-of-living. The final term is the hospital's share of charges devoted to operating costs and is defined as:

$$OPSH_{h,t} = \frac{CCR_{h,t}^{OP}}{CCR_{h,t}^{OP} + CCR_{h,t}^{CAP}}, \tag{B.3}$$

where $CCR^{OP}_{h,t}$ is the hospital's operating cost-to-charge ratio and $CCR^{CAP}_{h,t}$ is its capital cost-to-charge ratio. We observe $\overline{THRESH}$ in PC PRICER COBOL code and obtain CCR from the CMS Provider-Specific File, when available, and otherwise from CMS Impact files.

In practice, the national threshold was endogenous to gaming. Because Medicare did not understand that rising outlier payments came from excess charge growth, it responded by dramatically raising the threshold. In 1997, the threshold was $9,700, but by 2003, it had grown to $33,560.

We therefore must calculate a threshold that does not grow with gaming. To do so, we assume that absent gaming, the threshold would have been a fixed ratio of the national base payment rate $BASE$. Specifically, we estimate the following ratio for each month m during the fiscal years 2004-2008, after the loopholes were closed and outlier payment stabilized:

$$R_m = \frac{\overline{THRESH}_t}{\overline{BASE}_t},\ \overline{BASE}_t = \sum_u s_u \cdot BASE_{u,t}, \tag{B.4}$$

where s_u is the share of inpatient prospective payment system (IPPS) hospitals in urbanicity u in 1997 according to the CMS Impact file. The denominator $\overline{BASE}$ is the weighted average base payment rate across IPPS hospitals in that year. Let $\bar{R}$ be the average of the R_m, which we estimate to be 9.31.

We now define the formula-constant national threshold in each year as:

$$\overline{THRESH}_t^{FC} = \bar{R} \times \overline{BASE}_t. \tag{B.5}$$

And the formula-constant hospital-specific threshold is:

$$THRESH^{FC}_{h,t} = \overline{THRESH}_t^{FC} \times \left(\theta^L_t WAGE_{h,t} + \theta^{NL}_t COLA_{h,t}\right) \times OPSH_{h,t}. \tag{B.6}$$

Calculating Payments

With the DRG payment and outlier thresholds now known, we can calculate the outlier payment owed to the hospital for a given patient. The patient's "bill cost" is defined as their charges scaled by the cost-to-charge ratio:

$$BILLCOST_i = CHARGES_i \times CCR^{OP}_{h,t}. \tag{B.7}$$

It is immediately apparent from this formula that when hospitals grow their charges but the cost-to-charge ratio is not updated, the "bill cost" term will rise.

Now, we can calculate outlier payments. The "deductible" that hospitals must hit before Medicare begins making payments equals the threshold plus the DRG payment. Beyond this point, Medicare pays 80% at the margin. The general formula for these payments is:

$$OUTLIER_i = 0.8 \times \max\left(BILLCOST_i - THRESH_{h,t} - DRGPAY_i, 0\right). \tag{B.8}$$

Formula-constant outlier payments are thus equal to:

$$OUTLIER^{FC}_i = 0.8 \times \max\left(BILLCOST_i - THRESH^{FC}_{h,t} - DRGPAY_i, 0\right). \tag{B.9}$$

Other Formula Changes

The aforementioned formulas closely reflect the actual formulas used to calculate outlier payments during the gaming period. By design, they ignore certain formula changes that occurred during the full analysis period. For completeness, we now mention several of the key differences:

1. Before FY1995, the outlier payment threshold given by equation B.2 was calculated differently. It was the greater of two times the patient's DRG payment or an adjusted national threshold. At this time, only $THRESH$ (not $DRGPAY$) was subtracted from $BILLCOST$ to determine the outlier payment in equation B.9.

2. We hold fixed the marginal cost factor, written as 0.8 in equation B.9. Before FY1995, the marginal cost factor was 0.75. It changed to 0.8 in FY1995. In all years, Medicare used a higher marginal cost factor for burn DRGs of 0.9, which we ignore.

3. We ignore teaching and safety net adjustments, mimicking our approach for calculating DRG payments. In turn, we ignore a change in these adjustments. Before FY1998, charges were scaled down by these adjustments in equation B.7, but the outlier payments given by equation B.9 were scaled up by the adjustments. In FY1998, both of these scalings were dropped.

4. We ignore day outliers. This alternative outlier payment mechanism compensated hospitals for patients with long lengths of stay. When a patient would have emitted both day outlier payments and the outlier payments described here (called cost outliers), the hospital was paid the greater of the two amounts. Day outliers were phased out over time and eliminated in FY1998, with the funds set aside for them reallocated to cost outliers.

B.3 Holding Patients Constant

Our main approach to identifying gamers and non-gamers uses a constant sample of patients at the hospital and a constant set of outlier payment formulas (described previously), but allows their charges to grow along the actual path followed by the hospital. We now review how we calculate outlier payments under this approach.

We begin by assembling the set of patients treated at the hospital in FY1995-1996. Let t_0 be the fiscal year in which the patient was discharged and t be the target fiscal year for which we aim to simulate payments. We simulate the patient's DRG payment using the patient's actual DRG weight and the other parameters from the target year:

$$DRGPAY_i^{PC,t} = WEIGHT_{d,t_0} \times BASE_{u(h),t} \times \left(\theta_t^L WAGE_{h,t} + \theta_t^{NL} COLA_{h,t}\right). \quad \text{(B.10)}$$

To determine the "cost" of the patient as perceived to Medicare, we must scale their charges. To do so, define $\overline{CHARGES}_{h,t}$ as the average charge for patients at hospital h in fiscal year t. Then we can write:

$$BILLCOST_i^{PC,t} = CHARGES_i \times \frac{\overline{CHARGES}_{h,t}}{\overline{CHARGES}_{h,t_0}} \times CCR_{h,t}^{OP}. \quad \text{(B.11)}$$

Finally, we use these objects to calculate formula-constant outlier payments for the patient:

$$OUTLIER_i^{PC,t} = 0.8 \times \max\left(BILLCOST_i^{PC,t} - THRESH_{h,t}^{FC} - DRGPAY_i^{PC,t}, 0\right). \tag{B.12}$$

We now have, for every FY1995-1996 patient, their simulated DRG and outlier payments in each target fiscal year from 1993 through 2008. In practice, we use this data to calculate quarterly average DRG and outlier payments at each hospital holding both patients and formulas constant. To construct this series, we assume each patient is treated in the same quarter in the target year as in their actual treatment year.

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C Flow of Funds Calculation

We use cost report data to trace uses of excess revenue. We begin with the definitions. First, we define net worth (sometimes referred to as fund balance, net assets, or owner's equity) as assets minus liabilities:

$$NetWorth_t = Assets_t - Liabilities_t.$$

Assets include spending on fixed assets such as healthcare-specific equipment, as well as financial assets such as stocks and bonds. Liabilities represent the economic obligations of the organization to outsiders.

Next, we define net income as income less operating costs:

$$NetIncome_t = Income_t - OperatingCost_t.$$

In a hospital, income mainly comprises net revenue from patients (i.e., gross revenue less contractual discounts) and investment revenue, while operating costs primarily include spending on staffing and hospital services.

Finally, we define net deductions as deductions less additions to the hospital's net worth (i.e., fund balance):

$$NetDeductions_t = Deductions_t - Additions_t.$$

Unfortunately, we do not observe the descriptions of specific deductions and additions in our data. However, in general, net deductions capture transfers off the balance sheet, often to the parent company, other affiliates, or in the case of for-profit firms, shareholders.

Net income flows to net worth unless it is deducted, leading to the following identity in hospital cost reporting:

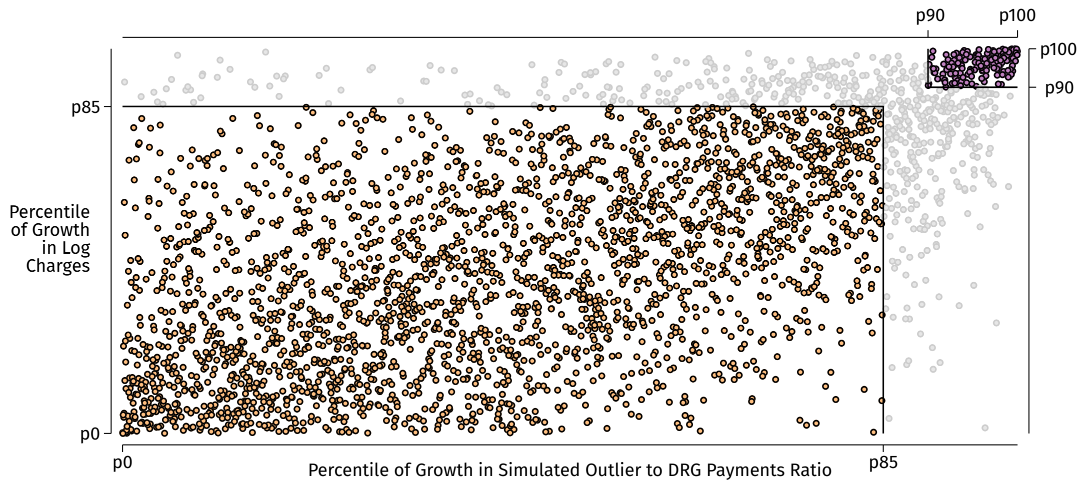
$$\Delta NetWorth_t = NetIncome_t - NetDeductions_t.$$

Finally, we expand $NetIncome$ and rearrange to produce the following identity with the three mutually exclusive and exhaustive outflow categories shown in the manuscript:

$$Income_t = OperatingCost_t + \Delta NetWorth_t + NetDeductions_t.$$

D Supplementary Figures and Tables

(a) Designating gamers (percentile values)



(b) Designating gamers (absolute values)

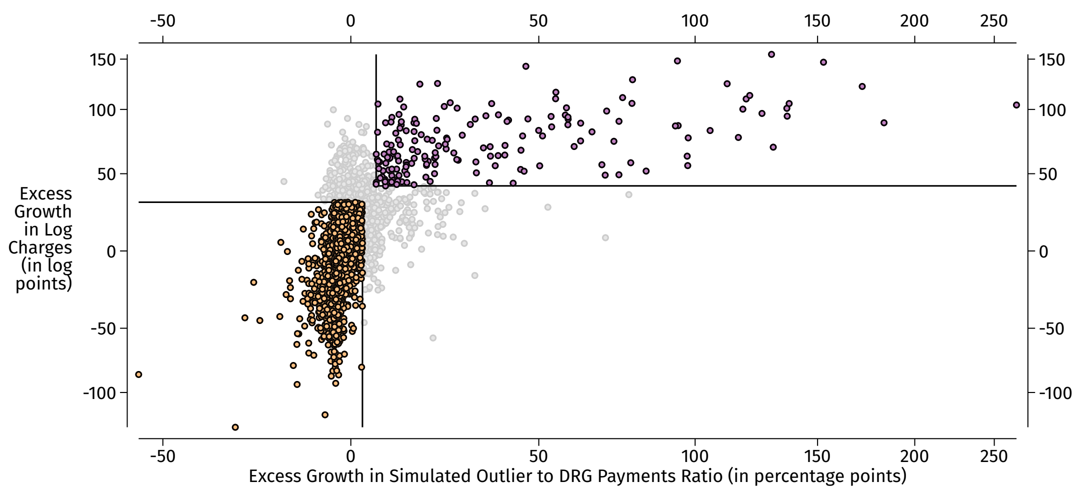
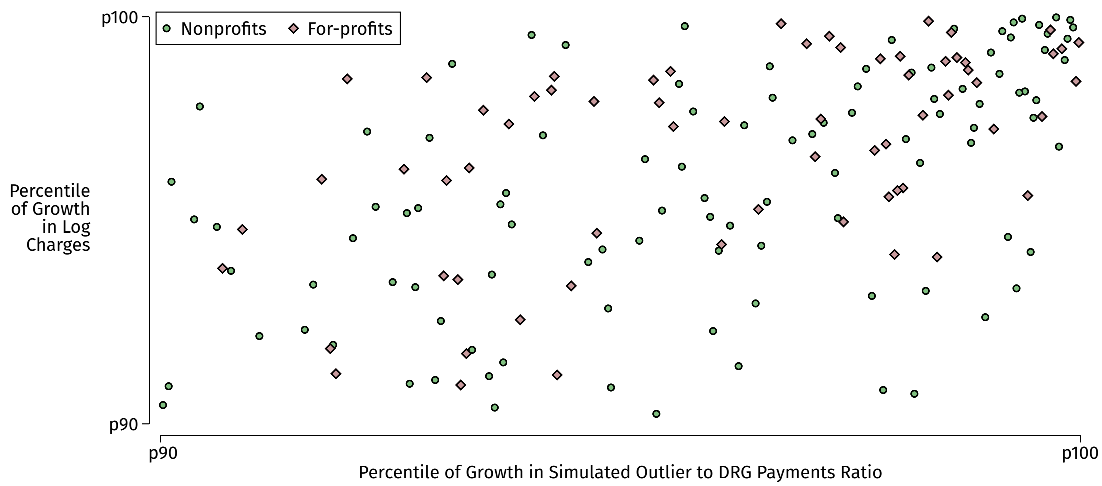


Figure D.1: Designating hospitals as "gamers"

Notes: These figures illustrate our approach to arriving at the set of hospitals we study as potential gamers. Each panel is a scatter plot with each dot denoting a separate hospital. The X-axis plots the growth in the ratio of simulated outlier payments to simulated DRG payments. The Y-axis plots the growth in log hospital charges. In Panel (a), the scales are in percentile terms, while in Panel (b), the scales are in absolute terms, and the axes use inverse hyperbolic sine to better display extreme values. Our approach to calculating growth rates is described in the main text. Hospitals that are on or above the 90^{th} percentile on both dimensions are designated "gamers" and constitute the "treated" group in our analysis. Hospitals above the 85^{th} percentile but below the 90^{th} percentile on one or both dimensions are excluded from the sample because their gaming status is indeterminate. Hospitals below the 85^{th} percentile on both dimensions form the pool of potential comparison hospitals. We further restrict the samples as described in the main text to form the analysis sample.

(a) Designating gamers, by ownership



(b) Gaming intensity by ownership

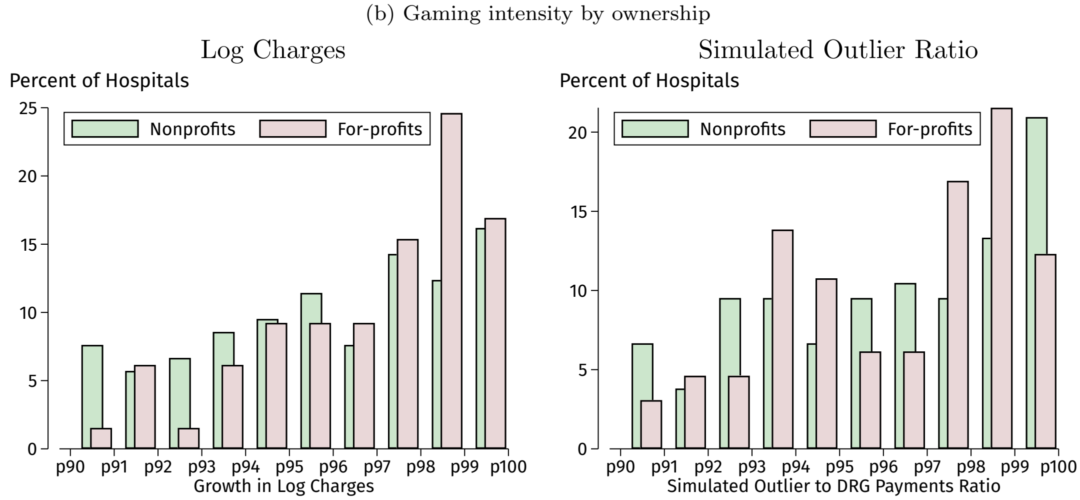


Figure D.2: Hospital ownership and gaming intensity

Notes: These figures illustrate the relationship between hospital ownership and the intensity of gaming. Panel (a) zooms in on the upper right area (p90+ on both axes) of Figure D.1(a). It distinguishes nonprofit and for-profit facilities. The limited number of flagged facilities that are government-owned or of unknown ownership, 10 in total, are suppressed. Panel (b) presents histograms of gaming intensity among the facilities displayed in upper panel. It shows distributions along the two dimensions used to define gaming, as described in the main text.

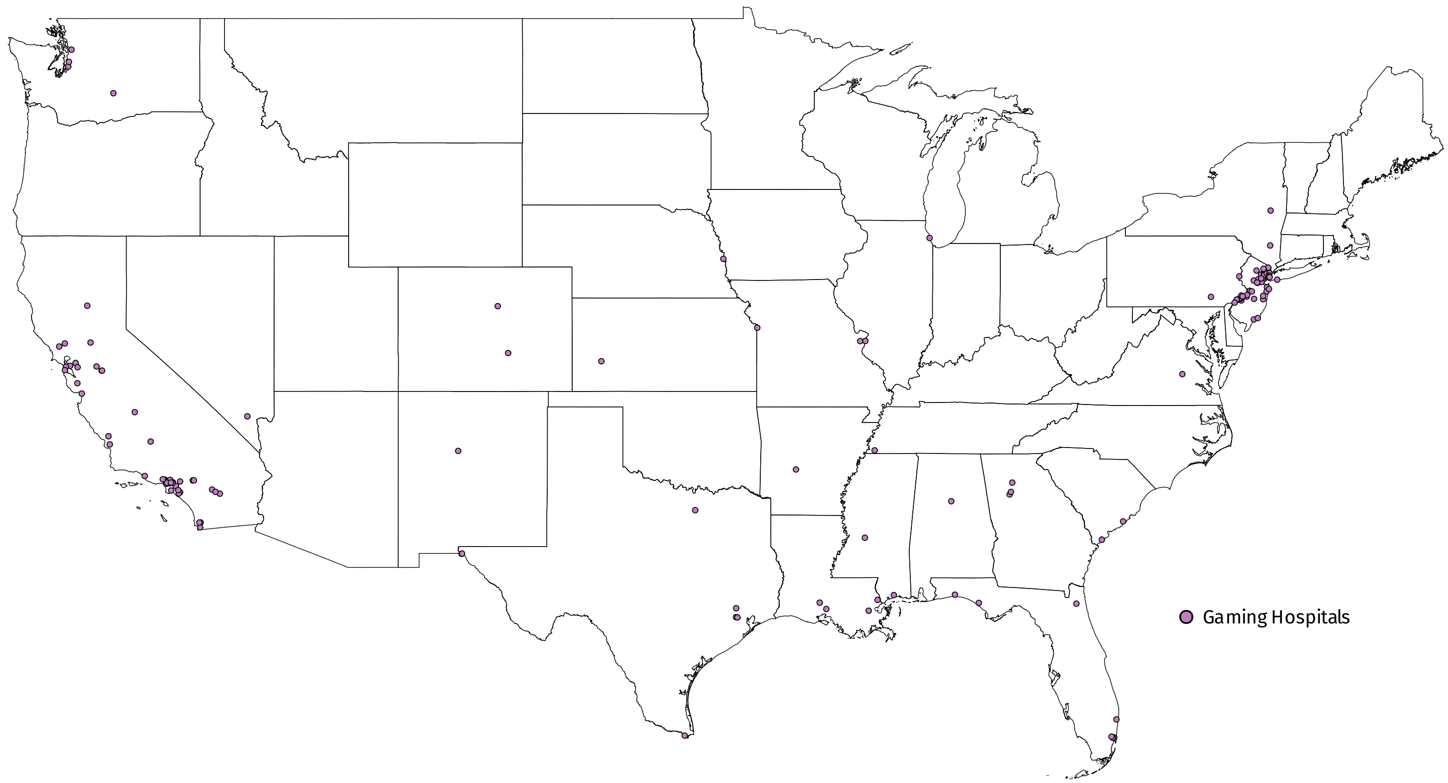
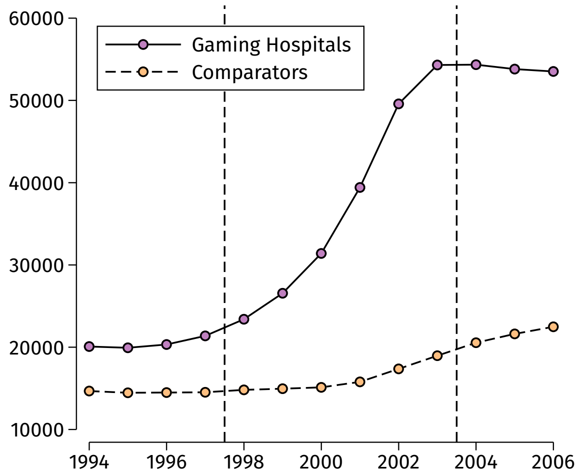


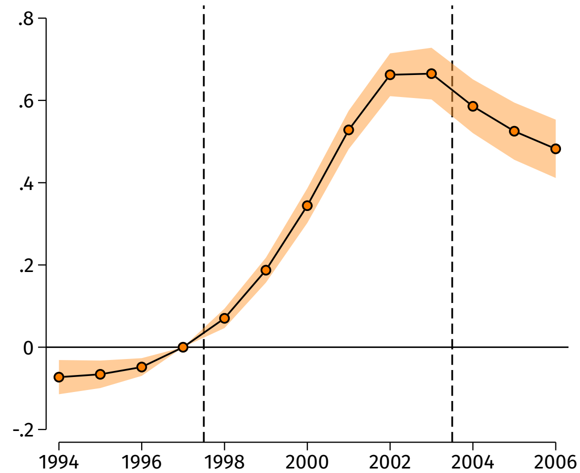
Figure D.3: Map of hospitals flagged as "gamers"

Notes: This figure displays the geographic distribution of the hospitals flagged as gamers of outlier payments and meeting analysis criteria. Hospital latitude and longitude are taken from American Hospital Association (2025) if available and otherwise from the hospital's ZIP code using data from Chandra et al. (2016); GeoNames (2025); SAS (2025). Map drawn from U.S. cartographic boundary files (U.S. Census, 2024).

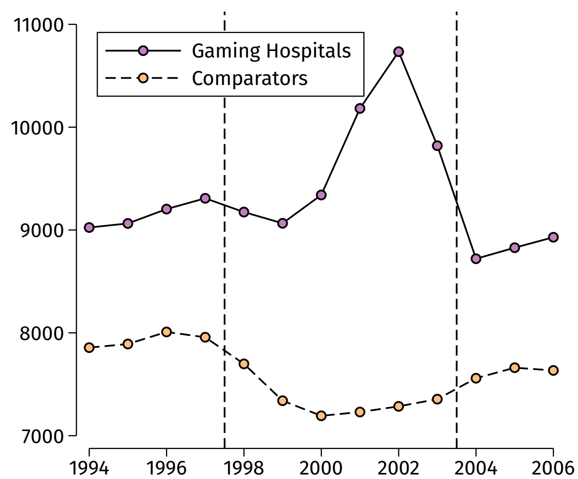
(a) Time Series, Charges per Patient



(b) Event Study, Log Charges per Patient



(c) Time Series, Payments per Patient



(d) Event Study, Log Payments per Patient

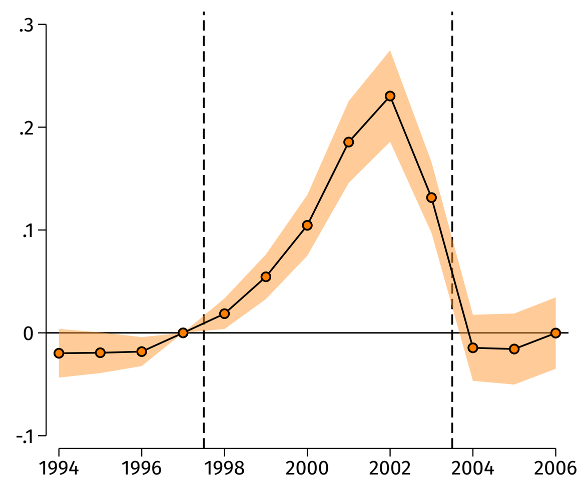


Figure D.4: Time Series and Event Study Plots of Medicare Inpatient Charges and Payments Per Patient

Notes: These figures visualize the evolution of average charges and payments per Medicare inpatient at hospitals in the analysis sample. Panel (a) plots average charges at gamers and non-gamers in the analysis sample, with the non-gamers weighted with the CEM weights used in regressions. Panel (b) shows the event study for average charges estimated with a Poisson model, so that the coefficients have a log-point interpretation. In the equation 2 (DD) analog to the event study, the average effect over the 1998–2003 period is 46.3 log points (s.e. 1.85), and the effect for just the 2001–2003 period is 67.1 log points (s.e. 2.41). Panels (c) and (d) present analogous exhibits for average Medicare inpatient payments. In the DD analog to the event study, the average effect over the 1998–2003 period is 13.5 log points (s.e. 1.33). The effect for just the 2001–2003 period is 19.7 log points (s.e. 1.85).

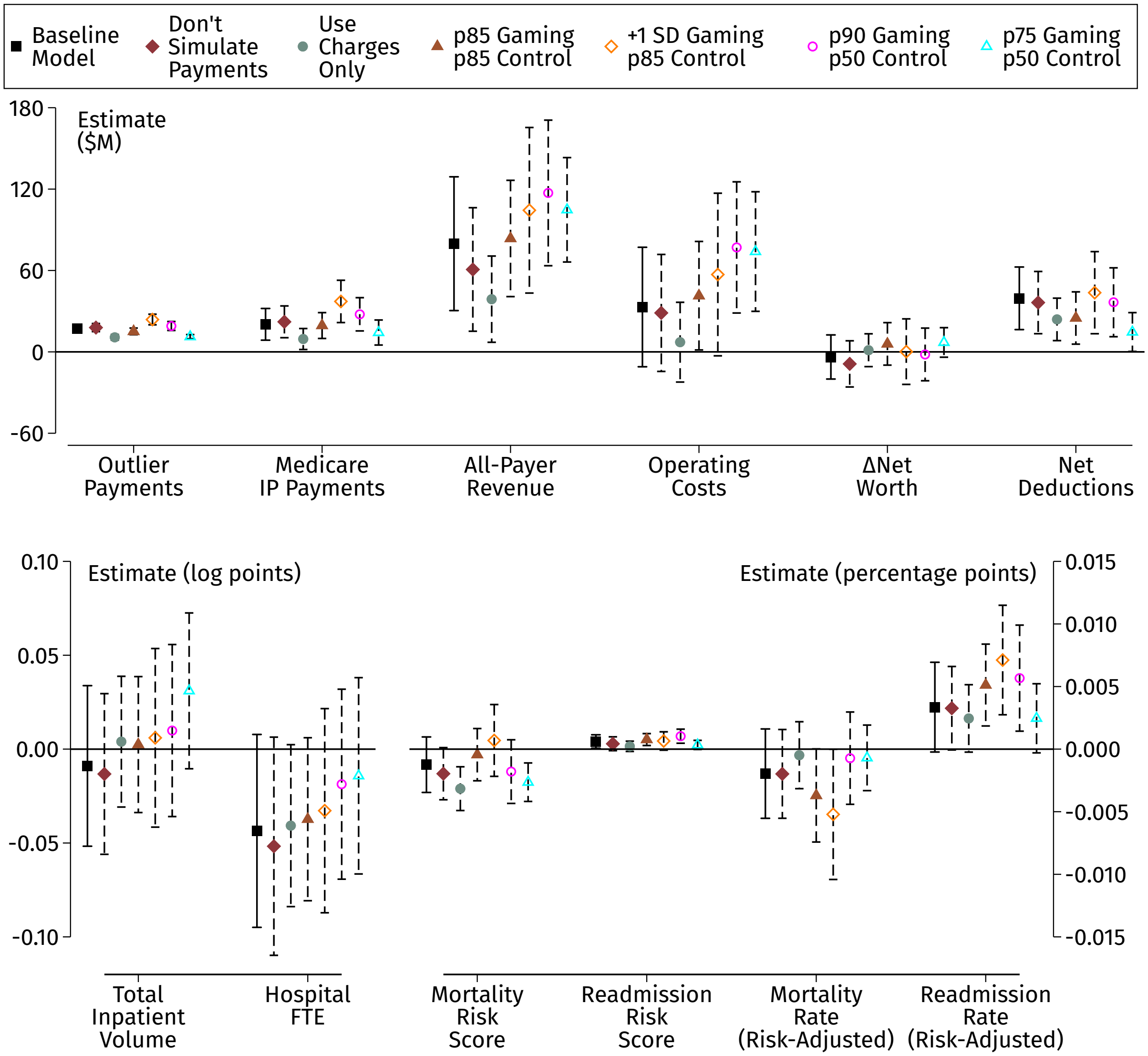


Figure D.5: Robustness checks: Alternate definitions of gaming

Notes: The figure presents estimates obtained from a number of robustness checks against using alternate definitions of gamers for key outcomes presented in Table 2. The dollar-valued estimates in the upper plot are analogous to the estimates from Table 2 column 2 multiplied by 6 to reflect the total flow over 1998–2003. The log point and percentage point estimates in the lower plot are analogous to the Table 2 column 2 estimates without multiplication to reflect the average effect during 1998–2003. See the main text for more details on the robustness models. The error bars depict 95% confidence intervals. Standard errors are clustered by hospital, which is the level of treatment in this analysis.

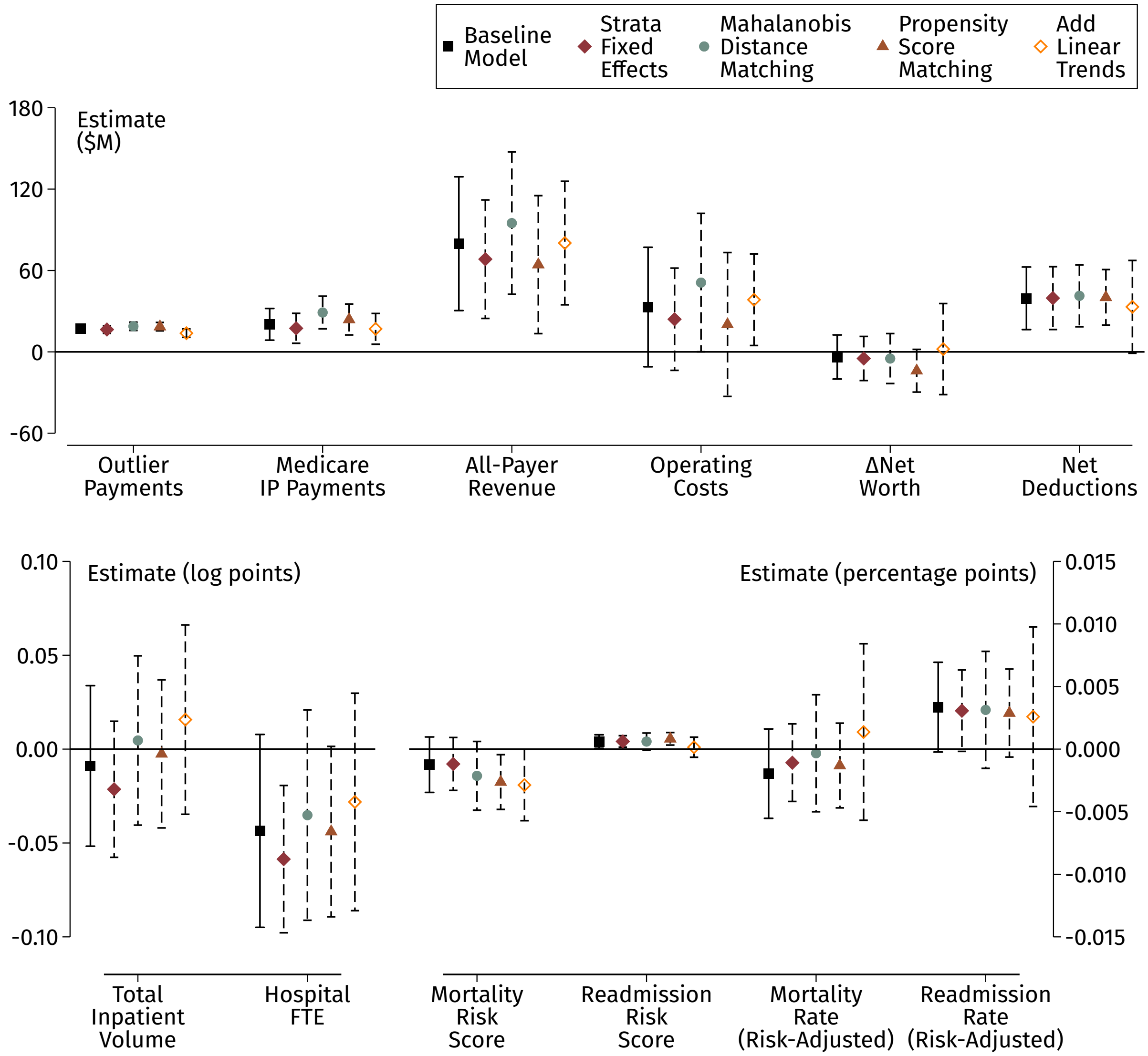


Figure D.6: Robustness checks: Alternate modeling assumptions

Notes: The figure presents estimates obtained from a number of robustness checks against changes to modeling assumptions for key outcomes presented in Table 2. The dollar-valued estimates in the upper plot are analogous to the estimates from Table 2 column 2 multiplied by 6 to reflect the total flow over 1998–2003. The log point and percentage point estimates in the lower plot are analogous to the Table 2 column 2 estimates without multiplication to reflect the average effect during 1998–2003. See the main text for more details on the robustness models. The error bars depict 95% confidence intervals. Standard errors are clustered by hospital, which is the level of treatment in this analysis.

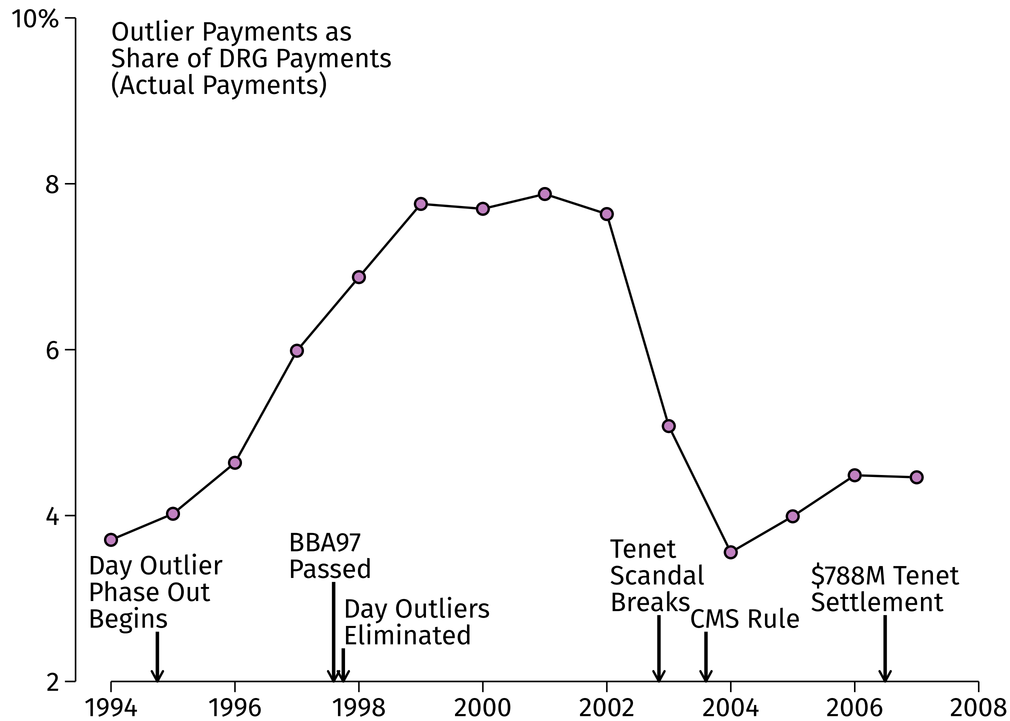


Figure D.7: Trend in Medicare outlier payments, actual payments

Notes: The figure presents outlier payments as a share of DRG (non-outlier) Medicare hospital payments, using actual payments made by Medicare during the time period. We also note key events associated with the Tenet scandal over this period. This plot differs in several ways from Figure 2, which shows the same time series using simulated payments holding the outlier formula constant. First, the CMS data does not allow us to distinguish "cost" outliers, the focus of this study and Figure 2, from "day" outliers, which were not gamed and are not our focus. We therefore show the sum of both here. Unfortunately, day outlier payments were phased out in the mid 1990s, obscuring when gaming began in this version. Second, while the figure in the main text holds outlier payment formulas constant, the figure here is based on payment formulas, including the "deductible", which update annually. Since CMS raised the deductible to blunt growth in payments, this feature of the data also obscures the scope and timing of gaming here. Third, in the CMS data we use, the DRG payments include both capital and operating payments, while the outlier payments include only operating outlier payments; the figure in the main text simulates only operating payments for both series. See Appendix B for more details on the outlier payment formulas and calculations.

Table D.1: Characteristics of Gamers

	(1)	(2)	(3)	(4)
	Bivariate Regressions		Multivariate Regressions	
	Charge Growth >p90	Flagged as Gamer	Charge Growth >p90	Flagged as Gamer
Payment Parameters				
Wage Index	0.354***	0.246***	0.420***	0.293***
	(0.0354)	(0.0269)	(0.0489)	(0.0393)
Safety Net (DSH) Adjustment	0.249***	0.263***	0.269***	0.243***
	(0.0554)	(0.0492)	(0.0718)	(0.0645)
Teaching (IME) Adjustment	-0.0175	0.117*	-0.268***	-0.168**
	(0.0534)	(0.0489)	(0.0668)	(0.0614)
Additional Hospital Characteristics				
Medicare Inpatient Share	-0.169***	-0.185***	0.0722	0.0313
	(0.0411)	(0.0310)	(0.0521)	(0.0351)
ln(Beds)	0.0215***	0.0338***	0.0159*	0.0208***
	(0.00596)	(0.00417)	(0.00700)	(0.00495)
Urban	0.0692***	0.0690***	-0.0288*	-0.0173*
	(0.00988)	(0.00616)	(0.0125)	(0.00765)
In System	0.0772***	0.0375***	0.0336**	0.0163*
	(0.0104)	(0.00775)	(0.0103)	(0.00770)
Ownership (Ref: Nonprofit)				
For-Profit	0.148***	0.0682***	0.140***	0.0651***
	(0.0202)	(0.0155)	(0.0210)	(0.0156)
Government	-0.0309**	-0.0352***	-0.00297	-0.00638
	(0.0106)	(0.00656)	(0.0110)	(0.00734)
Risk-Adjusted Outcomes (Non-Deferrable Patients)				
Mortality Risk-Adj	-0.177+	0.0213	-0.0214	0.0951
	(0.106)	(0.0768)	(0.110)	(0.0844)
Readmission Risk-Adj	0.194+	0.0880	0.0610	0.00709
	(0.104)	(0.0675)	(0.117)	(0.0718)
Risk Scores (Non-Deferrable Patients)				
Mortality Score	1.433***	0.678**	0.489	0.124
	(0.346)	(0.219)	(0.304)	(0.226)
Readmission Score	1.074	1.272*	-0.814	-0.0488
	(0.805)	(0.627)	(0.988)	(0.718)
Hospitals	3,087	3,087	2,852	2,852

Notes: This table presents the coefficients of a targeting regression that estimates the probability of a hospital turbocharging based on each hospital's characteristics in 1997 using the full hospital sample. The outcome variable for Columns 1 and 3 is equal to 1 if the hospital had charge growth greater than the 90^{th} percentile during the gaming period, and the outcome variable for Columns 2 and 4 is equal to 1 if the hospital was flagged as a gamer according to our algorithm described in Section 4.1. Bivariate regressions between each hospital characteristic and the outcome variables are presented in Columns 1 and 2, and multivariate regressions which jointly measure the influence of all hospital characteristics on each outcome are presented in Columns 3 and 4. Standard errors are in parentheses and are clustered by hospital. For the bivariate regressions, the bottom row reports the number of distinct hospitals in the regressions in the column; the number of hospitals in any individual regression may be lower. DSH: disproportionate share, IME: indirect medical education. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.2: Expanded Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	Gamers		Non-Gamers			
	All	In CEM	All	+ Restrict Markets	+ in CEM	+ Reweight
A. Payment Inputs Used for Matching						
Wage Index	1.115	1.099	0.959	0.944	0.944	1.086
Safety Net (DSH) Adjustment	0.129	0.0898	0.0507	0.0397	0.0278	0.0789
Teaching (IME) Adjustment	0.0516	0.0301	0.0276	0.0239	0.00984	0.0275
Medicare Inpatient Share	0.344	0.360	0.414	0.422	0.430	0.361
B. Additional Hospital Characteristics						
Beds	293.5	275.3	212.5	206.1	190.6	226.1
In System	0.727	0.730	0.528	0.524	0.520	0.523
Medicare Inpatient Payments	37.34	34.34	25.14	24.42	21.60	27.62
All-Payer Revenue	126.1	114.9	89.53	86.61	77.76	101.2
Ownership						
Non-Profit	0.648	0.650	0.859	0.864	0.857	0.866
For-Profit	0.352	0.350	0.141	0.136	0.143	0.134
Location						
Rural	0.0345	0.0417	0.311	0.336	0.350	0.106
Urban	0.966	0.958	0.689	0.664	0.650	0.894
C. Risk Scores (Non-Deferrable Patients)						
Mortality	0.138	0.138	0.134	0.134	0.133	0.134
Readmission	0.136	0.135	0.135	0.135	0.135	0.136
D. Risk-Adjusted Outcomes (Non-Deferrable Patients)						
Mortality	0.139	0.140	0.137	0.137	0.137	0.139
Readmission	0.141	0.139	0.136	0.134	0.133	0.137
Hospitals	145	120	1,789	1,655	1,396	1,396

Notes: The table extends Table 1 to show descriptive statistics on hospitals before matching and those in our final analysis sample. Column 1 presents the mean values for all turbocharging hospitals flagged as gamers by our algorithm that met the sample inclusion criteria. Column 2 limits this group to those that could be matched to a non-gamer hospital using coarsened exact matching (CEM). Column 3 shows means for the set of hospitals flagged as non-gamers. Column 4 removes non-gamers in the same markets as gamers (i.e., within 5 miles of any gamer). Column 5 further restricts to those matched to a gamer with CEM, yielding the set of comparators analyzed in the main text. Column 6 re-weights this group with the same weights used in the main analyses, targeting the treatment on the treated estimand. DSH: disproportionate share, IME: indirect medical education. See Table 1 for additional notes.

Table D.3: Summary Statistics by Hospital Ownership

	(1)	(2)	(3)	(4)	(5)	(6)
	Gamers in CEM			Non-Gamers in CEM, Unweighted		
	All	Non-Profits	For-Profits	All	Non-Profits	For-Profits
A. Payment Inputs Used for Matching						
Wage Index	1.099	1.124	1.053	0.944	0.949	0.913
Safety Net (DSH) Adjustment	0.0898	0.0810	0.106	0.0278	0.0271	0.0324
Teaching (IME) Adjustment	0.0301	0.0438	0.00483	0.00984	0.0107	0.00481
Medicare Inpatient Share	0.360	0.353	0.373	0.430	0.428	0.440
B. Additional Hospital Characteristics						
Beds	275.3	306.6	217.2	190.6	199.5	136.9
In System	0.730	0.595	0.976	0.520	0.461	0.874
Medicare Inpatient Payments	34.34	39.78	24.24	21.60	22.92	13.69
All-Payer Revenue	114.9	131.8	83.83	77.76	81.69	54.02
Ownership						
Non-Profit	0.650	1	0	0.857	1	0
For-Profit	0.350	0	1	0.143	0	1
Location						
Rural	0.0417	0.0256	0.0714	0.350	0.343	0.390
Urban	0.958	0.974	0.929	0.650	0.657	0.610
C. Risk Scores (Non-Deferrable Patients)						
Mortality	0.138	0.137	0.139	0.133	0.132	0.142
Readmission	0.135	0.135	0.137	0.135	0.134	0.136
D. Risk-Adjusted Outcomes (Non-Deferrable Patients)						
Mortality	0.140	0.141	0.139	0.137	0.137	0.136
Readmission	0.139	0.140	0.136	0.133	0.131	0.143
Hospitals	120	78	42	1,396	1,196	200

Notes: The table shows the characteristics of gamers and non-gamers in our main regression analyses by hospital ownership. Column 1 presents the mean values for gamers that entered our main regressions, replicating Column 1 of Table 1. Columns 2 and 3 show, respectively, the nonprofits and for-profits within this group. Column 4 shows means for non-gamers that entered our main regressions, albeit without CEM weights, replicating column 5 of Appendix Table D.2. Columns 5 and 6, respectively, show the nonprofits and for-profits in this group. DSH: disproportionate share, IME: indirect medical education. See Table 1 for additional notes.

Table D.4: Complete Regression Results for Full Sample

	(1) DV Mean	(2) 1998–2000	(3) 2001–2003	(4) 2004–2006	(5) Observations
ln(Medicare Charges/Patient)	20,430.4	0.254***	0.671***	0.577***	19,706
		(0.0198)	(0.0241)	(0.0322)	
Panel A. Income in Increasing Broadness					
Medicare Outlier Payments	1.715	1.331***	4.419***	-0.224	19,699
		(0.235)	(0.347)	(0.177)	
Medicare Inpatient Payments	32.94	1.537+	5.232***	-0.996	19,699
		(0.855)	(1.249)	(1.209)	
ln(Medicare Payments/Patient)	9,150.2	0.0732***	0.197***	0.00417	19,706
		(0.0114)	(0.0185)	(0.0161)	
All-Payer Revenue	111.0	4.794	21.79***	9.442	19531
		(3.142)	(5.781)	(7.841)	
Panel B. Outflows in Mutually Exclusive Categories					
Operating Costs	111.9	0.0624	10.96*	9.244	19586
		(2.754)	(5.054)	(7.097)	
Salaries	46.92	-0.153	1.583	1.904	19,699
		(1.317)	(2.047)	(2.783)	
ΔNet Worth	5.199	-3.317+	2.058	-3.923*	17,949
		(1.768)	(1.450)	(1.636)	
ΔTotal Assets	4.156	0.979	4.329*	-2.739	18,040
		(1.979)	(2.130)	(2.224)	
ΔFixed Assets	0.707	-0.173	0.410	-0.720	17,943
		(0.884)	(0.891)	(1.030)	
ΔLiabilities (subtracted)	-0.662	3.489*	1.989	0.335	18,009
		(1.694)	(1.534)	(1.637)	
Net Deductions	1.703	6.112**	7.048**	2.666	17,949
		(2.187)	(2.258)	(1.761)	
Panel C. Care Inputs					
ln(Total Inpatient Volume)	10812.4	-0.0160	-0.00192	-0.0185	19,519
		(0.0209)	(0.0256)	(0.0297)	
ln(Hospital FTE)	1076.8	-0.0526*	-0.0345	-0.0719+	19,505
		(0.0243)	(0.0312)	(0.0391)	
Panel D. Patient Risk (Non-Deferrable Conditions)					
Mortality	0.134	-0.000917	-0.00157	0.000200	19,064
		(0.00109)	(0.00139)	(0.00161)	
Readmission	0.135	0.000274	0.000941**	0.00134**	19,064
		(0.000259)	(0.000345)	(0.000476)	
Panel E. Patient Outcomes (Non-Deferrable Conditions)					
Mortality	0.139	-0.00208	-0.00183	-0.00166	19,064
		(0.00193)	(0.00219)	(0.00230)	
Readmission	0.134	0.00463*	0.00208	0.00238	19,064
		(0.00198)	(0.00213)	(0.00211)	

Notes: This table presents our complete regression results for the full sample. Each row presents effects on a different dependent variable estimated using Equation 2. Column 1 shows the mean of the dependent variables for gamers in the sample during 1994-1997. Columns 2-4 present, sequentially, the regression coefficients for the early (1998–2000) and late (2001–2003) gaming periods followed by the coefficient for the post-gaming period (2004–2006). Column 5 displays the number of observations in the regression. Effects on Medicare charges per patient and payments per patient are estimated using Poisson regression; these coefficients have a log-point interpretation. Standard errors are in parentheses and are clustered by hospital. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.5: Complete Regression Results for Effects for Nonprofit Gamers

	(1) DV Mean	(2) 1998–2000	(3) 2001–2003	(4) 2004–2006	(5) Observations
ln(Medicare Charges/Patient)	19,237.3	0.208***	0.672***	0.635***	15,819
		(0.0275)	(0.0310)	(0.0403)	
Panel A. Income in Increasing Broadness					
Medicare Outlier Payments	1.908	1.225***	4.580***	-0.259	15,813
		(0.303)	(0.431)	(0.241)	
Medicare Inpatient Payments	38.61	1.409	4.987**	-0.387	15,813
		(1.192)	(1.554)	(1.612)	
ln(Medicare Payments/Patient)	9,091.7	0.0790***	0.202***	0.0381*	15,819
		(0.0143)	(0.0200)	(0.0192)	
All-Payer Revenue	127.6	4.456	25.48**	20.41+	15,670
		(4.168)	(8.050)	(11.13)	
Panel B. Outflows in Mutually Exclusive Categories					
Operating Costs	132.8	2.998	16.19*	18.21+	15,705
		(3.879)	(7.165)	(10.14)	
Salaries	57.50	0.724	3.384	5.863	15,813
		(1.960)	(3.002)	(4.031)	
ΔNet Worth	4.682	-1.665	4.509*	-1.706	14,407
		(2.036)	(1.834)	(1.908)	
ΔTotal Assets	4.444	2.579	7.622**	0.931	14,465
		(2.691)	(2.886)	(3.144)	
ΔFixed Assets	0.781	0.192	0.966	0.717	14,389
		(1.162)	(1.184)	(1.374)	
ΔLiabilities (subtracted)	-0.300	3.716+	3.332	1.551	14,436
		(2.205)	(2.089)	(2.246)	
Net Deductions	0.540	2.392	3.718	3.362	14,407
		(2.252)	(2.399)	(2.172)	
Panel C. Care Inputs					
ln(Total Inpatient Volume)	12,576.0	-0.0285	-0.0204	-0.0310	15,679
		(0.0241)	(0.0300)	(0.0346)	
ln(Hospital FTE)	1,306.4	-0.0321	-0.0123	-0.0321	15,667
		(0.0288)	(0.0367)	(0.0468)	
Panel D. Patient Risk (Non-Deferrable Conditions)					
Mortality	0.132	0.00258*	0.00330*	0.00350+	15,344
		(0.00118)	(0.00143)	(0.00184)	
Readmission	0.134	0.000664*	0.00140***	0.00200***	15,344
		(0.000310)	(0.000408)	(0.000551)	
Panel E. Patient Outcomes (Non-Deferrable Conditions)					
Mortality	0.137	-0.00492*	-0.00339	-0.00217	15,344
		(0.00200)	(0.00252)	(0.00245)	
Readmission	0.133	0.00656**	0.00480+	0.00629*	15,344
		(0.00243)	(0.00269)	(0.00245)	

Notes: This table presents our complete regression results for the analysis of effects for nonprofit gamers. Each row presents effects on a different dependent variable estimated using Equation 2. Column 1 shows the mean of the dependent variables for gamers in the sample during 1994-1997. Columns 2-4 present, sequentially, the regression coefficients for the early (1998–2000) and late (2001–2003) gaming periods followed by the coefficient for the post-gaming period (2004–2006). Column 5 displays the number of observations in the regression. Effects on Medicare charges per patient and payments per patient are estimated using Poisson regression; these coefficients have a log-point interpretation. Standard errors are in parentheses and are clustered by hospital. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.6: Complete Regression Results for Effects for For-Profit Gamers

	(1) DV Mean	(2) 1998–2000	(3) 2001–2003	(4) 2004–2006	(5) Observations
ln(Medicare Charges/Patient)	22,646.2	0.325***	0.667***	0.474***	17,601
		(0.0228)	(0.0350)	(0.0389)	
Panel A. Income in Increasing Broadness					
Medicare Outlier Payments	1.355	1.536***	4.128***	-0.148	17,593
		(0.363)	(0.581)	(0.223)	
Medicare Inpatient Payments	22.42	1.725+	5.642**	-2.165	17,593
		(0.940)	(2.011)	(1.512)	
ln(Medicare Payments/Patient)	9,259.0	0.0631***	0.190***	-0.0606**	17,601
		(0.0181)	(0.0372)	(0.0225)	
All-Payer Revenue	80.51	5.165	14.70*	-11.09+	17,431
		(4.267)	(6.236)	(6.021)	
Panel B. Outflows in Mutually Exclusive Categories					
Operating Costs	73.21	-5.578*	1.071	-7.562	17,480
		(2.577)	(4.197)	(4.985)	
Salaries	27.29	-1.943*	-1.995	-5.694**	17,593
		(0.884)	(1.404)	(1.827)	
ΔNet Worth	6.139	-6.483*	-2.551	-8.022**	16,028
		(3.221)	(2.173)	(2.857)	
ΔTotal Assets	3.628	-1.944	-1.716	-9.466***	16,106
		(2.485)	(2.628)	(2.053)	
ΔFixed Assets	0.568	-0.907	-0.698	-3.497**	16,020
		(1.199)	(1.191)	(1.302)	
ΔLiabilities (subtracted)	-1.337	3.251	-0.285	-1.722	16,078
		(2.376)	(1.881)	(1.913)	
Net Deductions	3.818	12.94**	13.21**	1.462	16,028
		(4.375)	(4.440)	(2.909)	
Panel C. Care Inputs					
ln(Total Inpatient Volume)	7,432.2	0.0262	0.0561	0.0255	17,435
		(0.0381)	(0.0428)	(0.0508)	
ln(Hospital FTE)	633.8	-0.119**	-0.103*	-0.199***	17,420
		(0.0388)	(0.0498)	(0.0510)	
Panel D. Patient Risk (Non-Deferrable Conditions)					
Mortality	0.139	-0.00710***	-0.0101***	-0.00550*	17,037
		(0.00172)	(0.00202)	(0.00249)	
Readmission	0.136	-0.000460	0.0000764	0.000107	17,037
		(0.000427)	(0.000577)	(0.000811)	
Panel E. Patient Outcomes (Non-Deferrable Conditions)					
Mortality	0.141	0.00320	0.00109	-0.000598	17,037
		(0.00367)	(0.00380)	(0.00428)	
Readmission	0.136	0.00112	-0.00276	-0.00461	17,037
		(0.00296)	(0.00301)	(0.00319)	

Notes: This table presents our complete regression results for the analysis of effects for for-profit gamers. Each row presents effects on a different dependent variable estimated using Equation 2. Column 1 shows the mean of the dependent variables for gamers in the sample during 1994-1997. Columns 2-4 present, sequentially, the regression coefficients for the early (1998–2000) and late (2001–2003) gaming periods followed by the coefficient for the post-gaming period (2004–2006). Column 5 displays the number of observations in the regression. Effects on Medicare charges per patient and payments per patient are estimated using Poisson regression; these coefficients have a log-point interpretation. Standard errors are in parentheses and are clustered by hospital. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.7: Effects on Cost Components for Nonprofits

	(1) DV Mean	(2) 1998–2000	(3) 2001–2003	(4) 1998–2003	(5) Observations
A. Estimates Using Full Sample					
Operating Costs	132.8	2.998	16.19*	9.594+	15,705
		(3.879)	(7.165)	(5.286)	
Direct Costs	127.5	3.219	13.77*	8.494+	15,813
		(3.726)	(6.843)	(5.079)	
Salaries	57.50	0.724	3.384	2.054	15,813
		(1.960)	(3.002)	(2.395)	
Other (Non-Salary)	70.03	2.567	10.41*	6.487*	15,813
		(2.220)	(4.531)	(3.242)	
B. Estimates Using Data Starting in 1997					
Operating Costs	138.7	1.957	15.08*	8.520*	12,083
		(2.605)	(6.267)	(4.214)	
Direct Costs	133.7	0.608	11.10+	5.852	12,170
		(2.364)	(5.816)	(3.890)	
Salaries	59.28	-0.126	2.515	1.195	12,170
		(1.401)	(2.614)	(1.924)	
Other (Non-Salary)	74.44	0.701	8.498*	4.599+	12,170
		(1.555)	(4.000)	(2.644)	
Clinical	32.23	1.088	4.564*	2.826+	12,170
		(0.934)	(2.211)	(1.529)	
Admin	17.34	-0.789	2.088	0.650	12,170
		(1.048)	(1.683)	(1.256)	
Mixed	22.73	-0.460	0.392	-0.0336	12,170
		(0.775)	(1.182)	(0.920)	

Notes: The table presents the coefficients estimated using Equation 2 for nonprofit gamers. Each row presents coefficients from a separate regression on a different dependent variable. Column 1 presents the sample mean value of the dependent variable in 1994–1997. Columns 2 and 3 present the coefficients pertaining to the 1998–2000 and 2001–03 periods, respectively. Column 4 presents the average coefficient across 1998–2003. Column 5 presents the number of observations used for each regression. All dollar values are expressed in millions of real year 2000 dollars. The values for operating costs are repeated from Table 2. Direct costs are a slightly narrower measure of expenditures and are divided into salaries and other (non-salary) costs. Panel A uses all years of data, while Panel B uses data beginning in 1997, when our data reliably covers finely disaggregated expenditure categories. It then uses this data to show a decomposition of costs into clinical, administrative, and mixed clinical/administrative costs. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.8: Outcomes that are less likely to be affected by turbocharging

	(1) DV Mean	(2) During Gaming	(3) DV (NPs)	(4) During (NPs)	(5) DV (FPs)	(6) During (FPs)
Medicare Payments ex. Outliers	31.08	-0.543	36.56	-0.712	20.91	-0.286
		(0.662)		(0.878)		(0.849)
ln(Non-Medicare Inpatient Volume)	7193.7	0.00142	8395.2	-0.0150	4890.9	0.0561
		(0.0266)		(0.0306)		(0.0487)
ln(Hospital Beds)	273.8	-0.0271	307.2	-0.0340	211.8	-0.00964
		(0.0215)		(0.0264)		(0.0310)

Notes: This table presents our main pooled, nonprofit, and for-profit results for a set of plausibly unaffected outcomes where each row presents effects on a dependent variable estimated using Equation 2. The columns sequentially show results for all gamers, nonprofit gamers, and for-profit gamers. The odd columns show the mean of the dependent variables for gamers during 1994–1997. The even columns present the average coefficient for gaming for the 1998–2003 period. Standard errors are in parentheses and are clustered by hospital. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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